A Data Clustering Approach to Support Modular Product Family Design

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Abstract

Product Platform Planning is an emerging philosophy that calls for the planned development of families of related products. It is markedly different from the traditional product development process and relatively new in engineering design. Product families and platforms can offer a multitude of benefits when applied successfully such as economies of scale from producing larger volumes of the same modules, lower design costs from not having to redesign similar subsystems, and many other advantages arising from the sharing of modules. While advances in this are promising, there still remain significant challenges in designing product families and platforms. This is particularly true for defining the platform components, platform architecture, and significantly different platform and product variants in a systematic manner. Lack of precise definition for platform design assets in terms of relevant customer requirements, distinct differentiations, engineering functions, components, component interfaces, and relations among all, causes a major obstacle for companies to take full advantage of the potential benefits of product platform strategy.

The main purpose of this research is to address the abovementioned challenges during the design and development of modular platform-based product families. It focuses on providing answers to a fundamental question, namely, how can a decision support approach from product module definition to the determination of platform alternatives and product variants be integrated into product family design?

The method presented in this work emphasizes the incorporation of critical design requirements and specifications for the design of distinctive product modules to create platform concepts and product variants using a data clustering approach.

A case application developed in collaboration with a tire manufacturer is used to verify that this research approach is suitable for reducing the complexity of design results by determining design commonalities across multiple design characteristics. The method was found helpful for determining and integrating critical design information (i.e., component dimensions, material properties, modularization driving factors, and functional relations) systematically into the design of product families and platforms. It supported decision-makers in defining distinctive product modules within the families and in determining multiple platform concepts and derivative product variants.

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Chapter 1 : Introduction

1.1 Product Platform Planning and Its Challenges

A product family is defined as a set of products that share a common platform of design elements and addresses a set of market applications [1]. Similarly, a product platform can be defined as a set of subsystems and interfaces that form a common structure from which a stream of derivative products can be efficiently develop and produced. It can also be defined as a collection of assets that are shared by a set of products. These assets can be divided into: components, processes, knowledge, and people and relationships.

Figure 1 captures the major components of platform development [1]. The firm's current and new markets are shown at the top of the framework. Different levels of performance and price, company size or customer age are common separators to create tiers of niches within the target markets. The underlying building blocks for the common product architecture are core technologies, process and services and market understanding.

Well-known examples of platform-driven product families include Sony Walkmans, Black and Decker power tools, HP printers, and Microsoft Operation Systems. Figure 2 shows an example that includes all members of Black and Decker's cordless VersaPak family—cordless screwdriver, multipurpose saw, scrubber, 2-speed drill, and rotary tool—are derived from only two different motor sizes and battery types [2].

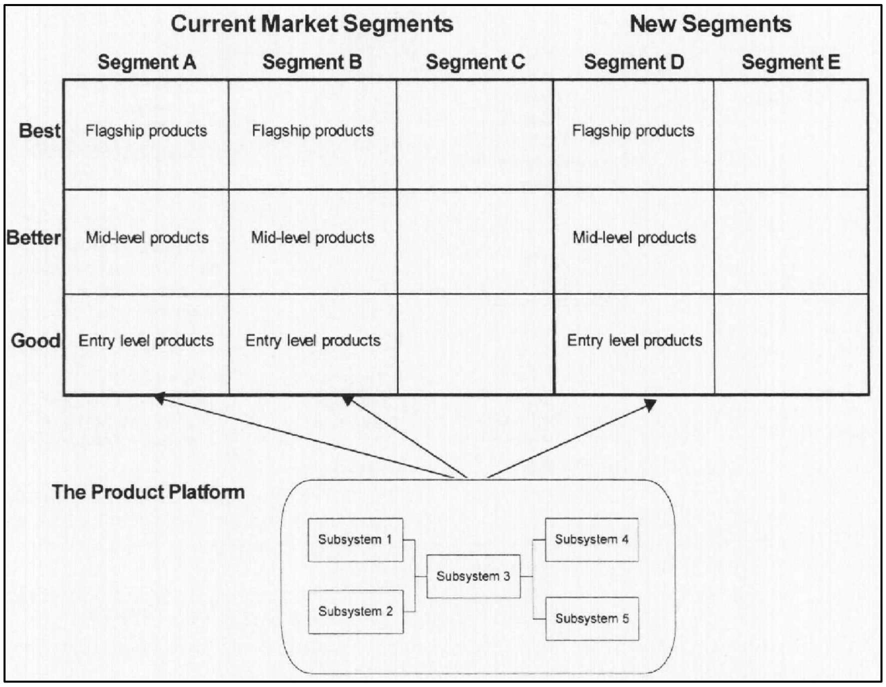
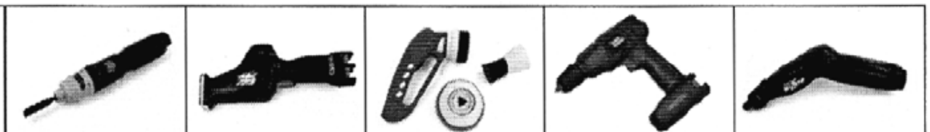


