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TRADE-OFF CHARACTERIZATION BETWEEN SOCIAL AND ENVIRONMENTAL IMPACTS USING AGENT-BASED MODELS AND LIFE-CYCLE ASSESSMENT

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ABSTRACT
Meeting the UN's sustainable development goals requires designers and engineers to solve multi-objective optimization problems involving trade-offs between social, environmental, and economic 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 the 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 using Pareto frontiers to find 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 product-level impacts. This analysis of impacts has the potential to help designers and engineers create more impactful products that contribute towards the UN sustainable development goals.

1 INTRODUCTION
The United Nations (UN) has published 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 (sometimes called the triple bottom line) [2] and can be considered a

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multi-objective optimization problem involving trade-offs [3] between those three dimensions. Designers seeking to create products that help humanity reach those goals would benefit from being able to quantify and compare the trade-offs involved between each impact category in order to make informed design decisions. Quantifying environmental impacts is important because the earth has limited resources that can be consumed and a limited ability to absorb emissions generated [4, 5]. Engineering for Global Development (EGD) research has emphasized the need for defining and quantifying the social impacts of designs in communities [6, 7]. In response to this need, researchers are starting to create methods that assess both social and environmental impacts of products the same time [8, 9]. Other studies have compared the trade-offs between social and economic impacts [10]. The goal of the present paper is to share an approach for quantifying social and environmental impacts 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 [11] combined with Life-Cycle Assessment (LCA) tools that have been developed to evaluate the pressures that different processes create on the environment [12]. The approach will be expanded in future research to include tools that quantify economic impacts, allowing designers to assess trade-offs between all three impact categories.

In an LCA, a product's damage on the environment is measured in three different categories, often called Areas of Protection (AOP) [12]. The three AOPs are damage to human health, damage to the ecosystem, and damage to resource availability [12, 13]. An LCA calculates the impact of a product on the environment during the product's life cycle (pre-production, material extraction, production, distribution, use and disposal of the product) [4, 4, 14]. At each stage of the life-cycle, the inputs and outputs of the processes involved in that stage create environmental pressures [12]. Those environmental pressures are linked to the three AOPs through characterization factors and damage pathways [13]. There are many methods for evaluating the impact of a product on the environment, such as the Eco-indicator99 method [15], the ReCiPe method [13], and the LC-IMPACT method [12]. 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) [16]. 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 [14].

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 cannot be modeled by LCA [17] however, therefore traditional LCA is not well-suited to model the complex, evolving nature of a new product's introduction into society [18]. The human behavior that needs to be modeled is sometimes referred to as the social and economic factors that influence LCA [19, 20]. 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 [21].

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 [18, 22]. ABM has the ability to model these social and economic factors [17] and has been used for predicting product adoption and exploring what-if scenarios [23]. Some important human behaviors that influence LCA include non-price-driven human behavior (i.e. irrational and social behaviors) [17, 23] 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 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 [17, 24, 25]. 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 [17]. Product adoption models generated by ABMs are also starting to be used both in parallel and in series with LCA to better predict the impacts of new products and policy changes on the environment [19, 22, 24, 25].

It has also been shown that LCA results are influenced by ABM results [26]. 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 [18], 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 [27, 28]. ABM results can also help designers and researchers understand all of the varying use cases that need to be modeled [21, 24, 25, 29]. These examples show that there is a need to integrate LCA and ABM when modeling impacts.

This paper will first present an approach for quantifying and comparing social and environmental impacts. It will then present an example of how to implement the approach using a mask design case study. Finally there will be a discussion about the approach and important findings. The goal of the approach is to enable designers to perform trade-off analyses between impact categories and create designs that minimize environmental impacts while maximizing positive and/or minimizing negative social impacts.

2 METHODOLOGY

There are three stages to integrating 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. [11] to model social impacts and product adoption, and the OpenLCA software package to calculate environmental impacts. Society definitions and models are created for the ABM using the method presented in Mabey et al. [11].

