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Proposal of Industry 5.0-Enabled Sustainability of Product–Service Systems and Its Quantitative Multi-Criteria Decision-Making Method

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Abstract: In the wake of Industry 4.0, the ubiquitous internet of things provides big data to potentially quantify the environmental footprint of green products. Further, as the concept of Industry 5.0 emphasizes, the increasing mass customization production makes the product configurations full of individuation and diversification. Driven by these fundamental changes, the design for sustainability of a high-mix low-volume product–service system faces the increasingly deep coupling of technology-driven product solutions and value-driven human-centric goals. The multi-criteria decision making of sustainability issues is prone to fall into the complex, contradictory, fragmented, and opaque flood of information. To this end, this work presents a data-driven quantitative method for the sustainability assessment of product–service systems by integrating analytic hierarchy process (AHP) and data envelopment analysis (DEA) methods to measure the sustainability of customized products and promote the Industry 5.0-enabled sustainable product–service system practice. This method translates the sustainability assessment into a multi-criteria decision-making problem, to find the solution that meets the most important criteria while minimizing trade-offs between conflicting criteria, such as individual preferences or needs and the life cycle sustainability of bespoke products. In the future, the presented method can extend to cover more concerns of Industry 5.0, such as digital-twin-driven recyclability and disassembly of customized products, and the overall sustainability and resilience of the supply chain.

Keywords: Industry 4.0; Industry 5.0; sustainability; product–service system; design for sustainability; multi-criteria decision making; analytic hierarchy process; data envelopment analysis

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1. Introduction

With the evolution of the digitalization revolution, especially after the impact of the COVID-19 epidemic, the landscape of modern industry has been changing dramatically in the past decade. Firstly, the fourth industrial revolution (Industry 4.0) is emerging in the global manufacturing industry and in the technical side, it is characterized by absorbing the internet of things (IoT), artificial intelligence (AI), big data analytics, blockchain, digital twin (DT), additive manufacturing, and various types of intelligent robots into manufacturing scenes, which empowers the smart factories by widely connecting and extensively integrating production systems [1]. These new technologies are enabling ever-higher levels of production efficiencies, and are transforming the production paradigm from mass production to mass customization. Furthermore, they also have the potential to dramatically influence social and environmental sustainable development. Industry 4.0 technologies have potential to benefit all 17 of the United Nations Sustainable Development Goals (SDGs) [2]. For instance, by means of IoT technology, data throughout the product life cycle (PLC), including raw material procurement, manufacturing, logistics and transportation, product use and maintenance, and recycling and processing, can be collected into cloud platforms and become accessible. Furthermore, big data analytics can enhance efficiency and optimization and lead to better management of energy and material consumption. Additive manufacturing offers numerous notable benefits, including direct production without the need for molds and tooling, enabling greater design flexibility, efficient material utilization, and environmentally friendly processes [3]. The DT model generates a new opportunity to identify and eliminate the unpredicted undesirable behavior, which has a major impact on the reduction in wasted resources in the life cycle of our systems [4]. The blockchain technology, which has proven to be compatible with Industry 4.0, allows for supporting an emissions trading application framework [5]. AI could impact sustainable products in many ways [6], such as facilitating designing business models for a circular economy considering the uncertainties of demand and supply, and optimizing product take-back and recycling with image recognition and robots. Therefore, the increasing number of studies that underline the relationship between Industry 4.0 and sustainability declare that sustainability is one pillar of smart manufacturing [7]. In addition, it is demonstrated that there are complex interrelationships and sometimes trade-offs between the impacts of the various emerging technologies on the "triple-bottom-line" (TBL) sustainability dimensions: environmental, social, and economic. These interrelationships and trade-offs between diverse industrial sectors can vary, leading to increased complexity, difficulty, and uncertainty in decision-making processes [8].

More recently, the Industry 5.0 concept [9] was forwardly proposed on the assumption that Industry 4.0 is believed to promote sustainable development, but it has ignored or misunderstood many prevailing sustainability concerns. Other scholars may prefer to label it as Industry 4.0 Plus, Industry 4.0 Symmetrical, Industry 4.0-S, or using other terminology, the key of which is to encourage a departure from uncritical thinking and narrow epistemologies that currently dominate our understanding of science and technology [10]. In a brochure published by the European Commission, Industry 5.0 is defined by a re-found and widened purposefulness, going beyond producing goods and services for profit, which embraces three core elements: human-centricity, sustainability, and resilience [11]. Sustainability emphasizes that a business focused solely on profit is increasingly challenging to sustain in a globalized and highly volatile environment. Resilience refers to the ability to deal with vulnerabilities that can occur on many levels, including the factory floor, supply network, and industrial system levels. The human-centric approach in industry puts core human needs and interests at the heart of the production process, instead of taking emergent technology as a starting point and examining its potential for increasing efficiency. For an industry to become a provider of true prosperity, it must include social, environmental, and societal aspects. The essence of Industry 5.0 is the symbiosis of the three segments: technological, social, and ecological [12]. Leng et al. [13] interpreted the connotation of Industry 5.0 as follows: Industry 5.0 prioritizes the welfare of workers by ensuring that manufacturing processes adhere to the ecological capacity of our planet, fostering a harmonious relationship between humans and machines to achieve societal goals beyond mere job creation and economic growth, ultimately advancing sustainable development toward a super-smart society with ecological values. Ivanov [14] reckoned that Industry 5.0 spanned three levels, society, network, and plant, and forms a new TBL of resilient value creation, human well-being, and sustainable society.

SDG 12 emphasizes the importance of responsible consumption and production practices, aiming to separate economic growth from unsustainable resource consumption and emissions. It also focuses on enhancing the management of hazardous substances and waste to promote sustainability [15]. Many people are paying more attention to sustainable consumption or socially responsible consumption now than before; in particular, Millennials and Generation Z especially indicate a willingness to achieve SDGs, including equality, climate change, peace, justice, eradicating poverty, and prosperity [16]. Attitude is the most significant factor that influences responsible consumption intentions, which entail a critical perspective on consumption, including responsible purchasing, waste production concerns, reduced consumption, non-consumption, and alternative approaches with environmental or social objectives in mind [17]. In modern times, businesses are constantly exploring new avenues to improve their interactions with clients. One crucial aspect of a company's sustainable strategy involves engaging stakeholders in the decision-making process. In pursuit of the dual goals of profitability and sustainability, leading organizations have integrated environmentally responsible practices into their business models. Sustainability considerations have become increasingly important factors for consumers and corporate purchasers when making buying and investment decisions, including assessing carbon footprints. The current decade may see an overall shift for corporations toward a growth model that emphasizes societal and environmental well-being alongside profits, highlighting the growing significance of sustainability in modern business practices.

Figure 1 schematically sums up the aforementioned vision. Briefly, we are at a decisive moment, in which some of the "old normal" will crumble and a "new normal" is becoming true. However, transition to the grand vision still faces severe challenges and arduous obstacles, especially with SDGs' deadline of 2030 approaching, and a lot of people increasingly argue that SDG 12 and its targets seem too ambitious to be fulfilled. The goal seems to be increasingly consistent and constructive, but the practice is highly isolated or full of differences. To argue the importance of this work more clearly, the following problems are further focused on:

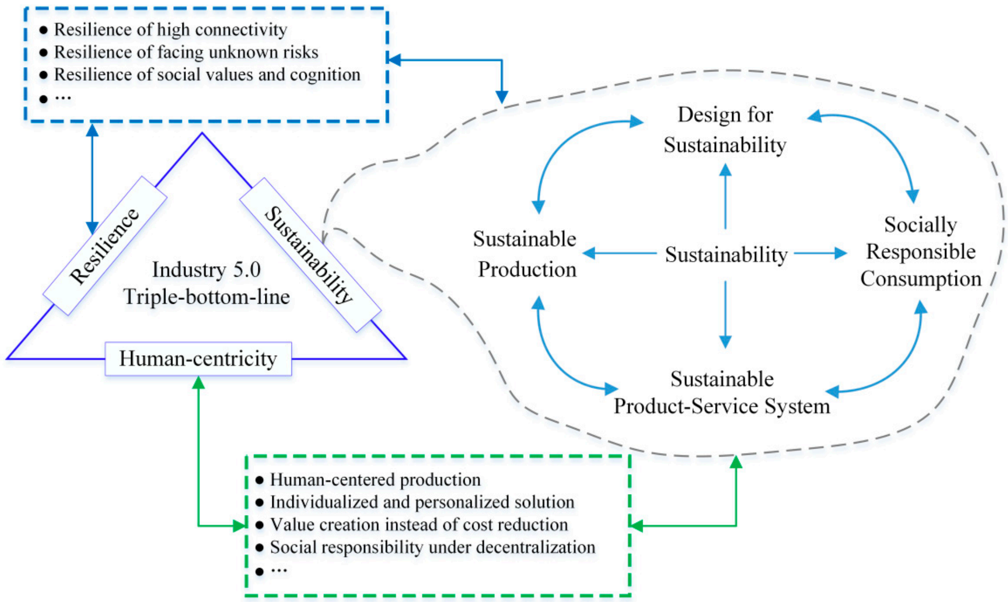

Figure 1. Conceptual links of sustainability under Industry 5.0.