Figure 1: Platform framework [2]



Function	Cordless Screwdriver	Multipurpose Saw	ScumBuster™ Scrubber	2-Speed Drill	Wizard™ Rotary Tool
Register / Unregister Battery	1 battery	2 batteries	1 battery	2 batteries	1 battery
Transmit Electricity	1 battery	2 batteries	1 battery	2 batteries	1 battery
Seal / Unseal Battery	-	-	yes	-	-
Input Signal	thumb	finger	finger	finger	thumb
Switch Power	forward/reverse/off	on/off/lock	on/off	forward/reverse/off/lock	low speed/high speed/off
Convert Electricity to Motion	motor A	motor B	motor A	motor B	motor A
Transform (T, ω)	transmission A	transmission B	transmission A	transmission D	-
Transmit Power	rotating shaft	translational blade	rotating shaft	rotating shaft	rotating shaft
Prevent Back Rotation	yes	-	-	-	-
Input Hand Torque	yes	-	-	-	-
Transform Motion	-	yes	-	-	-
Register / Release Tooling	hexagonal hole	blade carriage	three-prong chuck	three-prong chuck	three-prong chuck
Secure / Unlock Tooling	retaining clip	set screw	chuck housing	chuck housing	chuck housing
Permit Tool Positioning	product shape	handle	handle	trigger handle	trigger handle
Act on Object	rotate	cut	scrub	drill/rotate	grind

Figure 2: A Versapak portfolio of products [4]

A significant amount of research has established that product platform planning is an effective multiple product development and management strategy for companies in today's market [3]. In September 2005, the 11th Institute for International Research (IIR) Annual Innovation Convergence event in which innovation is looked at from numerous angle of an organization included product platform planning as a special event topic for establishing an enterprise-wide innovation culture [4]. Similarly, beginning in the 2005, American Society of Mechanical Engineering International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE) included a special session on product families and platforms [5]. Also, in 2005, the innovations in Product Development Conference held at Massachusetts Institute of Technology (MIT) discussed product families and platforms from the perspectives of strategic innovation to implementation [6].

Many industries have acknowledged the competitive advantages of product family and platform approaches [7]. Advantages from reuse, the incorporation of best practices and lessons learned, as well as lower costs across the life-cycle from families of products can be found in different business markets (software, power tools, automobile, etc.) and have made use of a variety of different methods (modularity, scaled up and down platforms, etc.). For example, Volkswagen reportedly saved $1.5 billion per year by using a common platform across its four brands (Volkswagen, Audi, Seat, and Skoda) and was very successful in producing new models [8]. More advantages are improved speed, quality, variety and flexibility in product development [1].

1.1.1 Motivation

While progress is encouraging, there remain significant challenges of product platform planning as a multiple product development management tool. This is particularly true for defining product platform technologies (modules, architecture, etc.) [9]. Lack of precise operational platform definitions causes a major obstacle for companies to take full advantage of the platform implementation capabilities. Example incidents might be failure on leveraging technology into new markets and leveraging existing competencies in creating different business [10]. To deal with such pitfalls, researchers suggest the establishment of systematic product platform development methods. It is anticipated that these methods result in the development of robust and competitive product platform architecture, effective product variants and clearly defined product modules.

1.1.2 Product Platforms and Families Planning Approaches

Product platform planning is markedly different from traditional product development process, which focuses on optimized designs for individual products [11]. Product development is defined as the transformation of a market opportunity and a set of assumptions about product technology into a product available for sale [12]. It is an iterative process. Ideally, it aims to capture customer requirements and needs in terms of product functions and then map the functions into a set of physical artifacts (components) as engineering characteristics as well as organizational and production capabilities are being considered. During the process, different levels of design abstraction are revisited continuously. Product realization is refined from functional structure (most abstract design realization) to physical components (most concrete product realization). Clearly, the coordination of the representations of the same product in different levels of abstraction is crucial, but equally challenging for design teams. Such coordination is one of the key design elements to align the features desired by customers with the final product performance. As one might expect, product realization becomes more complex and challenging for family and platform planning. Product family and platform planning requires coordination of a larger variety of design inputs, outputs, resources, stakeholders and processes simultaneously. It includes all the design tasks mentioned above, but in this instance, with the added challenge of identifying commonality within the family being defined while maintaining individual product specifications. For example, design decisions on the degree of commonality and the degree of openness of the interfaces to the platform have to be made [13]. In the family and platform development process, individual customization of products generally conflicts with the goal of maximizing platform commonality [14].