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, product attributes, process specifications, and material specifications (as shown in Fig. 1).

The first step is to define the materials and manufacturing processes used as accurately as possible so that the results of the LCA 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 results of the LCA. 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 a person's decisions to adopt the product and should be able to be applied to multiple versions of the product. Attributes should also have a scale associated with them. Examples of attributes include aesthetics, comfort, and reliability. 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 is what influences the agent's adoption decision in the model [11].

The results of this stage are a product definition that consists of materials used, manufacturing processes used, and ratings for each 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. The product analysis is broken down into three steps: 1) performing an attributional LCA of the product, 2) executing an ABM simulation, and 3) integrating the product adoption model from the ABM with the results of the LCA. The result of this analysis is data on the social and environmental impacts of the product.

2.2.1 ATTRIBUTIONAL LCA This step is illustrated by the box labeled "Attributional Life-Cycle Assessment" in Fig 1. The LCA is conducted using OpenLCA, a free LCA software package. Databases containing information about pressure placed on the environment by resource extraction, refining, and manufacturing processes are imported into OpenLCA. The information in the databases is used to create flows that represent the flow of materials and energy during different stages of the product's life cycle. These flows are linked together to form processes with inputs and outputs. The output for these processes should be a single unit of product. A product system is created using the processes and is then evaluated in OpenLCA.

There are many methods for evaluating environmental impacts. These methods all have similar midpoint and endpoint impact categories [12, 13, 15]. The ReCiPe(H) midpoint method will be used to perform the evaluation because it is a well established method in the literature [4, 30]. The midpoint method calculates the impact of environmental pressures and links them to 17 environmental impact categories [13]. Those impact categories include types of aciditification (increases in acidity), toxicity (presence of toxins in the food chain), eutrophication (presence of nutrients limiting aquatic biomass), and damages to the atmosphere [31]. The ReCiPe(H) endpoint method (which links environmental pressures to the three AOP's stated in the introduction [13]) can be used for a simpler analysis. Using the midpoint method will allow the designer to get a more detailed understanding of environmental impacts, but either method is acceptable for this analysis so long as the designer is able to understand the significance of the impact categories. The 17 midpoint impact categories and three AOPs are listed in Tables 1 and 2 respectively.

Once the either the midpoint or endpoint evaluation method has been chosen, the evaluation is performed. The results of the LCA represent the environmental impacts at a product-level (i.e. the impact one unit has on the environment). These impacts will be scaled to a population-level in the integration step.

2.2.2 AGENT-BASED MODEL This step is illustrated by the box labeled "Agent-Based Model" in Fig. 1. Using previously developed methods for social impact ABM [11], inputs for different submodels are used to construct the ABM. The purpose of the ABM is to inform the patterns of product adoption in the population and to understand the social impacts of the product. 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 im-

