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The role of carbon tax in the transition from a linear economy to a circular economy business model in manufacturing

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ABSTRACT

In recent years, the need to adopt Circular Economy (CE) business models has become increasingly evident. Nevertheless, the adoption of CE business models remains low, with companies continuing to use Linear Economy (LE) models. However, this may change with recent governmental measures: governments are increasingly implementing regulations and policies to reduce $CO_{2,eq}$ emissions, potentially encouraging firms to shift from LE to CE business models. Among the various regulations and policies, carbon taxes are prominent due to their effectiveness in reducing $CO_{2,eq}$ emissions. The adoption of carbon taxes could incentivize companies to prefer CE business models over LE, as CE would reduce $CO_{2,eq}$ emissions and, consequently, the taxes to be paid. The literature, however, has overlooked this aspect. No study has yet investigated the role of carbon tax and its influence on the choice between LE and CE business models in manufacturing organizations. This study aims to fill this gap by investigating the role of carbon tax in the choice between LE and CE and in the transition from the former to the latter. An integrated methodological framework was adopted, employing various methodologies, including simulation factorial experiments, sensitivity analyses, and decision tree algorithms. The results indicate that the current carbon tax values are too low to impact the transition from LE to CE. To support governmental bodies in determining the minimum carbon tax value needed to influence the business model decision-making process, carbon tax level curves were developed. The findings reveal that there is no single preferable minimum carbon tax value; instead, this minimum value depends on product characteristics in terms of costs and $CO_{2,eq}$ emissions.

1. Introduction

Human activities are causing ecological crises due to the unsustainable use of the planet's resources and the connected equivalent carbon dioxide ($CO_{2,eq}$) emissions (Persson et al., 2022; Richardson et al., 2023). Consequently, environmental concerns have grown in recent decades, as evidenced by the development of new business models to reduce $CO_{2,eq}$ emissions and limit the use of natural resources (Hauschild et al., 2020; Enyoghasi and Badurdeen, 2021; European Commission, 2024). In this context, circular economy (CE) business models have emerged widely, introducing new ways of designing, producing, and consuming products that enable shifting from the so-called linear economy (LE) to an economy that can reintroduce used products/components/materials at end-of-life (EoL) back into the value chains (Rosa et al., 2020; Enyoghasi and Badurdeen, 2021; Ciano et al., 2025).

However, despite the importance of transitioning towards a CE business model, its adoption is still very limited. In fact, according to CIRCLE Economy (2020), of the 100 billion tons of materials used every year to feed our economy, just 8.6% came from CE business models in 2020. Furthermore, this percentage has decreased, falling to 7.2% in 2022 (CIRCLE Economy, 2023). This trend is not only worrying but also surprising, considering the recent policies adopted by governmental bodies to reduce $CO_{2,eq}$ emissions and, hence, to foster the adoption of less carbon intensive business models (Best et al., 2020; Cao et al., 2020).

This is the case of carbon pricing mechanisms, such as carbon taxes and cap-and-trade systems, that are designed to internalize the environmental costs of carbon emissions, thereby incentivizing businesses to reduce their carbon footprint. Carbon taxes specifically impose a fee on

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the $CO_{2,eq}$ emissions associated with the production of goods and services. In contrast, cap-and-trade systems set a limit ("cap") on the total emissions a company can produce. If companies exceed this limit, they must either purchase additional allowances from lower-emitting companies or face penalties (Konstantaras et al., 2021; Luo et al., 2022).

These policies are considered to play a crucial role in promoting the transition from a LE to a CE by reshaping market dynamics and fostering sustainable business practices (Xu et al., 2017; Tsai et al., 2023; Wu et al., 2024). Ellen MacArthur Foundation (2024) also emphasizes that carbon pricing mechanisms can provide financial incentives for businesses to shift from linear to circular models by increasing the cost of environmentally damaging activities, thus encouraging investments in processes like recycling, remanufacturing, and repair.

In 2022, a review of 1513 articles on carbon policy conducted by Wang et al. (2022) identified the study of circular supply chain under carbon emission cost models as the main research trend in the last years. However, to date, no research has quantitatively examined how such carbon emission cost models affect the transition from LE to CE business models. In fact, as identified by Wang et al. (2022) and detailed in Section 2, existing literature predominantly explores either the tactical/operational and strategic decisions of circular supply chains operating under carbon emission cost models or the effects of these models on the performance of circular supply chains. It does not quantitatively address whether these policies have an impact on fostering this transition. Thus, the real effect of carbon policies on the LE-to-CE shift remains unclear (cf. Section 2). To bridge this gap, this work specifically focuses on carbon taxes, which have been recognized as one of the most effective market-based tools for reducing $CO_{2,eq}$ emissions (Konstantaras et al., 2021; Luo et al., 2022). Consequently, this study aims to address the following research question (RQ):

RQ: What is the role of the carbon tax in the transition from a LE to a CE?

By addressing this RQ, this study helps to identify whether the carbon tax truly influences the adoption of a CE and, if it does, when CE is more advantageous, and when LE is preferable. In doing so, it fills an important gap in the literature that has not yet been addressed, since it is often assumed that – under carbon tax regime - the adoption of CE business models is always to be preferred (Xu et al., 2017; Tsai et al., 2023; Ellen MacArthur Foundation, 2024; Wu et al., 2024). The study is conducted considering both economic and environmental performance of the two business models (CE and LE) and taking into account the product quality. This analysis will provide concrete insights into how carbon tax policies can influence business model decision-making process, promoting the transition to more sustainable practices both economically and environmentally. Furthermore, this work not only considers existing carbon tax regimes (with current carbon tax values) but also investigates how future changes in carbon tax regimes, with the adoption of new carbon tax values, will affect the business model decision-making process.

In doing so, this work offers a multifaceted contribution. First, it offers important insights into the effect of the current carbon tax measures on the business model decision-making process of manufacturing organizations. Furthermore, different scenarios in terms of carbon tax values are considered and analyzed, allowing for a deeper understanding of the carbon tax influences on the transition from a LE to a CE business model. Additionally, it identifies the minimum carbon tax values required to impact the business model decision-making process. This work is beneficial for both policy-makers and decision-makers within manufacturing organizations. Policy-makers gain a deeper understanding of how they can leverage carbon taxes to influence the shift from a LE to a CE business model in manufacturing organizations. Meanwhile, decision-makers now have a better overview of the business model to be adopted and how this choice is affected by changes in carbon tax values. This is something currently missing in the literature.

The remainder of the paper is structured as follows. Section 2 presents a literature review on the current research works on CE and carbon tax. Section 3 describes the problem under consideration and Section 4 reports the adopted methodological framework. Section 5 presents and discusses the results of this research, while section 6 emphases the theoretical and practical contributions, as well as the main limitations of this research that can pave the way for future research avenues. Finally, Section 7 summarizes and concludes the articles.

2. Literature analysis

This section first elaborates on the current research on carbon policy and CE (Section 2.1). This analysis enables the identification of the literature gap, which is described in detail in Section 2.2.

2.1. Current research on carbon policy and circular economy

The literature on CE and carbon policy is relatively recent. The research conducted by Wang et al. (2022) identified the exploration of relationships between circular supply chains, i.e., closed-loop supply chains, and carbon emission cost models as the main research trend on this topic. Such literature body can be furtherly split into two main research streams, which, however, differ from the main purpose of this work.

In fact, the first research stream focuses on decisions both at tactical/operational and strategic levels of circular supply chains under carbon emission cost models (carbon cap, carbon cap-and-trade, etc.). It is worth noting that this research stream is not directly related to the focus of the present study but the key works have been reported for the sake of completeness. Regarding the first level of decisions, i.e., the tactical/operational one, inventory management problems have been primarily investigated. A remarkable example is the study conducted by Liao et al. (2022), which focused on a case study of stringer pallet remanufacturing. The research aimed to investigate how carbon trading prices and uncertainties in market demand influence decision-making about inventory management. To achieve this, the authors proposed an extended economic ordering quantity model designed to optimize both environmental sustainability and economic efficiency. By incorporating empirical data from Beijing's carbon trading center, the study developed a balanced ordering strategy that considers both economic and environmental factors. The work of Jauhari et al. (2024), instead, developed a mathematical inventory model for a closed-loop supply chain involving a single manufacturer and retailer, focusing on stochastic demand, imperfect production, currency exchange rate disparities, green investments, and carbon tax policies. The model highlights the significant influence of carbon tax, production flaws, and exchange rate uncertainties on inventory management. Regarding the strategic level, instead, the literature mainly discusses the design of circular supply chains under carbon tax and other carbon emission cost models. An example is the work of Kondo et al. (2019), which focuses on decisions about supplier selection under carbon reduction schemes. More specifically, considering that different countries adopt different carbon tax values and that $CO_{2,\ eq}$ emissions vary among countries due to different energy mixes, they proposed a decision model for supplier selection that minimizes $CO_{2,eq}$ emissions and costs, taking into account these differences between countries. Similarly, Govindan et al. (2023), incorporated a carbon tax policy in the design of a circular supply chain network, evaluating decisions about supplier selection, facility locations, and order allocation under carbon tax policy. Cheng et al. (2022) and K.E.K et al. (2023), instead, investigated how carbon tax changes the relations among different organizations within the supply chain. The former explored how the implementation of carbon taxes influences the strategy that an Original Equipment Manufacturer (OEM) should use for regulating a Third-Party Remanufacturer activities, while the latter showed how the adoption of carbon tax incentivizes organizations to become involved in a sharing network relation. Similarly, Yu et al. (2023) investigated how a three-echelon closed-loop supply chain cooperation and coordination should change under differentiated carbon tax regulation. Finally, Golpîra and Javanmardan (2022) also addressed the design of a circular supply chains, but their work goes beyond this by considering how different carbon emission cost models influence the economic and environmental performance of the supply chain. More specifically, they considered three different carbon emission schemes: carbon cap, carbon cap-and-trade, and carbon tax. Their results showed that a circular supply chain designed under carbon tax was characterized by the lowest carbon emissions, which confirms the choice of this work to focus on carbon tax as carbon emission scheme.

This work can be considered borderline between the first research stream and the second one. The latter, indeed, focuses on how different carbon emission cost models influence the performance of circular supply chains. While this research stream is more aligned with the focus of the present study, it does not examine whether the carbon tax foster the transition from a LE to a CE, but it directly assesses the impact of carbon policy on economic and/or environmental performance of CE business models, referred as circular supply chains. One of the first works in this field, conducted by Fahimnia et al. (2013), developed an optimization model that balances economic and environmental performance, with carbon emissions expressed in terms of monetary costs. The study shows that while carbon pricing can reduce emissions, it also increases operational costs, and suggests that government subsidies may be necessary to support reverse supply chain activities under higher carbon price. Then, Allevi et al. (2018) analyzed the impact of environmental regulations in EU, such as the EU Emissions Trading System (EU-ETS) and carbon taxes, on the performance of a closed-loop supply chain. The results demonstrate that these regulations lead to reduced $CO_{2,eq}$ emissions, increased costs for manufacturers, and improved recycling efficiency, offering insights into the economic and environmental balance in supply chains under regulatory frameworks. Some years later, Hsieh and Tsai (2023a) performed a case study on knitted footwear circular supply chain and investigated the influence of four different carbon tax regimes on the company profits. They reported that certain carbon tax regimes do not impact company profits, making companies less likely to pay attention to the repercussions of carbon emissions. The same authors, then, extended their work to the glass industry, considering again only a CE business model (Hsieh and Tsai, 2023b). Similarly, Tsai et al. (2023) investigated the impact of different carbon emission schemes (such carbon tax, carbon cap-and-trade, etc.) on the profitability of a paper-making company in Taiwan. Moreover, in addition to investigating the impact of different carbon emission schemes on the company profitability, they also examined their impact on the company's optimal product-mix. Finally, Li et al. (2024) investigated how carbon taxes and tariffs impact transnational closed-loop supply chains. Specifically, they model three remanufacturing scenarios for an OEM that exports products, showing how high carbon tariffs can inadvertently discourage new product development and that carbon taxes are more effective than tariffs in motivating emission reductions.

This literature analysis reveals that there are currently no studies focusing on the impact of carbon tax or other carbon emission cost models on the transition from a LE to a CE. Most existing research primarily concentrates on either the tactical/operational and strategic decisions of circular supply chains operating under carbon emission cost models or the effects of these models on the performance of circular supply chains. This represents a significant gap in the literature because it is generally assumed that the implementation of a carbon tax directly encourages the adoption of CE business models, i.e., circular supply chains (Xu et al., 2017; Tsai et al., 2023; Ellen MacArthur Foundation, 2024; Wu et al., 2024). However, this assumption has not yet been demonstrated. This study aims to explore whether the carbon tax truly affects the transition from LE to CE and, if it does, under what conditions the CE model is more advantageous than the LE model, taking into account both economic and environmental performance.

This point is discussed in greater detail below, which supports the formulation of the RQ for this study.

2.2. Research gap

As highlighted in the previous sub-section, the current literature predominantly focuses on the role of carbon policy within the context of the CE without addressing the critical question of whether carbon tax policies can effectively support the transition from a LE to a CE paradigm. While previous studies (Xu et al., 2017; Tsai et al., 2023; Ellen MacArthur Foundation, 2024; Wu et al., 2024) assert that carbon taxes promote the adoption of CE practices, this claim has not been demonstrated yet. Furthermore, none of the existing research conducts a comparative analysis of LE and CE business models under the influence of carbon tax policies.

