

**Data-Driven Consumer Preference Prediction for Product Customization
Using Machine Learning and Crowdsourcing**

by

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ABSTRACT

DATA-DRIVEN CONSUMER PREFERENCE PREDICTION FOR PRODUCT CUSTOMIZATION USING MACHINE LEARNING AND CROWDSOURCING

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Product customization has become an increasingly popular paradigm driven by advances in manufacturing technology and demand for more personalized products. The customization process has many challenges and can be costly and complex for firms to implement. Decision support tools can help to guide firms through the customization process and offer objective recommendations on how customization strategies can be implemented. Through an extensive literary review, several shortfalls of current decision support methodologies have been found; namely that they lack comprehensiveness, structure, and automation. A data-driven approach to predicting consumer preferences for decision support is presented using 307 crowdsourced consumer preferences and a machine learning clustering model. Using a validation study, the model provides a 70% accuracy in the prediction of consumer preferences with opportunities for improvement with a larger data set. This method offers a novel approach to decision support for product customization that addresses shortfalls of other recommender systems.

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LIST OF SYMBOLS, ABBREVIATIONS OR NOMENCLATURE

Additive Manufacturing : AM

Computer Aided Design : CAD

Internet of Things : IoT

Customization as a Service : CaaS

Everything as a Service : XaaS

Information Technology : IT

Open Architecture Product/Customization : OAP

Small and Medium Enterprises : SME

Original Equipment Manufacturer : OEM

Mass Customization and Personalization Effectiveness Index : MCPEI

Computer Aided Manufacturing : CAM

Flexible Manufacturing Systems : FMS

Computer Numerical Control Systems : CNC

Natural Language Processing : NLP

Machine Learning : ML

Chapter 1 Introduction

The act of customizing is defined as “to build, fit, or alter according to individual specifications” (Merriam-Webster, 2022a). In terms of product customization, this idea has a wide variety of applications in nearly every industry, from automotive (Hu, 2013) to medical (Fung et al., 2020) and garment (Dong et al., 2012). The customization process involves understanding the needs of the customers, then transforming those needs into functional requirements by means of involving them at some stage of the design and manufacturing process (Duray et al., 2000). The overall customization process can be defined in four steps; deciding to customize, selecting a customization strategy, design customization and finally the production and sale of the product. Offering customization to consumers can take several different forms. It can be as simple as offering unique colors and sizes for a product line to more complex customization aspects like offering customization of the functionality of the product itself. Offering customized products can yield many benefits to both the consumer and the producer. Value creation for the customer is a major benefit that can be attained by offering customized products and can take different forms specific to what customization options are offered and what the customers desire (Squire et al., 2004). Arguably one of the most important forms of value creation is the willingness of customers to pay. A company is generally able to charge more for customized products compared to standard products (Piller et al., 2004). Another form of value creation is the creation of personal attachment to the product itself. When the customer is involved in the design of the product or the product has personally meaningful attributes to the customer, they are likely to associate it with a higher value (Green et al., 2017). The functionality of a product can also be improved by adding customizable features that allow for the product itself to better suit the requirements of the consumers, which also adds value (Cormier et al., 2008).

Mass customization was first presented in 1987 by Stanley Davis (Duray et al., 2000). It has since been the topic of numerous scholarly articles and journals as well as real world implementation by major corporations (Jiao, 2011). Mass customization is the unification of principles from mass production with those from craft production, to offer low-cost high volume customized products (Nambiar, 2009). The ability to offer a large variety of unique and customized products at such low costs and with near mass production efficiency represents a shift in consumer attitudes and a desire for greater product variety (Hu, 2013). Mass personalization has emerged with the integration of new technologies and Industry 4.0 concepts enabling a greater degree of customization of products (Wang et al., 2017). Personalization is a form of customization that provides truly unique products for customers on an individual basis. The level of customization involved in mass personalization is comparable to that of craft production but generally at higher costs than mass customization. Technologies such as additive manufacturing (AM), computer aided design (CAD), Internet of Things (IoT), smart sensors and augmented reality have allowed companies to offer personalized products while maintaining affordability (Aheleroff et al., 2019).

Although Industry 4.0 concepts can be an enabler of a higher degree of customization, it is important to note that implementing these technologies has challenges and personalized products

do not guarantee increased profits (Torn and Vaneker, 2019). Thus, it is important to consider all options for production and customization to offer the best solution. Decision support systems can aid in the entire product customization process, from the selection of a customization strategy to the physical design of the customized product. This idea ties into the concept of everything as service (XaaS) or in this case customization as a service (CaaS). XaaS can take many different forms such as industrial machines as a service, communication as a service, information technology (IT) as a service and many others. (Duan et al., 2015). These all share the commonality of providing platforms that perform a service, which would be offered by a decision support system.

Many different factors have been identified in prior work to be of significance to the success of customization such as market, manufacturing process, product design, and flexibility in management. However, rarely has work considered all factors in practice. Moreover, most work related to customization tends to have the basic assumption of mass customization realized by modularization and assembly configuration with conventional manufacturing processes. The evolution of additive manufacturing, communication, and automation techniques have created new opportunities and flexibility for product customization beyond modular design (Lacroix et al., 2021; Pech and Vrchota, 2022). All these trends lead to the rethinking of different customization strategies especially in early planning and design stages.

1.1 The Customization Process

The customization process can be broken down into three different distinct sections that can benefit from decision support tools; the decision to customize, the selection of a customization strategy and the design of the customized product as illustrated in Figure 1. The inception of a product is generally carried out before the decision to customize. This means firms have an existing product or product idea that they wish to bring to market. Customization generally occurs after the product is already conceptualized or being sold to meet a certain market need. The first step in offering customization is determining whether customization is a viable business model. The added complexity of product customization means additional costs and lead times (Banerjee et al., 2019). This means that the willingness of consumers to pay for customization is often used as an important factor in deciding to offer customization (Petruzzellis and Winer, 2023). The decision to customize must come first in the overall process as it will be the most important for firms in terms of being able to justify monetarily if customization makes sense. The second step in the customization process is determining how customization can be offered. Industry 4.0 technologies such as IoT, big data and cloud computing can allow for greater integration of consumers and more flexibility in manufacturing (Tortorella et al., 2022). In addition, IT enabled manufacturing technologies and principles help manufacturers take advantage of economies of scale offering customized products at reasonable prices and lead times (M. Zhang et al., 2015). However, the implementation of these systems is costly and often requires special training and qualifications to operate. For example, it has been suggested in literature that additive manufacturing should only be adopted for customization if it is readily available and there exists relevant expertise to operate the machines (Deradjat and Minshall, 2018). These kinds of decisions are necessary to consider prior to the

design process to make sure that the products designed are feasible for manufacturing. Selection of a proper customization strategy is highly important in the early product planning stage as it determines the product design, manufacturing process, and organizational structures. The third step in the customization process is the physical design of the product itself in terms of what kinds of features should be offered for customization. For example, modularity is a popular method of offering product customization. Wang and He (2022) examine a dual channel supply chain model for mass customization that can aid in decision making for product modularity, prices and return policies (Wang and He, 2022). Part of the model is the design of modular products that enable companies to facilitate the return of products and maintain flexible cost-effective production. For such design consideration to be made it is first necessary for the firm and designers to know what kind of customization strategy will be employed. The final stage of the customization process is common to the design of all products which is the final production and sale of the customized product to the end consumer.

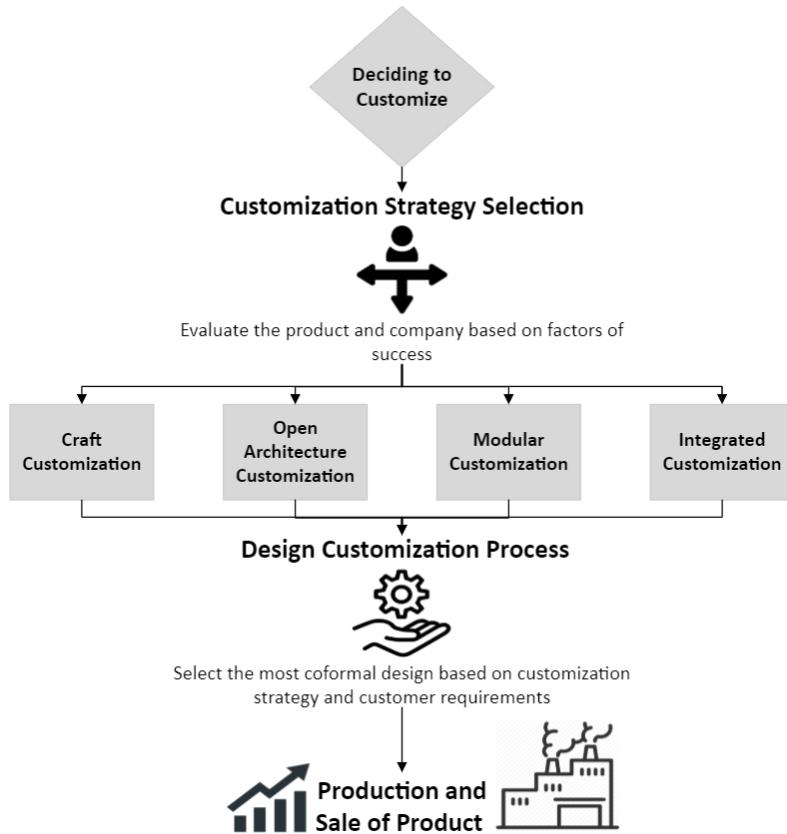


Figure 1: Customization Process Flow Chart

Through a detailed review of decision support tools for customization, we have found four distinct research gaps that exist; there are a lack of comprehensive decision support tools for the customization process, a lack of structured decision support tools for the customization process, a

lack of automated decision support tools and a lack of comprehensive consumer preference prediction tools. These research gaps will be addressed in more detail in Chapter 2 of this thesis.

1.2 Structure of Thesis

The research work presented in this thesis is focused to target some specific areas of the research gaps identified and is outlined in Figure 2. This thesis begins with a literary review of different customization strategies, factors of success in customization, decision support tools for customization and eliciting consumer preferences as well as research gaps found in this review in Chapter 2. In Chapter 3, a pilot study is outlined with an analysis of crowdsourced consumer preferences that guided the direction of the research for further development of a decision support tool for product customization. The development and implementation of the decision support tool is discussed in Chapter 4 of this thesis. A validation study and sensitivity analysis are conducted in Chapter 5 along with a discussion on some limitations of the model. Chapter 6 details some directions for future work and offers concluding remarks on the findings of this research. Chapter 2 takes a comprehensive review approach to decision support tools in product customization as well as identifying types of customization strategies and factors of success in customization. This work serves to guide the direction of the research and develop a comprehensive understanding of product customization. The research gaps identified were addressed with the decision support tool developed in Chapter 4 of this thesis. The tool developed in Chapter 4 provides automated and structured decision support for the decision to customize, and the design of customized products through the prediction of consumer preferences. The system is comprehensive in these areas; however, it does not deal with the selection of a customization strategy. This is something that will be addressed in future research and will be described in more detail in Chapter 6.

Decision Support Tool For Product Customization

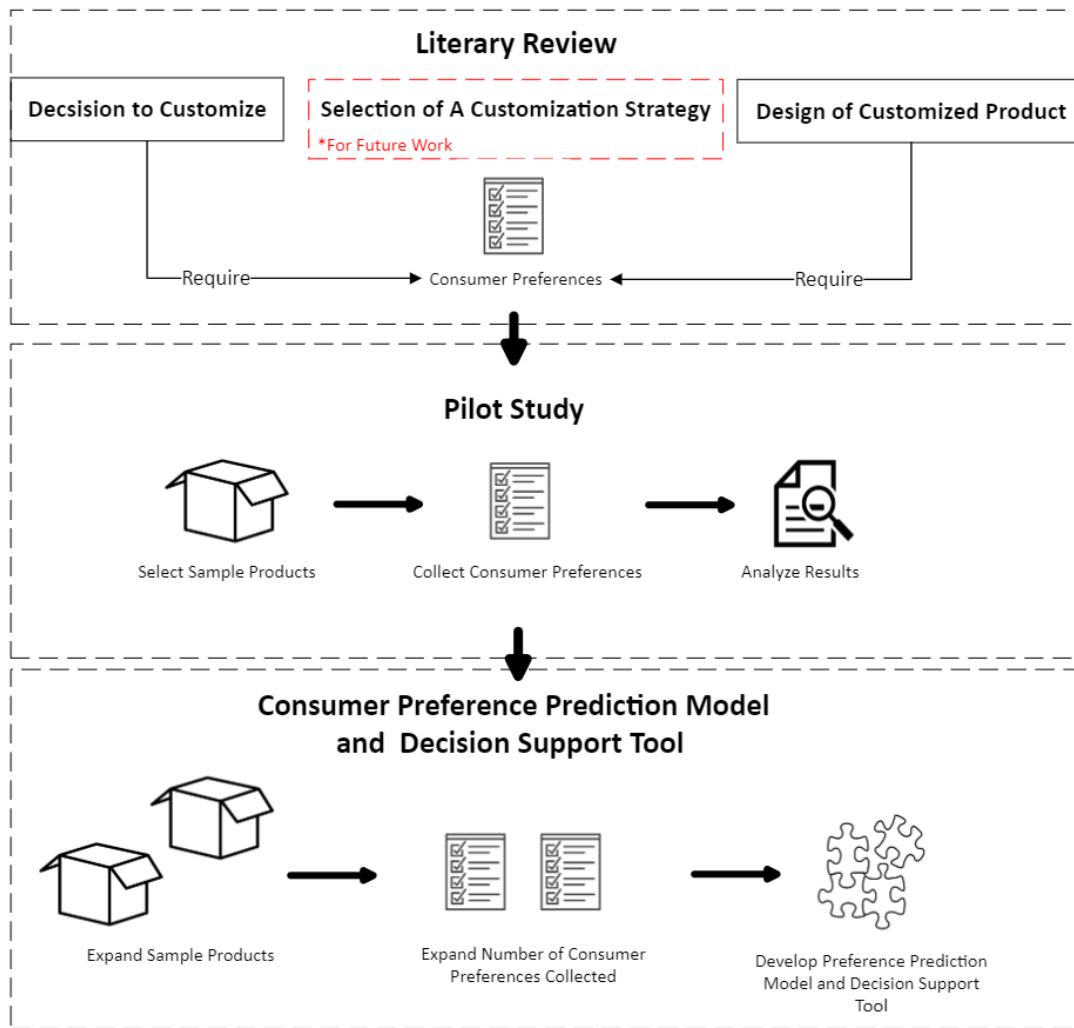


Figure 2: Thesis Structure

Chapter 2 Literature Review

This chapter serves to guide the direction of the research and identify gaps in current decision support tools for product customization. It is important to have a comprehensive understanding of the different types of customization strategies, factors of success in customization and decision support tools in customization. Through this review it was revealed that consumer preferences play an important role in many aspects of the customization process and thus methods of eliciting consumer preferences were also reviewed.

2.1 Classification of Customization Strategies

A customization strategy can be defined as a general set of guidelines, principles and characteristics that comprise a method of offering product customization to customers. Literature has classified customization and manufacturing strategies into different levels or classifications depending on a variety of factors. There is a lack of consistency as to the classification of strategies, but there are significant overlaps in the terms used. Table 1 presents a list of some of the different terms used in literature to classify customization strategies. From Table 1, two super categories of customization can be named, design customization and assembly customization. Based on previous work (Squire et al., 2004), this thesis extends the concepts of design and assembly customization to capture the new advances in customization research. Within these two categories, four specific strategies are proposed: craft customization, modular customization, open architecture customization (OAP) and an integrated approach using AM (noted as integrated approach in the following). Figure 3 presents these four specific strategies and their commonalities.

Craft customization and an integrated approach allow the consumer to customize all aspects of the product beginning in the design phase; thus, they are counted as design customization strategies. These two strategies allow the greatest degrees of freedom in terms of customization and generally take longer to produce products compared to a modular or OAP approach. Design customization approaches have been described in literature using a multitude of terms such as collaborative, transparent (Broekhuizen and Alsem, 2002; Krishnapillai and Zeid, 2006), pure customization (Büyüközkan, 2008), design to order, manufacture to order (Smith et al., 2013), product personalization (Green et al., 2017), fabrication customization, design customization (Squire et al., 2004), craft producer (Stojanova et al., 2012; Svensson and Barfod, 2002), co-design of products (Daaboul et al., 2012) and personalization (Hu, 2013).

Table 1: Types of Production Strategies Presented in Literature

Literature	Types of Production Strategies Presented	Literature	Types of Production Strategies Presented
(Mesa et al., 2019)	<ul style="list-style-type: none"> • Mass Production • Mass Customization • Mass Individualization (OAP) 	(Squire et al., 2004)	<ul style="list-style-type: none"> • Distribution Customization • Assembly Customization • Fabrication Customization • Design Customization
(Broekhuizen and Alsem, 2002)	<ul style="list-style-type: none"> • Collaborative • Transparent • Cosmetic • Adaptive 	(Krishnapillai and Zeid, 2006)	<ul style="list-style-type: none"> • Collaborative • Transparent • Cosmetic • Adaptive
(Büyüközkan, 2008)	<ul style="list-style-type: none"> • Pure Customization • Tailored Customization • Standard Customization 	(Svensson and Barfod, 2002)	<ul style="list-style-type: none"> • Craft • Industry • Systemic Industry • Mass Customization
(Smith et al., 2013)	<ul style="list-style-type: none"> • Design to Order • Manufacture to order • Assemble to Order • Deliver to Order 	(Stojanova et al., 2012)	<ul style="list-style-type: none"> • Craft Producer • Craft Customizer • Mass Customizer • Mass Producer
(Green et al., 2017)	<ul style="list-style-type: none"> • Product Personalization (Using AM) 	(Daaboul et al., 2012)	<ul style="list-style-type: none"> • Customized Services • Delayed Differentiation • Modularized Components • Integration & Response • Co-Design of Products
(Koren et al., 2015)	<ul style="list-style-type: none"> • Mass Production • Mass Customization (Modular) • Mass Individualization (OAP) 	(Hu, 2013)	<ul style="list-style-type: none"> • Mass Production • Mass Customization • Personalization
(Peng et al., 2018)	<ul style="list-style-type: none"> • Open Architecture Products 	(Brun and Zorzini, 2009)	<ul style="list-style-type: none"> • Rigid Customization • Postponed Customization • Modularized Customization • Flexible Customization
(Koren et al., 2013)	<ul style="list-style-type: none"> • Mass Production • Mass Customization (Modular) • Mass Individualization (OAP) 	(Duray et al., 2000)	<ul style="list-style-type: none"> • Fabricators • Involvers • Modularizers • Assemblers

Assembly customization refers to products that can be customized by means of how they are assembled, which can be achieved by modular customization and OAP. Often there are fewer customization options available to users through assembly customization since there are more constraints and fewer options to customize. Some works refer to OAP as a personalization and individualization strategy implying a higher degree of customization (Green et al., 2017; Koren et al., 2015, 2013; Mesa et al., 2019). This is due to the involvement of third parties providing modules allowing customers to engage in a higher degree of customization. There have been many

terms used to describe assembly customization approaches including mass customization (Hu, 2013; Koren et al., 2015, 2013; Mesa et al., 2019; Stojanova et al., 2012), standard customization (Büyüközkan, 2008), assemble to order (Smith et al., 2013), mass individualization (Koren et al., 2015, 2013), assembly customization (Squire et al., 2004), modularized components (Daaboul et al., 2012) and modularizers (Duray et al., 2000).

