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POLYTECHNIQUE MONTRÉAL

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Developing a Decision Support Tool for Co-Design of Open-Architecture Products Considering Sustainability Criteria

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Ce mémoire intitulé :

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présenté par **Fatemeh MIRZAEI**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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DEDICATION

To my beloved parents

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RÉSUMÉ

Les produits à architecture ouverte (OAP), en tant que produits centrés sur le client, se développent en réponse à l'évolution des besoins des clients et aux variations du marché international. Étant donné que les OAP sont des produits individualisés avec une grande variété définie par les clients lors de la phase de conception, la mesure, l'évaluation et la visualisation de la performance de durabilité des variantes de produit sont d'un grand intérêt pour la prise de décision vers le produit le plus durable. Ce mémoire présente un outil d'aide à la décision pour évaluer la performance de durabilité des OAP pendant la phase de conception et visualiser les résultats à des fins de prise de décision. Une variété de produits est créée en définissant différents composants personnalisés grâce à la génération de scénarios de conception basés sur la modification des caractéristiques des composants du produit. La performance en matière de durabilité des composants personnalisés de chaque variante de produit est mesurée en effectuant des analyses d'évaluation du cycle de vie environnemental (ELCA) et des coûts du cycle de vie (LCC) pour calculer les indicateurs de durabilité. Une méthode est proposée pour la pondération et l'agrégation de divers indicateurs de durabilité afin de construire l'indice de durabilité (SI) pour chaque alternative de conception. Une technique de visualisation appropriée est utilisée pour présenter les valeurs de durabilité des alternatives de conception qui peuvent fournir aux clients un outil efficace pour visualiser et comparer facilement les performances de durabilité du produit parmi différents scénarios et sélectionner la meilleure option durable. De plus, l'analyse de sensibilité (SA) est effectuée pour valider la robustesse du cadre proposé. L'analyse de sensibilité locale et globale est appliquée à l'analyse d'analyse du cycle de vie (ACV) pour étudier la robustesse des sorties de l'ACV et leur sensibilité à l'incertitude des données d'inventaire d'entrée. En outre, l'analyse de sensibilité est effectuée sur la méthode de pondération et d'agrégation choisie pour étudier la robustesse des résultats finaux de durabilité par comparaison avec d'autres approches de pondération et d'agrégation. Une étude de cas est menée avec un robot personnalisé à architecture ouverte pour démontrer l'utilité et l'efficacité de la méthodologie proposée. Trois scénarios de conception sont générés en changeant le matériau et la géométrie des composants personnalisés du robot. La performance de durabilité des alternatives de conception est mesurée en effectuant des analyses de durabilité environnementale et économique. En appliquant la méthode de pondération égale et une approche décisionnelle multi-attributs, c'est-à-dire GRA, l'indice de durabilité pour chaque scénario de conception est construit et présenté aux clients via la technique de visualisation, c'est-à-dire le treemap. La réalisation de l'analyse de sensibilité sur la modélisation ACV démontre que le résultat de l'étude d'impact environnemental est insensible à l'incertitude des variables d'entrée. De plus, pour valider les résultats de durabilité, la méthode AHP est utilisée pour le processus de pondération, et les méthodes TOPSIS et SAW sont appliquées pour l'opération d'agrégation. Sur la base des résultats, le classement des performances de durabilité des alternatives de conception n'est pas sensible aux changements dans les méthodes de pondération et d'agrégation sélectionnées.

ABSTRACT

The open-architecture products (OAPs), as customer-centric products, are developing in response to the changing customers' needs and variations in the international market. Since the OAPs are individualized products with a high variety defined by customers during the design stage, measuring, evaluating and visualization of the sustainability performance of the product variants is of great interest for decision making towards the more sustainable product. This dissertation presents a decision support tool to assess the sustainability performance of OAPs during the design stage and visualize the results for decision-making purposes. A variety of products is created by defining different personalized components through design scenario generation based on changing the features of product components. The sustainability performance of personalized components of each product variant is measured by performing environmental life cycle assessment (ELCA) and life cycle costing (LCC) analyses to calculate the sustainability indicators. A method is proposed for the weighting and aggregation of various sustainability indicators in order to construct the sustainability index (SI) for each design alternative. An appropriate visualization technique is utilized to present the sustainability values of the design alternatives which can provide customers with an effective tool for easily visualizing and comparing the sustainability performance of the product among different scenarios and selecting the best sustainable option. Moreover, the sensitivity analysis (SA) is performed to validate the robustness of the proposed framework. The local and global sensitivity analysis is applied to the life cycle assessment (LCA) analysis to study the robustness of the LCA outputs and their sensitivity to the uncertainty of input inventory data. Also, the sensitivity analysis is carried out on the chosen weighting and aggregation method to investigate the robustness of the final sustainability results through comparison with alternative weighting and aggregating approaches. A case study is conducted with a personalized open-architecture robot to demonstrate the utility and effectiveness of the proposed methodology. Three design scenarios are generated by changing the material and geometry of personalized components of the robot. The sustainability performance of the design alternatives is measured by conducting environmental and economic sustainability analyses. By applying the equal weighting method and a multi-attribute decision-making approach, i.e. GRA, the sustainability index for each design scenario is constructed and presented to customers through the visualization technique i.e., treemap. Performing the sensitivity analysis on the LCA modelling demonstrates that the environmental impact assessment result is insensitive to the uncertainty of input variables. Also, to validate the sustainability results, the AHP method is used for the weighting process, and TOPSIS and SAW methods are applied for aggregation operation. Based on the results, the ranking of the sustainability performance of design alternatives is not sensitive to changes in the selected weighting and aggregation methods.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND SYMBOLS

List of abbreviations

ABS	Acrylonitrile Butadiene Styrene
AD	Axiomatic Design
AHP	Analytic Hierarchy Process
Al	Aluminium
ANP	Analytic Network Process
BFN	Basic Function Need
CAD	Computer-Aided Design
CAE	Computer-Aided Engineering
CAM	Computer-Aided Manufacturing
CAPP	Computer-Aided Process Planning
CAST	Computer-Aided Sustainable Tool
CAX	Computer-Aided X
CE	Circular Economy
CI	Consistency Index
CNC	Computer Numerical Control
CPS	Cyber-Physical System
CR	Consistency Ratio
DfD	Design for Disassembly
DfE	Design for Environment
DfS	Design for Sustainability
DfX	Design for X
DMS	Dedicated Manufacturing System
DOE	Design of Experiments
DV	Degree of Variety
EIME	Environmental Improvement Made Easy
ELCA	Environmental Life Cycle Assessment
ELECTRE	ELimination Et Choix Traduisant la REalité

EoL	End-of-Life
ETO	Engineer-To-Order
FIT	Feature Interaction Technology
FMS	Flexible Manufacturing System
FU	Functional Unit
GA	Genetic Algorithm
GGA	Group Genetic Algorithm
GRA	Grey Relational Analysis
GRC	Grey Relational Coefficient
GRG	Grey Relational Grade
GSA	Global Sensitivity Analysis
GTR	General Technical Requirement
GUI	Graphical User Interface
HoQ	House of Quality
ICN	Individual Customer Need
ICT	Information and Communication Technology
IoT	Internet of Things
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCSA	Life Cycle Sustainability Assessment
LSA	Local Sensitivity Analysis
MADM	Multi-Attribute Decision Making
MAPs	Modular Architecture Principles
MCDM	Multi-Criteria Decision Making
MODM	Multi-Objective Decision Making
NPV	Net Present Value
OAP	Open-Architecture Product

OAPP	Open Architecture Product Platform
OEI	Overall Environmental Impact
OEM	Original Equipment Manufacturer
OFs	Operation Features
OMS	On-demand Manufacturing System
OTR	OAP’s Technical Requirement
PFs	Product Features
PLM	Product Lifecycle Management
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluations
QFD	Quality Function Deployment
QFDE	Quality Function Deployment for Environment
RI	Random Index
RMS	Reconfigurable Manufacturing System
SA	Sensitivity Analysis
SAW	Simple Additive Weighting
SI	Sustainability Index
SLCA	Social Life Cycle Assessment
SMEs	Small and Medium-sized Enterprises
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
TRIZ	Theory of Inventive Problem Solving
USD	United States Dollar
VR	Virtual Reality
WGRG	Weighted Grey Relational Grade

List of symbols

A_i	Aggregated score of the *i*th alternative
C_i	Cost of the *i*th component
CF_t	Cash flow at time t

D_i^+ , D_i^-	Euclidean distance from the *i*th alternative to the best and worst alternative
EI_i	Environmental impact of the *i*th component
EI_j	Environmental impact of the product for the *j*th indicator
k	Levels of factors
n	Number of factors
r	Discount rate
S_p	Sustainability value of the product
S^+, S^-	Positive and negative ideal solutions
v_{ij}	Weighted normalized value
w_j	Weight value of the *j*th attribute
x_{ij}	Normalized value of performance data
x_{0j}	Reference sequence
X_i	Inventory variables
y_{ij}	Performance value of the *i*th component over the *j*th attribute
y_{ij}^*	Target optimum performance value
Y	Response variable
α	Significance level
$\gamma(x_{0j}, x_{ij})$	Grey relational coefficient
γ_i	Grey relational grade
γ_{wi}	Weighted grey relational grade
Δ_{ij}	Absolute value of the difference between reference sequence (x_{0j}) and comparability sequence (x_{ij})
Δ_{min} , Δ_{max}	Smallest and largest values of the difference between x_{0j} and x_{ij}
ζ	Distinguishing coefficient
λ_{max}	Maximum eigenvalue
μ	Mean value
σ	Standard deviation
σ^2	Variance

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

1.1 Background information and problem statement

Due to the changing needs of customers, the changes in the international market, and the evolutions of enabling technologies, the manufacturing industry has evolved through three main paradigms, namely, mass production, mass customization, and mass individualization [1, 2]. With the invention of the moving assembly line and dedicated manufacturing system (DMS) in 1913, the ‘‘Mass Production’’ paradigm emerged enabling the massive manufacturing of single products with large volumes at a low cost. The product architecture is unified; thus, the product variety is very limited, and products are built and pushed to customers to buy [1-3]. Since the late 1980s, with the introduction of computer numerical control (CNC) technology and flexible manufacturing system (FMS), the ‘‘Mass Customization’’ manufacturing paradigm has emerged in response to global market competition, market segmentation, and consumer demands for high product variety. The manufacturers produce and offer product options or variants with high volumes and low cost to customers allowing them to choose the product that almost fits their desires. To generate product variety at a low cost, the product needs to have a modular architecture [1-3]. Currently, a new manufacturing paradigm, namely ‘‘Mass Individualization’’ has been introduced to enable the production of a mass of personalized products with variable functions to satisfy the individual customer requirements and preferences and various market segments in a cost-effective manner. Open-architecture products (OAPs) make this goal attainable by providing the opportunity to design personalized products by involving individual customers and small companies in designing and manufacturing products [1-3].

Table 1.1 Comparison of product manufacturing paradigms (Adapted from [1-4]).

Feature	Manufacturing paradigm		
	Mass production	Mass customization	Mass individualization
Timeline	1913-1980	1980-2010	2010-Nowadays
Production system	Dedicated manufacturing system (DMS)	Reconfigurable manufacturing system (RMS)	On-demand manufacturing system (OMS)
Technology enabler	Mechanical and electrical power	CNC technology, CAD/CAM	Cyber-physical systems (CPSs)
Paradigm goal	Cost	Variety	Efficacy
Product architecture	Integral structure	Modular and closed architecture	Modular and open architecture
Product type	Identical products, with a fixed functional configuration	Product variants, with an adaptable functional configuration but fixed to customer needs	Individualized products, with an adaptable and upgradable functional configuration adjusted to customer needs
Involved actors in lifecycle stages	Design and manufacturing phase: OEM Use phase: customer buys a single product	Design and manufacturing phase: OEM Use phase: customer chooses a customized product from offered options	Design and manufacturing phase: OEM, customer, vendors Use phase: customer acquires a personalized product, reconfigures, and upgrades the product

The comparison of the three manufacturing paradigms is summarized in Table 1.1. The main difference between these paradigms originates from the product architecture. The products in the mass individualization paradigm are designed by manufacturers with an open architecture enabling customers to be involved in the design of their individual products based on their needs and desires.

The number of product options depends on the creativity of involved customers and companies that design and produce personalized modules. In contrast, in the mass customization paradigm, the manufacturers design and offer all product options and customers select an option among a limited number of product variants. The mass production and mass customization paradigms do not consider any participation of customers in the design and manufacturing stages, while the mass individualization paradigm takes customer participation into account during the design, manufacturing, and use/operation stages to reconfigure and upgrade the product functional configuration and achieve highly personalized products. The mass individualization paradigm provides products with high variety, adaptability, and upgrading abilities to meet the changing customer requirements. In comparison, single products have an integral architecture and fixed functional configuration as well as customized products have a limited variety and their configuration is fixed to changing customer requirements [1-4].

Open-architecture products (OAPs) are personalized products composed of common platform modules supplied by the original equipment manufacturer (OEM) and adaptable interfaces for the integration of different functional add-on modules to meet changing customers' needs in the product lifetime. The specific customized add-on modules are designed and manufactured by OEM and connected to the product through closed and adaptable interfaces for customers' choice in the purchasing process. The unknown personalized add-on modules can be designed by customers during the design stage and provided by small and medium-sized enterprises (SMEs) or customers (subject to safety and geometric constraints set by OEM) and added to the product using open and adaptable interfaces in the future during the design and operation stages to meet the dynamic changes of customer requirements (Figure 1.1) [5, 6].

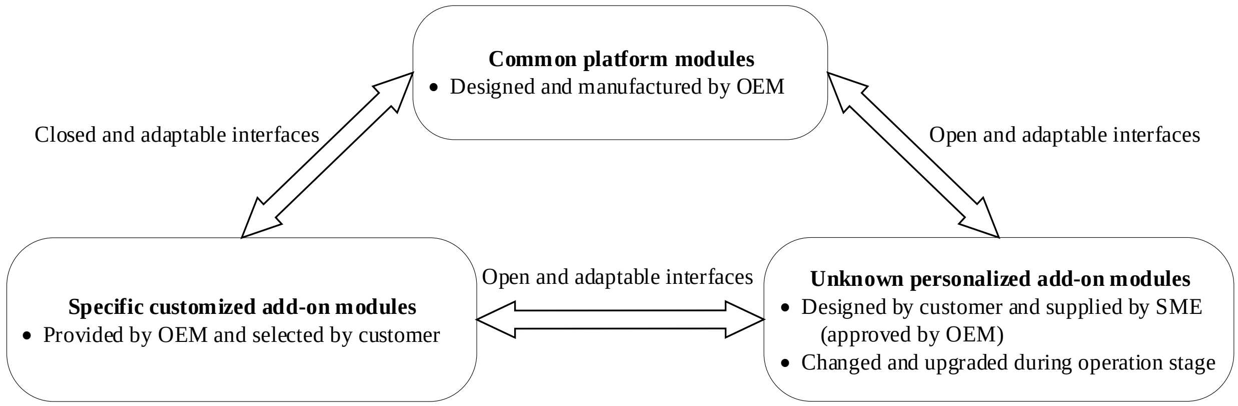


Figure 1.1 Key elements of an open-architecture product (OAP) (Adapted from [6-8]).

Nowadays, manufacturing industries are pushed towards developing sustainable products driven by legislation, changing customer attitudes, and market competition. Hence, industrial companies aim to design and manufacture sustainable products through the use of tools and strategies for reducing environmental, economic, and social impacts throughout the product life cycle stages [9, 10].

The design of open-architecture products is still under research and development. Zhao et al. [7, 8] proposed a quality function deployment (QFD)-based method for the modular design of OAPs to determine the various types of functional modules including common, customized, and personalized modules. Zhang et al. [11, 12] studied the design, evaluation, and improvement of open interfaces of OAPs to facilitate the interactions between the personalized modules and product platform. Zhao et al. [6] and Zhang et al. [5] focused on evaluating and enhancing the adaptability of OAPs allowing the product to accommodate the various personalized add-on modules through adaptable open interfaces during the product lifetime. Some studies developed cyber-enabled design tools and virtual reality (VR)-based methods for the co-design process of OAPs to enable customers to participate in the design of personalized products based on their needs [13-15]. In comparison with conventional products (i.e., single products and modular products), the design of open-architecture products (OAPs) with the attributes of modularity, upgrading, and reconfiguration offers more sustainability through higher product variety using fewer resources, extending the product lifetime in the operation stage, enhancing the end-of-life (EoL) operations and reducing waste because of easy disassembly tasks [3, 16]. However, the co-design of OAPs requires sustainability considerations regarding evaluation and enhancing the sustainability performance of the product. There are only a few studies aimed at considering the sustainability concept in developing OAPs. Mesa et al. [4] conducted a systematic literature review focusing on the attributes of OAPs and the strategies of the circular economy (CE) model. They identified research opportunities regarding the implementation of an integrated model of OAP and CE and formally integrating sustainability into the manufacturing paradigm and complex product development. In another study [16], they provided an analysis of modular architecture principles (MAPs) in the sustainable design and development of open-architecture products and discussed the advantages of the use of modularity in OAPs to improve the sustainability performance of OAPs through the product life cycle stages. Therefore, there is a need for sustainability studies regarding open-architecture products and analysis of modular and open architecture to enhance the sustainability performance of the product.

1.2 Research objectives

The overall objective of this research is to propose a methodology for the sustainable design of open-architecture products (OAPs) concerning the evaluation and visualization of the sustainability performance of the product defined by customers during the design phase for decision-making purposes. In order to reach this goal, the following three sub-objectives need to be accomplished:

First sub-objective: evaluation of the sustainability performance of the open-architecture product (OAP) defined by customers during the design stage.

Considering the features of OAPs which are individualized products with a high variety of unknown personalized modules defined by customers during the design phase, the sustainability performance of the product variants should be evaluated after defining personalized modules. As customers are allowed to participate in designing personalized modules based on their needs, different design alternatives can be created in which products have different sustainability values in comparison with each other, so that the sustainability performance of varieties of the personalized product should be measured.

Second sub-objective: development of the sustainability index (SI) for the decision-making process and visualization purposes.

After measuring the sustainability performance of the product varieties, a sustainability index (SI) needs to be developed for each product alternative. The sustainability index is a quantitative measure which is obtained through the integration of various sustainability indicators (i.e., environmental and economic indicators) with different measurement units and scopes. The value of the sustainability index shows the degree of sustainability for product variants. The sustainability index of design alternatives can be presented and communicated to customers and other involved decision-makers which facilitates decision-making towards the best sustainable design option.

Third sub-objective: validation of the robustness of the proposed decision support framework (i.e., first and second sub-objectives). The robustness of the results of sustainability assessment (first sub-objective) and sustainability index development (second sub-objective) which build the proposed decision support tool are studied. The robustness of the results of a model means how much the output variable of the model is affected by the variation or change in input parameters.

Due to employing the secondary data obtained from existing literature and database for the life cycle assessment (LCA) analysis of the product (first sub-objective), sensitivity analysis (SA) needs to be performed to check the robustness of the results to the uncertainty of input parameters. Also, to validate the results of sustainability index construction (second sub-objective), sensitivity analysis is carried out on the applied method through the comparison of results calculated by the chosen method with those obtained by alternative approaches (i.e., the use of different weighting and aggregation schemes).

It should be noted that a case study is conducted to demonstrate the utility and usefulness of the proposed methodology.

1.3 Dissertation structure

The remainder of the dissertation is organized as follows: Chapter 2 reviews the related work in the literature on the OAPs and sustainability analysis. Then, in Chapter 3, the proposed methodology for sustainability performance evaluation of OAPs is explained in detail. In Chapter 4, the application of the proposed method is described by providing a case study, and also the discussion of the results of sustainability analysis is presented. Finally, the conclusion of this dissertation and the proposed future work are presented in Chapter 5.

CHAPTER 2 LITERATURE REVIEW

In this Chapter, a literature review is conducted concerning open-architecture products (OAPs), co-design and interactive design, design for environment (DfE), visualization in DfE, and multi-attribute decision making (MADM) methods.

2.1 Open-architecture products (OAPs)

The design of open-architecture products is a new concept, and there are challenges including modular design [17, 18], adaptable design [5, 6], interface design [11, 12], cyber-enabled design tool [13], etc. for the development of OAPs, which are still under research and discussion. The adaptable design aims to design adaptable products that can be reconfigured and upgraded during the design and utilization stages through changing the modules and parameters for satisfying different customer requirements [5]. Modular design is a design approach for decomposing the product structure into discrete functional modules that can be changeable through well-defined interfaces to fulfill the specific function of the product [18]. Product interfaces are designed for connection, interaction, and transformation between modules and/or components in the modular product [12]. The open interfaces in the OAPs are designed for connecting the various personalized functional modules developed by third-party vendors or customers to the product platform to achieve desirable functions of the product [12]. The cyber-enabled design tool is a graphical-aided software package in a web-based environment which has the graphical user interface (GUI) and CAD system for the involvement of customers and designers in the design of open-architecture personalized products [13].

Koren et al. [3] explained the features of OAPs and the main challenges of OAPs that need to be addressed including developing new OAP design software (i.e., a web-based CAD system) for involving customers in the design of OAPs, finding new manufacturing and assembly systems to facilitate economical assembly of a large number of product variants, and developing cyber-physical manufacturing systems for interactions between consumers and platform and modules manufacturers. Zhao et al. [7] proposed a quantitative method for the modular design of OAPs using extended quality function deployment (QFD) to determine different functional modules including common modules, customized modules, and personalized modules. In addition to the use of basic function needs (BFN) and general technical requirements (GTR), OAP's individual customer needs (ICN) and OAP's technical requirements (OTR) were included in an extended QFD. The degree of variety (DV) was used as a quantitative measure for the variability of product components to divide components into three types of modules. The developed method was used for the modular design of open architecture household electrical appliances. Zhao et al. [8] integrated the extended quality function deployment (QFD) and expanded axiomatic design (AD) for module planning of OAPs to determine the various types of functional modules. They used the proposed approach for modular design of an OA paper-bag folding machine to develop three types of modules in order to satisfy changing requirements during the machine operation.

Mesa et al. [19] presented a functional characterization of mechanical joining methods based on the design for assembly and disassembly principles for the evaluation and robust selection of different types of joining methods in the design of OAPs. They calculated the joint complexity by defining characterization criteria, i.e., task complexity, tool complexity, alignment complexity, and fixtures requirement, taking into account the requirements of repetitive tasks of assembly and disassembly during the entire life cycle of OAPs, which facilitates the proper selection of joining methods during the design of OAPs. Zhang et al. [11] investigated the characteristics of open interfaces of personalized OAPs and proposed a new approach using module function correlation matrix, House of Quality (HoQ), and measures of the interface efficiency for design, evaluation, improvement, and operation of open interfaces of personalized products. This method was employed to design an open interface for connecting different battery packs (personalized modules) in a personalized electric vehicle. Zhang et al. [12] proposed a new method to enhance the adaptability of open interfaces of OAPs for facilitating the interactions between the product platform and add-on modules. This approach includes modelling an open interface by a platform interface, interface connectors, and assembling relations between the platform interface and interface connectors, quantifying the adaptability of the open interface considering functional, structural, manufacturing, and operational adaptabilities, and redesigning the interface to improve the adaptability of the open interface. The design of an open interface for an OA paper-bag folding machine was conducted using this method and the interface adaptability was evaluated and improved by redesigning and modifying the open interface. Hu et al. [20] proposed a systematic method for the adaptable open interface design of OAPs using the functional correlation matrix to generate interface plans, morphological matrix to form possible solutions for the interface, and fuzzy logic analysis to evaluate the plans and obtain the optimal design solution.

Zhao et al. [6] developed a quantitative evaluation method to measure and improve the adaptability of OAPs in terms of the compatibility of product common platform to accommodate personalized modules, the usability of add-on modules in the product lifetime, and openness of interfaces for users to meet the changing requirements. They employed the proposed method to evaluate and enhance the adaptability of an OA industrial painting machine. Zhang et al. [5] proposed a new robust adaptable design approach to develop an adaptable OAP with robust performance whose functional performances are insensitive to uncertainties in parameters. The product operation configuration states (in which open interfaces are used to connect with different add-on modules in the operation stage) and product design configuration candidates (design configurations of the platform and specific add-on modules) are modelled by parameters (design parameters and non-design parameters). The interactions between the platform and add-on modules are modelled by the input and output parameters of open interfaces. Then, the robustness of an OAP is evaluated, and a multi-level optimization method is developed to identify the optimal design configuration and parameters of an adaptable OAP with the best robustness so that the overall performance of the product is insensitive to the parameter variations caused by uncertainties. Chen et al. [13] developed mathematical models to identify the optimal configuration of OAPs considering the cost, adaptability, and openness of the existing product configurations. The proposed optimization method was implemented in a web-based design tool for the optimal adaptable design of OAPs and enabling users and vendors to participate in the personalized product development process. They utilized the developed method and tool for the optimal adaptable design of an OA industrial coating machine. Zheng et al. [17] proposed a conceptual framework of the personalized adaptable product configuration system based on the adaptable open architecture product platform (OAPP) with the adaptable interface to enable the customer-centric product development process and integrate OEM with various SMEs into a co-creation process. The configuration system consists of (i) the technical configurator for the interaction process between OEM and SMEs which is enabled by modular design and scalable design of the product by OEM to ensure the adaptability and scalability of product variety and to connect the personalized modules provided by SMEs, and (ii) the sales configurator for the interaction process between customers and OEM which is established by considering customer's preferences and conducting the product configuration process in an engineer-to-order (ETO) model in order to enable customers to create new individualized designs in a co-creation process. Table 2.1 summarizes the related works in the design of open-architecture products (OAPs).

Table 2.1 Related works on the design of open-architecture products (OAPs).

Related works	Description
Koren et al. [3]	Explain the features of OAPs and the main challenges in developing OAPs.
Zhao et al. [7, 8], Peng et al. [18]	Modular design of OAPs using a QFD-based method to determine different functional modules.
Zhao et al. [6], Zhang et al. [5], Chen et al. [13], Zheng et al. [17]	Adaptable design of OAPs to accommodate various personalized modules during the product lifetime.
Zhang et al. [11, 12], Hu et al. [20]	Open interface design of OAPs to connect personalized modules to the product platform.
Chen et al. [13], Zheng et al. [17], Zhang et al. [14]	Develop cyber-enabled design tools to enable customers to participate in the design of OAPs.