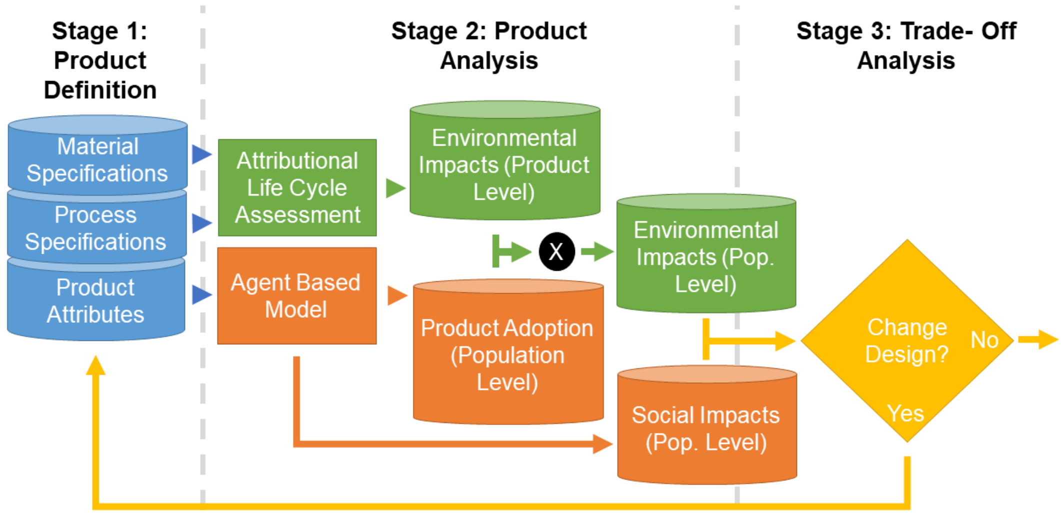

FIGURE 1: Block diagram illustrating approach for using LCA and ABM results to inform engineering decision making process. The results of the analysis are both environmental and social impacts that must be weighed by the designer in an impact trade-off analysis.

pacts are being investigated. Agents are ideally created based on data from real-world populations. This 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 for the social impact on agents based on their decision to adopt the product. It is important that these rules are created based on empirical data to more closely match the model to real-world behavior. Impact and adoption at the agent level can be aggregated to understand population level trends. ABM is usually a stochastic process, so it will be necessary to run the simulation a sufficient number of times to understand the distribution of results. More detailed information on the creation of social impact ABM can be found in [11]. This previously developed framework will output results for the number of agents that adopt the product and the social impacts investigated. The number of products adopted will be used to properly scale the LCA.

2.2.3 RESULTS INTEGRATION The product-level environmental impacts (ρ) calculated by the attributional LCA are scaled by the product adoption model (α) to produce the population-level environmental impacts (I), as shown in Fig. 1. The product adoption model is the number of units adopted by the population over the time period the simulation is executed. I for each environmental impact category is calculated using Eq. (1).

$$I = \rho \times \alpha \tag{1}$$

The results of this step are population-level environmental impacts that can be compared in Stage 3 to the population-level social impacts (see Fig. 1).

2.3 STAGE 3: IMPACT TRADE-OFF ANALYSIS

The impact trade-off analysis is the most valuable step in the integrated analysis. It is performed by comparing the environmental impacts with the social impacts. Each dimension of the environmental impacts (i.e. the AOPs or midpoint environmental impacts) should be compared to the each dimension of the social impacts calculated by the ABM. If the designer chooses to analyze several different product definitions then a Pareto frontier can be used to help designers determine which of the product definitions represent non-dominated solutions.

Figure 2 illustrates how two designs (*product definition 1* and *product definition 2*) can be compared. Overlaying a Pareto frontier onto the plot shows the designer that *product definition 1* contains all of the non-dominated solutions that maximize positive social impact while *product definition 2* contains all of the non-dominated solutions that minimize environmental impacts. If more product definitions are being analyzed then the Pareto frontier will be more complicated. From this analysis the designer can conclude that a better design would be a product definition that has social impacts equal to or better than *product definition 1* and environmental impacts equal to or better than *product definition 2*.

The designer can return to Stage 1, redefine the product based on potential improvements, and perform the analysis again. The new product definition (*product definition 3*) can be compared against the old product definitions (*product definitions 1 & 2*) so that the designer can evaluate whether or not the changes have resulted in a new non-dominated solution. The de-

TABLE 1: ReCiPe midpoint impact categories [13]

Midpoint Impact Category	Units
Climate change	kg CO_2-eq to air
Ozone depletion	kg CFC-11-eq to air
Ionising 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-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	$m^2 \times$ yr 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 [13]

Area of Protection	Units	Explanation
Damage to human health	DALY (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

signer can continue to perform iterations until a non-dominated solution is found for each comparison between environmental and social impacts. It is ideal if the non-dominated solutions all come from the same product definition. This means that that product definition represents the best trade-off between environmental and social impacts. Once the designer has finished iterations, the results of this process will be a product definition that represents the best trade-off between potential social and environmental impacts.