First, the decision-making process of green consumption is highly complex, and seldom becomes true as one wishes. The most prominent problem is that the sustainable consumption and sustainable production agendas are often isolated from each other. The lack of transparency and clarity in production chains and operations poses significant challenges for individuals seeking to understand the manufacturing processes involved. Additionally, the prevalence of long and complex supply chains in contemporary global trade makes it difficult to discern the connections between consumption and production, as these systems can span vast distances. Consumers are often faced with complex and confusing information about production and supply chains that demands significant cognitive resources. This can engender a sense of ignorance and uncertainty among consumers, which is further complicated by the demands of busy daily life. The difficulty of long-term information gathering and decision making in other areas exacerbates the challenge of comprehending the complexities of production chains in modern manufacturing. Credibility is especially a major challenge in the midst of an intensive and conflictive field of information [18]. While a significant number of consumers express concerns about environmental issues, their actual consumption habits often do not align with environmentally responsible practices. Entrenched in social norms, cultural traditions, and daily routines, individuals may find it challenging to transition toward greener consumption patterns. Additionally, a lack of comprehensive information, limited availability of sustainable products, and doubts regarding their quality can complicate the decision-making process associated with green consumption. These factors collectively contribute to the complexity of adopting environmentally friendly habits, potentially impeding the widespread acceptance and realization of greener consumption goals [19].

Second, the sustainable product–service concept driven by the coupling of technology and value is not yet mature for wide acceptance and practice. As mentioned above, because the production paradigm in the era of Industry 5.0 is mass individualization or mass personalization, the whole process will appear creative in design and complex in manufacturing. Mass personification allows the customers to customize the individualized product through digital technologies and e-commerce, while smart customization means providing smart user toolkits for co-design. Therefore, the customer can influence the product development before and after the purchase. This requires the deep coupling of the technology-driven and value-driven methods to fulfill the whole individualized manufacturing process in a reorganized symbiosis. One promising approach to tackle these challenges is the adoption of product–service systems (PSSs) [20]. A PSS is a value proposition that aims to provide user satisfaction by delivering an integrated system of products and services. If properly designed, PSS can create economic and competitive incentives for stakeholders to continually improve sustainable resource management practices. Recognizing the growing demand for customized products, manufacturers are shifting from a high-volume, low-variety production model to a low-volume, high-variety model [21]. The solution lies not only in making production methods more ecologically sound but also in influencing consumer behavior through the introduction of environmentally responsible products, services, and practices. Therefore, the successful implementation and widespread adoption of PSS innovations require collaboration among multiple actors rather than relying on a single entity or small network. Servitization is a business strategy that involves shifting focus from selling products to providing services and solutions that meet the needs of customers. Despite the potential benefits and driving factors mentioned above, the diffusion of sustainable product–service systems (SPSSs) remains limited.

Obviously, the multi-criteria decision making of sustainability issues is prone to fall into the complex, contradictory, fragmented, and opaque flood of information. Therefore, more practical studies are expected to reveal the implications of these emerging changes on SPSS and address the manufacturing companies' and designers' challenges. The analytical hierarchy process (AHP), analytical network process, case-based reasoning, and multi-criteria decision analysis are the common data-driven approaches for product sustainability assessment. For a large amount of data of the entire life cycle of the product, the collection can be effectively completed by IoT, and the customers demand information and the available product information can be collected through the mobile terminal and the database. In this research, we intend to propose an approach that combines AHP with a data envelopment analysis (DEA) to measure the sustainability of customized products and sustainable designs. Specifically, the contributions of this work include several aspects.

First, a data-driven quantitative evaluation method of SPSS is proposed. In the ranking and selection of SPSS practices, the proposed approach can facilitate the integration of qualitative and quantitative criteria for addressing environmental, economic, and social indicators. It is useful to increase environmentally sustainable innovation and green choices of the personalized products in mass customization.

Second, as a proof of concept, the design for sustainability (DfS) of refrigerators is demonstrated. In mass customization, some components of refrigerators have selectable variants (e.g., sources of energy, compressor, refrigerant, materials, sensors, network components, different after-sales service manners, and so on) or can be customizable due to the customization capability that the refrigerator company offers. The metric and correlation analysis of sustainability performance empower the design team to have a holistic approach to the Industry 5.0-enabled sustainability of customized refrigerators.

2. Methodology

2.1. Design for Sustainability of Product–Service System

Generally speaking, nearly 80% of all product-related environmental impacts are determined during the design phase [22]. Accordingly, the product designer must focus their attentions on the phases of the PLC that most significantly affect the environment so that its environmental impact can be greatly reduced [23]. Design for environment (DfE, US term) or eco-design (European term) or green product design (a coined term within the marketing field) has been increasingly used in sustainable manufacturing during recent decades [24]. Generally, "greenness" refers to the degree of sustainability performance of an eco-friendly product or a green product [25]. The ISO 14006 standards provide guidance for working on eco-design as part of an environmental management system [26]. Fiksel [27] discussed four principles of DfE: design for dematerialization, design for detoxification, design for revalorization, and design for capital protection and renewal. New technologies will partially determine the future of design for sustainability. Kuik et al. [28] described sustainable products using the 6Rs proposition, reduce, recycle, reuse, recover, remanufacture, and redesign, over the stages of the PLC.

In the wake of Industry 4.0 and incoming Industry 5.0, these DfS or DfE or eco-design methodologies are currently undergoing fundamental changes, such as becoming more proactive, big-data-driven, intelligent, and robust. Trollman H. and Trollman F. [29] performed a sustainability assessment of smart innovation in mass customization and digital manufacturing. They contend that the necessary flexibility in the manufacturing process for mass customization presents challenges related to optimizing material and energy consumption. However, the traceability of products and the availability of take-back options for reuse and recycling, as well as improved end-of-life (EoL) decisions, could serve as advantages for personalized products. Offering service solutions for customers and fostering long-lasting relationships between customers and products could enhance product life cycle performance. Cicconi [30] suggested an interactive, web-based platform as an eco-material tool, which could integrate recent technologies to develop digital mock-ups of products and consumers' preferences, encouraging innovative eco-material solutions. Keivanpour and Kadi [31] proposed online analytical processing as an effective approach for a multidimensional data analysis when evaluating complex product dismantling and disassembling based on material type, recyclability, replicability, and material scarcity. Additionally, Rojek et al. [32] showcased the application of DT in co-designing, planning, and monitoring manufacturing processes for sustainability in both manufacturing and maintenance. Industry 4.0 facilitates the adoption of eco-design tools and aids in removing some existing challenges of applying eco-design tools. Conceivably, emerging technologies, business models, and lifestyles will become a milestone marking the advent of a new, sustainable world.

Furthermore, digitalization has given rise to innovative digitally connected products, paving the way for sustainable product–service systems. While PSS alone may not guarantee sustainable consumption, the provision of PSS within a circular economy and circular business models is preferable to isolated product offerings, as PSS can reduce resource dependency in consumption. The evolution of PSS has transformed them from mere product ideas focused on environmental performance to comprehensive product–service systems that foster radical, systemic, and behavioral innovation. Digitalization has permeated everyday life and shifted power dynamics from marketers to consumers, empowering them to easily access peer reviews, assess service providers, and compare different offerings [33]. Further, the proliferation of internet connectivity has empowered consumers to demand more customized products and services. Companies are responding by offering co-design and participatory approaches that promote customer involvement in product development, enabling the generation of flexible and innovative solutions. Cloud platforms and data sharing play a crucial role in facilitating customization, supporting co-design, and meeting the increasing demand for personalized product–service solutions.

Considering the deep coupling of the technology-driven and value-driven requirements, herein, a basic method for the sustainability assessment of a product–service system is proposed as shown in Figure 2. Life cycle modelling considers the product as well as the technological infrastructure and the services [34]. The sustainability indicators (SIs) are identified according to the sustainability willingness of customers. Then, SIs are measured by the cloud platforms and database. These SIs may be quantitative or qualitative, often conflicting. Therefore, sustainability assessment can be translated into a multi-criteria decision-making problem, to find a solution that meets the most important criteria while minimizing trade-offs between conflicting criteria. The AHP method provides a systematic and logical approach to decision making, allowing decision makers to structure complex problems, prioritize criteria and alternatives, and reach a well-informed and rational decision based on both qualitative and quantitative inputs. In addition, DEA is a non-parametric method using linear programming techniques to measure the relative efficiency of decision-making units (DMUs) by comparing their input–output relationships with those of other DMUs. It allows for the inclusion of multiple inputs and outputs, both quantitative and qualitative, without requiring any information about the functional form or production technology of each DMU. Considering the features of sustainability assessment, herein, an approach that combines AHP with DEA is proposed to calculate the sustainability of customized products and sustainable designs.