2.2 Co-design and interactive design

Customers can perform the various roles as a co-innovator, co-designer, co-developer, co-producer, co-distributor, co-experience creator, etc. during the different life cycle stages of the product including conception, design, development, manufacturing, distribution, etc. in collaboration with other stakeholders and actors in order to co-create value for customers and achieve customer satisfaction [21, 22]. Co-design describes the participation of customers in the definition and design of products in collaboration and interaction with professional designers to satisfy customers' needs [22, 23]. To integrate users into the design process, co-design toolkits, i.e. product configuration toolkit [24] and embedded open toolkit [25, 26] were developed. Franke and Piller [24] proposed product configuration toolkits for mass customization which is a knowledge-based system allowing users to interact with toolkits to develop a product according to the specific requirements of customers. In the configuration process, the configuration toolkit allows customers to select from existing pre-defined product attributes and design parameters in the design stage to provide the target product fulfilling customer requirements. Gross and Antons [25] and Piller et al. [26]

developed embedded open toolkits for user co-design/co-creation by shifting and postponing certain design decisions and some specifications of the product into the user domain to achieve customer satisfaction. The open toolkits embedded in the product architecture with build-in flexibility enable users to modify and adapt a physical product through adaptable interfaces during the use stage based on their own needs. Kumtepe et al. [27, 28] proposed a smart mass customization design tool for users' interaction and involvement in the design process of customized products allowing them to modify design parameters based on their needs and expectations. To implement the methodology, they developed a parametric design tool for modular portable wheelchair ramps which enables customers to select design parameters and configure and customize their products.

The rapid advancements in information, communication, and manufacturing technologies (e.g., cloud computing, cyber-physical systems, Internet of Things (IoT), and additive manufacturing) enable customers to collaborate with designers and manufacturers and become more actively involved in the design and development of products to co-create individualized products with higher efficiency and variety [29, 30]. Co-design of personalized products provides the opportunity for both customers and designers of the product to exchange ideas and information during the design stage in order to co-create personalized products satisfying customers' individual requirements and co-create values for users [30, 31]. Zheng et al. [29] proposed a framework by integrating three main features of personalized products, i.e., user experience, co-creation (user participation), and modular design for the product development process for mass personalization. To describe the framework, a case study of personalized smart respiratory masks development was used in which users are involved in the co-design process through the online configuration system. To improve the user involvement in the design of personalized open-architecture products, Zhang et al. [14] developed a web-based interactive system to facilitate users' communication with designers of OEM and utilized virtual reality (VR) technologies for the interaction between users and the product allowing users to evaluate and operate the product in the design stage to meet their requirements. Song et al. [15] proposed a virtual reality (VR)-based interactive system to effectively enhance the user interaction and participation in the design process of OAPs. The system enables users to operate and experience the product model in the VR environment and provide their feedback to designers. Through recording and analyzing the users' data, designers can improve the product design to meet the users' needs. Zheng et al. [32] proposed a data-driven design approach by integrating co-development toolkits for active user involvement in the co-design and co-creation process of personalized smart connected products, with embedded information and communication technology (ICT) components, in which the interaction process between users and designers are enabled by establishing a cyber-physical product model in the cloud-based environment to capture the design data generated by users in real time. Zheng et al. [30] proposed that the co-design process of smart connected OAP for the interaction between user and designer/manufacturer in the product development process can be conducted through two procedures: (i) online configuration in which product architecture is composed of three layers, i.e. physical product layer, embedded hardware layer, and embedded software layer, and (ii) cyber-physical interaction in which users can change the physical design prototype based on their preferences and in-context data can be collected and transmitted in real time to drive the virtual twin model in the cyber space. Thus, both active (i.e., design data defined by the customer) and passive (i.e., design data predefined by the designer) involvement of customers enable value co-creation for users.

2.3 Design for environment (DfE)

Design for sustainability (DfS) aims to integrate environmental, economic, and social aspects into the product development process throughout product life cycle stages including raw material extraction, production, transportation, use, and end-of-life (EoL). Therefore, product sustainable design is classified into three categories including design for environment (DfE) or eco-design (environmentally conscious design), design for economy, and design for society [10, 33]. Environmental sustainability focuses on eco-friendly practices to reduce the negative environmental impacts through minimizing energy, raw materials and natural resources consumption, emission and waste generation. Economic sustainability relies on reducing time, cost, and errors issues for improving competitiveness. Social sustainability refers to improving the quality of human life and health by minimization of human health and safety risks [10, 33, 34]. The eco-design methods and tools aiming to evaluate and improve the environmental sustainability performance of products can be classified into the following groups: life cycle assessment (LCA) based tools, computer-aided design (CAD) integrated tools, quality function deployment (QFD) based tools, design for X (DfX) approaches (e.g., design for disassembly, design for recycling, etc.), diagram tools, checklists and guidelines, etc. and the integration of different existing tools [10, 35]. These eco-design methods and tools are explained as follows [34, 35]:

Design for material conservation: it is oriented to minimize material consumption in the product life cycle by robust design process to provide suitable geometries and manufacturing materials, optimized selection of materials, and utilizing renewable and recyclable materials.

Design for energy conservation: it is to minimize energy consumption throughout the product's useful life by using more efficient components and processes.

Design for chronic risk reduction: it is aimed at the use of low-impact materials including low carbon footprint and less-hazardous materials and reduction of hazardous waste and emission generation during the product life cycle.

Design for recovery: it aims to reduce waste generation, increase the use of recyclable materials, and make waste recoverable (through recycling, energy creation, etc.).

Design for disassembly: the purpose of design is to optimize the product disassembly process through ensuring easy access to fasteners and joints and minimizing tasks and tools required for the disassembly and separation process of components during the product operation and EoL stages in order to reduce disassembly time and cost and lower component destruction. Design for disassembly allows the realization of EoL options including reuse, remanufacturing, recycling, and incineration processes.

Design for assembly: it aims to develop techniques in the design stage for efficient assembly operation of products in order to reduce assembly time, cost, and error.

Design for reuse: the goal of design is to standardize components throughout the age of product models and increase the durability of components in order to reuse components for the same purpose without conducting any significant repair.

Design for remanufacturing: the objective of design is to enable disassembly, cleaning, repair, replacing, and reassembly of a used product that has reached the end of useful life and return the product to working conditions.

Design for recycling: the aim of design is to correct material selection, increase recyclable materials, and reduce material variety in the product for returning waste products to raw material format.

Life cycle assessment (LCA): the objective of the LCA method is to quantify and calculate the environmental impacts of products or services along the whole life cycle phases.

CAD integrated method: integration of CAD and LCA tools aims to analyze the environmental impacts of the design choice during the design phase through directly retrieving the product data needed from the CAD model to feed the LCA system for environmental impact assessment.

Quality function deployment (QFD): it is a design tool applied during the product design phase to translate customer requirements into the quality characteristics and technical requirements in order to meet the needs and improve the product quality. The quality function deployment for environment (QFDE) method is developed to support eco-design by incorporating the environmental issues into the extended QFD.

TRIZ (theory of inventive problem solving): this tool supports designers by finding ways of solving problems in designing a product; also, it can be used in the eco-design of products.

Diagram tools: it is used to estimate the environmental impacts of products through a qualitative or semi-quantitative evaluation when detailed information about the product life cycle is not available.

Checklists and guidelines: this approach is used for a quick and simplified evaluation of the product's environmental profile to guide designers, especially during the early design phases in choosing the best design solution.

The existing research works have focused mainly on the evaluation and improvement of sustainability in single and modular products using current eco-design strategies. Masui et al. [36, 37] extended QFD for incorporating environmental aspects into conventional design factors and product quality requirements to eco-design the product in the early stages of product development (during the conceptual design stage). Sakao [38] integrated LCA, QFDE (QFD for environment), and TRIZ (theory of inventive problem solving) tools for the environmentally conscious design of products. For the green modular design of the product family considering the end-of-life performance, Yu et al. [39] developed a QFD-based methodology (QFDE) and Yang et al. [40] proposed a group genetic algorithm (GGA) method to improve the reusability and recyclability of the product family. Tseng et al. [41] focused on the design for recycling strategy for product modular design aiming to increase the recycling value and decrease the disassembly cost of the EoL modular product. Kim and Moon [42] performed the sustainability assessment in terms of environmental, economic, and social aspects for the product family and also utilized multi-attribute decision-making (MADM) methods and a fuzzy inference system to identify the sustainable platform for the product variants in the product family design. Go et al. [43] developed an optimization model using the genetic algorithm (GA) approach to obtain the optimal disassembly sequence for components of an EoL product aiming to minimize the disassembly time and increase the reusability of the product components. Tian et al. [44] and Bentaha et al. [45] addressed the disassembly process planning problem for the EoL product by considering the uncertainty of disassembled component quality and varying disassembly operational cost by using mathematical modelling and stochastic approaches. Mandolini et al. [46] and Favi et al. [47] proposed an innovative procedure regarding design for disassembly (DfD) to analytically estimate the disassembly time and cost for the product and developed the DfD software tool to evaluate the product disassemblability and recyclability performances at the EoL based on the CAD model of the product during the design phase. Some studies have worked on the integration of LCA tools and computer-aided product development systems to evaluate and improve the environmental sustainability performance of products at the design stage through extracting the required data directly from the CAD model of the product [48-50]. Gaha et al. [51] and Slama et al. [52]

developed an environmentally conscious manufacturing process using an LCA and CAD/CAM/CAPP/PLM integration system for environmental impact analysis, a feature interaction technology (FIT) to generate different possible manufacturing process plan scenarios, and a multi-criteria decision support method to choose the greenest manufacturing scenario.

Sustainability is mostly applied to conventional products and there is limited research on the eco-design of OAPs. Mesa et el. [19, 53] studied the selection of joining methods in the design of OAPs based on the design for assembly and disassembly principles to improve the product sustainability through reducing the complexity of assembly/disassembly tasks and reduction of operational time and costs during the use and EoL phases. Mesa et al. [4] performed a literature review concerning the attributes of OAPs (modularity, product family, reconfiguration) and the strategies of the circular economy (CE) model (EoL strategies, useful life extension, life cycle thinking). They identified research gaps including formally integrating sustainability into the development of complex products, the complete integration of the OAPs attributes and CE concepts and the implementation of an integrated model of OAP and CE, and the integration of social and economic issues with environmental aspects. In another work [16], they analyzed the modular architecture principles (MAPs) to modularize products and described strategies based on modularity principles for improving the sustainability of OAPs containing reuse of modules, open interface design for easy assembly/disassembly, robust selection and evaluation of MAPs, and actions for user responsibility and corporate responsibility. They discussed the lack of sustainability studies regarding open-architecture products and the need of developing sustainability enhancement approaches taking into account the product architecture. Also, they proposed research opportunities relating to the design of joints and product interfaces oriented to improving the sustainability of OAPs and the establishment of effective supply chains between the product life cycle stages to improve sustainability regarding reuse, remanufacturing, and recycling. Hence, it is essential for further research about the eco-design of OAPs to evaluate and enhance the sustainability of the product. Table 2.2 summarizes the related works in the sustainable design of products.

Table 2.2 Related works on the sustainable design of products.

Related works	Description
Masui et al. [36, 37]	Eco-design of the product using extended QFD for incorporating environmental aspects into conventional design factors.
Sakao [38]	Integration of LCA, QFD, and TRIZ tools for the eco-design of products.
Tao et al. [48, 49], Chen et al. [50]	Integration of LCA tools and computer-aided product development systems to eco-design products at the design stage.
Go et al. [43], Mandolini et al. [46], Favi et al. [47]	Sustainable design of the product by focusing on the design for disassembly strategy to reduce the disassembly time and cost and improve the EoL performance.
Yu et al. [39]	Eco-design of the product family using a QFD-based method to improve the EoL performance.
Yang et al. [40]	Eco-design of the product family using a group genetic algorithm (GGA) method to improve the reusability and recyclability.
Tseng et al. [41]	Eco-design of the modular product based on the design for recycling strategy.
Kim and Moon [42]	Sustainable design of the product family using the combination of life cycle sustainability assessment, multi-attribute decision-making methods, and a fuzzy inference system.
Mesa et el. [19, 53]	Design of joints in OAPs based on the design for assembly and disassembly principles to improve sustainability.
Mesa et al. [4]	Propose the integration of the OAPs attributes (modularity, product family, reconfiguration) and the strategies of the circular economy (CE) model to enhance the sustainability performance.
Mesa et al. [16]	Propose strategies based on modularity principles for improving the sustainability of OAPs containing reuse of modules, open interface design for easy assembly/disassembly, robust selections of modularization principles, and actions for user responsibility and corporate responsibility.

2.4 Life cycle assessment (LCA) tools

The life cycle assessment (LCA) is a systematic framework to quantify the potential environmental impacts of the product along the whole life cycle phases and identify the hot spots [54]. Based on this methodology, there are several tools to perform LCA and calculate the environmental impacts for the sustainable design of products. There are professional LCA software tools, such as SimaPro, GaBi, Umberto, and OpenLCA to conduct a full and detailed LCA analysis to obtain accurate and reliable results, which require the collection of a large amount of life cycle related data, training to use the tools, and experience to interpret the LCA results [35, 55, 56]. SimaPro is a popular and commonly used software with a high license price, through which the user can model and analyze the environmental impacts of product life cycles in a transparent and clear way to generate clear and precise results [55, 56]. GaBi is a well-recognized and common paid LCA software tool for modelling the life cycle of products with the feature of graphical construction of the product life cycle allowing users to input flows and processes in a graphical way [57]. Umberto, a paid LCA software tool, is a powerful and efficient tool with a comprehensive graphical lifecycle modelling which is hard to use for ordinary users without professional knowledge of LCA due to the complicated diagram of the lifecycle [55, 57]. OpenLCA is a free and open-source LCA software tool developed by GreenDelta to perform LCA analysis. It is easy to handle and allows users to calculate all the stages of LCA. It is compatible with most of the life cycle inventory (LCI) databases and life cycle impact assessment (LCIA) methods existing in the market and users can import free or purchased methods and databases into software and perform an LCA [35, 55, 56]. One of the problems when performing an LCA analysis using different tools can be the variety of data formats, storage formats, system definitions, and software implementations. The selection of different LCA software tools may also lead to different assessment results and conclusions due to differences in the software databases for both inventory and impact assessment, which could affect the decision-making process [58, 59].

Conducting a complete LCA analysis using detailed LCA software tools is complex, costly, and time and resource-consuming due to the collection of a considerable amount of product data needed for life cycle inventory (LCI) analysis. Thus, the simplified LCA (SLCA) tools such as Quantis Suite 2.0, Sustainable Minds, EIME (Environmental Improvement Made Easy), ECO-it, etc. have been developed to calculate the simplified environmental impact of products without having complete data on the product, which reduce the complexity of a complete LCA. Using the SLCA software tools, simplification can happen at various stages including input data, computation methods, and graphic user interface, making them more user-friendly and useful for non-expert and ordinary software users. However, simplifications could cause incorrect interpretation of the results due to the incomplete data input [35, 55]. Quantis Suite is a web-based application that uses the ecoinvent 2.2 database. Modelling is performed by LCA phases and product stages with a drag-and-drop method of process selections [57]. Sustainable Minds is a web-based LCA tool which is helpful for non-expert users. The results may be not detailed enough for further analysis and the database cannot be modified by users and Internet access is required [55]. EIME is a widely used web-based application for environmental sustainability analysis. The user interface is well designed and friendly, but the embedded indicators are different from other LCA tools which causes interoperability issues [35, 55]. ECO-it is an LCA tool for quick screening with a limited database and methods which is useful for designers who have no professional knowledge in LCA to consider environmental aspects during the design process [55].

The need to analyze the environmental impacts of products during the design and development phase as well as establish the relationships among design parameters and environmental impacts of products has led to developing environmental impact assessment approaches and tools integrated and interfaced with computer-aided product design and development systems for eco-design of products, which can greatly reduce the environmental impacts [35, 48]. The CAD-integrated SLCA tools such as SolidWorks Sustainability [60] and ECO-fit [61] in which environmental impact assessment modules are embedded and integrated into CAD software can be utilized to estimate the environmental impacts of the product by extracting data directly from the product model at the design stage. These tools provide simplified LCA analysis and are useful to compare the environmental impacts of different product versions and identify and improve the environmental hotspots and criticalities of the product. However, compared to the professional dedicated LCA tools, they are not enough to acquire detailed and much accurate results due to the limitation of data in the databases, a limited number of environmental impact indicators, and simplification in the modelling of life cycle phases [35, 48, 55]. Marosky et al. [62] carried out the environmental impact assessment during the product development to design the environmentally friendly product by linking a CAD software tool (i.e., SolidEdge) and an LCA software tool (i.e., SimaPro) in which all relevant data is extracted from the CAD product model and manually transferred to the LCA software. Mathieux et al. [63] explored opportunities and challenges for connecting CAD software tools (e.g., CATIA) and product lifecycle management (PLM) systems (e.g., SmarTeam distributed by Dassault Systems) with LCA software tools (e.g., EIME) in order to automatically transfer needed data for assessing in real-time environmental performance of design alternatives in the early design process. Leibrecht [64] proposed a prototype tool, EcolgoiCAD, using a CAD-based environmental impact assessment method to retrieve CAD (i.e., Pro/Engineer) data for the LCA analysis. Morbidoni et al. [65, 66] developed a prototype eco-design tool, CAST (Computer-Aided Sustainable Tool) tool, based on the integration of sustainable life cycle methodologies (LCA and life cycle costing (LCC)) with CAD/PLM systems in order to design sustainable and green products. The required relevant information is retrieved from PLM, LCA, and LCC databases for conducting the simplified environmental and economic analyses in the early stage of the product design and development process. Tao et al. [49] and Chen et al. [50] developed a feature-based LCA prototype tool for the integration of environmental assessment with computer-aided product development systems to evaluate and improve the environmental sustainability performance of the product. In this approach which is focused on efficient life cycle related data collection and more accurate impact assessment results, feature-based data, namely Product Features (PFs, product related data) and Operation Features (OFs, process related data) are retrieved from computer-aided engineering tools, CAX systems (i.e., CAD, CAM, CAPP, CAE), for LCA analysis. The proposed method enables assessment and comparing various design alternatives and selecting the greenest one. Tao et al. [48] presented an innovative eco-design approach based on integrating LCA, CAD\CAE, and optimization tools for optimal sustainable product design and development. Through data exchange between CAD (e.g., UGNX) and CAE (e.g., Abaqus) systems, functional performance analysis of the product is performed. Then, the eco-optimization process is conducted to find the optimal design solution with the lowest environmental impact, while fulfilling the technical and functional requirements of the product.

Therefore, there are various LCA tools to evaluate the environmental impacts of products. Users can choose an appropriate LCA tool (professional, simplified, or prototype tools) to meet their requirements. The comparison of some current LCA tools is summarized in Table 2.3. The important criteria selected for comparison include the scope of the use of software, the cost of software, the accuracy of LCA modelling (i.e., how much the generated LCA model matches with the real model), and the expertise of users. In order to perform a complete LCA analysis with higher accurate results, it is recommended to use SimaPro, GaBi, Umberto, and also OpenLCA. Some

LCA tools are integrated with CAD software such as SolidWorks Sustainability which is useful for designers to assess the environmental impacts of the different design scenarios to select a greener solution. Moreover, to conduct simplified LCA when the accuracy of results is not much important, users can employ simplified LCA tools such as EIME. In some cases, CAD-integrated LCA prototype tools are developed to directly retrieve required data from CAD tools during the design stage for environmental impact assessment.

Table 2.3 Comparison of some current LCA software tools (Adapted from [35, 55-57]).

Name	Type	Accuracy of LCA model	User	Database	Cost	Other features
SimaPro	Complete LCA	High	Expert	Various databases, modified by user	Paid	Suitable for LCA comparison
GaBi	Complete LCA	High	Expert	GaBi LCA databases, Ecoinvent and US LCI, modified by user	Paid	Graphical lifecycle modelling
Umberto	Complete LCA	High	Expert	Ecoinvent and GaBi databases, not modified by user	Paid	Graphical lifecycle modelling
OpenLCA	Complete LCA	High	Expert	Various databases, modified by user	Free	Compatible with most databases and LCIA methods
SolidWorks Sustainability	Simplified LCA	Low	Expert	GaBi LCA databases, not modified by user	Paid	Integration with CAD software
ECO-fit	Simplified LCA	Low	Expert	Not modified by user	Paid	Integration with CAD software
Quantis Suite	Simplified LCA	Low	Expert and non-expert	Ecoinvent 2.2	Paid	Web-based application
Sustainable Minds	Simplified LCA	Low	Expert and non-expert	US-Ecoinvent database, not modified by user	Paid	Web-based application
EIME	Simplified LCA	Low	Expert and non-expert	Modified by user	Paid	Web-based application

2.5 Visualization in DfE

Visualization is a valuable tool to transform and map data to a visual representation in order to effectively communicate and analyze the information [67]. In the eco-design process, visualization of the results of LCA and sustainability assessment is important to support LCA experts, designers, consumers, and other stakeholders involved in the design and decision process in the presentation, interpretation, and decision-making [68, 69]. Uchil and Chakrabarti [70, 71] highlighted the issues in the visual representation of the environmental impact assessment results in the current LCA tools such as accuracy of interpretation and perceived insight, user performance, usability, and interactivity. They discussed the application of information visualization techniques as an interface for LCA tools in order to make the LCA results interpretable and usable by designers which helps them to take robust decisions towards reducing the environmental impacts of products. Hollberg et al. [72] conducted a comprehensive review on the visualization of LCA results during the design process of buildings. They classified the different visualization approaches, such as color map, treemap, heat map, radar chart, etc. based on the LCA goals and the amount of information displayed in the visualization [72, 73]. Oyarzo and Peuportier [74] utilized the radar charts to visualize and interpret the results of LCA analysis in the building sector aiming to compare different design alternatives and environmental impact categories. To analyze the LCA results in detail, Kiss and Szalay [75, 76] applied the sunburst diagram as a visualization tool in which the total environmental impact is divided into the life cycle stages and then further divided into other subcategories such as building components and materials. Also, the results are mapped and visualized onto the geometrical 3D model of the building where the color of the building elements represents the contribution to the overall environmental impact. Cerdas et al. [77] introduced cluster heat maps to report and visualize the LCA results and improve the decision-making process.

This visualization method allows to hierarchically cluster the product elements (components, materials, processes, etc.) and present complex information in such a way that is understandable for a various range of stakeholders. Keivanpour and Ait Kadi [78] employed clustering and treemap approaches for mapping and analyzing the eco-efficiency profile of the complex products comprised of many modules, components, and parts to facilitate the decision-making process. Ostad-Ahmad-Ghorabi et al. [79] investigated the requirements for the integration of eco-design into the CAD system and discussed the possibility of visualization of environmental impact evaluation results on the CAD model during the early product design stage. Müller and Hiete [80] developed a novel a posteriori visualization method to support decision-makers in life cycle sustainability assessment (LCSA) of products for comparing and identifying the most sustainable product alternative. This approach takes the three sustainability pillars into account and allows decision-makers and analysts to explore the sustainability performance of products over different weightings of the three sustainability dimensions.

The visualization technique can be useful for analyzing and communicating the sustainability assessment results in the co-design process of OAPs where customers and expert designers are involved in the design of the product. This facilitates interaction and cooperation between different stakeholders in the decision-making process for improving the sustainability performance of products.

2.6 Multi-attribute decision making (MADM) methods

Multi-criteria decision making (MCDM) is a supporting tool used for making decisions under multiple conflicting evaluation criteria [81]. Based on the different purposes and different data types, the MCDM methods can be classified into two main categories: (i) multi-attribute decision making (MADM) methods to evaluate discrete decision problems with a limited number of predetermined alternatives, and (ii) multi-objective decision making (MODM) methods to deal with continuous decision problems where the alternatives are not predefined [82, 83]. The MODM methods aim to achieve the optimal goals through optimizing the objective functions by considering a set of constraints [83]. The MADM methods aim to evaluate the performance of the alternatives with respect to a number of qualitative and/or quantitative criteria for the purpose of selection or ranking of alternatives [84]. There are several MADM methodologies with different features and calculation procedures to solve decision-making problems which can be selected and employed based on the structure and characteristics of the decision problem, the objectives of the analysis, the quality of the information available, and the preferences of decision-makers [85, 86]. The decision results and final ranking of the alternatives depend on the selected decision methodology and may be changed according to the applied method [85, 87, 88]. The most commonly used MADM methods include (i) pairwise comparison-based methods (e.g., AHP, ANP), (ii) scoring-based methods (e.g., TOPSIS, SAW, GRA), and (iii) outranking-based methods (e.g., ELECTRE, PROMETHEE) [89, 90].

The AHP (Analytic Hierarchy Process) proposed by Saaty [91] is based on building a hierarchical structure for the decision problem and creating pairwise comparison matrices for all the levels of hierarchy to calculate the single priority score for each alternative. The complete ranking of alternatives is determined by comparing the performances of alternatives in pairs with respect to several criteria through the subjective judgments and ratings of alternatives by decision-makers [92]. Saaty [93] further developed the ANP (Analytic Network Process) to cope with the problem of dependence and feedback among attributes [94]. The ANP is an extension of AHP with a network structure which enables interrelationships among the decision levels and attributes, while the AHP uses unidirectional relationships among elements in the hierarchy [95].

The TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method presented by Hwang and Yoon [96] aims at the complete ranking of alternatives and determining the best alternative based on performance scores obtained using normalization of performance values of alternatives with respect to criteria and calculation of the distance of each alternative from the positive and negative ideal solutions. The optimal alternative has the minimum distance from the positive ideal solution (optimal solution) with the best performance and the maximum distance from the negative ideal solution (inferior solution) with the worst performance [97, 98]. The SAW (Simple Additive Weighting) approach is applied to select the best option based on the total score calculated for each alternative through summation of multiplying the normalized value of each alternative performance by the corresponding attribute weight [99, 100]. The GRA (Grey Relational Analysis) proposed by Deng [101] is used for global comparison between alternatives based on the grade computed for each option through aggregating the weighted normalized values of alternatives' performances against each criterion.