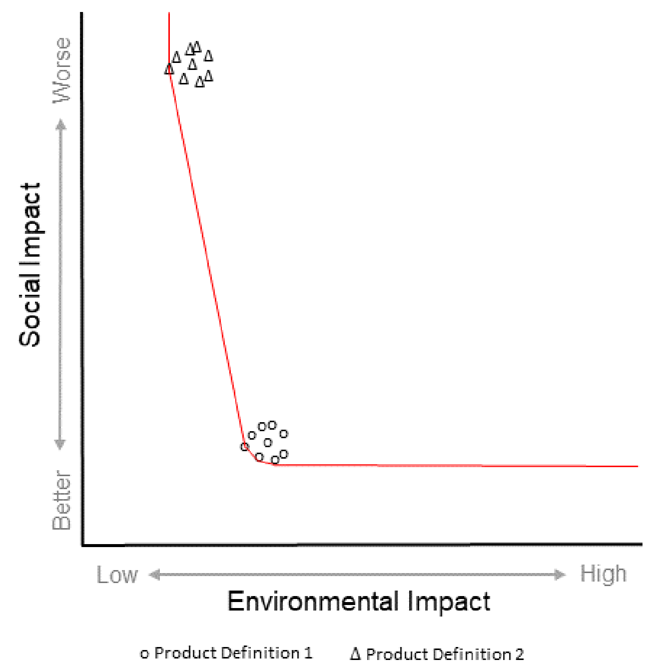

FIGURE 2: An example of the social impacts and scaled environmental impacts being compared. An environmental impact versus a social impact is plotted for two product definitions. A Pareto frontier is overlaid to show the non-dominated solutions in the trade-off. The goal is to minimize environmental impacts while maximizing positive social impacts and/or minimizing negative social impacts. Any changes to the product definition analyzed in further iterations should not be used unless they result in a non-dominated solution.

3 EXAMPLE

The approach presented in Section 2 will be demonstrated in a case study designing COVID-19 face masks. Masks were chosen for the case study because there is enough data on face masks and COVID-19 to perform social and environmental impact analyses [11]. Three mask designs will be compared in the case study. They are an N95 mask, a cloth mask, and a neck gaiter.

3.1 MASK DEFINITION

The first step in defining the masks is to define the materials and processes that are used to create the masks. The materials and quantities used to create each mask are defined in Table 3.

TABLE 3: Mask materials and material quantities

Mask Feature	Material	Mass [g]
	N95 Mask [32, 33]	
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

The processes used to create the masks were defined in OpenLCA using the Ecoinvent and Agribalyse databases and are represented by flow diagrams shown in Figs. 3, 4 & 5. Figure 3 shows the material and energy flows required to form an N95 mask [33–35]. The box labeled "Electricity" represents electricity that is into into 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) aesthetics. These attributes were chosen because they represent reasons people chose whether or not to adopt a mask [11]. Rating scales for each of the attributes were as follows: Effectiveness was rated on a scale of 0 to 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 uncomfortable and 0 being so comfortable that the mask is not noticeable. Aesthetics was rated on a scale of -5 to 5 with -5 being very unattractive and 5 being very attractive. 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. 3, 4 and 5, and the product attribute ratings in Table 4 represent the product definition that will be used in the next stage of the analysis.

