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This thesis is the result of two research publications, which together form a framework for the evaluation of product innovativeness with potential future applications to early design. Innovation is a challenging concept to quantify. Experts seemingly have a grasp of what innovation is when they see it, however this evaluation is highly subjective. To date, there is no accurate way of measuring a product's innovativeness. The research presented herein outlines a method to quantify product innovativeness based on three latent, or unobserved, variables. These latent variables were calculated based on several product attributes. The values of these measurable product attributes were associated with the probability that a product was selected as innovative. One attribute, product sustainability, is measured by environmental impact. As there was no environmental impact data available for the products used to generate the latent variable model, experiments were designed to collect such data. Life cycle assessment was performed on the products, as well as several other pairs of innovative and common products. These product's environmental impacts were compared at a high level with the entire product's impact, as well as at a more abstract level, with the functions and flows of each product. It was found that innovative products tend to have a higher environmental impact, which was concentrated in a small number of functions. With functional environmental impacts calculated, it will be possible to evaluate the environmental impact of designs during the

conceptual stages of design, when only a functional model is available. In addition, the framework for evaluating product innovativeness, using a latent variable model, can be used during the original design process to evaluate how innovative concepts or designs are. Together, these two evaluations have the capability of producing innovative and more sustainable products. Future directions for this research include the application of the framework in an original design to determine whether more innovative concepts can be generated. Additionally, environmental impacts of conceptual designs and functional architectures can be estimated to determine which concepts to pursue in detailed design. Comparing alternatives in functional designs will help to determine the conceptual design with the lowest environmental impact to pursue in detailed design.

Modeling Innovativeness in Consumer Products With the Influence of Environmental Sustainability

by

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APPROVED:

Major Professor, representing Mechanical Engineering

Head of the School of Mechanical, Industrial, and Manufacturing Engineering

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Brady Gilchrist, Author

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CONTRIBUTION OF AUTHORS

Dr. Chris Hoyle assisted with generation of the models in *Manuscript 1* and Carrie Rebhuhn helped with the data collection and processing. Dr. Irem Y. Tumer assisted with editing both manuscripts. Dr. Karl R. Haapala contributed to *Manuscript 2* with revisions and insights. Dr. Douglas L. Van Bossuyt and Ryan Arlitt assisted with data processing and interpretation in *Manuscript 2*, and Dr. Rob Stone helped with the vision and research direction.

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INTRODUCTION

With the human population nearing 7 billion, and standards of living rising across the world, demand for resources on the planet is expected to grow significantly in the future [1]. If everyone in the world lived similarly to a western lifestyle, between three and four planets worth of resources would be needed to maintain the population [2]. A specific example of a resource skyrocketing in future demand is the expected two to three fold increase in the worldwide demand of metals [3]. Without better utilization of these resources, their costs will increase significantly and availability will be threatened. Controlling costs and maintaining supply will require innovations in the way metals are extracted, refined, and transported, as well as the way components made from metal are manufactured, used, and ultimately recycled. To maintain the way of life many have grown accustomed to, keeping a watchful eye on the products we make and the way that we make them has the potential to spur future innovations and economic growth while reducing the overall impact on the environment around us. It has been said that a major driver for innovation is designing for sustainability [4]. This thesis will show that product sustainability is an important attribute in the perception of product innovativeness.

Getting a handle on what exactly product innovation is and how to quantify it could help designers to design better, more profitable products. By bringing more design decisions to earlier stages in design, their impact on the final design increases, and the cost of making those design decisions decreases [5]. In addition, a better understanding of innovation could fast track the development of technologies that can help solve the world's projected energy and resource shortages [1]. Innovation can be defined as providing novel value to the customer that produces growth and profit [6]. Another way of defining innovation is the application of novel and useful concepts [7]. Having a better idea of what makes innovative products innovative will give designers the opportunity to incorporate those aspects of product innovativeness earlier in the design process. This in turn will save companies time and money [5]

Innovations in materials, manufacturing processes, and product functionality are needed to continue to advance technology and improve the lives of billions on the planet without limiting the growth and prosperity of future generations. On a planet with limited resources, it is important to make the most efficient use of those resources and encourage sustainable development. Sustainable development has been defined by the Brundtland Commission as “development to meet the needs of the present generation without compromising the ability of future generations to meet their own needs” [8]. To better conform to this definition, being well informed of the life cycle impacts of the products we use, and more importantly, new products to be designed and developed will be necessary.

An emerging market worldwide is that of healthy and sustainable products [9]. As this market grows, the demand for sustainable products that reduce the environmental impact of previous product generations is bound to increase. In addition to consumer demand, if regulations and policies in the United States take the path that the European Union has taken, manufacturers will be required to consider the entire life of their products when designing and marketing. To inform consumers of the environmental impacts of products, “ecolabeling” has taken hold in many different types of markets. For a product to display an ecolabel on its packaging, the manufacturer must comply with strict standards that consider the entire life cycle of the product. Life cycle assessment is necessary to prove that all criteria for an ecolabel have been met. These labels give the consumer confidence that the product they are purchasing is free of exaggerated and deceptive sustainability claims, and is actually less environmentally impactful than similar products without an ecolabel [10]. Additional regulations in the EU require manufacturers to be responsible for their products after the use phase, necessitating proper disposal of electronic waste as well as restricting the use of certain chemicals in the manufacture of electronics [11, 12].

This thesis forms a framework to incorporate an evaluation of product innovation and sustainability into early design. A flow chart of the framework can be seen in Figure 1. It can be seen that the product level assessment of environmental impact, in addition to other product attributes, independently identified innovative products, and customer perceptions of those products, were inputs into the latent variable model. This latent variable model resulted in a choice model of product innovativeness, which determines whether or not a customer will select a product as innovative based on the product's physical attributes. Considering that environmental impact was an aspect of the model, an evaluation of early design environmental impact is needed to apply the latent variable model of product innovativeness to conceptual designs. Therefore, the function and flow level impact assessment can be seen as inputs into an early sustainability analysis. Using this framework, an evaluation of product innovativeness with a calculation of sustainability at the early stage of design is possible.

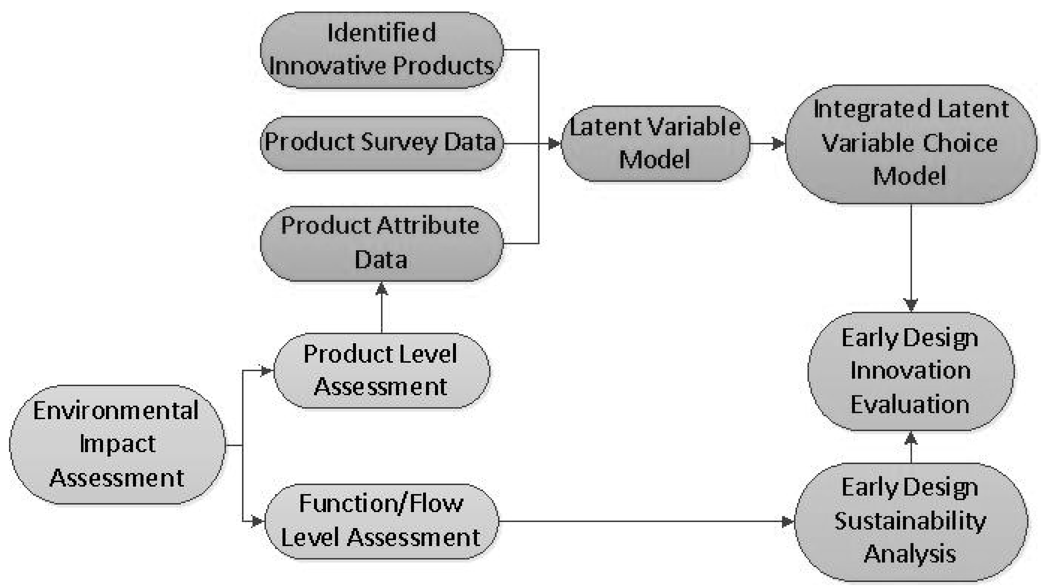

Figure 1: Thesis framework integrating sustainability assessment and evaluation of product innovativeness into early design

In this thesis, the first manuscript hypothesizes that the selection of a product as innovative can be modeled as a latent, or unobserved, variable. Innovation, though not directly quantifiable, has indicators that lead to its quantification, and hence meets the criteria for use in a latent variable model [13, 14, 15]. Various attempts at quantifying innovation have been made in the past; however, they focus on national and firm level innovations. Attempts at quantifying innovation at the firm level have resulted in several models based on parameters such as R&D expenditures and patent count [6, 16, 17, 18]. On the other hand, quantifying innovation at the national level typically involves innovative output of nations used for comparison between countries and to gauge national progress [19, 20]. Although these high level measures of innovation are fairly well accepted, a practical and accurate metric of product innovativeness has yet to be developed. Using a latent variable approach, perceptions of innovative products are first evaluated, and then product attributes are fit to the perception model, resulting in a model of product innovation based on customer selection.

Three different models were calculated in the first manuscript. First, a measurement model was calculated from survey data gathered from students in junior level design courses at Oregon State University. Using factor analysis, the survey responses were grouped into three significant factors that, based on the indicators that were significant to each, best resemble *Innovativeness*, *Usability*, and *Company Profile*. The model shows that three factors are essentially what customers are looking for when determining whether or not a product is innovative. Once this model was created, the physical, measurable product attributes were fit to the latent variables using linear regression. This formed the structural model, which relates product attributes to each of the three latent variables identified. Finally, using a logit choice model, the coefficients of each the latent variables for the choice of whether or not the product is innovative were calculated.

As stated previously, one of the attributes from the resulting latent variable model in the first manuscript was a measure of product sustainability. Sustainability itself can generally be described based on three pillars: environment, social, and economic. All three must be addressed to properly assess the sustainability of a product. However, because of the lack of available information about social and economic impacts of each of the innovative and common products, a sustainability evaluation in the form of environmental impact assessment was used. *Manuscript 2* details the environmental impact analysis of several innovative and common products to get a better understanding of how sustainability plays a role in products that are identified as innovative. Seeing that other attributes such as function, flow, energy use, and overall sustainability are potentially parts of the model, *Manuscript 2* delved deeper into the environmental impact of various aspects product design.

Using the functional basis, created by Stone and Wood [21], the environmental impact from each component was assigned to the functions it solves, as well as energy, material, and signal (EMS) flows through it. In addition to comparing the functional and flow impacts of innovative and common products, the second manuscript outlines the process necessary to populate a Product Function Impact Matrix (PFIM). This PFIM combines a Product Function Matrix (PFM) with a Function Impact Matrix (FIM) to give an estimate of the environmental impact of functions and flows in functional models. This can then be used during concept generation to determine the environmental impact of concept variants.

The two combined manuscripts propose a method of incorporating both product innovativeness considerations, and environmental impact evaluation into early design. Based on this research, the initial framework for evaluating design innovativeness can be applied to designs during the conceptual design processes. With sustainability being an attribute of the model of product innovativeness, a method has been proposed to evaluate the potential environmental impact of a concept. Designers can use this framework to target the most innovative concepts for detailed design, resulting in more innovative products. If reductions in environmental impact are a design goal, the impact assessment based on the PFIM can estimate the impact of different functional architectures and conceptual designs.

BACKGROUND

Evaluating the environmental impact of new products and processes is a fairly well established area of research, however the evaluation of how innovative those products are is inherently an abstract and qualitative process. A better understanding of both product innovation and sustainability will help to more effectively design for both. *Manuscript 1* of this thesis begins to explore the abstract concept of innovativeness at the consumer product level and how to quantify it.

