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Trade-Off Characterization Between Social and Environmental Impacts Using Agent-Based Product Adoption Models and Life Cycle Assessment

Meeting the United Nations (UN) sustainable development goals efficiently requires designers and engineers to solve multi-objective optimization problems involving trade-offs between social, environmental, and economical impacts. This paper presents an approach for designers and engineers to quantify the social and environmental impacts of a product at a population level and then perform a trade-off analysis between those impacts. In this approach, designers and engineers define the attributes of the product as well as the materials and processes used in the product's life cycle. Agent-based modeling (ABM) tools that have been developed to model the social impacts of products are combined with life cycle assessment (LCA) tools that have been developed to evaluate the pressures that different processes create on the environment. Designers and engineers then evaluate the trade-offs between impacts by finding non-dominated solutions that minimize environmental impacts while maximizing positive and/or minimizing negative social impacts. Product adoption models generated by ABM allow designers and engineers to approximate population level environmental impacts and avoid Simpson's paradox, where a reversal in choices is preferred when looking at the population level impacts versus the individual product-level impacts. This analysis of impacts has the potential to help designers and engineers create more impactful products that aid in reaching the UN sustainable development goals.
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1 Introduction

The United Nations (UN) has published the sustainable development goals that are intended to improve the quality of human life around the world while protecting the environment and increasing economic activity [1]. These goals have been linked to social, economic, and environmental impact categories [2,3] and can be considered a multi-objective optimization problem involving at least those three dimensions [4,5].

For any multi-objective design optimization problem there is potential for trade-offs to be present between objectives, particularly near optimal regions of the design objective space [6]. Designers seeking to create products that help humanity reach the sustainable development goals would benefit from being able to understand where trade-offs exist between impacts. Designers would also benefit from having tools that enable them to quantify and compare those trade-offs in order to make informed design decisions [4]. Engineering for global development research has emphasized the need for defining and quantifying the social impacts of designs in communities [7,8]. Likewise, quantifying environmental impacts is important because the earth has limited resources that can be consumed and a limited ability to absorb generated emissions [9,10]. In response to these needs, researchers are starting to create methods that simultaneously assess the social and environmental impacts of products [4,11,12]. Other studies have compared the trade-offs between social and economic impacts [13].

The goal of this paper is to share an adoption-based approach for quantifying social and environmental impact that designers can use to perform trade-off analyses and comparisons between designs. This approach uses agent-based modeling (ABM) tools that have been developed to model the social impacts of products [14]—as it relates to product adoption—combined with life cycle assessment (LCA) tools that have been developed to evaluate the pressures that different processes create on the environment [15]. The approach will be expanded in future research to include tools that quantify economic impacts. This will allow designers to assess where trade-offs between the three impact categories exist when design changes are proposed and will also allow designers to quantify those trade-offs.

In an LCA, the damage a product has on the environment is measured in three different categories, often called areas of protection (AOPs) [15]. The three AOPs are damage to human health, damage to the ecosystem, and damage to resource availability [15,16]. An LCA calculates the impact of a product on the environment during the product's life cycle (design and prototyping, material extraction, production, distribution, use and disposal of the product) [9,17]. At each stage of the life cycle, the inputs and outputs of the processes involved in that stage create environmental pressures [15]. These environmental pressures are related to the three AOPs through characterization factors and damage pathways

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[16]. There are many methods for evaluating the impact of a product on the environment, such as the IMPACT World+ method [18], the ReCiPe method [16], and the LC-IMPACT method [15]. These LCAs can be either attributional (focused on how the attributes of a product impact the environment) or consequential (focused on how the use of a product impacts the environment) [19]. The scope of an LCA (i.e., the system that consumes resources and creates emissions) can be product-based, company-based, consumer-based, or nationally based [17].

LCA has the potential to help predict the environmental impacts of new products before they are introduced into the market. Predicting impacts requires designers to define the materials and processes used in the product before the product is created. Human behavior, however, cannot be modeled by LCA [20]. Therefore, traditional LCA is not well suited to model the complex, evolving nature of a new product's introduction into society [21]. The human behavior that needs to be modeled is sometimes referred to as the social and economic factors that influence LCA [22,23]. These factors influence information about the product, such as adoption numbers and critical design details. This means that scaling the results of an attributional LCA to a population level without a product adoption model will not lead to accurate information about the environmental impacts of the product [24].

In order to accurately scale attributional LCA results, a tool is needed that can model product adoption. ABM is a predictive tool that can be used to assess the effects of new products that are not well established in the market place [21,25]. ABM has the ability to model these social and economic factors [20] and has been used to predict product adoption and explore *what if* scenarios [26–28]. Some important human behaviors that influence LCA include non-price-driven human behavior (i.e., irrational and social behaviors) [20,26] and the rebound effect.

Rebound effect occurs when a designer creates a product that is more efficient in order to reduce the product's impact on the environment. The consumer, however, uses more of the product because it is more efficient. This increased use of the product counters the reduced environmental impact that the designer was hoping for. The end result is a more efficient product with a greater environmental impact, which is the opposite of what the designer intended. ABM can help designers predict the rebound effect and account for it in their LCA [20,29,30]. A good example of this effect is smart homes designed to reduce electricity use. Policy makers hoped that smart homes would decrease the amount of energy used per home but ABM simulations indicated that an increase in smart homes would actually increase the amount of energy used per home [20]. The product adoption models generated by ABMs are also starting to be used in parallel and in series with LCA to better predict the impacts of new products and policy changes on the environment [22,25,29,30].

It has also been shown that LCA results are influenced by ABM results [31]. Some examples of how LCA can be altered by ABM results include the following: (1) LCA results can be altered by different product adoption results predicted in an ABM [21] and (2) LCA results can be calculated at different time intervals during the product adoption ABM and fed to the agents, influencing their decisions in the model [28,32]. ABM results can also help designers and researchers understand all of the varying use cases that need to be modeled [24,27,29,30]. These examples show that there is a need to integrate LCA and ABM when modeling impacts.

This paper seeks to understand environmental impacts at a population level using both LCA and ABM to estimate how many products are adopted throughout the population, thus indicating to what degree a product has an overall environmental impact, and to what degree a product impacts society as a whole. Under the reasonable possibility that there are trade-offs between environmental and social impact, the method presented allows decision-makers to more clearly understand those trade-offs.

This paper will first present an approach to quantifying and comparing social and environmental impacts. It will then present a simple illustration of how to implement the approach using the COVID-19 virus and face masks as an example. Finally, there will be a discussion about the approach and important findings. The goal of the approach is to enable designers to recognize how design changes result in trade-offs and help designers perform trade-off analyses between impact categories. This will result in designers having a greater understanding of how design changes affect these impact categories and will enable designers to identify designs that minimize environmental impacts while maximizing positive and/or minimizing negative social impacts.

2 Methodology

There are three stages to integrate LCA and ABM to assess the trade-offs between environmental and social impacts. The stages are: (1) product definition, (2) product analysis, and (3) impact trade-off analysis. The three stages and the steps involved are shown in Fig. 1.

The integrated analysis uses the ABM developed by Mabey et al. [14] to model social impacts and product adoption, and the OPENLCA software package to calculate environmental impacts. It is important to note, however, that any LCA tool capable of calculating environmental impacts and any ABM capable of calculating social impacts and product adoption numbers can be used in this method.

2.1 Stage 1: Product Definition. The first stage is the product definition stage. This stage is important because the product definition will influence the results of the LCA and the ABM. The product definition consists of three parts: material specifications, process specifications, and product attributes (as shown in Fig. 1).

The first step is to define the materials and manufacturing processes used as accurately as possible to ensure that the LCA results represent the actual impact of the product on the environment. Approximations about quantities, material types, processes, and other inputs may be made, but they will decrease the accuracy of the LCA results. It is up to the designer to decide how much accuracy is desired.

The second step is to create a list of product attributes that define key elements of the product. Product attributes are characteristics of the product that will affect the social impact of the product and a person's decisions to adopt the product. The attributes should allow for application to multiple versions of the product. They are quantifiable and describe performance requirements of the product. These product attributes are synonymous with the functional units of the product system [33]. Examples of attributes include esthetics, comfort, and effectiveness. The product definition contains the product's ratings for each attribute. When the designer makes changes to product features, the product should be re-rated for each attribute. These new ratings will be used in the new product definition. The product's rating for each attribute influences the agent's adoption decision in the model [14].