This lack of comparative analysis highlights a significant gap in the literature. Specifically, there is limited understanding of how carbon taxes impact the economic and environmental performance of these two business models, and even less insight into the conditions under which circular supply chains become more advantageous than linear ones. Addressing these dynamics is essential for designing effective policies that guide businesses toward sustainable practices.

This gap underscores the importance of the research question formulated in Section 1: "*What is the role of the carbon tax in the transition from an LE to a CE?*" It reflects the need to tackle a fundamental issue that has been overlooked in existing studies.

This study seeks to address this critical gap by quantitatively examining the role of carbon taxes in facilitating the transition from LE to CE. It provides a comprehensive comparative analysis of the performance of both business models under carbon tax regimes. In doing so, this study provides a unique contribution. First, it offers valuable insights into how current carbon tax measures influence the business model decision-making processes of manufacturing organizations. Additionally, it examines various scenarios with different carbon tax values, enabling a deeper understanding of how carbon taxation affects the transition from a LE to a CE business model. The analysis also identifies the minimum carbon tax thresholds needed to impact business model decisions effectively.

By addressing a critical gap in the literature, this study offers practical guidance to support sustainable transitions in manufacturing practices.

3. Problem description

As mentioned before, this work aims to analyze the effect of carbon tax measures on the business model decision-making process (i.e. whether to transition from a LE to a CE business model or not). Specifically, this study focuses on manufacturing organizations producing common consumer products that operate under an Extended Producer Responsibility (EPR) policy approach. The classical model of a product life cycle, which includes *sourcing*, *transformation*, *assembly*, *product use*, and *product EoL* (Van Den Berg and Bakker, 2015; Panza et al., 2022a,b; Panza et al., 2022), is used to define the decision problem of the current analysis, as depicted in Fig. 1.

The diagram outlines the process when a manufacturing company takes back its multi-component products after use, i.e. when they have reached their EoL, and needs to decide how to reintroduce the same product to the market, whether by creating it anew (i.e., LE) or recovering parts from older one (i.e., CE).

Once products are received, these go through a quality check to assess their condition (as well as of the condition of their components). This can be done visually by human operators or through advanced technologies such as image recognition software or data from sensors embedded in the products. At this point, the decision on whether an LE or CE business model should be adopted needs to be made.

In the LE model, the product is disposed in a landfill and it then needs to be produced again in new form. Raw materials and/or components are purchased (*sourcing*), these materials are eventually transformed into components (*transformation*), which are then assembled (*assembly*)

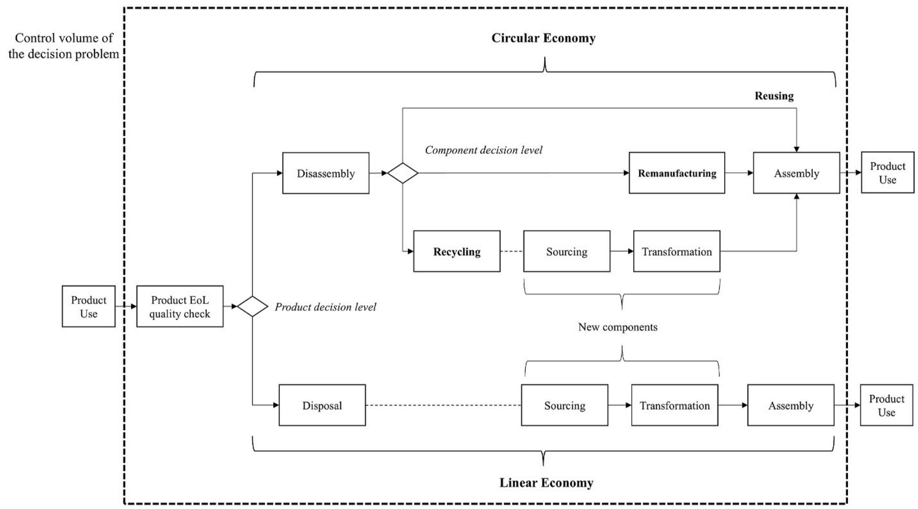

Fig. 1. Diagram of the decision problem considered in this work.

together with components purchased in the *sourcing* phase (if any), to create the final product.

In the CE business model, the product needs to be disassembled into its different components. The CE strategies at the EoL were selected according to one of the most widely adopted CE frameworks available in the literature, namely the 6R framework, which encompasses strategies such as Redesign, Reduce, Recovery, Reuse, Remanufacturing, and Recycle (Jawahir and Bradley, 2016). The product recovery phase is intrinsically included in this work, as the focus is on manufacturing organizations operating with a take-back program, which involves recovering products at the EoL. The Reuse, Remanufacturing, and Recycle strategies are mathematically modelled in this work. Instead, since the Reduce practice can be applied to both LE and CE business models, it was not considered in this work. Also, the Redesign aspect is not part of the analysis, as this study focuses only on the perspective of a manufacturing company facing decisions under take-back programs, as discussed above.

If a component is recycled, a new one needs to be produced through the *sourcing* and *transformation* phases described above. However, if a component is remanufactured, it needs to be restored to its nominal level of quality. If the component exhibits a quality equal to its nominal level, it can be reused directly. The new, remanufactured, and reused components, are then assembled to form the final product.

As can be easily understood, the decision on which business model to adopt needs to be driven by both economic and environmental criteria. Therefore, this decision relies on the minimization of the sum of both the economic and environmental terms associated with the phases within the control volume represented in Fig. 1. Specifically, as will be described later, the carbon tax affects the relevance and the weight of the environmental term.

Notably, inventory and outbound transportation phases are not considered in the decision problem since products undergo these phases regardless of the business model chosen. Both recovered and newly manufactured products typically require the same inventory management processes, such as storage, tracking, and order fulfillment. Similarly, the outbound transportation network used to deliver the products to customers is likely to remain the same, whether the product is newly manufactured or recovered by the manufacturing company. Finally, inbound transportation is considered since this might differ between LE and CE business models, and this will be elaborated on in Section 4.1.

4. Methodological framework

To answer the RQ described earlier *(What is the role of the carbon tax in the transition from a LE to a CE?)* it is essential to employ a methodology that enables the examination of the influence of the carbon tax on determining the optimal business model to adopt, i.e. whether CE or LE. Due to the complexity of the problem, an integrated methodological framework, composed by different methodological steps, has been adopted.

First, a mathematical model describing the decision problem reported in Fig. 1 was needed to identify the preferable business model, i.e. CE or LE. More specifically, this mathematical model needs to describe the decision problem not only from an economic perspective but also from an environmental one, given its relevance on the business model decision and the scope of this work.

Next, the mathematical model was implemented in MATLAB to perform a simulation factorial experiment. Main effect and interaction plots were employed to gain insight into the effect of the model parameters on the business model selection (CE or LE). In this way, the effect of carbon tax alone and in combinations with the other model parameters were evaluated.

Additionally, to further evaluate the influence and relevance of carbon tax on the decision-making process, a decision tree analysis was carried out. This involved developing a decision tree, which is a graphical tool that enables the visualization of the entire decision-making process, allowing for a practical understanding of whether or not the carbon tax plays a role in the decision-making process (Rodríguez et al., 2017; Prajapat et al., 2020; Cantini et al., 2022).

However, given their graphical nature, the main effect and interaction plots, along with the decision tree, only enable a qualitative evaluation of the relationship between the carbon tax and the business model selection. Therefore, to complement the analysis, a quantitative assessment was integrated in the methodological framework. Specifically, the Minimum Redundancy Maximum Relevance (MRMR) algorithm was employed to quantitatively evaluate the importance of each model parameter, particularly the carbon tax (Ding and Hanchuan, 2005; MATLAB, 2023; Panza et al., 2024). In this way, the role of carbon tax was thoroughly examined from both qualitative and quantitative perspectives.

Finally, to further enhance the understanding of how carbon taxes shape decision-making process for business model selection, a carbon tax sensitivity analysis was carried out. This aimed to shed lights on how changes in current carbon tax values might affect the decision-making process and to identify the minimum carbon tax values needed to exert influence on the decision-making process.

Before describing the different methodological steps in detail, a schematic representation of the adopted methodological framework is provided in Fig. 2.

4.1. Mathematical model

As anticipated, a mathematical model was developed to support the identification of the preferable business model, i.e. CE or LE. Before describing the model, the main assumptions are reported below.

- Given the absence of an established standard methodology to quantitatively assess the social dimension of sustainability, and considering that social data are subjective and influenced by various cultural values and perceptions, this work considers only the economic and environmental dimensions of sustainability, since they can be objectively assessed and measured (Panza et al., 2023).
- As commonly accepted in the literature, recovered components are restored to the same quality level as that of entirely new products (Delpla et al., 2022).
- All components are recoverable and made of recyclable materials. This assumption is a necessary premise for developing this work. Specifically, for a decision to be made between a LE or CE business model, component recoverability is essential. Without recoverable components, implementing a CE business model is not feasible, leaving the LE model as the only viable option.
- The quality of a component affects the remanufacturing cost with a linear dependency, as established in the literature (Delpla et al., 2022).
- The contribution of inbound transportation is directly included within the corresponding phases (sourcing, disposal, recycling). This modelling choice was made to simplify the number of parameters constituting the model, thereby fostering its applicability and adoption in real industrial settings.
- The cost structure of the product is modelled using a triangular distribution, a widely used approach in business modeling and simulation when data is limited, but minimum and maximum values are available. The triangular distribution is preferred for its flexibility, offering a reasonable approximation in the absence of more detailed data or complex distributions. It effectively captures uncertainty by reflecting variability between the extreme bounds (minimum and maximum) while placing greater emphasis on the most likely outcome. This balance accommodates both optimistic and pessimistic scenarios without introducing unnecessary complexity, making it a practical choice for cost modeling. Furthermore, in situations where the actual data distribution is unknown, the triangular distribution provides a pragmatic solution for managing uncertainty, a common challenge in many business applications (Kissell and James, 2017; AnyLogic, 2023; MathWorks, 2024).

Dealing with the description of the mathematical model, this describes the decision problem illustrated in Fig. 1 from both an economic and environmental perspective. As stated in the assumption, the social perspective is not considered due to the lack of an established standard methodology for its quantitative assessment, making its evaluation subjective and influenced by various cultural values and perceptions (Panza et al., 2023). Indeed, social impacts cover a broad range of issues, such as human rights, labour conditions, community engagement, well-being – just to name a few – which are inherently subjective and vary significantly across different cultures and regions. This diversity makes it difficult to develop universal indicators that are applicable in all contexts. Social impacts often involve qualitative data, such as perceptions of fairness or community well-being, which are difficult to measure in numerical terms. Converting these qualitative insights into quantifiable data is a significant challenge. In fact, differently from environmental impacts, which have relatively well-established metrics (e.g., carbon emissions, water usage, etc.), there is no universal agreement on how to measure social impacts. The lack of standardized indicators means different studies or assessments might use different criteria, leading to inconsistent results. Finally, gathering reliable data on social impacts can be difficult, especially in developing regions or informal sectors. Access to relevant information, transparency of data, and the reliability of sources are often major obstacles (Sousa-Zomer and Cauchick Miguel, 2018; Maister et al., 2020; UNEP Life Cycle Initiative

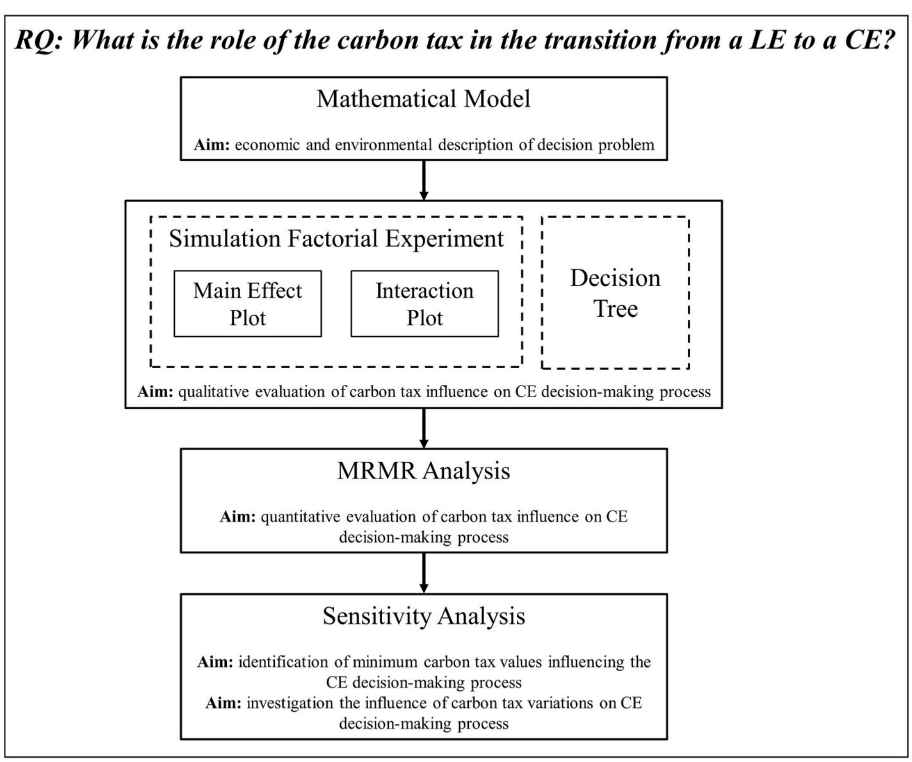

Fig. 2. Methodological framework adopted.

and Social LC Alliance, 2020; Bonilla-Alicea and Fu, 2021). Readers can refer to the included references for a more in-depth discussion of the social challenges.