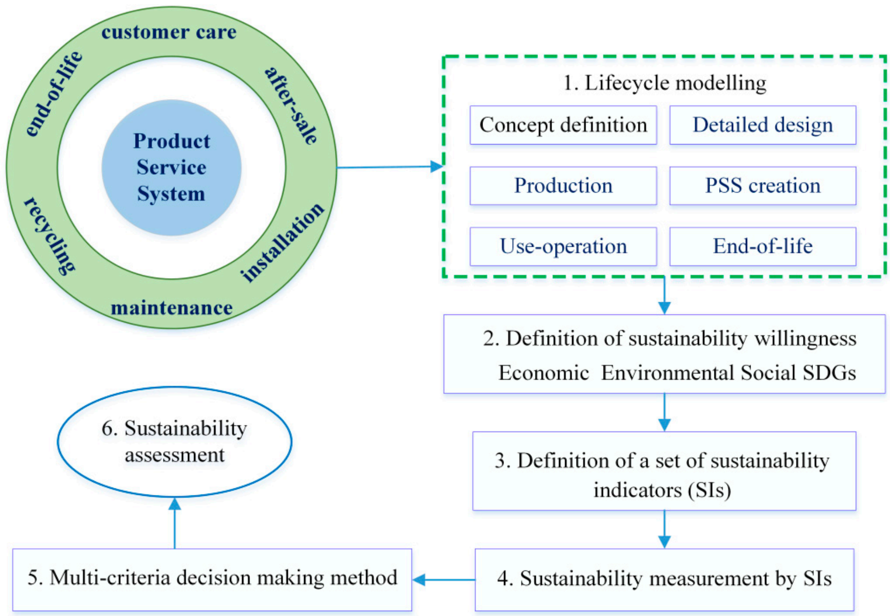

Figure 2. Method for the sustainability assessment of product–service system.

2.2. Analytic Hierarchy Process Method

AHP is a method of measurement through pairwise comparisons and relies on the judgments of individuals toward decision making [35]. As a multi-criteria decision-making (MCDM) tool, it also provides a methodology to calibrate the numeric scale for the measurement of quantitative as well as qualitative performances [36]. In order to quantify decision-making judgment and form a numerical value judgment matrix, an appropriate scale value must be introduced to measure the relationship among different relative importances. Some key and basic steps of the AHP are introduced as follows:

2.2.1. Evaluation Indicators for MCDM Problems

The evaluation indicator system is a comprehensive framework consisting of a set of indicators that represent the characteristics of the objects and their interrelationships.

Within this system, the elements are interconnected and interdependent and interact with each other. Typically, the evaluation indicator system is categorized into the target layer, criterion layer, and indicator layer.

2.2.2. Judgment Matrix

In the AHP, the relative importance between the paired factors at each layer is qualitative. The decision-making judgment is quantified by an appropriate scale value introduced to form a numerical value judgment matrix. T.L. saaty's 1~9 scale (as shown in Table 1) is applied to convert qualitative evaluation into quantitative evaluation. The numerical value measures the relationship between different relative importances, and the judgment matrix is built as follows:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

where n represents the order of the judgment matrix, $a_{nn} = 1,\ a_{1n} = \frac{1}{a_{n1}}$.

Table 1. Judgment matrix scale and its connotation.

Scale	Connotation
1	Means that the importance is the same in the comparison of two factors.
2	Between the mid-value of the two adjacent judgments above.
3	Means that one factor is slightly more important than the other in the comparison of two factors.
4	Between the mid-value of the two adjacent judgments above.
5	Means that one factor is significantly more important than the other in the comparison of two factors.
6	Between the mid-value of the two adjacent judgments above.
7	Means that one factor is much more important than the other in the comparison of two factors.
8	Between the mid-value of above two adjacent judgments.
9	Means that one factor is extremely more important than the other factor in the comparison of two factors.
Reciprocal	If the importance ratio of Factor a and Factor b is k, then the importance ratio of Factor b and Factor a is 1/k.

2.2.3. Calculate Indicator Weight

Having determined the judgment matrix A, we then use Matlab software of R2018a to obtain the maximum Eigen value λ_{max} and its corresponding Eigen vector V, and obtain the indicator weight W after performing normalization treatment on Eigen vector V.

2.2.4. Check Consistency

First, we arrive at the consistency indicator $CI = \frac{\lambda_{max}-1}{n-1}$, and then calculate the random consistency ratio $CR = \frac{CI}{RI}$, in which RI is the average consistency indicator of the judgment matrix. The RI value is selected by referring to Table 2. Finally, it depends on CR. If $CR < 0.1$, then consistency is satisfied. Otherwise, it is necessary to adjust the numerical value of the judgment matrix until satisfactory consistency is obtained.

Table 2. RI average value calculated based on sample capacity of 1000.

n	2	3	4	5	6	7	8	9	10	11	12
RI	0	0.514	0.893	1.118	1.249	1.345	1.420	1.462	1.487	1.516	1.541

AHP is predominantly used in the area of selection and evaluation. John et al. [37] used the integrated Life Cycle Assessment (LCA) and AHP approaches to evaluate four types of renewable energy (solar, wind, biomass, and mini-hydro energy) and select the best renewable energy source in Tatau, Sarawak. LCA is a well-established and widely accepted tool for determining the environmental profile of a product, and has been widely applied in order to reduce materials and energy and environmental pollution during product design and manufacturing. LCA is divided into four stages: objective and scope, life cycle inventory, life cycle impact assessment, and interpretation (ISO 14040:2006 [38]; ISO 14044:2006 [39]) [40].

Mainar-Toledo et al. [41] utilized the AHP method to prioritize the significance of the three TBL dimensions and their respective key performance indicators. This facilitated wine producers in identifying areas for enhancing production sustainability. Martin et al. [42] introduced a framework that combined environmental and social LCAs with a modified AHP methodology to assess nine disposal scenarios for polyethylene terephthalate (PET) bottle waste. Additionally, Bhyan et al. [43] employed fuzzy AHP to develop a comprehensive sustainability assessment system tailored to group housing in India across various stages of the building life cycle.

Despite numerous benefits, the complexity of the pairwise comparison process and the challenges associated with maintaining consistency in AHP present significant obstacles. The weighting process is vulnerable to the subjective consciousness, experience, and knowledge of the evaluators, potentially leading to biased and limited evaluation results. Moreover, the discrete scale of AHP often makes it difficult to compare different factors in the presence of uncertainty and ambiguity, compounded by the lack of sufficient information.

2.3. Data Envelopment Analysis Method

A data envelopment analysis (DEA) [44] is a widely used method for determining the relative efficiency of units based on multiple inputs and outputs, providing an assessment of the effectiveness of a set of peer entities known as DMUs. DEA is capable of handling both qualitative and quantitative data and serves as an effective decision-making tool for directing management attention to areas that require improvement [45]. Consequently, researchers often describe DEA as a tool for identifying best practices when organizations have multiple performance metrics or measures. Wang et al. [46] integrated economic and environmental factors within supply chains to create a sustainability indicator and proposed a supply chain greenness assessment method based on the multi-regional input–output model (MRIO) and DEA. Additionally, Andrijauskiene et al. [47] utilized DEA to evaluate the European Union's innovation efficiency from 2000 to 2020. Notably, Kuo and Kusiak [48] demonstrated that data-driven production research has transitioned from analytical models to data-driven approaches, with manufacturing and DEA emerging as the most popular application areas for these methodologies.

Here, the initial DEA model, as originally presented by Charnes, Cooper, and Rhodes (CCR), is introduced directly [49], which includes the non-Archimedes infinitesimal ε.

2.3.1. CCR Model with Non-Archimedes Infinitesimal ε

It is assumed that there are N products to be evaluated, constituting an evaluation system of N DMUs' multi-indicator input and multi-indicator output. Each DMU has m types of input $X_i = [x_{1i}, x_{2i}, \cdots, x_{mi}]^T$, $i = 1, \cdots, N$ and n types of output $\mathrm{Y_i} = [\mathrm{y_{1i}}, \mathrm{y_{2i}}, \cdots, \mathrm{y_{mi}}]^{\mathrm{T}}$, $\mathrm{i} = 1, \cdots, \mathrm{N}$. For convenience, P is set as the weight coefficient of input and Q as the weight coefficient of output, denoted by $P = [p_1, p_2, \cdots, p_m]^T$ and $Q = [q_1, q_2, \cdots q_n]^T$, in which X_i and $Y_i (i = 1, \cdots, \mathrm{N})$ are the input vector and output vector of $DMU_i = (X_i, Y_i)$, while P and Q are the weight vectors corresponding to m types of input and n types of output. For vector coefficients $P \in E^m$ and $Q \in E^n$, the efficiency index of DMU i (i.e., DMU_i, $1 \leq i \leq \mathrm{N}$) is

$$e_i = \frac{Q^T Y_i}{P^T X_i}, \; i = 1, \cdots, N \tag{2}$$

where the weight coefficient P and Q meet $e_i \leq 1, 1 \leq i \leq N$.