The results of this stage are a product definition consisting of materials used, manufacturing processes used, and ratings for each product attribute. Figure 1 shows how the attributes enter the ABM in stage 2 while the materials and processes used during the product life cycle enter the LCA in stage 2.

2.2 Stage 2: Product Analysis. The second stage of the process is the product analysis stage. This stage of the process is to model the potential social and environmental impacts of the product. The product analysis is broken down into four steps: (1) performing an attributional LCA of the product, (2) performing a sensitivity analysis of the results, (3) executing an ABM simulation to obtain population level adoption numbers and the product social impact data, and (4) integrating the product adoption model from the ABM with the results of the sensitivity analysis and LCA. Because the ABM and LCA results are independent of each other, they can be run in parallel. The result of this analysis is data on the social and environmental impacts of the product.

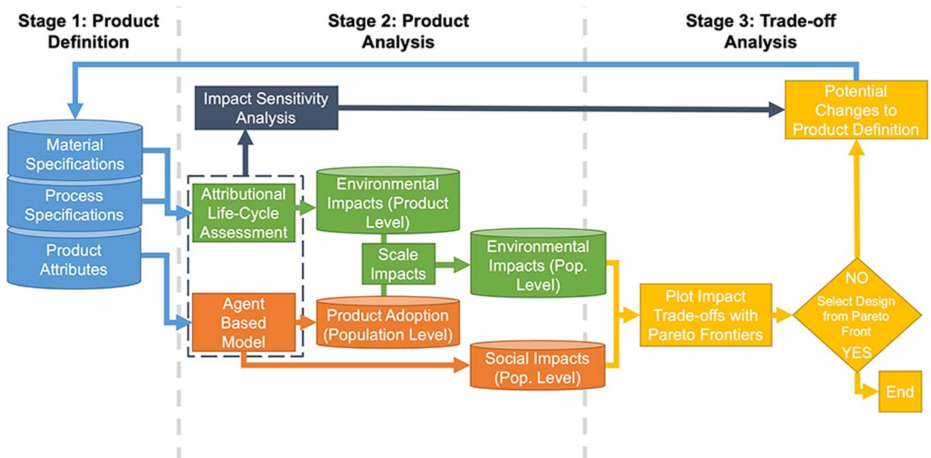

Fig. 1 Block diagram illustrating approach for using LCA and ABM results to inform engineering decision-making process. The results of the analysis are both environmental and social impacts that must be weighed by the designer in an impact trade-off analysis.

2.2.1 Attributional Life Cycle Assessment. This step is illustrated by the box labeled "Attributional Life Cycle Assessment" in Fig. 1. The LCA can be built using any LCA software package. The designer can also use any of the various databases containing information about pressure placed on the environment by resource extraction, refining, and manufacturing processes when building the LCA. Once the LCA is built, it will be used to evaluate the product's environmental impacts.

There are many methods for evaluating environmental impacts. All of these methods have similar midpoint and endpoint impact categories [15,16,34]. The ReCiPe(H) midpoint method will be used to perform the evaluation because it is a well-established method in the literature [9,35]. The midpoint method calculates the impact of environmental pressures and links them to 17 environmental impact categories [16]. Those impact categories include types of acidification (increases in acidity), toxicity (presence of toxins in the food chain), eutrophication (presence of nutrients limiting aquatic biomass), and damages to the atmosphere [36]. The ReCiPe(H) endpoint method (which links environmental pressures to the three AOPs stated in the introduction [16]) can be used for a simpler analysis. The 17 midpoint impact categories and three AOPs are listed in Tables 1 and 2, respectively. Because the midpoint method yields a more detailed understanding of environmental impacts, it will be used in this paper. When evaluating the environmental impacts, P represents the environmental impacts at a product level. If there are m impact categories, then P is defined by Eq. (1)

$$P = \left[p_1\, p_2 \ldots p_j \ldots p_m\right]^{\mathrm{T}} \tag{1}$$

where P is calculated using the LCA software (e.g., OPENLCA). The functions used in the LCA software to evaluate the environmental impacts of the input variables in the model are represented by $f(\mu)$, where

$$P = f(\mu) \tag{2}$$

and μ is a set of n variables of the form

$$\mu = \left[\mu_1\, \mu_2 \ldots \mu_i \ldots \mu_n\right]^{\mathrm{T}} \tag{3}$$

that represent the inputs to the LCA.

The results of the LCA evaluation are represented in Fig. 1 by the database symbol labeled "Environmental Impacts (Product Level)."

2.2.2 Agent-Based Model. This step is illustrated by the box labeled "Agent-Based Model" in Fig. 1. In the approach presented in this paper, the purpose of the ABM is to inform the patterns of product adoption in the population and to subsequently understand the social impacts of the product on the larger society. We use an ABM previously developed by the authors [14], where inputs for different sub-models are used to construct the ABM. This framework for social impact ABM requires information about the product, the society the product exists within, the particular scenario or context for the model, and what social impacts are being investigated. Possible areas of social impact should be explored, and indicators to measure the selected social impacts should be selected.

Table 1 ReCiPe midpoint impact categories [16]

Midpoint impact category	Units
Climate change	kg CO_2-eq to air
Ozone depletion	kg chorofluorocarbon (CFC)-11-eq to air
Ionizing radiation	kBq Co-60-eq to air
Fine particulate matter formation	kg PM2.5-eq to air
Photochemical oxidant formation: terrestrial ecosystems	kg NOx-eq to air
Photochemical oxidant formation: human health	kg NOx-eq to air
Terrestrial acidification	kg SO_2-eq to air
Freshwater eutrophication	kg P-eq to freshwater
Human toxicity: cancer	kg 1,4-dichlorobenzene (DCB)-eq to urban air
Human toxicity: non-cancer	kg 1,4-DCB-eq to urban air
Terrestrial ecotoxicity	kg 1,4-DCB-eq to industrial soil
Freshwater ecotoxicity	kg 1,4-DCB-eq to freshwater
Marine ecotoxicity	kg 1,4-DCB-eq to marine water
Land use	m^2 × year annual cropland-eq
Water use	m^3 water-eq consumed
Mineral resource scarcity	kg Cu-eq
Fossil resource scarcity	kg oil-eq

Table 2 ReCiPe endpoint areas of protection [16]

Area of protection	Units	Explanation
Damage to human health	Disability adjusted life years	Years lost due to disease or accident
Damage to ecosystems	Species·year	Disappeared species per year
Damage to resource availability	USD	Extra cost required for future resource extraction

Agents, which represent individuals within a population, are ideally created based on data from real-world populations. These data may be obtained through census data or surveys. Within the model, rules are created that govern the decision-making of agents and whether they will adopt the product. Rules are also made to govern the probability that the product will have a social impact on the agent based on the choice to adopt or not adopt the modeled product. An example of this would be, if a person adopts the use of cigarets, then there is an increased probability of lung disease. In that case, cigarets would be the product, the social impact category would be health and safety of that individual, and rates of lung disease as the indicator for the social impact. It is important that these rules are created based on empirical data to more closely match the model to real-world behavior.

The selection of impact categories and indicators will differ based on the product. Because social impact analysis has not yet reached the level of maturity that environmental impact analysis has, there is no commonly expected set of social impacts to include in a social impact model [2]. This requires the designer to define the social impact categories to model and select metrics to measure the social impacts. Difficulties in this process have been noted by the UN and include the following: (1) many social impacts are qualitative and it is difficult to consistently quantify results across different studies and (2) it can be expensive to collect the large amounts of data required to build social impact models when that data do not already exist [37].

To facilitate social impact modeling, the UN has published guidelines for choosing social impacts to measure in the United Nations Environment Program Guidelines for Social Life Cycle Assessment of Products [37]. An example of how to choose social impact categories can also be found in Ref. [2] where the UN sustainable development goals are used directly to create impact categories. Designers can use the guidelines in this paper when choosing which social impacts to model and which ABM tools to use.

Constructing an ABM of social impact is not trivial but it can be valuable since ABM can expose the connection between a product's impact on a single individual and its adoption across and impact on the larger population. Importantly, impact and adoption at the agent level can be aggregated to understand population level trends. These population level trends influence both social and environmental impacts.