Therefore, the mathematical model determines the business model (CE or LE) that minimizes the sum of an economic and of an environmental term. To make the two terms comparable, the environmental term was monetized using the carbon tax, which thus serves as a weighting factor for the environmental term. Consequently, the preferable business model between LE and CE is the one leading to the lowest total costs (sum of the economic cost and of the monetarized environmental cost).

It is worth mentioning that, to provide generality to the mathematical model, a generic consumer product made of n components was considered (the index i stands for the generic i-th component). Moreover, to achieve the same goal, each economic parameter was modelled as a fraction of the cost of product manufacturing $c_{product}$ (€), while each environmental parameter was modelled as a fraction of the carbon footprint of product manufacturing $cf_{product}$ (ton $CO_{2,eq}$). The former is expressed as rc_x, where the subscript x refers to the life cycle phase under consideration (e.g. assembly, transformation, etc.), while the latter is expressed as rcf_x, where again the subscript x refers to the life cycle phase under consideration.

For clarity, it is worth specifying that $c_{product}$ and $cf_{product}$ refer to the cost and carbon footprint of the product manufacturing, composed of the sum of the sourcing, transformation, and assembly phases previously discussed. Therefore, $c_{product}$ should not to be confused with the selling price.

Furthermore, as each economic parameter is multiplied by the economic cost of product manufacturing ($c_{product}$), and each environmental parameter is multiplied by the algebraic product of carbon footprint of product manufacturing and carbon tax ($ct \bullet cf_{product}$), the former acts as a weighting factor of the economic parameters, while the latter serves as a weighting factor for the environmental parameters.

Before providing the mathematical formulation for the two business models, the notation adopted is presented in the Table 1 and 2.

Table 1
Model variables.

Model variable	Description	Unit of measure
tc_{LE}	Total cost of linear economy business model	€
tc_{CE}	Total cost of circular economy business model	€
$tc_{product}$	Total cost of product manufacturing	€
$c_{disposal}$	Cost of product disposal	€
$cf_{disposal}$	Carbon footprint of product disposal	ton $CO_{2,eq}$
$tc_{disposal}$	Total cost of product disposal	€
$c_{disassembly}$	Cost of product disassembly	€
$cf_{disassembly}$	Carbon footprint of product disassembly	ton $CO_{2,eq}$
$tc_{disassembly}$	Total cost of product disassembly	€
$c_{assembly}$	Cost of product assembly	€
$cf_{assembly}$	Carbon footprint of product assembly	ton $CO_{2,eq}$
$tc_{assembly}$	Total cost of product assembly	€
$c_{sourcing,i}$	Cost of sourcing of i-th raw material/component	€
$cf_{sourcing,i}$	Carbon footprint of sourcing of i-th raw material/ component	ton $CO_{2,eq}$
$tc_{sourcing,i}$	Total cost of sourcing of i-th raw material/ component	€
$c_{trasnformation,i}$	Cost of transformation of i-th raw material/ component	€
$cf_{trasnformation,i}$	Carbon footprint of transformation of i-th raw material/component	ton $CO_{2,eq}$
$tc_{trasnformation,i}$	Total cost of transformation of i-th raw material/ component	€
$tc_{reusing,i}$	Total cost of reusing the i-th component	€
$tc_{remanufacturing,i}$	Total cost of remanufacturing the i-th component	€
$tc_{selling,i}$	Total cost of selling the i-th used component to recycler	€
$tc_{recycling,i}$	Total cost of recycling the i-th component	€

Table 2
Model parameters.

Input parameter	Description	Unit of measure
$c_{product}$	Cost of product manufacturing	€
$cf_{product}$	Carbon footprint of product manufacturing	ton $CO_{2,eq}$
ct	Carbon tax	€/ton $CO_{2,eq}$
n	Number of components	–
$rc_{disposal}$	Relative cost of product disposal	–
$rcf_{disposal}$	Relative carbon footprint of product disposal	–
$rc_{disassembly}$	Relative cost of product disassembly	–
$rcf_{disassembly}$	Relative carbon footprint of product disassembly	–
$rc_{assembly}$	Relative cost of product assembly	–
$rcf_{assembly}$	Relative carbon footprint of product assembly	–
cqi_i	Component quality index of the i-th component	–
$rc_{sourcing,i}$	Relative cost of sourcing of the i-th item	–
$rcf_{sourcing,i}$	Relative carbon footprint of sourcing of the i-th item	–
$rc_{transformation,i}$	Relative cost of transformation of the i-th item	–
$rcf_{transformation,i}$	Relative carbon footprint of sourcing of the i-th item	–
α_i	Multiplicative factor of remanufacturing cost of the i-th item	–
β_i	Multiplicative factor of remanufacturing carbon footprint of the i-th item	–
γ_i	Ratio between the selling price of scrap to recycler and its purchasing cost of the i-th item	–

4.1.1. The LE business model

As can be seen from Fig. 1, the LE business model is considered as follows: after the quality check, the product is *disposed* in a landfill and a new product must be fabricated from scratch, going through the *sourcing*, *transformation*, and *assembly* phases as described above. To each of these phases is associated both an economic and environmental cost, leading to the total cost tc_{LE}, expressed as following:

$$tc_{LE} = tc_{disposal} + tc_{product} = tc_{disposal} + tc_{sourcing} + tc_{transformation} + tc_{assembly} \quad (1)$$

Below, we describe the different phases in detail.

4.1.1.1. Disposal. The *product disposal* phase refers to the product discarded in a landfill, encompassing any associated transportation contribution. The cost of the disposal $c_{disposal}$ and its associated carbon footprint $cf_{disposal}$ are computed respectively by referring to the relative cost of product disposal $rc_{disposal}$ and to the relative carbon footprint of product disposal $rcf_{disposal}$, as follows:

$$c_{disposal} = rc_{disposal} \bullet c_{product} \quad (2)$$

$$cf_{disposal} = rcf_{disposal} \bullet cf_{product} \quad (3)$$

The total cost of disposal $tc_{disposal}$ is the sum of the economic and environmental costs, defined as follows:

$$tc_{disposal} = rc_{disposal} \bullet c_{product} + ct \bullet rcf_{disposal} \bullet cf_{product} \quad (4)$$

4.1.1.2. Sourcing. The *sourcing* phase refers to either the acquisition of raw materials that need further transformation to create components or the direct acquisition of outsourced components, encompassing any associated transportation contribution. The cost of sourcing $c_{sourcing}$ and its carbon footprint $cf_{sourcing}$ is obtained by totalling the cost and carbon footprint of each raw material/component i, respectively.

$$c_{sourcing} = \sum_{i=1}^{n} c_{sourcing,i}, \quad (5)$$

$$cf_{sourcing} = \sum_{i=1}^{n} cf_{sourcing,i}, \quad (6)$$

The economic cost and the carbon footprint of sourcing each raw material/component i are evaluated through the relative cost of sourcing $rc_{sourcing,i}$ and the relative carbon footprint of sourcing $rcf_{sourcing,i}$, respectively.

$$c_{sourcing,i} = rc_{sourcing,i} \bullet c_{product}, \forall i \in n \tag{7}$$

$$cf_{sourcing,i} = rcf_{sourcing,i} \bullet cf_{product}, \forall i \in n \tag{8}$$

The total cost of sourcing $tc_{sourcing}$ is hence the sum of the economic and environmental costs for all the acquired raw materials/components n needed to create the product.

$$tc_{sourcing} = c_{product} \bullet \sum_{i=1}^{n} rc_{sourcing,i} + ct \bullet cf_{product} \bullet \sum_{i=1}^{n} rcf_{sourcing,i} \tag{9}$$

4.1.1.3. Transformation. The *transformation* phase refers to any transformation that the company applies to the acquired raw materials/components. The total cost of transformation $tc_{transformation}$ is the sum of the economic cost $c_{transformation}$ and the environmental cost of its carbon footprint $cf_{transformation}$ for all the transformed raw materials/components; each cost can be computed in relative terms, as for the sourcing phase through the parameters $rc_{transformation,i}$ and $rcf_{transformation,i}$.

$$c_{transformation} = \sum_{i=1}^{n} c_{transformation,i}, \tag{10}$$

$$cf_{transformation} = \sum_{i=1}^{n} cf_{transformation,i}, \tag{11}$$

$$c_{transformation,i} = rc_{transformation,i} \bullet c_{product}, \tag{12}$$

$$cf_{transformation,i} = rcf_{transformation,i} \bullet cf_{product}, \tag{13}$$

$$tc_{transformation} = c_{product} \bullet \sum_{i=1}^{n} rc_{transformation,i} + ct \bullet cf_{product} \bullet \sum_{i=1}^{n} rcf_{transformation,i} \tag{14}$$

4.1.1.4. Assembly. The phase *product assembly* refers to the process of assembling components to get the final product. The total cost of product assembly $tc_{assembly}$ is computed by considering the economic cost $c_{assembly}$ and its carbon footprint $cf_{assembly}$. Each cost is then assessed in relative terms through $rc_{assembly}$ and $rcf_{assembly}$, respectively.

$$c_{assembly} = rc_{assembly} \bullet c_{product} \tag{15}$$

$$cf_{assembly} = rcf_{assembly} \bullet cf_{product} \tag{16}$$

$$tc_{assembly} = c_{product} \bullet rc_{assembly} + ct \bullet cf_{product} \bullet rcf_{assembly} \tag{17}$$

4.1.2. The CE business model

According to Fig. 1, the CE business model is composed of the following phases: after the product quality check, the product is *disassembled* into its components and new decisions need to be made at component-level. Specifically, each component i can be either *reused, remanufactured,* or *recycled.* The CE strategy selected per component is the one with the lowest total cost. After all the necessary components have been collected, they need to be *assembled* to create the final product. The formulation of the total CE cost tc_{CE} is expressed as follows:

$$tc_{CE} = tc_{disassembly} + \sum_{i=1}^{n} \min\{tc_{reusing,i}, tc_{remanufacturing,i}, tc_{recycling,i}\} + tc_{assembly} \tag{18}$$

Each phase is detailed below.

4.1.2.1. Disassembly. The phase *product disassembly* is the deconstruction of the product in its components. The total cost of product disassembly $tc_{disassembly}$ is computed by summing the economic cost $c_{disassembly}$ and the cost associated to its carbon footprint $cf_{disassembly}$. Each of them is assessed in relative terms, respectively, through $rc_{disassembly}$ and $rcf_{disassembly}$.

$$c_{disassembly} = rc_{disassembly} \bullet c_{product} \tag{19}$$

$$cf_{disassembly} = rcf_{disassembly} \bullet cf_{product} \tag{20}$$

$$tc_{disassembly} = c_{product} \bullet rc_{disassembly} + ct \bullet cf_{product} \bullet rcf_{disassembly} \tag{21}$$

4.1.2.2. Reusing. This work considers that the CE business model regenerates a product to the same quality level as a new one. Because of this, a component can be reused only if its quality level is equal to the nominal level. As done in the literature by Meng et al. (2017) and by Delpla et al. (2022), the quality of a component can be represented by a numeric index ranging from 0 (fully damaged) to 1 (fully performing). Hence, an input parameter named component quality index cqi_i is defined to represent the quality of the component i. In this case, the reusing option is permissible only when the quality of a component is entirely preserved (i.e. $cqi_i = 1$). This leads to a total cost $tc_{reusing,i}$ that is null since no actions are needed.

$$\begin{cases} tc_{reusing,i} = 0, \text{if } cqi_i = 1. \\ tc_{reusing,i} = \varnothing, \text{otherwise}. \end{cases} \tag{22}$$

4.1.2.3. Remanufacturing. The *remanufacturing* phase refers to restoring the used component to its nominal quality level (Liu et al., 2015). The total cost of remanufacturing the i-th component $tc_{remanufacturing,i}$ can be computed using the total cost of creating the i-th new component as in the literature (Delpla et al., 2022). Indeed, the literature assumes that the economic cost of remanufacturing a component depends on the economic cost of manufacturing a new one. The literature also assumes a linear relationship between the cost and the quality of the component. Hence, according to the literature, the cost of remanufacturing a component can vary between 0% and 100% of the cost of a new component (Delpla et al., 2022). The present work assumes a linear relationship as well, but, to make the model more flexible, we consider that the economic cost of remanufacturing a component can be higher than 100% of the economic cost of creating a new one, and we express its maximum through the parameter α_i. The same relationship and assumptions apply to the environmental cost, where β_i takes the place of α_i.

$$tc_{remanufacturing,i} = \alpha_i \bullet c_{product} \bullet \left(rc_{sourcing,i} + rc_{transformation,i}\right) \bullet (1 - cqi_i) + \beta_i \bullet ct \bullet cf_{product} \bullet \left(rcf_{sourcing,i} + rcf_{transformation,i}\right) \bullet (1 - cqi_i), \forall i \in n \tag{23}$$

Note that if $cqi_i = 1$, then $tc_{remanufacturing,i} = 0$, and the component can be reused.