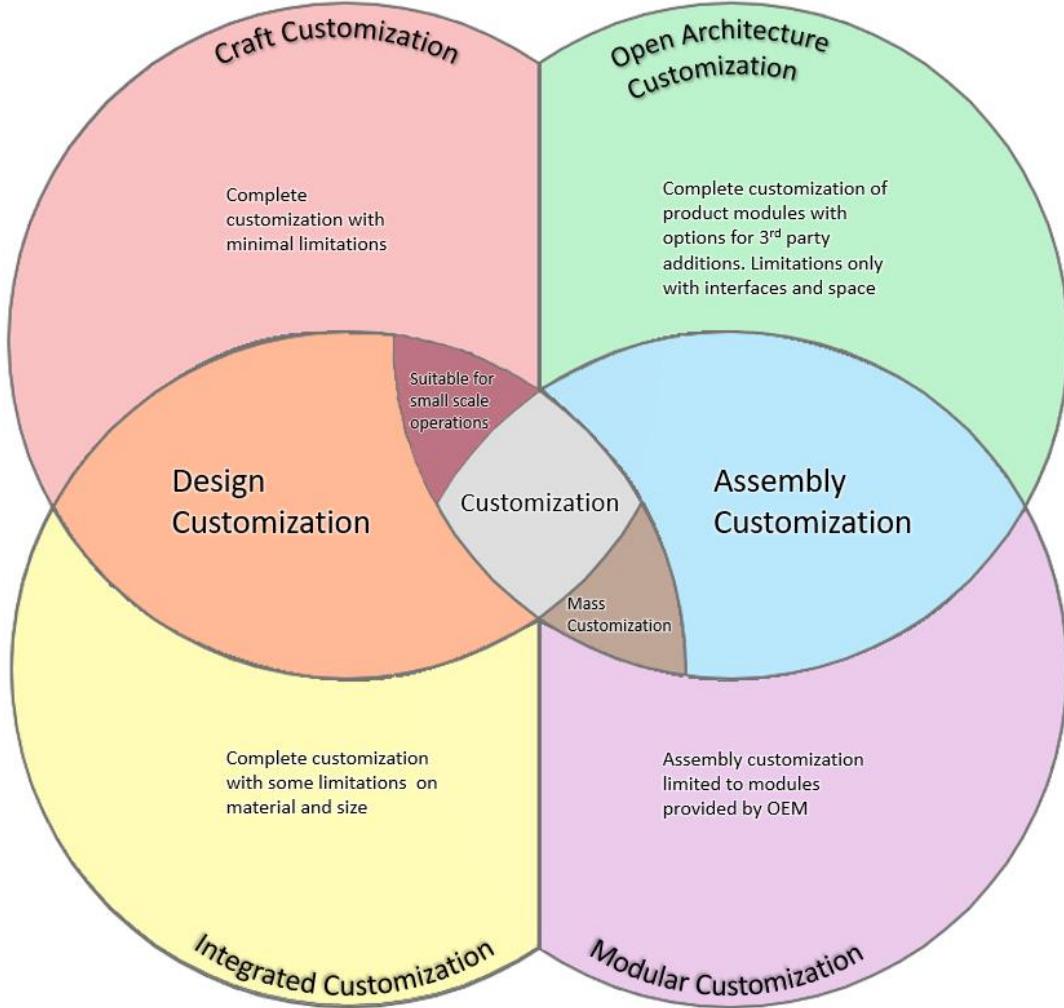


Figure 3: The Four Approaches to Customization

2.1.1 Craft Customization

The oldest form of customization is craft customization (Hu, 2013). The process can be directly related to the definition of a craft which is defined as “an occupation, trade, or activity requiring manual dexterity or artistic skill” (Merriam-Webster, 2022b). In the context of customization, this means that the customers’ requirements are used to create the final product in a skilled labor process. Craft production is characterized by four qualities that are encapsulated in a so called

“knowledge stair” (Svensson and Barfod, 2002). These four qualities are tacit knowledge, no documentation, no measuring, and Ad hoc development (Gamme et al., 2013; Stojanova et al., 2012; Svensson and Barfod, 2002). Craft customization typically is undertaken by small and medium enterprises (SME) with few employees and lower overall revenue (Stojanova et al., 2012). In fact, most SMEs in Europe are craft-oriented businesses (Gamme et al., 2013). The use of craft production can create a sense of increased value for the customer as the final product can be considered of higher quality to the user compared to mass produced items (Bernabei and Power, 2018). Examples of craft customized products are shown in Figure 4. Customization offers options for size, body, style, color, quality, and many add-ons. All products are hand crafted and custom built for each individual customer.



Figure 4: Craft production of custom hat (Watson’s Hat Shop, 2019) (Left) Custom Crafted Furniture (Timberware Handcrafted Furniture Co., 2022) (Right)

2.1.2 Modular Customization

A modular product is made up of any number of subassemblies or modules; that form the overall product to perform a specific function (Da Cunha et al., 2010). This allows the modules of a product to be swapped out and customized to suit the needs and requirements of the customer. The modular approach utilizes product family architectures by using a common platform and modules to increase commonality and reusability across different product varieties (Jiao and Tseng, 1999). Modularity is a popular approach to mass customization as it provides several benefits to the producer while allowing increased product flexibility to meet the needs of the customer (Gershenson et al., 2003). Some benefits that can be afforded by using modularity include reducing lead times on products, easing maintenance for the product by increasing the replaceability of parts, reduction of production costs, increased upgradability of the product and increased external product variety while keeping the internal product variety low (Bonvoisin et al., 2016).

Many different examples of modular products exist in the market. One example is the Dyson vacuum (Dyson, 2022) which uses a base platform with several attachments and accessories for different use scenarios. Another example is a ratchet and socket set made by Milwaukee

(Milwaukee, 2022) that uses a base platform of the ratchet and different sockets and extenders for various uses. Note that the modular components are made by Dyson and Milwaukee and not a third party.



Figure 5: Dyson Vacuum with Different Attachments (Dyson, 2022) (Left) Milwaukee Ratchet and Socket Set (Milwaukee, 2022) (Right)

2.1.3 Open Architecture Customization

OAPs are similar to modular products as they use modularity to allow for customization (Koren et al., 2013). The main difference between modular products and OAPs is that the modules for the OAPs can be produced by a third party, using the open architecture to facilitate the addition of their modules to the original equipment manufacturer platform (Koren et al., 2013). Interfaces within the product are very important to the openness of the platform and allow other vendors to create modules for it (J. Zhang et al., 2015). There are several factors that contribute to adaptability of the interfaces such as the general adaptability, the working performance, the assemblability and the economy of the interfaces (Hu et al., 2015). OAP allows companies to provide customers with a high degree of product customization and facilitate product innovation by involving third-party producers in the production process (Peng et al., 2018). OAPs have the advantage of being upgradable and offer greater replaceability of the modules, tying into the concept of a circular economy model and sustainability (Mesa et al., 2019). The use of third-party vendors for modules also creates opportunities for job creation in the economy in smaller companies who produce the modules (Koren et al., 2015). This can be beneficial SMEs and the original equipment manufacturer (OEM) as it can allow value creation at a lower cost (Zheng et al., 2017). Example products on the market include personal computers (Newegg, 2022) and custom bicycles (True North Cycles, 2022).

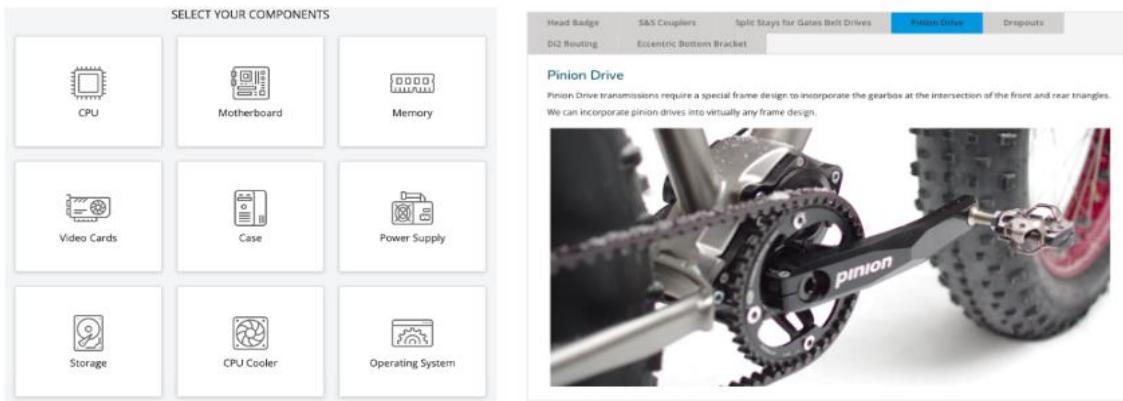


Figure 6: PC Configurator (Newegg, 2022) (Left) Custom Bicycle (True North Cycles, 2022) (Right)

The base platform of a computer is the motherboard which provides a common interface for the central processing unit, the memory, the storage, video cards, power supply and storage. For a bicycle, the base platform is the frame, with common interfaces for attachments such as different gear trains accessories etc. All attached components are available from a wide variety of manufacturers.

2.1.4 Integrated Approach Using AM

AM can deliver nearly unlimited product variety due to the great flexibility of the process and offer cost effective customization (Lacroix et al., 2021). There are two scenarios in which AM processes can be utilized in customization. The first scenario is where the entire product is created from an AM process such as medical implants and prosthetics (Pereira et al., 2019). The second is the customization of only certain parts of the product using an AM process and using standardized parts for other functions. An example is a car, where only some of the interior components are fabricated using AM to be customizable (Martens et al., 2020). Some of the key benefits of using AM include reduced expenses and production time without tooling, small batch customization, reduced waste, shortened supply chains, quick design changes and minimal design constraints (Deradjat and Minshall, 2017; Yu et al., 2020). The use of AM also eliminates the need to increase standardization in product families for cost reduction as customized parts can become cheaper and more easily available (Lei et al., 2016). There are some drawbacks that can limit the applications of AM for mass customization including limited object size, slow speed of printing, cost of AM materials and printers and poor surface quality (Shukla et al., 2018). Examples of integrated approach include Invisalign braces (Invisalign, 2022) and Riddell helmets (Riddell, 2022). The use of AM allows them to offer tunable lattices that can be customized for each customer's preferences in terms of protection, fit and comfort (Riddell, 2022).



Figure 7: Invisalign Braces (Invisalign, 2022) (Left) Riddell Football Helmet Liners (Riddell, 2022) (Right)

2.2 Key Factors in Customization Success

The success of a customized product depends on various factors that have been identified as key drivers or enablers for customization success. These factors of success are important to consider for decision support tools and should provide the basis for decision making in customization. Various classification approaches have been reported in literature (Broekhuizen and Alsem, 2002; Da Silveira et al., 2001; Nielsen et al., 2014). Neilson et al. (2014) compiled and organized a collection of customization metrics into three categories: choice navigation metrics, solution space development metrics and robust process design metrics. Within each category of metrics, the authors provided a list of quantitative measures that could be used to evaluate a customization process and provide insight into aspects of the customization process that can be improved. Storbjerg et al. (2014) provided three focuses for customization performance assessment including performance measurement, capability assessment and combined assessment. In this work, shortcomings of current assessment methodologies for customization were identified as narrow in scope and purpose, conceptual in nature, product focused and unilateral (Storbjerg et al., 2014). Da Silveira et al. (2001) identified six factors of success categorized as either market based or organizational based. The six factors identified in this work are customer demand for variety and customization, appropriate market conditions, a value chain that is ready, availability of technology, products that are customizable and knowledge sharing (Da Silveira et al., 2001). Another classification of factors presents five categories: customer factors, product factors, market factors, industry factors and organizational factors (Broekhuizen and Alsem, 2002). In these works, there are gaps in the critical factors in each category compared to those that have been identified in other works. Categories of factors identified in literature varied in terms and showed many overlaps and should be further decomposed or reorganized. Note that some works were published over 20 years ago and fell short in capturing the dynamics of customization in recent years, for example, AM-supported customization and IoT.

In this thesis, we propose a comprehensive framework for classifying success factors of product customization. The aim of this framework is to examine different works of literature pertaining to

customization and compile an overview of the factors of success presented in each respective work. The list of works presented is not meant to be exhaustive on the topic of success factors in customization, but rather serve to identify what the focuses of decision support tools should be. The framework should consider market factors, manufacturing process factors, product design factors, information technology factors and organizational factors. Figure 8 shows a framework for the different types of customizations that should be considered and related subfactors. Each factor is described in more detail in the following subchapters. Table 2 summarizes the literature that has been reviewed regarding factors for success in mass customization, and identifies the factors considered in each work. It is observed that the top considered factors for customization are the market, product design, and manufacturing process. None of the studies reviewed investigated all five factors from an integrated perspective, considering all the relevant subfactors.

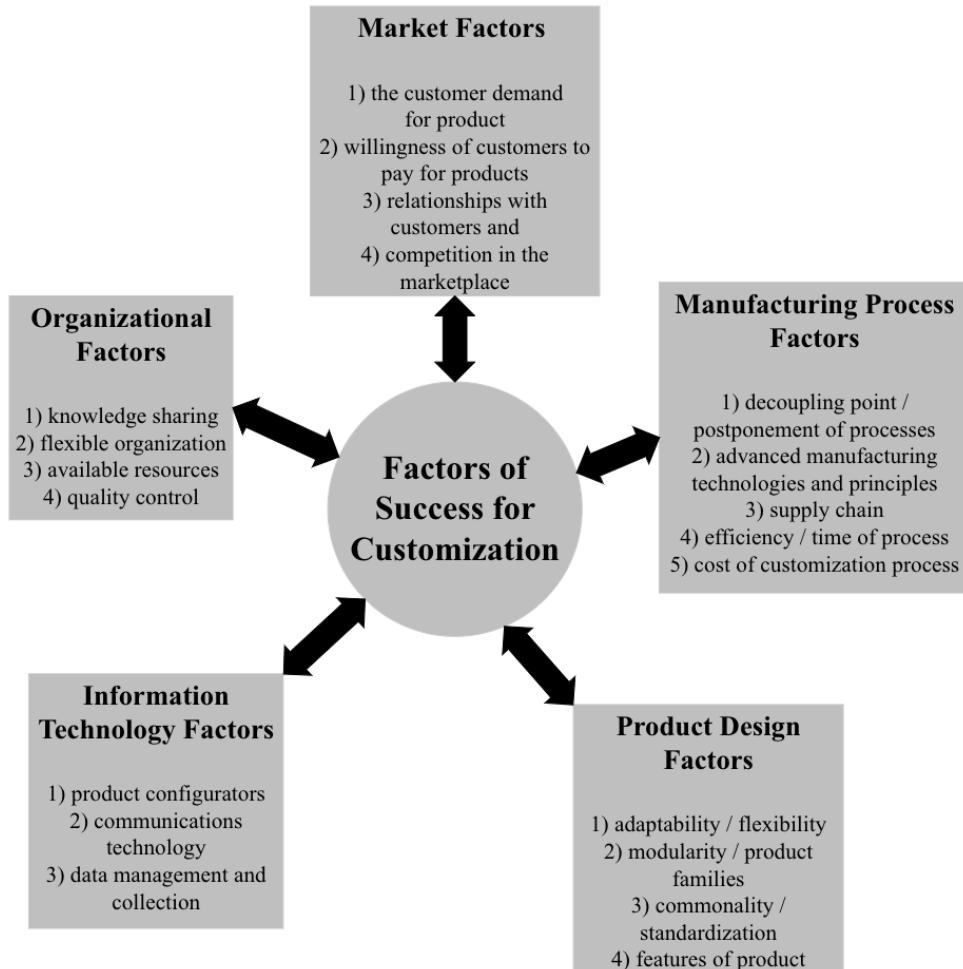


Figure 8: Factors of Success in Customization

Table 2: Summary of Factors Important to Customization from Literature

Market Factors	Product Design	Manufacturing Process	Information Technology	Organizational Structure	Type of Paper
(Piller et al., 2004)	X		(X)	X	Journal Article
(Cormier et al., 2008)		(X)			Conference Paper
(Kumar and Stecke, 2007)	(X)	(X)	(X)	(X)	Journal Article
(Jiao and Tseng, 2004)	(X)	(X)	(X)		Journal Article
(Welborn, 2009)			(X)		Journal Article
(Nielsen et al., 2014)	(X)	(X)	(X)	(X)	Literature Review
(Brun and Zorzini, 2009)	(X)	X	(X)		Journal Article
(Storbjerg et al., 2014)	(X)	(X)	(X)		Literature Review
(Fogliatto et al., 2012)	(X)	(X)	X	(X)	Literature Review
(Ullah and Narain, 2018)	X	(X)	X	X	Journal Article
(Daaboul et al., 2012)	X	(X)	(X)	(X)	Journal Article
(Blecker and Abdelkafi, 2007)	(X)	(X)	(X)		Journal Article
(Hermans, 2012)		(X)		(X)	Journal Article
(Wellige and Steiner, 2014)	(X)		(X)	X	Conference Paper
(Broekhuizen and Alsem, 2002)	X	(X)	X	(X)	Journal Article
(Pourabdollahian et al., 2013)	(X)		(X)	(X)	Conference Paper
(Fogliatto et al., 2003)		(X)	(X)		Journal Article
(Pech and Vrchota, 2022)			(X)	(X)	X
(Ciesla and Mleczko, 2021)	(X)	(X)	(X)	(X)	Journal Article

X denotes that a work has covered all the relevant subfactors for a category

(X) denotes that a work has only partially covered the subfactors for a category

2.2.1 Market Factors

Market related factors in terms of customization can be classified into four subcategories: 1) the customer demand that exists for a particular product 2) willingness of customers to pay for products 3) relationships with customers and 4) competition in the marketplace.

Customer demand and willingness to pay are crucial for the success of product customization. Piller et al. (2004) propose a model for value creation in mass customization that focuses in part on the increased willingness to pay for customized products. The increased willingness of a customer to pay is highly related to the satisfaction of customer requirements. It is important to understand what products will be most popular and sell the best to prevent waste (Ciesla and Mleczko, 2021). The customer demand is also major consideration that is often measured in terms of customer interest in certain features of the product that is also considered in developing a market-based mass customization and personalization effectiveness index (MCPEI) (Kumar and Stecke, 2007). Methods proposed in this work involve utilizing weightings assigned by the customer to gauge the importance of each product feature (e.g., RAM, wireless card) as well as the willingness to pay (Kumar and Stecke, 2007). The weightings of product features highlight the importance perceived by the customers. Another proposed method examines the customer perceived value of customization using a utility function (Jiao and Tseng, 2004). Like the MCPEI, the utility function is comprised of the customers preferences in terms of the different features a product has and leads to the calculation of a quantitative index (Jiao and Tseng, 2004). Several quantitative metrics exist to assist a company evaluating the marketplace and demand by using measures such as the customer churn rate metric (Nielsen et al., 2014), customer return rate metric (Nielsen et al., 2014), customer repurchase rate metric (Nielsen et al., 2014) and customer complaints rate metric (Blecker et al., 2003). By implementing these metrics, the level of satisfaction and demand for a given product can be analyzed, providing insight into the market conditions. The current market conditions are an important aspect of implementing a customization strategy to ensure that offering customization can translate to a competitive advantage (Da Silveira et al., 2001).

Maintaining a positive relationship between the customer and the producer is essential and has been identified by multiple works as a key factor of success (Broekhuizen and Alsem, 2002; Daaboul et al., 2012; Ullah and Narain, 2018; Wellige and Steiner, 2014). Ullah and Narain (2018) suggest that by maintaining a close relationship with customers, the needs and requirements of the consumers can be better understood and met. This concept is central to the offering of any customization strategy and will improve the overall satisfaction of the customers, generating more sales and higher value. Customer preferences can be elicited through surveys and interviews which allow for a company to offer better solutions that meet key customer requirements (Wellige and Steiner, 2014).

Competition in the marketplace is also an important consideration when pursuing a customization strategy. Benchmarking products against those already in existence from both internal and external

sources is one strategy that has been proposed to evaluate a product and understand how a potential product offering compares to others on the market (Kumar and Stecke, 2007; Wellige and Steiner, 2014). Da Silveira et al. (2001) point out the competitive advantages that can exist for a company when they begin to offer product innovation over other companies and how this can be a positive driver of success.

2.2.2 Manufacturing Process Factors

Five subcategories have been identified summarizing the different manufacturing processes factors. 1) decoupling point / postponement of processes 2) advanced manufacturing technologies and principles 3) supply chain 4) efficiency / time of process 5) cost of customization process.

The decoupling point is the point where customization is introduced in the manufacturing process and when customer specifications are introduced (Piller et al., 2004). Postponement is when the differentiation point of the product is delayed allowing for greater flexibility in the product variety at lower costs and effort (Yang et al., 2004). These concepts are interrelated and refer to the point at which customization will occur and the positioning of customer involvement in the overall process. There is greater flexibility and better risk management when using a postponement strategy as it reduces uncertainty (Brun and Zorzini, 2009). Employing these strategies, can also provide cost saving for producers in terms of inventory, planning and capacity utilization and stability (Piller et al., 2004). Martin and Ishii (1997) propose a differentiation point index (DPI) that measures the point at which the product differentiation occurs and the level of postponement.