It is important to note that ABM is a stochastic process, so it will be necessary to run ABM simulations a sufficient number of times to understand the distribution of results. The exact number of times the simulation needs to be run will vary based on the specific case, but at a minimum, it should be enough times that the standard deviation of results does not change significantly with more simulation runs. More detailed information on the creation of social impact ABMs can be found in Ref. [14]. This previously developed framework outputs results for the number of agents that adopt the product and the social impacts investigated. The number of agents who chose to adopt the product during the simulation is called the product adoption number. In Fig. 1, it is represented by the database symbol labeled "Product Adoption (Population Level)." It is also represented by the variable α and will be used to properly scale the attributional LCA results. The calculated social impacts are represented in Fig. 1 by the database symbol labeled "Social Impacts (Pop. Level)."

2.2.3 Scale Impacts. The product-level environmental impacts are scaled by the product adoption model to produce the population level environmental impacts in this step, as shown in Fig. 1. In Eq. (4), I represents the environmental impacts at a population level, while α is a scalar that represents the product adoption number calculated using the ABM. I is calculated by scaling P by α.

$$I = \alpha P \tag{4}$$

The results of this step are represented in Fig. 1 by the database symbol labeled "Environmental Impacts (Pop. Level)." I can be compared in stage 3 to the population level social impacts (see Fig. 1).

2.2.4 Impact Sensitivity Analysis. This step is illustrated by the box labeled "Impact Sensitivity Analysis" in Fig. 1. **S** is an $m \times n$ matrix that represents how P varies with respect to the variations in μ. Each column in **S** represents how the environmental impacts, P, are sensitive to a variation in input μ_i.

$$\mathbf{S} = \frac{\partial P}{\partial \mu} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1i} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2i} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & & & \vdots \\ s_{j1} & s_{j2} & & s_{ji} & & s_{2n} \\ \vdots & \vdots & & & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mi} & \cdots & s_{mn} \end{bmatrix} \tag{5}$$

The columns of **S** are calculated using Eq. (6)

$$S_i = f(\varepsilon_i) \tag{6}$$

where

$$\varepsilon_i = \Delta_i \mu \tag{7}$$

and Δ_i is an $n \times n$ identity matrix with the iith term replaced by δ where δ represents the percent variation

$$\Delta_i = \begin{bmatrix} 1 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & & & \vdots \\ 0 & 0 & & \delta & & 0 \\ \vdots & \vdots & & & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & 1 \end{bmatrix} \tag{8}$$

The results of Eq. (7) are a vector of the form

$$\varepsilon_i = \left[\mu_1\, \mu_2 \ldots \delta\mu_i \ldots \mu_n\right]^\top \tag{9}$$

It is important to note in Eq. (9) that only μ_i is scaled by δ. This means that each of the inputs to the LCA can be tested independently of the other inputs to determine its sensitivity to variation. The results of the sensitivity analysis represented in Fig. 1 are used when considering the impact of potential changes to the product definition.

2.3 Stage 3: Impact Trade-Off Analysis. This paper is based on the reasonable assumption that environmental impacts may be in conflict with social impacts [4] and that the designer would benefit from being able to characterize the trade-offs between them for the purpose of decision-making. There are various ways for designers to visualize or explore trade-offs between sustainability objectives [12]; finding and then visualizing Pareto frontiers, or Pareto sets, or simple non-dominated solution sets are one particular way, which we suggest as part of this paper.

We make this suggestion because of the rich literature existing on Pareto-based trade-off exploration [5,6,38–40], which demonstrates the value of plotting/visualizing non-dominated solution sets in a design objective space such as a sustainability space [12].

A non-dominated set of solutions (sometimes derived from Pareto frontiers in the literature) represent the set of solutions for which trade-offs are present, meaning to improve in one objective such as minimizing negative social impact, one must give up something in another objective such as minimizing negative environmental impact. The non-dominated set is important to designers because it represents the set of solutions from which an optimal solution can be selected. All dominated solutions are pragmatically worse in every way when compared to at least one solution in the non-dominated set, thus the non-dominated set is of interest.

Simple two- and three-dimensional Pareto sets can be easily visualized [41]. Larger n-dimensional spaces can also be easily explored through visual analytics techniques [38,39]. Once designers choose specific solutions from the Pareto set, the design parameters required to achieve that design can be easily known [5], thus informing how to change the design to achieve the desired outcome.

For Pareto-based exploration methods to be useful, a meaningful non-dominated set must first be acquired. There are various techniques used to acquire such sets, ranging from deterministic gradient-based methods, to stochastic genetic algorithms, to simply acquiring the set through brute force, and filtering [5]. When using this approach, the special case involving no conflict at all simply results in a single optimal design that optimizes all objectives without conflict. Therefore, the Pareto-based exploration approach presented herein works regardless of the presence of conflict. It is important to note, however, that the presence of a conflict is rarely known without performing a trade-off analysis, which is why this paper advocates that stage 3 (impact trade-off analysis) be carried out.

To perform the impact trade-off analysis, various instances of the design are considered. For each instance, the mean environmental impacts are compared with the mean social impacts. Each dimension of the environmental impacts (e.g., the AOPs or midpoint environmental impacts) should be compared to each dimension of the social impacts calculated by the ABM.

Figure 2 illustrates how various instances of a hypothetical design (*product definition 1* and *product definition 2*) can be compared. The plot shows the designer that both *product definition 1* and *product definition 2* contain non-dominated solutions. These are the solutions closest to the solid curve (or trade-off curve). This representation of the trade-offs helps the designer see not only which instance of a particular definition is best but also that there are environmental/social trade-offs between product definitions 1 and 2. Product definition 1 is shown to be best socially, but product definition 2 is shown to be best environmentally. Therefore, a trade-off exists between product definition 1 and product definition 2.

Furthermore, using **S** from Eq. (5), the designer can gain understanding of which inputs to the LCA have the greatest influence on environmental impacts. This can inform the designer which parts of the product definition to change. An easy way to interpret **S** is to

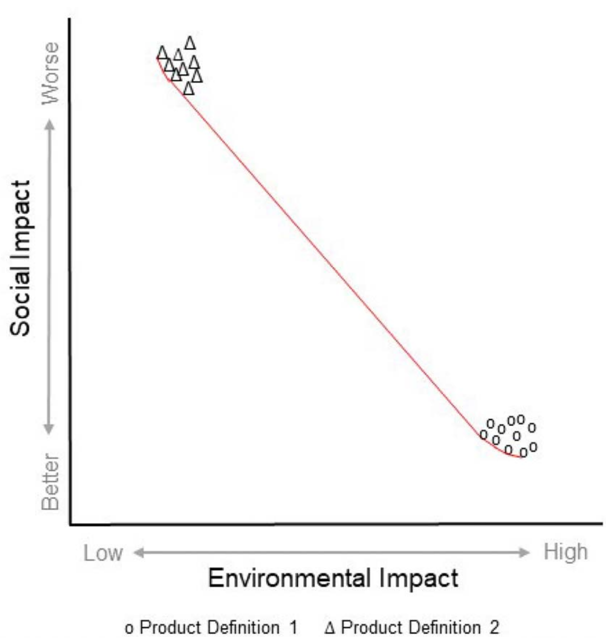

Fig. 2 An example of a social impact and a scaled environmental impact being compared using a trade-off curve

convert the elements of **S** into percent changes in impact. These percent changes in impact can be represented by the matrix **D**

$$\mathbf{D}=\begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1i} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2i} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & & & \vdots \\ d_{j1} & d_{j2} & & d_{ji} & & d_{2n} \\ \vdots & \vdots & & & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mi} & \cdots & d_{mn} \end{bmatrix} \tag{10}$$

where the elements of **D** can be calculated using Eq. (11).

$$d_{ji}=100\left(\frac{s_{ji}}{p_j}-1\right) \tag{11}$$

The elements of **D** represent the percent change (i.e., the sensitivity) of an environmental impact to δ_i. If δ_i is greater than 1 (representing an increase in input μ_i), then s_{ji} is generally greater than p_j and s_{ji}/p_j is greater than 1. The result of Eq. (11) is the percent increase in impact. The inverse is true when δ_i is less than 1 (representing an decrease in input μ_i). A higher percent change indicates a higher sensitivity. Designers can use this information to make informed decisions about which changes to the product definition will likely decrease certain environmental impacts.