The non-Archimedes infinitesimal ε is an abstract mathematical concept, and it is a number smaller than any positive number and bigger than 0 (usually $\varepsilon = 10^{-10}$). It serves to prevent negligence of an indicator's effect when the indicator's weight is 0 [50]. The CCR model with the non-Archimedes infinitesimal ε is described as follows:

$$\begin{cases} \max \frac{Q^T Y_0}{P^T X_0} \\ s.t. \frac{Q^T Y_0}{P^T X_0} \leq 1, i = 1, 2, \cdots, N \\ \frac{P^T}{P^T X_0} \geq \varepsilon a^T \\ \frac{Q^T}{Q^T Y_0} \geq \varepsilon b^T \end{cases} \tag{3}$$

where $a^T = [1, \cdots, 1]^T \in R^m$, $b^T = [1, \cdots, 1]^T \in R^n$, $X_0 = X_{i0}$, and $Y_0 = Y_{i0}$ are the input and output vectors of DMU_i. The solution to the preceding formula is relatively hard to obtain. Therefore, it is necessary to complete the Charnes–Cooper transformation, i.e., the dual transformation, and convert the non-linear model into an equivalent linear planning model. Let $\sigma = 1/P^T X_0$, $\varphi = \sigma P$, and $\phi = \sigma Q$, and it is easy to obtain:

$$\varphi^T X_0 = 1 \tag{4}$$

$$\phi^T Y_0 = \frac{Q^T Y_0}{P^T X_0} \tag{5}$$

$$\frac{\phi^T Y_0}{\varphi^T X_0} = \frac{Q^T Y_i}{P^T X_i} \leq 1,\ i = 1, \cdots, \mathrm{N} \tag{6}$$

Therefore, Equation (3) can be converted into

$$\begin{cases} \max \phi^T Y_0 \\ s.t.\ \varphi^T X_i - \phi^T Y_i \geq 0 \\ \varphi^T X_0 = 1 \\ \varphi^T \geq \varepsilon a^T \\ \phi^T \geq \varepsilon b^T \end{cases} \tag{7}$$

Its dual issue is

$$\begin{cases} \min\left(\hat{\xi}_1, \hat{\xi}_2, \cdots, \hat{\xi}_N, \rho_1^T, \rho_2^T, \varepsilon a^T, \varepsilon b^T\right)(0, \cdots, 0, 1)^T \\ s.t. \sum_{i=1}^{\mathrm{N}} \hat{\xi}_i X_i + \delta X_0 + \rho_1 = 0 \\ -\sum_{i=1}^{\mathrm{N}} \hat{\xi}_i Y_i + \rho_2 = Y_0 \\ \hat{\xi}_i \leq 0, i = 1, \cdots, N \\ \rho_1 \leq 0, \rho_2 \leq 0 \\ \delta \text{ has no symbol restriction} \end{cases} \tag{8}$$

in which $\rho_1 \in R^m$ and $\rho_2 \in R^n$ are both column vectors, denoted by $-\hat{\xi}_i = \xi_i$, $i = 1, \cdots, \mathrm{N}$, $-\rho_1 = \rho^-$, and $-\rho_2 = \rho^+$, and placed into the above formula. The following is obtained:

$$\begin{cases} \min\left[\delta - \varepsilon\left(a^T \rho^+ + b^T \rho^-\right)\right] \\ s.t. \sum_{i=1}^{\mathrm{N}} \xi_i X_i + \rho^- = \delta X_0 \\ \sum_{i=1}^{\mathrm{N}} \xi_i Y_i - \rho^+ = Y_0 \\ \xi_i \geq 0, i = 1, \cdots, N \\ \rho^- \geq 0 \\ \rho^+ \geq 0 \end{cases} \tag{9}$$

where δ is the efficiency evaluation parameter of DMU_i, ξ_i is the combination ratio of DMU_i, ρ^- and ρ^+ are slack variables (also called redundant variables), ρ^- represents invalid input or redundant non-expected output, and ρ^+ represents output insufficiency. The slack variables may convert an inequation into an equation and the nature can be discussed by solving the equation on the basis of the equation. At the same time, the scenario in which weak DEA is effective is identified. The optimal solution to Equation (9) is $\dot{\xi}$, $\dot{\rho}^{-}$, $\dot{\rho}^{+}$, and $\dot{\delta}$. So,

(1) If $\dot{\delta} < 1$, then DMU_{i_0} is non-DEA-effective.
(2) If $\dot{\delta} = 1$, and $\dot{\rho}^{-} = 0$ and $\dot{\rho}^{+} = 0$, then DMU_{i_0} is DEA-effective.
(3) If $\dot{\delta} = 1$, and $\dot{\rho}^{-} \neq \dot{\rho}^{+} \neq 0$, then DMU_{i_0} is weakly DEA-effective.

Therefore, it can be concluded that when the CCR model with non-Archimedes infinitesimal ε inspects the effectiveness of DMU_{i_0}, it needs to only judge whether $\dot{\rho}^{-}$ and $\dot{\rho}^{+}$ are 0 once, and it is unnecessary to inspect whether all $\dot{\rho}^{-}$ and $\dot{\rho}^{+}$ are 0. This has simplified the inspection of DEA effectiveness regarding DMUs.

For weakly DEA-effective and non-DEA-effective DMUs, the projection theorem can be used to improve a DMU into an effective DMU. The projection theorem is described as follows:

$$\begin{cases} X_0' = \delta^0 X_0 - \rho^{-0} = \sum_{i=1}^{N} X_i \xi_i^0 \\ Y_0' = Y_0 + \rho^{+0} = \sum_{i=1}^{N} Y_i \xi_i^0 \end{cases} \quad (10)$$

in which (X_0', Y_0') is the projection of DMU_{j_0}. According to the projection theorem, the projection of each product on the relatively effective surface of DEA production is calculated, and possible production improvements that can improve the green attributes of the product can be identified. The input and output of the product are determined according to the projection of the product on the effective surface of DEA production. Products of this configuration have higher sustainability.

2.3.2. Improved DEA (iDEA)

For the improved DEA, the CCR model has been improved to obtain more detailed results than the traditional CCR method. The aim of the improved model is to maximize the efficiency index of the best virtual products and minimize the efficiency index of the worst virtual products. Taking the optimal solution as the public weight, the efficiency value of each DMU is calculated. This model is able to avoid the failure to obtain the product efficiency index accurately because the traditional DEA model may arrive at infinite groups of weight. In other words, "non-uniform evaluation" under the traditional DEA approach is changed into "uniform evaluation". At the same time, this model reduces the uncertainty of weight coefficient selection and improves the reliability of evaluation results. A step-by-step application of the iDEA to customized product sustainability assessment is introduced as follows:

Step 1. Classify input and output indicators.

Each DMU is assumed to have m input indicators and n output indicators, and the input and output vectors of DMU_j are $X_j = \left(x_{1j}, x_{2j}, \cdots, x_{ij}, \cdots, x_{mj}\right)^T$ and $Y_j = \left(y_{1j}, y_{2j}, \cdots, y_{lj}, \cdots, y_{nj}\right)^T$, of which x_{ij} and y_{lj} are the values of the i input indicator and the l output indicator of DMU_j. When the DEA approach is used to classify indicators, "the smaller, the better" indicators are usually defined as input indicators, while "the bigger, the better" indicators are defined as output indicators.

Step 2. Introduce virtual solution.

The relatively best solution and the relatively worst solution are built and denoted by DMU_{N+1} and DMU_{N+2}. The scope of data envelopment is broadened to obtain a more appropriate public weight. At the same time, the value range of the efficiency index is expanded to sharpen the distinction among DMUs. The choice of virtual solution affects only the absolute value of the evaluation result but not the relative value of the sustainability of the bespoke products. In the construction of virtual products, the optimal value of the indicators of all DMUs is taken as the best virtual product and the worst value as the worst virtual product. Then, the input vector x_{N+1} and the output vector y_{N+1} of the best virtual product $N+1$ are as follows, respectively:

$$X_{N+1} = (x_{1,N+1}, x_{2,N+1}, \cdots, x_{i,N+1}, \cdots, x_{m,N+1})^T$$

$$x_{i,N+1} = min(x_{i1}, x_{i2}, \cdots, x_{iN}) i = 1, 2, \cdots, m$$

$$Y_{N+1} = (y_{1,N+1}, y_{2,N+1}, \cdots, y_{l,N+1}, \cdots, y_{n,N+1})^T$$

$$y_{i,N+1} = max(y_{l1}, y_{l2}, \cdots, y_{lN}) l = 1, 2, \cdots, n$$

The input vector x_{N+2} and the output vector y_{N+2} of the worst virtual product $N+2$ are as follows, respectively:

$$X_{N+2} = (x_{1,N+2}, x_{2,N+2}, \cdots, x_{i,N+2}, \cdots, x_{m,N+2})^T$$

$$x_{i,N+2} = max(x_{i1}, x_{i2}, \cdots, x_{iN}) i = 1, 2, \cdots, m$$

$$Y_{N+2} = (y_{1,N+2}, y_{2,N+2}, \cdots, y_{l,N+2}, \cdots, y_{n,N+2})^T$$

$$y_{l,N+2} = min(y_{l1}, y_{l2}, \cdots, y_{lN}) l = 1, 2, \cdots, n$$

Step 3. Input and output weight coefficients.