Attempts to quantify innovation have only been successfully shown at the national and corporate levels. Metrics such as the Innovation Union Scoreboard measure the innovative output of European nations such that countries can be compared to gauge technological competitiveness and progress [20]. Other measures of innovation measure innovative competitiveness at the firm level so that companies can determine the effectiveness of R&D spending and predict future trends [6, 16, 17, 18]. Little research has been conducted into the innovative aspects of products and how to design for innovation. Oman et al. isolated the unique functions of innovative products and populated a repository with the components that solve those functions. This repository was then used to computationally generate concepts [22]. Saunders et al. attempted to isolate the innovative features of mechanical products in [23]. This work resulted in the uncovering of the unique characteristics of innovative products. It was found that mechanical innovation is likely closely associated with the product's external user interactions.

The abstract nature of innovation and how consumers perceive innovativeness leaves it open to measurement by unconventional means. Innovation is not a measurable quantity in a product. The perception of a product's innovativeness is what makes it innovative. Latent variable models have been used in the past as a metric to quantify these types of psychological, unobservable factors [14]. These types of models have been used extensively by social and behavioral scientists, psychologists, and political scientists to explain the relationship between observable variables in terms of an unobserved variable [13, 15]. Recent research in engineering and design has transferred the method into modeling abstract concepts in both product and process evaluation [24, 25, 26, 27] and design [28, 29].

Application of latent variable models requires both a measurement model, which measures various psychological indicators of the latent variables, and a structural model, which associates physical attributes to the values of each latent variable. With sustainability as a proposed indicator in the measurement model, and a product attribute in the structural model, several methods are available to calculate environmental impact. One such method of determining the environmental impact of a product or process is Life Cycle Assessment (LCA) [30]. This method considers the entire life cycle, from raw material extraction through product use and end-of-life disposal, of a product. LCA assesses environmental impacts by first compiling an inventory of all the relevant emissions, material outputs, and energy uses. Next the impact of that inventory is calculated based on its effect to human health, the environment, and resource depletion [31].

Ullman has found that as much as 70% of a product's cost is set during the conceptual stages of design [32]. In addition to this, it is estimated that up to 80% of product-related environmental impacts are set in design [33]. Due to the importance that the early design phase has on cost and environmental impact, design methodologies and environmental impact evaluation techniques have been developed for the early phases of design. Modifying the Quality Function Deployment (QFD) methodology to include the environment as a customer has resulted in several design tools [34, 35, 36]. Fitzgerald et al. incorporated seven dimensions of eco-efficiency and the TRIZ contradiction matrix to identify ways of improving both functionality and environmental impact [37].

Several software packages are currently in use in academia and industry to evaluate the environmental impact of both products and processes. The SimaPro software package, for example, uses a graphical interface to calculate life cycle inventories [38]. From these inventories, different impact assessment methodologies and aggregation techniques are available to develop a complete picture of the impact of a product or process.

Because of the uncertainty existing in early design, a simplified LCA approach was taken using only a single score to evaluate environmental impact [39]. Several aggregation methodologies exist which compile all of the emissions, resource use, and damage to the environment information, then weight and normalize them based on different cultural perspectives and time frames of impact. These different impact perspectives incorporate the uncertainties present in the impact calculations [31]. Weights are given to environmental impact indicators based on short-term impacts, balanced between short term and long term, and long term impacts. ReCiPe is one such methodology that was developed based on the ISO 14040 and 14044 standards [40, 41]. ReCiPe combines LCI parameters into 18 midpoint indicators that carry a moderate degree of uncertainty. Using the various weighting and normalization schemes, these midpoint indicators are aggregated together into three endpoint indicators [42]. The hierarchist perspective of ReCiPe (balanced between short term and long term impacts) is based on common principles with respect to environmental impact and is the aggregation method used in this thesis [31].

Design repositories have been used in the past to catalogue, store, and reuse design information [33, 43, 44, 45]. The Design Repository at Oregon State has much of the pertinent information to generate the structural model of the overall latent variable model of innovation. Data on individual components of products like dimensions, mass, material, manufacturing process, function, and component connections is available [46]. Using the stored data, design tools like Function Component Matrices can be generated which aid in the creation of Function Impact Matrices. These FIMs are able to relate component environmental impacts to the functions they solve. The Design Repository was utilized for product data used in both manuscripts.

Manuscript 1 addresses the lack of accurate measures of product innovation, by quantifying product innovativeness with the use of a latent variable model. The previous uses of latent variable modeling for difficult-to-quantify concepts in social, behavioral, and medical sciences, have laid the groundwork for its application here [13, 15]. *Manuscript 2* explores the quantification of sustainability as a product attribute. Relying on LCA, the environmental impacts of the products used in the latent variable model were quantified. Taking this a step further, Function Impact Matrices are used to investigate the distribution of environmental impact within the innovative and common products. Background that is specific to each research topic can be found within the two manuscripts.

RESEARCH CONTRIBUTIONS

The main contributions of this work are in the calculation of a model of product innovativeness. This model takes into account measurable product attributes and customer perceptions of innovative and common products to determine whether or not a product is innovative. This model is time variant in that as products become well known and their technology is more understood, the products perception as innovative will decrease. With an evaluation of product innovativeness available earlier on in the design process, designers can target their design efforts in a way to increase the overall perception that a product is innovative.

A product sustainability attribute had to be determined so that it could be incorporated into the latent variable model. Environmental impacts at the product level were calculated for the model, however to incorporate an environmental impact analysis into early design, impacts were propagated down the functional and flow levels. With function and flow impacts calculated, it is possible to include a sustainability assessment at the functional design stage when not much is known about product form.

Together, these two contributions allow for the consideration of innovation and sustainability earlier on in the product design process. With a model for innovativeness, concepts can be screened for innovation at the conceptual design stage, and the most innovative concept can be selected for detailed design. If a reduction in environmental impact is desired, an estimation of design environmental impact can be calculated based on the functionality of the design. With evaluations of both innovation and sustainability in early design, designers can more effectively design for both.

A NEW TAKE ON QUANTIFYING INNOVATION: A LATENT VARIABLE APPROACH

Authors

Brady Gilchrist

Dearborn 102

Email: gilchrib@onid.orst.edu

Chris Hoyle

Rogers 418

Email: chris.hoyle@oregonstate.edu

Irem Y. Tumer

Covell 116

Email: irem.tumer@oregonstate.edu

Carrie Rebhuhn

Rogers 442

Email: carrie.rebhuhn@gmail.com

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Abstract

Innovation is a word that is used in the media and has been described as essential for a prosperous society. Where more emphasis has been placed on innovation, it remains not well understood and inherently difficult to quantify. This paper aims to take a new approach to quantifying innovation using a latent variable model. The latent variable model utilizes a psychometric survey approach to provide a measure of innovativeness (i.e., a measurement model), and product attributes to describe the structure of innovativeness (i.e., a structural model). Finally, a binary choice model is used to relate innovativeness and other latent characteristics of the product to its selection as an innovative product. This measure is capable of differentiating the innovativeness of products and determining which is more innovative.

The three latent variables uncovered using factor analysis are: product *innovativeness*, product *usability*, and *company profile*. Using these latent variables, the measurable attributes, and a choice model, a value for design innovativeness can be calculated and used for conceptual design selection, or further design refinement.

Introduction

Innovation is relatively easy to identify but extremely difficult to quantify. Experts can look at a product or process and determine whether or not it is innovative and why [47]. However, it is a highly subjective process. To date, there is no mutually accepted way to quantify how innovative one product is over another. The research presented herein attempts to: (1) show that the “innovativeness” of a product can be quantified using a latent variable model; and, (2) show that this metric for innovativeness, based on customer perceptions, can be extended to physical product parameters, which can in turn be used to measure the innovativeness of future designs. A latent variable is one that is abstract and difficult to quantify directly but has indicators that lead to its measurement [14].

It is necessary for the purposes of this study to define innovation. To best align with the goal of this study, a definition of innovation is taken from [6] as “providing novel value to the customer that produces growth and profit." Innovation has typically been measured as a means to gauge technological progress, however this paper intends to measure innovation as a way to gauge product innovativeness and eventually to select which concepts to pursue and products to develop.

The literature supports the use of models of innovation on the national level and the corporate level, but has yet to delve in to measuring the innovativeness of products [6, 16, 17, 18, 19, 20]. Innovation measurement at the firm level is used for comparisons between different businesses, using different models and indicators, such as patent count and R&D expenditures. Measuring innovation at the national level involves comparing innovative output between countries. These metrics are used to measure competitiveness between nations, or to gauge technological progress [20]. To increase the innovative output of first, companies, and in turn nations, a measure of the innovativeness of products can be used.

Methods exist to judge the creativity of a set of designs during the concept generation phase. One method, introduced by Shah et al., measures four different aspects of a concept. Quality, quantity, novelty, and variety are calculated for each concept, based on the different ways each product-function is solved, and used to help select a concept to pursue in detailed design [48]. Oman et al. took this a step further and isolated the metrics most closely associated with creativity (novelty and variety) and developed the comparative creativity assessment and multipoint creativity assessment method [49]. Pursuing and developing creative ideas to production can potentially result in innovative products.

This research contributes a quantitative measure of the innovativeness of products. All literature reviewed is proficient in calculating the innovativeness of companies, but not the specific products they produce. This metric can then be used to screen concepts, or select components and help designers to better understand the perceptions of the products they develop. In addition, a measurement model has been developed that links product attributes to the latent variables uncovered. Finally, a choice model that relates the product attributes to the product's selection as an innovative product was created.

The approach presented in this paper first uses a psychometric survey to gather information about the perception of the characteristics and traits of four pairs of products. The pairs are presented as one product identified as innovative and an associated product that has not had any outside source identifying it as innovative. Using factor analysis, the latent variables are uncovered and using a regression model, coefficients on the product attribute variables are calculated. Next, a binary logit choice model is used to relate the latent variable values for each product to its selection as innovative. The model is then presented with the values of the coefficients for each latent variable and product attribute are discussed. Potential applications of its use are presented with their benefits to conceptual design. Finally, conclusions that can be drawn from the results are offered along with future work.

Background

To design more innovative new products, it is necessary to know how innovative those products are. If innovativeness can be assessed earlier on in the design process, designers can better focus their efforts to create more innovative products. Current methods of identifying and characterizing whether a product is innovative are based on expert opinions Quality, less subjective, methods for calculating the innovativeness of products do not exist. It is hypothesized that innovativeness is a latent, or unobserved, variable which cannot be directly quantified.

This section first introduces currently used methods of quantifying innovativeness at both the national and firm levels. Next, methods of uncovering latent variables are described with their applications in behavioral and social sciences, as well as engineering and product development.

Methods of Quantifying and Characterizing Innovation

Metrics for quantifying innovation are few and far between. Some are single measures, such as R&D expenditures or patent propensity. Others are a combination of indicators, which give a more complete description of innovative activity. These measures have their drawbacks though. First, none of the measures of innovation are at the product level. They are used to keep track of trends in innovative activity. Indicators used to measure innovation are typically based on input to the innovation process and output measures of success and growth [17]. This work attempts to reveal the underlying perception of innovation and determine ways to design products such that consumers perceive them as innovative, edgy, and desirable.

One measure of innovation is patent propensity, or the number of patentable inventions that are patented [16]. However, this metric has its drawbacks that limit its accuracy. Not all products or innovations are patented, so the result is contingent upon whether the company has patents for their products. Some firms use secrecy to protect their ideas. Therefore measuring innovation based on the amount of patents protecting technology in a product or the product itself is not consistent. Arundel and Kabla surveyed over 600 companies in Europe to determine the rate of patented technology and found on average only 35% of innovations are patented [16]. In addition, the ratio of patents to R&D has declined in the past 40 years, showing a decrease in the use of patents to protect innovations [18]. Patent propensity is just one aspect of a larger model of innovation at the firm level.