Another key manufacturing process factor is the use of advanced manufacturing technologies and principles. There are several different types of technologies that are considered advanced manufacturing technologies that enable greater variety, flexible production, and reduced costs (Da Silveira et al., 2001). The flexibility of these systems are key to achieving greater variety at reduced costs (Ullah and Narain, 2018). Kumar and Stecke (2007) propose a list of technologies and practices that can provide benefits in the production cycle including rapid prototyping, lean enterprise, computer integrated advanced manufacturing, cellular processes and using six sigma principles. Some other common technologies include computer aided design (CAD), computer aided manufacturing (CAM), flexible manufacturing systems (FMS) and computer numerical control systems (CNC) (Broekhuizen and Alsem, 2002; Da Silveira et al., 2001; Kumar and Stecke, 2007; Pourabdollahian et al., 2013; Ullah and Narain, 2018).

To have an effective production system it is essential to have a supply chain that can deliver materials in a timely and efficient manner (Da Silveira et al., 2001). Integration of the supply chain using digital technologies aids in delivering quality affordable customized products with acceptable lead times (Pech and Vrchota, 2022). Effective management of supply chains can also be an enabler for companies to postpone purchasing and manufacturing (Ullah and Narain, 2018). This involves co-ordination within the supply chain to ensure smooth operation and includes adaptation across the supply chain (Daaboul et al., 2012). A reliable supply network also makes the manufacturing of individual orders easier, thus improving efficiency (Pourabdollahian et al.,

2013). Broekhuizen and Alsem (2002) highlight the importance of flexibility in the supply chain and the need to be able to deliver materials quickly and on time while keeping costs at a minimum.

A major consideration in manufacturing is the amount of time that it takes to offer customization. A customization metric has been proposed to evaluate a customization using the upper specification limit of the cycle time, the average cycle time, and the standard deviation of the cycle time (Jiao and Tseng, 2004). The metric can indicate that a process is considered cheap and easy or hard and expensive. Nielsen and Brunø (2013) present time to introduce a new variant metric, that measures the amount of time required to introduce a new product option, calculated based upon the time from product design until manufacturing and the number of new product options. The importance of time to manufacture customized products is supported by Brun and Zorzini (2009) in their examination of companies engaged in customization. Further, effective production planning was identified as a foundation of customization success with the objective of reducing lost working time and thus improving the efficiency of the production process (Ciesla and Mleczko, 2021).

Cost is a driving factor that can determine feasible production options for a product. (Welborn, 2009) Welborn proposed a customization index which is based upon the expected tool life, manufacturing batch size, tooling cost and the setup cost. The resulting index provided a measure for the evaluation of the flexibility of using a process for manufacturing based on cost. The cost to introduce a new product variant has also been explored by Nielsen and Brunø (2013) with the cost to introduce new product variant index, a ratio of the cost to the product options offered. The cost of customization was further investigated by Brun and Zorzini (2009) utilizing the total cost of offering customization in relation to the total production cost as an evaluation tool for mass customization companies.

2.2.3 Product Design Factors

The physical design of products plays a role in selecting a customization strategy and impacts the success of a customization strategy. From literature four subcategories have been identified that relate to the physical design of the product including adaptability / flexibility, modularity / product families, commonality / standardization, and features of the product.

The adaptability and flexibility of the product refers to the ease of which aspects of the product can be changed (Cormier et al., 2008). Cormier et al. (2008) propose a method of evaluating the flexibility of a design by examining three different areas of flexibility namely, flows between subsystems, connections between subsystems and geometry of subsystems. This evaluation is used to determine what aspects of the design can meet the needs of the customers and what aspects can be modified to provide a more flexible product. Jiao and Tseng (2004) also propose a design customizability index that measures the ease of customization in relation to the flexibility of the design. The process examines the performance of a design in satisfying the customization requirements. A design that would meet these needs means that it would be easy to customize and flexible. Broekhuizen and Alsem (2002) emphasize the importance of flexibility with a focus on

modularity being an enabler. Using practices that are flexible can maximize value while also minimizing waste.

Modularity has been identified by several sources as a key factor of success and enabler of mass customization. Kumar and Stecke (2007) propose the use of modular design in their mass customization index in conjunction with product innovation strategies, off-the-shelf products usage, and a marginal utility analysis. Modularity can provide benefits in reducing lead times, improving variety, and reducing costs (Brun and Zorzini, 2009; Ullah and Narain, 2018). In works cited by Brun and Zorzini (2009) they identify six different types of modularity: component-sharing modularity, component-swapping modularity, cut-to-fit modularity, mix modularity, bus modularity, sectional modularity. Modularity occurs on the product design level but can also be implemented elsewhere in the production process. Some works state that modularity is necessary for cost effective products, however this is not the case considering true mass customization were every product is completely custom (Da Silveira et al., 2001). Modular design is a critical enabler that has been deemed as key to mass customization, but it also dependent on other enablers (Ullah and Narain, 2018).

One method of creating an efficient production process is the use of commonality and standardization amongst parts. Both are interrelated and generally refer to practices of using common parts among product architectures to reduce costs and increase efficiency. Several different authors have proposed commonality metrics using different approaches. Blecker et al. (2003) present two different metrics to help evaluate the commonality of parts in a design, the module commonality metric, and the part commonality metric. They calculate the ratio of common modules and common parts compared to the total number of modules and parts respectively. These metrics can indicate the efficiency of a product architecture and provide insights into the cost of production (Nielsen et al., 2014). A total commonality metric has also been developed that considers the commonality the components and the product family (Blecker and Abdelkafi, 2007). The process utilizes the generic bill of materials which gives a measure of how product families can be produced with common components (Blecker and Abdelkafi, 2007). Brun and Zorzini (2009) discuss how standardization practices can reduce the shipping and inventory costs associated with production. They highlight Hewlett-Packard as an example, customizing power supplies at distribution centers rather than manufacturing plants and using standard components for a larger portion of their product thereby reducing their shipping and inventory costs by 25% (Brun and Zorzini, 2009).

When offering customization, one of the most important aspects is the actual physical characteristics and features of the product. These features and characteristics are what enable the product to meet the needs of the customer and are determining factors for other aspects of the production process. When evaluating the features of the product, it is important to take into consideration what the consumers desire. In the work of Kumar and Stecke (2007) they utilize the features of the product in conjunction with importance weightings from customers to calculate a customization index. Hermans (2012) examines various characteristics of the product and mass customization toolkits to analyze the solution space and toolkit itself. Features are defined as a

veneer, along with subcategories such as shape, material, structure etc. These subcategories comprise the characteristics of the product itself in conjunction with other design characteristics. Fogliatto et al. (2003) propose a quality function deployment matrix method of evaluating the flexibility of a design using process and product matrices. In this method the product matrix consists of the features of the product and associated weightings from both the customers and those involved in production. The features consist of different aspects of the product such as sub-assemblies, features of the products, aesthetics and even the packaging.

2.2.4 Information Technology Factors

Information technology enables companies to effectively communicate with customers, internal partners and external partners while also facilitating organization and management of production systems. Information technology factors can be categorized into three subcategories including: 1) product configurators 2) communications technology 3) data management and collection.

A product configurator is a system that enables a company to elicit requirements from the customers and offers them the ability to choose products and options that fulfil their needs. Two metrics that can offer insight into the performance of the configurator are the configuration abortion metric (Blecker et al., 2003), and configuration sales metric (Nielsen et al., 2013). These metrics can provide insight into how the solutions offered by the company are meeting the needs of the customers and the effectiveness of the configurators based upon the outcomes of customer interactions. Hermans (2012) also presented a method for the evaluation of product configurators using four mechanisms as an evaluation tool. The configurators were analyzed with a target outcome based upon three aspects: 1) product attributes 2) mechanisms (i.e., the way in which customization is offered) and 3) choice (i.e., the number of options presented to the user.)

Effective communication is also key to success in offering customization for a company. One important reason for using communication technology is to have effective communication between intercompany workgroups to improve response times to customer demands (Da Silveira et al., 2001). Ullah and Narain (2018) support this idea of increasing efficiency and even competitiveness with the use of communications technology within a company. Knowledge sharing across the company is also beneficial in increasing overall effectiveness, and well-developed communication networks allow for this to occur at a lower cost (Broekhuizen and Alsem, 2002). Another important aspect of communications technology is external communications. This includes communication with the customers and providing support to customers to about technical aspects of the products and taking feedback (Wellige and Steiner, 2014).

Data management and collection refers to how companies can utilize the information that they gather from customer orders to improve their offerings and streamline processes. This relates to the idea of sticky information, which can be defined as precise market information that would normally be of higher cost to attain (Piller et al., 2004). This information can be gathered and used to better understand the market and allow a company to better translate the needs of the customer

into customized products. Similar ideas are echoed by analyzing past orders for better future customization (Da Silveira et al., 2001) (Ullah and Narain, 2018).

2.2.5 Organizational Factors

In literature, four subcategories of organizational factors have been identified as critical to success. They are knowledge sharing, flexible organization, available resources, and quality control.

Knowledge sharing across an organization can help a company succeed in mass customization by allowing them to adapt to changes in market demands and allow production processes to run smoothly. Da Silveira et al. (2001) highlight the need for knowledge sharing across the entire value chain which includes suppliers, retailers, customers and internally. This can include the development of networks, engineering knowledge and the use of in-house processes to keep up with dynamic demands (Da Silveira et al., 2001). Ullah and Narain (2018) reinforce the importance of building networks to share information and provide access to knowledge that can allow improvement of products and new ideas. The authors also state the importance of knowledge sharing within an organization and ensuring that management has adequate knowledge to create a competitive advantage (Ullah and Narain, 2018). Broekhuizen and Alsem (2002) further emphasize the importance of sharing knowledge and discuss how the information flows of knowledge must be cohesive and collaborative to attain the greatest benefits in efficiency and cost reduction. Cross functional teams and sharing of knowledge have also been identified as a foundation of success for customization, leading to improved decision making and superior products (Ciesla and Mleczko, 2021).

Flexibility has already been discussed regarding the product design; however, the concept of flexibility can also be incorporated into the organization as well. Flexibility helps a company adapt to changes more easily without disrupting production or increasing costs. The use of industry 4.0 technologies like cloud technologies and automation enable more flexibility within organizations through data sharing and online configurators (Pech and Vrchota, 2022). These concepts are very important in customization where customer requirements are constantly changing. Ullah and Narain (2018), explain the importance of flexibility throughout the organization and specifically point out that flexibility in the areas of human resources can ease the effects of environmental factors on production. Flexibility is tied to the creation of innovation, less bureaucracy, and the ability to respond to a changing market. They also identified that flexibility for value network partners is important in a mass customization strategy, pointing out that adaptability is important through the supply chain which ties into the concepts of flexibility.

For an organization to be ready for customization, it must be equipped to handle the changes that need to occur and have access to resources that can facilitate these changes. This includes the availability of technology relating to both manufacturing and information for a successful transition to a customization strategy (Da Silveira et al., 2001). In some cases, the availability of such technologies is what allows for companies to offer customization in the first place. Ullah and Narain (2018) support this idea and the importance of analyzing the availability of resources in a

company regarding the workforce and the suppliers. These concepts fall under the umbrella of process management and understanding the capabilities of a given firm. The number of resources available can also refer to the costs of investments required to offer a customization strategy. Sizable investments must be made to acquire new capabilities and sustained investments may be required to maintain and improve process and systems (Broekhuizen and Alsem, 2002).

Quality control is a challenge that many companies offering customization face. It can be difficult to implement a quality control practice since products can differ greatly between customers. Traditional methods of quality control are also not applicable. There are a lack of methods available to assess the quality of customized products and there are also quality inconsistencies in these products (Da Silveira et al., 2001). This need for quality control is highlighted by Kumar and Stecke (2007), suggesting the use of computer aided quality control as a key factor in their calculation of their customization index. The delivery of high-quality items and steps to ensure quality across the production process are also discussed in other works as important aspects of offering customization (Daaboul et al., 2012; Ullah and Narain, 2018).

2.3 Decision Support Tools in Product Customization

Decision support tools can help to guide firms in each of the three stages of the customization process outlined in Figure 1. A key consideration for any decision support tool is the structure of the approach. A structured approach is a framework that includes a detailed decision-making process with objective recommendations to guide a firm through the customization process. This includes specific evaluation measures and clear recommendations for customization strategies. The following sub-chapters detail a structured literature review to determine the state-of-the-art for decision support tools in each area of the customization process.

2.3.1 Deciding to Customize

The decision to customize is pivotal to the success of a customization strategy. This step of the customization process is largely dependent on the market conditions, consumer preferences and demand. A search was conducted using the online repository Web of Science with two primary key words, “Product Customization” and “Mass Customization”. The secondary key word was “Decision Support” and the search results outlined in Table 3. The key words were queried with no requirements on date of publishing, source, or type of paper.

Table 3: Key Word Search Results from Web of Science for the Decision to Customize

Primary Key Word (General Topic)	Secondary Key Word	Number of Results from Query
“Product Customization” & “Product Customisation”	“Decision Support”	19
“Mass Customization” & “Mass Customisation”		105

From Table 3 there are several important observations that can be made. The first observation is that there is more literature focusing on mass customization compared to general product customization. Although all mass customization is considered product customization, there exist product customization strategies that cannot be considered mass customization. For a strategy to be considered mass customization it must take place on a large scale with high production volumes, which is not the case for craft customization. This is possibly since mass customization benefits from economies of scale and is generally a more attractive avenue for firms. However, mass customization is not always feasible, especially for SMEs given high startup costs.

The initial query returned one hundred and twenty-four total pieces of literature. Out of this selection of papers, each was evaluated on their relevancy on the topic of decision support tools and for deciding to customize. Under the umbrella of decision support, many of the one hundred and twenty-four total pieces of literature deal with other components of the production process. For example, Yetis et al. (2022) explore the use of blockchain technology in decision support for production management (Yetis et al., 2022), Guo et al. present a decision support methodology for designing the customer order decoupling point (Guo et al., 2019) and Schmid and Limère (2019) develop a decision support system for the assembly line feeding (Schmid and Limère, 2019). Works such as these do not address the decision to customize and were filtered out by first examining the titles of the work, then the abstracts. Papers that addressed the topic of deciding to customize based on these two descriptors were then further reviewed. To further refine the results, literature published before the year 2003 was excluded. Given the rapid development of manufacturing and information technology, literature from before this date may employ decision tools that are no longer relevant. Both articles and conference papers were considered for this review. After applying these criteria and utilizing the same filtering approach on papers queried in Chapters 2.1 and 2.2 of this thesis, five works remained to be evaluated as shown in Table 4.

Table 4: Literature on the Decision to Customize

	Structured Approach	Automated Decision Support
(Xu et al., 2017)	X	
(Aron et al., 2006)		
(Hoogeweegen et al., 2006)		X
(Banerjee et al., 2019)	X	
(Cavusoglu et al., 2007)	X	

The decision to customize is a topic that is not well covered in terms of product customization. Very few approaches provide structured decision support in the actual decision to offer customized products compared to standard ones. Xu et al. (2017) presented a decision support model to evaluate different product solutions. Their method used an analysis of the costs of customization and the consumer preferences along with a genetic algorithm to find the optimal result. This method provides a quantitative method to evaluate different levels of customization for a product and different manufacturing strategies; however, it does not do so in an automated manner. Aron et al. (2006) investigated the effect of the level of customization on consumer behaviors in terms of the willingness to pay and accept customized products. Their model presents an analytical

evaluation of the tradeoffs consumers make when deciding to purchase a customized product and they discuss the implications for firms. The work done in this paper does not provide a structured approach to decision support, but instead utilizes the findings to offer insight into business development. The decision support system presented by Hoogeweegen et al. (2006) took an approach of using a business networking game to simulate the effect of customization and the changes in business structures from stable to dynamic. The goal of the game is to help decision makers evaluate how different types of customizations and investments can facilitate customization. The framework is meant to simulate different decisions and does not provide structured decision making but is automated. Banerjee et al. (2019) explore the effects of customization level and number of product configurations on customer satisfaction. Their model attempts to reduce the complexity of offering many product configurations while maintaining an optimum level of customer satisfaction. Their work found that generally, complexity reduction reduces customer satisfaction, but this can be offset by lower prices afforded by mass production. The framework is structured and provides specific indications of what number of configurations can lead to optimal customer satisfaction; however, it requires extensive data collection and analysis that is not automated. Cavusoglu et al. (2007) present a method of selecting a customization strategy with a two-step approach that begins with whether a company should customize then moves to selecting the type of mass customization that should be adopted. This method focuses heavily on the costs of customization compared to the benefits. Factors considered include the costs of eliciting customer information, costs of manufacturing technology compared to the prices that customers are willing to pay as well as the competition in the marketplace. An important aspect of this method is that companies are not always better off customizing their products (Cavusoglu et al., 2007). This is a structured approach because it presents decision making recommendations but is not automated.

Although the decision to customize is a very important step in the customization process, there is a distinct lack of decision support tools to guide firms through this initial stage and decide to customize. There is a need to develop more structured and automated decision support tools for this application.

2.3.2 Customization Strategy Selection

The aim of this chapter is to review current customization selection strategies to develop decision-making models for selecting the optimal customization strategy based on various factors identified in Chapter 2.1, such as product attributes and company capabilities, etc. Decision support for customization strategy selection can take several different forms. A customization strategy is defined as the manner in which customization can be implemented and how to manufacture the product as outlined in Chapter 2.1. The query conducted in Chapter 2.3.1 did not return any literature that focused on the selection of a customization strategy that aligns with the four strategies identified in Chapter 2.1. A new search was conducted on Web of Science using the key words outlines in Table 5. The key words were queried with no requirements on date of publishing, source, or type of paper.

Table 5: Key Word Search Results from Web of Science for Customization Strategy Selection

Primary Key Word	Secondary Key Word	Third Key Word	Number of Results from Query
“Product Customization” & “Product Customisation”	“Craft”	“Decision”	0
	“Modular”		5
	“Open Architecture”		0
	“Additive Manufacturing”		4
“Mass Customization” & “Mass Customisation”	“Craft”	“Decision”	2
	“Modular”		35
	“Open Architecture”		1
	“Additive Manufacturing”		13

The initial query returned a total of fifty-nine pieces of literature. Literature focusing on modularity returned the most results by a large margin. This is likely since modularity is a very popular approach to customization. However, as outlined in Chapter 2.1 of this thesis, other types of customization strategies have benefits over modularity in certain scenarios and thus are also important to consider. Overall, there is limited literature that specifically focuses on decision support for the selection of a customization strategy, specifically in the product customization category.

From the fifty-nine total pieces of literature, each were evaluated on their relevancy to selecting a customization strategy for customization. Some papers that were returned in the search query were not relevant to the selection of a customization strategy such as works by Benbouja et. al that deal with supply chain integration and mention modularity (Benbouja et al., 2021). After evaluating the papers by their titles, abstracts and content, further refinement of the literature was conducted with works published before 2003 omitted from the final review. Both articles and conference papers were considered. Nine works remained to be evaluated including some found by applying these filtering techniques to papers searched in Chapters 2.1 and 2.2 of this thesis and are presented in Table 6.