The public weight coefficient is used to calculate the efficiency index of each product, and deliver more comparable evaluation results and an effective evaluation of product sustainability. The iDEA evaluation model is used to determine the public input indicator's weight coefficient p_k and the output indicator's weight coefficient q_r. In this way, the uncertainty over the selection of public weight is reduced and the DMUs have consistent evaluation criteria. The linear planning model is described as

$$\begin{cases} \min \sum_{r=1}^{n} q_r y_{r,\mathrm{N}+2} \\ s.t. \sum_{k=1}^{m} p_k x_{k,\mathrm{N}+2} = 1 \\ \quad \sum_{r=1}^{n} q_r y_{r,\mathrm{N}+1} - \sum_{k=1}^{m} p_k x_{k,\mathrm{N}+2} = 0 \\ \quad \sum_{r=1}^{n} q_r y_{rj} - \sum_{k=1}^{m} p_k x_{kj} \leq 0, j \neq N+1 \\ \quad p_k \geq \varepsilon k = 1, 2, \cdots, m \\ \quad q_r \geq \varepsilon r = 1, 2, \cdots, n \end{cases} \tag{11}$$

Step 4. Product efficiency index.

Based on the input and output weight coefficients p_k and q_r inferred from Equation (11), the efficiency index e_j of object j is determined as follows:

$$e_j = \frac{\sum_{r=1}^{n} q_r y_{rj}}{\sum_{k=1}^{m} p_k x_{kj}} j = 1, 2, \cdots, \mathrm{N}+2 \tag{12}$$

When it comes to one-dimensional sustainability evaluation, the efficiency index equals the sustainability of products, and therefore its value can serve as a yardstick by which to measure the sustainability of products. A higher index value indicates a greater level of environmental friendliness for the product.

2.4. Integration of AHP and iDEA

AHP can help break down a complicated issue into a set of indicators on different layers and involving different factors, and then the weight of each indicator layer can be obtained. However, it does not apply to decision-making issues demanding a high degree of quantification. The iDEA method can be used to obtain the efficiency index of each DMU, making the evaluation results more objective. However, the iDEA method is only able to make judgment about whether a DMU is DEA-effective, and it is unable to sort the DMUs being evaluated. The combination of DEA with AHP is able to address some of the disadvantages of traditional DEA. These two methods can be combined to deliver a comprehensive evaluation of the greenness of products and solve the problems existing in each method effectively [51]. The idea of combining the AHP and DEA is not new [52]. Gupta et al. [53] formulated an integrated multi-objective optimization model for an extended capacitated sustainable transportation problem in a coal mining industry by integrating AHP and DEA. The integration of AHP and DEA was also utilized in the multi-criteria analysis of a people-oriented urban pedestrian road system [54].

2.4.1. MCDM-Based Framework for the Sustainability Evaluation

A reference framework of the green product configuration design process can be found in paper [55]. A hierarchy of indicators is created to capture various indicators of the sustainability of customized products. The hierarchical model of indicators for the evaluation of customized products constructed by applying the AHP is shown in Figure 3. The sustainability indicator system covers energy efficiency, refrigerant management, EoL management, consumer engagement, and social concerns. The sustainability indicator system for customized products is defined as follows:

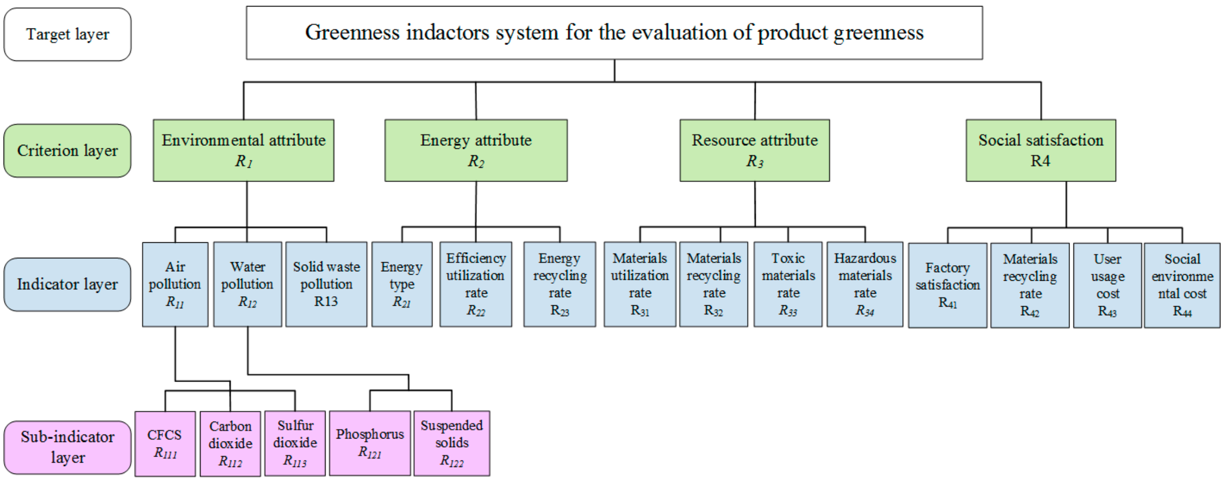

Figure 3. Proposed framework for the evaluation of product sustainability.

Target layer: R
Criterion layer: $R_x = \{R_1, R_2, R_3, R_4\}, x = 1, 2, 3, 4$
Indicator layer: R_{xy}, R_{xy} represents the y^{th} indicator under attribute R_x
Sub-indicator layer: R_{xyz}, R_{xyz} represents the z^{th} sub-indicator under R_{xy}

2.4.2. Indicator Layer Judgment

The judgment matrix $A_{d\times d}$ of qualitative indicators on the indicator layer of the evaluation indicator system for customized products is created. The AHP is applied to obtain the corresponding weight W_{xy} of each indicator on the indicator layer; the iDEA method is used to obtain the efficiency index e_{xy} of each DMU based on R_{xy} on the indicator layer. $A_{d\times d}$ represents a comparison of relative importance among the indicators on the indicator layer, d is the number of indicators corresponding to each attribute, W_{xy} is the weight of the y^{th} qualitative indicator under attribute R_x, and $e_{xy} = \{e_{xy1}, \cdots, e_{xy,N+2}\}$ represents the efficiency index of the y^{th} qualitative indicator under the attribute R_x.

2.4.3. Criterion Layer Judgment

Where the indicators have a sub-indicator layer, the green attribute R_x of the indicator layer is obtained by multiplying the weight W_{xy} and the efficiency index e_{xy} corresponding to each indicator on the indicator layer:

$$R_x = W_{xy}^T \times e_{xy} \tag{13}$$

where the indicators have no sub-indicator layer, the iDEA method is applied to obtain the efficiency index e_x of each attribute, i.e., the green attribute R_x of the criterion layer:

$$R_x = e_x \tag{14}$$

In the formula, $e_x = \{e_{x1}, \cdots, e_{x,N+2}\}$ represents the efficiency index of attribute R_x on the criterion layer.

2.4.4. Target Layer Judgment

The judgment matrix $A_{s\times s}$ of the criterion layer of the evaluation indicator system for customized products is created, and the AHP is applied to obtain the weight W_x corresponding to each indicator on the criterion layer; R_x is obtained through Equations (9) and (13), the product of which is the sustainability R of customized products:

$$R = W_x^T \times R_x \tag{15}$$

where $A_{s\times s}$ represents a comparison of relative importance among the attributes on the criterion layer, s is the number of attributes corresponding to the target layer R, and W_x is the weight of the x^{th} attribute on the target layer R.

3. Case Study

The global refrigerator industry has been making strides toward sustainability, driven by technological advancements, regulatory changes, and increasing consumer awareness. Manufacturers have been focused on enhancing the energy efficiency of refrigerators through the use of advanced insulation materials, energy-efficient compressors, and improved temperature control systems, and the adoption of energy-saving technologies such as inverter compressors. These efforts have led to significant reductions in energy consumption and greenhouse gas emissions associated with refrigerator operation. The industry has been actively transitioning away from high-global-warming-potential (GWP) refrigerants such as hydrofluorocarbons (HFCs) toward low-GWP alternatives, including hydrocarbons (such as isobutane and propane) and natural refrigerants like carbon dioxide and ammonia. Stringent energy efficiency standards and regulations have been implemented in various regions, compelling manufacturers to produce refrigerators that meet specific energy performance criteria. While significant progress has been made, there are ongoing challenges, especially maintaining a focus on continuous improvement in sustainability initiatives across the entire product life cycle. In the context of mass individualization or mass personalization, the decision making to buy bespoke and green refrigerators is still complex and they especially become personalized to balance individual preferences or needs (e.g., large capacity, multi-purpose, and intelligent interaction) and the life cycle sustainability. Theretofore, collaboration among industry stakeholders, policymakers, and consumers remains crucial for further advancing the sustainability of the refrigerator industry.

A sustainability evaluation indicator system for refrigerators can provide an objective basis for the comprehensive performance evaluation of refrigerators [56,57]. Xiao et al. [58] provided a cradle-to-grave LCA for a typical made-in-China refrigerator to evaluate the environmental impacts. Today, the refrigerator enterprises are also facing the customer- and data-driven personalized customization production, and they have the responsibility to provide evaluation reports of the bespoke refrigerators' sustainability according to relevant regulations. Generally, a data-driven analytics framework for sustainability performance includes four basic steps: data acquisition, storage and preprocessing, data mining, and data application services [59]. Here, the data collection method based on the IoT is not covered [60], and the data application service is dedicated to the evaluation of the refrigerator sustainability.