R&D input, or investment, is used as a measure of innovation output in Mairesse and Mohnen's work. Data was collected in France based on new products introduced in the market. Indicators of innovation include quantities such as R&D per employee, share of sales by new products, and share of sales of products protected by patents. It was also noted in this work that the indicators were highly subjective, further strengthening the need for a less subjective measure. This work aimed to determine the effect of R&D on various innovative indicators, and resulted in a positive correlation for all indicators measured [50]. As is the case with patent propensity, R&D expenses do not give a complete view of innovation. In addition, it is simply another measure of firm innovation, not product innovation.

Shapiro proposed a new measure of innovativeness based on the percentage of revenue from "new platforms" in [6]. A platform is essentially a base design from which product variants are developed. This is combined with a measure of revenue from new products to give more insight into the successful development of innovative new products.

As with the previously introduced measures of innovation, the following are metrics of either national innovation or firm innovation that combine multiple indicators to show areas of strength or weakness. The European Union publishes the Innovation Union Scoreboard (IUS) yearly. This report outlines the innovative performance of European Union nations based on several indicators, which include; percentage of population completing tertiary education, number of international scientific publications, venture capital investments, and R&D expenditures [20]. Measuring innovation at the national level, Mairesse and Mohnen created a framework using metrics such as innovation intensity, propensity of innovation, and size of the firm [19]. Another example of measuring firm innovativeness is the Composite Innovation Index developed by Carayannis and Provance. The index is based on three major factors: innovation posture, propensity and performance [17].

Finally, looking specifically at innovative products themselves, Saunders and Seepersad surveyed 197 products identified by outside sources as innovative. By comparing to a competing product and isolating the characteristics that made those products innovative, they were able to compile a list of five major categories of innovation: functionality, architecture, external interactions, user interactions, and cost [23].

Uses of Latent Variable Models

Intrinsically, latent variable models are used to measure “hidden” variables. Essentially they cannot be directly observed. The idea behind this concept is that there are other observable and quantifiable factors that contribute to the variable of interest. A latent variable model is based on the idea that the number of driving forces on a given variable is less than the number of available measurements [24].

In the past, mainly behavioral and social scientists have used latent variable models to describe quantities of interest. Things such as preferences, attitudes, ambition, intelligence, personality traits, and behavioral intentions have been quantifiable due to latent variable models [15, 51]. More recently, the technique has been applied to other areas, for example, to model the occurrence of diseases such as alcoholism, Muthen applied a latent variable model [52]. Varying degrees of alcohol dependence can be measured using indicators such as amount, frequency, frequency of high consumption, and selected demographic information. Alcoholism, like other latent variables, is not something that is directly observable, but it can be estimated using other observable variables [52].

There is some recent research in applying the latent variable concept to industrial processes [24, 25, 28]. Kim et al. used the concept to model the forging process and to identify defects and problems without necessitating visual inspection, saving time and money [26]. Robustness of a membrane manufacturing process has also been modeled as a latent variable in [27].

The goal in this manuscript is that using a latent variable method, it can be determined what people perceive as innovative and why. It is hypothesized that latent variables will uncover attributes of products that lead people to think of them as innovative. Applying the concept to customer preference, Wassenaar, et al. created an integrated model of passenger vehicles. It was proposed that consumers do not necessarily purchase cars based on attributes such as design, number of seats, engine power, or other variables, but that they are mainly concerned with safety, reliability, and comfort. From this model, the authors were able to gain a better understanding of how customer desires relate to vehicle attributes [29].

Latent Variable Models of Innovation

Little research exists linking the concept of "innovation" to latent variables. Innovation itself is a very good example of a latent variable. It cannot be directly measured, yet everyone has some sense of what it is. Leder and Carbon considered "innovativeness" to be an aspect of vehicle interior design. Showing customers a series of vehicle interiors with different attributes, such as the shape of the steering wheel, they were able to create a model of customer perceptions. They also used a questionnaire to uncover the customer's perception of innovativeness [53]. Trigo and Vence measured innovative cooperation between companies in the service sector using latent class analysis, a type of discrete latent variable analysis, to measure how companies cooperate to innovate new ideas [54]. Innovative attitude was used as an indicator in a latent variable model for "level of technology" as it was applied to agriculture and the adoption of new technology by Esposti and Pierani [55]. The "innovativeness" of IT firms has also been measured using latent variables. Lopes created an Innovation Index based on the results of the model created in [56].

Summary

While innovativeness has been previously characterized and measured on the national and firm level, it has yet to be quantified on the product level. It has been shown that a latent variable approach can be used to determine what physical attributes contribute to the more abstract latent variables. Innovation, being something inherently abstracts and not directly discernible fits the criteria to apply a latent variable approach for its quantification. The method of applying the concept of a latent variable model to measuring the innovativeness of individual products is presented next.

Method

Several steps were necessary to generate the latent variable model of innovative product choice. First a psychometric survey was administered to junior level mechanical engineering design students to determine their perceptions of the characteristics of innovative and common products. Using this data, a measurement model is calculated that relates the indicators from the survey to the hidden, latent variables. This measurement model is estimated based on the indicator values derived from the psychometric survey.

Next a structural model is calculated that describes how each of the measurable product attributes relates to the latent variables. This model shows which product attributes contribute to the three latent variables. Finally, the product attribute values are fit to the factor scores using linear regression.

Lastly, the choice model is derived from both the measurement model and the structural model. Assuming that the customer will select the innovative product each time, a logit choice model was used to determine the factor scores for each product.

Relating this process to the diagram seen in Figure 1, the survey questions administered represent the indicator values, **I**. Using factor analysis, the latent variables, **L**, are determined using the collected **I**. Next, using the product attribute values, **A**, and a regression model, the attribute coefficients, **γ**, are calculated. Finally, a binary logit choice model is used to relate latent variables, **L**, and product attributes, **A,** to model the relationship between the choice of products as innovative, and the qualitative and quantitative attributes of the products.

The number of responses needed to estimate the three models shown in Figure 2 can be determined from a number of empirical relationships. To estimate a choice model, a minimum of 150 responses is generally recommended [57]. To estimate the latent variables from the indicators, a good practice is to have at least four indicators per latent variable [13]. Additionally, a general rule for identification of latent variable models is that the number of unknown parameters should be less than the number of variances and covariances in the observed covariance matrix of the data. In other words, the unknown parameters should be less than or equal to $p(p + 1)/2$ for p observed variables [14]. In this work we have 20 observed variables, so we can have no more than 210 unknown model parameters.

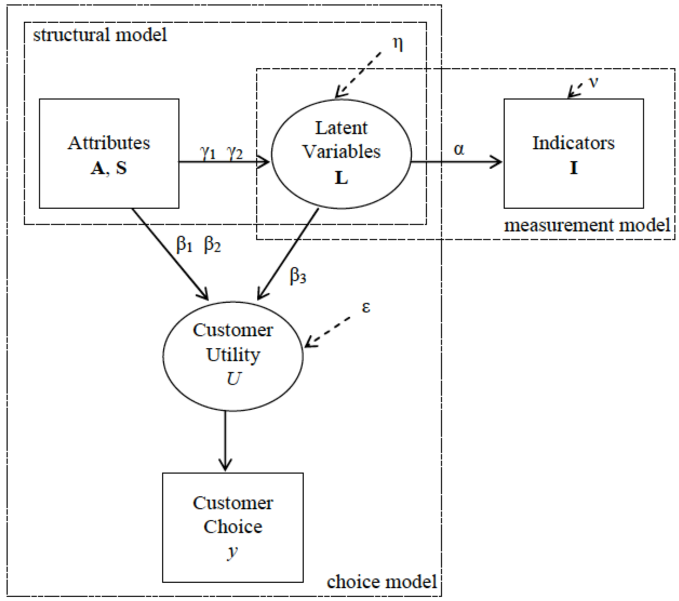

Figure 2: Integrated latent variable model with structural model, measurement model, and choice model [14].

Measurement Model

Calculation of the measurement model is done in reverse. Survey questions are used as a way to get an indication of the value of each latent variable. The use of a psychometric survey data gives a more accurate representation of the customer's perceptions of the products used in the study. The survey used consisted of 20 questions that pertained to the products listed in Table 1 and range from questions about the specific product functionality to the company's influence around the world. A full list of the IRB approved survey questions can be found in Appendix A. Each question has a scale between one and seven with one being in very low agreement and seven being in high agreement. Each participant was asked to respond to one set of survey questions for an innovative product, as well as its associated common product.

Table 1: Products used for latent variable survey.

Innovative Product	**Common Comparative Product**
Dyson Air Multiplier™ [58, 59]	Holmes® Fan
Powermat® [60]	Journey's Edge Dual Powered Charging Station
Oliso® Smart Iron [61]	Proctor Silex® Iron
KidSmart Vocal Smoke Detector [62]	First Alert Basic Smoke Alarm

Sources such as Popular Science's "Best of what's New," IDSA's "IDEA" awards, and TIME Magazine's "Best Inventions of…" were used to identify the innovative products used in the study. The common products were chosen based on the absence of claims that the product was innovative in their product descriptions. The surveys responses were collected in pairs of one innovative product and one common product. An example of a product pair, the Dyson Air Multiplier™ and the Holmes® Fan, can be seen in Figure 3. The two products have the same black box functionality, to move air, but use different means to achieve it. The Dyson has an impeller in the base which channels air around the multiplier ring where it uses the process of inducement to draw air into the flow and accelerate it forward [63]. A list of the innovative features of the innovative products used in the study can be seen in Table 2.

Figure 3: Innovative Dyson Air Multiplier™ (left) with its comparison product, Holmes® Fan (right).

Table 2: Innovative features of the innovative products.

Product	Innovative Feature
Dyson Air Multiplier^{TM}	Bladeless fan. Air pulled in through the base and pushed out using an impeller around a circular airfoil [58, 59].
Powermat®	Magnets align the device with the pad and using magnetic induction, the pad charges the device [60].
Oliso® Smart Iron	When the handle is released, the iron automatically lifts itself an inch above the ironing board [61].
KidSmart Vocal Smoke Detector	Uses a parents recorded voice to wake children and provide evacuation instructions [62].

Some of the indicators used were based on modified selection criteria from the innovative products lists use for this study. One of the sources, Popular Science, uses several criteria to judge innovative products, including significance of design, quality of design, and originality [64]. As can be seen in Appendix A, selection criteria from the sources used for the innovative products in the study have been adapted and expanded to form the product innovativeness survey.

To determine what the indicator values are for each of the products a psychometric survey was used. They survey was administered during the 2012-2013 school year in junior level mechanical design courses at Oregon State University. The subject population was targeted because of their knowledge of engineering principles and product design. The physical products listed above were available for the participants to manipulate and use during the survey to better understand their functionality.

A total of 133 surveys were collected in pairs of one innovative and one common product for a total of 266 responses. Using this data, factor analysis was implemented on the responses. This follows the approach outlined by Loehlin in [13] to determine the number of latent variables being measured. This was done to describe the covariance relationships among all of the random variables in terms of a few underlying variables. The data from the psychometric survey was input into STATA for the initial factor analysis [65]. To determine what factors are significant, the Kaiser-Guttman rule was applied to the factor correlation matrix, where an eigenvalue of greater than one indicates significance [13]. As seen in the Scree Plot in Figure 4, the first three factors have eigenvalues above one, indicating significance. Using the scree test to confirm factor significance, where the curve of decreasing eigenvalues changes from rapidly decreasing to a flat gradual slope, it was determined that the first three factors are significant [13, 14].