Returning to stage 1, the designer can redefine the product based on potential improvements and perform the analysis again. The new product definition (*product definition 3*) can be compared with the old product definitions (*product definitions 1 and 2*) so that the designer can evaluate if the changes have resulted in a new non-dominated solution. Changes to the product definition should be evaluated again because it is possible that changes intended to reduce environmental impacts may have negative effects on social and/or environmental impacts. The designer can continue to make changes to the product definition and perform the analysis until the product definition results in non-dominated solutions. Ultimately it is up to the designer choose a single design from the non-dominated set, which he/she believes will be best when trying to meet the UN sustainable development goals or other sustainability goals.

3 Simple Illustrative Example

In this section, the method presented in Sec. 2 is illustrated by a simple design example. The product being designed in the illustration is a face mask intended to slow the transmission of COVID-19. The simple case of designing COVID-19 face masks was chosen because the problem, candidate solutions, and health impacts can be understood with minimal text to introduce them. In addition, there is enough citable data on face masks and COVID-19 to perform social and environmental impact analyses without the need for lengthy discussion or the need to overburden the paper with data [14].

It is not the intent of the authors to propose a new mask design or to use the results of this simple illustration to affect policy or anything of the sort. Instead, the purpose of the illustration is to show how a designer, working through the design process, would evaluate the environmental and social impacts of alternative design concepts.

The social impact considered in this example is the total number of COVID-19 cases per 10,000 people [14], and the environmental impacts considered are the environmental pressures created by all steps in the production of the mask as listed in Table 1.

In this simple example, three COVID-19 mask designs are compared. They are an N95 mask, a cloth mask, and a neck gaiter (see Fig. 3). The authors chose to use OPENLCA and the ABM created by Mabey et al. [14], even though various LCA and ABM models could be used. For simplicity, the LCA used here only considers the environmental impacts during production, not during

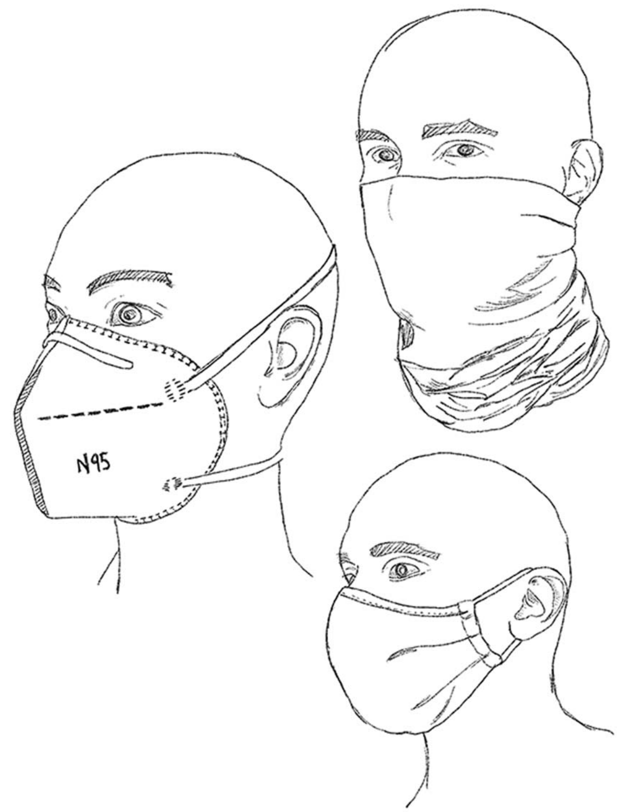

Fig. 3 Three COVID-19 face mask designs considered in the example: N95 (right), gaiter (top), and cloth mask (bottom)

distribution, use, or disposal. While this is the case for this simple illustration, there is nothing about this paper's overall framework (presented in Sec. 2) that prevents these LCA elements from being considered. Similarly, social impacts are considered only for the use phase. Social impacts during production, distribution, and disposal, such as the health of manufacturing line workers, were not included. A full life cycle analysis of this problem would, of course, need to include these other important parts of a product's life cycle. The justifications for these choices in constructing this simple model are that: (1) approximately 75% of energy consumption in garment manufacturing occurs before the use and disposal phases [42], (2) in the case of cotton garment production, it is estimated that 88% of the water consumed during the garment's life cycle also occurs in the production phase [42], (3) there is an abundance of data on COVID mask effectiveness and COVID transmission rates from which to make accurate social impact models for the use phase, and (4) these model simplifications allow us to illustrate the approach without overburdening the paper with a larger more complex model.

Table 3 Mask materials and material quantities

Mask feature	Material	Mass (g)
N95 mask [43,44]		
Face covering	Polypropylene	6.57
Straps	Synthetic rubber	1.75
Nose bridge	Aluminum	0.99
Foam nose guard	Polyurethane	0.05
Cloth mask		
Face covering	Cotton	13.68
Straps	Cotton	7.06
Neck gaiter		
Face covering	Polyester	36.01

3.1 Stage 1: Mask Definition. The first step in defining the masks is to articulate the materials and processes used to create the masks. The materials and quantities used to create each mask are defined in Table 3.

The processes used to create the masks were defined in OPENLCA using data from Ecoinvent and Agribalyse found in the Environmental Footprints (Nexus version 4) and the AGRIBALYSE v3.0 (Nexus version 1) databases downloaded from the OPENLCA Nexus. These processes were represented by flow diagrams shown in Figs. 4–6. Figure 4 shows the material and energy flows required to form an N95 mask [44–46]. The box labeled "Electricity" represents electricity that is required for different processes. The boxes labeled "Polypropylene Fiber," "Aluminum Extrusion," "Synthetic Rubber Straps," and "Polyurethene Flex Foam" on the far left of the flow diagram represent materials that are found in the Ecoinvent and Agribalyse databases. These materials go through different processes (represented by the other boxes) and the output of the processes is an N95 mask that can be sent to market.

After defining the materials and processes, the next step is to create a list of product attributes that each design can be rated on. The attributes chosen to define these masks are (1) effectiveness, (2) comfort, and (3) esthetics. These attributes were chosen because they were identified in surveys of potential face mask users as aspects of the mask that can be changed from a design perspective that affect a person's choice of whether to adopt a face mask [48]; ratings for comfort and esthetics were based upon this survey data from 745 participants. Effectiveness also affects how well a mask prevents a person from spreading or contracting COVID-19. The effectiveness was based upon research on the filtration effectiveness of different mask types [49,50]. Rating scales for each of the attributes were as follows: effectiveness was rated on a scale of 0–5 with 0 being completely ineffective in stopping the spread of COVID-19 and 5 being completely effective. Comfort was rated on a scale of −5 to 0, with −5 being extremely

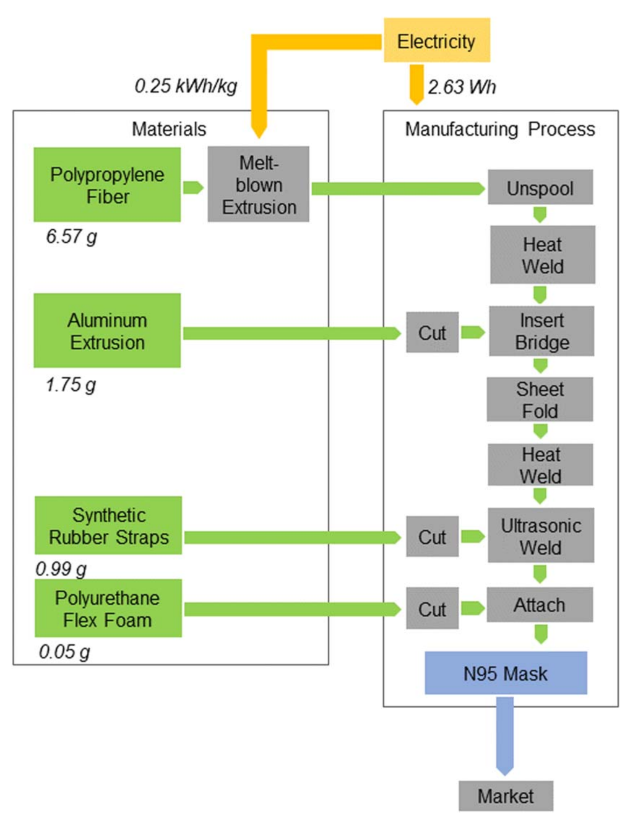

Fig. 4 Material and energy flow for production of an N95 mask [44–46]