3.1. Sustainability Indicators of Refrigerator

Broken down into input and output indicators, the data of each indicator of bespoke refrigerators are shown in Tables 3–6.

Table 3. Indicator data of environmental attributes by refrigerator.

Bespoke Product	Environmental Attributes					
	Air Pollution			Water Pollution		Solid Waste Pollution
	Input Indicators			Input Indicators		Input Indicators ($\mu g/m^3$)
	Chlorofluorocarbons (CFCs) ($\mu g/m^3$)	Carbon Dioxide ($\mu g/m^3$)	Sulfur Dioxide ($\mu g/m^3$)	Phosphorus ($\mu g/m^3$)	Suspended Solids ($\mu g/m^3$)	
Refrigerator 1	0	2.80	0.11	0.08	5.70	100
Refrigerator 2	0	2.80	0.11	0.09	7.80	100
Refrigerator 3	0	2.80	0.13	0.09	7.10	80.0
Best product	0	2.80	0.11	0.08	5.70	80.0
Worst product	0	2.80	0.13	0.09	7.80	100

Table 4. Indicator data of energy attributes by refrigerator.

Bespoke Product	Energy Attributes		
	Input Indicator	Output Indicator	
	Energy Efficiency Ratio	Energy Utilization Rate	Energy Recycling Rate
Refrigerator 1	0.88	0.74	0.10
Refrigerator 2	0.84	0.61	0.090
Refrigerator 3	0.95	0.60	0.080
Best product	0.84	0.74	0.10
Worst product	0.95	0.60	0.080

Table 5. Indicator data of resource attributes by refrigerator.

Bespoke Product	Resource Attributes			
	Input Indicators		Output Indicators	
	Toxic Material Rate	Hazardous Material Rate	Material Utilization Rate	Material Recycling Rate
Refrigerator 1	1.01	1.51	0.71	0.41
Refrigerator 2	1.86	2.50	0.35	0.38
Refrigerator 3	2.28	2.34	0.59	0.38
Best product	1.01	1.51	0.71	0.41
Worst product	2.28	2.50	0.35	0.38

Table 6. Indicator data of social satisfaction by refrigerator.

Bespoke Product	Social Satisfaction			
	Input Indicators		Output Indicators	
	User Usage Cost	Social Environmental Cost	Factory Satisfaction	Outside the Factory Satisfaction
Refrigerator 1	6.50	1.40	0.950	0.75
Refrigerator 2	8.00	2.30	0.900	0.73
Refrigerator 3	8.00	1.40	0.806	0.74
Best product	6.50	1.40	0.950	0.75
Worst product	8.00	2.30	0.806	0.73

3.2. Indicator Layer Judgment

3.2.1. Apply AHP to Obtain the Weight of the Indicator Layer

The sustainability indicator system involves the ratings given by Little Swan, a home appliance manufacturer. That is assuming that with the help of experts or eco-design tools, customers build the judgment matrix of the indicator layer of the refrigerator evaluation indicator system as shown in Table 7. After balancing individual preferences or needs and the sustainability concerns, the judgment matrix is expressed as

$$\begin{pmatrix} 1 & 4 & 5 \\ 1/4 & 1 & 2 \\ 1/5 & 1/2 & 1 \end{pmatrix}$$

Table 7. Weight judgment matrix of the indicator layer of environmental attributes.

Environmental Attributes	Air Pollution	Water Pollution	Solid Waste Pollution
Air pollution	1	4	5
Water pollution	1/4	1	2
Solid waste pollution	1/5	1/2	1

The weight vector of the indicators under the environmental attribute is $W = (0.6833, 0.1998, 0.1168)^T$. In this matrix, the maximum feature value is λ_{max}; the consistency indicator is CI. When $n = 3$, the average random consistency indicator $RI = 0.5$, and then the random consistency ratio $CR = CI/RI = 0.0239$. Since the consistency criterion of the judgment matrix is $CR < 0.1$, the judgment matrix passes the consistency check and it is concluded that the judgment matrix is correctly built, and the weight in this way is the weight of each indicator.

3.2.2. Apply iDEA to Obtain the Efficiency Index

With air pollution as the metric, the efficiency indexes of the refrigerators are calculated. Refrigerator 1, Refrigerator 2, and Refrigerator 3 are three DMUs, while the best virtual product and the worst virtual product correspond to two virtual DMUs. The indicators are classified by environmental attributes into input and output indicators. Among them, fluoride, carbon dioxide, and sulfur dioxide are taken as input indicators, with the specific data shown in Table 8. As there is no output indicator on the sub-indicator layer of air pollution, its output indicator is set to 1.

Table 8. Classification of input and output indicators of air pollution.

Target Layer		Indicator Type	Indicator Layer	Refrigerator 1	Refrigerator 2	Refrigerator 3	The Best Product	The Worst Product
Environmental attributes	Air pollution	Input indicators	CFCs	0	0	0	0	0
			Carbon dioxide	2.80	2.80	2.80	2.80	2.80
			Sulfur dioxide	0.11	0.11	0.13	0.11	0.13
		Output indicator	Indicator value	1	1	1	1	1

The air pollution input vector on the indicator layer is defined as X_{11} and the output vector as Y_{11}. $X_{11} = \begin{pmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 2.80 & 2.80 & 2.80 & 2.80 & 2.80 \\ 0.11 & 0.11 & 0.13 & 0.11 & 0.13 \end{pmatrix}$, $Y_{11} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \end{pmatrix}$. As per Equation (7), the optimized model is created as follows:

$$\begin{cases} \min q_{11} \\ s.t. 2.8p_{12} + 0.13p_{13} = 1 \\ \quad q_{11} - 2.8p_{12} - 0.11p_{13} = 0 \\ \quad q_{11} - 2.8p_{12} - 0.11p_{13} \leq 0 \\ \quad q_{11} - 2.8p_{12} - 0.11p_{13} \leq 0 \\ \quad q_{11} - 2.8p_{12} - 0.13p_{13} \leq 0 \\ \quad q_{11} - 2.8p_{12} - 0.13p_{13} \leq 0 \\ \quad p_{11}, p_{12}, p_{13} \geq \varepsilon \\ \quad q_{11} \geq \varepsilon \end{cases} \tag{16}$$

The weight vector corresponding to output indicators under air pollution is arrived at, $Q_{11} = (0.8462)$, while the weight vector corresponding to input indicators is $P_{11} = (0, 0, 7.6923)^T$. Likewise, the output weight vector, input weight vector, and efficiency index vector of water pollution and solid waste pollution can be obtained, with the specific data shown in Table 9.

Table 9. Weight and efficiency index of each indicator under environmental attributes.

Environmental Attributes	Air Pollution	Water Pollution	Solid Waste Pollution
Output weight vector	0.8462	0.7308	0.8000
Input weight vector	0, 0, 7.692	0, 0.1282	0.0100

3.2.3. Obtain the Green Attribute of the Indicator Layer

With air pollution as the metric, Equation (12) is used to obtain the efficiency index of Refrigerator 1. The calculation process is $\frac{Q_{11} \times y_{11}}{0 \times x_{11} + 0 \times x_{21} + 7.692 \times x_{31}} = \frac{0.8462 \times 1}{0 + 0 + 7.692 \times 0.11} = 1$. The calculation of the efficiency indexes of Refrigerator 2 and Refrigerator 3, the best virtual product, and the worst virtual product is omitted here. The vector thus obtained is $e_{11} = (1.000, 1.000, 0.8462, 1.000, 0.8462)$. Similarly, the weight of each indicator layer and the efficiency index based on environmental attributes can be obtained, with the specific data shown in Table 10.

Table 10. Calculate refrigerators' efficiency index based on the sub-indicators under environmental attributes.

Criterion Layer	Indicator Name	Refrigerator 1	Refrigerator 2	Refrigerator 3	The Best Product	The Worst Product
Environmental attributes	Air pollution (0.6833)	1.000	1.000	0.8462	1.000	0.8462
	Water pollution (0.1998)	1.000	0.7308	0.8028	1.000	0.7308
	Solid waste pollution (0.1168)	0.8	0.8	1	1	0.8

Equation (13) is used to obtain the green attribute corresponding to the indicator layer of refrigerators, and the calculation process of Refrigerator 1 is $1 \times 0.6833 + 1 \times 0.1998 + \times 0.1168 = 0.976$. Similarly, the green attribute of each refrigerator based on environmental attributes is determined, respectively: 0.976, 0.922, 0.855, 1.00, and 0.817.

3.3. Criterion Layer Judgment

By Equations (12) and (13), we arrive at the weight coefficients and efficiency indexes corresponding to the input and output indicators of energy attributes, resource attributes, and social satisfaction of Refrigerator 1, Refrigerator 2, and Refrigerator 3 as well as the best virtual product and the worst virtual product, with the specific data shown in Table 11.