The ELECTRE (ELimination Et Choix Traduisant la REalité) method was introduced by Roy [102] and different types of this approach (e.g., ELECTRE I, II, III, IV, IS, A) are utilized to solve three main problems, i.e. choosing, ranking, and sorting. These outranking methods consist of two main phases including (i) making pairwise comparisons of alternatives' performances on the different criteria based on the concordance and discordance concepts (for estimation of concordance and discordance indexes) and constructing outranking relations between alternatives on these concordance and discordance indexes, and (ii) exploiting the outranking and preference relations to provide the results based on the given problematic [103]. The PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) methods developed by Brans and Vincke [104] are applied for partial ranking of the alternatives (e.g., PROMETHEE I) through the calculation of positive and negative outranking flows for each alternative, as well as for complete ranking of the alternatives (e.g., PROMETHEE II) by calculation of net outranking flow for each alternative. For this purpose, an overall preference index is computed for each pair of alternatives using the preference function in which the difference between the evaluations of alternatives on each criterion is translated into a preference degree ranging from zero to one. Then, the outranking flows for each alternative are obtained by averaging the values of preference indexes [105]. The main characteristics of the different MADM methods are summarized in Table 2.4.

Table 2.4 Features of the different MADM methods.

Method	Type	Input	Output	Other features
AHP	Pairwise comparison-based method	- Pairwise comparisons of the criteria (with respect to the goal) and alternatives (with respect to criteria) on a ratio scale to measure their relative importance.	- Assign a multicriteria score to each alternative. - Complete ranking of alternatives and selection of the best alternative.	- Hierarchy structure. - Used for calculation of the weights of criteria. - Potential for inconsistencies between judgments.
ANP	Pairwise comparison-based method	- Pairwise comparisons between all elements (criteria, sub-criteria, and alternatives) on a ratio scale and considering interdependencies in a supermatrix.	- Complete ranking of alternatives based on the scores to select the best alternative.	- Network structure. - More accurate than AHP. - Dependence and feedback relationship between elements. - Potential for inconsistencies between judgments.
TOPSIS	Scoring-based method	- Normalization of data. - Aggregation operation. - Criteria weights.	- Assign a closeness score to each alternative. - Complete ranking of alternatives.	- Distance principle. - Calculation of distance from positive and negative ideal solutions. - Handle objective and quantitative data.
SAW	Scoring-based method	- Normalization of data. - Aggregation operation. - Criteria weights.	- Assign an aggregated score to each alternative. - Complete ranking of alternatives.	- Weighted average principle. - Simple computation procedure. - Handle objective and quantitative data.

Table 2.4 Features of the different MADM methods (cont'd).

Method	Type	Input	Output	Other features
GRA	Scoring-based method	- Normalization of data. - Aggregation operation. - Criteria weights.	- Assign a grade to each alternative. - Complete ranking of alternatives.	- Different normalization functions. - Relatively complex procedure. - Deal with objective and quantitative data.
ELECTRE	Outranking-based method	- Pairwise comparisons of alternatives against each criterion (for estimation of concordance and discordance indexes). - Threshold values (concordance and discordance). - Criteria weights.	- Classification with pairwise outranking degrees. - Find a kernel solution; partial ranking of the alternatives.	- Only consider criteria and do not include the sub-criteria. - The ranking of alternatives depends on the size of thresholds; it is unknown how to determine the appropriate threshold.
PROMETHEE	Outranking-based method	- Pairwise comparisons of alternatives on each criterion. - The preference function for each criterion. - Preference and indifference thresholds for each criterion. - The weights of criteria.	- Classification with pairwise outranking degrees and scores. - The PROMETHEE I for the partial ranking of the alternatives from the best to the worst; and the PROMETHEE II for the complete ranking of the alternatives.	- Only consider criteria and do not include the sub-criteria. - Allows the use of different units, ordinal, and cardinal scales. - The selection of the preference function cannot be fully justified.

2.7 Synthesis

According to the literature review conducted in this Chapter, it is concluded that the design of OAPs is under development and integrating the sustainability aspects into the design process of OAPs is of importance. The existing studies have focused mainly on the modular design of OAPs to determine the different types of functional modules of the product, adaptable design of OAPs to accommodate various personalized modules during the product lifetime, design of open interfaces to connect personalized add-on modules to the product platform, and developing cyber-enabled design tools for co-design of OAPs to enable customers to participate in the co-creation of the product. However, there is limited research discussing the importance of considering the sustainability concept in the design and development of OAPs. Most of the existing research works have studied the sustainable design of traditional products using the current eco-design methods and tools (e.g., LCA, QFD, design for disassembly, etc.). Therefore, it is required to incorporate sustainable design strategies into the co-design process of OAPs. In the co-design process of OAPs where customers and other stakeholders (e.g., OEM and SMEs) are involved in the design and manufacturing of personalized products, not only the functional performance of the product variants defined by the customer need to be analyzed but also evaluating and presenting the sustainability performance of the design choices to customers is essential. To this end, the main objective of this dissertation is to propose a methodology to evaluate and communicate the sustainability performance of personalized products to customers during the design stage. As the first sub-objective, the sustainability performance of the product variants designed by customers is required to be measured. For this purpose, the environmental life cycle assessment (ELCA) and life cycle costing (LCC) methodologies are utilized to assess the sustainability performance of the personalized product in terms of environmental and economic aspects. Regarding the second sub-objective, it is essential to integrate the different calculated sustainability indicators (in the first step) to construct a single sustainability index (SI) for each product variant. Therefore, in this research, the sustainability assessment of personalized products is regarded as a multi-criteria decision problem. To address this challenge, the MADM approaches with the features of weighting and aggregation of sustainability indicators, i.e., scoring-based methods such as GRA are employed to calculate the sustainability scores and rank the design alternatives. Also, the visualization technique (e.g., treemap approach) is utilized to facilitate the decision-making process for customers and other involved stakeholders. Finally, as the third sub-objective, sensitivity analysis is conducted to validate the robustness of the proposed methodology through a design of experiments (DOE)-based method (for LCA modelling) and using different weighting and aggregation approaches (for sustainability index development).

CHAPTER 3 METHODOLOGY

3.1 Overview

The research methodology of this study mainly consists of four steps (Figure 3.1). First, a comprehensive literature review is conducted to review the related works on open-architecture products, sustainability analysis, visualization, and multi-criteria decision-making methods (Chapter 2). Then, a decision support tool is developed to evaluate and visualize the sustainability performance of the OAP defined by customers at the design stage (Chapter 3). The proposed framework is also validated by performing sensitivity analysis on the life cycle assessment modelling and sustainability index development process (Chapter 3). A case study of a robot is conducted in Chapter 4 to extract the results of sustainability assessment and sensitivity analysis in order to demonstrate the utility and usefulness of the proposed methodology.

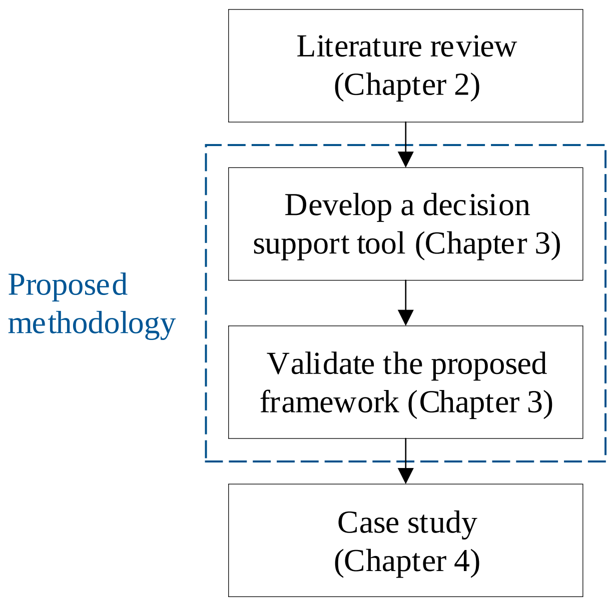


Figure 3.1 The research methodology.

3.2 Proposed methodology

This dissertation presents a methodology to evaluate, visualize, and validate the sustainability performance of the open-architecture product (OAP) developed by the participation of customers. The proposed methodology contains developing a decision support tool (first and second sub-objectives) and validating the robustness of this framework using sensitivity analysis (third sub-objective). Figure 3.2 depicts the framework of the proposed decision support tool which includes four main phases. In phase 1, different design scenarios (product variants) that can be defined by customers are generated. In phase 2, the sustainability performance of the product for each design scenario is measured by performing the environmental and economic sustainability analyses (i.e., ELCA and LCC). In phase 3, the sustainability index (SI) is developed for each product alternative by applying appropriate weighting and aggregation approaches. For this purpose, the equal weighting method and a multi-attribute decision-making (MADM) approach, namely GRA are utilized for weighting and aggregating the results from the two different sustainability assessments into the total sustainability value for each design alternative. Finally, in phase 4, a treemap approach is applied as a visualization tool to present and communicate the sustainability results of product alternatives with customers and other involved stakeholders to facilitate the decision-making process towards the selection of the best sustainable alternative. To validate the robustness of the proposed decision support tool, the sensitivity analysis is performed. The local and global sensitivity analyses are conducted in the second phase of the framework on the LCA modelling to check the robustness of the results to the input inventory data uncertainties. The one-at-a-time approach as well as a design of experiments (DOE)-based method are respectively used for local and global sensitivity analyses. Also, the sensitivity analysis is carried out in the third phase of the framework by employing different weighting and aggregation approaches in order to validate the final sustainability results obtained by the applied methods and monitor the robustness of results to changes in the chosen methods. To this end, the AHP method is utilized for the weighting process, and TOPSIS and SAW methods are applied for aggregation operation. These steps are explained in detail in the following Sections.

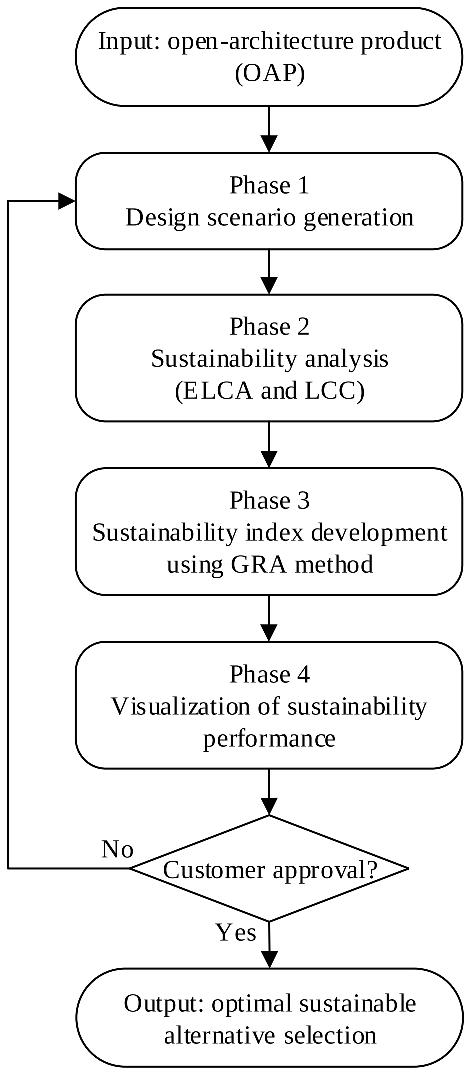


Figure 3.2 The flowchart of the proposed decision support tool.

3.3 Decision support tool

3.3.1 Phase 1: Design scenario generation

Considering the features of OAPs in which customers are involved in the design of personalized components based on their demands, different design scenarios can be created. The product has different sustainability performances for each design alternative defined by customers. Customers can participate in designing personalized products taking into account their needs and design constraints defined by the original equipment manufacturer (OEM). They are allowed to change the features of personalized components, such as geometry, material, etc. based on their preferences and design constraints. After defining personalized components, their functional and sustainability performances need to be evaluated and presented to consumers. Thus, customers are able to visualize the analysis results and select the optimal option satisfying their requirements.

3.3.2 Phase 2: Sustainability analysis

The life cycle sustainability assessment (LCSA) methodology aims to quantify and evaluate the sustainability performance of products over the entire life cycle taking environmental, economic, and social aspects into account [106]. In this study, we have focused on the environmental and economic aspects of the life cycle sustainability assessment methodology. The environmental and economic sustainability analyses are applied for assessing the sustainability performance of the personalized components of the product for different design scenarios defined by the customer. The values of environmental and economic sustainability indicators for personalized modules of the product for each design scenario are estimated by performing environmental life cycle assessment (ELCA) and life cycle costing (LCC) analyses.

3.3.2.1 Environmental life cycle assessment (ELCA)

The environmental life cycle assessment (ELCA) is a tool to address the environmental dimension of the LCSA and obtain the environmental sustainability indicators. The ELCA methodology is used for assessing the potential environmental impacts of products taking the full life cycle into consideration [107]. According to ISO 14040/14044, the ELCA modelling consists of four phases as follows [54]:

Step 1: *Goal and scope*

The goal and scope definition stage describes the purpose of the ELCA study, functional unit (the function of product or system to be assessed), system boundaries (the processes included in the analysis of a system), assumptions and limitations of the assessment.

Step 2: *Life cycle inventory*

The life cycle inventory (LCI) analysis is to identify and quantify the input and output flows for each process in the system scaled to the functional unit. Inventory flows include inputs of materials, energy, and other resources consumption and environmental releases to air, water, and land in relation to each life cycle stage.

Step 3: *Life cycle impact assessment*

The life cycle impact assessment (LCIA) phase is the evaluation of the potential environmental impacts associated with input and output flows of each life cycle stage identified and calculated during the LCI phase.

Step 4: *ELCA results*

The last phase is to interpret and analyze the LCA results and identify critical areas for environmental improvement in a process or system.

By performing ELCA analysis for the product components, the environmental impact of the *i*th component (EI_i) of the product along its life cycle, for each impact category is obtained using Equation (3.1):

$$EI_i = EI_i\,(\text{material}) + EI_i\,(\text{production}) + EI_i\,(\text{transportation}) + EI_i\,(\text{use}) + EI_i\,(\text{end-of-life}) \qquad (3.1)$$

3.3.2.2 Life cycle costing (LCC)

The life cycle costing (LCC) is a life cycle-based method to address the economic pillar of sustainability in the LCSA and obtain the economic sustainability indicators [108, 109]. The LCC analysis is a method to assess the overall costs supported by all actors throughout the whole life cycle of the product system [110]. For the economic sustainability indicator, the conventional LCC is conducted for the product to measure the costs directly incurred during the life cycle stages, namely material cost, production cost, transportation cost, use cost, and end-of-life cost [111]. The LCC for the *i*th component (LCC_i) of the product is calculated as the following equation [42]:

$$\text{LCC}_i = C_i\,(\text{material}) + C_i\,(\text{production}) + C_i\,(\text{transportation}) + C_i\,(\text{use}) + C_i\,(\text{end-of-life}) \qquad (3.2)$$

For the calculation of raw material cost for producing the *i*th component, the unit price of the material is multiplied by the material weight of the *i*th component. The production cost is related to the manufacturing cost (energy consumption), capital cost, labour cost, etc. for producing the *i*th component. The transportation cost is calculated by a product of the unit cost of transportation and the weight of the *i*th component. The cost of the use stage supported by the user for the *i*th component is calculated through the multiplication of the unit cost of consumed energy by the weight of the component during the usage phase. The end-of-life (EoL) treatment cost depends on the scenario that the *i*th component experiences in its EoL, which includes reuse, remanufacturing, recycling, incineration, and disposal in landfill. Thus, the EoL cost supported by the user and/or society for the *i*th component is obtained by multiplying the unit cost of the EoL treatment and the weight of the component.

It should be noted that the life cycle costs of a product are produced over a period of time and the monetary aspects have a time-variant nature and vary on a yearly basis; thus, the discount rate is used to convert the future value of costs into present values [106, 112]. In general, the net present value (NPV) of future economic flows is determined using Equation (3.3):

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} \tag{3.3}$$

where CF_t, t, and r are respectively the sum of all cash flows at time t, time of the cash flow, and discount rate. In this study, the life cycle cost of the *i*th component (LCC_i) is converted into NPV and obtained as follows:

$$\mathrm{LCC}_i = \sum_{t=1}^{n} \frac{C_{i_t}}{(1+r)^t} \tag{3.4}$$

where C_{i_t}, t, and r are respectively the sum of the costs of the *i*th component at year t, year of the cost flow, and discount rate.

3.3.3 Phase 3: Sustainability index development

The life cycle sustainability assessment (LCSA) consists of the integration of results from environmental life cycle assessment (ELCA), life cycle costing (LCC), and social life cycle assessment (SLCA) [113]. Klöpffer [114] formulated LCSA as the combination of the assessment of the different sustainability dimensions as follows:

$$\mathrm{LCSA} = \mathrm{ELCA} + \mathrm{LCC} + \mathrm{SLCA} \tag{3.5}$$

In this research, the sustainability analysis is performed by considering two pillars of sustainability, namely environmental and economic aspects (i.e., performing ELCA and LCC). Apart from measuring the sustainability performance of products, to efficiently interpret and communicate the sustainability assessment results and satisfy the expectations of various stakeholders involved in the decision-making process to make informed decisions, the sustainability indicators with different goals need to be integrated to construct the sustainability index (SI) [115, 116]. For this purpose, it is required to provide weights for the sustainability dimensions and their indicators and perform an aggregation process to integrate weighted indicators into a single sustainability value [116-118]. There are various approaches for the weighting and aggregation of sustainability indicators. The weighting methods can be classified into (i) equal weighting to assign the same weight to all the indicators, (ii) statistical-based weighting (e.g., regression analysis) to derive weights using statistical models, and (iii) participatory-based methods (e.g., AHP) to determine the weights of indicators based on various stakeholders' opinions and judgments [117, 119, 120]. The aggregation methods can be categorized into (i) additive aggregation methods (e.g., arithmetic mean) which utilize additive functions to sum up the normalized values of indicators to form a sustainability index, (ii) geometric aggregation methods (e.g., geometric mean) that employ multiplicative instead of additive functions, and (iii) non-compensatory aggregation methods (e.g., multi-criteria analysis) which contain the properties of aggregation functions and the perspective of multi-criteria decision making (MCDM) [117, 119, 120]. Selecting an appropriate weighting and aggregation approach is dependent on decision makers' needs and preferences, decision process objectives, and scope and purposes of sustainability assessment and development of SI [118, 121]. Kim and Moon [42] conducted the life cycle sustainability assessment for the product variants in the product family design and then applied the AHP method for weighting the three sustainability dimensions and their indicators and used a MADM approach, i.e. GRA to aggregate the values of sustainability indicators and compute a single sustainability value for the components of product variants. Tan et al. [122] combined the AHP with GRA as the decision-making methodology and tool for weighting and aggregating the evaluation criteria including environmental impacts, as well as the market value factors, i.e. benefits, opportunities, costs, and risks in order to rank design alternatives and select the best green product when design and developing a new product. Chan and Tong [123] applied the GRA method to rank and select the proper material for the production process of products with respect to the environmental, economic, and technical criteria.

3.3.3.1 Grey relational analysis (GRA) for calculation of sustainability value

In this study, environmental and economic sustainability analyses are conducted to evaluate the sustainability indicators for the different design alternatives. To compare and rank the sustainability performance of product alternatives based on the sustainability assessment results obtained by ELCA and LCC analyses, the sustainability scores need to be developed for each design alternative. The sustainability index (SI) is formulated by including the two sustainability dimensions (as criteria) and their indicators (as sub-criteria) for different product alternatives, and thus the sustainability assessment can be regarded as a multi-criteria decision problem. In order to solve the problem and construct the single total sustainability value for each design alternative, weighting and aggregation processes need to be applied. Therefore, (i) for the weighting process, the equal weighting method is utilized for assigning the relative importance to the two sustainability aspects (criteria) and the indicators within each dimension (sub-criteria), and (ii) for the aggregation process, the grey relational analysis (GRA) as a multi-attribute decision making (MADM) approach is employed for aggregating the performance data of alternatives on each criterion. As explained in Section 2.6, there are different MADM approaches (i.e., comparison-based methods, scoring-based methods, and outranking-based methods) which are subjectively selected by decision makers based on the structure and scope of the decision problem [85, 86]. Based on the features of MADM methods described in Table 2.4, the GRA method (as the scoring-based method) is chosen and employed for integrating the values of all sustainability indicators (i.e., environmental and economic indicators) with different goals and measurement units into a total sustainability value. Unlike the other MADM approaches such as AHP in which the computation process of sustainability index is through the experience-based judgments of alternatives' performances against different indicators [92], the GRA allows the global comparison among the alternatives based on the quantitative data measured by sustainability analysis of the alternatives in terms of different sustainability criteria. The GRA method contains data normalizing operation (with different normalization formulas), identifying weightings, and aggregation process [101] in order to aggregate the indicators' weighted normalized values and develop a single sustainability value for each product alternative. Calculation of the single sustainability index for each design alternative using the GRA, as a helpful decision supporting tool, assists customers and other decision makers in ranking and comparing the sustainability performance values of alternatives and identifying the design scenario with higher sustainability value.

The GRA is applied to aggregate values of all sustainability indicators with different dimensions and scope into a total single sustainability value that is dimensionless and ranges from 0 to 1. Grey relational analysis (GRA) is performed according to the following steps:

Step 1: *data normalization*

To convert the performance values of alternatives against the various criteria into a total performance score for each alternative, the first step in GRA is normalizing the collected raw data of performance values (sustainability indicators values) between 0 and 1 to avoid the effect of adopting different units and reduce the variability. In this step, which is also called grey relational generating, three types of quality characteristics can be used; the-larger-the-better, the-nominal-the-better, and the-smaller-the-better (Equations 3.6-3.8). Depending on the structure of attributes (whether the sustainability indicator is to be minimized or maximized), the performance value of the alternatives is normalized by using one of the following formulas:

$$x_{ij} = \frac{y_{ij} - \min y_{ij}}{\max y_{ij} - \min y_{ij}} \quad \text{i = 1, 2, …, m; j = 1, 2, …, n; the-larger-the-better.} \tag{3.6}$$

$$x_{ij} = 1 - \frac{\left|y_{ij} - y_{ij}^{*}\right|}{\max\left[\max y_{ij} - y_{ij}^{*}\ ,\ \ y_{ij}^{*} - \min y_{ij}\right]} \quad \text{i = 1, 2, …, m; j = 1, 2, …, n; the-nominal-the-better.} \tag{3.7}$$

$$x_{ij} = \frac{\max y_{ij} - y_{ij}}{\max y_{ij} - \min y_{ij}} \quad \text{i = 1, 2, …, m; j = 1, 2, …, n; the-smaller-the-better.} \tag{3.8}$$

where x_{ij} is normalized value for y_{ij} which is the performance value of the *i*th alternative (i.e., component) over the *j*th attribute (i.e., sustainability indicator), y_{ij}^{*} is the target optimum value, and $\max y_{ij}$ and $\min y_{ij}$ are the largest and smallest values of y_{ij} for the *j*th attribute, respectively. Basically, the higher value of normalized indicators data indicates better performance and the best one should be equal to 1.

Step 2: *calculation of grey relational coefficient (GRC)*

After normalizing the performance values of alternatives (i.e., sustainability indicators values), the grey relational coefficient (GRC) is calculated to measure the degree of absolute distance between comparability and reference values with the following formula:

$$\gamma\left(x_{0j}\ , x_{ij}\right) = \frac{\Delta_{min} + \zeta .\, \Delta_{max}}{\Delta_{ij} + \zeta .\, \Delta_{max}} \tag{3.9}$$

where,

$\Delta_{ij} = \left|x_{0j} - x_{ij}\right|$

$\Delta_{min} = min\left(\Delta_{ij}\right)$ i = 1, 2, …, m; j = 1, 2, …, n.

$\Delta_{max} = max\left(\Delta_{ij}\right)$ i = 1, 2, …, m; j = 1, 2, …, n.

$\zeta \in [0, 1]$

where $\gamma\left(x_{0j}, x_{ij}\right)$ is GRC, and ζ is the distinguishing coefficient varying in the range of [0, 1] which is generally taken as 0.5. Δ_{ij} is the absolute value of the difference between reference sequence, $x_{0j} = 1$, and comparability sequence, x_{ij}. Δ_{min} and Δ_{max} are the smallest and the largest values of the difference between x_{0j} and x_{ij}. The grey relational coefficient denotes the relationship between the ideal and the actual performance of alternatives.

Step 3: *calculation of grey relational grade (GRG)*

Grey relational grade (GRG) is calculated by averaging the grey relational coefficient values of each performance characteristic, and it is defined as

$$\gamma_i = \frac{1}{n}\sum_{j=1}^{n}\gamma\left(x_{0j}, x_{ij}\right) \tag{3.10}$$

where γ_i is GRG (sustainability value) of the *i*th alternative (component) and *n* is the number of attributes (indicators). The influence and importance of each criterion can be established by assigning the weight factor for each one. Weighted grey relational grade (WGRG) is computed as follows:

$$\gamma_{wi} = \sum_{j=1}^{n} w_j\,\gamma\left(x_{0j}, x_{ij}\right) \tag{3.11}$$

$$\sum_{j=1}^{n} w_j = 1$$

where γ_{wi} is WGRG and w_j is the weight value of the jth attribute sum of which is equal to 1. The equal weight can be used to determine the WGRG or depending on the relative importance of each criterion (indicator), different weights can be assigned to attributes. The larger value of GRG means that the corresponding alternative (component) has higher sustainability performance among other alternatives.

3.3.4 Phase 4: Visualization

Visualization is an important step in the sustainability assessment process to present the results of building the sustainability index (SI) which helps to clearly, quickly, and accurately communicate the results to decision-makers [116, 119]. There are various ways to visualize the results of SI, such as tables, charts, diagrams, etc. that can convey the information effectively to customers, decision-makers, and other important stakeholders [116, 119]. In this work, the result of sustainability values calculated by the GRA method for various design alternatives is mapped and visualized using the treemap technique. This approach aids customers to have a better understanding of the sustainability performance of products and easily make decisions towards the more sustainable choice. Using a treemap, we can provide branches of the tree (as rectangles) for modules of the product. Then, each branch or module is divided into its sub-branches (smaller rectangles within each module) namely components. In this study, both size and color of rectangles of treemap represent the sustainability value. The color and size (area) of each rectangle show the sustainability performance of modules and components of the product. The components and modules with the greater size and brighter color of rectangles show those that have higher sustainability value. Also, the color distribution of the treemap demonstrates the sustainability performance of the product. The product with higher sustainability performance has lighter color distribution in comparison with other product variants.