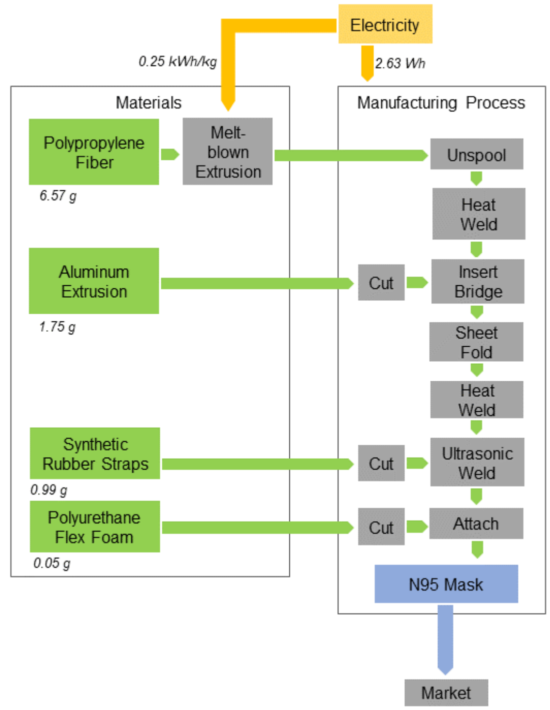

FIGURE 3: Material and energy flow for production of an N95 mask [33–35]

TABLE 4: Mask attribute ratings for an N95 mask, a cloth mask, and a neck gaiter [11]. These ratings are part of the product definition that will be used in the ABM.

Mask Type	Effectiveness	Comfort	Aesthetics
N95	4.75	-4.5	-3
Cloth	2.5	-2.5	3
Neck gaiter	1	-0.5	3

3.2 MASK ANALYSIS

3.2.1 MASK LCA The inputs and outputs of the flow diagram shown in Fig. 3 are used to define a product system in OpenLCA that represents the process involved in creating an N95 mask. Similar product systems are created in OpenLCA based on the flows shown in Figs. 4 and 5 that represent the process of creating a cloth mask and a gaiter respectively. An attributional LCA is then performed for each mask design in OpenLCA using the ReCiPe(H) midpoint method. In total, three LCAs were per-

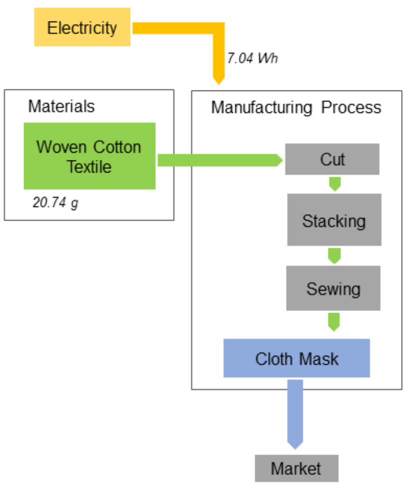

FIGURE 4: Material and energy flow for production of a cloth mask [33, 35, 36]

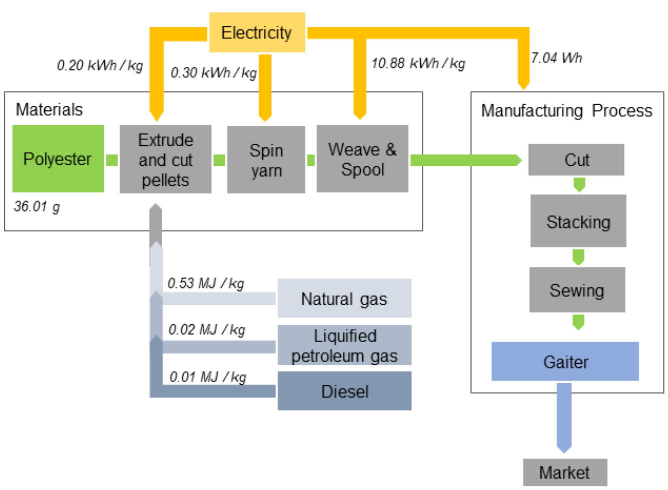

FIGURE 5: Material and energy flow for production of a gaiter [33, 35, 36]

formed: 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 found in Table 5.