4.1.2.4. Recycling. The *recycling* phase refers to selling the component (in the form of scrap) to recyclers. This implies two main consequences. First, earning a profit from the sale of the scrap, which can be represented as the percentage of the sourcing cost through parameter γ_i, encompassing any associated transportation contribution. Second, sending a component to recycler implies the process of creating a new one from scratch (and hence going through the *sourcing* and *transformation* phases described above). Thus, the total cost of component recycling can be expressed as follows:

$$tc_{recycling,i} = tc_{selling,i} + tc_{sourcing,i} + tc_{transformation,i} = -\gamma_i \bullet c_{product} \bullet rc_{sourcing,i} + c_{product} \bullet \left(rc_{sourcing,i} + rc_{transformation,i}\right) + ct \bullet cf_{product} \bullet \left(rcf_{sourcing,i} \bullet + rcf_{transformation,i}\right), \forall i \in n \tag{24}$$

4.1.3. Numerical constraints of the model parameters

The mathematical model is subjected to a set of constraints, mainly related to the limit values that the model parameters can assume. These values have been obtained from discussions with practitioners working in the manufacturing of common consumer products. More specifically, data were collected through an online workshop where fifteen practitioners, covering different roles in companies manufacturing common consumer products, provided their insights on the minimum and maximum values that each model parameter can possibly assume. Whenever possible, these values were also compared with data available in the literature. Notably, to ensure the reliability of the data collected, only practitioners with at least 5 years of experience participated in the workshop. Detailed information on the practitioners is reported in Table 3.

The cost of product manufacturing in our study ranges from €1 and €500. As described above, this coincides with the aggregated cost of sourcing, transformation, and assembly operations and not with the selling price.

$$1 \leq c_{product} \leq 500 \tag{25}$$

The carbon footprint of product manufacturing relating to consumer products considered in this work can vary between 0.01 $CO_{2,eq}$ tons and 0.500 $CO_{2,eq}$ tons, as reported by (Eupedia, 2021). Also, in this case, the carbon footprint of product manufacturing refers to the aggregated carbon footprint of sourcing, transformation, and assembly operations.

$$0.01 \leq cf_{product} \leq 0.500 \tag{26}$$

According to statista (2023), carbon tax values can vary between less than €1 per $CO_{2,eq}$ ton and almost €140, and therefore we rounded up the values as described in the following constraint:

$$1 \leq ct \leq 140 \tag{27}$$

As discussed above, only multi-component products were considered. In this work, based on authors' experience and discussion with practitioners, it is assumed that a product can be composed of a maximum of 50 components. Therefore, the following constraint applies to the number of components n:

$$2 \leq n \leq 50 \tag{28}$$

Table 3
Overview of practitioners participating in the online workshop.

Practitioner ID	Role	Seniority (years)	Type of product
1	Head of Industrial Digital Division	5	Electronics
2	Production Planner	8	Home appliances
3	Process Improvement Manager	10	Electronics
4	Engineering, automation and digitalization manager	8	Bicycles & Mobility
5	Product Manager Industrial Edge	8	Home appliances
6	VP Smart Factory	12	Home appliances
7	Business Development Manager	7	Bicycles & Mobility
8	Project Engineer	5	Clothing
9	Head of Logistics Department	10	Electronics
10	Project Engineer	6	Clothing
11	Factory Automation Sales Specialist	8	Electronics
12	Head of Design team	18	Home appliances
13	Product Manager	6	Home appliances
14	Head of Procurement Department	5	Bicycles & Mobility
15	Production Planner	7	Electronics

The relative cost of sourcing for each item $i \in n$ can potentially vary between 0 and 1, excluding extreme values. The same constraint applies to the relative carbon footprint of sourcing:

$$0 < rc_{sourcing,i} < 1 \tag{29}$$

$$0 < rcf_{sourcing,i} < 1 \tag{30}$$

The relative cost of transformation for each item $i \in n$ can potentially vary between 0 (included) and 1 (excluded). The case of the cost being equal to 0 applies when the company acquires outsourced components and assembles them to create a product without transforming them. The same constraint applies to the relative carbon footprint of transformation:

$$0 \leq rc_{transformation,i} < 1 \tag{31}$$

$$0 \leq rcf_{transformation,i} < 1 \tag{32}$$

The relative cost of product assembly can vary between 0 (excluded), when the cost of assembly is negligible, and 0.50, as proposed by (Poli, 2001; WONDER, 2019). The same constraint can be applied to the relative carbon footprint of assembly:

$$0 < rc_{assembly} \leq 0.50 \tag{33}$$

$$0 < rcf_{assembly} \leq 0.50 \tag{34}$$

The economic costs of sourcing, transformation, and assembly ($c_{sourcing}$, $c_{transformation}$ and $c_{assembly}$, respectively) correspond to the economic cost of product manufacturing $c_{product}$, and therefore the sum of the corresponding relative costs needs to be equal to 1:

$$\sum_{i=1}^{n} \left(rc_{sourcing,i} + rc_{transformation,i}\right) + rc_{assembly} = 1 \tag{35}$$

The same constraint applies also for what concerns the relative carbon footprint of sourcing, transformation, and assembly:

$$\sum_{i=1}^{n} \left(rcf_{sourcing,i} + rcf_{transformation,i}\right) + rcf_{assembly} = 1 \tag{36}$$

The component quality index cqi_i can vary between 0 (fully damaged) and 1 (fully performing), as already proposed by (Delpla et al., 2022):

$$0 \leq cqi_i \leq 1 \tag{37}$$

The relative cost of product disassembly $rc_{disassembly}$ can vary between 0 excluded when the cost is negligible and an upper limit. The value of the upper limit is unknown in the literature. However, based on experience and on discussions with practitioners, it is reasonable to assume the same upper limit as for the relative cost of assembly. The same constraint is applied to the relative carbon footprint of disassembly $rcf_{disassembly}$:

$$0 < rc_{disassembly} \leq 0.50 \tag{38}$$

$$0 < rcf_{disassembly} \leq 0.50 \tag{39}$$

The literature also lacks data on the relative cost of product disposal $rc_{disposal}$. Again, through discussions with practitioners, it was decided to apply the same variation as the relative cost of product disassembly $rc_{disassembly}$. The same constraint is applied to the relative carbon footprint of product disposal $rcf_{disposal}$.

$$0 < rc_{disposal} \leq 0.50 \tag{40}$$

$$0 < rcf_{disposal} \leq 0.50 \tag{41}$$

The multiplicative factor of the relative cost of remanufacturing α_i can vary between 1 and 3 based on the authors' experience and from discussions with practitioners. The same constraint applies for the multiplicative factor of the relative carbon footprint of remanufacturing β_i.

$$1 \leq \alpha_i \leq 3 \tag{42}$$

$$1 \leq \beta_i \leq 3 \tag{43}$$

The ratio between the selling price of the scrap to recyclers and the cost of sourcing a new item can vary between 0 excluded (if the profit from recycling is negligible) and 0.6 (according to the authors' experience and from discussions with practitioners).

$$0 < \gamma_i \leq 0.6 \tag{44}$$

The summary of the numerical constraints of the model parameters is reported in Table 4. As already mentioned, data has been collected from the literature and validated with practitioners. Data not available in the literature has been directly gathered by discussion with practitioners. For example, Practitioner #6 indicated that a high-quality washing machine, with durable metal components, advanced motor systems, and electronic controls, typically costs around 500€ to manufacture. In contrast, Practitioner #8 mentioned that a plain cotton t-shirt, mass-produced with basic stitching and simple designs, generally costs around 1€ to manufacture, considering the fabric and labor costs in low-cost production regions.

4.2. Simulation factorial experiment

Once the mathematical model was developed, it was then possible to start investigating the importance of the carbon tax on the business model decision-making process. As can be easily understood from the previous section, the choice of the business model to be adopted depends not only on the carbon tax but also on other independent variables, i.e. the parameters of the mathematical model. In light of this, the mathematical model was implemented in MATLAB, and a simulation factorial experiment was performed, which is regarded as an efficient tool to investigate the effect of multiple variables on model performance (Montgomery, 2017). More specifically, the importance of the carbon tax on the business model decision-making process was qualitatively assessed through the analysis of the main effect plots and of the interactions plots.

A main effect plot is a graphical representation used to visualize the impact of individual independent variables (model parameters) on a dependent variable (model response), while keeping the other model variables constant at specific levels. Each independent variable is typically plotted on the x-axis, and its corresponding effect is shown on the y-axis. To show how changes in the levels of each independent variable affect the outcome of the dependent variable, the plot typically consists of a line. This makes it easy to understand the relative importance of the independent variables in the experiment. In this work, the dependent variable is the business model to be adopted (CE or LE), while the individual independent variables are the carbon tax and all the other parameters of the mathematical model. Indeed, although our focus is on the carbon tax, all the model parameters need to be considered to understand the relative effect of the model parameters.

An interaction plot, instead, allows for the visualization of the interaction effects between two or more independent variables (model parameters) on a dependent variable (model response, i.e. CE or LE). Interaction effects occur when the impact of one independent variable on the dependent variable varies depending on the level of another independent variable (Montgomery, 2017). Therefore, the interaction plot is necessary to investigate whether the carbon tax, combined with other parameters of the mathematical model, affects the business model decision-making process.

The factorial experiment in this research was conducted on two levels, where the values assumed by each model parameter coincided with their admissible extreme values according to the constraints described above and reported for convenience in Table 3. It is worth

Table 4
Values adopted for the 2-levels simulation factorial experiment. Examples from discussion with practitioners are reported in the "Source" column when data were not available in the literature.

Model parameter	Values	Units of measure	Source	
			Literature	Authors experience and discussions with practitioners.
$c_{product}$	[1, 500]	€		e.g., €500 for a washing machine and €1 for a t-shirt.
$cf_{product}$	[0.01, 0.5]	ton $CO_{2,eq}$	Eupedia (2021)	
ct	[1, 140]	€/ton $CO_{2,eq}$	(statista, 2023)	
n	[2, 50]	–		e.g., 2 components for a bottle and up to 50 components for a smartphone.
$rc_{disposal}$	[10e-06,[1] 0.5]	–		e.g., negligible disposal cost for bottles or cans, and high disposal cost for refrigerators or washing machines.
$rcf_{disposal}$	[10e-061, 0.5]	–		Similar to disposal costs.
$rc_{disassembly}$	[10e-061, 0.5]	–		e.g., negligible disassembly cost for bottles or cans, and high disassembly cost for smartphone and high-tech products.
$rcf_{disassembly}$	[10e-061, 0.5]	–		Similar to disassembly costs.
$rc_{assembly}$	[10e-061, 0.5]	–	(WONDER, 2019), (Poli, 2001)	
$rcf_{assembly}$	[10e-061, 0.5]	–		Similar to assembly costs.
cqi_{peak}	[0, 1]	–	(Delpla et al., 2022), (Kalgren et al., 2006)	
$rc_{sourcing,peak}$	[10e-06[1], 1)	–		e.g., negligible sourcing cost for paper/tissue napkins and very high sourcing cost for luxury jewellery or watches.
$rcf_{sourcing,peak}$	[10e-06[1], 1)	–		Similar to sourcing costs.
$rc_{transformation,peak}$	[0, 1)	–		e.g., negligible transformation cost for plastic cutlery and very high transformation cost for handcrafted leather goods.
$rcf_{transformation,i}$	[0, 1)	–		Similar to transformation costs.
α_i	[1, 3]	–		e.g., multiplicative factor of remanufacturing costs equals to 1 for vacuum cleaners and up to 3 for smartphones.
β_i	[1, 3]	–		Similar to multiplicative factor of remanufacturing costs.
γ_i	[10e-061, 0.6]	–		e.g., negligible selling price for dirty aluminum foil and up to 0.6 for copper scraps.

[1] A value of 10e-06 has been assigned to represent the case of 0 excluded.

mentioning that all the component-related model parameters are assumed to follow a triangular distribution of cardinality *n*, with the lower and upper limits equal to the admissible values and with the peak of each distribution varying within the allowed domain. As already mentioned in the assumption of the mathematical model, the choice of the triangular distribution is justified by its widespread use in business simulations, particularly when the actual distribution is unknown or when data is limited. This distribution is preferred for its simplicity and flexibility, providing a reasonable approximation in the absence of more complex data. By reflecting variability between the extreme bounds (minimum and maximum) and assigning greater weight to the most likely outcome, the triangular distribution effectively captures uncertainty. This balance ensures that both optimistic and pessimistic scenarios are considered without introducing unnecessary complexity, making it a practical tool for cost modeling and uncertainty management in business contexts. (Kissell and James, 2017; AnyLogic, 2023; MathWorks, 2024).

4.3. Decision tree analysis

Then, to further evaluate the influence and relevance of carbon tax on the CE decision-making process, a decision tree analysis was conducted by developing a decision tree. The choice of adopting a decision tree algorithm relies on the fact that it is a graphic tool that allows a thorough visualization of the decision-making process, displaying the parameters that participate in the decision-making process (Rodríguez et al., 2017; Prajapat et al., 2020; Cantini et al., 2022).

To develop the decision tree, a decision tree algorithm was leveraged, which is a supervised classification technique that predicts the class to which an item belongs based on a given set of features (Nasiriany et al., 2019; Cantini et al., 2022). In the present work, the set of features includes the carbon tax and the other model parameters, while the class to predict is the model response (CE or LE). The decision tree algorithm was applied on a dataset created with a simulation factorial experiment where all the model parameters varied on 4 different levels. The extreme levels remained the same as listed in Table 4, and two intermediate, equally spaced, levels were added for each model parameter in order to increase the number of explored scenarios.