3.4 Sensitivity analysis

Sensitivity analysis (SA) investigates how the variation and uncertainty of input factors in a model affect the variability and performance of the model output [124]. A model is sensitive to a parameter if a small change in the parameter leads to a large change in the model result [125]. In this dissertation, SA is conducted for the life cycle assessment (LCA) modelling to assess the impact of uncertain input parameters on the results of LCA. Also, SA is performed on weighting and aggregation methods used in the development of sustainability index (SI) in order to study the robustness of the final results and their sensitivity to changes in chosen methods.

3.4.1 Sensitivity analysis of LCA analysis

During LCA analysis, uncertainty can result from a number of factors, such as quality and variability of inventory data, system boundaries, assumptions, functional units, choice of impact assessment methods, etc. so that the LCA results can be affected by uncertainties of input parameters [126, 127]. Hence, sensitivity analysis (SA) is carried out in the LCA to determine the effects of uncertainty and variation of input factors on the robustness of LCA output results [127, 128]. There are two major types of SA methods, namely local sensitivity analysis (LSA) and global sensitivity analysis (GSA) [124, 128]. The LSA procedure aims at assessing the impact of a certain predefined change in the input factor on the output value while keeping the other factors constant [124, 125, 128]. The LSA can be conducted through the one-at-a-time approach, a commonly used method, in which the output variability is obtained by a small change around a reference value of one of the input factors at a time, while all others are kept fixed. The other approach for LSA is using scenario analysis which involves calculating different scenarios to analyze the influence of discrete choices on possible changes to the output parameter value [124, 125]. Cellura et al. [127] employed the scenario analysis technique to study the robustness and sensitivity of LCA results to the uncertainty of input secondary inventory data as well as the uncertainty of the chosen impact assessment methods. The global sensitivity analysis (GSA) method aims to evaluate the variability and sensitivity of the output to the variation of the entire input space together with including joint effects and interactions among input factors on the output parameter [124, 125, 128]. Rivera and Sutherland [126] and Khang et al. [129] applied the design of experiments (DOE) approach and regression analysis for global sensitivity analysis and assessing the influence of input parameter (life cycle inventory data) uncertainties in the LCA.

In this study, the global sensitivity analysis (GSA) procedure is conducted in the LCA to analyze the influence of inventory data uncertainties on the estimated environmental impact when the input factors (inventory variables) vary over a significant range of uncertainty. For this purpose, a design of experiments (DOE) approach and regression analysis is applied to establish a predictive model for environmental impact assessment and identify factors that have a major contribution to the variation of the overall environmental impact of the product. Furthermore, local sensitivity analysis (LSA) is performed using the one-at-a-time approach to measure the sensitivity of the LCA results to the small changes in input parameters.

3.4.2 Sensitivity analysis of weighting process

In the development of the sustainability index (SI) in the sustainability analysis, uncertainty can occur due to several factors, such as the selection of appropriate indicators, normalization technique used to bring the indicators into the same unit, selection of weighting method to assign weights to indicators, and choice of aggregation technique to integrate various indicators into a single sustainability index [119]. The sensitivity analysis (SA) is conducted to compute the impact of parameter uncertainty on the robustness of the sustainability results through the use of different normalization, weighting, and aggregation schemes [114, 116, 119]. In this research, a MADM technique, i.e., the GRA method is employed to aggregate the sustainability indicators and construct a single sustainability value in which equal weighting is used to assign the same weight to all sustainability indicators and sub-indicators. Therefore, sensitivity analysis is applied to determine how the final sustainability scores and ranking of design alternatives change under different weighting and aggregation schemes.

The only subjective and uncertain input in the GRA method is the criteria weighting phase. Hence, sensitivity analysis (SA) is employed in the weighting process to validate the results of GRA and study the effect of the weighting of indicators (criteria) and sub-indicators (sub-criteria) on the final results. For this purpose, the participatory approach (e.g., AHP) is utilized to assign unequal weights to the three sustainability pillars and their indicators (impact categories). The most common MADM method for determining the weights of criteria is the AHP method, in which the preferences are obtained from the judgments of participants [106]. The calculation of the weights of criteria by using the AHP method consists of the following steps [91]:

Step 1: construct pairwise comparison matrices for criteria with respect to the overall goal as well as for sub-criteria within each criterion to compare all the elements in pairs in terms of which element dominates the other by using Saaty’s verbal ratio scale (1-9).

Step 2: calculate the relative weight of the criteria and sub-criteria through normalizing the pairwise comparison matrices (performed by dividing each element of the matrix by its column total) and then finding the average of the rows.

Step 3: consistency test to evaluate the consistency of pairwise comparison matrices and check whether the decision maker's judgments are consistent or not. The consistency is determined by calculating the consistency ratio as CR = CI/RI, where CI is the consistency index, and RI is the random consistency index defined according to the matrix size (*n*) [91]. The CI is computed using CI = (λ_{max}-*n*) / (*n*-1), where *n* is the size of the matrix and λ_{max} is the maximum eigenvalue. The comparisons are consistent if the value of CR does not exceed 0.1 (10%), otherwise; judgments should be reviewed and improved.

Thus, the results of sustainability scores and ranking of alternatives obtained by the GRA method are compared by using different weighting schemes, i.e. equal weighting approach and the AHP method.

3.4.3 Sensitivity analysis of aggregation process

In this work, the multi-criteria analysis (i.e., GRA) is applied to aggregate the various sustainability indicators into a total substantiality index (SI). The result of GRA is validated by performing a sensitivity analysis to determine how the final ranking of alternatives changes under using different MADM methods. The sensitivity analysis (SA) is conducted to investigate the influence of the aggregation method selected for integrating sustainability indicators on the final ranking of alternatives. Hence, to identify the impacts caused by changing aggregation methods, the GRA result is compared with those obtained via other scoring-based MADM methods, i.e. TOPSIS and SAW which can be used for aggregation of sustainability indicators into a single score.

3.4.3.1 TOPSIS method

The TOPSIS method is a distance-based method to rank the alternatives based on the scores obtained on performance data of alternatives against different criteria. This method contains normalizing, identifying weights for criteria, and calculating the geometric distance between each alternative and the ideal alternative in order to obtain a single performance score for each alternative. The TOPSIS method consists of the following steps:

Step 1: the normalized value (x_{ij}) of collected raw data (y_{ij}) is calculated as follows:

$$x_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} {y_{ij}}^2}} \quad i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{3.12}$$

where y_{ij} is performance value of the *i*th alternative (i.e., product component) over the *j*th attribute (i.e., sustainability indicator).

Step 2: the weighted normalized value (v_{ij}) of performance data of alternatives is calculated as:

$$v_{ij} = w_j \times x_{ij} \quad i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{3.13}$$

$$\sum_{j=1}^{n} w_j = 1$$

where w_j is the importance weight of the *j*th criterion. For the weighting of criteria, equal weights can be given to the criteria or weights can be determined by using other techniques such as the AHP method.

Step 3: for each criterion (indicator), the ideal alternative with the best performance (S^+) and the worst performance (S^-) is determined. The positive ideal solutions (S^+) and negative ideal solutions (S^-) are specified as follows:

$$S^+ = \{v_j^+ | j = 1, 2, \ldots, n\} = \left\{\left(\max_i v_{ij} \middle| j \in J^+\right), \left(\min_i v_{ij} \middle| j \in J^-\right)\right\} \tag{3.14}$$

$$S^- = \{v_j^- | j = 1, 2, \ldots, n\} = \left\{\left(\min_i v_{ij} \middle| j \in J^+\right), \left(\max_i v_{ij} \middle| j \in J^-\right)\right\} \tag{3.15}$$

where J^+ and $J^-$are associated with benefit and cost criteria, respectively.

Step 4: for all criteria, the Euclidean distance from the *i*th alternative to the best alternative (D_i^+) and worst alternative (D_i^-) are computed as:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \quad (3.16)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \quad (3.17)$$

Step 5: the relative closeness and similarity of the *i*th alternative to the positive ideal solution is obtained by:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}\ ;\ 0 \le C_i \le 1 \quad (3.18)$$

The alternatives are ranked based on the obtained performance scores (C_i). The best alternative has the biggest value of C_i with the intention to minimize the distance from the positive ideal solution and maximize the distance from the negative ideal solution.

3.4.3.2 SAW method

The SAW method is utilized for ranking the alternatives through the sum of the weighted performance value of each alternative on all attributes. This method contains normalizing, specifying weights for criteria, and aggregation operations to calculate the total score for alternatives. This method consists of the following steps:

Step 1: normalization of the performance data of alternatives (i.e., components) using the following equations:

$$x_{ij} = \frac{y_{ij}}{\max(y_{ij})} \quad \text{i = 1, 2, …, m; j = 1, 2, …, n; the-larger-the-better.} \quad (3.19)$$

$$x_{ij} = \frac{\min(y_{ij})}{y_{ij}} \quad \text{i = 1, 2, …, m; j = 1, 2, …, n; the-smaller-the-better.} \quad (3.20)$$

where x_{ij} is normalized value for y_{ij} which is the value of the *j*th attribute (indicator) for the *i*th alternative (component), and $\max y_{ij}$ and $\min y_{ij}$ are the largest and smallest values of y_{ij} for the *j*th criterion, respectively. When the attribute *j* is a positive criterion, Equation (3.19) is used for normalizing, while for a negative attribute *j*, Equation (3.20) is used for the normalization of data. In this study, since lower amounts of sustainability indicators are desirable, Equation (3.20) is employed to normalize the indicators data.

Step 2: aggregation of weighted normalized values as follows:

$$A_i = \sum_{j=1}^{n} w_j \times x_{ij} \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n. \tag{3.21}$$

$$\sum_{j=1}^{n} w_j = 1$$

where A_i is the aggregated score of the *i*th alternative and w_j is the weight of the *j*th criterion. The best alternative is the one with the highest aggregated score.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Overview

A case study has been conducted with the open-architecture robot DARwIn-OP (Figure 4.1) in order to demonstrate the utility and usefulness of the proposed methodology for the sustainability assessment of the open-architecture products (OAPs). That is, based on the proposed decision support tool in Section 3.3, the sustainability analysis is performed on the personalized modules of the robot for different design alternatives and the sustainability index results are visualized using the treemap visualization approach. Then, the obtained sustainability results are validated through the sensitivity analysis technique proposed in Section 3.4.

The humanoid robot DARwIn-OP (Dynamic Anthropomorphic Robot with Intelligence-Open Platform) is the latest humanoid robot with advanced features, such as advanced computational power, sophisticated sensors, high payload capacity, and dynamic motion ability to enable many exciting research, education, and outreach activities. DARwIn-OP is an open platform robot allowing users to modify both the hardware and software. The modular design of DARwIn-OP enables users to fabricate all the hardware with relatively inexpensive tools. The robot DARwIn-OP is an open-architecture product composed of common and personalized modules to meet various customer needs. The personalized modules of the robot which can be changed by customers during the design stage include the mechanical parts of the head, arms, and legs. The other components of the robot are considered common modules which are shared among all product variants and include the chest, pelvises, electronics, actuators, and fasteners.

Figure 4.1 Robot DARwIn-OP.

4.2 Phase 1: Design scenario generation for the case study

Customers can define personalized modules of the robot (i.e., the mechanical parts of the head, arms, and legs) during the design stage based on their needs. Thus, different scenarios can be generated by changing personalized modules for which product has different sustainability performances. The characteristics of the mechanical parts of personalized modules (for the first design scenario) are presented in Table 4.1.

Here, by considering the first design scenario as the base scenario, the other two design scenarios are proposed which can be defined by customers through changing the material and geometry of personalized components. The second design scenario is created by changing the material of personalized modules of the robot. It is assumed that customers are allowed to change the material of Aluminium (Al) components (frame components of personalized modules) into Steel material. The third design scenario is generated by changing both the material and geometry of the personalized modules. It is supposed that customers are able to change the material of Aluminium components to Steel and also reduce their thickness from 1.5 mm or 2 mm to 1 mm (Table 4.2).

Table 4.1 The features of the mechanical parts of the head, arms, and legs, as the personalized modules of robot DARwIn-OP (design scenario 1).

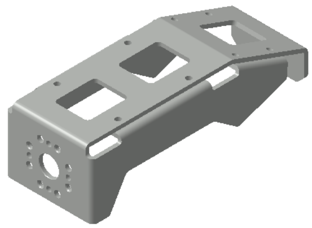
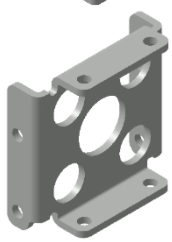
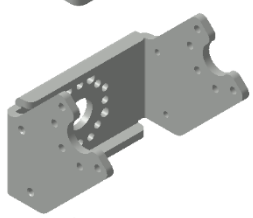
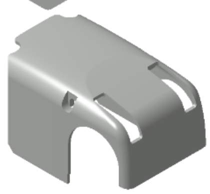
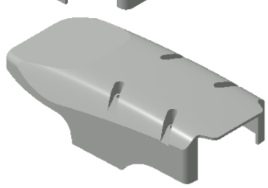
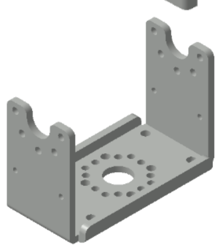
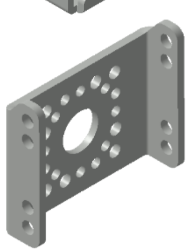
Part Name	Module	CAD Model	Quantity	Material	Weight (kg)	Manufacturing process
Hand	Arm		2	Aluminium	0.024	Machining
Arm Actuator Mount	Arm		2	Aluminium	0.005	Machining
Angled Actuator Bracket	Arm		4	Aluminium	0.013	Machining
Arm Cover Upper	Arm		2	ABS	0.006	Injection Molding
Arm Cover Lower	Arm		2	ABS	0.012	Injection Molding
U-Actuator Bracket	Leg		2	Aluminium	0.014	Machining
Leg Actuator Mount	Leg		2	Aluminium	0.004	Machining

Table 4.1 The features of the mechanical parts of the head, arms, and legs, as the personalized modules of robot DARwIn-OP (design scenario 1) (cont'd).

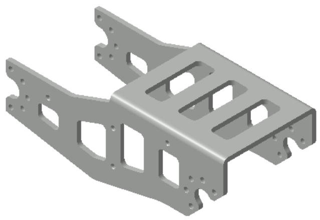
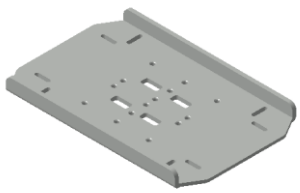
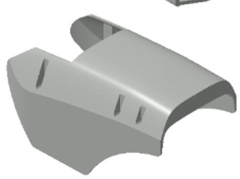
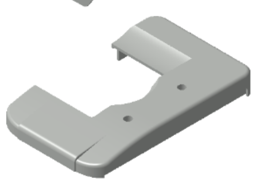
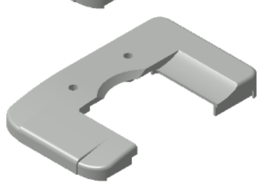
Part Name	Module	CAD Model	Quantity	Material	Weight (kg)	Manufacturing process
Actuator Connector	Leg		4	Aluminium	0.001	Machining
Knee Bracket	Leg		2	Aluminium	0.034	Machining
Foot	Leg		2	Aluminium	0.040	Machining
Leg Cover	Leg		2	ABS	0.022	Injection Molding
Left Foot Cover	Leg		1	ABS	0.010	Injection Molding
Right Foot Cover	Leg		1	ABS	0.010	Injection Molding
Head Bracket	Head		1	Aluminium	0.010	Machining

Table 4.1 The features of the mechanical parts of the head, arms, and legs, as the personalized modules of robot DARwIn-OP (design scenario 1) (cont'd).

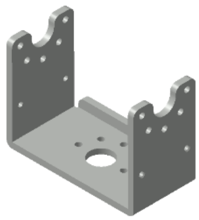
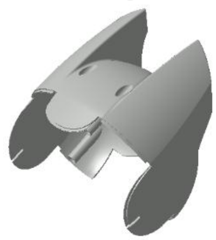
Part Name	Module	CAD Model	Quantity	Material	Weight (kg)	Manufacturing process
Neck Bracket	Head		1	Aluminium	0.012	Machining
Back Head Cover	Head		1	ABS	0.028	Injection Molding
Front Head Cover	Head		1	ABS	0.017	Injection Molding
Head LED Cover	Head		1	ABS	0.0005	Injection Molding
Left Eye Cover	Head		1	ABS	0.001	Injection Molding
Right Eye Cover	Head		1	ABS	0.001	Injection Molding
Left Pupil	Head		1	ABS	0.0003	Injection Molding
Right Pupil	Head		1	ABS	0.0003	Injection Molding

Table 4.2 Design scenario generation by changing the features of the personalized components of the robot.

Design scenario No.	Feature	
	Material	Geometry (thickness)
Scenario 1	Aluminium	1.5 mm or 2 mm
Scenario 2	Steel	1.5 mm or 2 mm
Scenario 3	Steel	1 mm

4.3 Phase 2: Sustainability analysis of robot DARwIn-OP

The sustainability performance of personalized components of open-architecture robot DARwIn-OP for the three design scenarios is evaluated in terms of environmental and economic sustainability aspects. The values of environmental and economic sustainability indicators for the personalized modules of the robot for each scenario are estimated by performing environmental life cycle assessment (ELCA) and life cycle costing (LCC) analyses.

4.3.1 Environmental sustainability and indicators

For environmental sustainability indicators, the environmental impacts of personalized components of the robot DARwIn-OP along the life cycle stages are measured for different design scenarios by performing the environmental life cycle assessment (ELCA) analysis. The ELCA modelling consists of four phases as follows:

Step 1: *Goal and scope*

The goal is to analyze the environmental impacts of personalized components of the robot DARwIn-OP for the three design scenarios (Table 4.2). After measuring the environmental indicators for personalized components of the robot for three design options, the related data are used as inputs for the third phase of the proposed decision support tool in order to compute the sustainability index of each scenario using the MADM method for the comparison of sustainability performances of different design scenarios. For environmental sustainability analysis, the mechanical parts of the personalized modules of the robot (Table 4.1) are considered for the analysis, and common modules of the robot are excluded from the environmental impact analysis because these components are common among different design scenarios and their impacts are not changed. The functional unit (FU) and system boundary are defined as follows:

- Function and functional unit (FU): the function of the robot DARwIn-OP is to perform research and education activities. The functional unit is defined as one year of use of one robot in a European country (i.e., France). It is assumed that the robot works 4 hours per day.
- System boundary: the cradle-to-grave analysis is conducted on personalized components of the robot throughout the life cycle stages. Figure 4.2 shows the flow diagram of the system boundary for the LCA analysis of personalized components of the robot for the three design scenarios. The system boundary takes into account the raw material extraction process, manufacturing process, transportation process, use process, and end-of-life (EoL) process. In each scenario, personalized components (i.e., mechanical parts of arms, legs, and head) are composed of metal material and polymer material. This boundary includes the production of Aluminium (the first scenario), Steel (the second and third scenarios), and ABS (all scenarios) materials, manufacturing of personalized components by the same manufacturer through machining (Aluminium and Steel) and injection molding (Acrylonitrile-Butadiene-Styrene (ABS)) processes, transportation of the product to users by ocean freight, consumption, and disposal to landfill (metal components) as well as disposal to incineration (plastic components) operations. It should be noted that this system boundary is associated with only personalized components of the robot and related processes for the three design scenarios. The common modules of the robot containing mechanical parts of chest and pelvises modules, electronic components (i.e., battery, camera, fan, antenna, speaker, power switch, wires, etc.), actuators, and fasteners as well as their related processes are excluded from the LCA analysis of the three scenarios. Since these common components are shared among all design scenarios and their impacts are not changed for three scenarios, they are not considered for the LCA analysis for

comparison purposes. Regarding the battery, it is assumed that the lifetime of the battery is the same in the three scenarios and can be excluded from the LCA analysis.

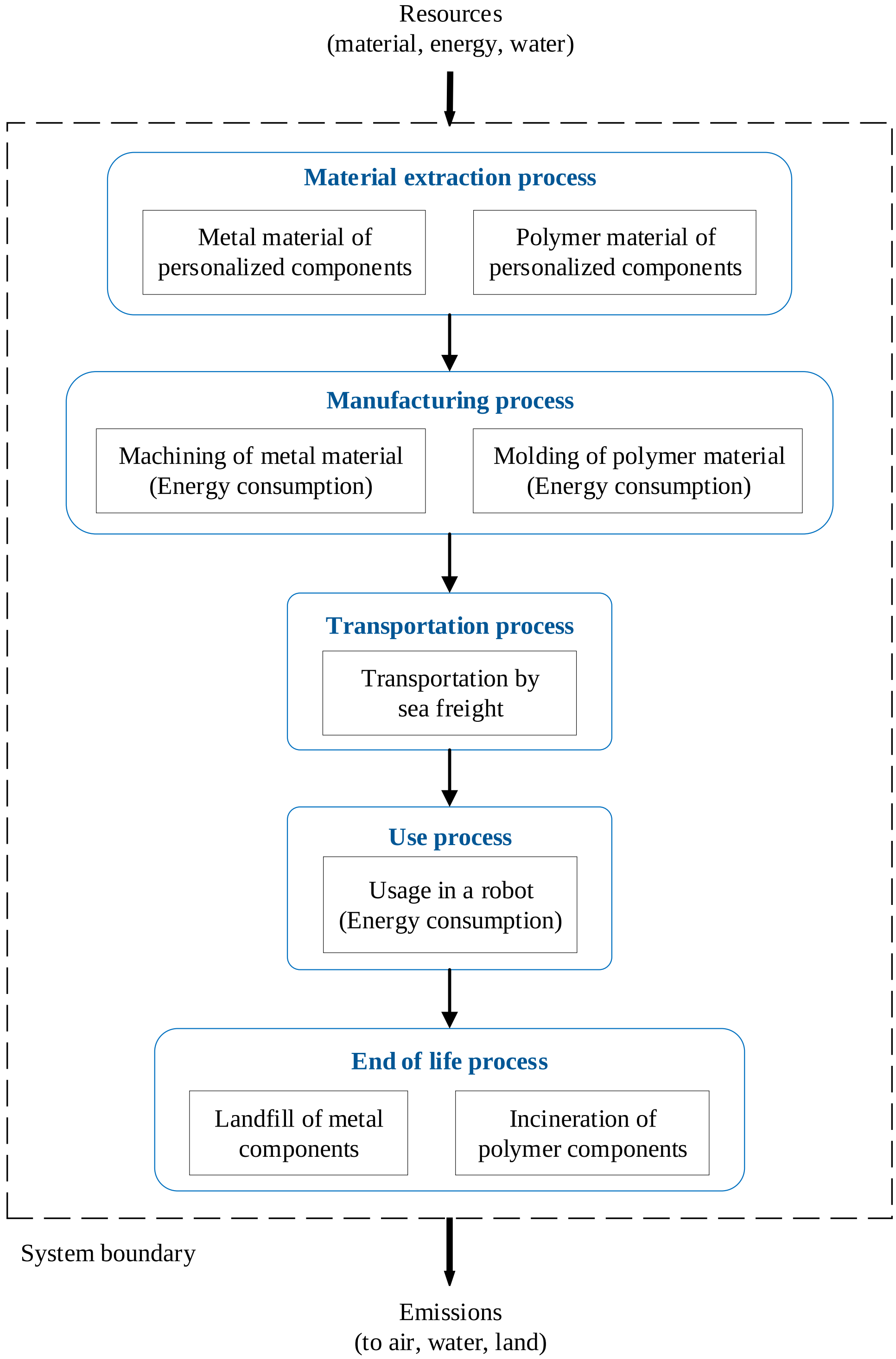


Figure 4.2 Flow diagram of system boundary for personalized components of the robot in the three design scenarios.

Table 4.3 The required parameters for the ELCA of personalized components of the robot in the three design scenarios.

Material	Manufacturing	Transportation	Use	End of life
Aluminium (1^{st} scenario)	Machining, 0.42 kWh/kg	Sea freight, 1.60E+04 km	Electricity consumption, 11.18 kWh/kg	Disposal to landfill
Steel (2^{nd} and 3^{rd} scenarios)	Machining, 0.63 kWh/kg	Sea freight, 1.60E+04 km	Electricity consumption, 11.18 kWh/kg	Disposal to landfill
ABS (all scenarios)	Injection molding, 1.86 kWh/kg	Sea freight, 1.60E+04 km	Electricity consumption, 11.18 kWh/kg	Disposal to incineration

Step 2: *Life cycle inventory*

The required parameters for the ELCA of personalized components of the robot in the three design scenarios are shown in Table 4.3. In this study, it is assumed that all materials are produced in Asia (i.e., China) and all personalized components are made by the same manufacturer in China and then transported to Europe (i.e., France) to be utilized and disposed. In the raw material production process, the environmental impact of the material used for producing each personalized component is calculated through multiplying raw material weight (kg) by the related impact factor value. The impact factors per unit of inventory flows extracted from the ecoinvent 3.3 database are described in Appendix A. The material weight retrieved from the CAD model is provided in Appendix B. In the manufacturing process, the environmental impact is computed through the multiplication of material weight (kg), manufacturing electricity consumption (kWh/kg), and impact factor value. In this study, the electricity consumption for machining Aluminium and Steel parts is considered approximately 0.42 (kWh/kg) and 0.63 (kWh/kg), respectively [130, 131]. Also, the energy consumption of the polymer material injection molding manufacturing process is estimated as 1.86 (kWh/kg) [130, 132]. It is supposed that the required electricity for the manufacturing stage is generated using non-renewable energy resources (i.e., coal) in China. The transportation of components from China to France is carried out by ship and the distance between countries for ocean transportation is estimated to be 1.60E+04 (km) [133]. The environmental impact of the transportation phase for the selected mode (sea freight) is calculated by multiplication of the transported component weight (ton), transportation distance (km), and related impact factor value. The weight of each component retrieved from the CAD model is given in Appendix B. In the use phase, the environmental impact of usage of each component is obtained through multiplying the component weight (kg), electrical energy consumption (kWh/kg), and impact factor value. The battery used for the operation of the robot is a Li-Po battery (11.1 V and 1000 mAh) which can provide the required energy for 30 minutes. The whole weight of the robot (base scenario) is 2.9 (kg). It is assumed that the useful life of the product is 1 year operating four hours per day. Thus, the required electricity in the use phase is estimated 11.18 (kWh/kg). It is supposed that the required electricity for the use stage is generated using non-renewable energy resources (i.e., nuclear) in France. Finally, at the EoL stage of the product, it is assumed that Aluminum and Steel components are directly sent to landfill. Also, the EoL treatment of plastic parts is selected as incineration. The environmental impact of the EoL for each component is obtained through multiplying the component weight (kg) by its related impact factor value. Main flows scaled to the functional unit for each of the three design scenarios are provided in Appendix D.