Table 6: Literature on the Selection of a Customization Strategy from Key Word Search

	Types of Customizations Strategies Considered					Is this Approach Structured?
	Craft	Modular	OAP	Integrated	General Implementation Guidelines	
(Xiong et al., 2018)		X				Yes
(Shamsuzzoha and Piya, 2020)		X				No
(Song et al., 2021)		X				Yes
(Mesa et al., 2020)		X	X			No
(Lacroix et al., 2023)				X		Yes
(Deradjat and Minshall, 2018)				X		Yes
(Mchunu et al., 2003)					X	No
(Alfnes and Skjelstad, 2009)		X			X	No
(Büyüközkan, 2008)	X	X				Yes

X denotes that a work has thoroughly covered the customization strategy in detail

(X) denotes that a work has only partially covered the customization strategy and lacks details

Xiong et al. (2018) presents a framework for modular product platforming with considerations for supply chain postponement. The objective of their work is to develop an optimization method that allows for decision-making in terms of how to structure product platforms and when to introduce postponement. The work focusses solely on modular product design and provided quantitative and structured outputs to help firms when developing products. Shamsuzzoha and Piya (2020) identify the driving factors behind product modularity and what can hinder modular products. In their work, they find there are 18 factors that can present challenges for implementing modularity. The paper is comprehensive in the scope of factors affecting modularity and is consistent with the factors identified in Chapter 2.2 of this thesis. However, it does not cover any other type of product customization. The work also does not provide any sort of structured decision making, but instead is meant to highlight potential challenges so that designers and managers can more easily identify and solve them in the production process. Song et al., (2021) propose a decision support system that aims to derive the optimal product configurations to minimize production costs. In their work they only focus on the use of modularity and standardization with no consideration for other customization strategies; however, a structured decision support system is presented. Mesa et al. (2020) present a framework for using modular architecture principles in both modular products and OAP strategies with a focus on sustainability. They propose a framework for selecting different modular architecture principles that includes examining the benefits of each approach, sustainability implications and the requirements of the customers (Mesa et al., 2020). This work does not provide a structured approach for selecting a strategy but rather offers a framework for comparison of modular architecture and how they can be applied. The focus is solely on modular and OAP strategies and does not consider other types of customization.

Lacroix et al. (2023) develop a framework for decision support in the utilization of AM technology for mass customization with the objective of increasing profits. Their model considers primarily the implementation of an AM strategy; however, it focusses on the use of AM in conjunction with other mass customization strategies which are defined broadly as any other technologies that can be used to achieve customization. As such, there is no specific consideration for other types of customization strategies. The work does provide a structured method to evaluate different production strategies involving the use of AM and outputs quantitative measures. Deradjat and Minsha (2018) also present a framework for selecting additive manufacturing. In this work the authors use eight different decision trees to guide companies in the process of selecting an integrated approach. The decision trees cover corporate strategy, technological – overall process, technological – front end, technological – additive manufacturing machine, technological back end, operational, organizational, and external competencies (Deradjat and Minshall, 2018). The competencies that are covered in this work are consistent with the factors of success that were presented in Chapter 2.2 of this thesis. This is one of the most comprehensive frameworks reviewed in terms of evaluating capabilities.

Mchunu et al. (2003) propose a framework for selecting a mass customization strategy that is based upon the use of a data acquisition workbook, focused site tours and competency profiles. They propose five factor variables that have an impact on the ability of a company to mass customize namely, effective product variety management, communication and information management efficiency, support from top level management, supply chain management efficiency and new product development efficiency. The factors they outline are comprehensive when compared to the one presented Chapter 2.2 of this thesis, however the framework does not actually provide any recommendations or a structured approach for selecting a customization strategy, instead implementation guidelines are presented. Alfnes and Skjelstad (2009) also propose a set of guidelines for the implementation of mass customization based upon case studies. Three performance objectives are specified: low cost, short delivery time and degree of customization. A set of guidelines for decision areas in mass customization are compiled with eight categories: market interaction, products, information and communication technologies, manufacturing technologies, processes, manufacturing planning and control, supply chain integration and work organization (Alfnes and Skjelstad, 2009). These decision-making areas are consistent with the ones presented in Chapter 2.2 of this thesis; however, the work is not a structured approach to select a customization strategy and no specific customization strategy is presented.

Büyüközkan (2008) proposes a quantitative approach to selecting a customization strategy using an analytic network process. In this method, factors such as the design, production, distribution as well as related performance criteria like quality, costs, time, and flexibility are used in the analysis. In this paper they consider three types of customization: pure customization, tailored customization and standard customization (Büyüközkan, 2008). These classifications represent craft customization and a modular approach. The methodology presented here is one of the few structured quantitative approaches to customization selection but lacks consideration for all the customization strategies and factors of success.

It is observed that structured strategy selection frameworks are less extensively covered in this selection of literature with most works focusing on the processes, actions, and attributes a company should have and follow for pursuing customization. Further, most selection strategies focus on either one or two customization strategies or focus on general implementation guidelines for customization. The most commonly examined strategy is modularization.

2.3.3 Design Customization Process

The design customization process refers to the selection of a product design that best fulfils the needs of the customers and the goals of a company. Figure 9 illustrates the design customization process from understanding the needs of the customers and constraints of design and manufacturing to selecting an optimal product design for production. Other works have proposed frameworks for the design process in relation to customized products, however they tend to be tailored to the specific methodology being implemented in the work. For example, Jiang et al. (2022) propose a data-driven generative design framework that has five steps; requirement analysis, conceptual design, detailed design, manufacturing, and service (Jiang et al., 2022). A more general framework mass personalization design is proposed by Ozdemir et al. (2022) In their work they define mass personalization as a more user involved process compared to mass customization. The design framework begins with a designer translating the customer needs into requirements, which then allows the identification of design parameters and the development of a “seed” design that is essentially the starting design. This seed design is then modified by the user in a back-and-forth process with the designer until the final design is selected (Ozdemir et al., 2022) . The design customization process in Figure 9. represents a general design process for product customization and build upon the works of Jiang et al. (2022) and Ozdemir et al. (2022) while also considering the literature reviewed in this chapter. Selecting a product design includes choosing the features of the product that would be customized and how the customization strategy will be implemented for the product. For example, in a modular product this would include choosing the different types of modules to be offered and how modularity can be incorporated into the product design. Mapping customer needs to the functional requirements is also a part of the design customization process. It is of utmost importance for the designers and companies to effectively understand the needs of the customers to design products that can meet customer needs and produce products that can be sold. The objective of this chapter is to examine different design selection strategies in literature to identify areas for the development of a comprehensive decision-making model for customization strategy selection.

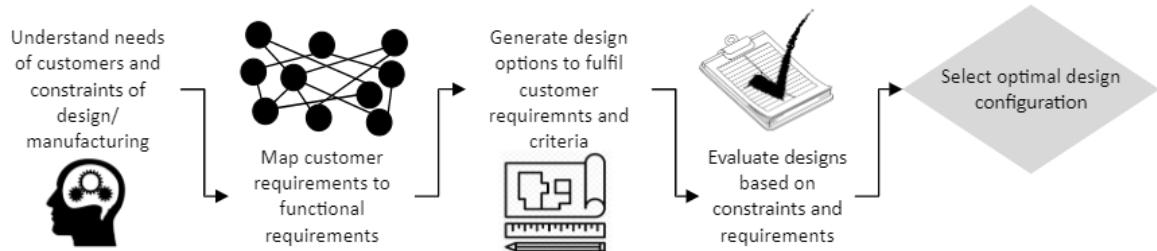


Figure 9: Design Customization Process

With an increased utilization of industry 4.0 technologies and principles in product customization, automation is a critical aspect in attaining higher levels of product personalization while minimizing associated production costs. Aheleroff et al. (2021) present a case study for the implementation of mass personalization as a service and explore how industry 4.0 technologies such as IoT, AM, big data, cloud manufacturing, digital twin, and blockchain can be implemented to achieve high levels of customization (Aheleroff et al., 2021). A commonality of these technologies is automation, which helps expedite and streamline collecting and understanding consumer preferences as well as designing products for each individual user. This idea of automation and use of digital tools in the design customization process is further supported by Barata et al (2023). These types of automated and digital engineering tools lead to more participation from the consumer and keep costs low (Barata et al., 2023). Literature for this chapter was sourced in a structured manner considering the concepts of industry 4.0 and their impact on the customization design process, specifically automation. A search was conducted on Web of Science using the key words outlined in Table 7.

Table 7: Key Word Search Results from Web of Science for the Design Customization Process

Primary Key Word (General Topic)	Secondary Key Word	Third Key Word	Fourth Key Word	Number of Results from Query
“Product Customization” & “Product Customisation”	“Decision”	“Design”	“Automation”	4
“Mass Customization” & “Mass Customisation”			-	65
“Product Customization” & “Product Customisation”	“Decision”	“Design”	“Automation”	16
“Mass Customization” & “Mass Customisation”			-	301

Decision support tools for the design of customized products are generally well covered in literature with three hundred and sixty-six papers published on this topic. However, automated decision support tools for this task have had significantly less coverage. The resulting search in Table 7 initially returned twenty total pieces of literature to be reviewed on the topic of automated decision support for the design of customized products. These twenty papers were then filtered to

exclude those published before 2003. Both journal papers and conference papers were considered. The remaining papers were then evaluated for relevancy on the topic by evaluating the titles, abstracts, and content, leaving four papers to review.

Bianconi et al. (2019) proposed a methodology that involves automated design and modeling for mass customization with a focus on housing. Their work involves generative modeling of building designs to personalize different features through collaboration with the end users and web-based catalogues (Bianconi et al., 2019). This approach is specially tailored to the construction industry and does not include any applications in product design. The method does showcase an automated tool to help firms generate design alternatives in the context of customization, however it still requires inputs that includes consumer preferences and thus requires manual leg work before the automated tool can be used. Elgh and Johansson (2014) provide an overall framework for the design of an automated design tool. Their work does not provide a specific decision support tool, but instead lays out how an automated design tool for product customization can be created using a so-called knowledge object (Elgh and Johansson, 2014). The knowledge object essentially takes a list of parameters and a method of processing the parameters to generate certain outputs. The work does not show details of a specific decision support tool for product design customization, but rather details how the knowledge object can be used to create design automation tools. Orsborn and Cagan (2008) developed a method of generating form variants of products for customization. Their tool uses a series of rules and a customer utility model to generate various form configurations to serve as the basis for further design modifications to the product. They utilize the example of a sports utility vehicle to illustrate how the proposed method functions (Orsborn and Cagan, 2008). The method provides an automated generation of design alternatives; however, the scope is limited to the form and still requires input information in the form of a design survey from consumers. Johansson et al. (2017) explore the adoption of design automation for use in an automotive fixture for control measuring. They utilize a generative knowledge-based engineering approach incorporating product service systems aspects. Their methodology allows the automation of developing the automotive fixtures with greater customization by changing design parameters quicker (Johansson et al., 2017). Analyzing customer order data has also been suggested to determine customer preferences that can allow for better management and optimal design selection (YETIS and KARAKOSE, 2018). This can be applied through the analysis of data mined from mass customization production and extracting the most popular design configurations to be mass produced (YETIS and KARAKOSE, 2018). This idea still relates to the overall concept of mass customization; however, the focus is on achieving very high efficiency in production akin to mass production.

There also exists many decision support methodologies that are not automated in their implementation. To increase the scope of this review, several pieces of literature that propose manual methods are also reviewed. Zha et al (2004) suggest the use of knowledge decision support system for the evaluation and selection of a strategy for product family design. This method utilizes a multi-step process to find the optimal design solution for customization. Different variants are evaluated regarding factors such as desirability, customer preferences, utility, features, the market, manufacturability, and investments that must be made to offer the product. The system uses

clustering and ranking to determine an optimal design solution that best satisfies the needs of the customers (Zha et al., 2004). Another method of design selection uses a preference survey and logistic regression model to determine optimal design solutions (Yao and Xu, 2018). Sales, profit and return on investment are used as measurements of the success of selecting a design model as well as production factors like the customer ordering decoupling point. The customer preferences combined with revenue determine the probability of success and a sensitivity analysis is used to evaluate the profitability of design options under different circumstances (Yao and Xu, 2018). Another method incorporates customer preferences, product features and cost to optimize product design (Xu et al., 2017). This method treats the design of the product as an optimization problem aiming to maximize profit and minimize production costs (Xu et al., 2017). A fuzzy decision-making process has also been proposed to determine the optimal design solutions based upon the customer needs (Liu et al., 2012). In this method, the needs of customers along with the opinions of experts are analyzed in a conjoint analysis that provides optimum design solutions for a given product (Liu et al., 2012). Another approach to design selection is presented by Modrak et al. (2015) that involves generating all the possible product configurations based upon the number of components or modules. Here, complexity is used as the determining factor for the evaluation of the product designs in this approach. (Modrak et al., 2015) The approaches to the design customization process outlined here are intended to be implemented after the selection of a customization strategy, and the methods generally assume a customization strategy has already been selected. The methods are also implemented manually and the results must be interpreted. They represent an essential component of the customization process, but do not constitute complete decision-making tools for the customization process.

The translation of customer requirements to physical product characteristics is another aspect of the design customization process that is important to offering effective products. Works covering this topic again do not constitute complete customization implementation frameworks but are an integral part of the overall customization process. Yu et al. (2008) present a learning-based hybrid method to model the relationship between customer needs and product specifications. This process uses a knowledge based artificial neural network with a classification and regression tree (CART) to facilitate mapping. The neural network is trained using transaction records from past sales to form functional relation templates based on the requirements of the customer and the training data. Decision rules can then be formed, and future orders can be mapped to the functional relation templates to aid in decision making and provide design guidelines (Yu et al., 2008). Another method to aid in decision making in the product design process involves translating affective customer needs, expressed through feeling or emotions, into functional requirements (Jiao et al., 2007). In this process they use augmented reality and virtual reality technology to help with the elicitation of customer needs by building virtual environments and assessing customer reactions to determine affective needs. An optimal design solution can be determined that includes the affordability and customer satisfaction using proposed utility functions (Jiao et al., 2007). Another proposed method of mapping customer needs to functional requirements was presented by Krishnapillai and Zeid (2006). The objective is identifying, classifying, selecting, and mapping customer needs to design parameters using a matrix method. This approach identifies the customer requirements and formulates them into a functional requirement hierarchy. Then most conformal

product design is identified using a customization index considering both the designer and customer input (Krishnapillai and Zeid, 2006).

2.3.4 Eliciting Consumer Preferences

Consumer preferences play an important role in the design of customized products (Liu et al., 2012; Wang and Tseng, 2014). Understanding how to satisfy the needs of the customers and meet their requirements is a challenge faced by product designers and can be a significant challenge when developing novel products. In the context of product customization, the requirements of consumers determine whether to offer a customized product in the first place and the design of the customized product (Xu et al., 2017).

In literature there has been a variety of proposed methods to obtain customer preferences and try to understand the market for a novel product. A popular method of obtaining consumer preferences is through surveys (Golovacheva et al., 2022; Kalantari and Johnson, 2018; Oliveira et al., 2019). Surveys provide an effective way to gather information from a large group of respondents (Hays et al., 2015). However, using a survey alone for product design is generally limited to gathering information on one specific product. This means an entirely new type of survey would be needed for each new product, adding additional costs and time to the product development cycle.

Another popular approach to eliciting consumer preferences involves examining product reviews to extract consumer preferences (Han and Moghaddam, 2021; Horch et al., 2015; Rai, 2012). These approaches generally use data mining techniques to sort through customer reviews, usually in an online format. The reviews are then analyzed using a natural language processing (NLP) algorithm. The type of algorithm varies based on the goals of the analysis; however, some common approaches include part of speech tagging (Rai, 2012) and sentiment analysis (Han and Moghaddam, 2021; Horch et al., 2015). NLP-based approaches using product reviews generally provide good results in terms of extracting consumer preferences; however, they require large amounts of data in the form of consumer reviews. For novel products this type of customer review information simply does not exist, and it may not be easily accessible for existing products.

Prediction of consumer preferences can also be used to elicit preferences. Prediction models can work with more limited information and generally require less direct interaction with consumers. A prediction model can be effective for novel product applications and can provide effective insight into consumer preferences for both the decision to customize a product and the design of the product itself. Chen employed machine learning (ML) techniques for the purpose of predicting consumer preferences with a case study on coffee makers (Chen, 2023). In this work, consumers were shown different pictures of coffee makers, then asked to rate them based on their preferences for the pictures they were shown. Using deep learning and the images of the coffee makers, the author was able to show that ML consistently performed better when predicting consumer preferences for these products in a comparison to an affinity graph and analytical hierarchy method. Another prediction model was presented by Li et al. (2020) with a goal of predicting consumer color preferences for shoes (Li et al., 2020). In this model images of the products were

again used along with sales, inventory data and market trends. Combining these three data sources, a logit model is used to predict consumer color preferences using linear functions and neural networks for the utility functions. The authors claim their work can help retailers better manage their supply of desirable color options to meet consumer demand. An interactive generative algorithm for the customized design of suit coats was proposed by (Zhu et al., 2020). In this method, potential consumers are shown different styles of suit coats and input their satisfaction with the design and style of the coat. An iterative process is used to generate new designs that are then evaluated again with the goal of increasing user satisfaction to the highest level. The work on predicting consumer preference highlights the possibilities and success of using ML techniques and big data to predict consumer preferences. However, these preference prediction models in literature solely focused on one specific product and do not have the ability to predict consumer preferences for products outside the scope initially defined in the method.

Predicting consumer preferences can also involve the prediction of consumer satisfaction or ratings for products. These types of predictions are highly related to consumer preferences but focus more on the satisfaction of consumers with the product features, the potential success of products and recommending products or configurations to consumers. Khan et al. (2021) performed an extensive review on the use of deep learning techniques for rating predictions that are used in recommender systems (Khan et al., 2021). They identify three types of recommender systems that exist, collaborative filtering, content-based recommender, and hybrid recommender systems. The collaborative filtering approach assumes that consumers who have shared common interests in the past will continue to do so, while content-based approaches assume that individual consumers will have similar preferences as they did in the past. The hybrid approach uses some combination of these approaches. According to the review, recommender systems have several shortfalls including accuracy, scalability, cold start, and data sparsity (Khan et al., 2021). Qu et al. (2017) developed an approach to user response prediction using a product based neural network with an application of determining the likelihood of consumers clicking specific ads (Qu et al., 2017). They use information in their prediction model relating to the user, ad publisher and ad information as data in a deep neural network and add an additional layer to cope with data sparsity. The results of their model and the addition of the product layer perform better compared to other deep learning methods that struggle with data sparsity. A key takeaway from these two works is that there exist issues in data collection and analysis of data for consumer preference prediction. Data is scarce and using deep learning methods can be challenging with this sparse data.

Another methodology that can be used to predict consumer preferences is clustering. Kalantari and Johnson (2018) explored this type of approach with a focus on consumer willingness to pay and wait for customized products in the Australian market (Kalantari and Johnson, 2018). In their work, they examine three different product types with three attributes: degree of customization, price, and delivery time. Data collection was done through an online questionnaire where respondents answer questions about their personal socio-demographic and rate the importance of the attributes for the products. The authors used the information collected to form customer market segment clusters and determine the importance of the attributes for the different clusters. A product configuration management approach is presented by Kusiak et al. (2007) using clustering and sales

data (Kusiak et al., 2007). In this approach, historical sales data is used to find consumer preferences, then identify product configurations that best suit the needs of customers. The objective is to reduce the number of product configurations through clustering, thus allowing companies to save money in the production stages.

2.4 Research Gaps

Based on the comprehensive review, we identified four research directions that will need more attention to better support the decision-making process in product customization. The details of the identified research directions are discussed in the following subchapters.

2.4.1 Lack of Comprehensive Frameworks for the Customization Process

There is a lack of complete frameworks and guidelines for the customization process that considers all the strategies for customization and all the factors of success. A comprehensive framework will guide a firm through the entire process outlined in Figure 1 and take into consideration all the strategies for customization presented in Chapter 2.1 as well as the factors of success outlined in Chapter 2.2.

Reviewed literature in Chapter 2.3.2 lacks consideration of all four customization approaches and generally only focuses on one or two strategies. Most works suggest modularity for customization, in some instances suggesting that modular design is an essential component of customization. This thesis has shown through product examples and a review of other literature that other methods of customization exist and can be successful. OAP, integrated, and craft approaches are rarely presented as options for customization. A narrow scope in terms of strategies can limit the potential success of a firm in adopting customization.

Papers reviewed on the topic of deciding to customize, customization strategy selection and the design customization process generally did not take a comprehensive view of the factors of success. This stems from the fact that works do not take a comprehensive view of the customization process and generally only focus on one specific aspect of the customization process. This means papers only focus on factors of success that are explicitly relevant to the area of the customization process they are focusing on. This thesis has shown that a comprehensive view of the factors of success is key to guiding a firm through the customization process to ensure the highest probability of success.

There is a lack of comprehensive frameworks for customization strategy selection as evidence by other literature (Fogliatto et al., 2012; Suzić et al., 2018). The lack of comprehensive frameworks is a distinct research gap, that can be addressed with the development of a decision support tool that takes into consideration the customization strategies and factors of success outlined in this thesis.