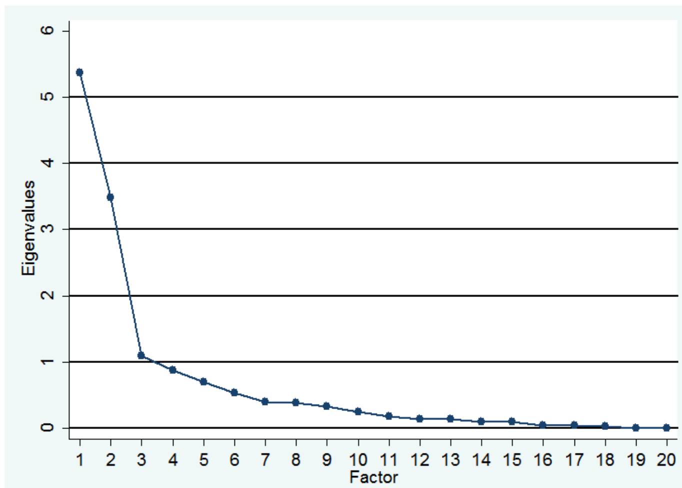

Figure 4: Scree plot of all potential factors.

These twenty survey questions are reduced to three significant factors. Once these factors were identified, the factor pattern matrix was rotated using the Varimax rotation developed by Kaiser [66]. Varimax rotates the factor matrix by an arbitrary factor such that it results in the principal factor matrix. All of the factors are orthogonal to each other after this (i.e. the factor correlation matrix has 0 off-diagonal terms), which makes it possible to identify each factor loading with just a single or small number of factors. Finally, only factor loadings with absolute values greater than 0.35 (after Varimax rotation) are included in the measurement model. This is because a level of 0.35 corresponds to about 12% of the variance in the indicator being explained by the factor; therefore, values of indicators less than 0.35 are not well explained by a given factor. Loading on each of the variables presented in Table 3.

Table 3: Factor loadings for each indicator variable.

	innovativeness	**usability**	**company profile**
success_product	-0.5878	0.4391	
performance		0.6022	
success_globally	-0.8244		
influence_globally	-0.5462		
efficiency		0.5968	
company_reputation			0.7202
company_influence			0.9063
quality		0.3956	
complexity	0.5502		
originality	0.6563		0.4133
user_benefits		0.5475	
aesthetics	0.6348		0.4370
familiarity	-0.5759		
easy_of_use		0.4726	
features_satisfaction		0.6296	
high_tech	0.7784		0.3656
trendy	0.7082		0.4585
adjustability		0.3736	
sustainability			
risk			

Based on what indicators were significant to each factor uncovered, the three factors most likely resemble *innovativeness*, *usability*, and *company profile*. *Innovativeness* of a product was found to relate to several variables, some of them negatively. The positive indicator coefficients of product *innovativeness* include product complexity, originality, aesthetics, and perceptions of “high tech” and “trendiness.” Interestingly, this factor had several negative loadings that would make practical sense. How successful the product was, global success of a product, influence of the product on society, as well as familiarity with its design and features all have an inverse relationship with innovativeness. Intuitively, as a product is more prevalent across the world, and the public becomes more familiar with its use, its perception of innovativeness decreases. This equation for *innovativeness* passively takes into account the passage of time and widespread adoption of a technology in determining whether it is innovative or not.

A second factor, determined to be product *usability* based on the inclusion of the indicators of performance, efficiency, quality, benefits to the user, ease of use, satisfaction with the products' features, and adjustability of the product. These variables were determined to be most associated with how the product is used, and thus its *usability*. This factor is interpreted as preference toward more usable products.

The final significant factor that was uncovered is *company profile*. This factor relates to the reputation of the company that produced the product, the influence that company has on the market, how original the product is, and how trendy it is. It is assumed that this latent variable is a measure of brand equity, or the value of having a familiar company. Equation 1 is the basic measurement model used in the overall latent variable choice model. It should be noted that as this equation is written, the indicators are the effects that the latent variables cause. The method used in this research took the opposite approach, calculating the causes based on the effects.

$$\mathbf{I} = \alpha\mathbf{L} \tag{1}$$

Structural Model

Now that the three significant factors have been identified, the structural model, linking the measurable product attributes to the latent variables (found previously) can be generated. First, a list of product attributes that could potentially be related to the latent variables was compiled based on the literature. Data for each product was collected from the physical product itself and product information available online. Attributes such as power usage, part count, product cost, number of different materials, and number of patents were used as inputs to the structural model. Some of the attributes are difficult to conceptualize; therefore, definitions of all product attributes are included in Appendix A.

An initial pass at the structural model using a regression on the raw product attributes resulted in highly correlated attributes and a model that only contained six attributes. To diminish the issues caused by multicollinearity of the observed variables, they were grouped together into latent variables [67]. Following the same method as was used to generate the latent variables in the measurement model, factor analysis was performed on the product attributes. After, once again, invoking the Kaiser-Guttman rule the factored data resulted in two significant factors. Rotation of the factor pattern matrix, again, using the Varimax rotation resulted in the factor loadings on factored attributes $\mathbf{A_1}$ and $\mathbf{A_2}$ seen in Table 4. A scree plot of the factors can be seen in Figure 5 with the cut off value of eigenvalues greater than one marked, verifying the selection of only two factors. Attributes that aren't explained well by the factor, with coefficients less than 0.4, were dropped. Using this method, a total of nine product attributes were incorporated into the model.

Table 4: Factored product attribute coefficients.

	factor 1 ($\mathbf{A_1}$)	factor 2 ($\mathbf{A_2}$)
power_usage		0.9564
co_patents	0.9373	
product_materials		0.8541
product_parts	0.8393	0.4595
product_features		0.9714
product_sustainability	0.9782	
product_functions	0.6944	0.6528
product_flows	0.9143	
product_cost	0.9526	

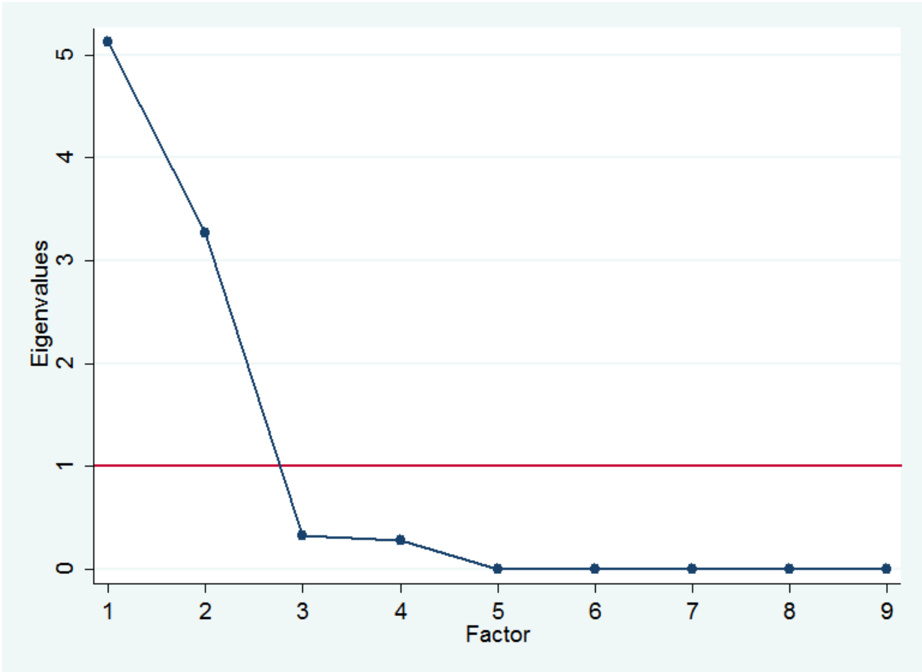

Figure 5: Scree plot of factored product attributes.

Factor 1 resembles the design of the product. Its significant variables include number of company patents, total product part count, product sustainability, product functions, flows, and cost. These variables relate more to the design of the product than how it is used. These are attributes that are manufactured into the final physical product.

Factor 2 relates mostly to the performance of the product. Important factors include power usage, total number of different materials used, total part count, number of different features, and number of different functions. This appears to capture how people view the product when they buy it. Most of these attributes are things you would see on the packaging of the product when you purchase it.

A regression is performed to generate Equation (2). Product attributes are normalized to improve model estimation and allow comparison of model parameters on a normalized scale. Calculating a linear regression on each of the factors and attributes resulted in the coefficients of the two factored product attributes that are significant to each latent variable. The model shown below in Equation (2) calculates the value of each latent variable, **L**, based on the factored product attributes, **A**, and each attribute variables associated coefficient, γ. Because of the homogeneity of the participants of the survey, socio-demographic attributes, **S**, were omitted from the model.

$$\mathbf{L} = \gamma_1 \mathbf{A} + \gamma_2 \mathbf{S} \tag{2}$$

Each of the cells in Table 5 are the resulting coefficients, γ values, of each attribute associated with the latent variable to which they are significant.

Table 5: Coefficients associated with each latent variable and product attribute variable.

	Innovativeness	**Usability**	**Company Profile**
Factor 1 (A_1)	0.755	-0.023	0.404
Factor 2 (A_2)	0.096	-0.045	-0.274

Table 6 shows the value of the latent variables for each of the product pairs. The highest score for each latent variable within the pairs is bolded. Notice that for the *innovativeness* latent variable, all but one of the previously identified innovative products scores higher than their common competitors.

Table 6: Latent variable scores for innovative and common products.

	Innovativeness	**Usability**	**Company Profile**
Dyson Air Multiplier™	**297.56**	-11.79	**138.22**
Holmes® Fan	52.63	**-4.04**	9.33
Powermat®	**71.56**	-4.04	**23.91**
Journey's Edge Dual Powered Charging Station	30.84	**-1.99**	8.39
Oliso® Smart Iron	106.35	-9.73	6.73
Proctor Silex® Iron	**146.96**	**-8.87**	**44.70**
KidSmart Vocal Smoke Detector	**43.05**	-2.65	**12.71**
First Alert Basic Smoke Alarm	27.50	**-1.71**	7.95

Binary Choice Model

Once the factored and rotated matrix was generated, the model was fit to a binomial logit choice model which models the relationship between the qualitative latent attributes of the product (**L**) and a product's selection as an innovative product. Logistic regression is used because there is a binary choice of innovative product or not which measures the relationship between a categorical variable to a continuous variable. This choice model takes into account product *innovativeness*, product *usability*, and *company profile* in customer selection of an innovative product. Equation (3) outlines the integrated latent variable choice model with Table 7 showing the latent variable coefficients.

$$\text{Choice} = \beta_1 \mathbf{L_1} + \beta_2 \mathbf{L_2} + \beta_3 \mathbf{L_3} \qquad \textbf{(3)}$$

Table 7: Latent variable coefficient values.

k	Latent Variable (L_k)	Coefficient (β_k)
1	Innovativeness	4.90
2	Usability	0.53
3	Company Profile	1.16

Using the qualitative attributes, the choice model assumes that the innovativeness of a product is explained by perceived attributes of the products, such as its *innovativeness* or *usability*, as opposed to quantitative measures, such as the product's weight or number of parts.

This model links product attributes, the latent variables, and the selection of the product as innovative. Here, it is assumed that customers make purchasing decisions that maximize their utility, and that utility is a function of key customer desired attributes, **L**, and product attributes, **A**. It is further assumed that the customer desired attributes are not easily quantifiable.