Detailed information on how the decision tree algorithm works can be found in the literature (Sgarbossa et al., 2021; Cantini et al., 2022).

4.4. MRMR algorithm

As discussed before, the main effect and interaction plots offer valuable insights into the relationships between the carbon tax and the business model to be selected. Similarly, the decision tree displays the model parameters governing the choice of the business model. However, they do not provide a quantitative evaluation of the significance of these parameters. Therefore, the MRMR algorithm was used to quantitatively assess the importance of the carbon tax and other model parameters on the business model selection. Indeed, the MRMR algorithm allows for the quantitative identification of the set of parameters that highly affect the model response (i.e. CE or LE), making it a suitable methodology to evaluate whether the carbon tax among them (Ding and Hanchuan, 2005; MATLAB, 2023; Panza et al., 2024). The MRMR algorithm and how it works are described in detail in Appendix A.

4.5. Carbon tax sensitivity analysis

As discussed above, the last part of this work deals with the carbon tax sensitivity analysis. The objective of the carbon tax sensitivity analysis is to shed lights on how changes in current carbon tax values might affect the decision-making process and to identify the minimum carbon tax values required for it to be considered relevant in the business model decision-making process.

More specifically, to define a parameter as relevant or not in the business model decision-making process, the Pareto rule was leveraged as follows: starting from the importance score of each model parameter evaluated with the MRMR algorithm, if a parameter falls within the cumulative relative importance of 80%, it is considered relevant; otherwise, it is not. Therefore, given that the carbon tax represents the weighting factor of the environmental terms (cf. mathematical model described in Section 4.1), a specific carbon tax value was considered relevant if, upon its adoption, either the carbon tax itself or at least one environmental parameter of the mathematical model contributed to a cumulative relative importance of 80%. Consequently, the minimum carbon tax value that met the above-mentioned condition was determined.

However, such a minimum carbon tax value depends on the values assumed by the product manufacturing cost $c_{product}$, the weighting factor of the economic criterion, and by the carbon footprint of product manufacturing $cf_{product}$, the weighting factor of the environmental criterion, together with the carbon tax. In fact, as shown in the mathematical model presented in Section 4.1, each environmental parameter associated with a lifecycle phase (rcf_x) is multiplied by the algebraic product between the carbon footprint and the carbon tax ($cf_{product} \bullet ct$), assuming the role of weighting factor for the environmental criterion. Similarly, each economic parameter associated with a lifecycle phase (rc_x) is multiplied by the cost of product manufacturing $c_{product}$, i.e., the weighting factor for the economic criterion. The cost of product manufacturing $c_{product}$ and the carbon footprint of product manufacturing $cf_{product}$ rely solely on the manufacturing company's capabilities to create economically and environmentally affordable products. The carbon tax ct, instead, is an external factor for the manufacturing organizations, and its value can alter the importance of the environmental criterion.

Therefore, a unique value of carbon tax cannot be defined. Thus, it is possible to develop carbon tax level curves that can depict different minimum carbon tax values, depending on the product cost $c_{product}$ and on the carbon footprint $cf_{product}$. To develop such carbon tax level curves, a series of 2-level simulation factorial experiment were carried out, wherein the values of product manufacturing cost $c_{product}$ and of product manufacturing carbon footprint $cf_{product}$ were kept fixed, while the carbon tax value ct varied until the above-mentioned condition was met (either the carbon tax itself or at least one environmental parameter of the mathematical model is included in the cumulative relative importance of 80% according to the Pareto rule). This procedure was repeated for different combinations of $c_{product}$ and $cf_{product}$; in this way, it was possible to develop the carbon tax level curves representing, for different combinations of product manufacturing cost $c_{product}$ and of product manufacturing carbon footprint $cf_{product}$, the minimum carbon tax values ensuring that either the carbon tax itself or at least one environmental parameter of the mathematical model influences the decision-making process according to the Pareto rule.

5. Results and discussion

The results from the application of the methodological framework described above are presented and discussed below. The first part of the results deals with the simulation factorial experiment. As a first step, the main effects plot was analyzed (Fig. 3) to gain insights about the effect of the carbon tax. It is worth noting that the main effects plot reports the relative effect of the model parameters, and hence all the model parameters need to be considered, not only the carbon tax.

As can be seen from Fig. 3, the effect of the carbon tax alone is negligible when compared with the influence of other model parameters. In fact, the main effect plot is a graphical tool used in statistical analysis to show how the mean response of a dependent variable changes across the levels of an independent variable. Specifically, a flat line on the plot indicates that the independent variable has no significant effect on the response variable, whereas a sloped line suggests an

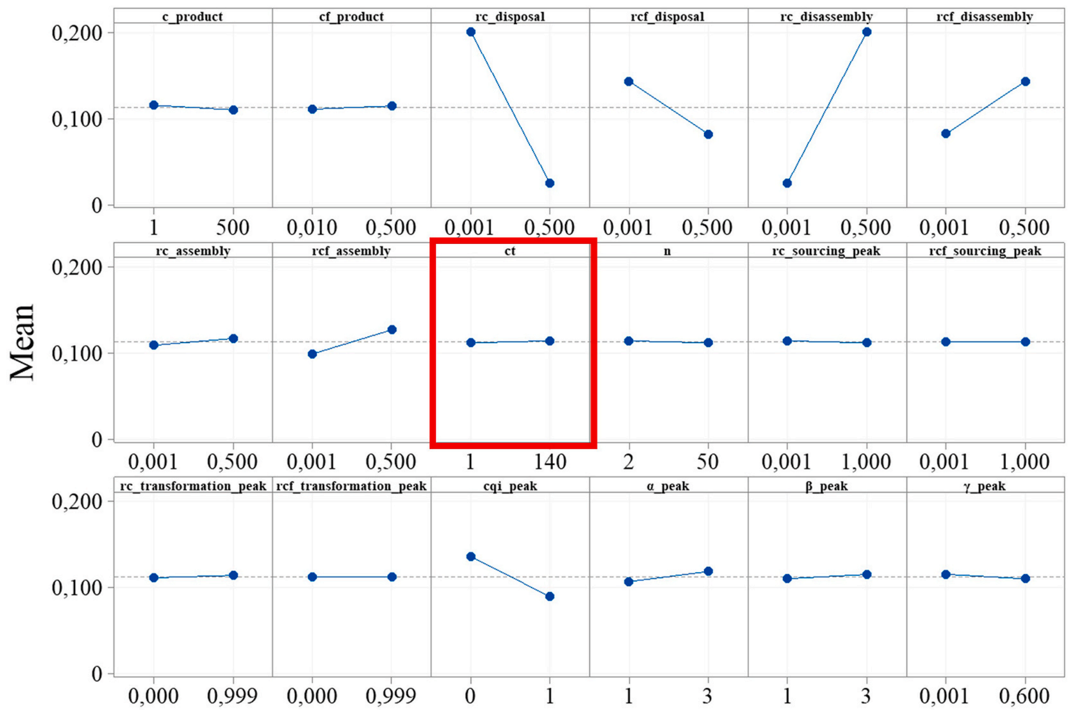

Fig. 3. Main effects plot of the business model; the response value for the business model is reported in the y-axis ('0' stands for CE and '1' for LE). Steeper lines indicate a greater influence of the model parameter on determining the business model.

impact, with steeper slopes representing stronger effects. The direction of the slope indicates whether the relationship is positive (response variable increases as the independent variable increases) or negative (response variable decreases as the independent variable increases). The magnitude of the change is reflected by the vertical difference between levels, with larger differences indicating greater effects. In this work, five model parameters seem to impact the decision on the business model selection much more significantly. Specifically, the relative cost of product disposal $rc_{disposal}$ and the relative cost of product disassembly $rc_{disassembly}$ have the largest impact on the determination of the optimal business model. They are followed by the peak of the triangular distribution adopted for the component quality index cqi_{peak}, by the relative carbon footprint of product disposal $rcf_{disposal}$, and by the relative carbon footprint of product disassembly $rcf_{disassembly}$.

Based on the main effects plot analysis, the impact of the carbon tax alone on the selection of the business model (CE or LE) can be deemed negligible. This can be explained considering that in the mathematical model developed to determine the preferable business model, the carbon tax assumes a role of weighting factor for environmental parameters, determining their importance compared to the economic parameters.

However, due to its role of weighting factor for environmental parameters, it can be expected that the carbon tax might impact the

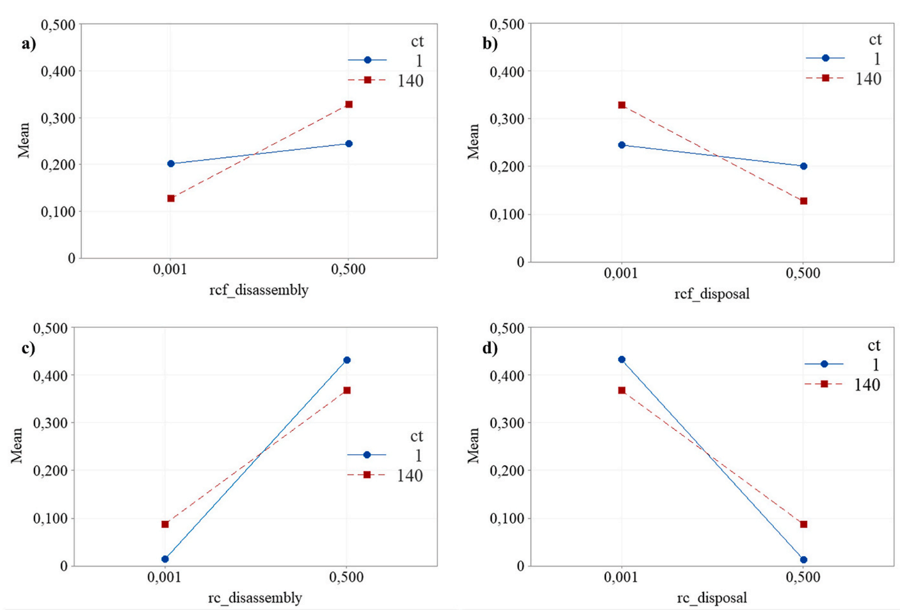

Fig. 4. Strongest interaction plots of the carbon tax on the determination of the business model. Variations in the slope of the lines reflect the impact of the carbon tax on the influence of the model parameter in determining the preferred business model.

business model decision-making process when combined with other parameters. To investigate this, its interactions with the other model parameters were explored. Fig. 4 displays the non-negligible interactions found, while all the interaction plots analyzed are available in Appendix B.

The interaction plot displayed consists of four panels (a, b, c, and d), each illustrating the relationship between carbon tax values ct and different model's parameters—specifically, relative carbon footprint of product disassembly $rcf_{disassembly}$, relative carbon footprint of product disposal $rcf_{disposal}$, relative cost of product disassembly $rc_{disassembly}$, and relative cost of product disposal $rc_{disposal}$. The purpose of this plot is to understand if the effect that a model's parameter exerts on the model's response is influenced by the value adopted by another model's parameter (in this case the carbon tax ct).

The y-axis represents the mean response of the model (dependent variable), while the x-axis denotes the varying levels of these model's parameters (independent variables). On each panel are represented two distinct lines. The blue lines represent the effect of the model's parameter when the minimum carbon tax value ($ct = 1$) is adopted, while the red dashed lines represent the effect of the model's parameter when the maximum carbon tax value ($ct = 140$) is adopted. The interaction effect can be assessed by examining how the lines differ in their slopes. Because the effect of a model's parameter is represented by the slope of the line, if the lines cross or diverge, it suggests that the effect of one variable depends on the level of the other variable (ct). For example, by looking at Fig. 4a and b, it is possible to observe that the slopes of the lines is different based on the carbon tax value considered. More specifically, for $rcf_{disassembly}$ (Fig. 4a), its effect on the model response is stronger (steeper slope) when the carbon tax ct is set to 140 €/ton $CO_{2,eq}$ compared to when it is set to 1 €/ton $CO_{2,eq}$, demonstrating a greater positive interaction at higher carbon tax values. Similarly, for $rcf_{disposal}$ (Fig. 4b), the mean response of the model decreases more sharply when ct is 140 €/ton $CO_{2,eq}$, indicating a more pronounced negative impact under higher carbon tax conditions. This means that the importance of the $CO_{2,eq}$ emissions generated during disassembly and disposal operations can be controlled by the carbon tax value adopted.

Additionally, the carbon tax value affects the influence of the economic cost associated with product disassembly $rc_{disassembly}$ (Fig. 4c) and product disposal $rc_{disposal}$ (Fig. 4d). Here, a higher weighting on the environmental criterion diminishes the influence of the economic criterion. As a result, the slope of the lines for these two parameters decreases when higher values of carbon tax are adopted (Fig. 4c and d).

Based on this and on the analysis of the main effects plot (cf. Fig. 3) for these four parameters, it seems that the carbon tax might impact the business model decision-making process. To further evaluate this, a decision tree analysis was performed to determine whether any of these four parameters ($rcf_{disassembly}$, $rcf_{disposal}$, $rc_{disassembly}$, and $rc_{disposal}$) appear in the decision-making process (Fig. 5).