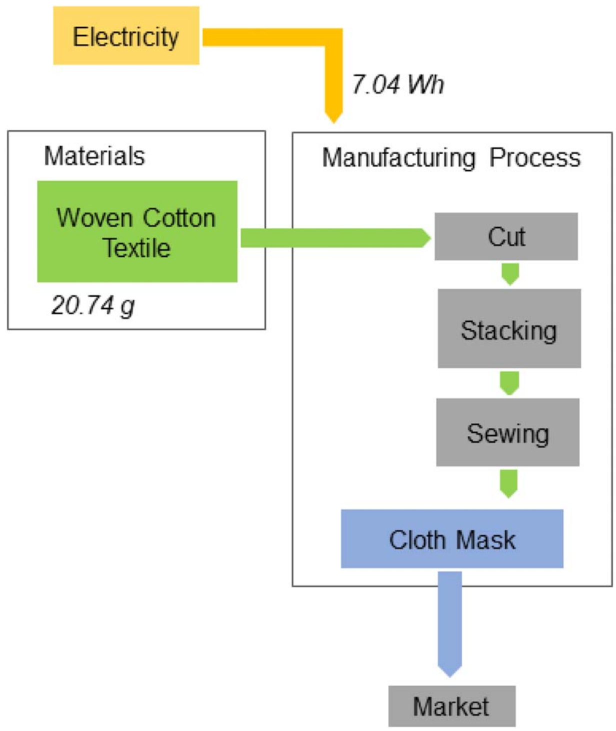

Fig. 5 Material and energy flow for production of a cloth mask [44,46,47]

uncomfortable and 0 being so comfortable that the mask is not noticeable. Esthetics was rated on a scale of −5 to 5 with −5 being very unattractive and 5 being very attractive. All ratings were normalized negative or positive between 0 and 5. Maximum comfort was 0 given that all masks produce discomfort. Minimum filtration was 0 given that masks cannot produce a negative filtration. And esthetics ranged from −5 to 5 indicating that esthetics can persuade and dissuade mask adoption. Ratings for the attributes of the three masks can be found in Table 4.

The materials listed in Table 3, the flows defined in Figs. 4–6, and the product attribute ratings in Table 4 represent the product definition that are used in the next stage of the analysis.

3.2 Stage 2: Mask Analysis. In this stage, an LCA, ABM simulations, and a sensitivity analysis were performed for the different mask product definitions to illustrate the approach. Using discrete choice analysis, a binomial or multinomial choice model can be used [51]. In the ABM, a binomial choice model was used in order to isolate the impacts of a single mask type. Although a multinomial choice model would mimic society more closely, it would be difficult to isolate differences in impact between the designs. Using a binomial choice model allows the designer to compare the relative results at the population level. The data generated in this stage will be used in stage 3 to analyze the trade-offs between the different product definitions.

3.2.1 Mask Life Cycle Assessment. The inputs and outputs of the flow diagram shown in Fig. 4 represent the processes involved in creating an N95 mask. Using OPENLCA, a free LCA software package, flows were created that represent the flow of materials and energy during different stages of the product's life cycle. These flows were linked together to form processes with inputs and outputs. The output for these processes is a single unit of product. A product system that could be evaluated was then created in OPENLCA using the processes.

Similar product systems were created in OPENLCA based on the flows shown in Figs. 5 and 6 for a cloth mask and a gaiter, respectively. An attributional LCA was then performed for each mask design in OPENLCA using the ReCiPe(H) midpoint method. In total, three LCAs were performed: one for the gaiter, one for the cloth mask, and one for the N95 mask. These LCAs calculated the product-level impacts of each mask design on the environment. The results of the LCA evaluation are found in Table 5.

3.2.2 Mask Agent-Based Model. A previously developed ABM on COVID-19 and face masks was extended to meet the needs of this study [14]. The ABM used data from the *2019 American Community Survey* [52], *American Time Use Survey* [53], and 2020 survey data on mask use [48,54] to build a population of agents and the rules that govern their behavior. Virus parameters such as

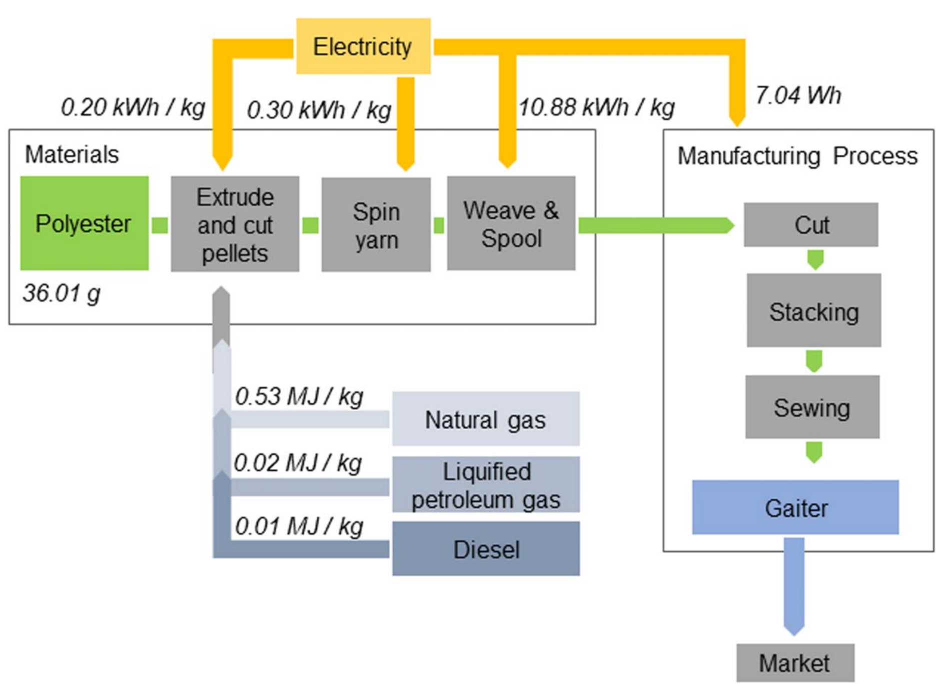

Fig. 6 Material and energy flow for production of a gaiter [44,46,47]

Table 4 Mask attribute ratings for an N95 mask, a cloth mask, and a neck gaiter [14]

Mask type	Effectiveness	Comfort	Esthetics
N95	4.75	−4.5	−3
Cloth	2.5	−2.5	3
Neck gaiter	1	−0.5	3

Table 6 Social impact (COVID-19 case numbers) of masks

Mask type	$\text{Cases}_{\text{Median}}$ (per 10,000 ppl)	$\text{Cases}_{\text{StdDev}}$ (per 10,000 ppl)
N95	62	11.31
Cloth	97	36.6
Gaiter	528.5	251.86

the replication rate and duration of illness were set according to data provided by the United States Centers for Disease Control and Prevention [55]. The adoption framework used in the model is based on using discrete choice analysis [56] with the theory of planned behavior [57] as done by Pakravan and MacCarty [58]. This approach allows for taking into account attitudes toward face masks, social influences, government mandates, virus severity, and face mask attributes when an agent is making the decision to adopt the use of a face mask. Mask mandates fall under a term called perceived behavioral control in the theory of planned behavior. This term relates to how much control a person has over his or her own choices regarding the behavior. In the case of this model, the perceived behavioral control term was held constant to focus on how changes to mask attributes change the number of cases of COVID-19. We acknowledge that using sociotechnical system models can help inform policy decisions such as government mandates, but we have limited the scope of this model to focus on changes to the product.

For simplicity of illustration, we included only one social sustainability measure in this COVID-19 mask example. While we believe there are various social sustainability measures that could be included such as how education is impacted by COVID-19 infection and COVID-19 mask usage, or how paid work has been affected by COVID-19 and COVID-19 mask usage, we choose not to include them in this illustration, simply to keep the example short and relatively obvious. Readers who are interested in the author's methods for including various social impacts into a product evaluation are referred to Ref. [59], which details social impact aggregation, but does it outside of the context of LCA.

The ABM simulated the mask adoption number (the number of people per 10,000 who would choose to adopt the mask) and calculated the social impact of each mask type on the population (number of COVID-19 cases per 10,000 people). The stochastic nature of any ABM yields a distribution of results. Therefore, 100 repetitions of the simulation were executed for each mask type so that the range of results of adoption and social impacts could be found. This number of repetitions was selected because for additional simulation runs the standard deviation of the results changed less than 1%, and the variation was sufficiently captured. Although the validation of predictive sociotechnical models is difficult, this model was validated using macrovalidation and microvalidation techniques as described by North and Macal [60]. Microvalidation is the validation of individual components of the model. In this model, microvalidation was carried out to ensure that virus parameters matched real-world estimates, the synthetic population of agents matched the demographics of the real-world population, and that mask parameters match lab studies and surveys. It is difficult to perform quantitative macrovalidation on each of the model outputs, but adoption rates generally align with those observed in the literature [61]. Complete details on the model creation and validation can be found in Ref. [14].