2.4.2 Lack of Structured Decision Support tools in the Customization Process

As defined in Chapter 2.3, a structured approach for decision support for customization is a method that can guide a firm through the customization process with specific decisions and recommendations. Few of the reviewed works from Chapter 2.3 present structured methods to customization strategy selection. Of those that do, the methods provide decision making and guidance that are limited in their scope and comprehensiveness.

Specific and objective recommendations in decision areas enable companies that lack knowledge and expertise on customization strategies and the design process to make better choices leading to higher probabilities of success. This would especially be true in SMEs, where there are fewer employees and a smaller knowledge base to draw upon. Structured decision support removes ambiguity in the customization process and increases efficacy and efficiency of the entire production cycle.

The lack of structured approaches can be addressed in the development of a selection tool and service platform that allows companies to take their product and operations from the initial stages of development and planning to the final stages of distribution and sale in a structured manner.

2.4.3 Lack of Automated Decision Support Tools in the Customization Process

There is a lack of automated processes to perform decision support tasks in the customization process. Commonly used methods include optimization algorithms, conjoint analysis, decision trees, matrices and pairwise comparisons to evaluate different strategies. These methods can be very time-consuming and often require manual interpretation of the results. Reviewed works that do utilize automated process for decision support focus on the design customization and do not consider the entire customization process.

The transition to industry 4.0 can be viewed as an evolution, with the final step being the concept of self-optimizing systems (Torn and Vaneker, 2019). A self-optimizing system means that the system can make decisions on its own and provide decision support to companies based on data collected and analyzed. Utilizing such a decision support model would form a structured comprehensive decision-making tool and offer CaaS to assist companies in offering customization in a more efficient and cost-effective manner.

2.4.4 Lack of Comprehensive Automated Consumer Preference Prediction Tools

A commonality in the customization process is the need for consumer preferences in both the decision to customize and the design of the product itself. The challenges associated with collecting consumer preferences highlight the need for a more efficient, cost-effective, and accurate method of eliciting preferences. Traditional methods such as surveys, focus groups or the designers' best guess are employed in this stage of the product development cycle. Surveys and focus groups are excellent methods to obtain specific targeted information on consumer

preferences. However, it can be very costly, time-consuming and difficult for firms to elicit responses from consumers. Additionally, the information collected from the surveys or focus groups is only applicable to the specific product they focus on, meaning each new product would require a new study.

Some common data types in prediction models include socio-demographic information of the consumers, historical sales, and consumer review data. These data types require a significant amount of work to collect or require that the product itself must have a sales history. For novel products, especially those from small and medium sized enterprises, this is a challenge as human resources and monetary funds are generally limited. There exists a need for consumer prediction models that can operate with no prior sales information, limited input data, have functionality for a wide range of products and provide accurate preference predictions. Most prediction tools are also focused on a single type of product. This means that they are not comprehensive in terms of the types of products they can predict preferences for.

An automated and comprehensive consumer preference prediction tool eliminates the need for company interaction with consumers to elicit preferences and offers an efficient and cost-effective means for decision support in the product customization process.

Chapter 3 Pilot Study

This chapter presents a pilot study to understand and analyze consumer preferences and develop a better decision support methodology. The work in this thesis aims to present a data-driven approach to aid the decision to customize the design of customized products. This is accomplished by predicting consumer preferences using ML techniques based on product attributes and crowdsourced consumer preference data, then providing recommendations in key customization decision areas. Considering the product itself and similarities in the types of attributes and functionalities they have can help to address the issues with current prediction models, yet such a method has not yet been explored in literature.

To explore how such a method can be implemented, a pilot study was first conducted to gather a data set of consumer preferences for various products using surveys. The results of the pilot study can be analyzed to determine how a machine learning approach can be implemented in this context.

3.1 Survey Design

One method of crowdsourcing consumer preferences is through surveys. Online surveys have been shown to be a time effective method for collecting data (Sing et al., 2009). Results are automatically stored in a database that can be easily imported into other software and users are able to easily answer questions at their leisure. The distribution of surveys can present a challenge as it is often difficult to collect responses. There are several options available to distribute surveys, including the use of email, online forums, and professional associations. Previous works have found that online forums have the highest response rate when compared to other channels for distribution (Sing et al., 2009).

A crucial element of effective data collection is a user-friendly and easy to use design (Regmi et al., 2017). Considering the survey is intended to gather responses from all demographics, each question needs to be simply worded and easy to understand. These questions must also be carefully crafted to elicit the information to attain the goals of the study.

Five different surveys were used to collect the data on twenty-five different products. The twenty-five products were distributed evenly across the five surveys. Respondents were shown a picture of the product along with a generic name for the product and the price. An example survey layout is shown in Figure 10. The product pictures were sourced from Amazon along with the accompanying price information. Generic names were used to avoid any brand bias that might influence consumer preferences. The respondents were then asked a series of questions relating to the suitability of the product for customization and their preferences for customization of features, which are detailed in the following subchapters.

* Required

Product 1.27 : Laptop Computer

Estimated price : \$699.99



1

Would customizing either part or all of this product increase its usefulness or appeal? *

Yes

No

2

Would you be willing to pay more than the estimated price for a customized version of this product? *

Yes

No

3

Would you be willing to wait to receive a customized version of this product? Or would you prefer to purchase it instantly from a store? *

Figure 10: Example of Consumer Preference Survey

The suitability of a product for customization can be determined by the factors of success in customization as outlined in Chapter 2.2 of this thesis. One of the primary objectives of customization is to increase the utility of a product and better suit the needs of customers. The added utility and increased usefulness are what create value for the customer and ultimately drives them to purchase the customized product over a mass-produced product. To tailor products to the specifications of individual customers, there is an added cost both monetarily and time wise since traditional mass production techniques cannot be used. Sometimes specialized equipment is needed to produce the products and more hours of labor are needed in the manufacturing process. In the interest of keeping the survey short and simplistic to target all demographics and maximize the response rate, three areas of primary concern were chosen to evaluate products on their suitability for customization. These three areas include the usefulness and appeal of customization, the willingness to pay for a customized product and the willingness of consumers to wait for a customized product.

Product features can be classified into different categories based upon the functions and characteristics of the product. To make the collected data generalizable for other similar products, categorizing the features is essential. Given the nearly infinite possibilities of product features, it would be impossible to collect consumer preference data on every conceivable feature.

Several works have utilized the classification of product features with a variety of goals in mind. One such work uses online product reviews to determine consumer sentiments towards products and incorporate these inputs into the design process (Güneş, 2020). A kettle is used as an example product, where an NLP and machine learning based model identifies user sentiments towards the product and extracts frequently mentioned aspects of the product. These aspects are classified in four categories: part, material, action, and performance. In a review of smart connected products, expert opinions and other literature were used to determine different types of features (Xihui Liu et al., 2022). In this work, four feature clusters were identified: appearance, function, experience and meaning. Frutos et al. (2004) proposed a decision support model for customization that utilized specific customer inputs to help in the product configuration process (Frutos et al., 2004). In their work they use the example of an apartment to illustrate their decision support model and gather customer preferences in several feature categories, then determine optimal configurations for these customers. The categories they utilize are price, aesthetics, durability, cleanliness, interchangeability, delivery time and resale.

Based on the literature reviewed, five different categories are proposed to be evaluated in this survey: aesthetics, form, functional features, complexity, and quality/cost. Aesthetics refer to any features of the products that relate to aspects of the coloring, style, texture, material, and overall appearance. Form relates to the shape of the product and the size. Functional features are any part of the product that relates to the function of the product and can be utilized by the consumer. Complexity is the ability to add a lot of features to the product and change the power source. Quality/cost relates to aspects of the durability of the product, the perceived quality of the product and aspects relating to how much the product will cost.

In the survey, respondents are provided with brief descriptions of what each category of features represents. Then, they are asked to rate their interest in customizing each category of features on a scale ranging from “no interest” to “very interested”.

Data collection took place over the period of several weeks with the objective of obtaining one hundred total responses between the five different surveys (Powell, 2023a, 2023b, 2023c, 2023d, 2023e), with equal distribution. Based on guidance from literature, online forums provide the best response rate for surveys (Sing et al., 2009). Several different online forums were targeted, namely on the social media platforms Reddit and Facebook. Specific groups on these platforms oriented around surveys were utilized, with posts being made regularly including a brief overview of the goals of this study. Respondents were allowed to skip questions to maximize the response rate, this is considered in the results as all metrics are evaluated as percentages.

3.2 Pilot Study Results

Figure 11 shows a graphical representation of the responses collected. The figure presents the percentage of positive responses to increasing usefulness and appeal for customization on the X-axis and the number of positive responses to an increased willingness to pay on the Y-axis. The size of the bubbles are indicative of the consumers' willingness to wait to receive a customized version of the products. Larger bubble sizes mean a greater willingness to wait for customization.

From Figure 11, there is a clear positive correlation between consumers seeing the increased usefulness and appeal of customized products and their willingness to pay more for customized products. This trend is likely driven by the fact that the increased usefulness and appeal for a customer makes the product more valuable for them thus increasing their willingness to pay more for it. There is also a positive correlation between the willingness to pay, the usefulness and appeal of customization and the willingness of consumers to wait for a customized product. This can be seen in the figure as the bubble sizes increase with the X and Y axis. Again, the increased usefulness and appeal is likely influencing the willingness of the customer to wait to receive the product. Another important observation from the figure is the existence of three distinct product clusters. In Figure 11 these clusters are labeled cluster 1,2 and 3 and are indicated by the greyscale coloring of the product labels. The existence of these clusters indicates that the products within these clusters share similarity in terms of consumer preferences for their customization. The clusters afford the opportunity to group products together due to their similarity in terms of consumer preferences.

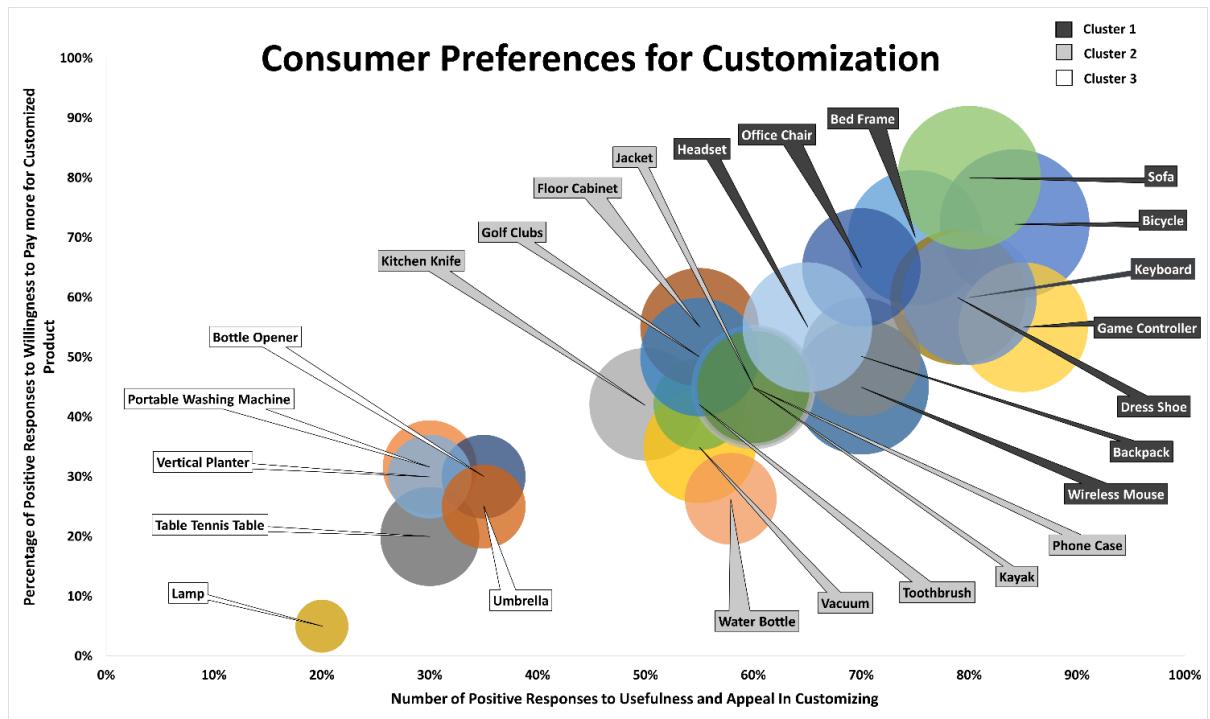


Figure 11: Consumer Preferences for Product Customization. Larger bubble size means increased willingness to wait to receive customized products.

As described in Chapter 3.1, respondents to the survey were asked to evaluate the product feature categories based on their interest in customizing them. After the collection of consumer responses, the products were organized into the clusters defined in the previous subchapter and the results tabulated in Table 8. The percentage of responses to each level of interest are color coded to visually represent the trends amongst the clusters. Based on the color-coding system, a trend would be indicated by the colors for each column lining up within the clusters. In Cluster 1, there is a strong trend in the form and quality/cost most consumers are either interested or very interested in customizing these features. Considering Cluster 1 represents the products that were most desirable for customization, it makes sense that most consumers have an interest in customizing features of the product. The interest in customizing the complexity of these products was less uniform. There is a weak trend towards little or no interest in customizing complexity.

Table 8: Consumer Feature Preferences for Customization

	Aesthetics					Functional Features					Form					Complexity					Quality/ Cost				
Cluster 1																									
Bed Frame	10%	10%	40%	20%	20%	5%	11%	11%	32%	42%	0%	39%	22%	33%	6%	28%	17%	28%	17%	11%	5%	21%	26%	16%	32%
Sofa	10%	0%	10%	30%	50%	10%	5%	15%	35%	35%	11%	0%	5%	32%	53%	25%	25%	0%	15%	35%	5%	10%	10%	25%	50%
Office Chair	20%	10%	25%	10%	35%	16%	5%	16%	32%	32%	17%	11%	17%	28%	28%	40%	20%	20%	0%	16%	11%	11%	32%	32%	
Bicycle	5%	15%	35%	10%	35%	15%	15%	10%	25%	35%	12%	18%	18%	18%	35%	20%	20%	20%	20%	10%	5%	15%	25%	45%	
Headset	15%	15%	15%	35%	20%	20%	10%	30%	30%	10%	15%	20%	15%	40%	10%	25%	30%	15%	20%	10%	15%	15%	40%	15%	
Keyboard	11%	0%	16%	37%	37%	5%	10%	20%	25%	40%	17%	0%	6%	44%	33%	10%	10%	30%	20%	30%	5%	10%	15%	40%	30%
Game Controller	10%	10%	30%	25%	25%	10%	10%	25%	35%	20%	15%	20%	15%	35%	15%	16%	21%	26%	32%	5%	5%	20%	10%	40%	25%
Dress Shoes	5%	5%	5%	42%	42%	26%	5%	0%	32%	37%	11%	6%	6%	39%	39%	37%	11%	11%	26%	16%	5%	0%	21%	21%	53%
Backpack	5%	5%	30%	30%	30%	10%	10%	25%	30%	25%	11%	11%	17%	22%	39%	25%	35%	15%	10%	15%	15%	10%	20%	15%	40%
Wireless Mouse	20%	10%	0%	30%	40%	5%	10%	10%	40%	35%	11%	5%	11%	37%	37%	30%	5%	15%	30%	20%	5%	15%	15%	25%	40%
Cluster 2																									
Jacket	15%	20%	10%	25%	30%	15%	20%	15%	25%	25%	20%	10%	10%	30%	30%	20%	40%	10%	20%	10%	15%	15%	15%	20%	35%
Floor Cabinet	5%	30%	15%	30%	20%	15%	25%	5%	30%	25%	5%	16%	26%	16%	37%	20%	40%	10%	15%	15%	5%	25%	15%	15%	40%
Golf Clubs	35%	25%	20%	10%	10%	30%	15%	5%	30%	20%	30%	20%	5%	10%	35%	45%	15%	5%	20%	15%	30%	15%	10%	25%	20%
Kitchen Knife	30%	30%	15%	5%	20%	20%	10%	25%	25%	20%	20%	10%	35%	25%	10%	42%	42%	5%	5%	5%	15%	5%	15%	30%	35%
Water Bottle	20%	25%	20%	10%	25%	25%	10%	10%	35%	20%	16%	5%	26%	32%	21%	45%	20%	30%	5%	0%	20%	10%	20%	15%	35%
Vacuum	30%	25%	30%	5%	10%	10%	20%	35%	10%	25%	30%	25%	15%	20%	10%	20%	25%	25%	20%	10%	25%	15%	15%	25%	20%
Toothbrush	25%	20%	25%	20%	10%	10%	5%	5%	45%	35%	16%	0%	42%	26%	16%	26%	21%	16%	32%	5%	0%	21%	16%	32%	32%
Kayak	15%	20%	15%	40%	10%	10%	15%	20%	35%	20%	16%	21%	21%	26%	16%	30%	35%	15%	10%	10%	10%	15%	25%	25%	25%
Phone Case	15%	10%	20%	25%	30%	10%	15%	25%	30%	20%	32%	5%	37%	11%	16%	35%	25%	20%	10%	10%	20%	5%	20%	10%	45%
Cluster 3																									
Bottle Opener	35%	15%	20%	15%	15%	30%	10%	15%	15%	30%	25%	20%	15%	20%	20%	40%	25%	10%	10%	15%	20%	20%	15%	10%	35%
Vertical Planter	40%	25%	25%	5%	5%	35%	10%	20%	15%	20%	33%	17%	11%	22%	17%	40%	10%	20%	15%	15%	40%	10%	10%	5%	35%
Portable Washing Machine	35%	20%	10%	30%	5%	15%	20%	15%	30%	20%	33%	6%	28%	28%	6%	11%	37%	32%	11%	11%	25%	10%	20%	20%	25%
Table Tennis Table	40%	15%	10%	25%	10%	45%	20%	0%	20%	15%	50%	20%	10%	10%	10%	45%	25%	20%	5%	5%	40%	15%	15%	10%	20%
Lamp	20%	15%	20%	20%	25%	37%	21%	26%	16%	0%	22%	39%	11%	22%	6%	37%	37%	21%	5%	0%	32%	26%	11%	26%	5%
Umbrella	30%	10%	25%	20%	15%	30%	20%	5%	25%	20%	28%	11%	22%	28%	11%	45%	25%	25%	0%	5%	30%	15%	20%	10%	25%
Red fill indicates the percentage of responses are between 0 and 20% Yellow fill indicates the percentage of responses are between 21% and 40% Green fill indicates the percentage of responses are greater than 41%																									

Cluster 2 shows a slight trend in the aesthetics category with most consumers showing no interest in customizing this aspect of the product. There is a strong trend in the responses to customizing the complexity of the product with a large majority of users showing no interest in customizing

this aspect. The functional features and the quality/cost categories both show trends towards and interest in customizing these aspects and the form has no discernable trends.

In Cluster 3, there is generally a trend towards consumers having little or no interest in customizing the feature, which is consistent with the characteristics of this cluster that represents. the least desirable products for customization. It is notable that there is some interest in all five categories and with the most distinct mix of opinions in the quality/cost category. Considering the strong trend in the other clusters for this category, it highlights the importance of cost to consumers and indicates that offering options to customize the quality/cost of a product is almost always a popular option for customization.

The use of feature categories in surveys to gather consumer preferences for customization allows the data collected to be generalized to other similar products. Based on the findings of the pilot study, there are clearly three distinct product clusters. These clusters indicate similarities between the products within them. It is reasonable to hypothesize that if this study were extended and the surveys were conducted on other products, the consumer preferences would follow similar trends. That is to say, there would exist clusters and corresponding trends in these clusters in the consumer preferences for customization of the feature categories.

In the design of new customized products, the data already collected in this study can be used to offer insight into whether the new product should be customized and what kinds of features of the product are desirable for customization. This can be accomplished by matching the new product with one of the clusters identified, then one or more of the products within that cluster. This matching can occur based on product information such as function, usage, or category. For example, Company A has a new briefcase they are bringing to market and would like to evaluate the suitability of their product for customization. Based on the survey results, it would fit into Cluster 1 because contained within Cluster 1 is a backpack. Both the briefcase and the backpack fall into a similar category, that is being a bag. They also have a similar use and function which is to carry items. Since this item falls into Cluster 1, the information from the surveys regarding the demand for customizing this type of product and the preferences of features desirable for customization can be applied to the design of the new product.