Results

Using the coefficients for each latent variable found in the choice model, and the values for each latent variable found in the structural model, a utility score can be calculated that is the probability each product is selected as innovative. The scores for each product pair can be seen in Table 8 with the highest score within the product pairs in bold.

Table 8: Utility scores for each product pair.

	Product	**Utility Score**
Innovative	Dyson Air Multiplier™	**1611.20**
Common	Holmes® Fan	266.48
Innovative	Powermat®	**376.08**
Common	Journey's Edge Dual Powered Charging Station	159.74
Innovative	Oliso® Smart Iron	523.64
Common	Proctor Silex® Iron	**766.90**
Innovative	KidSmart Vocal Smoke Detector	**224.19**
Common	First Alert Basic Smoke Alarm	143.00

This is an ordinal measure of innovativeness in that the highest utility score between product pairs is selected as innovative. It cannot be said that the innovative Dyson Air Multiplier™ is more innovative than the, also innovative, Powermat®**.** Here, it can be seen that with the exception of the Oliso® Smart Iron, the results of the model coincide with the outside sources identifying the products as innovative. Each innovative product scored higher than their common competitor.

Discussion and Conclusions

In the context of conceptual design, it is assumed here that the latent variables resemble customer requirements. This view is shared by Chen et al. in [14]. These customer requirements cannot always be directly quantifiable, or are difficult to quantify with a single engineering requirement [68]. The product attributes can be thought of as engineering requirements, which lead to fulfillment of the customer requirements, or latent variables.

The model developed in this paper is a choice model for innovative products. It incorporates product *innovativeness*, *usability*, and the *company profile* of the manufacturer. With product success, global success, global influence, and familiar with the product being negatively correlated to the latent variable of innovativeness, the model can take into account changes in the market. This measure of product innovativeness is time invariant in that as the technology is more understood and widespread, and as product success and influence increases, the perception of a product's innovativeness decreases. More unknown, less understood products would be considered more innovative.

Usability will definitely have an effect on a customer's choice of product. The *usability* latent variable incorporates the indicators that are associated with the user's interaction with the product such as efficiency, quality, ease of use, etc. Customers want to purchase a product that is usable and does what they want it to do.

The *company profile* latent variable appears to capture the influence a company's innovative identity plays on the perception of its products. It has been found that what customers know about a company can influence what they think about a new product manufactured by that company [69]. Products from companies that are seen to be innovative get a boost in their perception of innovation based on the company's innovative attitude. The Dyson Air Multiplier™ for example is perceived to be innovative partly because of the innovative nature of the Dyson Company. Their products use new technology, or utilize technology in a different way to create new products.

The usefulness of the product innovativeness model comes during product development. The model presented herein results in a way to measure the innovativeness of a new product or design based on physical attributes of that product or design.

With this model, it is possible to calculate the innovation score of a design. Using this information, it would be possible to consider how innovative a product is earlier on in the design phase. This in turn will help designers to better direct their design efforts on new technology and less well-known methods of solving the functions inherent in the design problem. Concepts can be screened for innovation before they become detailed designs, resulting in better, more appealing designs.

Future Work

First of all, it is important to determine a way to fill in unknown attribute values for each of the products used in the study. Several attribute values were unavailable and had to be omitted. For example, the products that were from private companies had no available stock price. A metric for calculating the dollar value of a company other than its stock price is needed. Therefore, some sort of measure of the value of the manufacturer can be used. In addition to this, the model would be more accurate if more product attributes are used.

With this less subjective method of quantifying the innovativeness of products, the authors hope to propagate this "score" down to the component level such that each component has a value for its innovativeness. It is still unknown how component interactions affect each individual component's innovativeness, which is to be determined in future work by the authors.

With components having scores for innovativeness, and the connections between those components known, it is possible to develop conceptual designs with different target levels of innovativeness. These conceptual designs can be generated by a computer, and presented to the designer for further consideration.

The usefulness of this method needs to be evaluated based on a real world design problem. Using target values for each of the latent variables, it is possible to calculate the design attributes needed to achieve those levels, and proceed with a detailed design accordingly.

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FUNCTIONAL ENVIRONMENTAL IMPACT OF INNOVATIVE AND COMMON PRODUCTS

Authors

Brady Gilchrist

Dearborn 102

Email: gilchrib@onid.orst.edu

Douglas L. Van Bossuyt

Dearborn 102

Email: Douglas.VanBossuyt@gmail.com

Irem Y. Tumer

Covell 116

Email: irem.tumer@oregonstate.edu

Ryan Arlitt

Dearborn 103

Email: arlittr@onid.orst.edu

Robert B. Stone

Rogers 208

Email: rob.stone@oregonstate.edu

Karl R. Haapala

Rogers 312

Email: karl.haapala@oregonstate.edu

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Abstract

Innovation has been touted as a means toward providing sustainability. Innovations in materials, manufacturing, and product design can lead to a reduction of global environmental impacts while helping to realize the goals of a sustainable society. This research aims to explore whether or not product functionality has an effect on environmental impact and if the flow of energy, materials, and signals (EMS) have an effect on product environmental impact. Innovative and common products are identified and life cycle assessment is performed for each product at the component level. Using function impact matrices, the environmental impacts of the product components are propagated back to the functional level, where their impacts are compared. The innovative products of the comparisons conducted appear to be more environmentally impactful, however more work must be done to understand whether the result is generalizable. The intended use of this research is during the conceptual design phase when little is known about the final form of a product. With approximate impacts of functions known, designers can better utilize their design efforts to reduce overall product environmental impact.

Introduction

As new products are designed and existing products are improved upon, it is important to remain vigilant on the environmental impact of those products. “Green washing” has become a serious problem in the sustainable products market, where companies exaggerate or misleadingly present their product’s sustainability claims [70]. With a population nearing seven billion and standards of living increasing across the globe, it will be ever more important to maintain a high degree of product responsibility in the coming years.

Sustainable development has been defined as “…development to meet the needs of the present generation without compromising the ability of future generations to meet their own needs” [8]. To align better with this definition and to adopt responsible practices, regulations around the world are requiring manufacturers to be responsible for their products through their entire life cycle [11]. These regulations motivate sustainable product development, which is defined as the process of making products and/or services to be more sustainable throughout their entire life cycle [71]. Even incremental changes in product design can help realize a large reduction in environmental impact. An example of product development with sustainability in mind can be seen in laundry detergents designed for cold water. If all users were to adopt this type of detergent across the U.S., it could cut 3% of the country's overall energy use by avoiding water heating [72]. In addition, cold water detergents are more concentrated, requiring less packaging, and further reducing the environmental impact of the product [72].

Life cycle assessment (LCA) is a standard approach to determine whether or not successive generations of products are more environmentally sustainable than before, by focusing on the relative environmental impacts as measured by such indicators as ecotoxicity, ozone depletion, and land use, among others. To conduct a comprehensive product LCA, it is necessary to have a detailed design, with component geometries and materials chosen. However, during the concept generation phase of design, not much is known about the form of the product and what materials and manufacturing processes will be selected. Without this information, calculating an approximate environmental impact is very difficult. Unfortunately, however, as much as 80% of a product's environmental impact is established during the conceptual phase of design [33]. Thus, there is a disconnect between the product information available in the conceptual design phase and the desired environmental impact information.

Quantifying a product's environmental impact at the functional phase of design is necessary in order to properly leverage the importance of conceptual design on environmental impact. No direct mapping between function and environmental impact exist, however, it is understood that functions lead to form, embodied by components, and environmental impact can be derived from existing components. Using these relationships, the environmental impact of components can be mapped to the functions they perform. This information can then be used when designing a new product by guiding the designer in selecting functions that have low impacts and targeting their design efforts on product functions that have higher impacts.

Comparisons can thus be made at a high level by decomposing actual products and identifying materials and production processes used in creating the products. Life cycle inventories can then be formed and impacts calculated using commercially available LCA software (e.g., SimaPro 7.3) [38]. It is important to note that, due to the dearth of comparable social and economic impact methods for products, sustainability comparisons are solely on an environmental impact basis.

This paper explores the hypothesis that innovative products are more environmentally sustainable than their common counterparts, and that lower environmental impacts are realized on both the functional and flow level. This work is an extension of prior work reported by Gilchrist et al. [73], with the key difference in this research being that the overall product environmental impacts are distributed to the functions solved within the product. Previous research by the authors only assessed the environmental impact of the product as a whole, not on the basis of its individual components and functions. It is assumed that if designers can create environmentally friendly product concepts at the functional level, then innovative solutions can arise, but there is not evidence that this premise has been previously tested. Additionally, this research examines what functions and flows most affect a design's environmental impact. Once a function's impacts have been identified, a comparison can be made between different functional approaches to accomplish the same user-related functionality (i.e., functions that are associated with accomplishing the needs of a user).

The motivations for performing product LCA studies are introduced below. This then leads to a description of the products to be examined and the methodology employed. Assumptions and limitations of the study are presented next, followed by a discussion of the results. Finally, future work to apply and strengthen the methods and findings of this research is discussed.

Research Contributions

This research compares the environmental impact of innovative and common products on both the product-related functional level, as well as the impact of EMS flows. The products used in this research have been identified as innovative by popular media, and are compared with similar products that make no claims of innovativeness (i.e., common products). While there is no concrete definition of innovation, most agree that it involves the application of novel and creative ideas [7].

The hypothesis of this work is that the innovative products have lower environmental impacts than common versions of the same product. To test this hypothesis, the products were decomposed both physically, by disassembly to the component level, and functionally, using the functional basis developed by Stone and Wood [74]. The selection of function and flow for a product is also discussed in the context of reducing environmental impact.

This research begins to develop a method of determining if components that perform the same functions have comparable environmental impacts. This is achieved by the introduction of a novel Product Function Impact Matrix (PFIM), a modification and extension of the Product Function Matrix (PFM) [75] generated by the Design Repository [46]. The PFIM populates a matrix of products and the functions of those products in order to calculate average functional impacts of product groups.

Background

Companies across the world are starting to realize the value in designing products in a more sustainable way. This is resulting in significant environmental impact reductions, aided by LCA. Understanding the role LCA plays in design and how it can benefit sustainable design is important to the research presented in this paper. Several tools and methods that take advantage of the power of LCA are described below. They range from QFD-based tools to the one used in this research, namely, function impact matrices.

In this section, research related to incorporating innovation and sustainability into product design is first presented. Next, the LCA method is explained, which is then followed by an explanation of how it can be employed in design. This sets the stage to describe the function impact matrix method used in this research, which combines the QFD and LCA methods.

Innovation and Sustainability in Design

Although technology development has stimulated economic growth, it also has resulted in detrimental resource use and waste generation. A variety of solutions are available to achieve sustainability, and both long-term and short-term solutions need to be employed [76, 77]. In the short term, a product can be redesigned to create a solution with lower overall environmental impacts than the prior product generation. Environmentally sustainable long-term solutions will require a paradigm shift in the way designers think about the products that they develop.

An emerging market trend is that of healthy and sustainable products. This ranges from hybrid and electric vehicles to organic and eco-friendly materials used in consumer products [9]. Sauers and Shekar reported that 5-10% of consumers are willing to pay more for environmentally friendly products and services; while another 70-75% are indifferent as long as the product meets their needs [72]. With sustainability becoming more accepted by mainstream consumers, this market will continue to grow. It has been shown by Abele et al. that, when given the choice, a customer will select an environmentally friendly product over its common competitor when supplied with proper information about its environmental impact [78]. As a result, consumers will likely continue to increase their expectations for more environmentally friendly products.