Step 3: *Life cycle impact assessment*

To measure the potential environmental impacts of the product components, the Impact 2002+ (endpoint) impact assessment method is applied in the life cycle impact assessment (LCIA). This method computes life cycle impacts in 14 midpoint categories and 4 damage categories namely, climate change (kg CO_2 eq), ecosystem quality (PDF-m^2-year), human health (DALY), and resources (MJ) [134]. The ELCA calculations are performed using MS Excel.

Step 4: *ELCA results*

For the three design scenarios, the environmental indicators and their corresponding values for personalized components of the robot are presented in Tables 4.4-4.6. It is observed that for all impact categories, the third design scenario has obtained the lowest values in comparison with other alternatives. The data of Tables 4.4-4.6 are used (as inputs) for the MADM analysis (the third step of the proposed decision support tool) to compare and visualize the sustainability performance of the three design scenarios for selecting the optimal option.

Here, we also provide a contribution analysis using stacked diagrams to compare the three design scenarios for different environmental indicators per life cycle stage (Figure 4.3). In the first design scenario, the material stage contributes to the highest value for all environmental indicators. In the second and third design options, for all indicators except for the resource category, the material stage contributes to the highest value. For the resource impact category, the use stage has the highest value. Moreover, the manufacturing stage has a higher impact in the second and third scenarios (Steel material) than in the first scenario (Aluminium material). It should be noted that the result of Figure 4.3 is not useful for ordinary customers in the decision-making process. Thus, the data in Tables 4.4-4.6 are used in the next step of the proposed methodology to facilitate decision making for customers through the MADM approach.

Table 4.4 The environmental and economic sustainability indicators and their corresponding values for the personalized components of the robot (design scenario 1).

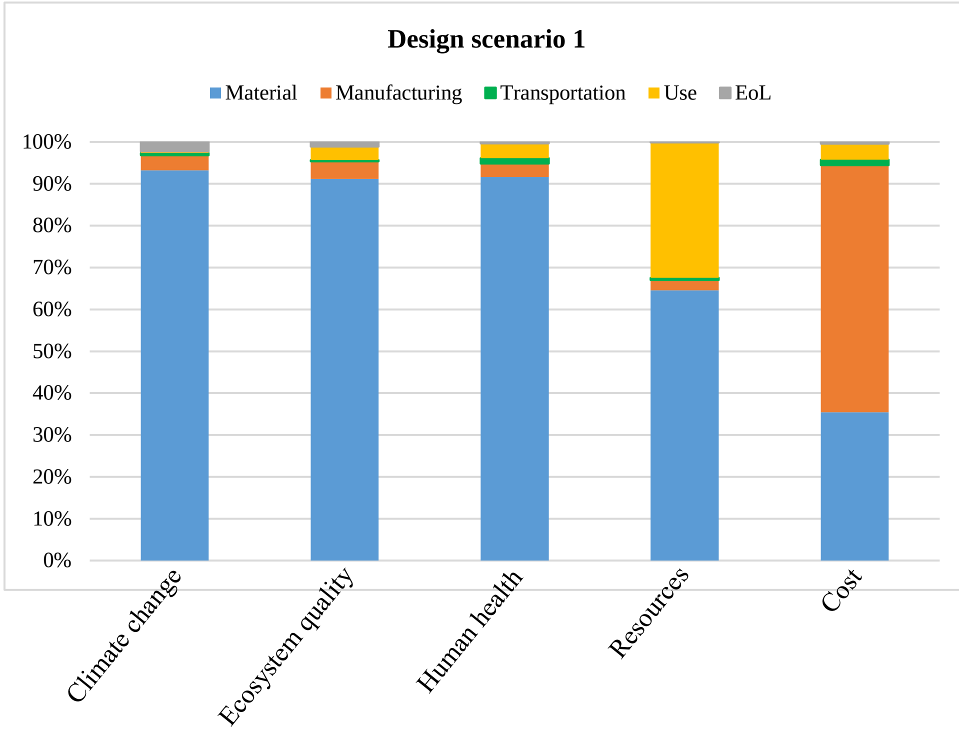
Component name	Environmental indicator				Economic indicator
	Climate change	Ecosystem quality	Human health	Resources	Cost
Hand	4.81E-04	2.19E-04	6.84E-04	3.44E-04	3.40E+00
Arm Actuator Mount	3.72E-05	1.74E-05	5.44E-05	3.38E-05	5.28E-01
Angled Actuator Bracket	2.18E-04	1.01E-04	3.16E-04	1.89E-04	2.58E+00
Arm Cover Upper	1.05E-05	2.18E-06	9.30E-06	2.25E-05	4.01E-01
Arm Cover Lower	2.03E-05	4.19E-06	1.79E-05	4.33E-05	4.71E-01
U-Actuator Bracket	8.80E-05	4.13E-05	1.29E-04	8.38E-05	1.46E+00
Leg Actuator Mount	2.40E-05	1.13E-05	3.52E-05	2.29E-05	6.35E-01
Actuator Connector	4.39E-05	2.01E-05	6.28E-05	3.30E-05	8.00E-01
Knee Bracket	3.18E-04	1.47E-04	4.59E-04	2.64E-04	2.50E+00
Foot	2.01E-04	9.50E-05	2.98E-04	2.06E-04	1.60E+00
Leg Cover	3.82E-05	7.90E-06	3.37E-05	8.16E-05	5.66E-01
Foot Cover	1.81E-05	3.75E-06	1.60E-05	3.87E-05	4.05E-01
Head Bracket	3.92E-05	1.82E-05	5.70E-05	3.44E-05	4.53E-01
Neck Bracket	3.50E-05	1.65E-05	5.16E-05	3.43E-05	5.68E-01
Back Head Cover	2.43E-05	5.01E-06	2.14E-05	5.18E-05	3.01E-01
Front Head Cover	1.48E-05	3.07E-06	1.31E-05	3.17E-05	2.15E-01
Head LED Cover	4.64E-07	9.59E-08	4.10E-07	9.91E-07	7.52E-02
Eye Cover	1.89E-06	3.92E-07	1.67E-06	4.05E-06	1.37E-01
Pupil	5.91E-07	1.22E-07	5.22E-07	1.26E-06	1.12E-01
Total	1.61E-03	7.13E-04	2.26E-03	1.52E-03	1.72E+01

Table 4.5 The environmental and economic sustainability indicators and their corresponding values for the personalized components of the robot (design scenario 2).

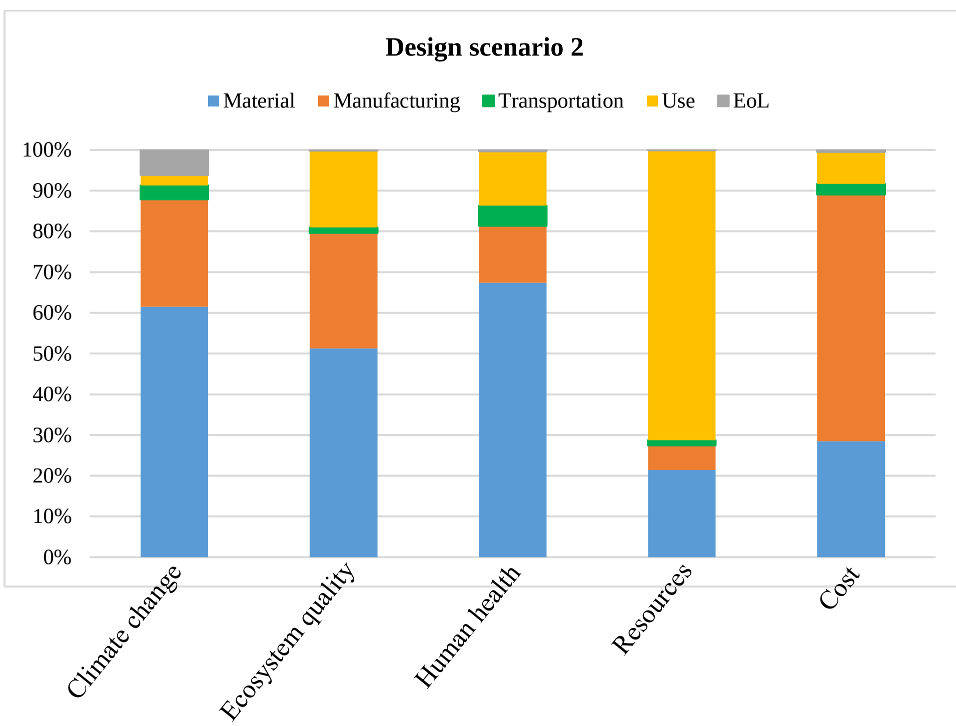
Component name	Environmental indicator				Economic indicator
	Climate change	Ecosystem quality	Human health	Resources	Cost
Hand	1.41E-04	7.40E-05	3.72E-04	2.53E-04	5.23E+00
Arm Actuator Mount	1.16E-05	6.81E-06	3.36E-05	4.08E-05	4.79E-01
Angled Actuator Bracket	6.66E-05	3.82E-05	1.89E-04	2.11E-04	2.87E+00
Arm Cover Upper	1.05E-05	2.18E-06	9.30E-06	2.25E-05	4.01E-01
Arm Cover Lower	2.03E-05	4.19E-06	1.79E-05	4.33E-05	4.71E-01
U-Actuator Bracket	2.75E-05	1.65E-05	8.13E-05	1.08E-04	1.28E+00
Leg Actuator Mount	7.50E-06	4.50E-06	2.21E-05	2.94E-05	5.44E-01
Actuator Connector	1.30E-05	6.97E-06	3.49E-05	2.75E-05	5.12E-01
Knee Bracket	9.60E-05	5.40E-05	2.68E-04	2.74E-04	3.23E+00
Foot	6.40E-05	3.97E-05	1.94E-04	2.89E-04	1.71E+00
Leg Cover	3.82E-05	7.90E-06	3.37E-05	8.16E-05	5.66E-01
Foot Cover	1.81E-05	3.75E-06	1.60E-05	3.87E-05	4.05E-01
Head Bracket	1.20E-05	6.94E-06	3.44E-05	3.94E-05	3.73E-01
Neck Bracket	1.10E-05	6.71E-06	3.29E-05	4.58E-05	4.07E-01
Back Head Cover	2.43E-05	5.01E-06	2.14E-05	5.18E-05	3.01E-01
Front Head Cover	1.48E-05	3.07E-06	1.31E-05	3.17E-05	2.15E-01
Head LED Cover	4.64E-07	9.59E-08	4.10E-07	9.91E-07	7.52E-02
Eye Cover	1.89E-06	3.92E-07	1.67E-06	4.05E-06	1.37E-01
Pupil	5.91E-07	1.22E-07	5.22E-07	1.26E-06	1.12E-01
Total	5.79E-04	2.81E-04	1.38E-03	1.59E-03	1.93E+01

Table 4.6 The environmental and economic sustainability indicators and their corresponding values for the personalized components of the robot (design scenario 3).

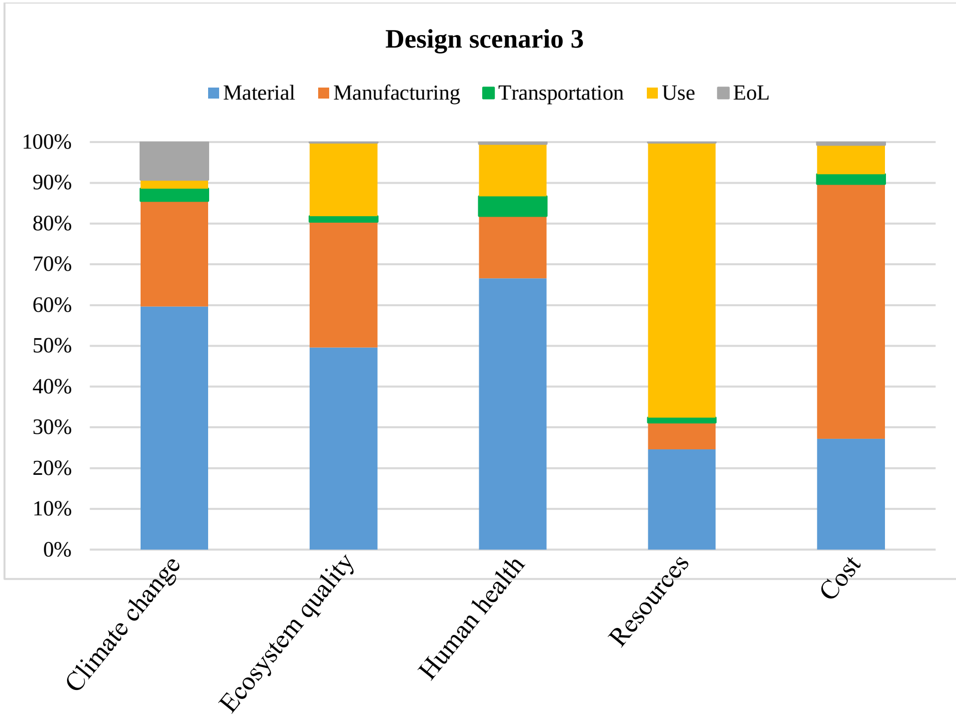
Component name	Environmental indicator				Economic indicator
	Climate change	Ecosystem quality	Human health	Resources	Cost
Hand	9.38E-05	4.91E-05	2.47E-04	1.64E-04	3.52E+00
Arm Actuator Mount	7.73E-06	4.51E-06	2.23E-05	2.66E-05	3.06E-01
Angled Actuator Bracket	3.30E-05	1.87E-05	9.27E-05	9.68E-05	1.34E+00
Arm Cover Upper	1.05E-05	2.18E-06	9.30E-06	2.25E-05	4.01E-01
Arm Cover Lower	2.03E-05	4.19E-06	1.79E-05	4.33E-05	4.71E-01
U-Actuator Bracket	1.36E-05	8.04E-06	3.96E-05	4.93E-05	5.96E-01
Leg Actuator Mount	4.88E-06	2.80E-06	1.39E-05	1.56E-05	3.50E-01
Actuator Connector	1.01E-05	5.26E-06	2.65E-05	1.65E-05	3.91E-01
Knee Bracket	4.79E-05	2.68E-05	1.33E-04	1.33E-04	1.62E+00
Foot	3.20E-05	1.99E-05	9.72E-05	1.44E-04	8.74E-01
Leg Cover	3.82E-05	7.90E-06	3.37E-05	8.16E-05	5.66E-01
Foot Cover	1.81E-05	3.75E-06	1.60E-05	3.87E-05	4.05E-01
Head Bracket	7.98E-06	4.57E-06	2.27E-05	2.52E-05	2.44E-01
Neck Bracket	5.47E-06	3.28E-06	1.61E-05	2.14E-05	2.15E-01
Back Head Cover	2.43E-05	5.01E-06	2.14E-05	5.18E-05	3.01E-01
Front Head Cover	1.48E-05	3.07E-06	1.31E-05	3.17E-05	2.15E-01
Head LED Cover	4.64E-07	9.59E-08	4.10E-07	9.91E-07	7.52E-02
Eye Cover	1.89E-06	3.92E-07	1.67E-06	4.05E-06	1.37E-01
Pupil	5.91E-07	1.22E-07	5.22E-07	1.26E-06	1.12E-01
Total	3.86E-04	1.70E-04	8.25E-04	9.69E-04	1.21E+01


Design scenario 1
Material
Manufacturing
Transportation
Use
EoL
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Climate change
Ecosystem quality
Human health
Resources
Cost

(a)


Design scenario 2
Material
Manufacturing
Transportation
Use
EoL
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Climate change
Ecosystem quality
Human health
Resources
Cost

(b)



(c)

Figure 4.3 Comparison of the three design scenarios for different environmental and economic indicators per life cycle stage.

4.3.2 Economic sustainability and indicators

In this study, the goal of the life cycle costing (LCC) analysis is to obtain the economic sustainability indicator for personalized components of the robot in the three design scenarios in order to integrate the cost indicator into the environmental indicators (4 impact categories) for comparing the sustainability of three design options. The life cycle costs of common modules of the robot (i.e., chest, pelvises, electronics, actuators, and fasteners) are excluded from the analysis because these components are shared among all product variants and their costs are considered fixed for comparing the sustainability of different scenarios.

Here, the economic indicator for each personalized component of the robot is calculated using Equation (3.2) which is the total cost of the material, manufacturing (energy consumption), transportation, use (energy consumption), and EoL stages. Due to the fact that the objective is to compare the sustainability of the three design scenarios, the other costs of production including capital cost, human resource cost, service cost, etc. are excluded from the LCC calculation of each personalized component of the robot since we assume that these costs are the same in the three design scenarios. Thus, in order to compute the total life cycle cost of the personalized components of the robot, the material, manufacturing (energy cost), transportation, use (energy cost), and EoL costs are obtained. For the material cost, the unit price for Aluminium, Steel, and ABS materials is considered 10.10 (USD /kg), 3.11 (USD/kg), and 2.54 (USD/kg), respectively. The manufacturing cost of components (machining of Aluminium and Steel parts and injection molding of polymer parts) is estimated using the SolidWorks Costing tool [135] which is depicted in Appendix C. The SolidWorks Costing is a CAD integrated analysis tool that calculates the cost of material and manufacturing process of parts by retrieving data directly from the CAD model. For the transportation cost, the unit cost of sea transportation is assumed to be 0.5 (USD/kg) to carry the product from the manufacturer (China) to the users (France). In this study, the required energy in the use phase (one year of use of the robot) is estimated 11.18 (kWh/kg) and the price of electrical energy is selected as 0.15 (USD/kWh). Thus, the unit cost of consumed electrical energy in the use process is computed 1.68 (USD/kg). In order to estimate the EoL cost, it is supposed that the unit cost of incineration of plastic parts and landfilling of metal components (Aluminium and Steel) supported by the municipality are 0.59 (USD/kg) and 0.045 (USD/kg), respectively.

As mentioned earlier, for the calculation of LCC, the discount rate is used to convert the future value of costs into present values. Here, it is assumed that the whole life cycle of the product from material production through the EoL stage is about 3 years. The cost flows of the first year (t = 1) are related to the material, manufacturing, and transportation costs. The cost flow of the second year (t = 2) is associated with the use phase cost, and the cost flow of the third year (t = 3) is associated with the EoL cost. Thus, by selecting the discount rate (r = 10%), the net present value of LCC for the ith personalized component of the robot is calculated using Equation (3.4) as follows:

$$\mathrm{LCC}_i = \frac{C_i(\text{material, manufacturing, transportation})}{(1+r)^1} + \frac{C_i(\text{use})}{(1+r)^2} + \frac{C_i(\text{EoL})}{(1+r)^3} \qquad (4.1)$$

For the three design scenarios, the economic sustainability indicator (i.e., total cost) and the corresponding value for personalized components of the robot are shown in Tables 4.4-4.6. It is observed that among the three scenarios, design scenario 3 has obtained the lowest total life cycle cost, followed by design scenarios 1 and then design scenario 2. The data in Tables 4.4-4.6 is used for the MADM analysis (the third phase of the proposed decision support tool) to compute the sustainability index for each scenario for comparing the sustainability of design options. In addition, here the comparison of the total cost of the three design scenarios per life cycle stage is shown in Figure 4.3. It is found that in all scenarios, the manufacturing stage contributes to the highest cost.

A sensitivity analysis is conducted to investigate the impact of the choice of discount rate on the LCC results. We make small changes of ± 5% around the selected value of the discount rate (r = 10%) and calculate the variation of the LCC in each scenario. Based on the result in Table 4.7, the total life cycle cost is not sensitive to small changes in the discount rate value.

Table 4.7 The variation of the LCC under the changes in the discount rate.

Design scenario No.	LCC (-5%)	LCC	LCC (+5%)	Variation (%)
Scenario 1	17.282	17.200	17.118	±0.47
Scenario 2	19.414	19.318	19.223	±0.49
Scenario 3	12.202	12.141	12.082	±0.49

4.4 Phase 3: Grey relational analysis (GRA) for calculation of sustainability value

The GRA method is applied to rank and compare design alternatives based on the total sustainability value calculated for each product variant. Considering the personalized components of the robot for the three design scenarios (as alternatives) and their performance values over different sustainability indicators (as criteria) (Tables 4.4-4.6), three steps of the GRA approach are performed to aggregate the values of various indicators into a single sustainability value for each component of the product. Since lower amounts of sustainability indicators are desirable, Equation (3.8) (the-smaller-the-better quality characteristic) is employed to normalize the collected raw data of sustainability indicators calculated from environmental and economic sustainability analyses. After data normalization, the values of GRCs are calculated using Equation (3.9), as shown in Table 4.8. Then, by assigning equal weight to all sustainability dimensions and their indicators, the environmental and economic sustainability indicators are converted to a single sustainability value, i.e., GRG, for each personalized component. The calculated sustainability values (GRGs) of personalized components for each design scenario obtained using GRA are given in Table 4.9. The sustainability values can be used to determine which component is more sustainable, and the component with higher sustainability value has better performance. According to the results, for each design scenario, Head LED Cover has the highest sustainability value, while the Hand has the lowest sustainability value.

Table 4.8 The calculated values of GRCs from the grey relational analysis.

Design scenario No.	Component name	Indicator	Environmental				Economic
			Climate change	Ecosystem quality	Human health	Resources	Cost
		Weight	0.50				0.50
		Sub-weight	0.25	0.25	0.25	0.25	1.00
		Final weight	0.125	0.125	0.125	0.125	0.50
1	Hand		0.33	0.33	0.33	0.33	0.44
	Arm Actuator Mount		0.87	0.86	0.86	0.84	0.85
	Angled Actuator Bracket		0.52	0.52	0.52	0.48	0.51
	Arm Cover Upper		0.96	0.98	0.97	0.89	0.89
	Arm Cover Lower		0.92	0.96	0.95	0.80	0.87
	U-Actuator Bracket		0.73	0.73	0.73	0.67	0.65
	Leg Actuator Mount		0.91	0.91	0.91	0.89	0.82
	Actuator Connector		0.85	0.85	0.85	0.84	0.78
	Knee Bracket		0.43	0.43	0.43	0.40	0.51
	Foot		0.55	0.54	0.54	0.46	0.63
	Leg Cover		0.86	0.93	0.91	0.68	0.84
	Foot Cover		0.93	0.97	0.96	0.82	0.89
	Head Bracket		0.86	0.86	0.86	0.84	0.87
	Neck Bracket		0.87	0.87	0.87	0.84	0.84
	Back Head Cover		0.91	0.96	0.94	0.77	0.92
	Front Head Cover		0.94	0.97	0.96	0.85	0.95
	Head LED Cover		1.00	1.00	1.00	1.00	1.00
	Eye Cover		0.99	0.99	0.99	0.98	0.98
	Pupil		0.99	0.99	0.99	0.99	0.99
2	Hand		0.63	0.60	0.48	0.41	0.33
	Arm Actuator Mount		0.96	0.94	0.91	0.81	0.86
	Angled Actuator Bracket		0.78	0.74	0.64	0.45	0.48
	Arm Cover Upper		0.96	0.98	0.97	0.89	0.89
	Arm Cover Lower		0.92	0.96	0.95	0.80	0.87
	U-Actuator Bracket		0.90	0.87	0.81	0.62	0.68
	Leg Actuator Mount		0.97	0.96	0.94	0.86	0.85
	Actuator Connector		0.95	0.94	0.91	0.87	0.86
	Knee Bracket		0.72	0.67	0.56	0.39	0.45
	Foot		0.79	0.73	0.64	0.37	0.61

Table 4.8 The calculated values of GRCs from the grey relational analysis (cont'd).

Design scenario No.	Component name	Indicator	Environmental				Economic
			Climate change	Ecosystem quality	Human health	Resources	Cost
		Weight	0.50				0.50
		Sub-weight	0.25	0.25	0.25	0.25	1.00
		Final weight	0.125	0.125	0.125	0.125	0.50
	Leg Cover		0.86	0.93	0.91	0.68	0.84
	Foot Cover		0.93	0.97	0.96	0.82	0.89
	Head Bracket		0.95	0.94	0.91	0.82	0.90
	Neck Bracket		0.96	0.94	0.91	0.79	0.89
	Back Head Cover		0.91	0.96	0.94	0.77	0.92
	Front Head Cover		0.94	0.97	0.96	0.85	0.95
	Head LED Cover		1.00	1.00	1.00	1.00	1.00
	Eye Cover		0.99	0.99	0.99	0.98	0.98
	Pupil		0.99	0.99	0.99	0.99	0.99
3	Hand		0.72	0.69	0.58	0.51	0.43
	Arm Actuator Mount		0.97	0.96	0.94	0.87	0.92
	Angled Actuator Bracket		0.88	0.85	0.79	0.64	0.67
	Arm Cover Upper		0.96	0.98	0.97	0.89	0.89
	Arm Cover Lower		0.92	0.96	0.95	0.80	0.87
	U-Actuator Bracket		0.95	0.93	0.90	0.78	0.83
	Leg Actuator Mount		0.98	0.98	0.96	0.92	0.90
	Actuator Connector		0.96	0.95	0.93	0.92	0.89
	Knee Bracket		0.83	0.80	0.72	0.57	0.63
	Foot		0.88	0.85	0.78	0.54	0.76
	Leg Cover		0.86	0.93	0.91	0.68	0.84
	Foot Cover		0.93	0.97	0.96	0.82	0.89
	Head Bracket		0.97	0.96	0.94	0.88	0.94
	Neck Bracket		0.98	0.97	0.96	0.89	0.95
	Back Head Cover		0.91	0.96	0.94	0.77	0.92
	Front Head Cover		0.94	0.97	0.96	0.85	0.95
	Head LED Cover		1.00	1.00	1.00	1.00	1.00
	Eye Cover		0.99	0.99	0.99	0.98	0.98
	Pupil		0.99	0.99	0.99	0.99	0.99

Table 4.9 The sustainability values (GRGs) of the personalized components for the three design scenarios from the GRA method.