As already mentioned, a decision tree is a visual tool used to model decision-making processes and outcomes based on various conditions or factors. Each internal node of the tree represents a decision on an attribute (a model parameter), with branches leading to further nodes or final outcomes based on the results of that test. The root node is the starting point, and each subsequent node represents a condition or split in the data. The branches represent different possible outcomes of these conditions, leading to terminal nodes, or leaves, which show the final decision or prediction. The decision tree helps identify the most significant factors influencing the outcome and shows how decisions are made at each step. As can be seen, only two of the four parameters showing a strong interaction with the carbon tax appear in the decision tree (i.e. $rc_{disassembly}$ and $rc_{disposal}$). It is interesting to note that these are both economic model parameters, while the environmental model parameters $rcf_{disassembly}$ and $rcf_{disposal}$ do not appear in the decision-making process. This means that the environmental model parameters do not influence the decision on the business model to adopt. Thus, with the current values of the carbon tax ct, the economic criterion dominates the decision-making process and the environmental criterion is negligible. This might indicate that, contrarily to what seemed to emerge from the analysis of the main effects and interaction plot, the environmental parameters might not affect the business model decision-making process. Being the carbon tax the weighting factor for the environmental model parameters, if these do not influence the decision-making process as suggested by the decision tree analysis, then it means that the weighting factors are currently too low.

Therefore, at this stage, the analysis of the main effects and interaction plots suggests that the carbon tax influences the business model decision-making process (not directly, but through interaction with environmental parameters), while the decision tree analysis indicates that the environmental parameters do not participate in the decision-making process. To clarify this, the MRMR algorithm can be leveraged, as it provides a quantitative evaluation of the model parameters' importance, allowing to determine which parameters most affect the business model decision-making process. This is reported in Fig. 6, together with the corresponding Pareto chart.

A Pareto chart applied to the importance scores calculated with the MRMR algorithm visually represents the relative importance of features or variables (in this case, the model parameters) in a dataset. The chart consists of two components: bars and a cumulative line. Each bar represents a feature, with its height corresponding to its importance score, which is calculated based on the MRMR algorithm. Features are arranged in descending order of importance from left to right, so the most significant features are placed at the far left. The cumulative line, shown in a secondary y-axis, represents the cumulative percentage of the total importance, helping to visualize the proportion of total relevance captured by the most important features. The cumulative line shows how much of the total relevance is explained by the top features,

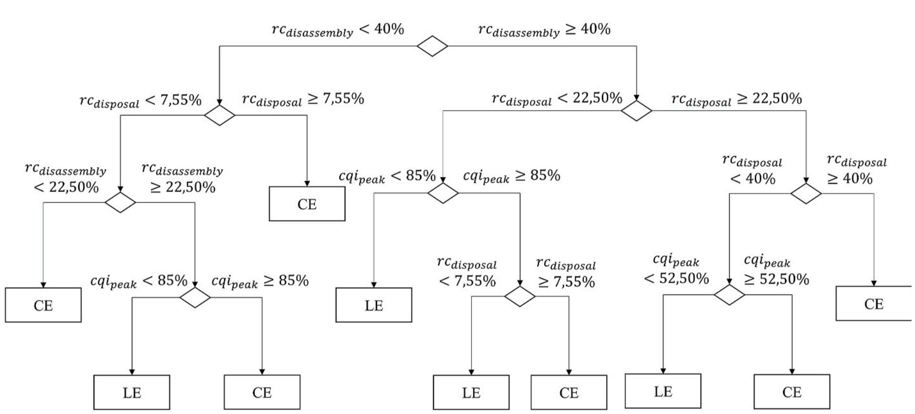

Fig. 5. Visualization of the decision-making process in a form of decision tree under the current carbon tax regime.

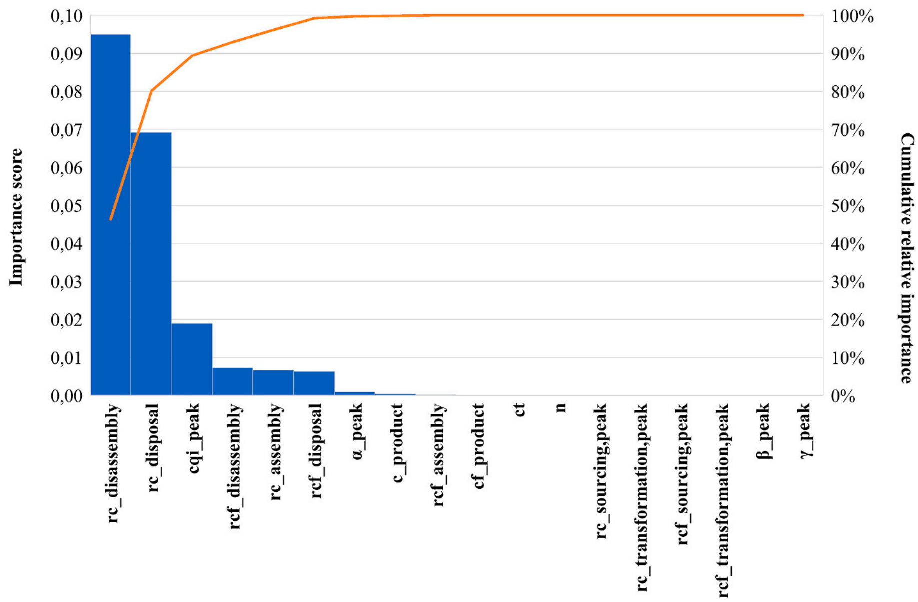

Fig. 6. Relative importance of the model parameters and the corresponding Pareto Chart under the current carbon tax regime. The height of the bar represents the significance of the model parameter in determining the preferred business model.

allowing to quickly assess whether a small number of features dominate the relevance or if a more even distribution is observed. This chart helps prioritize the most critical features for modeling or decision-making while understanding the overall contribution of each feature to the data's predictive power.

As can be seen, the economic cost of product disassembly ($rc_{disassembly}$) and product disposal ($rc_{disposal}$) are the most important model parameters in determining the choice between CE or LE. Together, they account for 80% of the importance needed to make the decision, as evinced by the Pareto chart depicted in orange. They are followed by the component quality index (cqi_{peak}) which brings the cumulative importance of the model parameters to around 90%. In contrast, the environmental parameters of product disposal ($rcf_{disposal}$) and of product disassembly ($rcf_{disassembly}$), along with the economic cost of product assembly ($rc_{assembly}$), have residual importance, bringing the cumulative importance of the model parameters close to 100%. All other model parameters have negligible importance, including the carbon tax, as qualitatively anticipated by the main effects plot in Fig. 3.

This analysis confirms what emerged from the decision tree analysis, i.e., that the environmental model parameters play a very limited role in the decision-making process, with $rcf_{disposal}$ and $rcf_{disassembly}$ having a relative importance of 3,07% and 3,56%, respectively. This indicates that the existing carbon tax values are insufficient to make a significant contribution to the transition from LE to CE business models. This aligns with the results of (Hsieh and Tsai, 2023a), who found that some of the carbon tax regimes they considered did not impact the profits of a knitted footwear circular supply chain, and hence did not affect the transition from LE to CE business models.

Since the carbon tax is the weighting factor of the environmental model parameters, if these do not influence the decision-making process, it means that the weighting factors are currently too low. Conversely, it can be affirmed that the carbon tax values make a significant contribution to the transition from LE to CE business models when the environmental model parameters do influence the decision-making process. To determine such carbon tax values that render the environmental model parameters significant in the business model decision-making process, a sensitivity analysis has been performed. This analysis investigated how governmental bodies can adjust the carbon tax values to alter the importance of the environmental parameters in the decision-making process. Specifically, this analysis aims to understand the minimum value that the carbon tax should assume to make the $CO_{2,eq}$ emissions influential the decision-making process, based on the economic cost of product manufacturing ($c_{product}$) and of the carbon footprint of product manufacturing ($cf_{product}$), resulting in the development of the carbon tax level curves. These carbon tax level curves were developed following the procedure explained in Section 4.5, and are represented in Fig. 7.

Fig. 7 can be interpreted as follows: Each level curve represents a specific carbon tax value (ct) and indicates whether the decision between LE and CE business models is influenced by environmental parameters. For a given level curve (i.e., a particular carbon tax value), environmental parameters are considered relevant to the decision-making process if a point representing the product's manufacturing cost ($c_{product}$) and carbon footprint ($cf_{product}$) lies on or below the level curve. If the point lies above the level curve, the decision-making process is driven exclusively by economic factors (i.e., the economic criterion). For instance, when examining the level curve for $ct = 200$ €, the decision between CE and LE models is influenced solely by economic parameters for products with a manufacturing cost $c_{product}$ and carbon footprint $cf_{product}$ that fall above the level curve. In contrast, for products with a manufacturing cost and carbon footprint that are on or below the level curve, the decision is influenced by both economic and environmental parameters.

These carbon tax level curves represent an important tool for policymakers to understand how to define their carbon tax policies that effectively influence the business model decision-making process. Even considering the highest carbon tax value currently adopted (around 140 €/ton $CO_{2,eq}$), carbon tax level curves barely impact the decision-making process: only a small portion of products—with high $CO_{2,eq}$ emissions and low manufacturing costs—lie below the corresponding level curve (in red) and are hence affected by the environmental parameters; the majority of the products lie above and are thus not affected by any environmental considerations.

This confirms the conclusions drawn so far that the current values of carbon tax are insufficient to make a significant contribution to the transition from LE to CE business models. Hence, carbon taxes should be increased to expand the portion of products that fall below the level curve so that the environmental parameter will be a driver in the LE/CE decision-making process.

Based on these observations, the investigation focused on how a new

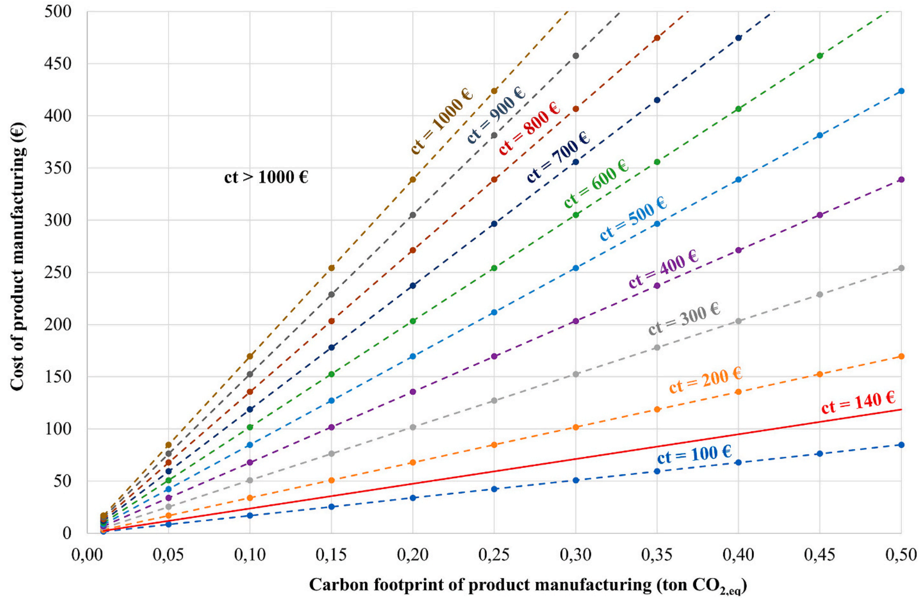

Fig. 7. Carbon tax level curves (the solid red line represents the maximum value currently present). When products fall on or below the level curve, the LE/CE decision making process includes also environmental considerations, otherwise it is driven only by economic considerations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

carbon tax regime, capable of rendering the environmental criterion relevant, would change the business model decision-making process. Thus, a new simulation factorial experiment was run in MATLAB under the assumption of a new carbon tax regime. Specifically, for each combination of the cost of product manufacturing $c_{product}$ and carbon footprint of product manufacturing $cf_{product}$, the carbon tax value was varied over four equally spaced levels, ranging from the value indicated in the carbon tax level curves in Fig. 7 up to twice that value. All other model parameters, instead, were varied over the same 4 levels as done in the previous analysis (i.e., the extreme levels are the extreme values as listed in Table 4, and the other two intermediate levels are equally spaced).

The decision-making process under the new carbon tax regime is visualized in the form of a decision tree, as previously done. Its representation is displayed in Fig. 8.

Focusing on the comparison of the decision-making processes developed for the two carbon tax regimes (Fig. 5 for the current carbon tax regime and Fig. 8 for the new carbon tax regime), it is possible to note that the main driver of the decision-making process remains the relative costs of product disassembly $rc_{disassembly}$. However, with the new carbon tax regime, environmental parameters now appear in the decision tree, proving their non-negligible impact on the decision-making process. This is the case for the relative carbon footprint of product disassembly $rcf_{disassembly}$ and of product disposal $rcf_{disposal}$.

Before moving forward, it is worth discussing decision trees briefly. This tool, in addition to showing which parameters participate in the decision-making process, also serves as a user-friendly decision support tool that allows practitioners to perform quick and reliable decisions about the selection of the preferable business model. By answering few simple questions, practitioners can determine the most suitable business model (CE or LE), with high global accuracy (i.e., 89.43% and 87.74% for the decision trees in Figs. 5 and 8, respectively). Moreover, it also allows for drawing some general managerial insights on whether to adopt CE or LE as business model and how this choice is affected by changes in carbon tax values (for the sake of brevity and to not go out of the scope of this work, these are reported in section 6.1 discussing the practical contribution of this research).