Aside from addressing the voice of the customer, to be competitive in the global market companies must design products to address emerging environmental policies such as the European Waste Electrical and Electronic Equipment (WEEE) and Restriction of Hazardous Substances (RoHS) directives [11, 12]. To help designers comply with these regulations, several novel design methodologies have been developed. Eco-innovation has been defined by the Organization for Economic and Co-operative Development (OECD) as "the creation…of new, or significantly improved, products (goods and services), processes, marketing methods, organizational structures and institutional arrangements which…lead to environmental improvements compared to relative alternatives" [79]. When sustainability is considered earlier in the design process, the potential for reducing the environmental impact of the final product is greatly increased.

As alluded to above, eco-innovation is a type of design process that focuses on innovation and sustainability in design. As the practice is in its infancy and has yet to be implemented on a wide scale, there is little literature available on eco-innovation techniques to aid designers. Most methods are TRIZ-oriented and based on seven eco-innovation elements including material reduction, energy reduction, and product durability [80, 81, 82, 83, 84]. TRIZ is a design methodology whose Russian acronym can be translated to "Theory of Inventive Problem Solving" and is based on contradictions in parameters that exist during design. Design principles are used to solve those contradictions [80, 82, 83, 84].

Another approach for eco-innovation in design takes advantage of the Quality Function Deployment (QFD) methodology, created by Sakao, which works to minimize the negative environmental impacts and costs while evaluating functions based on customer importance [36]. First, an LCA is conducted to get a baseline of environmental impacts. Problem areas are then highlighted and used as inputs to the QFDE (Quality Function Deployment for Environment) as environmental customer requirements in part two of the method. From the QFDE, conflicts with engineering requirements are identified and, using TRIZ inventive principles, those contradictions are solved. It was discovered that a component that has a small environmental impact may have a function that largely affects environmental impacts [36].

These approaches for eco-innovation in design show that there is the potential to reduce environmental impact by focusing on function rather than form, which can address limitations of only focusing on materials and manufacturing based environmental impact reduction. Thus, a broader design methodology incorporating functional changes to reduce impact, rather than just material changes could prove to be useful in reducing environmental impacts of new products.

Life Cycle Assessment in Design

When products are redesigned, they typically have improvements in performance, functionality, and quality [85]. As environmental regulations and policies become more restrictive, products will need to be increasingly designed for environmental sustainability to be sold in the marketplace. Comparative LCA studies can be used to determine whether redesigned products improve upon previous versions environmentally. LCA can be used to examine environmental impacts using a number of different methods. Examining the differences in functionality and components needed to solve functions will give insight into how the innovative products differ from their common competitors.

The backbone of this research is a comparative LCA of an innovative product and a common version of the same product. Using a similar approach, Joshi compared the environmental impacts of steel fuel tanks and plastic fuel tanks [86]. It was found that the steel tanks had a greater environmental impact than the plastic ones in almost all categories of impact. Taking a parallel approach, Hartikainen et al. used a comparative LCA study to determine whether the application of a novel new material for superconducting electromagnets had a smaller environmental impact than the currently used copper electromagnets [87]. Although using superconductor wire requires significantly less material, it requires a more energy intensive process to produce. This results in the copper magnets having a lower impact than the superconducting magnet. Product families were established by Collado-Ruiz and Ostad-Ahmad-Ghorabi to set benchmark values of environmental impact to help target future design efforts. Families of product packaging were compared, including bottles, cans, foils, and storage containers [88]. Such comparative LCA studies for products are commonly reported in the literature [89, 90, 91].

To conduct an LCA, a life cycle inventory (LCI) is compiled to account for material and energy flows of each process across the product life cycle. In the case of the products studied in the research reported herein, not everything was known about the specific materials used and manufacturing processes necessary to produce the products. To assist in developing the LCI for the products considered, the Design Repository housed at Oregon State University was used to gather component data [92]. The Design Repository is used to capture and reuse design data about components, functions, failure modes, and other product information [93]. Within the Design Repository products are broken down into assemblies, and by individual components within the assemblies. Information is recorded for component material, mass, dimensions, and manufacturing processes [92].

In this study, the Design Repository is used to catalog components of each product. Materials are entered through a drop down menu with a specific set of materials. Metal alloys are generalized as “metal.” In this study, metals are assumed to be steel. A similar approach was taken by Deng et al. by assuming the various types of metal in the study were common steel [94]. Similarly, components made of various types of plastic were assumed to be polypropylene, and rubber or synthetic rubber components were assumed to be styrene butadiene. In addition to component data, the Design Repository has functional models of every product in the study. This functional information indicates which functions are performed by which components, as well as the general energy, material, and signal (EMS) flow paths through the system.

LCA is typically used throughout the design process [95], but the uncertainty that exists in the early design stages increases the difficulty of performing accurate LCA. However, it has been shown that it is possible to obtain representative LCI data using information stored within The Design Repository. Bohm et al. estimated the environmental impact of virtual concepts in early design using such data for existing products and found comparable predicted environmental impacts for virtual concepts and actual products [33]. Another approach to assessing environmental impact in the conceptual design phase is with the use of modified design structure matrices (DSMs). Rocco et al. used DSMs to record the interaction of the concept with the outside environment and between its functions [96].

Function and Environmental Impact

With every design there is functional intent behind the selection of components. The designer is focused on what needs to be accomplished, not how [32]. Functional design is a way to abstract the design problem in such a way as to increase understanding of the problem and create an opportunity for creative solutions [32].

Work done by Devanathan et al. has shown the feasibility of associating environmental impact with its given function with the use of a Function Impact Matrix

(FIM) [97, 98, 99]. There is no way to directly calculate environmental impacts of the functions in a product. Impacts can be found for components, and components solve functions. Therefore, one can deduce that a function leads to a component, and component information is what is needed to calculate an environmental impact. LCA is inherently product design oriented, and working with the early stages of design and a functional model, environmental impact information is difficult to incorporate. The result of Devanathan et al.'s work is the Function Impact Matrix (FIM), which is used to distribute environmental impact to functions of the product.

The FIM combines LCA with several aspects of QFD. The function component matrix is a binary matrix that shows the connections between components in the product and the functions they solve [43]. A FIM is created by combining a function component matrix with the environmental impact data calculated from each component, then distributing that impact data over the functions of the product. Devanathan et al. used the FIM to isolate dominantly impactful functions and target them for redesign to reduce environmental impact. With their case study, they showed that environmental impacts could be reduced without compromising product functionality.

Method

Several steps must be performed in order to determine functional environmental impacts for innovative and common products. First, the products used in the study are introduced and their selection explained. Next, the products must be decomposed physically to the component level as well as conceptually at the functional level. After product decomposition, LCI data can be taken for each component. Then, using FIMs, the environmental impact of the component's various functions can be calculated. With this data gathered, functions as well as flows for innovative and common products can be compared.

Product Population

As mentioned previously, this study examined the environmental impacts of innovative and common products. All of the innovative products that are examined in this study are selected based on their inclusion in various lists of the most innovative products of recent years. The lists used in this research are the Popular Science “Best of What’s New Award” from various years [60, 64], the TIME Magazine “50 Best Inventions Award” [58], the Good Housekeeping “Very Innovative Products Award” [59], and the IDSA “International Design Excellence Award” [62, 100]. The selection process by these magazines is based on the opinions of industry experts rather than a rigorous, objective method since innovation is something that is inherently difficult to quantify.

Selection methods are inherently subjective and vary for each award. Popular Science, for example, uses a panel of expert judges in the categories of innovations being selected e.g., computing, engineering, gadgets, home technology, health, and green technology. Some of the judging criteria include significance of design, quality of design, and originality [64]. The products that have been identified as innovative in this research are listed in Table 9, along with the source that identified each product as innovative and the common products to which the innovative products are being compared.

Table 9: Selected innovative and corresponding common products for comparison.

Innovative Product	**Source**	**Comparable Common Product**
Dyson Air Multiplier™	Time Magazine- 50 Best Inventions of 2009 [58], Good Housekeeping- Very Innovative Products 2011 [59]	Holmes® Fan
Milwaukee M12™ Copper Tubing Cutter	Popular Science, Best of What's New 2009 [101]	RIDGID Tube Cutter
Clorox® ReadyMop®	IDSA- IDEA Awards 2003 [100]	Libman Wonder® Mop, Libman Microfiber Floor Mop
Milwaukee M12™ Palm Nailer	Popular Science, Best of What's New 2010 [60]	Grip Right Mini Palm Air Nailer
KidSmart Vocal Smoke Detector	IDSA- IDEA Awards 2006 [62]	First Alert Basic Smoke Alarm
RIDGID JobMax™	Popular Science, Best of What's New 2010 [60]	Craftsman®Nextec Multi Tool, Dremel® Multi-Max™

While the black box, or user-related, functionality of the products being compared is the same, in some cases the basic technology is vastly different. For example, while the Dyson Air Multiplier™ and the Holmes® Fan have the common black box function to provide user cooling through air flow, each uses a different principle to direct the air flow. The Dyson unit uses an impeller to channel the air flow around a ring, and then exports fast moving air, while the Holmes® fan is a conventional fan that uses an electric motor and rotating blades to export fast moving air. Both fans can be seen in Figure 6. A summary of the innovative features of all of the products in the study, and their black box functions, can be seen in Table 10.

Table 10: Innovative features that result in product identification as innovative.

Innovative Product	**Innovative Feature(s)**	**Black-Box Function**
Dyson Air Multiplier™	Bladeless fan. Air pulled in through the base and pushed out using an impeller around a circular airfoil [58, 59].	Move air to cool user.
Milwaukee M12™ Copper Tubing Cutter	First cordless pipe cutter. Jaws hold pipe while cutter rotates at 500 rpm. Increases plumber efficiency [101].	Cut copper tube
Clorox® ReadyMop®	Disposable cloth technology on mop head, onboard cleaning solution with one touch dispensing [100].	Mop floors
Milwaukee M12™ Palm Nailer	Powerful, cordless, lithium-ion battery powered, palm hammer. Ability to hammer nails in tight spaces [60].	Nail nails
KidSmart Vocal Smoke Detector	Uses a parents recorded voice to wake children and provide evacuation instructions [62].	Sense for smoke
RIDGID JobMax™	Ability to drill, tighten/loosen bolts, and drive nails in tight spaces due to interchangeable tool heads [60].	Drill/nail/tighten/loosen bolts

Figure 6: Innovative Dyson Air Multiplier™ (left) is compared to the common Holmes® Fan (right).

Other products being compared are similar in their architecture and operating principles. For example, the RIDGID JobMax™ is compared to two other similar handheld multi-tools – one that is battery powered and one that plugs into a wall socket, as seen in Figure 7.

Figure 7: The innovative RIDGID JobMax™ (bottom) is compared to the Dremel® Multi-Max ™ and Craftsman® Nextec Multi-Tool (top).

All of the products used in the comparison study are contained within the Design Repository, which also contains the pertinent information to perform a screening-level life cycle assessment of the products. There are many products that are similar to the common ones selected for the study. These products may use different materials or have different specifications, which could potentially change the outcome of the study. The purpose of this work is to identify the level of sustainability for innovative products by focusing on several examples; expansion of the product set is left to future work. Common products selected are intended as benchmarks to gage the relative level of environmental impacts.

Step 1: Product Decomposition

The first step in the methodology reported herein is to decompose products into individual components. The Design Repository [46] provides an opportunity to store new product deconstructions and utilize existing product breakdowns. The functional basis developed by Stone and Wood was used to describe product function in a verb-noun (function-flow) format [74]. Flows are energy, material, or signals that are inputs and outputs to functions. Functions, on the other hand, are operations performed on the associated flows [74]. Functions for every component are included in the data recorded in the Design Repository [46]. For example, the "impeller" in the Dyson Air Multiplier™ solves the functions "transfer gas" and "convert mechanical energy to pneumatic energy."