Module name	Component No.	Component name	Sustainability value		
			Design scenario 1	Design scenario 2	Design scenario 3
Arm (M1)	1	Hand	0.385	0.431	0.527
	2	Arm Actuator Mount	0.855	0.885	0.927
	3	Angled Actuator Bracket	0.509	0.567	0.731
	4	Arm Cover Upper	0.919	0.919	0.919
	5	Arm Cover Lower	0.889	0.889	0.889
Leg (M2)	6	U-Actuator Bracket	0.683	0.740	0.861
	7	Leg Actuator Mount	0.862	0.889	0.932
	8	Actuator Connector	0.813	0.886	0.916
	9	Knee Bracket	0.468	0.516	0.678
	10	Foot	0.573	0.623	0.764
	11	Leg Cover	0.844	0.844	0.844
	12	Foot Cover	0.903	0.903	0.903
Head (M3)	13	Head Bracket	0.863	0.901	0.938
	14	Neck Bracket	0.851	0.894	0.950
	15	Back Head Cover	0.907	0.907	0.907
	16	Front Head Cover	0.940	0.940	0.940
	17	Head LED Cover	1.000	1.000	1.000
	18	Eye Cover	0.985	0.985	0.985
	19	Pupil	0.993	0.993	0.993
			S_p = 0.802	S_p = 0.827	S_p = 0.874
		Rank	3	2	1

In order to compare the sustainability performance value of the three design scenarios defined by customers, the sustainability value of the product for each scenario is calculated and presented to customers. The total sustainability value of each alternative (S_p) is computed as the mean of the sustainability values (GRG values) of the personalized components of the product for each scenario. The total sustainability value is a quantitative index that can be used to determine the degree of sustainability for design alternatives. Table 4.9 shows the sustainability values of the product for the three design scenarios. The sustainability scores of the product are obtained for the design scenario 1 (S_p = 0.802), design scenario 2 (S_p = 0.827), and design scenario 3 (S_p = 0.874). By comparing the three design alternatives, it can be seen that design scenario 3 has higher sustainability value and is more sustainable, while the product in design scenario 1 has lower sustainability performance. Therefore, by presenting these values to customers, they will be able to compare the scenarios and choose the optimal design.

In this study, it is assumed that customers are not allowed to be involved in the weighting process for the aggregation of sustainability indicators into a sustainability index for each design scenario. Here, by assigning equal weighting to indicators, the third scenario is selected as a more sustainable alternative. However, assigning unequal weighting values may lead to a different ranking of alternatives.

4.5 Phase 4: Visualization of sustainability results

In this study, the treemap approach is employed for the visualization of the sustainability performance value of the design scenarios using MATLAB 2018b, based on the results of the sustainability analysis of the product components. The sustainability values estimated for the product components using the GRA method are mapped to visualize the sustainability performance of the design alternatives. Figure 4.4 illustrates the sustainability treemap of the personalized modules and components of the product for the three design scenarios, based on the results of Table 4.9. In this 2D map, the sustainability performance of the product modules and components can be visualized using rectangles. Both the size and color of the rectangles present the same feature, namely sustainability performance value. The rectangles with a larger size represent the modules and components with higher sustainability value. In other words, the rectangles with bright yellow color show more sustainable modules and components, and less sustainable modules and components belong to the rectangles with dark green color. Also, the color distribution of the treemap represents the sustainability performance of the scenarios. The scenario with a higher sustainability value has brighter yellow color distribution and the scenario having lower performance shows a darker green color distribution.

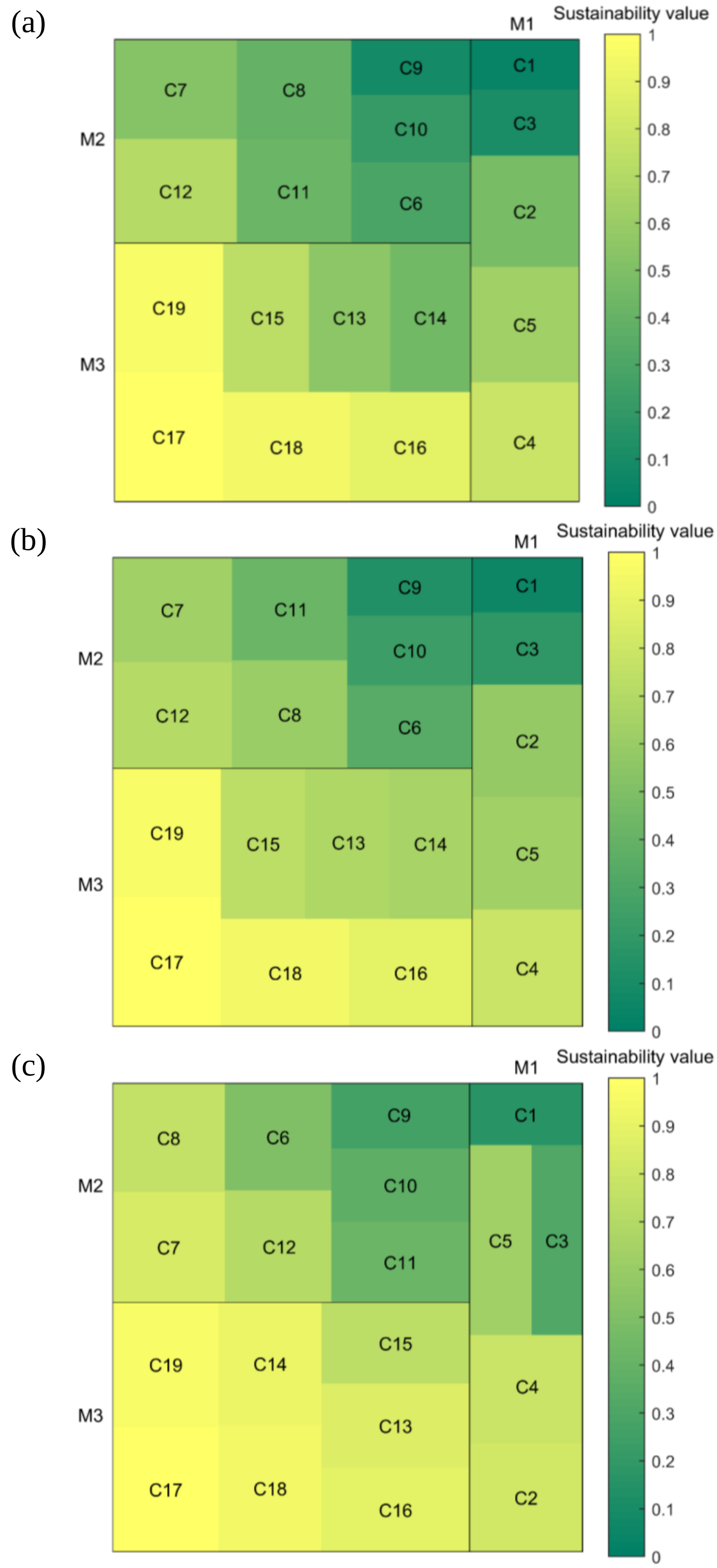


Figure 4.4 Sustainability treemap of the personalized product (a) design scenario 1 (Sp = 0.802), (b) design scenario 2 (Sp = 0.827), and (c) design scenario 3 (Sp = 0.874).

As it can be seen, for each design scenario of this study, module M3 (Head) has the larger size (area) of the rectangle as well as brighter yellow color distribution; thus, it has a higher sustainability performance than other modules in the product. Also, module M1 (Arm) with the smaller size of the rectangle (i.e., darker green color distribution) has lower sustainability performance in the product. In addition, for each design alternative, the component C17 (Head LED Cover) belonging to module M3 (Head) has a brighter yellow color with a larger size of the rectangle which means that it has higher sustainability performance than other components in each scenario. Also, component C1 (Hand) within module M1 (Arm) with the smaller size of the rectangle and darker green color has a lower sustainability performance value in each scenario.

It should be noted that the visualization results can be employed for the comparison of the sustainability performance of different design scenarios and their modules and components. In this research, by increasing the sustainability value of the scenarios, modules, and components, the color distribution of the treemap goes from dark green color towards bright yellow color. Also, the size of rectangles of treemap in each design alternative increases with the enhancement of sustainability performance values of modules or components. For example, as can be seen in Figure 4.4, the third design scenario (S_p = 0.874) is more sustainable than the other two alternatives and has a brighter yellow color distribution. Also, based on the color distribution in this figure, the first design scenario (S_p = 0.802) has the lowest sustainability performance with a less yellow color distribution. In the case of sustainability value comparison of modules of design alternatives, it is observed that modules M3 (Head), M2 (Leg), and M1 (Arm) of the third design scenario have higher sustainability value (with lighter yellow color distribution) than those modules of other two scenarios. Furthermore, regarding the sustainability performance of components of the design scenarios, the treemap can be effectively used for the comparison of the sustainability values of components of the alternatives. For instance, component C7 (Leg Actuator Mount) of the third design scenario has a higher sustainability value (with brighter yellow color) followed by the C7 of scenario 2 and then the C7 of scenario 1 (with darker green color).

Therefore, employing the visualization technique eliminates the need to interpret the long list of sustainability values of scenarios for comparison and decision-making purposes. The ordinary users and other involved actors with limited knowledge can be easily benefited from visualization results for comparison of different alternatives and related modules and components in order to take decisions towards the selection of the optimal design choice.

4.6 Sensitivity analysis

4.6.1 Sensitivity analysis of LCA analysis

The sensitivity analysis is carried out for the ELCA of the base scenario (design scenario 1). The DOE and statistical analysis are performed in Minitab statistical software.

The design of experiments (DOE) technique is used to design the conduct of experiments in order to establish the relationship between inputs and outputs of a process and statistically analyze the impacts of input variables on the process outcome. The LCA can be regarded as a computational experiment [129]. DOE is conducted to assess how the changes of input parameters in the LCA analysis affect the total environmental performance of the product. The input inventory data in the LCA are treated as the factors in DOE and the LCA results are used as the response of DOE. By considering the inventory data (Table 4.3) as a set point and making small changes around the set point (± 10%), the sensitivity of the LCA results to the variation and uncertainty in inventory variables is investigated. The computational experiments are designed according to the full factorial design approach in which the number of experiments with n factors each at k levels is obtained as k^n tests. Table 4.10 lists the input variables and their levels. With four factors (n = 4) each of which has two levels (k = 2), a two-level factorial design (2^4) is planned which generates 16 experimental trials. The result of the experimental design containing the combinations of the levels of the factors and the response of experiments is provided in Table 4.11, where X_i is the input inventory variable and Y is the output variable (i.e., overall environmental impact (OEI)).

It should be noted that the ELCA focuses on quantifying the different environmental impact categories (environmental indicators) which need to be combined to provide the total environmental impact of the product. For this aim, the impact categories are weighted and aggregated into an overall environmental impact (OEI) score calculated via Equation (4.1) [129]:

$$OEI = \sum_{j=1}^{n} w_j EI_j \tag{4.1}$$

where w_j are the weight of each impact category obtained using the AHP method (Section 4.6.2) and EI_j is the environmental impact of the product for the jth indicator. The AHP is used to determine the relative contribution of each impact category to overall environmental impact. The weight of each environmental impact category is assigned based on their relative importance in comparison with the others, and then the weighted impacts are summed into an environmental single score. Thus, the response of experiments in DOE is the overall environmental impact (OEI) of the product, as given in Table 4.11. Computations are carried out to investigate the relationship between input factors of LCA and the environmental impact of the product, where the inputs vary in the range of ± 10% of the reference values. According to the design of computational experiments, a second-order polynomial regression model can be derived as shown in Equation (4.2) to perform global sensitivity analysis [129]:

Table 4.10 Variable settings for the design of experiments.

Variable	Coded variable	Unit	Low level (-1)	Midpoint	High level (+1)
Electricity consumption (manufacturing, Al)	X_1	kWh/kg	0.378	0.42	0.462
Electricity consumption (manufacturing, ABS)	X_2	kWh/kg	1.674	1.86	2.046
Transportation distance	X_3	km	1.44E+04	1.60E+04	1.76E+04
Electricity consumption (use)	X_4	kWh/kg	10.062	11.18	12.298

Table 4.11 Full factorial design of experiments with values of input variables and response of experiments.

Run No.	Electricity consumption (Al) X_1	Electricity consumption (ABS) X_2	Transportation distance X_3	Electricity consumption (use) X_4	Response Y (OEI)
1	0.378	1.674	1.44E+04	10.062	1.8281E-03
2	0.462	1.674	1.44E+04	10.062	1.8337E-03
3	0.378	2.046	1.44E+04	10.062	1.8340E-03
4	0.462	2.046	1.44E+04	10.062	1.8396E-03
5	0.378	1.674	1.76E+04	10.062	1.8319E-03
6	0.462	1.674	1.76E+04	10.062	1.8375E-03
7	0.378	2.046	1.76E+04	10.062	1.8378E-03
8	0.462	2.046	1.76E+04	10.062	1.8434E-03
9	0.378	1.674	1.44E+04	12.298	1.8645E-03
10	0.462	1.674	1.44E+04	12.298	1.8701E-03
11	0.378	2.046	1.44E+04	12.298	1.8704E-03
12	0.462	2.046	1.44E+04	12.298	1.8761E-03
13	0.378	1.674	1.76E+04	12.298	1.8683E-03
14	0.462	1.674	1.76E+04	12.298	1.8739E-03
15	0.378	2.046	1.76E+04	12.298	1.8742E-03
16	0.462	2.046	1.76E+04	12.298	1.8798E-03

$$Y = C_0 + \sum_{i=1}^{n} C_i X_i + \sum_{i<j}\sum C_{ij} X_i X_j \tag{4.2}$$

where X_i are the input variables in the LCA model provided in Table 4.10, C_i are regression coefficients, and Y is the model output (i.e., OEI). This model allows assessing the singular and interaction effects of the variables on the response. The fitted regression equation between OEI and input parameters is as follows:

$$OEI = 1.596 \times 10^{-3} + 6.690 \times 10^{-5}\, X_1 + 1.587 \times 10^{-5}\, X_2 + 1.169 \times 10^{-9}\, X_3 + 1.628 \times 10^{-5}\, X_4 - 3.465 \times 10^{-18}\, X_1X_2 - 1.575 \times 10^{-21}\, X_1X_3 - 2.276 \times 10^{-18}\, X_1X_4 - 1.806 \times 10^{-22}\, X_2X_3 + 7.846 \times 10^{-19}\, X_2X_4 - 7.447 \times 10^{-23}\, X_3X_4 \tag{4.3}$$

Using this relationship equation, the environmental impact estimated by ELCA can be predicted from the input factors. The regression model can be used to predict the change of the OEI when the input parameters are changed. Also, the model can provide insights into the effects of different variables and their interactions on the variability of the OEI when varying them all at the same time. The results of the global sensitivity analysis in Table 4.12 show that electricity consumption (manufacturing, Al), electricity consumption (manufacturing, ABS), transportation distance, and electricity consumption (use) have significant effects on the overall environmental impact (P-value ≤ 0.05). The P-value is employed to determine the significance of the model coefficients. The influence of the input variable on the model output is significant if the P-value is less or equal to a certain significance level (α-level). Considering a 95% confidence level (α = 0.05) for regression, the P-value of the above parameters is less than 0.05 which means that these factors are significant to the model output. Moreover, the estimated coefficients indicate the relative magnitude of the effects of factors on the model outcome. The factors with negative coefficients will have positive environmental impacts and vice-versa. Therefore, to reduce the environmental impact, it is necessary to minimize electricity consumption (manufacturing, Al), electricity consumption (manufacturing, ABS), transportation distance, and electricity consumption (use) which have positive coefficients. By eliminating the insignificant parameters whose P-value is greater than the significance level (P-value > 0.05) and their effects are negligible, the estimated regressing model for the environmental impact is rewritten in terms of significant factors as below:

Table 4.12 The estimated coefficients of the regression model and P-value.

Term	Estimate	P-value
X_1	6.690×10^{-5}	0.000 (< 0.05)
X_2	1.587×10^{-5}	0.000 (< 0.05)
X_3	1.169×10^{-9}	0.000 (< 0.05)
X_4	1.628×10^{-5}	0.000 (< 0.05)
$X_1 \times X_2$	$- 3.465\times10^{-18}$	0.785 (> 0.05)
$X_1 \times X_3$	$- 1.575\times10^{-21}$	0.312 (> 0.05)
$X_1 \times X_4$	$- 2.276\times10^{-18}$	0.307 (> 0.05)
$X_2 \times X_3$	$- 1.806\times10^{-22}$	0.593 (> 0.05)
$X_2 \times X_4$	7.846×10^{-19}	0.143 (> 0.05)
$X_3 \times X_4$	$- 7.447\times10^{-23}$	0.216 (> 0.05)

$$OEI = 1.596 \times 10^{-3} + 6.690 \times 10^{-5}\, X_1 + 1.587 \times 10^{-5}\, X_2 + 1.169 \times 10^{-9}\, X_3 + 1.628 \times 10^{-5}\, X_4 \tag{4.4}$$

To describe the behavior of the response (OEI) considering the range of variation of inventory variables near the midpoint (uncertainty in the inventory variables), the mean (expected value, μ) and variance (σ^2) of the response is calculated using the following formulas [136]:

$$\mu = E[f(X)] \tag{4.5}$$

$$\sigma^2 = Var[f(X)] = E[f(X)^2] - (E[f(X)])^2 \tag{4.6}$$

The mean (μ) and standard deviation (σ) values for the inventory variables which are treated as random variables are provided in Table 4.13. It is supposed that the midpoints in Table 4.10 represent the mean, and the standard deviation is determined by assuming that the distance between the low and high levels of the variables corresponds to $\pm2\sigma$. By taking the response as OEI = f(X) and applying the relations displayed in Equations (4.5) and (4.6) to Equation (4.4), the following equations are obtained:

Table 4.13 The characteristics of random variables (inventory variables).

Variable	Mean (μ)	Standard deviation (σ)
X_1	0.42	0.021
X_2	1.86	0.093
X_3	1.60E+04	0.08E+04
X_4	11.18	0.559

$$\mu = 1.596 \times 10^{-3} + 6.690 \times 10^{-5}\,\mu_1 + 1.587 \times 10^{-5}\,\mu_2 + 1.169 \times 10^{-9}\,\mu_3 + 1.628 \times 10^{-5}\,\mu_4 \tag{4.7}$$

$$\sigma^2 = 4.476 \times 10^{-9}\,{\sigma_1}^2 + 2.519 \times 10^{-10}\,{\sigma_2}^2 + 1.367 \times 10^{-18}\,{\sigma_3}^2 + 2.651 \times 10^{-10}{\sigma_4}^2 \tag{4.8}$$

Using Equations (4.7) and (4.8), the mean and variance of the response (OEI) is obtained 1.8540E-03 and 8.7861E-11, respectively. Therefore, the results demonstrate that the response variability associated with uncertainty in the inventory variables is ± 2σ = ± 1.875E-05 which is very small indicating that the estimated environmental response (OEI) is not sensitive to the small changes in inventory data.

The local sensitivity analysis (LSA) is also carried out to compute the response variability due to changes in the input variables. Table 4.14 represents the results of local sensitivity analysis for the LCA outcome with a variation range of ± 10% from the reference value of input variables. Using the one-at-a-time approach, the variation of the OEI is estimated by making small changes (± 10%) in each input factor (input inventory data) while keeping other factors constant. It is observed that for all variables, the variation of the OEI is small and thus the LCA results are insensitive to the variation and uncertainty of input parameters.

Table 4.14 The variation of the OEI under the changes in input factors.

Variable	OEI (-10%)	OEI	OEI (+10%)	Variation (%)
Electricity consumption (Al)	1.8511E-03	1.8540E-03	1.8568E-03	±0.15
Electricity consumption (ABS)	1.8510E-03	1.8540E-03	1.8569E-03	±0.16
Transportation distance	1.8521E-03	1.8540E-03	1.8558E-03	±0.10
Electricity consumption (use)	1.8358E-03	1.8540E-03	1.8722E-03	±0.98

4.6.2 Sensitivity analysis of weighting process

The sensitivity analysis is carried out on the weighting process used in the GRA method in order to investigate the impact of the selection of the weighting method on the total sustainability value and the final ranking of design alternatives. By performing steps 1-3 of the AHP method for the two sustainability aspects (as criteria) and their sub-indicators (as sub-criteria), their relative weights can be computed as shown in Tables 4.15 and 4.16. The consistency test needs to be applied for the comparison matrix whose size (*n*) is greater than two (i.e., pairwise comparison matrix of environmental sub-indicators) and the comparison matrix with the size of two is always consistent. To measure the consistency of the results of the comparison matrix related to sub-indicators of environmental dimension, the consistency test is carried out by constructing the weighted sum matrix ($A \times w$) and calculating the eigenvalues using the relation of $A \times w = \lambda_{max} w$, where $A_{n \times n}$ is the pairwise comparison matrix, w is the priority vector, and λ_{max} is the maximum eigenvalue. By applying $\lambda_{max} = \lambda_{max} w/w$ (dividing the elements of the weighted sum matrix by respective priority vector element) and computing the average of the eigenvalues, the λ_{max} is obtained 4.049 ($\lambda_{max} = (4.040+4.013+4.089+4.054)/4$), as follows:

Table 4.15 Pairwise comparison matrix and relative weights for the two sustainability indicators.

Indicator	Environmental	Economic	Weight
Environmental	1	3	0.750
Economic	1/3	1	0.250
			$\sum = 1.000$

Table 4.16 Pairwise comparison matrix and relative weights for the sub-indicators of the environmental indicator.

Indicator	Climate change	Ecosystem quality	Human health	Resources	Weight
Climate change	1	3	1/4	1/2	0.150
Ecosystem quality	1/3	1	1/6	1/5	0.063
Human health	4	6	1	2	0.502
Resources	2	5	1/2	1	0.284
					$\sum = 1.000$

$\lambda_{max} = 4.049$, CI = 0.016, RI = 0.90, CR = 0.018 < 0.100 OK.

A	Climate change	Ecosystem quality	Human health	Resources		w		$\lambda_{max}w$		$\lambda_{max}w/w$
Climate change	1.000	3.000	0.250	0.500		0.150		0.608		4.040
Ecosystem quality	0.333	1.000	0.167	0.200	$\times$	0.063	$=$	0.254	$\Rightarrow$	4.013
Human health	4.000	6.000	1.000	2.000		0.502		2.052		4.089
Resources	2.000	5.000	0.500	1.000		0.284		1.153		4.054

Then, the consistency index is found as CI = (4.049-4) / (4-1) = 0.016 and the random consistency index is selected for the matrix size of four as RI = 0.90. Therefore, the consistency ratio is calculated as CR = 0.016/0.90 = 0.018 which is lower than 0.1 indicating that the comparisons are consistent, and the inconsistency is very low and acceptable. The weights resulting from the AHP calculation are provided in Table 4.17.

Table 4.17 Relative and global weights of the sustainability indicators and sub-indicators obtained using the AHP method.

Indicator	Weight	Sub-indicator	Weight	Global weight
Environmental	0.750	Climate change	0.150	0.113
		Ecosystem quality	0.063	0.047
		Human health	0.502	0.376
		Resources	0.284	0.213
Economic	0.250	Cost	1.000	0.250

By assigning the unequal weights obtained by AHP to the sustainability dimensions and their indicators in the GRA method, the total sustainability value (S_P) for design scenarios is calculated as shown in Table 4.18. Based on the sensitivity analysis results, it is found that the total sustainability value of design alternatives and the final ranking of scenarios is not sensitive to the weighting process of the sustainability indicators. In other words, by applying different weighting techniques, i.e., equal weighting method and participatory approach (e.g., AHP), the ranking of the design alternatives in terms of their sustainability performance remains the same. It should be noted that the sensitivity analysis results can be affected by assigning different weighting values to the sustainability indicators.

Table 4.18 Comparison of sustainability index (Sp) and ranking of alternatives by using different weighting methods in the GRA.

Design scenario No.	Equal weighting method	AHP method	Rank
Scenario 1	0.802	0.800	3
Scenario 2	0.827	0.828	2
Scenario 3	0.874	0.874	1

4.6.3 Sensitivity analysis of aggregation process

The sensitivity analysis is performed to determine the influence of selecting the different aggregation methods on the final ranking of the sustainability performance of design alternatives.

4.6.3.1 TOPSIS method

By assigning equal weighting to the environmental and economic sustainability dimensions and the indicators within the dimensions as well as aggregating the data using the TOPSIS method, the single sustainability value (C_i) is calculated for the personalized components of the product alternatives. The results are provided in Table 4.19. By averaging the sustainability values of components, the total sustainability value (S_p) for each product variant is obtained. It can be seen that among alternatives, design scenario 3 has obtained larger value (S_p = 0.921), followed by design scenario 2 (S_p = 0.874), and design scenario 1 (S_p = 0.825), respectively.

Table 4.19 The sustainability values of the personalized components for the three design scenarios from the TOPSIS method.

Module name	Component No.	Component name	Sustainability value		
			Design scenario 1	Design scenario 2	Design scenario 3
Arm (M1)	1	Hand	0.158	0.454	0.611
	2	Arm Actuator Mount	0.918	0.941	0.964
	3	Angled Actuator Bracket	0.527	0.663	0.837
	4	Arm Cover Upper	0.962	0.962	0.962
	5	Arm Cover Lower	0.942	0.942	0.942
Leg (M2)	6	U-Actuator Bracket	0.787	0.841	0.928
	7	Leg Actuator Mount	0.930	0.946	0.969
	8	Actuator Connector	0.895	0.944	0.960
	9	Knee Bracket	0.376	0.586	0.787
	10	Foot	0.586	0.687	0.837
	11	Leg Cover	0.905	0.905	0.905
	12	Foot Cover	0.950	0.950	0.950
Head (M3)	13	Head Bracket	0.918	0.948	0.967
	14	Neck Bracket	0.918	0.943	0.974
	15	Back Head Cover	0.943	0.943	0.943
	16	Front Head Cover	0.965	0.965	0.965
	17	Head LED Cover	1.000	1.000	1.000
	18	Eye Cover	0.993	0.993	0.993
	19	Pupil	0.996	0.996	0.996
			S_p = 0.825	S_p = 0.874	S_p = 0.921
		Rank	3	2	1

4.6.3.2 SAW method

By applying the SAW method to the different sustainability indicators of personalized components in the three design scenarios considering the equal weights for all indicators, the single aggregated score (A_i, sustainability value) for personalized components is computed. Then, the total sustainability score (S_p) for each product alternative is obtained by averaging the sustainability values of product components, as provided in Table 4.20. According to the results, design alternative 3 has obtained a higher score (S_p = 0.199) indicating that it has better sustainability performance compared to the other design scenarios.