3.2.2 MASK ABM A previously developed ABM on COVID-19 and face mask was extended to meet the needs of this study [11]. The ABM used data from the *2019 American Community Survey* [37], *American Time Use Survey* [38], and 2020 survey data on mask use [39, 40] to build the population of agents and the rules that govern their behavior. The ABM simulated the mask adoption number (the number of people per 10,000 that would chose to adopt the mask) and calculated the social impact of each mask type on the population (number of COVID cases per 10,000 people). 100 repetitions of the simulation were executed for each mask type so that trends and distributions in adoption and social impacts could be found. This model was validated using macro-validation and micro-validation techniques as described by North and Macal [41]. Complete details on the model creation and validation can be found in [11].

Changes to the ABM were to tabulate the total number of masks used by the population. The mask adoption number only represents the number of people who chose to adopt a mask (M from Eq. (2)), not the total is not total number of masks used by the community (α from Eq. (1)). α from Eq. (1) is found using Eq. (2). M is scaled by the number of masks that each person who adopted a mask used (γ) and the number of people in the population ($P = 300,000,000$) [42].

$$\alpha = \frac{M}{10,000} \times \gamma \times P \tag{2}$$

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 run for each mask design.

According to Grand View Research, the value of the reusable mask market in 2020 was USD 19.2 billion and the 28.4% of that market that was in North America [43]. Based on these numbers, 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 [44]. 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 [42]. Based on this data, there are approximately 246 million reusable mask users in the US. The average price of the top 40 masks brought up by a search on Amazon.com for "reusable face mask" was USD 5.85. 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 4 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 [45] and the CDC recommends that N95 masks be used no more than five times by healthcare workers [46]. Based on this information, it will be 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 stan-

TABLE 5: Midpoint Impacts at a product-level and at a population-level as calculated in the *Attributional LCA* and *Results Integration* steps. Cases where Simpson's paradox occurs are bolded and highlighted.

	Product-Level			Population-Level		
Midpoint Impact Category	**N95**	**Cloth**	**Gaiter**	**N95**	**Cloth**	**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}
Ionising 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 ($m^2\times$ yr 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}	$\mathbf{2.9}\times10^{7}$

dard 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 ABM LCA RESULTS INTEGRATION

The 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. (1). 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

TABLE 6: Social impacts of masks reported as COVID case numbers

Mask Type	Cases_{Median} [/10,000 ppl]	Cases_{StdDev} [/10,000 ppl]
N95	62	11.31
Cloth	97	36.6
Gaiter	528.5	251.86

TABLE 7: Adoption numbers from ABM simulations

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

paradox is called Simpson's paradox. Simpson's paradox occurs when sets of data appear to have a certain trend but that trend is reversed when the data is aggregated [47]. 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 not the best for the environment. This is similar to the re-bound effect that can occur with products intended to decrease environmental impacts [17,24,25]. Examples of Simpson's paradox are highlighted in the bottom four rows of Table 5.

3.3 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. Plots like the one in Fig. 2 allow designers to consider social impacts versus environmental impacts and visualize the trade-offs that exist. In the case of the masks, two plots have been generated that illustrate this trade-off. In Fig. 6, one plot represents the trade-off between climate change and COVID cases and the other plot represents the trade-off between water consumed and COVID cases. In the climate change plot, a Pareto frontier shows that the non-dominated solutions are all N95 masks. This means that the N95 has the best trade-off between COVID cases and climate change of the three masks analyzed. The water consumed plot shows that the all the non-dominated solutions that minimize water use are gaiters and all of the non-dominated solutions that minimize COVID cases are N95 masks. The cloth mask is a dominated solution in both of these comparisons and so it does not represent the best mask design when seeking to minimize climate change versus COVID cases or water consumed versus COVID cases. Plots like the ones in Fig. 6 should be made for each social and environmental impact comparison so that designers can visualize all of the trade-offs between social and environmental impacts.