Step 2: Component LCI and Impact Assessment

The second step determines the LCIs of every component of each product. The products must have the same black box use-phase functionality in order to justify product selection for pairwise comparison. For example, the black box functionality of both the Dyson Air Multiplier™ and the Holmes® Fan are to move air. The functional unit used for comparison is the black box function of each product pair performed over a fixed time period.

Several assumptions are made based on the usage cycle of each product as well as any components that will need replacement throughout the life of the product. Considering that it is unknown how the consumer will dispose of the product, an end-of-life disposal scenario of landfilling is assumed. The packaging materials and shipment of the final product however are not considered. For the purposes of this research, it is assumed that variations in these product stages produce negligible impacts compared to cradle-to-grave impacts for the product pairs. SimaPro [38] was used for the environmental impact assessment.

Use phase impacts are based on an estimated lifetime of each product and the duty cycle each exhibits. Based on previous literature, the lifespan of an electric motor can vary between three years for heavy use to eight years for light use [102]. Considering the electric motor is one of the most critical components to the functionality of each electric product, it will limit the products lifetime. With this assumption in place, the lifetime energy use of all of the electronic products can be found. The power tools in the set (RIDGID JobMax™, Craftsman® Nextec Multi-tool, Dremel® Multi-Max™, Milwaukee M12™ Copper Tubing Cutter, Milwaukee M12™ Palm Nailer, and Grip Rite Mini Palm Air Nailer) are all assumed to be used for an average of one hour per week for a total of six years. The six year assumption is based on the fact that they will see variable loads and potentially high stresses during use, resulting in an intermediate lifetime.

The smoke detectors in the set are assumed to have a useful life of ten years, based on suggestions from the manufacturer, with batteries being replaced every year. The floor mop product variants are expected to require replacement mop heads at different intervals. Some of the mop heads are designed for multiple uses, while the others are disposable.

The desk fans are expected to be used for two hours per day for a total lifetime of eight years. This is considered light use because the motors in the fan will reach full speed and maintain that speed, resulting in constant stresses. The other products with electrical components see more variable loads, increasing the stress on their components.

To calculate the cradle-to-grave (material extraction through end-of-life treatment) environmental impacts, ReCiPe 2008 is used [31]. This methodology classifies eighteen impact categories at the midpoint level (ozone depletion, human toxicity, water depletion, etc.) and aggregates them into three endpoint indicators (damage to human health, damage to ecosystem diversity, and damage to resource availability). There are three different weighting and normalization methods based on short term impacts through long-term impacts (heirarchist, egalitarian, and individualist). These weightings can aggregate the endpoint indicators into a single metric for evaluation. The weighting perspective used in this research is the hierarchist perspective, which is balanced between short-term and long-term impacts. Because of the coarseness of the final evaluation in this research, specific midpoint indicators are not useful. As the design's detail increases, more specific impact indicators can be used.

Step 3: Function Impact Matrices

Using function impact matrices (FIMs), the component's environmental impacts can be assigned to the product functions they solve. To generate function impact matrices, each component's contribution to each function needs to be distributed to the various functions they solve. Devanathan et al. [97] suggest assigning percentages to component-function mappings to reflect the extent to which each component contributes to accomplishing each specific function. However, there exists no generally accepted method to reliably distribute these percentages. A repeatable method is critical for avoiding the unnecessary addition of further uncertainty at this highly abstract stage of design. Therefore, this work uses a simple heuristic: the contribution of each component is distributed evenly to the functions it solves. This increases the repeatability of the approach and reduces the amount of variability in the study.

The size of the full FIM is too large to present, hence part of the FIM for the Dyson Air Multiplier^{TM} can be seen in Table 11. The total impact of each component is listed under the "Impact" column and the individual contribution to each function is in the associated cell. As described earlier, the impact of components that solve more than one function, for example “base motor,” gets distributed evenly to each function (i.e., import electrical energy, convert electrical to mechanical, and export mechanical energy).

Table 11: Portion of the Dyson Air Multiplier™ function impact matrix.

Dyson Air Multiplier	**Impact**	**Export mech. energy**	**Import mech. energy**	**Convert electrical to mech. energy**	**Import electrical energy**
angle slider	**0.0257**				
base	**0.0210**	0.0105	0.0105		
base motor	**0.0194**	0.0065		0.0065	0.0065
circuit board	**1.2404**				
control plate	**0.0088**				

This process is repeated for all of the products in the study, by distributing environmental impact based on the functions each component solves. By summing the impact contributions of each component associated with that function, it is possible to calculate the impact of that function.

Step 4: Function–Flow Impacts

Finally, similar functions from the common and innovative products can be compared and analyzed to determine whether or not function has an effect on environmental impact. In addition, the impact of the flow of material, signal, and energy are analyzed based on adding the impact of all functions associated with each flow in the system. For example, there are five flows associated with the Dyson Air Multiplier™ and Holmes® Fan: electrical energy, mechanical energy, control signals, human material and energy, and gas (air).

Assumptions and Limitations

There are several assumptions and limitations about the data used in the study. First, the material assumption introduced earlier applies to all products in the study. Plastic, metal, and rubber are all assumed to be the same type for each component in the study. Second, certain components were comprised of multiple materials, but were incapable of being further disassembled without destroying the component. An example of this is the outer case of several devices. These housings for hand-held devices were primarily plastic, but also contained a type of synthetic rubber for the handgrip. The actual mass of each material in the component was unknown for these instances, so an approximation was used.

Additionally, when material types for a component were not reported in the Design Repository, they were assumed to be the same as the materials reported for similar components in the repository sample set. When mass data for a component was not contained in the Design Repository, that component was omitted from the analysis. These components were typically screws and small fasteners that had negligible mass.

It is likely that the products were not designed with environmental sustainability in mind. If they were, different materials may have been chosen, or special processing techniques could have been used, which is not captured in this analysis. There are also differences in the durability of the product pairs. For example, a product made primarily of plastic components is more likely to require replacement of components before the life of the product is over. Conversely, a product with metal components is likely to be more robust and last longer. Actual impacts will also depend on whether or not the customer will replace the components, or simply purchase a new product. It is assumed that the products in the study are small and inexpensive enough, such that when a component of the product breaks, the product will be thrown away and a replacement will be purchased. It would be extremely difficult and time consuming to disassemble the products and recycle or reuse its constituent materials. For a proper evaluation of the impact of the durability and replacement differences of each product, failure data along with repair and replacement rates is necessary, but is outside the scope of this current study.

Results and Discussion

Results of the functional LCA show that for all of the products, innovative and common, there are four or less product-related functions that dominate the environmental impact before the use phase of the product life cycle is considered. All of the products in the study contain function impacts that, when combined, contribute at least 44% of each products' overall environmental impact. The product with the lowest number of product-related functions is the Libman Microfiber Floor Mop with 15. As a result, at least 44% of the environmental impact can be attributed to less than 27% of its functions. In all of the products that use electricity, functions associated with electricity dominate product environmental impact. An example of impact clustering can be seen in Figure 8 with the Dyson Air Multiplier™. The "Other" category accounts for the impact of 21 other product-related functions.

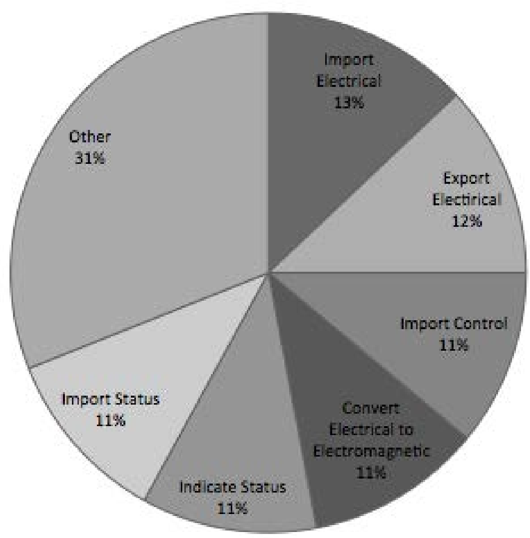

Figure 8: Relative functional environmental impact for the Dyson Air Multiplier™.

When the use phase is taken into account, it plays a large role, contributing at least 27% of the impact, in three innovative products and four common products. The innovative products with significant use phase impacts are the KidSmart Vocal Smoke Detector, Dyson Air Multiplier™, and the Milwaukee M12™ Palm Nailer. The high impact use phase common products are the First Alert Basic Smoke Alarm, Holmes® Fan, Craftsman® Nextec Multi Tool, and Dremel® Multi-Max™.

In almost every product comparison, the innovative product had a larger total number of total component functions. The only exception was the First Alert Basic Smoke Alarm. Rather than the actual product design, this anomaly could potentially be a result of how information is entered into the repository and the variability due to subjectivity of data entry. More likely, a larger number of functions can be attributed to more functional complexity. More functions give rise to more components, and ultimately, higher environmental impact.

When considering overall product environmental impact, innovative products outperform common products in two cases: the Dyson Air Multiplier™ and Clorox® ReadyMop® (Figure 9). The RIDGID JobMax™ outperforms one of its common competitor products. One final aspect that was considered for each product was the impact of each EMS flow through the system. Only two of the innovative products had higher impacts across all flows being compared: the Milwaukee M12™ Palm Nailer and Milwaukee M12™ Copper Tube Cutter.

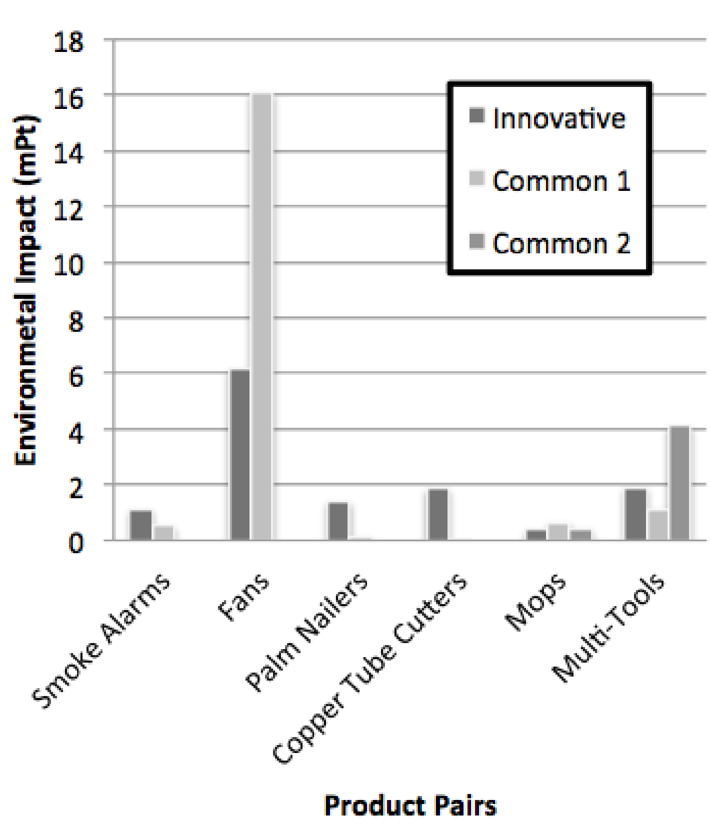

Figure 9: Environmental impact comparison for innovative and common products (ReCiPe 2008 Hierarchist archetype).

The RIDGID JobMax™ had one flow with a lower impact than its comparison products. The final four product comparisons had two or more flows with lower impacts. Figure 10 shows the EMS flow impacts for the two desk fans, and indicates that the innovative product has several dominant flows with lower impacts.