Chapter 4 Consumer Preference Prediction Model and Decision Support Methodology

This chapter presents the overall methodology employed to develop a consumer preference prediction model to offer decision support. Based on the pilot study, products that exhibit similarities in their function and purpose can be grouped together and used to predict consumer preferences. This is based on the idea that products that share similarities in attributes will also share similarities in consumer preferences, which draws from the concept of a content-based recommender system (Khan et al., 2021). Grouping products can be achieved through clustering, where the cluster centroids are comprised of the consumer preferences for product customization, but the clusters themselves are formed by user-defined clustering variables.

4.1 The Overall Framework

In the following chapter, the approach to implementing a data-driven preference prediction model is presented in Figure 12. This methodology consists of four different modules that form the overall prediction and decision support model.

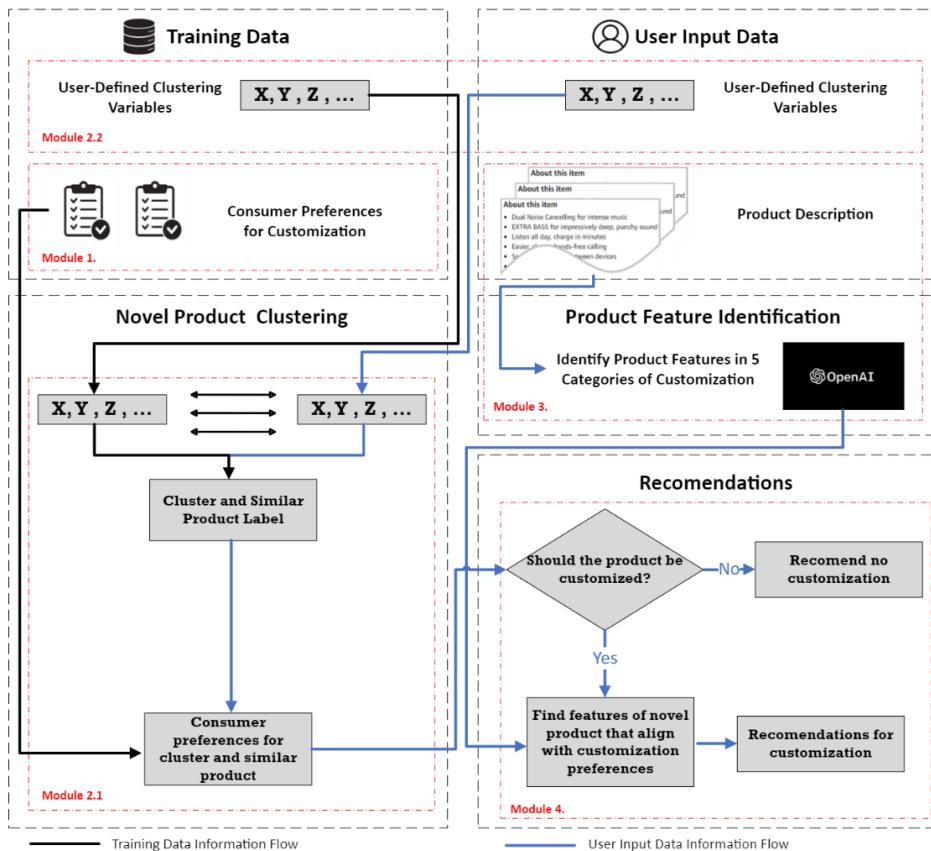


Figure 12: Framework for Data Driven Approach to Predicting Consumer Preferences with Decision Support

4.2 Module 1: Consumer Preference Crowdsourcing

Consumer preference data is required to form the training data and the basis of the cluster centroids. Nine different surveys were used to gather this training data set and utilized the same design as the pilot study (Powell, 2023f, 2023g, 2023h, 2023i, 2023e, 2023d, 2023c, 2023b, 2023a). A total of 307 responses were recorded through online forums primarily on the social media platforms Reddit and Facebook. A total of forty different products were evaluated over the nine surveys, thirty-seven comprising the training data set and three comprising a validation study. These forty products include the original twenty-five products in the pilot survey and were chosen semi-randomly with consideration to diversify the selection as much as possible. The full product list used for the collection of preference data is shown in Table 9.

Table 9: Product List for Data Collection

Headset	Kayak	Office Chair	Lamp	Backpack	Game Controller
Keyboard	Sofa	Golf Clubs	Umbrella	Phone Case	Water Bottle
Vertical Planter	Jacket	Bottle Opener	Toothbrush	Wireless Mouse	Floor Cabinet
Table Tennis Table	Dress Shoe	Bed Frame	Portable Washing Machine	Kitchen Knife	Vacuum
Bicycle	Barstool	Slippers	Cheese Grater	Treadmill	Laptop Computer
Hockey Stick	Desk	Spatula	Dishwasher	Ice Scraper	Hooded Sweatshirt
Table Fan	Digital Camera*	Tent*	Sunglasses*		

Note: Products labeled with an asterisk are validation study products, all others are training data products

4.3 Module 2: Product Clustering

There are two modules in the product clustering process. The first module, Module 2.1, deals with the selection of a clustering algorithm. The second module, Module 2.2 deals with the selection of user-defined clustering variables. It is necessary to select a clustering algorithm first to test the performance of the user-defined clustering variables. There also needs to be a benchmark for comparison of the results and to evaluate the effectiveness of the user-defined clustering variables.

4.3.1 Module 2.1: Clustering Algorithm Selection

Clustering allows the grouping of products by their similarities, then prediction of consumer preferences for new products can be based on the cluster they are assigned to. Two types of clustering were performed in this evaluation including clustering based on consumer preferences collected from the surveys and clustering based on user-defined clustering variables. Several

different types of clustering algorithms were tested from the SK-Learn clustering kit (Scikit-learn developers, 2023). Each algorithm and its use case are shown in Table 10.

Table 10: Types of Clustering Algorithms and Their Uses Adapted from (Scikit-learn developers, 2023)

Method name	Parameters	Scalability	Use case	Geometry (metric used)
K-Means	Number of clusters	Very large n_samples, medium n_clusters with MiniBatch code	General-purpose, even cluster size, flat geometry, not too many clusters, inductive	Distances between points
Spectral clustering	Number of clusters	Medium n_samples, small n_clusters	Few clusters, even cluster size, non-flat geometry, transductive	Graph distance (e.g., nearest-neighbor graph)
Agglomerative clustering	Number of clusters or distance threshold, linkage type, distance	Large n_samples and n_clusters	Many clusters, possibly connectivity constraints, non-Euclidean distances, transductive	Any pairwise distance

To evaluate the accuracy of clustering, there are several different methods available. K-Means clustering uses a criterion known as inertia, which is the cluster sum of squares defined in Equation 1 (Scikit-learn developers, 2023).

$$\sum_{i=0}^n \min_{\mu_j \in C} (\|x_i - \mu_j\|^2) \quad (1)$$

Where, n is the number of samples, x_i is the sample at index i , C is the number of disjoint clusters, μ_j is the mean of the samples in the cluster.

Inertia is also the metric by which clusters are formed in K-Means clustering, with the objective of minimizing the inertia across the clusters. When comparing different algorithms, it can be challenging to achieve a direct comparison of the accuracy since not all algorithms use the same metrics. Another issue with using accuracy metrics that measure variability between the clusters becomes evident when user-defined clustering variables are introduced. The intention of this prediction model is to be able to cluster novel products that do not have consumer preferences. This means that using consumer preferences as clustering variables is not possible and new user-defined clustering variables need to be developed. The selection and definition of new clustering will be discussed in Module 2.2. However, it is first necessary to select a clustering algorithm and develop a means to compare the accuracy of the clustering algorithms using the consumer preferences variables as well as using user-defined clustering variables. To accomplish this, a new metric is needed that will be referred to as threshold testing.

The threshold testing refers to the accuracy of clustering in relation to the consumer preferences. This can be found by summing the number of product consumer preference metrics in a cluster that exceeds the centroid for each consumer preference metric. This is possible because the products we are clustering have associated consumer preferences collected from the surveys. To understand how this works, it is important to visualize the data collected from the consumer preference surveys. Table 11 shows a sample of the data collected. Respondents were initially asked in the survey to rate their interest in customizing the products' aesthetics, functional features, form, complexity, and quality/cost aspects with five options. These five options were included in the original survey design with the intention of collecting a large amount of data to allow for differentiation of the consumer interests. However, after the results were collected, it was found that the inclusion of five options for consumers overrepresented the consumer preferences which made data processing and computation cumbersome. These five options were condensed into three to reduce the computational effort required while clustering and processing the data. It was determined that combining the 'interested' and 'very interested' categories and the 'no interest' and 'little interest' categories still adequately captured consumer preferences. These combinations were made by simply adding the responses for the respective options and reduced the number of consumer preference metrics per product by ten.

Table 11: Excerpt of Consumer Preference Data from Surveys

Category		Headset	Kayak	Office Chair	Lamp	Backpack
Positive responses to increased usefulness and appeal in customization		0.686	0.600	0.571	0.400	0.657
Positive responses to increased willingness to pay for customization		0.486	0.429	0.514	0.200	0.457
Positive responses to increased willingness to wait for customization		0.657	0.486	0.486	0.229	0.514
Aesthetics	Not interested	0.286	0.286	0.371	0.343	0.229
	Somewhat Interested	0.114	0.229	0.229	0.143	0.200
	Interested	0.600	0.486	0.400	0.514	0.571
Functional Features	Not interested	0.286	0.314	0.324	0.529	0.343
	Somewhat Interested	0.314	0.229	0.176	0.206	0.200
	Interested	0.400	0.457	0.500	0.265	0.457
Form	Not interested	0.257	0.353	0.303	0.576	0.333
	Somewhat Interested	0.257	0.206	0.212	0.091	0.152
	Interested	0.486	0.441	0.485	0.333	0.515
Complexity	Not interested	0.457	0.543	0.543	0.588	0.571
	Somewhat Interested	0.286	0.171	0.229	0.294	0.200
	Interested	0.257	0.286	0.229	0.118	0.229
Quality/ Cost	Not interested	0.257	0.286	0.324	0.559	0.343
	Somewhat Interested	0.200	0.229	0.147	0.147	0.200
	Interested	0.543	0.486	0.529	0.294	0.457

This leaves each product with eighteen consumer preference metrics. For example, 68.6% of respondents see an increased usefulness and appeal in customizing the product and 60% of respondents are interested in customizing the aesthetics. For a given cluster, finding the centroid involves calculating the average value of each of the eighteen consumer preference metrics for the

cluster. For example, If the headset and kayak were in the same cluster and the only products in the cluster the centroid for positive responses to increased usefulness and appeal in customization consumer preference metric would be calculated as 68.6% plus 60% divided by the number of products, in this case two. A general form of the equation is presented in Equation 2.

$$\text{Cluster}_j \text{ Attribute}_i \text{ Centroid} = \frac{\sum x_{j,i}}{n_j} \quad (2)$$

Where, $x_{j,i}$ is the product consumer preference metrics j at index i , n_j is the number of products in the cluster j .

Using Equation 2 to find the centroid for each consumer preference metric, threshold testing can be applied by taking a threshold value and examining how many of the product consumer preference metrics exceed the threshold. This comparison is shown in Equation 3.

$$1 - \frac{\sum \left| \frac{\sum x_{j,i}}{n_j} - p_i \right| > T_h}{T_x} * 100\% \quad (3)$$

Equation 3 returns a percentage value of how many consumer preference metrics exceed the threshold defined. This can be used to determine if the clustering variables accurately group the products based on the consumer preferences. For example, choosing a 5% threshold, the centroid for each consumer preference metric can be calculated then and the number of consumer preference metrics exceeding the threshold can be counted to determine an accuracy rating.

Using Equation 3, the three clustering algorithms were tested with both a 5% and 10% threshold. Figure 13 shows the results of this testing with different cluster numbers and compares the total percentage of consumer preference metrics exceeding the threshold to the number of clusters. From these tests K-Means clustering and Agglomerative clustering both outperform spectral clustering at the 5% and 10% thresholds. Agglomerative clustering has a slightly better performance than K-Means clustering for both thresholds. However, their performance is very similar. There is a clear relationship between the number of clusters and the overall accuracy. For agglomerative and K-means clustering, there is a near-linear relationship between the number of clusters and the accuracy with a 5% threshold. With a 10% threshold evaluation, the relationship resembles a more negative exponential function. Selecting a cluster number of thirteen provides an accuracy of approximately 63% using a 5% threshold and approximately 90% percent using a 10% threshold. This means that 63% and 90% of the consumer preference metrics in the thirteen clusters are within 5% and 10% of the cluster consumer preference metric centroids respectively.

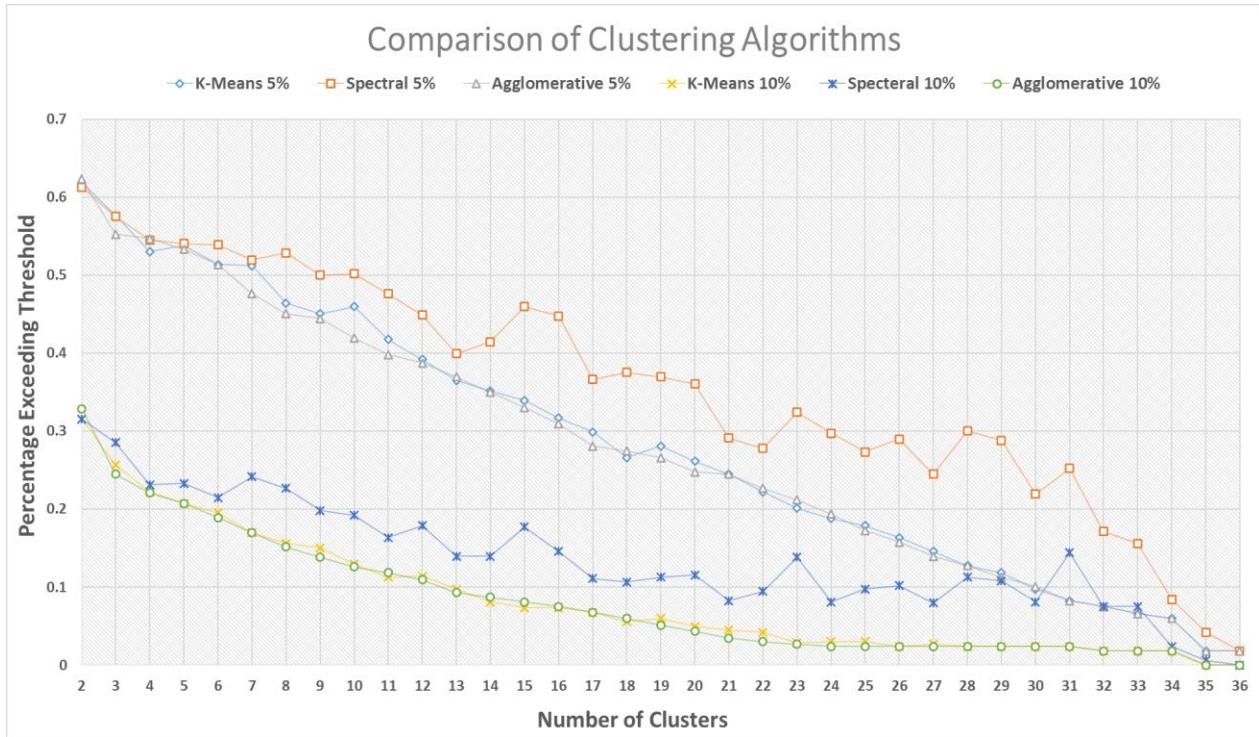


Figure 13: Comparison of Clustering Algorithms on Survey Data

4.3.2 Module 2.2: User Defined Clustering Variables

To eliminate the need to gather consumer preferences for clustering, an alternate set of variables can be used to represent the products. The alternate set of variables, referred to as user-defined clustering variables, are expected to effectively replace the consumer preferences in the clustering process and describe the product attributes that influence consumer purchasing behavior. The objective of using user-defined clustering variables is to emulate the clusters formed in Chapter 4.3.1 by the consumer preference-based clustering. To evaluate how closely the user-defined variables emulate the consumer preferences, threshold testing can be used to compare the accuracies of the respective clustering. The process of deciding these variables is shown in Figure 14.

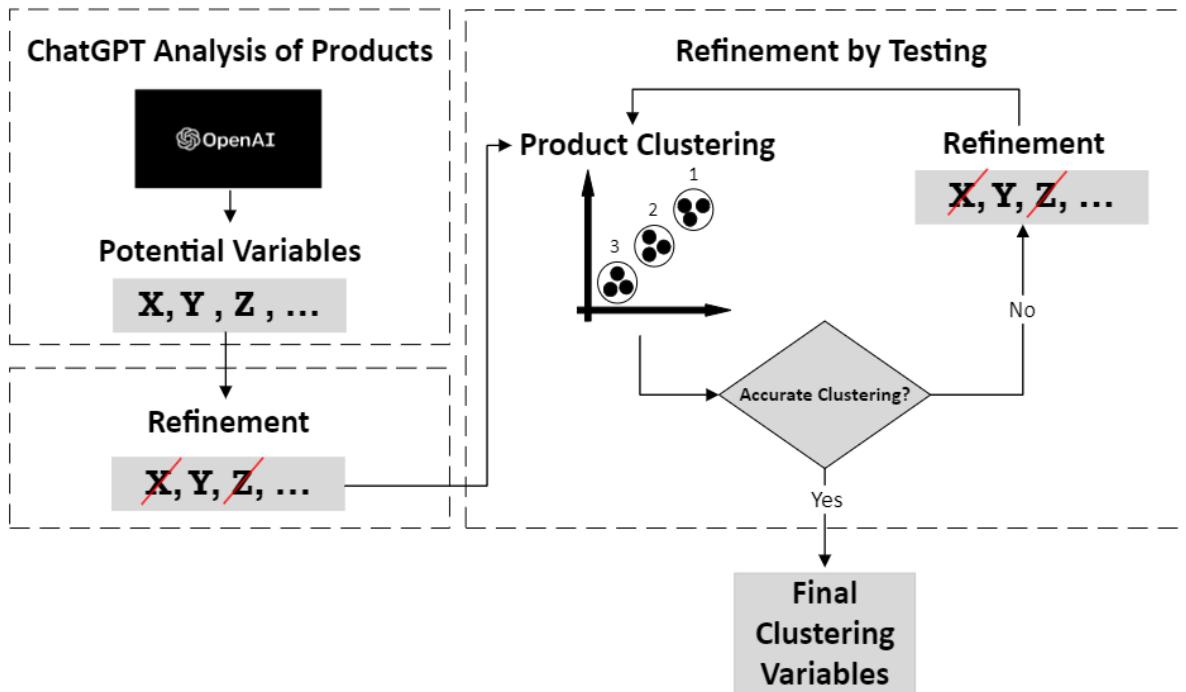


Figure 14: Selection of Clustering Variables

The first step in selecting variables uses the large language model from OpenAI ChatGPT (OpenAI, 2023). ChatGPT uses reinforcement learning from human feedback with a proximal policy optimization reward model. The model can take textual inputs from a user, then analyze and output results. The model was used to evaluate the products as it requires very little input information and draws upon its vast training data to understand the inputs it is given. This is similar to how a consumer would look at a given product and use their past life experiences to evaluate a product. These similarities mean that ChatGPT emulates the thought process of a consumer in a purchasing situation, which can provide insight into what kinds of variables can be used to describe a product in relation to consumer preferences. This emulation of consumer behavior serves as a valuable tool in the development of this decision support model because it can operate in an automated manner and eliminates the need for direct interaction with consumers to gather similar information. Generating a list of user-defined variables could have been done manually with consumers evaluating product, or by expert opinion. However, if the product set is expanded to include more training data products, then this task becomes increasingly more involved and time consuming. Even with the current data set of thirty-seven training products, the process of analyzing and compiling a list of user-defined variables is complex and would take significant effort. The use of ChatGPT in this capacity speeds up the process significantly and allows for simultaneous analysis of all products at once. This type of approach also serves as a basis for future work that would involve the use of more training data products and require an automated approach to determining user defined variables that will be discussed more in Chapter 6.