In this paper, changes were made to the ABM developed in Mabey et al.'s study in order to tabulate the total number of people who adopted masks in the population (M). This number was different from α in Eq. (4). M represented the number of people who chose to adopt the mask whereas α represented the total number of masks used by the community. The reason for this difference was the assumption made by the authors that people adopting a mask were likely to use multiple product units. To relate α to M, Eq. (12) was used. M was scaled by the number of masks that each person who adopted a mask used (γ) and an approximation of the number of people in the US population ($\rho = 300,000,000$) [62].

$$\alpha = \frac{M}{10{,}000}\gamma\rho \tag{12}$$

The social impacts of the different masks can be found in Table 6. These values represent the median number of cases and the standard deviation between the number of cases for the 100 simulations for each mask design.

According to Grand View Research, the value of the reusable mask market in 2020 was USD 19.2 billion and 28.4% of that market that was in North America [63]. Based on these numbers,

Table 5 Environmental impacts at a product level and at a population level

Midpoint impact category	Product level N95	Product level Cloth	Product level Gaiter	Population level N95	Population level Cloth	Population level Gaiter
Climate change (kg CO_2-eq)	1.3×10^{-2}	5.0×10^{-1}	9.5×10^{-2}	7.97×10^{7}	5.89×10^{8}	1.14×10^{8}
Ozone depletion (kg CFC-11-eq)	4.4×10^{-9}	1.1×10^{-6}	3.9×10^{-8}	2.74×10^{1}	1.23×10^{3}	4.59×10^{1}
Ionizing radiation (kBq Co-60-eq)	2.1×10^{-3}	5.1×10^{-2}	1.2×10^{-2}	1.28×10^{7}	5.95×10^{7}	1.37×10^{7}
Fine particulate matter formation (kg PM2.5-eq)	1.8×10^{-5}	1.1×10^{-3}	2.1×10^{-4}	1.12×10^{5}	1.24×10^{6}	2.53×10^{5}
Photochemical oxidant formation: terrestrial ecosystems (kg NOx-eq)	2.8×10^{-5}	1.1×10^{-3}	2.1×10^{-4}	1.7×10^{5}	1.3×10^{6}	2.5×10^{5}
Photochemical oxidant formation: human health (kg NOx-eq)	2.6×10^{-5}	1.1×10^{-3}	2.0×10^{-4}	1.6×10^{5}	1.3×10^{6}	2.4×10^{5}
Terrestrial acidification (kg SO_2-eq)	4.6×10^{-5}	2.0×10^{-3}	3.4×10^{-4}	2.9×10^{5}	2.4×10^{6}	4.0×10^{5}
Freshwater eutrophication (kg P-eq)	5.3×10^{-6}	2.5×10^{-4}	5.1×10^{-5}	3.3×10^{4}	2.9×10^{5}	6.1×10^{4}
Human toxicity: cancer (kg 1,4-DCB-eq)	5.9×10^{-4}	2.8×10^{-2}	3.9×10^{-3}	3.7×10^{6}	3.3×10^{7}	4.7×10^{6}
Human toxicity: non-cancer (kg 1,4-DCB-eq)	7.5×10^{-3}	3.3×10^{-1}	5.6×10^{-2}	4.6×10^{7}	3.8×10^{8}	6.7×10^{7}
Terrestrial ecotoxicity (kg 1,4-DCB-eq)	1.4×10^{-2}	6.7×10^{-1}	1.1×10^{-1}	8.7×10^{7}	7.8×10^{8}	1.3×10^{8}
Freshwater ecotoxicity (kg 1,4-DCB-eq)	4.3×10^{-4}	2.2×10^{-2}	4.4×10^{-3}	2.7×10^{6}	2.6×10^{7}	5.3×10^{6}
Marine ecotoxicity (kg 1,4-DCB-eq)	5.7×10^{-4}	2.7×10^{-2}	5.7×10^{-3}	3.6×10^{6}	3.2×10^{7}	6.8×10^{6}
Land use ($m^2 \times$ year annual cropland-eq)	$\mathbf{5.5\times10^{-4}}$	2.0×10^{-1}	$\mathbf{1.1\times10^{-3}}$	$\mathbf{3.4\times10^{6}}$	2.4×10^{8}	$\mathbf{1.3\times10^{6}}$
Water use (m^3 water-eq)	$\mathbf{1.9\times10^{-4}}$	4.8×10^{-2}	$\mathbf{6.4\times10^{-4}}$	$\mathbf{1.2\times10^{6}}$	5.7×10^{7}	$\mathbf{7.6\times10^{5}}$
Mineral resource scarcity (kg Cu-eq)	$\mathbf{2.8\times10^{-5}}$	7.0×10^{-4}	$\mathbf{7.5\times10^{-5}}$	$\mathbf{1.8\times10^{5}}$	8.2×10^{5}	$\mathbf{8.9\times10^{4}}$
Fossil resource scarcity (kg oil-eq)	$\mathbf{6.0\times10^{-3}}$	1.2×10^{-1}	$\mathbf{2.4\times10^{-2}}$	$\mathbf{3.7\times10^{7}}$	1.4×10^{8}	$\mathbf{2.9\times10^{7}}$

Note: Cases where Simpson's paradox occurs are bolded.

Table 7 Adoption numbers from ABM simulations

Mask type	M_{Median} (per 10,000 ppl)	M_{StdDev} (per 10,000 ppl)	$\gamma_{\text{Individual}}$ (masks/ adopter)	α_{Median} (masks)
N95	8279	31.90	25	6.21×10^9
Cloth	9746	16.91	4	1.17×10^9
Gaiter	9931.5	106.11	4	1.19×10^9

the value of masks sold in North America was USD 5.45 billion. According to a survey conducted by McKinsey and Co. 77% of women and 71% of men wore a reusable mask at least once a week [64]. The U.S. Census reports that the US population was 331,449,281 people in 2020 and that 50.8% of the population are women [62]. Based on these data, there are approximately 246 million reusable mask users in the USA. The average price of the 40 top selling reusable masks on Amazon.com was USD 5.85 at the time this study was performed. The number of reusable masks sold was 932 million based on the average cost per mask and the market value of masks sold in North America in a year. This means that the average reusable mask user bought 3.79 masks per year. Because people cannot own part of a mask, this number is rounded up to four masks per year or $\gamma=4$ for each person who adopts a cloth mask or gaiter.

Studies suggest that each N95 mask can be used up to 25 times before filtration decreases [65] and the CDC recommends that N95 masks be used no more than five times by healthcare workers [66]. Based on this information, it is assumed that each person who adopts an N95 mask uses it 15 times before replacing it. Assuming one use per day means that the N95 mask will be replaced every 15 days and 25 masks will be used in a year or $\gamma=25$ for N95 masks.

The median mask adoption numbers, mask adoption standard deviation, individual adoption number, and adoption number are found in Table 7. These values represent the 100 repetitions for each mask in the ABM.

3.2.3 Scale Impacts. The environmental impacts of each mask calculated during the LCA step (see Table 5) are scaled by the number of masks used by the population, α (see Table 7), using Eq. (4). The α value for each simulation is used to scale each environmental impact. The median population level impacts for each mask design calculated in this step are found in Table 5. One important detail to note is that some designs have a lower impact relative to the other designs at a product level (individual-level) but a higher impact relative to the other designs at a population level and vice versa. This paradox is called Simpson's paradox. Simpson's paradox occurs when a dataset appears to have a certain trend but that trend is reversed when the data are aggregated [67]. In this case, some mask designs appear to have lower relative environmental impacts until those impacts are scaled by a product adoption model. This paradox is a good example of why using product adoption models to scale LCA results is important. Impacts not scaled by a product adoption model can lead designers to make trade-offs that are unintentionally worse for the environment. This is similar to the rebound effect that can occur with products intended to decrease environmental impacts [20,29,30]. Examples of Simpson's paradox are highlighted in Table 5.