Additionally, the relative importance of each model parameter was calculated using the MRMR algorithm. Their results, along with the Pareto graph, is displayed in Fig. 9.

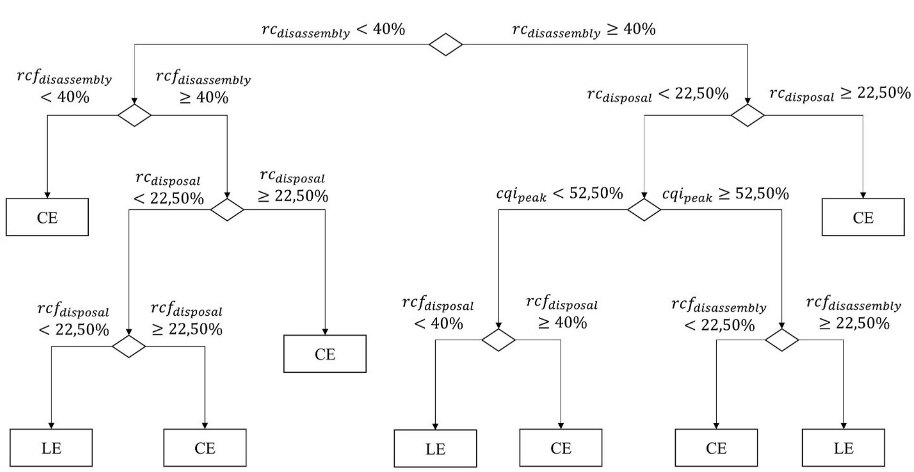

Fig. 8. Visualization of the decision-making process in a form of a decision tree under a new carbon tax regime.

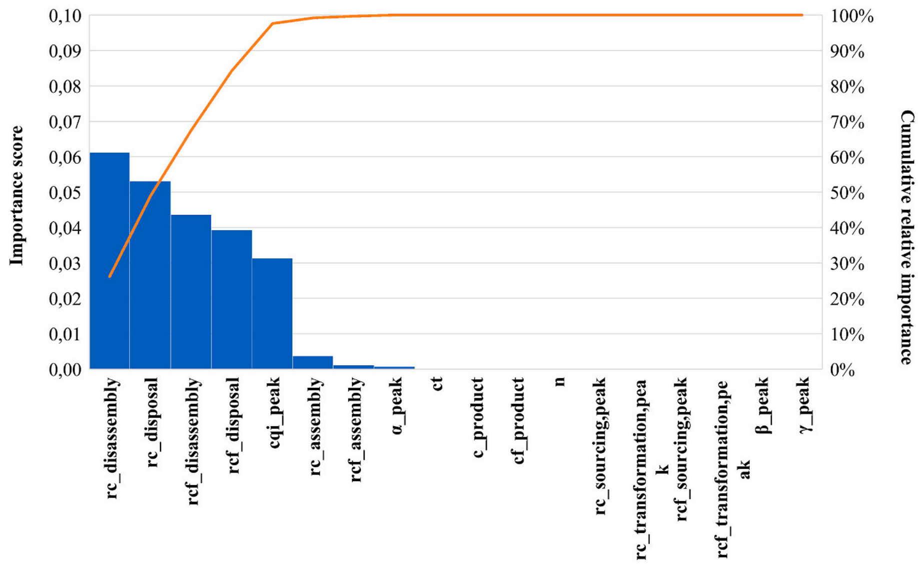

Fig. 9. Relative importance of the model parameters and the Pareto Chart with a new carbon tax regime. The height of the bar represents the significance of the model parameter in determining the preferred business model.

It is clear that the increased importance of the environmental parameters affects the decision-making process. In fact, the new carbon tax regime conveys a redistribution of the relative importance of the model parameters: while the relative cost of product disassembly and disposal ($rc_{disassembly}$ and $rc_{disposal}$) remain the most important parameters in the decision-making process, the corresponding environmental parameters ($rcf_{disassembly}$ and $rcf_{disposal}$) have now gained significant importance, surpassing even the peak of the component quality index distribution in their influence. The 80% cumulative importance of the model parameters is now achieved by including both the economic costs and carbon footprints associated with the product disassembly and disposal. By also including the component quality index, the cumulative importance approaches 100%.

Finally, further elaboration was conducted on the implementation of a new carbon tax regime capable of making the environmental parameters impactful in the decision-making process. To do so, the investigation focused on (i) how the transition from LE to CE is influenced by evaluating how the number of scenarios where CE is convenient varies with changes in the carbon tax regime, and (ii) how the performance of the two business models (CE and LE) varies when selected as preferable business model under the two different carbon tax regimes.

More specifically, the performance of the two business models was evaluated in terms of (a) economic performance, expressed by the average percentage cost savings resulting from choosing the optimal business model, (b) environmental performance, expressed by the average percentage $CO_{2,eq}$ savings resulting from choosing the optimal business model, and (c) total performance, represented by the average percentage total cost savings resulting from choosing the optimal business model.

Regarding (i), the number of scenarios where a transition from LE to CE should occur increased from 74% to 92%. Despite the clear and significant rise that a new carbon tax regime would contribute to the adoption of CE business models, it is noteworthy that presently, although it has been demonstrated that the environmental aspect is negligible in the current business model decision-making process, a considerable number of scenarios exists where CE adoption is more convenient than LE adoption. This aligns with (Korhonen et al., 2018), who affirmed that a CE business model benefits not only the environmental aspect but also the economic one, with their implementation expected to be worthy nearly 1000 billion US dollars per year. However, the number of scenarios where a CE business model is more convenient than an LE one is markedly higher than the current level of CE adoption, which stands at 7.2% in 2022 (CIRCLE Economy, 2023).

This means that, before acting on the alteration of the current carbon tax values, governments should prioritize overcoming the existing challenges of CE adoption. For instance, Triguero et al. (2022) provided empirical evidence that public financial support is essential for facilitating the implementation of some CE practices. Additionally, the lack of information throughout the product life cycle is another significant barrier to CE adoption. In fact, a CE business model necessitates information regarding the location, conditions, and availability of resources throughout the value chain and requires effective coordination between material and information flows (Kurilova-Palisaitiene et al., 2015; Berg et al., 2020; Panza et al., 2022a,b; Jensen et al., 2023). Governmental bodies are recently moving in this direction by requiring the establishment of a digital product passport to support the effective management of product lifecycle information (European Commission, 2022; Panza et al., 2023).

Moreover, according to Acerbi et al. (2022) and Sassanelli and Terzi (2023), another major reason for the low circularity adoption is the lack of suitable tools to support practitioners in their decision-making process and the need to better exploit data and information. This work can support this aspect since, as discussed above, the decision trees not only show which parameters participate in the decision-making process but also serve as a user-friendly decision support tool that allows practitioners to perform quick and reliable decisions about the selection of the preferable business model. Other relevant challenges for the CE adoption can be found in (Santibanez Gonzalez, Koh and Leung, 2019; van Loon and Van Wassenhove, 2020; Abdelmeguid et al., 2022; Triguero et al., 2022).

Regarding (ii), the performance of the two business models when selected as the preferable business models are displayed in Fig. 10.

The adoption of a new carbon tax regime has two different implications on the performance of the selected business models. On the one hand, there is an increase in environmental performance, expressed by $CO_{2,eq}$ savings, for both the business models (CE and LE). Therefore, the implementation of higher carbon tax values can effectively reduce $CO_{2,eq}$, even when LE is still the preferred business model. Indeed, as seen in the Figure, under the new carbon tax regime, the average $CO_{2,eq}$ savings for the LE business model becomes positive (under the current carbon tax regime they are negative). On the other hand, the new carbon tax regime results in a small reduction in the economic performance, represented by the cost savings, for both the business models when selected.

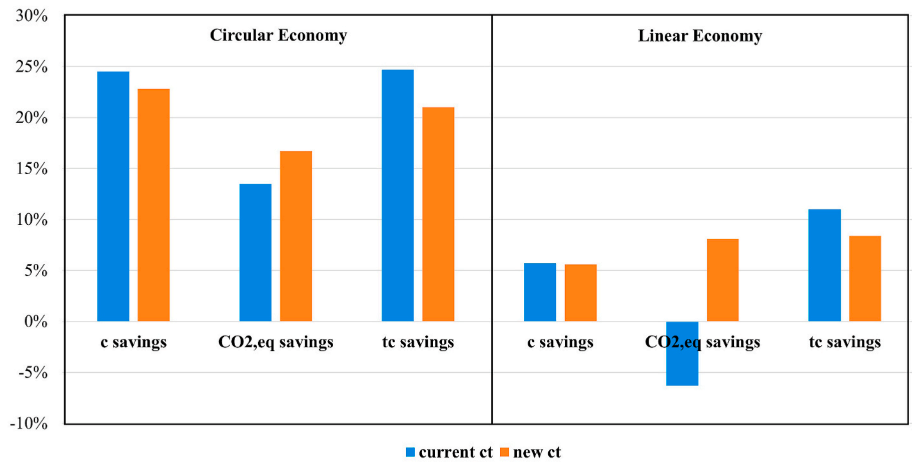

Fig. 10. Average economic, environmental, and total performance of the CE and LE business models when selected as preferable business model under the current and new carbon tax regimes.

Indeed, under the new carbon tax regime, the economic criterion, despite remaining the primary driver in the decision-making process, has a significance that slightly diminishes in favour of a greater emphasis on the environmental criterion. This reduced economic performance following the adoption of carbon tax is not new in the literature, as reported for example in (Alkhayyal, 2019). Since the economic criterion continues to be the main driver of the decision-making process, the total performance, expressed by the total cost savings, mirrors the behaviour of the economic performance, resulting in a slight decrease.

In conclusion, it is noteworthy to highlight that CE performances are consistently superior, on average, compared to LE performances. This underscores the overall advantages of pursuing the CE business model. In fact, the average total cost savings achievable by pursuing a CE ranges from 21,0% to 24,7%, in line with the study of Tolio et al. (2017), who forecasted a reduction in product prices approximately of 25% with the implementation of a CE.

The findings from this research highlight important theoretical and practical implications, which will be discussed in the next section, along with considerations on limitations and directions for future research.

6. Implications of this study and future research avenues

This section presents the key practical contributions of the research (Section 6.1) and discusses its theoretical implications (Section 6.2). Additionally, it addresses the main limitations and outlines future research directions (Section 6.3).

6.1. Practical implications

This study offers a significant contribution to practitioners and managers in manufacturing organizations. The decision trees developed in this research serve as user-friendly decision support tools to visualize the business model decision-making process. By following these decision trees, practitioners can easily assess whether a LE or a CE business model is more suitable for their organizations, as well as how this choice may vary with different carbon tax regimes. This approach enables organizations to enhance their economic and environmental performance. Specifically, the decision trees provide practitioners with valuable insights when deciding between LE and CE models. The main insights derived from the decision tree in Fig. 5, based on current carbon tax values, are elaborated below.

First, the economic cost of product disassembly $rc_{disassembly}$ represents the main driver of the decision. If this cost remains under 40% of the cost of product manufacturing, the CE is almost always the preferable business model. This holds true for all the scenarios where the economic costs of product disposal $rc_{disposal}$ are not very low (i.e. higher than 7.55% of the product manufacturing cost). In other scenarios where the product disposal costs are very low, the LE becomes the preferable business model, notably if the quality of the components is low. Things change when the economic cost of the product disassembly increases (i.e. $rc_{disassembly} \geq 40\%$). From the right-hand side of the decision tree, it is clear that the CE is no longer the predominant business model suggested and that the suitability of the CE and LE business models depends greatly on the combination of the values assumed by the economic costs of product disposal $rc_{disposal}$ and the peak of the component quality index distribution cqi_{peak}. In particular, much depends on the economic costs of product disposal $rc_{disposal}$: when this is high (i.e. greater than 22.5% of product manufacturing cost), the CE is the preferable business model, unless the peak of the component quality index distribution cqi_{peak} is very low; instead, when the relative cost of product disposal is low, the LE can be the preferable business model, even when the peak of the component quality index distribution cqi_{peak} assumes high values.

Considering the decision tree for the new carbon tax regime (Fig. 9), the general insights are as follows. When the relative cost of product disassembly $rc_{disassembly}$ is low (i.e. below 40%), the decision-making process is now mainly driven by the relative carbon footprint of product disassembly $rcf_{disassembly}$ and not by the relative cost of product disposal $rc_{disposal}$. Moreover, in these scenarios of low $rc_{disassembly}$ (i.e. left-hand side of the decision tree), the quality of components, i.e. the peak of the component quality index distribution cqi_{peak}, do not affect the decision-making process, which is only governed by the economic and environmental parameters of product disassembly and disposal. Conversely, when the relative cost of product disassembly $rc_{disassembly}$ is high (i.e. above 40%), the environmental parameters of product disassembly and disposal still affect the decision-making process, but they have a lower impact than the relative cost of product disposal $rc_{disposal}$ and the quality of components.

Additionally, companies gain insights into how fluctuations in carbon tax values may influence their choice between LE and CE business models, highlighting the additional benefits of adopting CE. Higher carbon tax rates would lead to greater savings $CO_{2,eq}$ emissions. Furthermore, as mentioned earlier, the decision trees address one of the primary barriers to the adoption of circularity: the lack of effective tools to assist practitioners in their decision-making processes.