Part of this analysis requires the designer to use engineering judgement 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 407,000,000L over the course of a year globally. That is equivalent to the amount of water consumed by 27,000 people in Rwanda or 15,000 people in Sierra Leone during the same time period [48]. The design engineer needs to understand both the significance of the trade-offs being made and where the trade-offs will be made. Many environmental impacts are felt by the global community (ex. climate change) or in the communities where resource extraction and manufacturing occur (ex. water consumed). The social impacts in this analysis are felt in the community that is being modeled in the ABM. Translating environmental and social impacts into real world equivalents (like was demonstrated with water consumed) gives designers more perspective on what the impacts of their designs mean. The designer will have to decide where the impacts are felt and whether the trade-off is worth it. In this example, the designer has to decide whether the potential for lives saved by decreasing COVID cases is worth the potential for lives lost due to less water availability.

In this example examining water consumed versus COVID cases and climate change versus COVID cases, changes should be made to the N95 or gaiter product definitions to create a new product definition that will result in new non-dominated solutions for water consumed versus COVID cases if the designer wants to find a product definition that is non-dominated for all trade-offs between impacts. Closer examination of the data in Table 5 shows that the N95 mask has a relatively lower product-level impact and relatively higher population-level impact on water consumed compared to the gaiter. This observation was pointed out in the discussion about Simpson's paradox in Section 3.2.3. This means that either the number of people adopting the N95 mask or the number of N95 masks used by each adopter is causing the impact to be greater at a population-level. This is a good example of how product adoption affects environmental impacts. Product adoption is influenced by the the product attributes which means that all three elements of the product definition (materials, process, and product attributes) can affect environmental impacts. This is important because it means the designer can adjust any of the variables associated with the product definition when trying to minimize environmental impacts, including the product attributes. 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