Table 4.20 The sustainability values of the personalized components for the three design scenarios from the SAW method.

Module name	Component No.	Component name	Sustainability value		
			Design scenario 1	Design scenario 2	Design scenario 3
Arm (M1)	1	Hand	0.012	0.008	0.013
	2	Arm Actuator Mount	0.078	0.090	0.140
	3	Angled Actuator Bracket	0.016	0.015	0.032
	4	Arm Cover Upper	0.116	0.116	0.116
	5	Arm Cover Lower	0.091	0.091	0.091
Leg (M2)	6	U-Actuator Bracket	0.029	0.034	0.073
	7	Leg Actuator Mount	0.070	0.086	0.135
	8	Actuator Connector	0.053	0.086	0.113
	9	Knee Bracket	0.016	0.013	0.026
	10	Foot	0.025	0.024	0.047
	11	Leg Cover	0.073	0.073	0.073
	12	Foot Cover	0.106	0.106	0.106
Head (M3)	13	Head Bracket	0.090	0.112	0.171
	14	Neck Bracket	0.073	0.104	0.199
	15	Back Head Cover	0.134	0.134	0.134
	16	Front Head Cover	0.191	0.191	0.191
	17	Head LED Cover	1.000	1.000	1.000
	18	Eye Cover	0.396	0.396	0.396
	19	Pupil	0.728	0.728	0.728
			S_p = 0.173	S_p = 0.179	S_p = 0.199
		Rank	3	2	1

The results of the comparison of ranking of design alternatives obtained using the GRA method, TOPSIS, and SAW methods are given in Table 4.21. It can be seen that by employing these three approaches, design alternative 3 is selected as the best scenario and has better sustainability performance, followed by alternative 2 and alternative 1, respectively. Thus, the final ranking of alternatives is not sensitive to the selection of MADM methods.

Table 4.21 Comparison of alternatives rankings computed using different MADM methods.

Design scenario No.	GRA		TOPSIS		SAW	
	Score	Rank	Score	Rank	Score	Rank
Scenario 1	0.802	3	0.825	3	0.173	3
Scenario 2	0.827	2	0.874	2	0.179	2
Scenario 3	0.874	1	0.921	1	0.199	1

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In response to increasing legal pressures and market competition as well as changing customers' attitudes, developing sustainable products is considered an important and challenging topic for industrial companies. Thus, manufacturing industries tend to design and manufacture sustainable products through applying appropriate strategies with the intention of reducing environmental, economic, and social impacts from the product life cycle stages. The open-architecture products (OAPs), as a new manufacturing paradigm, are personalized products with variable functions developed by involving customers and different companies in order to satisfy the individual customer requirements and various market segments in a cost-effective manner. To improve the sustainability performance of OAPs, evaluation and visualization of the sustainability performance of this type of product are of importance in order to enable customers involved in the co-design process to select the optimal sustainable design option. The existing research has focused mainly on the design and development of OAPs to allow customers to participate in the co-design process of the product. However, there is limited research discussing the importance of considering the sustainability aspects in the design and development of OAPs. Therefore, it is required to incorporate sustainable design strategies into the co-design process of OAPs. This research aims to propose a decision support tool to assess and communicate the sustainability performance of personalized products to customers during the design stage.

The main challenge in the sustainable design of OAPs is how to evaluate and visualize the sustainability performance of the product. The sustainability performance of the product is assessed in terms of environmental and economic aspects. Since these sustainability indicators have different dimensions and scopes, it is required to apply an effective methodology for weighting and aggregating the indicators into a single meaningful sustainability index. To address this challenge, this dissertation presents a methodology to measure the sustainability performance of OAPs during the design stage. The robot DARwIn-OP, as an open-architecture product composed of common and personalized modules, is employed to implement the proposed decision support tool in order to demonstrate the utility of the framework. The material and geometry of the personalized components (i.e., head, arms, and legs) of the open-architecture robot are changed based on the customer preferences and design constraints to create product variants (three design scenarios). The environmental life cycle assessment (ELCA) and life cycle costing (LCC) analyses are performed to measure the sustainability performance of the personalized components for the three product variants. To integrate the sustainability results of environmental and economic sustainability assessments, the equal weighting method and the grey relational analysis (GRA) approach are applied to the three design scenarios (three personalized products) for weighting and aggregation of the values of the sustainability indicators of each component into a single sustainability value for the product components. By averaging the sustainability values of product components for each scenario, the total sustainability value of each product variant (S_p) is obtained and presented to customers through the treemap visualization technique. The visualization of the sustainability results facilitates decision-making for customers towards the optimal alternative selection. The treemap of each design scenario describes the sustainability performance of the product modules and components based on the size and color of the rectangles. Also, treemap visualization can be effectively used for the comparison of the sustainability performance of design scenarios based on the color distribution. Based on the results, the product in the third design scenario has a higher sustainability value ($S_p = 0.874$) and brighter yellow color distribution in the treemap, while the product in the first design scenario has a lower sustainability performance ($S_p = 0.802$) with the darker green color distribution.

In addition to sustainability performance evaluation, in this study, we conduct the sensitivity analysis to validate the robustness of the proposed framework. A DOE-based scheme and one-at-a-time approach are used for global and local sensitivity analysis of the LCA modelling. The local sensitivity analysis (LSA) reveals that the LCA results are not sensitive to the variation of input inventory data. Also, using the global sensitivity analysis (GSA), a regression model is derived to predict the overall environmental impact of the product and identify the inventory parameters significantly affecting the LCA results. Moreover, the sensitivity analysis is carried out to validate the sustainability results in which different weighting and aggregation schemes are utilized to compute the sustainability scores of product alternatives and compare the final results with those obtained by the chosen approaches. The results demonstrate that both the equal weighting method and the AHP method lead to the same ranking of product alternatives. Also, the ranking of the design alternatives is consistent with employing various multi-attribute decision-making approaches, namely GRA, TOPSIS, and SAW methods.

The aim of this research is to develop a methodology for the sustainable design of open-architecture products (OAPs). The main research contributions are summarized as follows:

1- A sustainability analysis containing environmental life cycle assessment (ELCA) and life cycle costing (LCC) is conducted for the personalized product to measure the sustainability performance of the product variants in terms of environmental and economic indicators.

2- A weighting and aggregation approach (i.e., using multi-attribute decision-making (MADM) methods) is employed to integrate the different sustainability indicators (i.e., environmental and economic indicators) into a single sustainability index (SI) for product variants. The total sustainability value of product varieties is presented and communicated to customers and other involved decision-makers by applying an appropriate visualization technique (e.g., treemap approach) which facilitates decision making towards the best sustainable design option.

3- A design of experiments (DOE)-based method is developed for performing sensitivity analysis in the life cycle assessment (LCA) modelling to check the robustness of the results to uncertainty in input parameters. Also, to validate the final ranking of product alternatives in terms of their sustainability performance, sensitivity analysis is carried out for the sustainability index construction through employing different weighting and aggregation processes (e.g., using GRA, TOPSIS, and SAW methods).

The outcome of this framework can be implemented in a cyber-enabled design tool for sustainable design of OAPs in which customers are allowed to define, visualize, and select the sustainable design option.

5.2 Future work

This dissertation provided a methodology for evaluation, visualization, and validation of the sustainability performance of open-architecture products (OAPs). The following subjects are suggested for future research topics:

1- In this research, the steps of the proposed decision support tool, including modification in personalized components, sustainability analysis, and multi-criteria decision-making process are performed manually. To remove this limitation, it is desirable to develop a fully automated framework for integrating computer-aided design, manufacturing, and engineering (CAD/CAM/CAE) and LCA/LCC tools to evaluate the functional performance and sustainability impacts of personalized products designed by customers. It is also useful to visualize the sustainability results on the CAD model of the product. Thus, it is recommended to develop a web-based prototype tool using programming languages to automatically implement the steps of the proposed framework and all specifications and data exchanges between different environments for evaluation and visualization processes.

2- In this study, all calculations for sustainability analysis are performed manually. It is proposed to utilize software tools, such as OpenLCA, SimaPro, or GaBi for the life cycle assessment analysis.

3- Due to the fact that open-architecture products (OAPs) are composed of known common and customized modules and unknown personalized modules which provide a high variety of products, it is essential to study the problem of disassembly modelling and planning under the uncertainty of personalized components and related variable disassembly parameters. A mathematical modelling and statistical analysis can be proposed to solve and optimize the disassembly process planning problem of open-architecture products (OAPs).

4- In this study, we assumed that all personalized components of the product are provided by the same manufacturer as well as required manufacturing energy is obtained from non-renewable sources. These parameters have effects on the sustainability of products in terms of environmental and economic aspects. It is proposed to investigate the results of sustainability analysis when different manufacturers located in various countries are involved in producing the product parts and different types of energy resources are employed for manufacturing processes. These variants can be considered to create alternative design scenarios for which the sustainability performance of products can be calculated and presented to customers to select the optimal option.

5- Although the final result of the proposed decision support tool is mapped using the treemap visualization technique for quick and easy decision making, it is desirable to test and evaluate the usefulness and appropriateness of the visualization technique by real customers.

REFERENCES

[1] S. J. Hu, J. Ko, L. Weyand, H. A. ElMaraghy, T. K. Lien, Y. Koren, H. Bley, G. Chryssolouris, N. Nasr, and M. Shpitalni, "Assembly system design and operations for product variety," *CIRP annals,* vol. 60, no. 2, pp. 715-733, 2011.

[2] S. J. Hu, "Evolving paradigms of manufacturing: From mass production to mass customization and personalization," *Procedia Cirp,* vol. 7, pp. 3-8, 2013.

[3] Y. Koren, S. Hu, P. Gu, and M. Shpitalni, "Open-architecture products," *CIRP Annals,* vol. 62, no. 2, pp. 719-729, 2013.

[4] J. A. Mesa, I. Esparragoza, and H. Maury, "Trends and perspectives of sustainable product design for open architecture products: Facing the circular economy model," *International Journal of Precision Engineering and Manufacturing-Green Technology,* vol. 6, no. 2, pp. 377-391, 2019.

[5] J. Zhang, D. Xue, and P. Gu, "Adaptable design of open architecture products with robust performance," *Journal of Engineering Design,* vol. 26, no. 1-3, pp. 1-23, 2015.

[6] C. Zhao, Q. Peng, and P. Gu, "Evaluation of open-architecture product adaptability using quantitative measures," *Computer-Aided Design and Applications,* vol. 13, no. 4, pp. 449-458, 2016.

[7] C. Zhao, Q. Peng, P. Gu, and Z. Zhang, "Module development method for Open architecture product using extended QFD," *CIE43 proceedings,* pp. 1-15, 2013.

[8] C. Zhao, Q. Peng, and P. Gu, "Development of a paper-bag-folding machine using open architecture for adaptability," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,* vol. 229, no. 1_suppl, pp. 155-169, 2015.

[9] D. Maxwell and R. Van der Vorst, "Developing sustainable products and services," *Journal of Cleaner production,* vol. 11, no. 8, pp. 883-895, 2003.

[10] B. He, F. Li, X. Cao, and T. Li, "Product sustainable design: a review from the environmental, economic, and social aspects," *Journal of Computing and Information Science in Engineering,* vol. 20, no. 4, 2020.

[11] J. Zhang, P. Gu, Q. Peng, and S. J. Hu, "Open interface design for product personalization," *CIRP Annals,* vol. 66, no. 1, pp. 173-176, 2017.

[12] J. Zhang, G. Xue, H. Du, A. Garg, Q. Peng, and P. Gu, "Enhancing interface adaptability of open architecture products," *Research in Engineering Design,* vol. 28, no. 4, pp. 545-560, 2017.

[13] Y. Chen, Q. Peng, and P. Gu, "Methods and tools for the optimal adaptable design of open-architecture products," *The International Journal of Advanced Manufacturing Technology,* vol. 94, no. 1, pp. 991-1008, 2018.

[14] Z. Zhang, Q. Peng, and P. Gu, "Improvement of user involvement in product design," *Procedia Cirp,* vol. 36, pp. 267-272, 2015.

[15] H. Song, Q. Peng, J. Zhang, and P. Gu, "A VR-based interactive system to improve users' involvement in OAP development," *Procedia CIRP,* vol. 56, pp. 13-18, 2016.

[16] J. A. Mesa, I. Esparragoza, and H. Maury, "Modular architecture principles–MAPs: a key factor in the development of sustainable open architecture products," *International Journal of Sustainable Engineering,* vol. 13, no. 2, pp. 108-122, 2020.

[17] P. Zheng, X. Xu, S. Yu, and C. Liu, "Personalized product configuration framework in an adaptable open architecture product platform," *Journal of Manufacturing Systems,* vol. 43, pp. 422-435, 2017.

[18] Q.-J. Peng, Y.-H. Liu, J. Zhang, and P.-H. Gu, "Personalization for massive product innovation using open architecture," *Chinese journal of mechanical engineering,* vol. 31, no. 1, pp. 1-13, 2018.

[19] J. A. Mesa, D. Illera, I. Esparragoza, H. Maury, and H. Gómez, "Functional characterisation of mechanical joints to facilitate its selection during the design of open architecture products," *International Journal of Production Research,* vol. 56, no. 24, pp. 7390-7404, 2018.

[20] C. Hu, Q. Peng, and P. Gu, "Adaptable interface design for open-architecture products," *Computer-Aided Design and Applications,* vol. 12, no. 2, pp. 156-165, 2015.

[21] A. K. Agrawal and Z. Rahman, "Roles and resource contributions of customers in value co-creation," *International Strategic Management Review,* vol. 3, no. 1-2, pp. 144-160, 2015.

[22] L. Sánchez de la Guía, M. Puyuelo Cazorla, and B. de-Miguel-Molina, "Terms and meanings of “participation” in product design: From “user involvement” to “co-design”," *The Design Journal,* vol. 20, no. sup1, pp. S4539-S4551, 2017.

[23] M. Sinclair and I. Campbell, "A classification of consumer involvement in new product development," in *DRS International Conference*, 2014, pp. 1582-1598.

[24] N. Franke and F. T. Piller, "Key research issues in user interaction with configuration toolkits in a mass customization system," *International Journal of Technology Management (IJTM),* vol. 26, no. 5, pp. 578-599, 2003.

[25] U. Gross and D. Antons, "Embedded open toolkits for user innovation: Postponing new product development decisions into the customer domain," in *Wirtschaftsinformatik*, 2009, pp. 835-840.

[26] F. Piller, C. Ihl, and F. Steiner, "Embedded toolkits for user co-design: A technology acceptance study of product adaptability in the usage stage," in *2010 43rd Hawaii International Conference on System Sciences*, 2010: IEEE, pp. 1-10.

[27] E. D. Kumtepe, A. N. Başoğlu, E. Corbacioglu, T. U. Daim, and A. Shaygan, "A smart mass customization design tool: a case study of a portable ramp for wheelchair users," *Health and Technology,* vol. 10, no. 3, pp. 723-737, 2020.

[28] E. D. Kumtepe, E. Çorbacıoğlu, A. N. Başoğlu, T. U. Daim, and A. Shaygan, "Design based exploration of medical system adoption: Case of wheelchair ramps," *Technology in Society,* vol. 66, p. 101620, 2021.

[29] P. Zheng, S. Yu, Y. Wang, R. Y. Zhong, and X. Xu, "User-experience based product development for mass personalization: a case study," *Procedia CIRP,* vol. 63, pp. 2-7, 2017.

[30] P. Zheng, Y. Lin, C.-H. Chen, and X. Xu, "Smart, connected open architecture product: an IT-driven co-creation paradigm with lifecycle personalization concerns," *International Journal of Production Research,* vol. 57, no. 8, pp. 2571-2584, 2019.

[31] M. Tseng, R. Jiao, and C. Wang, "Design for mass personalization," *CIRP annals,* vol. 59, no. 1, pp. 175-178, 2010.

[32] P. Zheng, X. Xu, and C.-H. Chen, "A data-driven cyber-physical approach for personalised smart, connected product co-development in a cloud-based environment," *Journal of Intelligent Manufacturing,* vol. 31, no. 1, pp. 3-18, 2020.

[33] J. H. Spangenberg, A. Fuad-Luke, and K. Blincoe, "Design for Sustainability (DfS): the interface of sustainable production and consumption," *Journal of Cleaner Production,* vol. 18, no. 15, pp. 1485-1493, 2010.

[34] A. N. Arnette, B. L. Brewer, and T. Choal, "Design for sustainability (DFS): the intersection of supply chain and environment," *Journal of cleaner production,* vol. 83, pp. 374-390, 2014.

[35] M. Rossi, M. Germani, and A. Zamagni, "Review of ecodesign methods and tools. Barriers and strategies for an effective implementation in industrial companies," *Journal of Cleaner Production,* vol. 129, pp. 361-373, 2016.

[36] K. Masui, T. Sakao, S. Aizawa, and A. Inaba, "Quality function deployment for environment (QFDE) to support design for environment (DFE)," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2002, vol. 36231, pp. 415-423.

[37] K. Masui, T. Sakao, M. Kobayashi, and A. Inaba, "Applying quality function deployment to environmentally conscious design," *International Journal of Quality & Reliability Management,* vol. 20, no. 1, pp. 90-106, 2003.

[38] T. Sakao, "A QFD-centred design methodology for environmentally conscious product design," *International journal of production research,* vol. 45, no. 18-19, pp. 4143-4162, 2007.

[39] S. Yu, Q. Yang, J. Tao, and X. Xu, "Incorporating quality function deployment with modularity for the end-of-life of a product family," *Journal of Cleaner Production,* vol. 87, pp. 423-430, 2015.

[40] Q. Yang, S. Yu, and D. Jiang, "A modular method of developing an eco-product family considering the reusability and recyclability of customer products," *Journal of cleaner production,* vol. 64, pp. 254-265, 2014.

[41] H.-E. Tseng, C.-C. Chang, and C.-J. Cheng, "Disassembly-oriented assessment methodology for product modularity," *International Journal of Production Research,* vol. 48, no. 14, pp. 4297-4320, 2010.

[42] S. Kim and S. K. Moon, "Sustainable platform identification for product family design," *Journal of cleaner production,* vol. 143, pp. 567-581, 2017.

[43] T. Go, D. Wahab, M. A. Rahman, R. Ramli, and A. Hussain, "Genetically optimised disassembly sequence for automotive component reuse," *Expert Systems with Applications,* vol. 39, no. 5, pp. 5409-5417, 2012.

[44] G. Tian, M. Zhou, and P. Li, "Disassembly sequence planning considering fuzzy component quality and varying operational cost," *IEEE Transactions on Automation Science and Engineering,* vol. 15, no. 2, pp. 748-760, 2017.

[45] M.-L. Bentaha, A. Voisin, and P. Marangé, "A decision tool for disassembly process planning under end-of-life product quality," *International Journal of Production Economics,* vol. 219, pp. 386-401, 2020.

[46] M. Mandolini, C. Favi, M. Germani, and M. Marconi, "Time-based disassembly method: how to assess the best disassembly sequence and time of target components in complex products," *The International Journal of Advanced Manufacturing Technology,* vol. 95, no. 1, pp. 409-430, 2018.

[47] C. Favi, M. Marconi, M. Germani, and M. Mandolini, "A design for disassembly tool oriented to mechatronic product de-manufacturing and recycling," *Advanced Engineering Informatics,* vol. 39, pp. 62-79, 2019.

[48] J. Tao, L. Li, and S. Yu, "An innovative eco-design approach based on integration of LCA, CAD\ CAE and optimization tools, and its implementation perspectives," *Journal of Cleaner Production*, vol. 187, pp. 839-851, 2018.

[49] J. Tao, Z. Chen, S. Yu, and Z. Liu, "Integration of Life Cycle Assessment with computer-aided product development by a feature-based approach," *Journal of cleaner production,* vol. 143, pp. 1144-1164, 2017.

[50] Z. Chen, J. Tao, and S. Yu, "A feature-based CAD-LCA software integration approach for eco-design," *Procedia CIRP*, vol. 61, pp. 721-726, 2017.

[51] R. Gaha, B. Yannou, and A. Benamara, "Selection of a green manufacturing process based on CAD features," *The International Journal of Advanced Manufacturing Technology*, vol. 87, no. 5, pp. 1335-1343, 2016.

[52] H. Ben Slama, R. Gaha, and A. Benamara, "Proposal of new eco-manufacturing feature interaction-based methodology in CAD phase," *The International Journal of Advanced Manufacturing Technology,* vol. 106, no. 3, pp. 1057-1068, 2020.

[53] J. A. Mesa, I. Esparragoza, and H. Maury, "Development of a metric to assess the complexity of assembly/disassembly tasks in open architecture products," *International Journal of Production Research,* vol. 56, no. 24, pp. 7201-7219, 2018.

[54] ISO, *ISO 14040:2006 Environmental management – Life cycle assessment – Principles and framework; ISO 14044:2006 Environmental management – Life cycle assessment – Requirements and guidelines*. Geneva, 2006.

[55] D. Su, Z. Ren, and Y. Wu, "Guidelines for selection of life cycle impact assessment software tools," in *Sustainable Product Development*: Springer, 2020, pp. 57-70.

[56] A. Iswara, A. Farahdiba, E. Nadhifatin, F. Pirade, G. Andhikaputra, I. Muflihah, and R. Boedisantoso, "A Comparative Study of Life Cycle Impact Assessment using Different Software Programs," in *IOP Conference Series: Earth and Environmental Science*, 2020, vol. 506, no. 1: IOP Publishing, p. 012002.

[57] L. M. Haselbach and Q. Langfitt, "Transportation Life Cycle Assessment (LCA) Synthesis: Life Cycle Assessment Learning Module Series," University of Alaska Fairbanks. Center for Environmentally Sustainable …, 2015.

[58] I. T. Herrmann and A. Moltesen, "Does it matter which Life Cycle Assessment (LCA) tool you choose?–a comparative assessment of SimaPro and GaBi," *Journal of Cleaner Production,* vol. 86, pp. 163-169, 2015.

[59] R. Speck, S. Selke, R. Auras, and J. Fitzsimmons, "Life cycle assessment software: Selection can impact results," *Journal of Industrial Ecology,* vol. 20, no. 1, pp. 18-28, 2016.

[60] "SolidWorks Sustainability," www.solidworks.com.

[61] P. Jain, "Design of an interactive eco-assessment GUI tool for computer aided product design," *Bachelor thesis project. Indian Institute of Technology Guwahati, Department of Design,* 2009.

[62] N. Marosky, J. Dose, G. Fleischer, and R. Ackermann, "Challenges of data transfer between CAD and LCA software tools," in *3rd International Conference on Life Cycle Management, University of Zurich at Irchel*, 2007.

[63] F. Mathieux, L. Roucoules, L. Lescuyer, and D. Brissaud, "Connecting CAD and PLM systems with ecodesign software: Current experiences and future opportunities," in *DS 42: Proceedings of ICED 2007, the 16th International Conference on Engineering Design, Paris, France, 28.-31.07. 2007*, 2007, pp. 467-468 (exec. Summ.), full paper no. DS42_P_425.

[64] S. Leibrecht, "Fundamental principles for CAD-based Ecological Assessments (9 pp)," *The International Journal of Life Cycle Assessment,* vol. 10, no. 6, pp. 436-444, 2005.

[65] A. Morbidoni, C. Favi, and M. Germani, "CAD-Integrated LCA Tool: Comparison with dedicated LCA Software and Guidelines for the improvement," in *Glocalized solutions for sustainability in manufacturing*: Springer, 2011, pp. 569-574.

[66] A. Morbidoni, C. Favi, F. Mandorli, and M. Germani, "ENVIRONMENTAL EVALUATION FROM CRADLE TO GRAVE WITH CAD-INTEGRATED LCA TOOLS," *Acta Technica Corviniensis-Bulletin of Engineering,* vol. 5, no. 1, 2012.

[67] H. E. Otto, K. G. Mueller, and F. Kimura, "Efficient information visualization in LCA," *The International Journal of Life Cycle Assessment,* vol. 8, no. 4, pp. 183-189, 2003.

[68] S. Sala and J. Andreasson, "Improving interpretation, presentation and visualisation of LCA studies for decision making support," in *Designing Sustainable Technologies, Products and Policies*: Springer, Cham, 2018, pp. 337-342.

[69] H. E. Otto, K. G. Mueller, and F. Kimura, "Efficient information visualization in LCA: Application and practice," *The International Journal of Life Cycle Assessment,* vol. 9, no. 1, pp. 2-12, 2004.

[70] P. Uchil and A. Chakrabarti, "An interface between life cycle assessment and design," in *ICoRD'15–Research into Design Across Boundaries Volume 2*: Springer, 2015, pp. 251-259.

[71] P. Uchil and A. Chakrabarti, "Communicating life cycle assessment results to design decision makers: Need for an infomration visualization approach," in *DS 75-5: Proceedings*

of the 19th International Conference on Engineering Design (ICED13) Design For Harmonies, Vol. 5: Design for X, Design to X, Seoul, Korea 19-22.08. 2013, 2013.

[72] A. Hollberg, B. Kiss, M. Röck, B. Soust-Verdaguer, A. H. Wiberg, S. Lasvaux, A. Galimshina, and G. Habert, "Review of visualising LCA results in the design process of buildings," *Building and Environment*, vol. 190, p. 107530, 2021.

[73] M. Rio, F. Blondin, and P. Zwolinski, "Investigating product designer LCA preferred logics and visualisations," *Procedia CIRP*, vol. 84, pp. 191-196, 2019.

[74] J. Oyarzo and B. Peuportier, "Life cycle assessment model applied to housing in Chile," *Journal of cleaner production*, vol. 69, pp. 109-116, 2014.

[75] B. Kiss and Z. Szalay, "A visual method for detailed analysis of building life cycle assessment results," in *Applied Mechanics and Materials*, 2019, vol. 887: Trans Tech Publ, pp. 319-326.