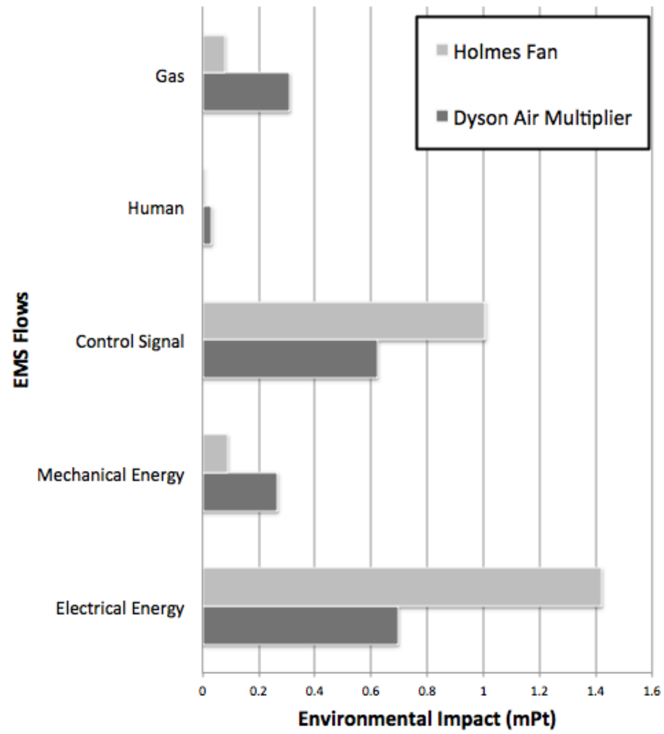

Figure 10: Environmental impacts associated with the EMS flows for the two desk fans (ReCiPe 2008 hierarchist archetype).

Conclusions

The results of this analysis strengthen the findings in previous work [73]. There appears to be an inverse relationship between innovation and sustainability, not only on a basis of materials and manufacturing process environmental impacts, but also, innovative products tend to have higher environmental impacts at the function and flow level. It is unknown whether or not these results are generalizable to different pairs of innovative and common products, as the results and conclusions of this research apply only to this specific product set.

It was found that the innovative products have a higher environmental impact than common versions of the same product across their flows. Two of the innovative products had higher impacts across all flows, two had higher impacts across 80% of flows, and the remaining two had higher impacts across 75% and 25% of their flows. If this conclusion holds true for different product sets in different domains, it can be used to explore different flow options and functional architectures for a product. This warrants further investigation to determine whether the findings of this research can be extended.

Innovative products, in all but one case, have a larger total number of functions than common products. This could simply be a result of inconsistencies within the Design Repository or innovative products may be more functionally complex than common products. More functions can give rise to more components, resulting in a larger environmental impact.

The individual FIMs that were generated can be combined into an overall PFIM. As the environmental impact of more products in the Design Repository is added, the PFIM will be populated with more functional impacts. From this matrix, average impacts can be calculated for each function. This can then be used in the conceptual design phase to calculate the estimated environmental impact of a concept and select concepts to be pursued accordingly. This is a potential application of the tool that could result from populating a large PFIM with the functional impact of many products.

As consumers begin to demand more environmentally sustainable products, such tools will continue to need to be developed to support design and manufacturing efforts. Results of this research are intended to highlight the need for more emphasis on sustainability in early design. Eco-design and Eco-innovation tools are available, but the reported work intends to bring sustainability considerations earlier in design.

This work has also demonstrated that designers must consider the potential impacts of innovative products on the environment, as they can result in functional expansion, as well as simultaneous increases in components and the materials and energy needed to implement them within a product.

Future Work

To further develop this research, it is proposed that environmental impact data be added to components in the Design Repository. The component material and physical parameter data necessary to add this type of information is already available for many components in the repository. Propagating this information to the functions that each of those components solves, which could be done automatically, is the next logical step.

This will provide a large database of components that solve a particular function, and a more accurate representation of each function's environmental impact could be calculated. This information could be used in the early stages of design when designers are working with only a functional model of the design. Knowing the environmental impact of the functions selected could drive designers to use different, less conventional means of accomplishing their intended design, resulting in lower impact, innovative products.

Another area of future work is in revisiting the assumption of evenly distributed functionality between components. While this simplifying assumption was made in the absence of a repeatable function allocation method, it was observed that certain common types of connections between components, functions, and flows could be leveraged to perform function impact mapping. For example, most designers would agree that the most important function of an electric motor is to convert electrical energy to rotational energy, and other functions such as guiding electrical energy are negligible compared to this conversion. Identification of these types of heuristics based on available product data may lead to repeatable and automatic generation of more accurate FIMs.

A limitation of this research is the determination of what is considered an innovative product. The products used in this study were all chosen based on popular media or organizations using expert opinions and judging criteria. If a more impartial method for scoring the "innovativeness" of these products is developed, their label of "innovative" can be further justified and/or other products identified. Innovativeness itself is difficult quantify, although there are attributes of products that lead to innovativeness. The authors are pursuing quantification of product innovativeness based on a latent variable model, which will measure innovativeness based on product attributes.

By undertaking additional innovative-to-common comparisons based on the approach demonstrated herein, an improved justification for the innovativeness of the products used, and implementation of sustainability indicators beyond environmental impact, any existing links between innovation and sustainability can be exposed and exploited to stimulate a greater emphasis on sustainability in innovation design.

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CONCLUSION AND FUTURE WORK

The contribution of this research is a framework that quantifies and evaluates product innovativeness for a specific set of electromechanical products. Three models were created that capture various aspects of product innovativeness. The measurement model measures the response of each of the three latent variables to specific pairs of common and innovative products. The structural model captures the contributions of product attributes to the three latent variables. Finally, the choice model gives the probability that a product will be selected as innovative based on the scores of each of the three latent variables. In addition, as sustainability was found to be a significant attribute to the product innovativeness model, a deeper analysis of the environmental impact of innovative and common products was conducted. Environmental impact was calculated at a high level on the overall products themselves, down to a more abstract level. Environmental impacts were propagated from the product as a whole down to both the function and flow levels.

Both manuscripts show an inverse relationship with innovation and sustainability. It was found that innovative products are generally more environmentally impactful than common versions of the same product. *Manuscript 1* shows this with a positive coefficient on the sustainability attribute. This means that as product environmental impact increases, the probability that the product is selected as innovative will increase as well. *Manuscript 2* shows the inverse relationship with higher environmental impacts on most of the independently identified innovative products. That higher impact was realized on multiple levels of abstraction.

The method for evaluating product innovativeness has been demonstrated in this thesis, however it needs to be further tested to determine its usefulness in the original design process. Developing concepts and scoring the concepts based on the innovativeness model generated would determine the usefulness of this metric for concept generation.

By propagating environmental impact information down to the functional level, the information can be stored and reused during conceptual design. With sufficient data, variations between the impacts of functions that appear in multiple products will be negligible. With further research, this method could be expanded to encompass the entire design repository. All of the pertinent information to perform a screening level life cycle assessment exists within the repository. Once component environmental impacts have been determined, design tools needed to generate function impact matrices can be automatically generated from data in the repository. With the current tools available, the only human interaction needed is the distribution of the environmental impact of a component that solves more than one function. The method used in this thesis distributed the impact evenly between functions. However this may not be the most ideal heuristic to use. Future work will revisit this distribution for a more realistic method.

The second manuscript calculated the functional impacts of a total of 14 products. These products were limited to small, electromechanical consumer products, as was the case in *Manuscript 1*. Additional work is necessary to populate a Product Function Impact Matrix that can be used for concept generation. It is unknown whether or not this method can be used for products in different domains, or scaled up to larger, more complex electromechanical systems. Expanding the product set further will increase the number of functional impacts available for population of a Product Function Impact Matrix.

The results of both manuscripts have applicability in evaluating current products for innovativeness and environmental impact, as well as applications in conceptual design. With a less subjective calculation of levels of product innovativeness, current designs can be evaluated, and areas of improvement can be identified. An alternative approach would be to score each concept variant during concept generation on their innovativeness and select the highest scoring concept to pursue in detailed design. In addition to improving upon product and design innovativeness, environmental impact information has been propagated to product-related functions and flows of energy, material, and signal by the use of a Function Impact Matrix. With expanded product environmental impact evaluations and subsequent application with function impact matrices, environmental impact assessment can be considered earlier in the design process.

Limitations to this work are mainly due to the limited product set available for evaluation. Currently there is a small set of innovative and common product pairs in the Design Repository (repository.designengineeringlab.org). A deeper understanding of product innovativeness could be gained by increasing this data set. Unavailable product attribute data that was used to generate the structural model would have less of an effect if the dataset were much larger as well. The latent variable model of innovation was calculated based on a specific set of innovative and common products. To apply this more broadly, a much larger product set is needed.

With respect to the functional environmental impact analysis, without a larger dataset, the functional impacts could only be used for the forward design process if the product to be designed was in the same domain as the products used to create the Product Function Impact Matrix. In addition to the limited dataset, only one aspect of sustainability (i.e. environmental) was considered. Both societal and economic sustainability were not taken into account when evaluating how sustainable the products in the latent variable model were. There is limited research into evaluation of societal sustainability, and the only available economic sustainability data accessible was the cost of each product. With respect to the latent variable model of *Manuscript 1*, cost can be thought of an aspect of economic sustainability, which makes up the "product cost" product attribute of the structural model.

In addition, considering that each of the three models (structural, measurement, and choice) were estimated individually, the error in the fit of the models is not taken into account. A much more accurate way to calculate the model would be to estimate all three simultaneously. This will be addressed in a forthcoming journal version of *Manuscript 1*.

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APPENDIX

Appendix A

Survey Questions Administered and Product Attributes:

The following survey questions were approved by the Oregon State University IRB board and were used as part of the survey developed for this research. Responses were on a scale of 1-7 with one being in very low agreement, 4 being somewhat in agreement, and 7 being in high agreement.

1. What is your perception on how successful the product has been?
2. How successfully does the product function?
3. What is your perception of how successful the product has been on a global scale?
4. How influential is the product to society?
5. How efficiently does the product perform its task?
6. How well known is the company that made the product?
7. How influential is the company that produced the product?
8. How well was the product made?
9. How complex is the product?
10. How original is each product? i.e. is it based on a product that already exists?
11. How beneficial is the product to its user?
12. How aesthetically appealing is the product?
13. How familiar are you with the product's design and functionality?
14. How easy is this product to use?
15. How satisfied are you with the amount of features present in the product?
16. How "high tech" is the product?
17. How "trendy" is the product?
18. How adjustable is the product?
19. How sustainable is the product?
20. How risky does the product appear to be?

The following is a list of attributes used in the latent variable model and their definitions.

Attribute	Definition
product_patents	The total number of patents present in the product.
power_usage	Expected power usage over the products lifetime.
co_public	Whether or not the product's manufacturer of the product is a publicly traded company.
no_employees	Total number of people the product's manufacturer employs.
co_products	Total number of different products and models the manufacturer sells.
co_patents	Total number of patents the product's manufacturer owns.
co_stock	Stock price of the product's manufacturer.
product_materials	Number of different materials used in the product.
product_parts	Total part count of the product.
product_features	Total number of different features the product has.
adjustability	How many adjustability settings the product has.
product_sustainability	Environmental impact of the product over its lifetime. Calculated in SimaPro using the ReCiPe methodology with the hierarchist weighting scheme
product_functions	Number of different product-related functions the product performs.
product_flows	Number of different energy, material, or signal flows through the product.
product_cost	Cost of the product.