Table 11. Weight and efficiency index of each indicator with energy, resource and social satisfaction attributes.

Target Layer	Energy Attributes	Resource Attributes	Social Satisfaction
Output weight vector	0, 8.842	0.6239, 0	0.6407, 0
Input weight vector	1.0526	0.4386, 0	0, 0.4348
Efficiency index of Refrigerator 1	0.9546	1.000	1.000
Efficiency index of Refrigerator 2	0.9000	0.2677	0.5766
Efficiency index of Refrigerator 3	0.7074	0.3681	0.8484
Efficiency index of the best virtual product	1	1	1
Efficiency index of the worst virtual product	0.7074	0.2184	0.5164

3.4. Target Layer Judgment

3.4.1. Apply AHP to Obtain the Weight of the Criterion Layer

The judgment matrix of the criterion layer of the refrigerator evaluation indicator system is built, and the subjective weight vector is calculated as $W = (0.6326, 0.1428, 0.1428, 0.0818)^T$. And the judgment matrix passes the consistency check. From the calculation result, the green attribute of each refrigerator can be concluded, based on environmental attributes, energy attributes, resource attributes, and social satisfaction, and is shown in Table 12 and Figure 4.

Table 12. Sustainability of the refrigerators by attributes.

	Indicator Name	Refrigerator 1	Refrigerator 2	Refrigerator 3	The Best Product	The Worst Product
Sustainability of the refrigerators	Environmental attributes	0.9760	0.9220	0.8550	1.000	0.8170
	Energy attributes	0.9546	0.9000	0.7074	1.000	0.7074
	Resource attributes	1.000	0.2677	0.3681	1.000	0.2184
	Social satisfaction	1.000	0.5766	0.8484	1.000	0.5164

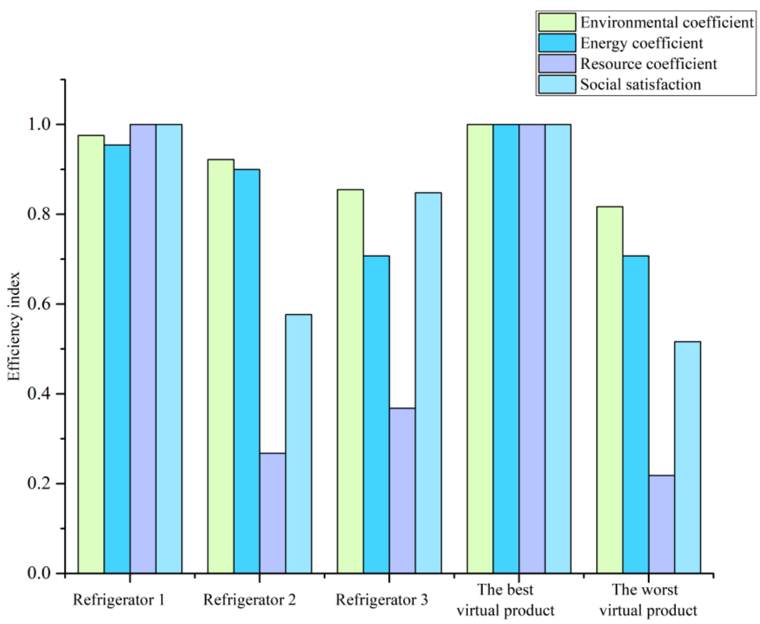

Figure 4. Efficiency index of refrigerators.

3.4.2. Calculate the Sustainability of Refrigerators

Equation (15) is used to obtain the sustainability of Refrigerator 1, Refrigerator 2, and Refrigerator 3 as well as the best virtual product and the worst virtual product throughout their life cycle, that is, 0.9783, 0.7972, 0.7639, 1, and 0.6913. The calculation process of Refrigerator 1 is $0.6326 \times 0.976 + 0.1428 \times 0.9546 + 0.1428 \times 1 + 0.0818 \times 1 = 0.9783$, and the calculation process of the rest is omitted here.

The preceding bar chart shows that except the virtual products, Refrigerator 1, Refrigerator 2, and Refrigerator 3 have different performances under different criteria.

(1) Throughout their life cycle, the sustainability of Refrigerator 1, Refrigerator 2, and Refrigerator 3 is 0.7873, 0.8618, and 0.8561, respectively, and Refrigerator 2 has the best sustainability as per the comprehensive evaluation result.
(2) If the refrigerators are measured by environmental attributes, Refrigerator 2 > Refrigerator 3 > Refrigerator 1; the green attributes of Refrigerator 1, Refrigerator 2, and Refrigerator 3 are 0.7506, 0.9241, and 0.9083, respectively. It can be concluded that Refrigerator 2 shows the best environmental attributes. An analysis of the sub-indicators under environmental attributes is presented as follows:
    a. As for the air pollution, the efficiency indexes of Refrigerator 1, Refrigerator 2, and Refrigerator 3 are 0.7, 1, and 0.875, respectively. Refrigerator 1 should decrease emission under the air pollution indicator.
    b. As for the water pollution, the efficiency indexes of Refrigerator 1, Refrigerator 2, and Refrigerator 3 are 0.9783, 0.7972, and 0.7639, respectively, and Refrigerator 1 needs to improve its technology in emission related to water pollution.
    c. With solid waste pollution as the metric, the efficiency indexes of Refrigerator 1, Refrigerator 2, and Refrigerator 3 are 0.8, 0.8, and 1, respectively. There is not much difference between the performance indicators of Refrigerator 1 and Refrigerator 2, while Refrigerator 3 needs to decrease the solid waste indicator.
(3) If the refrigerators are measured by energy attributes, the efficiency indexes of Refrigerator 1, Refrigerator 2, and Refrigerator 3 are 0.9564, 0.9, and 0.7074, respectively, Refrigerator 1 > Refrigerator 2 > Refrigerator 3, and there is not much difference in energy indicators between Refrigerator 1 and Refrigerator 2. Therefore, Refrigerator 3 should adopt reasonable production processes to achieve the goal of saving and improving resource utilization.
(4) If the refrigerators are measured by resource attributes, the efficiency indexes of these refrigerators are 1, 0.2677, and 0.3681, respectively, and Refrigerator 1 > Refrigerator 3 > Refrigerator 2. Refrigerator 2 and Refrigerator 3 underperform compared to Refrigerator 1 in resource attributes and can do better by cutting the content of toxic and hazardous materials and increasing resource utilization and recycling.
(5) If the refrigerators are measured by social satisfaction, the efficiency indexes of these refrigerators are 1, 0.5766, and 0.8484, respectively, and Refrigerator 1 > Refrigerator 3 > Refrigerator 2. To improve its economy, Refrigerator 2 needs to decrease its economic indicators.

3.5. Result Discussion

For non-DEA-effective DMUs, the projection on the production front surface is calculated by judgment of the slack variables, to arrive at improved values of the input and output variables of each DMU. The improved values are analyzed to arrive at the calibrated values of specific indicators in the production improvement direction. Equation (9) calculates the efficiency evaluation parameters of Refrigerator 1, Refrigerator 2, and Refrigerator 3. The result is $\delta = 1$, $\rho^+ \neq 0$, and $\rho^- \neq 0$, indicating that Refrigerator 1 is weakly DEA-effective. The projected target improved values by refrigerator are shown in Table 13 and Figure 5.

Table 13. Slack variables of input and output indicators.

	Slack Variables	Refrigerator 1 (δ = 1)	Refrigerator 2 (δ = 0.9733)	Refrigerator 3 (δ = 0.9867)
ρ^-	CFCs	0	0	0
	Carbon dioxide	0	0	0
	Sulfur dioxide	0	0	0.0197
	Phosphorus	0	097	099
	Suspended solids	0	2.0440	1.3813
	Solid waste pollution	20	19.4667	0
	Energy efficiency ratio	0.0400	0	0.1085
	Toxic material rate	0	0.8273	1.2531
	Hazardous material rate	0	0.9636	0.8189
	User usage cost	0	1.4600	1.4800
	Social environmental cost	0	0.8760	0
ρ^+	Energy utilization rate	0	0.1103	0.1301
	Energy recycling rate	0	073	0.0187
	Material utilization rate	0	0.3411	0.1105
	Material recycling rate	0	0.0191	0.0245
	Factory satisfaction	0	0.0247	0.1313
	Outside the factory satisfaction	0	0	0

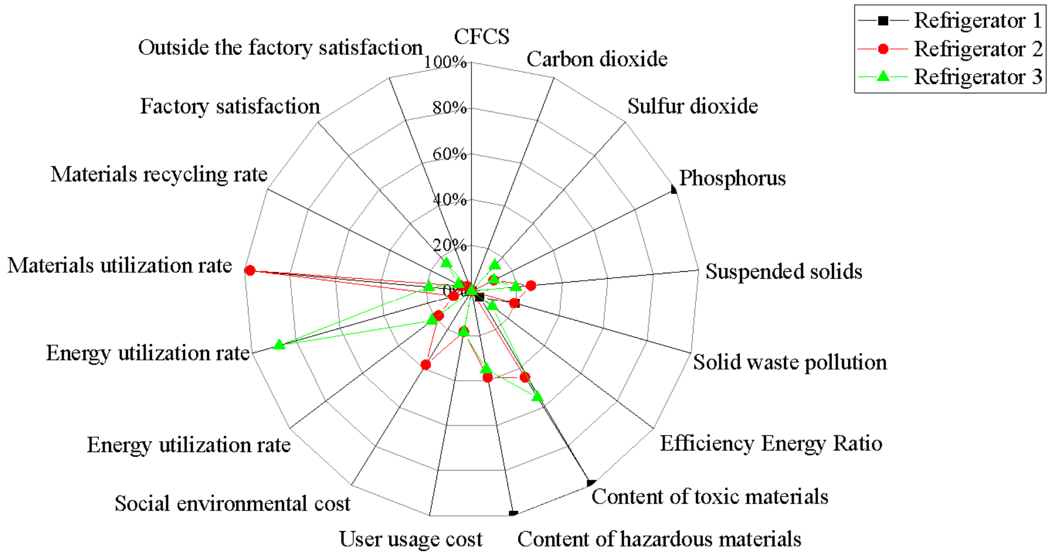

Figure 5. The percentage of improved values of refrigerator indicators.