[76] B. Kiss and Z. Szalay, "Modular approach to multi-objective environmental optimization of buildings," *Automation in Construction*, vol. 111, p. 103044, 2020.

[77] F. Cerdas, A. Kaluza, S. Erkisi-Arici, S. Böhme, and C. Herrmann, "Improved visualization in LCA through the application of cluster heat maps," *Procedia CIRP*, vol. 61, pp. 732-737, 2017.

[78] S. Keivanpour and D. Ait Kadi, "Strategic eco-design map of the complex products: toward visualisation of the design for environment," *International Journal of Production Research*, vol. 56, no. 24, pp. 7296-7312, 2018.

[79] H. Ostad-Ahmad-Ghorabi, D. Collado-Ruiz, and W. Wimmer, "Towards integrating LCA into CAD," in *DS 58-7: Proceedings of ICED 09, the 17th International Conference on Engineering Design, Vol. 7, Design for X/Design to X, Palo Alto, CA, USA, 24.-27.08. 2009*, 2009.

[80] D. P. Müller and M. Hiete, "Visualization supported corporate decision making for life cycle sustainability assessment–Illustrated using a case study for selecting a sustainable packaging system for self-leveling compounds," *Journal of Cleaner Production*, vol. 313, p. 127768, 2021.

[81] E. K. Zavadskas, Z. Turskis, and S. Kildienė, "State of art surveys of overviews on MCDM/MADM methods," *Technological and economic development of economy*, vol. 20, no. 1, pp. 165-179, 2014.

[82] G. A. Mendoza and H. Martins, "Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms," *Forest ecology and management*, vol. 230, no. 1-3, pp. 1-22, 2006.

[83] S. L. Gebre, D. Cattrysse, E. Alemayehu, and J. Van Orshoven, "Multi-criteria decision making methods to address rural land allocation problems: A systematic review," *International Soil and Water Conservation Research*, vol. 9, no. 4, pp. 490-501, 2021.

[84] I. Vinogradova, "Multi-attribute decision-making methods as a part of mathematical optimization," *Mathematics*, vol. 7, no. 10, p. 915, 2019.

[85] T. Özcan, N. Çelebi, and Ş. Esnaf, "Comparative analysis of multi-criteria decision making methodologies and implementation of a warehouse location selection problem," *Expert Systems with Applications,* vol. 38, no. 8, pp. 9773-9779, 2011.

[86] A. Nesticò and P. Somma, "Comparative analysis of multi-criteria methods for the enhancement of historical buildings," *Sustainability,* vol. 11, no. 17, p. 4526, 2019.

[87] M. E. Banihabib, F.-S. Hashemi-Madani, and A. Forghani, "Comparison of compensatory and non-compensatory multi criteria decision making models in water resources strategic management," *Water Resources Management*, vol. 31, no. 12, pp. 3745-3759, 2017.

[88] F. Tscheikner-Gratl, P. Egger, W. Rauch, and M. Kleidorfer, "Comparison of multi-criteria decision support methods for integrated rehabilitation prioritization," *Water,* vol. 9, no. 2, p. 68, 2017.

[89] M. Aruldoss, T. M. Lakshmi, and V. P. Venkatesan, "A survey on multi criteria decision making methods and its applications," *American Journal of Information Systems,* vol. 1, no. 1, pp. 31-43, 2013.

[90] P. Miraj and M. A. Berawi, "Multi-criteria decision making for photovoltaic alternatives: a case study in hot climate country," *International Journal of Sustainable Energy Planning and Management,* vol. 30, pp. 61-74, 2021.

[91] T. L. Saaty, *Analytical Hierarchy Process*. NY, USA: McGraw Hill Company, 1980.

[92] A. Soltani, K. Hewage, B. Reza, and R. Sadiq, "Multiple stakeholders in multi-criteria decision-making in the context of municipal solid waste management: a review," *Waste Management,* vol. 35, pp. 318-328, 2015.

[93] T. L. Saaty, *Decision making with dependence and feedback: The analytic network process* (no. 2). RWS publications Pittsburgh, 1996.

[94] T. Soota, "INTEGRATED APPROACH TO MULTI-CRITERIA DECISION MAKING FOR SUSTAINABLE PRODUCT DEVELOPMENT," *International Journal for Quality Research*, vol. 8, no. 4, pp. 543-556, 2014.

[95] C.-N. Liao, C.-H. Lin, and Y.-K. Fu, "Integrative model for the selection of a new product launch strategy, based on ANP, TOPSIS and MCGP: a case study," *Technological and Economic Development of Economy,* vol. 22, no. 5, pp. 715-737, 2016.

[96] C. L. Hwang and K. Yoon, "Multiple attribute decision making, methods and applications," *Lecture Notes in Economics and Mathematical Systems,* vol. 186, 1981. Now York: Springer-Verlag.

[97] G. Işıklar and G. Büyüközkan, "Using a multi-criteria decision making approach to evaluate mobile phone alternatives," *Computer Standards & Interfaces,* vol. 29, no. 2, pp. 265-274, 2007.

[98] Z. Wu and G. Abdul-Nour, "Comparison of multi-criteria group decision-making methods for urban sewer network plan selection," *CivilEng,* vol. 1, no. 1, pp. 26-48, 2020.

[99] A. Afshari, M. Mojahed, and R. M. Yusuff, "Simple additive weighting approach to personnel selection problem," *International Journal of Innovation, Management and Technology,* vol. 1, no. 5, pp. 511-515, 2010.

[100] N. Nurmalini and R. Rahim, "Study approach of simple additive weighting for decision support system," *Int. J. Sci. Res. Sci. Technol*, vol. 3, no. 3, pp. 541-544, 2017.

[101] J. Deng, "Introduction to grey system theory," *The Journal of grey system*, vol. 1, no. 1, pp. 1-24, 1989.

[102] B. Roy, "The outranking approach and the foundations of ELECTRE methods," in *Readings in multiple criteria decision aid*: Springer, 1990, pp. 155-183.

[103] K. Govindan and M. B. Jepsen, "ELECTRE: A comprehensive literature review on methodologies and applications," *European Journal of Operational Research*, vol. 250, no. 1, pp. 1-29, 2016.

[104] J.-P. Brans and P. Vincke, "Note—A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making)," *Management science*, vol. 31, no. 6, pp. 647-656, 1985.

[105] M. Behzadian, R. B. Kazemzadeh, A. Albadvi, and M. Aghdasi, "PROMETHEE: A comprehensive literature review on methodologies and applications," *European journal of Operational research*, vol. 200, no. 1, pp. 198-215, 2010.

[106] C. Wulf, J. Werker, C. Ball, P. Zapp, and W. Kuckshinrichs, "Review of sustainability assessment approaches based on life cycles," *Sustainability*, vol. 11, no. 20, p. 5717, 2019.

[107] S. A. I. Corporation and M. A. Curran, "Life-cycle assessment: principles and practice," ed: National Risk Management Research Laboratory, Office of Research and …, 2006.

[108] W. Klöpffer, "Life-cycle based methods for sustainable product development," *The International Journal of Life Cycle Assessment*, vol. 8, no. 3, pp. 157-159, 2003.

[109] T. E. Swarr, D. Hunkeler, W. Klöpffer, H.-L. Pesonen, A. Ciroth, A. C. Brent, and R. Pagan, "Environmental life-cycle costing: a code of practice," *The International Journal of Life Cycle Assessment*, vol. 16, no. 5, pp. 389-391, 2011.

[110] M. Traverso, M. Finkbeiner, A. Jørgensen, and L. Schneider, "Life cycle sustainability dashboard," *Journal of industrial ecology*, vol. 16, no. 5, pp. 680-688, 2012.

[111] D. Costa, P. Quinteiro, and A. Dias, "A systematic review of life cycle sustainability assessment: Current state, methodological challenges, and implementation issues," *Science of the total environment*, vol. 686, pp. 774-787, 2019.

[112] B. Gencturk, K. Hossain, and S. Lahourpour, "Life cycle sustainability assessment of RC buildings in seismic regions," *Engineering structures*, vol. 110, pp. 347-362, 2016.

[113] E. Ekener, J. Hansson, A. Larsson, and P. Peck, "Developing Life Cycle Sustainability Assessment methodology by applying values-based sustainability weighting-Tested on biomass based and fossil transportation fuels," *Journal of cleaner production*, vol. 181, pp. 337-351, 2018.

[114] W. Klöpffer, "Life cycle sustainability assessment of products," *The International Journal of Life Cycle Assessment*, vol. 13, no. 2, pp. 89-95, 2008.

[115] P. Tarne, M. Traverso, and M. Finkbeiner, "Review of life cycle sustainability assessment and potential for its adoption at an automotive company," *Sustainability*, vol. 9, no. 4, p. 670, 2017.

[116] S. Kwatra, A. Kumar, and P. Sharma, "A critical review of studies related to construction and computation of Sustainable Development Indices," *Ecological Indicators,* vol. 112, p. 106061, 2020.

[117] X. Gan, I. C. Fernandez, J. Guo, M. Wilson, Y. Zhao, B. Zhou, and J. Wu, "When to use what: Methods for weighting and aggregating sustainability indicators," *Ecological indicators,* vol. 81, pp. 491-502, 2017.

[118] R. K. Singh, H. R. Murty, S. K. Gupta, and A. K. Dikshit, "An overview of sustainability assessment methodologies," *Ecological indicators,* vol. 9, no. 2, pp. 189-212, 2009.

[119] M. Nardo, M. Saisana, A. Saltelli, and S. Tarantola, *Tools for composite indicators building*. Joint Research Centre, European Comission, Ispra, Italy, 2005.

[120] J. R. C.-E. Commission, *Handbook on constructing composite indicators: methodology and user guide*. OECD publishing, 2008.

[121] H. V. Rowley, G. M. Peters, S. Lundie, and S. J. Moore, "Aggregating sustainability indicators: beyond the weighted sum," *Journal of environmental management,* vol. 111, pp. 24-33, 2012.

[122] Y.-S. Tan, H. Chen, and S. Wu, "Evaluation and implementation of environmentally conscious product design by using AHP and grey relational analysis approaches," *Ekoloji,* vol. 28, no. 107, pp. 857-864, 2019.

[123] J. W. Chan and T. K. Tong, "Multi-criteria material selections and end-of-life product strategy: Grey relational analysis approach," *Materials & Design,* vol. 28, no. 5, pp. 1539-1546, 2007.

[124] F. Pianosi, K. Beven, J. Freer, J. W. Hall, J. Rougier, D. B. Stephenson, and T. Wagener, "Sensitivity analysis of environmental models: A systematic review with practical workflow," *Environmental Modelling & Software,* vol. 79, pp. 214-232, 2016.

[125] F. Michiels and A. Geeraerd, "How to decide and visualize whether uncertainty or variability is dominating in life cycle assessment results: A systematic review," *Environmental Modelling & Software,* vol. 133, p. 104841, 2020.

[126] J. Rivera and J. Sutherland, "A design of experiments (DOE) approach to data uncertainty in LCA: application to nanotechnology evaluation," *Clean Technologies and Environmental Policy,* vol. 17, no. 6, pp. 1585-1595, 2015.

[127] M. Cellura, S. Longo, and M. Mistretta, "Sensitivity analysis to quantify uncertainty in life cycle assessment: the case study of an Italian tile," *Renewable and Sustainable Energy Reviews,* vol. 15, no. 9, pp. 4697-4705, 2011.

[128] W. Wei, P. Larrey-Lassalle, T. Faure, N. Dumoulin, P. Roux, and J.-D. Mathias, "How to conduct a proper sensitivity analysis in life cycle assessment: taking into account correlations within LCI data and interactions within the LCA calculation model," *Environmental science & technology,* vol. 49, no. 1, pp. 377-385, 2015.

[129] D. S. Khang, R. R. Tan, O. M. Uy, M. A. B. Promentilla, P. D. Tuan, N. Abe, and L. F. Razon, "Design of experiments for global sensitivity analysis in life cycle assessment: the case of biodiesel in Vietnam," *Resources, Conservation and Recycling,* vol. 119, pp. 12-23, 2017.

[130] H.-S. Yoon, J.-Y. Lee, H.-S. Kim, M.-S. Kim, E.-S. Kim, Y.-J. Shin, W.-S. Chu, and S.-H. Ahn, "A comparison of energy consumption in bulk forming, subtractive, and additive processes: Review and case study," *International Journal of Precision Engineering and Manufacturing-Green Technology,* vol. 1, no. 3, pp. 261-279, 2014.

[131] J. B. Dahmus and T. G. Gutowski, "An environmental analysis of machining," in *ASME international mechanical engineering congress and exposition*, 2004, vol. 47136, pp. 643-652.

[132] A. Thiriez and T. Gutowski, "An environmental analysis of injection molding," in *Proceedings of the 2006 IEEE International Symposium on Electronics and the Environment, 2006.*, 2006: IEEE, pp. 195-200.

[133] "Sea distances/port distances - an online tool for calculation of distances between sea ports," *www.sea-distances.org*, 2021.

[134] O. Jolliet, M. Margni, R. Charles, S. Humbert, J. Payet, G. Rebitzer, and R. Rosenbaum, "IMPACT 2002+: a new life cycle impact assessment methodology," *The international journal of life cycle assessment,* vol. 8, no. 6, pp. 324-330, 2003.

[135] "SolidWorks Costing," *www.solidworks.com*, 2017.

[136] J. E. Beard and J. W. Sutherland, "Robust suspension system design," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 1993, vol. 11818: American Society of Mechanical Engineers, pp. 387-395.

APPENDIX A: IMPACT FACTORS EXTRACTED FROM THE ECOINVENT 3.3 DATABASE.

Process	Location	Unit	Climate change (point)	Ecosystem quality (point)	Human health (point)	Resources (point)
Material						
Aluminium, primary, production	China	kg	2.30E-03	1.03E-03	3.24E-03	1.41E-03
Steel, low alloyed, production	Global	kg	1.63E-04	7.72E-05	4.87E-04	1.33E-04
Acrylonitrile-butadiene-styrene (ABS) copolymer, production	Global	kg	4.01E-04	2.21E-05	2.63E-04	6.70E-04
Electricity						
Electricity, high voltage, hard coal, production	China	kWh	1.07E-04	5.60E-05	1.35E-04	6.80E-05
Electricity, high voltage, nuclear, production	France	kWh	1.23E-06	4.34E-06	1.51E-05	9.29E-05
Transport of Goods						
Transport, freight, sea, transoceanic ship	Global	tkm	1.12E-06	2.20E-07	3.91E-06	1.14E-06
Disposal						
Disposal, aluminum, to sanitary landfill	RoW*	kg	3.86E-06	2.44E-05	1.29E-05	4.07E-06
Disposal, steel, to inert material landfill	Europe	kg	5.20E-07	1.98E-07	1.34E-06	1.07E-06
Disposal, plastic, mixture, to municipal incineration	Europe	kg	2.37E-04	1.20E-06	2.14E-05	3.01E-06

*RoW: Rest of World

APPENDIX B: THE WEIGHT OF MATERIALS AND COMPONENTS EXTRACTED FROM THE CAD MODEL.

Design scenario 1:

Component name	Material	Quantity	Material weight (kg)	Component weight (kg)
Hand	Aluminium	2	0.1019	0.0242
Arm Actuator Mount	Aluminium	2	0.0078	0.0053
Angled Actuator Bracket	Aluminium	4	0.0230	0.0134
Arm Cover Upper	ABS	2	0.0061	0.0061
Arm Cover Lower	ABS	2	0.0117	0.0117
U-Actuator Bracket	Aluminium	2	0.0185	0.0144
Leg Actuator Mount	Aluminium	2	0.0050	0.0039
Actuator Connector	Aluminium	4	0.0047	0.0015
Knee Bracket	Aluminium	2	0.0671	0.0335
Foot	Aluminium	2	0.0421	0.0399
Leg Cover	ABS	2	0.0220	0.0220
Foot Cover	ABS	2	0.0104	0.0104
Head Bracket	Aluminium	1	0.0165	0.0101
Neck Bracket	Aluminium	1	0.0147	0.0125
Back Head Cover	ABS	1	0.0279	0.0279
Front Head Cover	ABS	1	0.0171	0.0171
Head LED Cover	ABS	1	0.0005	0.0005
Eye Cover	ABS	2	0.0011	0.0011
Pupil	ABS	2	0.0003	0.0003

Design scenario 2:

Component name	Material	Quantity	Material weight (kg)	Component weight (kg)
Hand	Steel	2	0.2961	0.0704
Arm Actuator Mount	Steel	2	0.0231	0.0155
Angled Actuator Bracket	Steel	4	0.0669	0.0389
Arm Cover Upper	ABS	2	0.0061	0.0061
Arm Cover Lower	ABS	2	0.0117	0.0117
U-Actuator Bracket	Steel	2	0.0539	0.0420
Leg Actuator Mount	Steel	2	0.0147	0.0114
Actuator Connector	Steel	4	0.0135	0.0043
Knee Bracket	Steel	2	0.1950	0.0973
Foot	Steel	2	0.1227	0.1161
Leg Cover	ABS	2	0.0220	0.0220
Foot Cover	ABS	2	0.0104	0.0104
Head Bracket	Steel	1	0.0481	0.0293
Neck Bracket	Steel	1	0.0428	0.0362
Back Head Cover	ABS	1	0.0279	0.0279
Front Head Cover	ABS	1	0.0171	0.0171
Head LED Cover	ABS	1	0.0005	0.0005
Eye Cover	ABS	2	0.0011	0.0011
Pupil	ABS	2	0.0003	0.0003

Design scenario 3:

Component name	Material	Quantity	Material weight (kg)	Component weight (kg)
Hand	Steel	2	0.1974	0.0448
Arm Actuator Mount	Steel	2	0.0154	0.0100
Angled Actuator Bracket	Steel	4	0.0334	0.0173
Arm Cover Upper	ABS	2	0.0061	0.0061
Arm Cover Lower	ABS	2	0.0117	0.0117
U-Actuator Bracket	Steel	2	0.0270	0.0188
Leg Actuator Mount	Steel	2	0.0098	0.0057
Actuator Connector	Steel	4	0.0107	0.0021
Knee Bracket	Steel	2	0.0975	0.0467
Foot	Steel	2	0.0613	0.0581
Leg Cover	ABS	2	0.0220	0.0220
Foot Cover	ABS	2	0.0104	0.0104
Head Bracket	Steel	1	0.0321	0.0185
Neck Bracket	Steel	1	0.0214	0.0166
Back Head Cover	ABS	1	0.0279	0.0279
Front Head Cover	ABS	1	0.0171	0.0171
Head LED Cover	ABS	1	0.0005	0.0005
Eye Cover	ABS	2	0.0011	0.0011
Pupil	ABS	2	0.0003	0.0003

APPENDIX C: MANUFACTURING COSTS OF COMPONENTS OF THE ROBOT FOR THREE DESIGN SCENARIOS.

Component name	Quantity	Manufacturing cost (design scenario 1)	Manufacturing cost (design scenario 2)	Manufacturing cost (design scenario 3)
Hand	2	1.580	3.620	2.460
Arm Actuator Mount	2	0.400	0.320	0.200
Angled Actuator Bracket	4	1.800	2.000	0.920
Arm Cover Upper	2	0.380	0.380	0.380
Arm Cover Lower	2	0.400	0.400	0.400
U-Actuator Bracket	2	1.170	0.900	0.410
Leg Actuator Mount	2	0.580	0.460	0.300
Actuator Connector	4	0.680	0.360	0.280
Knee Bracket	2	1.260	1.940	0.980
Foot	2	0.740	0.640	0.340
Leg Cover	2	0.400	0.400	0.400
Foot Cover	2	0.340	0.340	0.340
Head Bracket	1	0.310	0.200	0.130
Neck Bracket	1	0.450	0.240	0.135
Back Head Cover	1	0.190	0.190	0.190
Front Head Cover	1	0.150	0.150	0.150
Head LED Cover	1	0.080	0.080	0.080
Eye Cover	2	0.140	0.140	0.140
Pupil	2	0.120	0.120	0.120

APPENDIX D: MAIN FLOWS PER FUNCTIONAL UNIT FOR PERSONALIZED COMPONENTS OF THE THREE DESIGN SCENARIOS.

Design scenario 1:

Compnent name	Material	**Raw materials** (Al, ABS, China) (kg)	**Manufacturing** (Electricity, coal, China) (kWh)	**Tranportation** (Sea freight, China to France) (tkm)	**Use** (Electricity, nuclear, France) (kWh)	**EoL** (Landfill (Al), Incineration (ABS), France) (kg)
Hand	Aluminium	0.20376	0.08558	0.77509	0.54160	0.04844
Arm Actuator Mount	Aluminium	0.01568	0.00659	0.17012	0.11887	0.01063
Angled Actuator Bracket	Aluminium	0.09185	0.03858	0.85571	0.59792	0.05348
Arm Cover Upper	ABS	0.01213	0.02256	0.19405	0.13559	0.01213
Arm Cover Lower	ABS	0.02334	0.04341	0.37344	0.26094	0.02334
U-Actuator Bracket	Aluminium	0.03701	0.01555	0.46215	0.32293	0.02888
Leg Actuator Mount	Aluminium	0.01009	0.00424	0.12597	0.08802	0.00787
Actuator Connector	Aluminium	0.01860	0.00781	0.09385	0.06558	0.00587
Knee Bracket	Aluminium	0.13411	0.05633	1.07050	0.74801	0.06691
Foot	Aluminium	0.08424	0.03538	1.27786	0.89290	0.07987
Leg Cover	ABS	0.04396	0.08177	0.70336	0.49147	0.04396
Foot Cover	ABS	0.02086	0.03880	0.33376	0.23321	0.02086
Head Bracket	Aluminium	0.01653	0.00694	0.16122	0.11265	0.01008
Neck Bracket	Aluminium	0.01471	0.00618	0.19924	0.13922	0.01245
Back Head Cover	ABS	0.02790	0.05189	0.44640	0.31192	0.02790
Front Head Cover	ABS	0.01708	0.03177	0.27328	0.19095	0.01708
Head LED Cover	ABS	0.00053	0.00099	0.00855	0.00597	0.00053
Eye Cover	ABS	0.00218	0.00405	0.03488	0.02437	0.00218
Pupil	ABS	0.00068	0.00126	0.01088	0.00760	0.00068

Design scenario 2:

Compnent name	Material	**Raw materials** (Steel, ABS, China) (kg)	**Manufacturing** (Electricity, coal, China) (kWh)	**Tranportation** (Sea freight, China to France) (tkm)	**Use** (Electricity, nuclear, France) (kWh)	**EoL** (Landfill (Steel), Incineration (ABS), France) (kg)
Hand	Steel	0.59228	0.37314	2.25352	1.57464	0.14084
Arm Actuator Mount	Steel	0.04617	0.02909	0.49461	0.34561	0.03091
Angled Actuator Bracket	Steel	0.26741	0.16847	2.48788	1.73841	0.15549
Arm Cover Upper	ABS	0.01213	0.02256	0.19405	0.13559	0.01213
Arm Cover Lower	ABS	0.02334	0.04341	0.37344	0.26094	0.02334
U-Actuator Bracket	Steel	0.10789	0.06797	1.34367	0.93889	0.08398
Leg Actuator Mount	Steel	0.02936	0.01849	0.36625	0.25592	0.02289
Actuator Connector	Steel	0.05408	0.03407	0.27285	0.19066	0.01705
Knee Bracket	Steel	0.38990	0.24564	3.11237	2.17477	0.19452
Foot	Steel	0.24534	0.15457	3.71525	2.59603	0.23220
Leg Cover	ABS	0.04396	0.08177	0.70336	0.49147	0.04396
Foot Cover	ABS	0.02086	0.03880	0.33376	0.23321	0.02086
Head Bracket	Steel	0.04812	0.03031	0.46874	0.32753	0.02930
Neck Bracket	Steel	0.04283	0.02698	0.57927	0.40476	0.03620
Back Head Cover	ABS	0.02790	0.05189	0.44640	0.31192	0.02790
Front Head Cover	ABS	0.01708	0.03177	0.27328	0.19095	0.01708
Head LED Cover	ABS	0.00053	0.00099	0.00855	0.00597	0.00053
Eye Cover	ABS	0.00218	0.00405	0.03488	0.02437	0.00218
Pupil	ABS	0.00068	0.00126	0.01088	0.00760	0.00068

Design scenario 3:

Compnent name	Material	**Raw materials** (Steel, ABS, China) (kg)	**Manufacturing** (Electricity, coal, China) (kWh)	**Tranportation** (Sea freight, China to France) (tkm)	**Use** (Electricity, nuclear, France) (kWh)	**EoL** (Landfill (Steel), Incineration (ABS), France) (kg)
Hand	Steel	0.39485	0.24876	1.43460	1.00243	0.08966
Arm Actuator Mount	Steel	0.03078	0.01939	0.32028	0.22380	0.02002
Angled Actuator Bracket	Steel	0.13370	0.08423	1.11030	0.77582	0.06939
Arm Cover Upper	ABS	0.01213	0.02256	0.19405	0.13559	0.01213
Arm Cover Lower	ABS	0.02334	0.04341	0.37344	0.26094	0.02334
U-Actuator Bracket	Steel	0.05394	0.03399	0.60288	0.42126	0.03768
Leg Actuator Mount	Steel	0.01957	0.01233	0.18338	0.12813	0.01146
Actuator Connector	Steel	0.04281	0.02697	0.13565	0.09478	0.00848
Knee Bracket	Steel	0.19495	0.12282	1.49464	1.04438	0.09342
Foot	Steel	0.12267	0.07728	1.85762	1.29801	0.11610
Leg Cover	ABS	0.04396	0.08177	0.70336	0.49147	0.04396
Foot Cover	ABS	0.02086	0.03880	0.33376	0.23321	0.02086
Head Bracket	Steel	0.03208	0.02021	0.29541	0.20642	0.01846
Neck Bracket	Steel	0.02141	0.01349	0.26627	0.18606	0.01664
Back Head Cover	ABS	0.02790	0.05189	0.44640	0.31192	0.02790
Front Head Cover	ABS	0.01708	0.03177	0.27328	0.19095	0.01708
Head LED Cover	ABS	0.00053	0.00099	0.00855	0.00597	0.00053
Eye Cover	ABS	0.00218	0.00405	0.03488	0.02437	0.00218
Pupil	ABS	0.00068	0.00126	0.01088	0.00760	0.00068