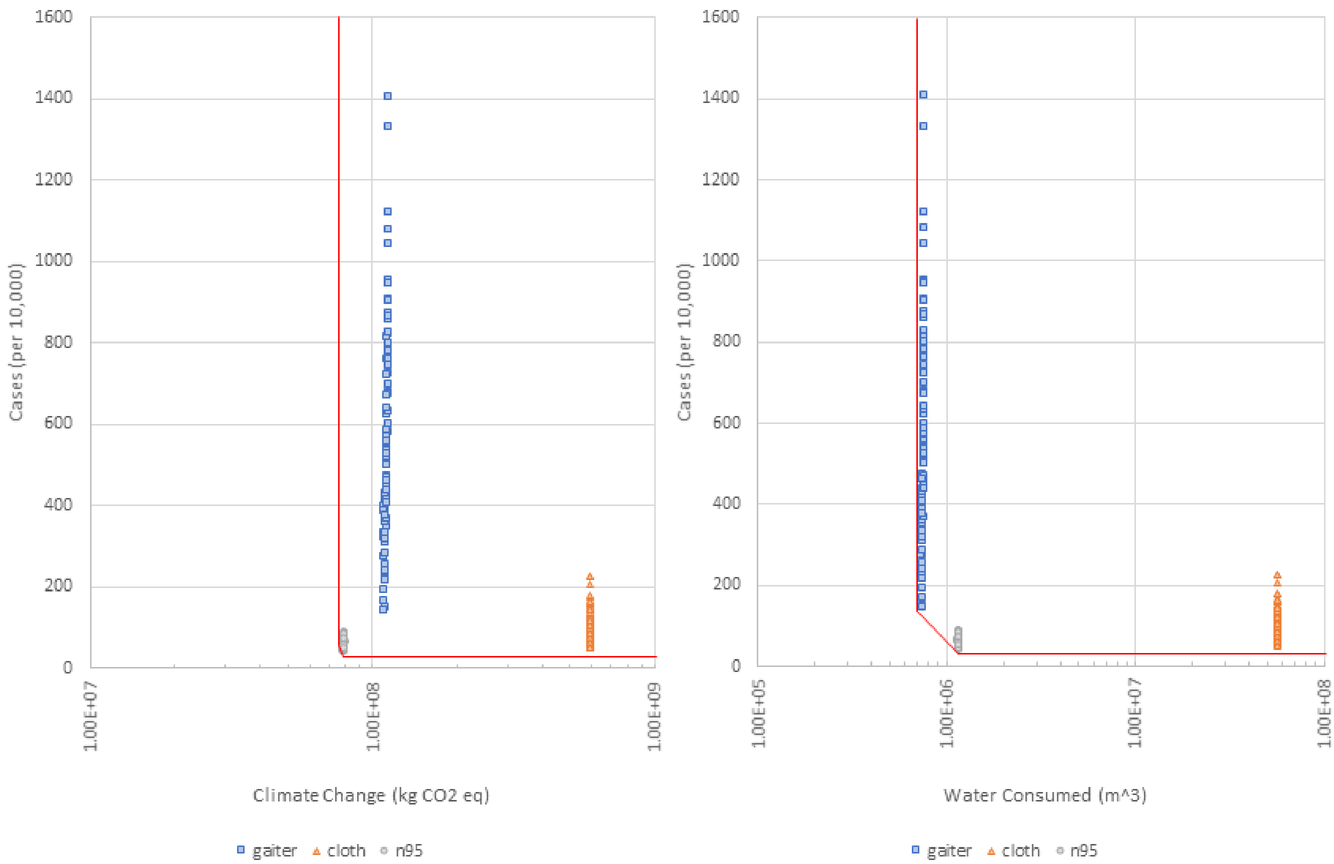

FIGURE 6: The plot on the left shows the impact on climate change versus COVID cases that each mask type has. The plot on the right shows the impact on water consumption versus COVID cases. All 100 simulations for each mask type are plotted and a Pareto frontier has been overlaid to show the non-dominated solutions for each trade-off.

of the updated product definition to the old product definitions. The ideal design is one that contains all of the non-dominated solutions for each social and environmental impact trade-off.

4 DISCUSSION

This approach has shown that there are trade-offs between social and environmental impacts. Quantifying and comparing those trade-offs allows designers to better understand what the trade-offs are. The use of a Pareto frontier can help designers find non-dominated solutions in each trade-off.

There are approximations made in the example, such as the approximations made about the number of masks each adopter will use and the approximations made about the mask attribute ratings, materials, and processes used. These approximations represent approximations that need to be made though by designers defining a new product and do not invalidate the approach. Depending on where the designer is in the product development process, approximations like this will need to be made. The further along the designer is in the process, the less approximations there will be. Regardless of where the designer is in the process though, some approximations will need to be made. The ABM simulation was run 100 times for each mask type for the same reason. The results of the ABM represent likely trends in mask adoption and social impacts and are useful when viewed as approximations. All of these approximations combined 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.

The trade-offs between impacts vary depending on the product definition and also depending on whether product-level or population-level environmental impacts are used in the comparison. Using product adoption models to scale environmental impacts to the population-level allows designers to avoid Simpson's paradox. Product adoption models can scale environmental impacts differently which means that if designers do comparisons using product-level impacts, there is the risk that the to trade-offs solutions will not actually be the non-dominated solutions. This would result in design decisions doing more damage to environment than the designer intended.

It also is important in this analysis for designers to consider which communities will be affected by the impacts of a product when examining the Pareto frontiers in trade-offs. This awareness, combined with quantified impacts, can help designers protect both vulnerable communities and the global community while performing trade-off analyses. 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 social and environmental impacts of the product.

Lastly, it is important to note that all three parts of the product definition influence the environmental impacts of the product. 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. The differences in case numbers in Table 6 helps illustrate this. 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.

5 CONCLUSION

Designing products that contribute towards the UN sustainable development goals can be viewed as a multi-objective optimization 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 Pareto frontiers to find non-dominated solutions that minimize impacts. The three stage of this approach are: 1) Product Definition, 2) Product Analysis, and 3) Impact Trade-off Analysis. This approach is simple and the results allow designers to compare impacts and iterate on their designs. 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. Future work will expand this approach to include economic impact trade-offs. This approach is 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.

Data Availability

Data will be available for download at https://www.design.byu.edu/resources

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