3.2.4 N95 Mask Sensitivity Analysis. The N95 mask has the largest set of materials in its product definition compared to the other masks being analyzed so it was used as the example for conducting the sensitivity analysis. In practice, designers should conduct a sensitivity analysis for each product definition.

In this sensitivity analysis, $\delta=1.2$ and $\delta=0.8$ were used for each input. This represents a 20% variation plus or minus in each input parameter. Each input to the LCA model (electricity, polypropylene fiber, aluminum, synthetic rubber, and polyurethane flex foam) was varied by $\delta=1.2$ and then by $\delta=0.8$ and the model was evaluated. These steps are represented by Eqs. (5), (6), and (8). The two $\mathbf{S}$ matrices, $\mathbf{S}_{1.2}$ and $\mathbf{S}_{0.8}$, were then converted to percentages using Eq. (11). The resulting $\mathbf{D}$ matrices, $\mathbf{D}_{1.2}$ and $\mathbf{D}_{0.8}$, are found in Table 8.

3.3 Stage 3: Mask Impact Trade-Off Analysis. In the trade-off analysis, the population level social impacts in Table 6 are compared to the population level environmental impacts in Table 5. To acquire the non-dominated set for this paper, we carried out the ABM simulation 100 times, collected the results, and filtered them to retain only the set of non-dominated solutions. All the solutions have been included in the plots but the non-dominated

Table 8 Results of the sensitivity analysis for the N95 mask expressed as percent changes in impact due to δ

		Percent change in impact due to δ									
		Aluminum		Foam		Strap		Polypropylene fiber (PPF)		Electricity	
Impact category	Unit	$\delta=1.2$	$\delta=0.8$	$\delta=1.2$	$\delta=0.8$	$\delta=1.2$	$\delta=0.8$	$\delta=1.2$	$\delta=0.8$	$\delta=1.2$	$\delta=0.8$
Fine particulate matter formation	kg PM2.5-eq	0.362	−0.362	**16.316**	**−16.316**	1.196	−1.196	2.127	−2.127	0	0
Fossil resource scarcity	kg oil-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Freshwater ecotoxicity	kg 1,4-DCB	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Freshwater eutrophication	kg P-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Global warming	kg CO_2-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Human carcinogenic toxicity	kg 1,4-DCB	−0.001	0.001	**19.971**	**−19.971**	0.001	−0.001	0.029	−0.029	0	0
Human non-carcinogenic toxicity	kg 1,4-DCB	−0.006	0.006	**19.694**	**−19.694**	0.024	−0.024	0.289	−0.289	0	0
Ionizing radiation	kBq Co-60-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Land use	m2a crop-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Marine ecotoxicity	kg 1,4-DCB	−0.226	0.226	**8.680**	**−8.680**	0.501	−0.501	**11.045**	**−11.045**	0	0
Marine eutrophication	kg N-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Mineral resource scarcity	kg Cu-eq	−1.261	1.261	4.007	−4.007	**12.684**	**−12.684**	4.570	−4.570	0	0
Ozone formation, human health	kg NOx-eq	1.103	−1.103	**8.736**	**−8.736**	3.649	−3.649	**6.512**	**−6.512**	0	0
Ozone formation, terrestrial ecosystems	kg NOx-eq	1.080	−1.080	**8.949**	**−8.949**	3.576	−3.576	**6.395**	**−6.395**	0	0
Stratospheric ozone depletion	kg CFC11-eq	0	0	**20.000**	**−20.000**	0	0	0	0	0	0
Terrestrial acidification	kg SO_2-eq	0.426	−0.426	**15.657**	**−15.657**	1.410	−1.410	2.507	−2.507	0	0
Terrestrial ecotoxicity	kg 1,4-DCB	−0.001	0.001	**19.992**	**−19.992**	0	0	0.009	−0.009	0	0
Water consumption	m3	0	0	**20.000**	**−20.000**	0	0	0	0	0	0

Note: Cases where δ results in a percent change in impact greater than 5% are bolded.

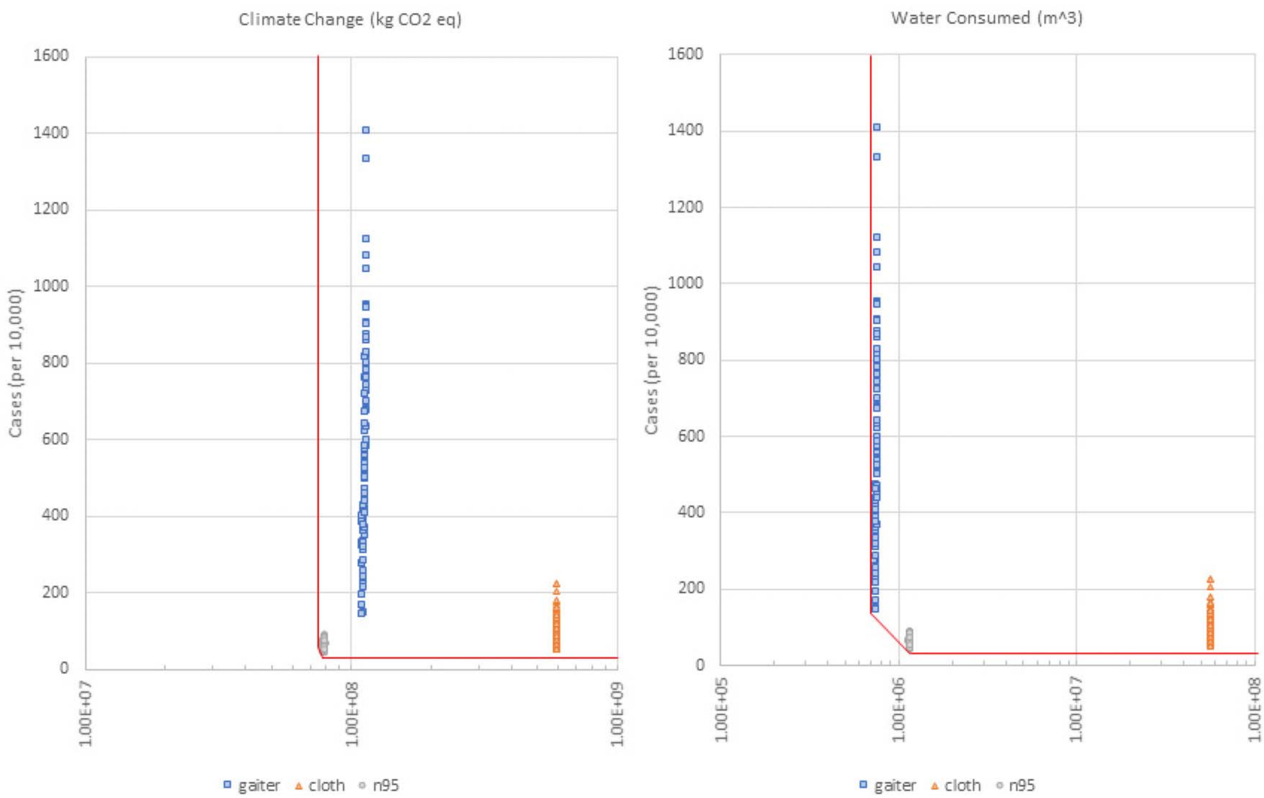

Fig. 7 (Left to right) Plot of climate change versus COVID-19 cases and plot of water consumption versus COVID-19 cases. A Pareto frontier (solid line) shows the non-dominated solutions for each trade-off.

solutions are shown using overlaid trade-off curves (shown as solid lines).

Plots like the one in Fig. 2 allow designers to visualize trade-offs between social impacts and environmental impacts. In this example, two plots have been generated to illustrate the trade-offs. In Fig. 7, one plot represents the trade-off between climate change and COVID-19 cases and the other plot represents the trade-off between water consumed and COVID-19 cases. In the climate change plot, a trade-off curve shows that the non-dominated solutions are all N95 masks. This means that in the simulations, the N95 offers the best solutions for minimizing COVID-19 cases and climate change. From a practical point of view, the designer can be satisfied that the N95 mask is better at minimizing climate change and reducing the number of COVID-19 cases than the other mask concepts.

The water consumed plot, however, shows that the non-dominated set of solutions originates from both the gaiter design and the N95 mask design, and that all solutions belonging to the cloth mask design are dominated. From a practical point of view, the designer will need to consider if lowering the number of COVID-19 cases is worth the increased water consumption to manufacture the mask, or if the reduced number of COVID-19 cases justifies the increase use of water in the mask's production.