To determine the user-defined variables, ChatGPT was only given the generic names of the products used in the training data set and asked to suggest twenty-five different variables that could be used to cluster products together. The initial output from this exercise is displayed in Table 12. The list provided by ChatGPT provides a starting point for deciding the final variables to use for clustering. However, some of the twenty-five variables provided are unsuitable for the purposes of clustering to predict consumer preferences.

Table 12: Initial Variables Proposed by ChatGPT

1. Functionality	10. Product size	19. Availability of replacement parts
2. Purpose	11. Price range	20. Average customer rating
3. Frequency of use	12. Material(s) used	21. Number of customer reviews
4. Customer Demographic	13. Primary color(s)	22. Manufacturing origin/country
5. Usage Location	14. Weight of product	23. Environmental sustainability
6. Style	15. Primary use of product	24. Type of product (e.g. electronic, furniture, sports equipment, etc.)
7. Portability	16. Brand reputation	25. Average lifespan of product
8. Maintenance	17. Durability of product	
9. Ease of Use	18. Warranty offered	

The first round of revisions was made based on suitability of the objectives of the study with considerations for the types of information presented to consumers in the preference surveys as well as the types of features available for customization. Given that the products themselves were unbranded with all logos and branding removed from the images and names, variable 16, brand recognition was removed. No information about the warranty, customer reviews or manufacturing origin were provided so variables 18, 20, 21 and 22 were removed. Likewise, information on the availability of replacement parts and environmental sustainability of the product was not provided so variables 19 and 23 were removed.

The durability and average lifespan of the product are too general and largely depend on how careful the user is with the product and how well they maintain it. For this reason, variables 17 and 25 were removed. The material, primary color and weight of the product are also very general and do not differentiate products from one another, for this reason variables 12, 13 and 14 were removed. The customer demographic is also difficult to judge as any demographic can use many products. Also, no information on customer demographic was collected as a part of the consumer preference surveys. This means variable 4 can be removed. The type of product has too many possibilities to capture in clustering variables effectively; thus, variable 24 can be removed. Variable 15 (the primary use of the product) and variable 2 (purpose) are very similar and thus can be combined.

After removing fourteen variables from the initial list proposed from ChatGPT, the remaining variables along with justification for their inclusion are shown in Table 13. The general basis for the inclusion of user-defined variables in the final list is that the variable must allow for differentiation between different products or influence the consumers perceptions of the products.

Table 13: Justification for User-defined Variables

VARIABLE	JUSTIFICATION FOR INCLUSION
FUNCTIONALITY	The functionality of a product is a key defining features that can differentiate how products are used. Products that serve advanced function are significantly different in terms of design, appearance, etc. compared to those that perform simple functions.
PURPOSE	Purpose can differentiate different products as this is often a driving factor in how the product is designed. The intended purpose of the product also influences consumers expectations for the product.
FREQUENCY OF USE	The frequency of use of a product influences the consumers perceptions through the user requirements and their interaction with it. For example, a product that is only intended to be used on specific occasions, like a kayak, is vastly different from one that is intended to be used daily, like a phone case in terms of its design and the customers intentions.
USAGE LOCATION	The location of use differentiates products because of the design considerations and consumer expectations. For example, products intended to be used outdoors, like a tent, are expected to perform in a much harsher environment compared to those used indoors, like a lamp.
STYLE	The style of a product varies greatly depending on the type of product and allows for significant differentiation. For example, generally products that are visually appealing and stylish are vastly different from those that are used in a utilitarian manner.
PORTABILITY	Products that are meant to be portable like a backpack have significantly different requirements and designs than those that are intended to be stationary such as a bed frame. This allows for differentiation between products and affects how consumers perceive them.
MAINTENANCE	How much and how frequently a product requires maintenance can offer differentiation. For example, a high maintenance product such as a dishwasher that requires cleaning and refilling is vastly different from a product like a bottle opener which requires no maintenance at all.
EASE OF USE	The learning curve to use a product can offer differentiation and impacts consumer perceptions. For example, using golf clubs requires a certain skill set and talent, however using an ice scrapper requires no skill or training.
FORM FACTOR	The general size of a product can offer differentiation between products and influences how consumers perceive them. For example, large products such as a desk have vastly different characteristics and customer requirements compared to a small product like a game controller.
PRICE RANGE	The price of a product is something that influences the perceptions of consumers and is a factor that can differentiate most products. For example, a consumer would expect a laptop to cost more on average than a spatula and can for this reason differentiate products.
TYPE OF USE	How a product is used can allows for significant differentiation. For example, a decorative item like a lamp is vastly different from a wearable item like a jacket in terms of its design and how consumers perceive them.

The rating scale was again generated with the assistance of ChatGPT due to its functional similarity to consumer decision making. ChatGPT was prompted to propose a scale to evaluate the products in relation to each of the clustering variables listed in Table 13. An example of the proposed scale is shown in Table 14.

Table 14: Example of Proposed Scale from ChatGPT

Variable	Scale			
Functionality:	Low: Limited functions	Moderate: Average functions	High: Advanced functions	
Purpose	Basic: Essential functionality	Leisure: For entertainment or leisure activities	Convenience: To make life easier	Performance: To enhance performance
Usage Location	Home: Used in a home setting	Outdoor: Used outside of a home	Leisure: Used in a leisure setting	

The scale proposed by ChatGPT provided a good basis for labeling the products; however, there were several issues with the scale that needed to be addressed before it could be implemented. The first issue is the use of similar terms to describe different aspects of the product. For example, one option for the purpose variable is leisure, which is also given as an option for the usage location variable. Although these are defined to mean different things, this repetition could lead to confusion amongst the user who would be assigning values to these variables. A product's purpose could be leisure, but the usage location may not be a leisure environment. This issue was present in several other categories of variables as well and was addressed in the refined scale by ensuring that the evaluation scale did not repeat terms. The second issue with the proposed scale is the fact that multiple evaluation levels could apply to the same product. For example, a product that has a purpose of leisure may have a usage location in a home setting and a leisure setting. This again could lead to confusion because the leisure setting could be in a home setting or outside the home. This was addressed in the refined scale by adding more levels of evaluation for some of the variables to differentiate products and by refining the definitions of the levels of evaluation to ensure there is no overlap. The use of ChatGPT to suggest a scale allowed for the quick generation of a preliminary list of variables and provided insight into how consumers may perceive products due to the fact ChatGPT processes information in manner like consumers.

The variables after the first round of refinement are shown in Table 15 along with the scale used to evaluate them. The numeric scale used to evaluate the variables is necessary to create a feature vector that can allow for clustering. The scale allows for each variable to be assigned a value of 1 – 4 with various meanings as described in Table 15. The scale of 1 – 4 was chosen because it was sufficient to differentiate all the products for the training data set. The addition of more products to the training data could require the retuning of the variables that is further discussed in Chapter 6. It is notable that the scale is not numerically representative of importance, i.e., 4 does not mean more important or significant than 1.

Table 15: Refined Variables and Evaluation Scale

	1	2	3	4
Functionality	Simple function	Few simple functions	Multiple Simple Functions	Multiple advanced functions
Purpose	Tool	Entertainment or Leisure	Furniture	Sport
Frequency of use	Used specific occasions	Used monthly	Used at least once a week	Used everyday or almost everyday
Usage Location	Used in a home setting	Used outside of the home (i.e., outdoors, public places)	Used at work	Used everywhere
Style	Stylish design	Utilitarian design	Focuses on comfort	Both utilitarian and stylish
Portability	Easy to carry and transport	Average level of portability	Difficult to transport	Item is usually stationary
Maintenance	Require little to no maintenance and maintenance is easy to perform	Requires some simple maintenance infrequently	Requires some simple maintenance frequently	Requires frequent maintenance that is complex
Ease of Use	Very easy to use (Can be operated and set up with no prior knowledge)	Easy to use (May require some knowledge to use or set up, like reading an instruction manual)	Average level of ease of use (Requires some practice to use and would require instructions to set up)	Difficult to use (Requires practice and skill to operate and set up properly)
Form Factor	Very Small Product (Can fit in your hand)	Small Product (Slightly larger than a handheld object)	Medium Sized Product (Size of a small child)	Large Product (Larger than a small child)
Price Range	Very Cheap (usually less than \$50)	Cheap (Usually between \$50 - \$100)	Moderately Priced (Usually between \$100 - \$250)	Expensive (Usually > \$500)
Type of Use	Wearable	Handheld	Other interactive	Decorative

After the refined variables have been decided, the next step is to do further refinement by testing the accuracy of clustering. The first step in clustering the products is to label each individual product according to the scale defined in Table 15. The labeling of the products is done manually with two design experts based on census, forming thirty-seven individual feature vectors each with eleven values as shown in Figure 15. Each feature vector element corresponds to the clustering variable in order, i.e., element 0 of the vector is functionality, element 1 of the vector is purpose, etc.

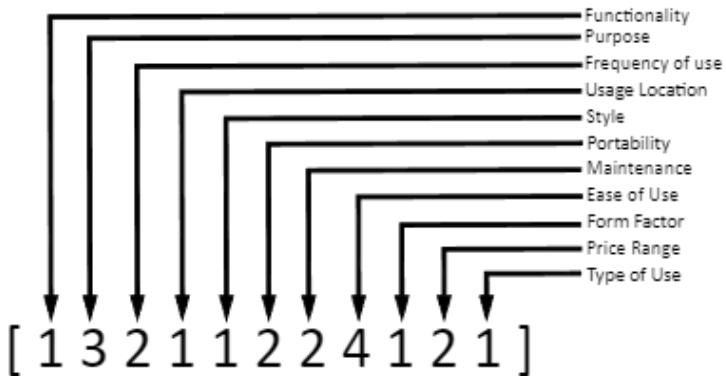


Figure 15: Example Feature Vector

As a benchmark, agglomerative clustering and K-Means clustering were applied to the consumer preference data collected from the surveys using the eighteen product consumer preference metrics described in Module 2.1 and evaluated with the proposed threshold testing. This benchmark provides a theoretical maximum of the best possible clustering that can be attained. The benchmark is also the objective accuracy that indicates whether the user-defined variables are effectively emulating consumer preferences. Figure 16 shows the percentage of consumer preference metrics for all products that exceed the thresholds set out for several different clustering scenarios with different numbers of clusters. One objective of clustering is to attain the highest accuracy with the least number of clusters. There is a trade off as increasing the number of clusters will lead to better accuracy, but too many clusters reduce the usefulness of the model. Figure 16 illustrates the relationship between higher cluster numbers and accuracy of clustering, representing an almost linear relation for all the clustering scenarios. Overall, twelve different clustering scenarios were examined.

From Figure 16 the performance of all the clustering variables is slightly worse than that achieved by the benchmark for both thresholds and algorithms. However, it is notable that the trend in the accuracy maintains a similar linear relation to the number of clusters. To improve the clustering accuracy, a series of trials were conducted where a single variable was removed at a time and the overall accuracy of the clustering was evaluated. The overall accuracy was determined using the average value of the percentage exceeding the threshold over all thirty-five different trials with different cluster numbers. A higher overall accuracy indicates that the removal of a specific variable improves the clustering accuracy. This testing found that removing the clustering variables portability and maintenance led to the optimum performance with the K-Means algorithm. Removing the variables usage location, portability and price range led to the best performance using the agglomerative algorithm. The overall average accuracy when using K-Means clustering at a 10% threshold and removing two variables is 85.2% which is marginally better compared to removing three variables using agglomerative clustering at a 10% threshold with an overall accuracy of 85.1%. In benchmark testing, it was found that the overall accuracy for agglomerative clustering and K-Means clustering at a 10% threshold are 91.7% and 91.5% respectively. Both algorithms are within approximately 6% accuracy of the benchmark. Although

these results are still not as accurate as the benchmark testing, they do represent an improvement over the results obtained from clustering using all the variables. The close proximity of the user-defined variable clustering to the benchmark test accuracy indicates that the user-defined variables effectively emulate the consumer preferences, and that the clusters for both approaches are similar. The fact that removing certain variables increases the accuracy of clustering implies that the variables removed do not impact consumer preferences for product customization. Thus, the final prediction model will utilize K-Means clustering with nine clustering variables: functionality, purpose, frequency of use, usage location, style, ease of use, form factor, price range and type of use.

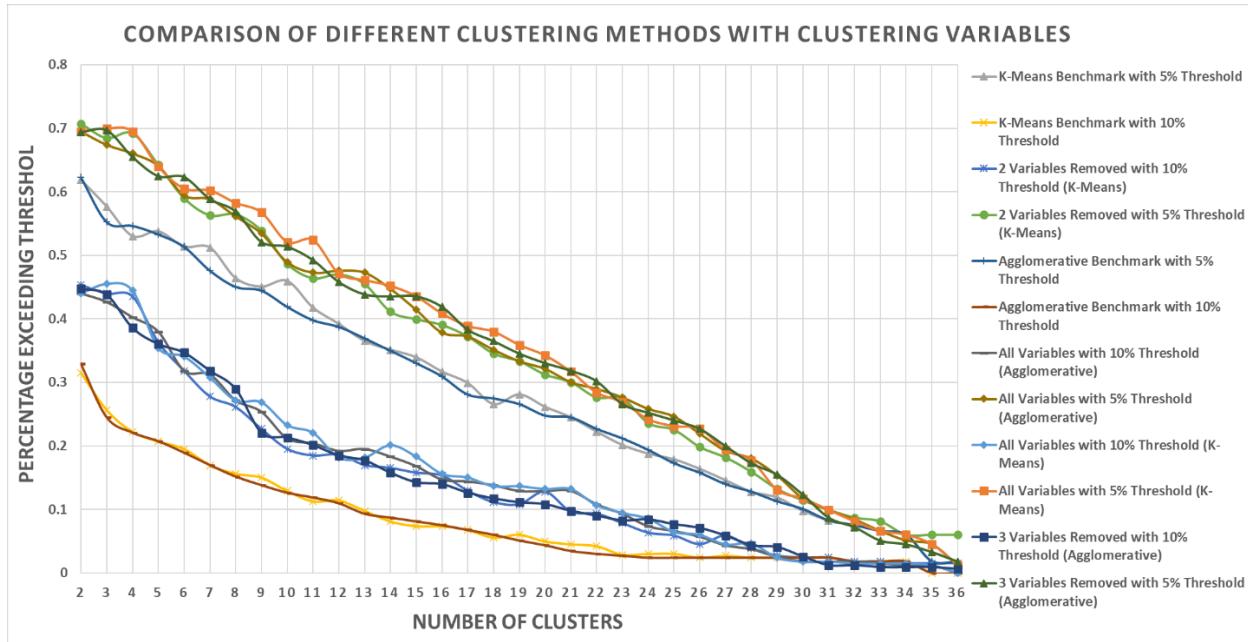


Figure 16: Threshold Evaluation of Clustering

4.4 Module 3: Product Feature Extraction

Categorizing product features allows the collection of consumer preference data that can be generalized to other products. The categorization has been defined into five categories as summarized in Module 1: aesthetics, functional features, form, complexity, and quality/cost. For firms looking to customize their novel products, it may not always be clear as to what types of features fall into each category. In addition, it can be time consuming for designers to identify these features. Automation not only speeds up the design process, but it also reduces costs, especially for firms that lack knowledge or expertise in product design. This is especially true for SMEs. SMEs generally do not have as many resources as larger firms and must move through the product development process and make decisions as quickly and cost effectively as possible. The use of ChatGPT for product feature identification enables the quick and efficient identification of

product features from the product description and can also help suggest product features that may not be explicitly mentioned in the description as will be shown later in this chapter.

To categorize types of product features, it is necessary to obtain information about the product and the types of features it has. A product description provides a convenient method for obtaining this type of information and must be generated by the firm producing the product as part of the product development cycle. Extraction of the actual features in an automated manor can be implemented using the large language model ChatGPT (OpenAI, 2023).

ChatGPT was first provided with the five different categories of features and a brief description of each category. The system was then prompted to take a product description and extract features from the product description that fall into each of the five categories. An example input prompt and output are shown in Table 16. The ability of ChatGPT to take minimal user input, make assumptions and follow instructions make it an ideal candidate for this type of feature extraction. The sample product description in Table 16 is for a multifunctional gaming controller sourced from Amazon. Given the five categories of features, ChatGPT was able to identify certain features from the product description and make assumptions based on the type of product. For example, in the complexity category, the product description does not explicitly mention that the controller is powered, however ChatGPT correctly assumes that there must be a power source for a gaming controller. The ability to make assumptions based on the type of product with no external input from the user provided a great utility and flexibility for the tool to help product designers identify types of features of a product that may be candidates for customization even when the features are not explicitly mentioned in the product description. This functionality can also be useful when the product itself lacks a product description at all. Instead of using a specific product description for the product, a generic name could be inputted as a prompt and used to generate possible candidate features for customization. This functionality can help to prompt product designers to consider new product features that may have been overlooked before. For designers who lack experience, suggestions for product features can also improve the quality of their designs and in turn the quality of the products, making them more appealing to consumers.

Table 16: ChatGPT Feature Extraction

Product Description Prompt	ChatGPT Response
Razer Wolverine Ultimate: 6 Remappable Multi-Function Buttons and Triggers - Interchangeable Thumbstick and D-Pad - Razer Chroma Lighting - Gaming Controller works with Xbox One and PC", "short_description": null, "product_description": "Razer Wolverine Ultimate Gaming Controller - Customizable Controller With 6 Programmable Buttons - Compatible with Xbox One. Zero slow-turn concave analog joysticks. 3.5 mm audio port for stereo audio output and microphone input.", "alternate_description": "With interchangeable thumbsticks and two interchangeable D-Pads, swap between optimized thumbstick heights and shapes, and quickly change between a tilting or individual D-Pad button layout. The Razer Wolverine Ultimate comes loaded with a slew of extra buttons for advanced gaming - 2 remappable Multi-Function bumpers, 4 Multi-Function triggers and a Quick Control Panel. With the remapping function both on-the-fly or with Razer Synapse for Xbox, you can master next-level techniques like moving and aiming with both thumbsticks. Show off your personal style with Razer Chroma's wide selection of lighting effects and stunning profiles, completely customizable through Razer Synapse for Xbox. Optimized ergonomics that stays comfortable after hours of practice, and interchangeable parts so it adapts to your hands and playstyle", "otherDescriptions": "Razer Wolverine Ultimate Gaming Controller - Customizable Controller With 6 Programmable Buttons - Compatible with Xbox One. Zero slow-turn concave analog joysticks. 3.5 mm audio port for stereo audio output and microphone input.", "factsExpander": null}	<p>Aesthetics:</p> <ul style="list-style-type: none"> Razer Chroma Lighting (LED lighting effects) <p>Functional:</p> <ul style="list-style-type: none"> 6 Remappable Multi-Function Buttons and Triggers Customizable Controller With 6 Programmable Buttons Interchangeable Thumbsticks Interchangeable D-Pads Quick Control Panel 3.5 mm audio port for stereo audio output and microphone input <p>Form:</p> <ul style="list-style-type: none"> Not explicitly mentioned in the description <p>Complexity:</p> <ul style="list-style-type: none"> Remapping function (on-the-fly or with Razer Synapse for Xbox) Powered controller (assumed, but not explicitly mentioned) Power source not mentioned <p>Quality and Cost:</p> <ul style="list-style-type: none"> Optimized ergonomics for comfort during extended use Interchangeable parts for adaptation to different hand sizes and playstyles

4.5 Module 4: Recommendations for Customization

Module 4 pertains to the actual recommendations for customization and represents a culmination of Modules 1 – 3. Once a cluster number has been assigned to a novel input product based on the user defined clustering variables, each of the 18 consumer preference metrics for the cluster, as described in Module 2.1, can then be used as the prediction for consumer preference for the novel product.