This work is also expected to benefit policymakers by providing a clearer understanding of the implications of carbon tax values on both the choice between LE and CE business models and the economic and environmental performance of these models. Higher carbon tax values are shown to significantly reduce $CO_{2,eq}$ emissions. Moreover, policymakers will note that even within the current carbon tax framework, CE is favored in over 70% of the scenarios analyzed, suggesting that companies should adopt this model. Consequently, it becomes evident that the low level of CE adoption should not be addressed solely by increasing carbon tax rates but rather by fostering a shift in mindset among practitioners and actively promoting CE practices. This can be achieved by enhancing financial support for CE initiatives and facilitating efficient information flow and coordination throughout the product lifecycle.

6.2. Theoretical implications

This research enhances the understanding of the carbon tax's role in business model decision-making, offering valuable insights to theory in two main ways. First, it reveals that current carbon tax rates are inadequate for significantly facilitating the transition from LE to CE business models. The findings indicate that the carbon tax does not directly influence the decision to switch from a LE to a CE model, as it alone does not determine whether to adopt a CE or LE business model. Instead, it strongly affects how environmental parameters influence the decision-making process. Specifically, the carbon tax significantly impacts the role of $CO_{2,eq}$ emissions related to product disassembly and disposal in this decision-making process. With the current carbon tax rates, these environmental factors have a minimal impact on decision-making. Consequently, the choice between adopting a CE or LE business model is primarily driven by the economic costs associated with product disassembly and disposal, as well as the quality of the product at its end of life (EoL). Therefore, existing carbon tax rates are insufficient to facilitate the transition from LE to CE business models, differently from how it is commonly acknowledged in the literature (Xu et al., 2017; Tsai et al., 2023; Ellen MacArthur Foundation, 2024; Wu et al., 2024).

Second, this study advances current theory by developing carbon tax level curves, which outline the minimum carbon tax values needed to significantly support the transition from LE to CE business models. Policymakers interested in promoting environmental sustainability can refer to these curves to determine appropriate carbon tax levels. The implications of adopting the suggested carbon tax values from these curves indicate that such a new regime could increase the likelihood of transitioning from LE to CE by approximately 20%.

Importantly, even under the current carbon tax regime, CE is favored in over 70% of the analyzed scenarios. This highlights the need for governments to tackle the low level of CE adoption by addressing the primary challenges it faces before considering adjustments to carbon tax rates. For example, this could involve providing increased financial support for CE practices and facilitating the efficient integration and coordination of information throughout the product lifecycle. Moreover, implementing a new carbon tax regime would improve the environmental performance of both business models. By establishing higher carbon tax rates, policymakers can effectively reduce $CO_{2,eq}$ emissions, even in the situations when LE is the preferred model. Consequently, the carbon tax level curves developed in this study can serve as a valuable reference for policymakers to set appropriate carbon tax levels that encourage companies to prioritize sustainable practices and reduce their environmental impact.

6.3. Limitations and future research avenues

This study also has some limitations that warrant acknowledgment. First, the findings require empirical validation through case studies. Implementing real-world examples will enhance the reliability and applicability of the results, allowing for a deeper understanding of how carbon tax policies impact business model decisions in practice.

Second, the implications of higher carbon taxes may extend beyond individual organizations to affect entire supply chains. As companies incur increased costs for raw materials, transportation, and other operational aspects, this could create a cascading effect on the overall cost structure of the final product, as noted by (Tsai et al., 2023). Additionally, to meet emission reduction targets and comply with evolving carbon regulations, companies may need to invest in new technologies and equipment. The initial costs associated with adopting cleaner, more sustainable technologies can significantly impact the budgets and profitability of manufacturing organizations. Therefore, further research is essential to analyze the economic implications of stricter carbon tax measures and their effects on supply chain dynamics.

Third, it would be beneficial to apply the analysis conducted in this study to other carbon emission cost models, such as cap-and-trade systems. Understanding how different carbon pricing mechanisms perform in facilitating the transition from linear to circular business models could provide valuable insights for policymakers and practitioners.

Moreover, the range of CE strategies explored in this study could be expanded. Future research could examine additional options, such as repair, refurbishment, or repurposing, to provide a broader spectrum of sustainable choices for businesses and decision-makers. This could also include an exploration of how various CE strategies interact with carbon tax policies, offering a more comprehensive view of their combined impact on sustainability efforts.

Finally, an important limitation of this study is the exclusion of social criteria in the analysis. As already mentioned, the social perspective is not considered due to the lack of an established standard methodology for its quantitative assessment, making its evaluation subjective and influenced by various cultural values and perceptions. Indeed, social impacts cover a broad range of issues such as human rights, labour conditions, community engagement, and well-being, which are inherently subjective and vary significantly across cultures and regions. This diversity makes it difficult to develop universal indicators applicable in all contexts. Unlike environmental impacts, which have relatively well-established metrics (e.g., carbon emissions, water usage), there is no universal agreement on how to measure social impacts. The lack of standardized indicators means different studies or assessments may use different criteria, leading to inconsistent results. Moreover, gathering reliable data on social impacts, particularly in developing regions or informal sectors, is often challenging. Future research could address these challenges by exploring methodologies for quantifying social impacts and developing more standardized indicators, thus enhancing the integration of social considerations into sustainability frameworks.

7. Conclusions

The CE is an appealing business model designed to address significant environmental challenges. In light of recent regulations and policies introduced by various governments to mitigate $CO_{2,eq}$ emissions, such as the implementation of carbon taxes, less carbon-intensive business models like CE should be flourishing. However, this is not the case; despite its potential and these governmental initiatives, the adoption of the CE model remains low, with a declining trend observed in recent years. Thus, contrary to assertions made in existing literature, these governmental measures appear to have little effect on the transition from a LE to a CE, despite the expectation that they should. The reasons for this discrepancy remain unclear.

Indeed, the literature on this topic is limited, as no existing research focuses on understanding how carbon taxes or other carbon reduction schemes impact the transition from a LE to a CE. This study aims to fill this gap by exploring this phenomenon and examining the role of carbon tax in facilitating the transition from LE to CE business models in manufacturing organizations. This represents the first study of its kind, as no prior research has investigated the effect of carbon tax on the business model decision-making process.

To achieve this objective, an integrated methodological framework consisting of several methodological steps has been adopted, given the complexity of the issue. First, a mathematical model has been developed to assist in identifying the preferable business model, either CE or LE. This mathematical model incorporates not only economic criteria but also environmental considerations, reflecting their significance in the decision-making process. Within this model, the carbon tax serves as a weighting factor for the environmental criterion, thereby influencing its importance in the business model decision-making process.

Using this mathematical model, a simulation factorial experiment was conducted to assess the impact of the carbon tax and other parameters on the model's response (CE or LE). The effects were thoroughly analyzed, beginning with a qualitative assessment using graphical tools such as main effects and interaction plots, as well as a decision tree. This was followed by a quantitative analysis employing the MRMR algorithm.

To deepen the understanding of how carbon taxes influence the decision-making process for selecting a business model, a sensitivity analysis of the carbon tax was performed. This analysis resulted in the creation of carbon tax level curves that illustrate the minimum carbon tax value required to significantly contribute to the transition from LE to CE business models. Finally, the study examined how the adoption of these new carbon tax values alters the decision-making process.

In summary, the findings revealed that the current carbon tax rates are too low to affect the transition from LE to CE. At these rates, the decision to adopt either LE or CE business models is predominantly driven by economic factors, rendering the carbon tax ineffective. The analysis of the carbon tax level curves clearly demonstrated that current carbon tax values have little influence on the LE/CE decision for nearly all common consumer products. Therefore, increasing carbon tax values is essential to make environmental factors relevant in the choice between LE and CE, which would subsequently encourage greater adoption of CE practices.

The practical implications of this study suggest that manufacturing organizations can use the developed decision trees as tools for evaluating business model choices in light of carbon tax policies. By understanding the economic and environmental trade-offs, practitioners can make more informed decisions that align with sustainability goals. Theoretically, this research fills a critical gap in the literature by establishing the link between carbon tax mechanisms and business model decision-making, offering a foundation for future studies to explore other carbon pricing models and their effects on sustainability practices. By addressing these aspects, the study contributes to both academic discourse and practical applications in the field of sustainable manufacturing.

CRediT authorship contribution statement

Luigi Panza: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mirco Peron:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices.

Appendix A

The MRMR aims to identify the set of parameters that are both maximally dissimilar from one another and highly effective in representing the response variable (Ding and Hanchuan, 2005; MATLAB, 2023; Panza et al., 2024). The algorithm identifies the best set S of parameters that maximizes V_S, the relevance of S concerning the response variable y, and minimizes W_S, the redundancy of S.

V_S and W_S are defined using the mutual information I:

$$V_S = \frac{1}{|S|}\sum_{x \epsilon S} I(x, y) \tag{C1}$$

$$W_S = \frac{1}{|S|^2}\sum_{x,z\ \epsilon S} I(x, z) \tag{C2}$$

$|S|$ is the cardinality of S, x and z are two generic parameters belonging to the parameters set, i.e., the model parameters in Table 2. For each parameter, the algorithm computes the mutual information quotient MIQ_x, which is used to rank the parameters by importance.

$$MIQ_x = \frac{V_x}{W_x} \tag{C3}$$

V_x and W_x are the relevance and redundancy of a parameter:

$$V_x = I(x, y) \tag{C4}$$

$$W_x = \frac{1}{|S|}\sum_{z\ \epsilon S} I(x, z) \tag{C5}$$

MIQ_x can be used to rank features through an importance score. In this way, the assessment process of the relative importance of the model parameters can be quantitively performed. The MRMR algorithm was implemented in MATLAB. More theoretical details can be found in MATLAB documentation (MATLAB, 2023).

Appendix B

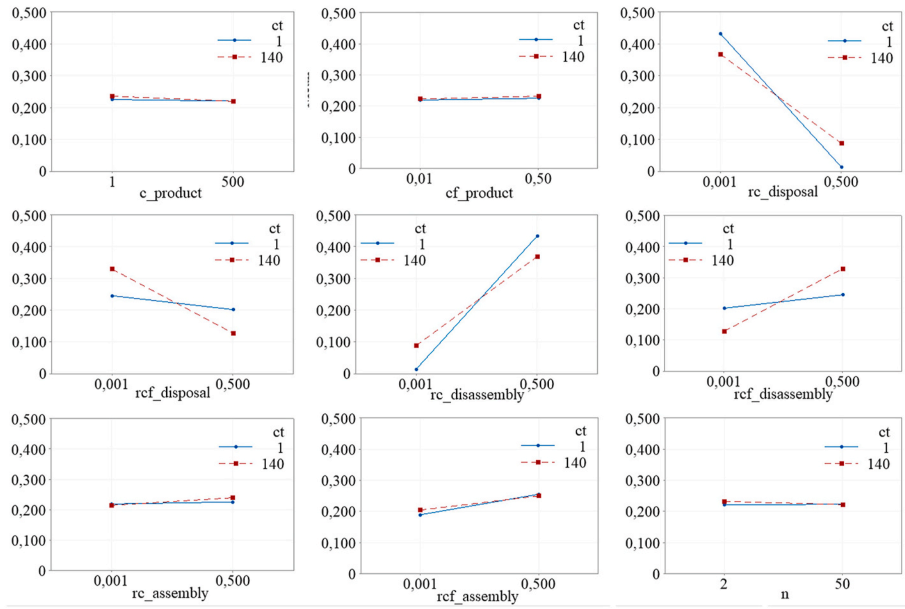

Fig. B1. Interaction plots of the carbon tax and the first set of model parameters.

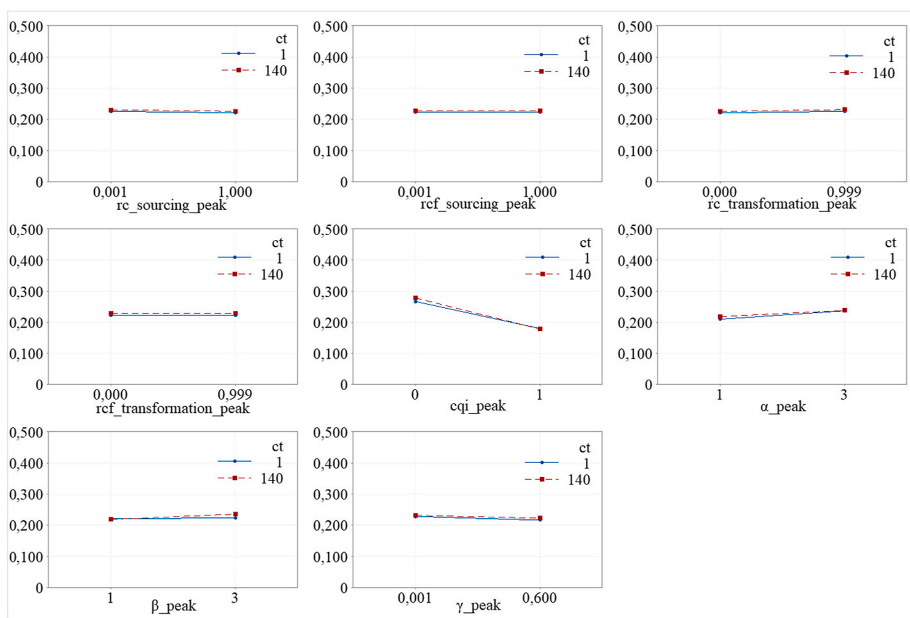

Fig. B2. Interaction plots of the carbon tax and the second set of model parameters.

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