As mentioned earlier, the data used in this case study have been simplified. Thus these two plots should not be considered a full life cycle analysis, but a simplified example to demonstrate how the method can be used. A full analysis would include trade-off studies like the plots in Fig. 7 of each combination of social and environmental impacts. Trade-off curves can help designers understand the comparable suitability of each product design.

Part of this analysis requires the designer to use engineering judgment to assess the significance of the differences in impact. Based on the data in Table 5, the difference in water consumed between the gaiter and the N95 mask is 407,000,000 L over the course of a year. The effect of this additional water usage depends on where the masks are produced. In some areas of high mask production, such as India and the western United States, water availability is a major consideration. In other locations, such as China and Vietnam, water availability is less of a concern, although water pollution is still an important focus [68,69]. The designer needs to understand both the nature of the trade-offs and how the impact may differ regionally in the world.

One benefit of this method is that design changes can be made to products to create new non-dominated solutions in the trade-off analysis. For the purpose of this illustration, steps will now be taken to reduce the amount of water consumed while not increasing the number of COVID-19 cases. The new product definition would ideally result in a new non-dominated solution that is a better trade-off than the previous solutions.

Proper understanding of the sensitivity analysis results in Table 8 helps designers understand where to make changes to the product definition in order to reduce certain environmental impacts. Table 8 gives designers an intuitive understanding of which input parameters are contributing most to each environmental impact. It shows the percent changes in impact due to variations in input parameters. It is worth noting that the sum of the rows of Table 8 always add up to the total percent variation in the input parameters, i.e., if the parameters are independently varied by ±20%, the sum of all of those variations in impact on the product will be ±20%. This is intuitive because it is expected that the environmental impacts would all increase by a certain percentage if the input parameters were simultaneously increased by the same certain percentage.

Higher percent changes in impact categories indicate areas where designers should focus their efforts when creating a new product definition. These represent areas where changes to the product will have the greatest impact on the environment. In the N95 example, many of the environmental impacts are sensitive to changes in the amount of foam used. This is especially true of the amount of water consumed. If the designer is trying to reduce the amount of water consumed by the N95 mask production, reducing the amount of foam used in the mask would be a good initial change to the product definition.

Product adoption also impact population level social and environmental impacts and is influenced by the product attributes. As such, all three elements of the product definition (materials, process, and product attributes) can be considered for change by the designer. Once the designer has made changes to the product definition, another iteration of the analysis should be executed so that the designer can compare the impacts of the updated product definition to the previous product definitions.

4 Discussion

The relatively simple illustration provided in the previous section has shown that there can be trade-offs between social and environmental impacts and that quantifying and comparing those trade-offs allows designers to better understand what the trade-offs are and how to change the design to improve both environmental and social impacts. The use of a trade-off curve help designers focus on non-dominated solutions in the design space.

We acknowledge that there are limitations to the illustration provided in the previous section, which include (1) the low number of social impacts that were modeled compared to the number of environmental impacts and (2) the simplification resulting from considering only the production phase of the product's life cycle in the LCA, and only the use phase of the product in the social impact assessment. While these decisions were made to simplify the illustration, they are not limitations in frame work presented in Sec. 2.

The single social impact indicator was used because there was an abundance of data available about COVID-19 cases with which to calibrate the ABM [14]. This single social impact works well for the purpose of illustrating the importance of the method presented, but the example does not illustrate the multifaceted nature of social impact [70] nor how to combine multiple social impacts, nor how to prioritize competing stakeholder needs [59]. Both of these topics are the subject of other work by the authors. Nevertheless, the method would work similarly with any ABM that can calculate social impacts and product adoption numbers.

Other simplifications made included the number of masks each adopter uses, the mask attribute ratings, and the materials and processes used. The ABM simulation was run 100 times for each mask type to understand the distribution of results that happen due to the stochastic nature of ABMs. The results of the ABM represent likely trends in mask adoption and social impacts and are useful when viewed as approximations. Many of these approximations represent real assumptions that designers have to make during the design process when details about the product are still unknown. These approximations do not invalidate the method but rather combine to give the designer a good understanding of what the impacts of the product could be. For this reason, the accuracy of the results of the analysis are dependent on the accuracy of the assumptions made.

It was shown in the example that the environmental impacts of two product definitions can differ relative to each other depending on whether the impacts are at a product level or a population level. When this occurs, it is called Simpson's paradox. In Simpson's paradox, the data appear to support a certain conclusion at a local level, but actually supports a different conclusion at a population level. This can lead designers to make incorrect assumptions about what the product's environmental impacts will be. In the example, Simpson's paradox occurs because of two factors: (1) the difference in the number of adopters between the N95 mask and the gaiter and (2) the difference in the number of product units that each adopter uses. Those differences are large enough that the lesser impact becomes greater and vice versa when the impacts are scaled to the population level. Using product adoption models to scale environmental impacts to the population level allows designers to avoid Simpson's paradox.

The unintended damage to the environment created by Simpson's paradox is similar to the unintended damage that the rebound effect can have. In both cases, human factors that could not be modeled by LCA [20] were the cause of the unintended impacts. Scaling the environmental impacts with the product adoption model results is similar to performing a consequential LCA analysis. In many consequential LCA studies, the goal is to influence policy decisions [25]. The goal in this approach, however, is to influence design decisions.

To that end, it is important for designers to consider which communities will be affected by the impacts of a product when examining the trade-off curves. This awareness, combined with quantified impacts, can help designers protect both vulnerable communities and the global community. The goal of this approach is to enable designers to create products that contribute to reaching the UN sustainable development goals so minimizing impacts to vulnerable communities and the global community are an important part of reaching this goal. Designers can also specify maximum (or minimum) acceptable social and environmental impacts. Those limits can be used in the trade-off analysis stage to increase consistency in decision-making, keeping in mind that the ultimate goal of the method is to minimize the negative social and environmental impacts of the product.

An especially interesting finding is that all three parts of the product definition influence the environmental impacts of the product, not just the materials and processes. Changing the materials and processes used in the product definition can also affect the social impacts of the product. For example, in the mask analysis, the material used for the filtration part of the mask directly impacts the effectiveness of the mask at preventing the spread of COVID-19. The differences in case numbers in Table 6 help illustrate this. Also, the discussion earlier about Simpson's paradox shows how a change in mask use predicted by the ABM (which uses the product attributes) can alter the environmental impacts dramatically without the materials and processes being changed. These relationships show that the social and environmental impacts are linked to each other. Trade-off analyses are a good tool for designers to understand these relationships and find non-dominated solutions that minimize impacts.

In order to integrate a method for calculating economic impacts to this approach, an additional step could easily be added where economic impacts are calculated. The economic impacts could then be compared to the social and environmental impacts. This would give designers understanding of the triple bottom line of their products. More work on relating environmental, social, and economic impacts to the UN sustainable development goals and integration of that work into this approach would create a powerful tool for designers to understand how their product's contribute towards sustainable development as defined by the UN.

5 Conclusion

Designing products that contribute towards meeting the UN sustainable development goals can be viewed as a multi-objective design problem involving trade-offs between social, environmental, and economic impacts. The approach presented in this paper helps designers quantify social and environmental impacts and analyze the trade-offs between those impacts using a non-dominated set of solutions that minimize negative impacts and maximize positive impacts. The three stages of this approach—(1) product definition, (2) product analysis, and (3) impact trade-off analysis—are simple and the result allows designers to compare impacts and iterate on their designs. When using predictive models, it is helpful to keep in mind that the goal of the model is to improve the decision-making process. Although there is uncertainty associated with predictive social and environmental impact models, they can still provide useful information in making improved design decisions. This approach helps designers understand the relationships between environmental and social impacts and also helps designers avoid

Simpson's paradox by using environmental impacts scaled by population adoption models.

The contribution of this paper is the ability to scale the environmental impacts of a product based on modeled adoption patterns, which is influenced by the social impacts experienced by the population while using the product. This allows for making design decisions based on the dynamic adoption of a product, and the scaled environmental impacts of increased manufacturing and use. In realistic cases, there will be trade-offs between the social and environmental impacts and this method provides guidance on how to analyze trade-offs and move forward in making design decisions.

Future work can expand this approach to include economic impact trade-offs. This expanded approach would be a valuable tool for designers seeking to create products that contribute towards reaching the UN sustainable development goals and improving the quality of life for people around the world.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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