A hypothetical output for a computer mouse is shown in Figure 17. The graphical results displayed reveal to the firm producing the novel product several key pieces of information. The first is the recommendation to customize, which for the mouse is to offer customization if there is no significant additional cost to the firm. The recommendation to customize is given based on the number of positive consumer responses to seeing the usefulness and appeal in customization, willingness to pay more for customization and the willingness to wait for customization. In the example of the mouse, 42% of consumers would pay more for a customized version of the product, 67% of respondents see an increased usefulness and appeal in customizing and 61% would wait for a customized version of the product. This means that if the company were to offer customization, most consumers would not want to pay more for the product. However, if the

company can offer options for customization at little to no additional cost, the predicted preferences indicate that consumers would be interested in the product which could lead to the company attracting new customers and selling more product. Another suggestion for offering customization would be to offer customization only if it did not significantly increase lead times for the product. This suggestion would be given if less than 50% of respondents were willing to wait for a customized version of the product but greater than 50% of respondents were willing to wait for or see an increased usefulness and appeal in customizing. It could also be suggested that customization should be offered if it did not increase lead times and did not add significant cost to production. This recommendation would be given if less than 50% of the responses to seeing an increased willingness to pay and wait for customization are positive and more than 50% of respondents saw and increased usefulness and appeal in customizing. If less than 50% of responses to all three questions were positive, then a recommendation to not customize the product at all would be given.

If the recommendation is to customize the product, then the next step is to recommend the specific product features for customization. The consumer responses to questions relating to feature customization were recorded as “not interested”, “somewhat interested”, or “interested”. Instead of using a threshold to determine if a particular feature should be customized, the five categories of features will be presented with specific examples along with the percentage of consumers interested in customizing those features. The specific examples of product features are extracted from the novel products description as outlined in Module 3. The feature customization for this product is displayed graphically using pie charts indicating consumer preferences in terms of their interest. Specific examples of product features are found in the product description using ChatGPT and presented as options that the company can offer for customization. For this example, no product description was available and ChatGPT was prompted with a generic mouse to extract the features.

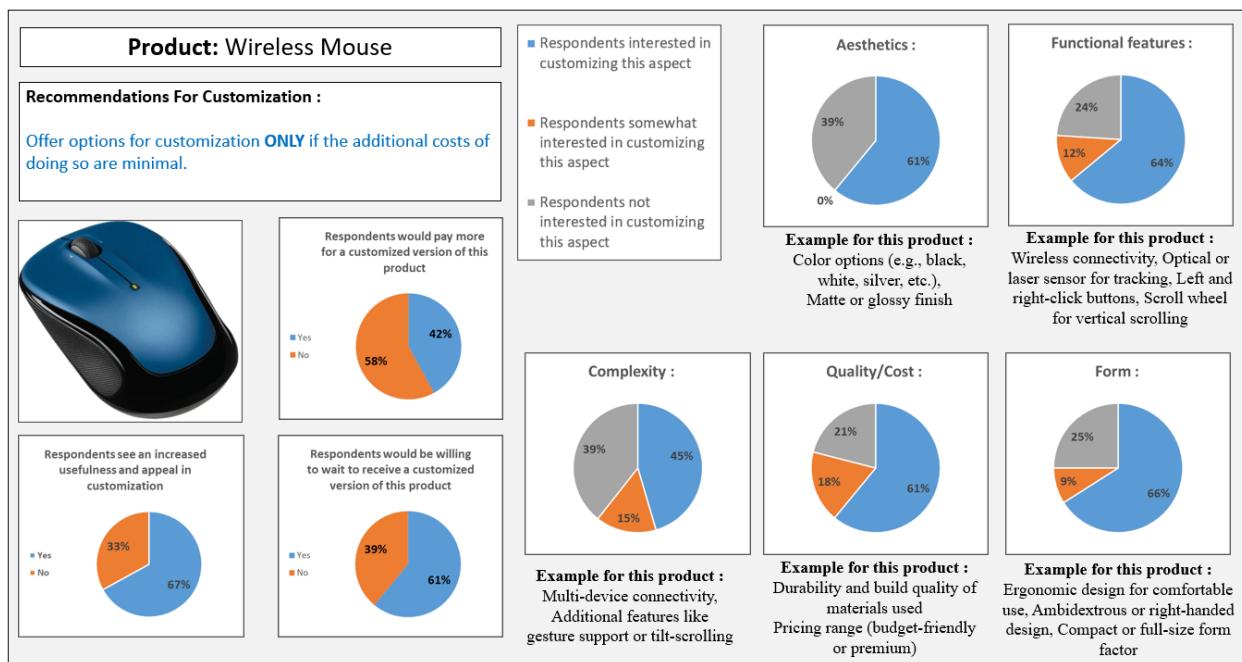


Figure 17: Example Recommendations for Customization

Chapter 5 Validation Study and Sensitivity Analysis

This chapter details a validation study and sensitivity analysis that were conducted using the model developed in Chapter 4. The validation study was used to evaluate the accuracy of the predictive model and illustrate how the model works. The accuracy can also be impacted by the sample size of the crowdsourced consumer preferences. Thus, a sensitivity analysis was conducted to determine this effect.

5.1 Validation Study

Three products were selected for analysis: a digital camera, a tent and sunglasses as shown in Figure 18. Validating the accuracy of the model requires information on the consumer preferences for each of the three products. To gather this information, an additional validation survey was used as outlined in Module 1. The actual predictive model does not need this consumer preference information to function; however, validation of the accuracy of the model is not possible without using the threshold testing method. In total, thirty-five responses were collected for the validation study using the same collection method described in Module 1.



Figure 18: Digital Camera (Left), Tent (Center), Sunglasses (Right)

The next step of the validation study is to label the products with the scale defined in Table 15 of Module 2.2 and the nine corresponding user-defined clustering variables to develop the feature vectors. The results of the labeling are shown in Table 17.

Table 17: Labeled Validation Study Products

	Digital Camera	Tent	Sunglasses
Functionality	4	1	1
Purpose	2	4	1
Frequency of use	1	1	4
Usage Location	4	2	2
Style	2	2	1
Ease of Use	4	2	1
Form Factor	2	4	1
Price Range	4	3	1
Type of Use	2	3	1

Using the feature vectors, K-Means clustering can be used with the new products so they can be labelled with their corresponding cluster. A cluster number of thirteen was chosen for this evaluation as it has shown in Module 2.1 to provide a reasonable tradeoff between accuracy of clustering and minimization of the number of total clusters. The cluster averages for each consumer preference metric can be compared to the values obtained for each product from the validation study surveys. The products were assigned cluster numbers of 0, 1 and 9 for the camera, tent, and sunglasses respectively. Table 18 shows a sample of the consumer preference metric averages for the predicted clusters and results obtained from the validation study. Using a threshold of 20%, each of the consumer preference metrics for the validation study products that exceed the threshold are indicated with an asterisk. consumer preference metrics 0 – 17 represent the consumer preference metrics described in Module 2.1 and the values are the centroids for the clusters that are calculated from the data obtained from the preference surveys. For the sunglasses, the accuracy can be calculated by summing the number of consumer preference metrics that exceed the 20% threshold (i.e., three), then dividing by the total number of consumer preference metrics (i.e., eighteen). One minus this value multiplied by 100% percent gives a resulting accuracy of approximately 83%. Similarly, the accuracy for the camera and tent can be calculated as approximately 89% and 39% respectively.

The overall accuracy of the validation study is approximately 70%, which can be calculated as the average of the individual accuracies. The sunglasses and camera performed better than the tent, which had a relatively low accuracy. A possible explanation for the poor performance of the tent is that no other products in the training data set are similar to the tent. As such, one limitation of this model is that it lacks accuracy when predicting preferences for products that are not closely represented in the training data set.

Table 18: Comparison of Validation Study Products for Sunglasses

		Cluster Consumer Preference Metric Centroids	Sunglasses Survey Results
Positive responses to increased usefulness and appeal in customization		0.530	0.600
Positive responses to increased willingness to pay for customization		0.377	0.543
Positive responses to increased willingness to wait for customization		0.455	0.486
Aesthetics	Not interested	0.463	0.257*
	Somewhat Interested	0.135	0.114
	Interested	0.401	0.629*
Functional Features	Not interested	0.288	0.457
	Somewhat Interested	0.159	0.257
	Interested	0.552	0.286*
Form	Not interested	0.330	0.314
	Somewhat Interested	0.232	0.171
	Interested	0.438	0.514
Complexity	Not interested	0.499	0.657
	Somewhat Interested	0.168	0.171
	Interested	0.333	0.171
Quality/ Cost	Not interested	0.326	0.400
	Somewhat Interested	0.168	0.171
	Interested	0.507	0.429

Note: * represents the predicted value exceeding the surveyed result over 20% threshold.

5.2 Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the effect of survey sample size on the accuracy of clustering. For the analysis, three different sample size scenarios were tested, with ten, twenty and thirty responses per survey. Note that the number of responses per survey is the same as the number of responses per product and only the training products were considered in the sensitivity analysis. The data collected through the consumer preference surveys is recorded in a database in chronological order. The first step is to obtain an equal number of responses to all the surveys and across all the products. Each survey got a minimum of thirty responses, so some responses were eliminated to achieve thirty per survey. This was accomplished by removing the most recent survey responses. Next a set of ten and twenty unique random numbers were selected. These random numbers would represent the survey response that would be removed for the sensitivity analysis. Using a 10% threshold analysis, the clustering accuracies of both the consumer preferences and the user-defined clustering variables for the three different scenarios were evaluated as shown in Figure 19. From the figure, it is evident that a smaller sample size of ten responses per survey, which equates to eighty total unique responses, performs the worst with both the consumer preference-based clustering and the user defined variable clustering. There are significant improvements when increasing the sample size to twenty response per survey, or one hundred and sixty unique responses, and further improvement when the sample size is increased to thirty response per survey or two hundred and forty unique responses. The trends shown in the sensitivity analysis indicate that the accuracy of the model could be improved with the collection of more consumer preferences.

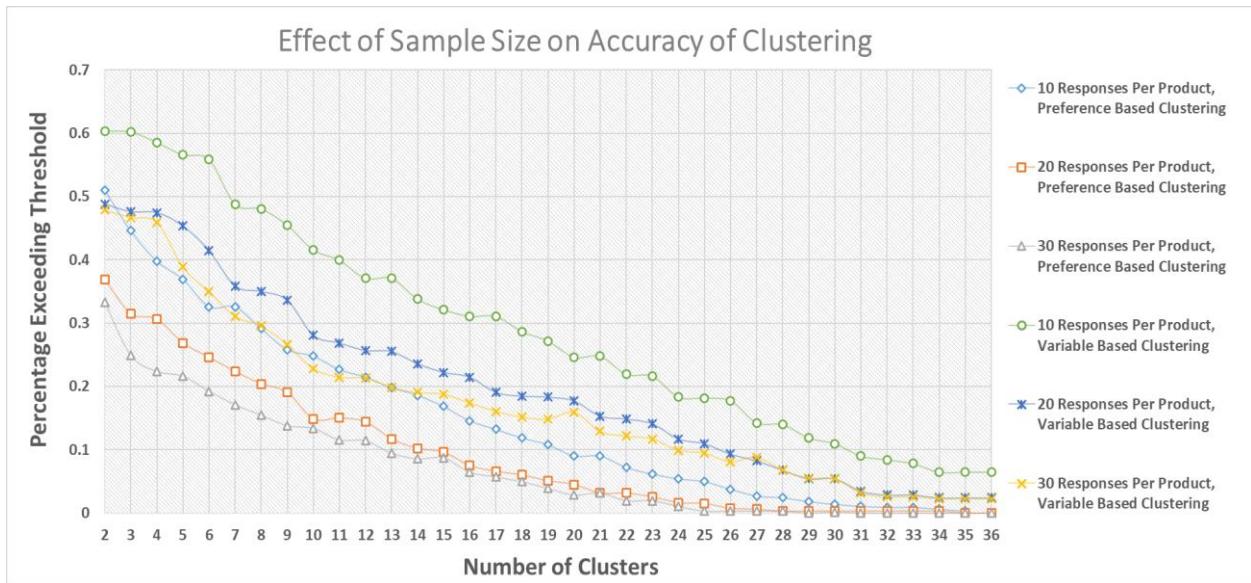


Figure 19: Effect of Survey Sample Size on Clustering Accuracy

5.3 Discussion

The preliminary results obtained from the validation study indicate that good results were achieved overall and show that this type of methodology of using user-defined variables to cluster products has merit in the prediction of consumer preferences. Two of the three validation study products had accuracies of over 80%. The third product in the validation study saw a significantly lower accuracy with a 39% accuracy in prediction of the consumer preferences. In theory, a traditional survey approach asking consumers what specific features they would want to customize should have a 100% accuracy because the consumer preferences are directly elicited from consumers. However, there are significant drawbacks to using surveys that were highlighted in Chapter 2 of this thesis including the amount of time, cost, and effort they take to administer compared to ML approaches to predicting preferences. Other consumer preference prediction methods using ML such as the approach by Chen saw an accuracy of 75% (Chen, 2023). The method employed by Chen only focused on the prediction of preferences for coffee makers based on the preferences for other coffee makers and did not predict preferences for other types of products. Given that the approach presented in this thesis was able to achieve a 70% accuracy overall, this indicates that the methodology proposed is comparable to other ML methods that exist in terms of accuracy.

The validation study provides some critical insight into one of the primary limitations of the current model. That is, products without representation in the training data see a low accuracy in the prediction of the preferences. The reason behind this is two-fold. First, it is unrealistic to assume that any ML model will be able to predict consumer preferences for products that have no close matches due to the nature of ML approaches. The second reason behind the low predicted accuracy is the fact that the user-defined clustering variables are optimized for the current training data set.

Based on the methodology presented in Chapter 4.3.2, ChatGPT was prompted to output a list of potential clustering variables based on the product set and an optimization process was conducted using threshold testing based upon the accuracy of clustering using the training data. These variables were chosen and optimized based on the current training data and adding new products that are not represented in the training can not be expected to perform well in the prediction of their preferences.

The use of the surveys themselves presents another limitation of the model. In the surveys, no personal information was collected from consumers to minimize privacy concerns and maximize the number of responses collected. However, this means that there is no information available about the demographics of the respondents, which could influence consumers preferences for customization.

The use of ChatGPT in the design process of products is novel. ChatGPT provides several key benefits when used in this context, including emulating the decision-making process of consumers, providing suggestions that may have otherwise been overlooked, increasing efficiency, and reducing effort. In this model, ChatGPT was utilized in two modules of the framework, the suggestion of user-defined variables and product feature extraction. In both instances, ChatGPT was not allowed to function without supervision and the outputs were verified by the author in the case of the user-defined variable selection and the end user (in this case the author, but in a real world setting a product designer) through the product feature extraction. Due to the novelty of ChatGPT and the fact that it is essentially a black box, more work needs to be done to verify the accuracy of the outputs. This verification is out of the scope of this thesis, as the intention was to leverage the benefits previously described under the supervision of domain experts.

The predictive decision support tool considers the three of the four different research gaps identified by the literary review. Due to time constraints, it only covers the decision to customize and the design of customized products. It did not cover the selection of a customization strategy, meaning it is not a complete recommender system for the customization process.

Chapter 6 Conclusions and Future Works

6.1 Conclusions

In this thesis, the concept of decision support tools for product customization in a modern production environment is reviewed with a methodology presented for a data-driven approach to decision support using the prediction of consumer preferences. Four different strategies for customizations are identified: craft customization, modular customization, OAP, and an integrated approach. Each strategy has its own unique benefits and drawbacks, highlighting the importance of selecting an optimal customization strategy. Reviewed works have identified factors of success in product customization that can be summarized into five different categories: market factors, manufacturing process factors, product design factors, information technology factors and organizational factors. Within each of these categories exist subcategories of factors that more specifically describe the factors of success and their relationship to customization. The customization process was introduced with four different steps: deciding to customize, selecting a strategy for customization, customization of the design and production and sale of the product. papers were reviewed to examine different frameworks for the decision to customize, customization strategy selection and design selection. Generally, existing works do not consider all the factors of success for customization and are narrow in scope in terms of the types of customization strategies they consider. Most strategy selection frameworks are also unstructured and lack specific decision making. Different methodologies of design customization selection were examined as well. Methods here are mostly manual processes and did not constitute comprehensive decision-making tools as they only focused on the design aspects of the customization process. This review identified four distinct research gaps: a lack of comprehensive framework for the customization process, lack of structured decision support tools in the customization process, a lack of automated process for decision support in the customization process and a lack of comprehensive automated consumer preference prediction tools.

A methodology is presented for predicting consumer preferences using a data driven approach for application in the design of customized products. Using crowdsourced consumer preferences for a training set of thirty-seven different products, a prediction model was developed consisting of five different modules. Module 1 pertains to the collection of consumer preferences through a survey designed to extract critical factors of success relating to customization and categorical representations of consumer preferences. Module 2.1 deals with the selection of a clustering algorithm for use in the prediction model. For this application, three different types of clustering algorithms were evaluated including K-Means, Spectral, and agglomerative clustering. K-means was found to have the best overall performance. Module 2.2 presents the selection of user-defined clustering variables using analysis from ChatGPT to generate an initial list of variables, then undergoing a refinement process to narrow down a final list of nine clustering variables. Module 3 implements ChatGPT in a different context to extract product features from product descriptions to make specific recommendations for customization. Finally, Module 4 outputs recommendations for customization. A validation study consisting of three products was conducted to verify the

accuracy of the model. The results indicate that the overall accuracy for validation tests is approximately 70% with better individual performances for products that are well represented in the training data set.

6.2 Future Works

The result of the validation study presents an opportunity for future work to add more products to the training data set and optimize the product set to represent as many different types of products as possible. This process could utilize the same methodology of using ChatGPT to analyze the product list and suggest a list of clustering variables, manually refining the clustering variables then using threshold testing to evaluate the accuracy of clustering. The expanded training data set could then be tested with a larger set of validation study products to evaluate and identify any gaps in the scope of the training data and ensure that the training data can provide accurate predictions for a wide range of products, potentially with better accuracies. This process could also involve the use of more user-defined clustering variables or adjusting the scale of the current set of user-defined clustering variables. As indicated, the user-defined variables and the scale proposed in this model were optimized to the products that are currently in the training data set. By adding more products to the training data set, it may be necessary to expand the number of variables and use a scale that allows for better differentiation with more products. This could be accomplished using the same process outlined in Chapter 4.3.2 of this thesis.

Another area for future improvement is the implementation of other ML algorithms. Clustering was chosen based upon the pilot study results from Chapter 3. However, as pointed out in Chapter 2 of this thesis, deep learning has been applied in the prediction of consumer ratings and could see similar applications here. The use of other ML algorithms could take a different approach to using the user-defined clustering variables and matching new products with those in the training data. More types of clustering algorithms could also be explored for this application.

Based on the results of the sensitivity analysis, expanding the respondent pool of consumers would serve to increase the accuracy of the model. It can be hypothesized that by increasing the respondent pool of consumers the preferences of consumers converge to a common value. However, as outlined in Chapter 5.3, the demographics of the survey respondents are not known. This issue could be addressed in future work through two avenues. The first would be to collect personal information on consumers to ensure that there is a diverse pool of respondents; however, this would be challenging considering the privacy concerns as well as the hesitancy of consumers to provide personal information in a survey. The second and more attractive option to address this issue is by allowing for consumers to skip products on the survey they would not have any intention of purchasing. This option was considered in the current study but was not implemented to maximize the number of respondents to the surveys, a task that proved challenging without additional hurdles.

The use of ChatGPT in product design can also be explored further. The results relating to the product feature extraction could be compared to those that are manually extracted by an expert on

customization. This could give an accuracy measure as to how many product features ChatGPT was able to extract and correctly sort from a product description compared to an expert. In terms of suggesting clustering variables, a similar approach could be taken that would compare the variables suggested by ChatGPT to those that were generated through expert opinions or collected from consumers. This could lead to the fully automated operation of ChatGPT for these purposes that would not require the human oversight used in the current model. ChatGPT could also be used to label products with the user-defined clustering variables that would make the consumer preference prediction model fully automated. Full automation would further extend the efficiency benefits of using large language models in product design and presents an interesting new avenue for research.

In the future, a similar data driven approach to decision support can be applied to the development of a tool that can help firms in the selection of a customization strategy. This type of tool would consider the factors of success that are covered in Chapter 2.2 of this thesis relating to the companies' capabilities and utilize surveys from companies already engaged in customization to apply machine learning in the selection of an appropriate customization strategy. This could be combined with the preference prediction model to offer a full customization as a service model that would guide firms through the entire customization process in an automated and structured manner.

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