By analyzing the improved values of the products, we can provide the specific values of improvement in the products, and the sustainability of refrigerators can be improved by upgrading the production technologies. Here, we take the input indicator sulfur dioxide as an example. The improved value of Refrigerator 3 accounts for the biggest percentage, indicating that the input is too much, and the emission of sulfur dioxide is the highest. For the purpose of better sustainability of Refrigerator 3, the air pollution caused by sulfur dioxide must be reduced, and according to the improved value, this indicator must be reduced by 0.0197 μg/m^3. As for the output indicator of material recycling, the improved value of Refrigerator 3 accounts for the highest percentage, indicating that the output is too small and material recycling is at a low level. For the purpose of better sustainability of Refrigerator 3, it is necessary to increase material recycling. According to the improved value, this indicator should be increased by 6.45%. The analysis of other indicators is the same.

3.6. Product Improvement Suggestion

Using the CCR model with non-Archimedes infinitesimal ε in the DEA method and the projection theorem of the decision unit on the production relative effective surface, the projection of each refrigerator on the production relatively effective surface can be calculated. Through the calculation of the projected value, the specific improvement direction of each indicator in the entire life cycle of the product can be determined.

Using the CCR model with non-Archimedes infinitesimal ε, we can calculate the optimal solution of the DMU_{i0}, $\xi^0 = (\xi_1^0, \xi_1^0, \cdots, \xi_n^0)$, ρ^{-0}, ρ^{+0}, and δ. Then, according to the projection theorem, the projection of each product on the relative effective surface of DEA production is calculated, so as to determine the production improvement direction to improve the green property of the product. The input and output of the product are determined according to the projection of the product on its DEA production effective surface. The sustainability of the product fabricated according to such an improvement direction will definitely be improved.

Due to $\delta = 1$, Refrigerator 1 was a weakly DEA-effective DMU. A weakly DEA-effective DMU means that the quantity of each input cannot be reduced proportionally unless the quantity of output is decreased; the quantity of each output cannot be increased proportionally unless the quantity of input is increased. In this scenario, the inputs cannot be reduced or the outputs increased proportionally. However, it is possible to decrease one or several (but not all) inputs, or increase one or several (but not all) outputs. From the perspective of production theory, this is considered technically efficient rather than scale-efficient. As depicted in Table 14, the projected values for Refrigerator 1 are identical to the virtual optimal values after projection.

Table 14. Projected target improved values by refrigerator.

		Refrigerator 1 (δ = 1)		Refrigerator 2 (δ = 0.9733)		Refrigerator 3 (δ = 0.9867)	
		Actual Value	Projection Value	Actual Value	Projection Value	Actual Value	Projection Value
Input indicators	CFCs	0	0	0	0	0	0
	Carbon dioxide	2.80	2.80	2.80	2.80	2.80	2.80
	Sulfur dioxide	0.11	0.11	0.11	0.11	0.13	0.1103
	Phosphorus	0.08	0.08	0.09	0.08	0.09	0.08
	Suspended solids	5.70	5.70	7.80	5.76	7.10	5.72
	Solid waste pollution	100	80.0	100	80.5	80.0	80.0
	Energy efficiency ratio	0.88	0.84	0.84	0.84	0.95	0.84
	Toxic material rate	1.01	1.01	1.86	1.03	2.28	1.03
	Hazardous material rate	1.51	1.51	2.50	1.54	2.34	1.52
	User usage cost	6.50	6.50	8.00	6.54	8.00	6.52
	Social environmental cost	1.40	1.40	2.30	1.42	1.40	1.40
Output indicators	Energy utilization rate	0.74	0.74	0.61	0.72	0.60	0.73
	Energy recycling rate	0.10	0.10	0.090	0.097	0.080	099
	Material utilization rate	0.71	0.71	0.35	0.69	0.59	0.70
	Material recycling rate	0.41	0.41	0.38	0.40	0.38	0.40
	Factory satisfaction	0.950	0.950	0.900	0.925	0.806	0.937
	Outside the factory satisfaction	0.75	0.75	0.73	0.73	0.74	0.74

According to the above analysis, the sustainable attribute of each refrigerator and its projection value on the production relative effective surface are calculated as shown in Table 14.

4. Conclusions

In the era of Industry 4.0, the ubiquitous networks and sensors open new doors for the quantification of the environmental footprint of green products. Also, the mass customization production mode and the customers' needs are full of individuation and diversification [61]. The results led by climate change become more serious, and the theme of sustainability is becoming increasingly pressing. Strategically synthesizing sustainability and Industry 5.0 creates potential for companies to build new and resilient value creation networks or to even achieve sustainable platform-based business models [62]. Clearly, as a highly cross-cutting issue, the "truth" of design for sustainability is an evolving process rather than one thing, and will depend on the thinking and acting stakeholders carry out now [63]. To this end, this work presented a data-driven quantitative method for the sustainability assessment of a product–service system by integrating AHP and DEA to measure the product sustainability and promote the Industry 5.0-enabled sustainable product–service system practice. This method attempts to translate the sustainability assessment into a multi-criteria decision-making problem, to find a solution that meets the most important criteria while minimizing trade-offs between conflicting criteria, such as individual preferences or needs and the product life cycle sustainability. This method also can fulfill the complex coupled assessment of technology-driven product solutions and value-driven human-centric goals. However, the presented method cannot cover all the concerns of Industry 5.0, and some limitations of the current work also indicate future research opportunities.

As one further step, the proposed Industry 5.0-enabled sustainable product–service system logic and framework should organically be fused with the configuration representation of the as-designed product in the three-dimensional design environment, and even in the digital twin environment [64]. With the help of the digital-twin-driven design method, ensuring the recyclability and disassembly of customized products, as well as implementing effective recycling programs, becomes possible and accessible to reduce waste and environmental impact. DT also helps to enable transparency of the manufacturing chains of products, balance customization with the energy efficiency standard, and provide a holistic approach to understand the overall efforts of sustainability. As such, the design paradigm for sustainability will become more proactive, accessible, and intelligent, to bring out ahead-of-production responsible decisions. Encouraging informed decision making and responsible use of personalized refrigerators can contribute to overall sustainability efforts.

In addition, owing to the inherent complex interconnections of the TBL dimensions of sustainability, the practice effects of the proposed method cannot do without the data quality assessment and the benchmark and classes of the environmental performance. The Product Environmental Footprint (PEF) method that was launched by the European Commission can provide the beneficial reference to improve this point [65]. Furthermore, the intelligent and systematic level of the current scheme should be enhanced by introducing deep learning, big data analytics, and more open architectures that cover different enterprise layers (strategy, business, data, application, and technology) [66]. In particular, mass personalization may introduce complexity into the supply chain, as manufacturers need to manage a wider variety of components, configurations, and production processes to accommodate individualized products. This complexity can cause inefficiencies, longer lead times, and increased transportation emissions, impacting the overall sustainability and resilience of the supply chain. Industry 5.0 and Society 5.0 also highlight the circular economy and sharing economy principles [67]; hence, designing products for disassembly, utilizing recycled materials, and establishing reverse logistics systems for component recovery can contribute to a more sustainable product life cycle [68,69].

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Nomenclature

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
CCR	Charnes, Cooper, and Rhodes
CFCs	Chlorofluorocarbons
DEA	Data Envelopment Analysis
DfE	Design for Environment
DfS	Design for Sustainability
DMU	Decision-Making Unit
DT	Digital Twin
EoL	End of Life
GWP	Global Warming Potential
iDEA	Improved Data Envelopment Analysis
Industry 4.0	The Fourth Industrial Revolution
IoT	Internet of Things
LCA	Life Cycle Assessment
MCDM	Multi-Criteria Decision Making
MRIO	Multi-Regional Input–Output Model
PEF	Product Environmental Footprint
PET	Polyethylene Terephthalate
PLC	Product Life Cycle
PSS	Product–Service System
SDGs	United Nations Sustainable Development Goals
SI	Sustainability Indicator
SPSS	Sustainable Product–Service System
TBL	Triple-Bottom-Line

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