Integral platforms—There are different approaches to create a product family and platform to address the challenges mentioned above. One way is an integral platform [15]. In general, an integral platform consists of a single part, which will be shared across the product family being developed. Individual design elements are added to the platform to derive new products. In integral product architectures, a one-to-one mapping between functional elements and physical components of a product is nonexistent, and interfaces shared between the components are coupled, or highly interdependent [16]. However, Mikkola and Gassmann [17] point out that integral architecture designs enhance knowledge sharing and interactive learning as team members rely on one other's expertise. Also they have observed that integral architectures are designed with maximum performance in mind, and the implementation of functional elements may be distributed across multiple physical elements. An example is the Formula One car [17]. Formula One car designers believe that it is necessary for various parts of the design to be highly interdependent for achieving high levels of performance in the final product. Changes to one component cannot be made without making changes to other components.

Modular platforms—Contrary to integral platforms, modular platforms are used commonly as they are flexible in leveraging a large number of product variations [18]. In this approach, a platform is a set of modules that is reused across a product family. For example, Figure 3 shows a generic architecture of interplanetary spacecraft [15]. In the figure, product varieties (Variant A, B, and C) are accomplished by swapping the modules of the products by others of different size or functionality. Variant B for an outer-planet spacecraft in Figure 3, for example, does not require solar panels (module 2) for its deep-space mission. A modular architecture enables firms to minimize the physical changes required to achieve a functional change. It also enables a firm to achieve cost savings through economies of scale from component commonality, inventory and logistics, and developing technologically improved products more rapidly. Established companies usually have a set of modules already designed for previous products that could be reused, as well as the resources to design new versions of the same modules or modules with new functionality [15]. Computer and automobile industries use the modular design approach very broadly.

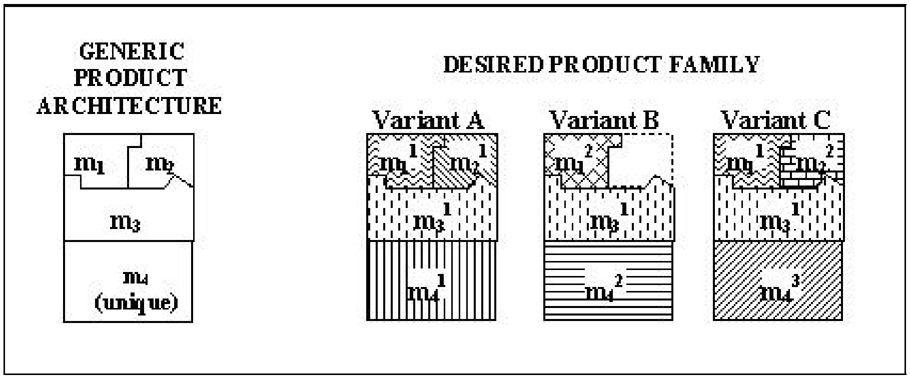


Figure 3: Elements of a modular product family [15]

Regardless of the implemented approach, there exists a two sided relationship between companies' platform/family technology decisions (architecture, interfaces, core performance, etc.) and their business strategies. Companies match their target market segments and decide value and type of product innovation and resource allocation according to their product family technology options. Such technology options need to be based on the organizational internal and external business drivers and their interrelations. From the systems engineering point of view, such architectural decisions are encouraged as early as possible in the conceptual design phase, when design changes are the most flexible and cost the least in general [19].

Top-Down versus Bottom-Up Approaches—In addition to different architectural ways for configuring product families and platforms, different design perspectives to achieve the same architecture can be demonstrated. This raises additional challenges for the definition of the families and platforms. For example, an integral platform can be constructed both from bottom-up and top-down approaches. In the bottom-up approach, the platform is decided from common component(s) among the products in anticipation of satisfying functional requirements of the product family. As this grants a physical platform realization which the company is capable of providing or producing, it may not guarantee a direct match between the physical structure and the features (defined by customers and represented in terms of functions). On the other hand, the platform can be driven from common functional requirements in the family toward its physical realization. Here, the customer desires are defined and represented in the platforms clearly, but the physical realization of product solutions might end up being away from the company's core capabilities.

1.1.3 Product Modularity

Similarly, modularity has been described in many different ways as a product design strategy. Fixson [20] categories existing product modularity concepts in the literature from three different perspectives: systems, hierarchy, and life cycle. In his framework, the systems perspective includes constructing modularity concepts with respect to product development elements (components, functions, production processes, etc.) or their interfaces or both elements and interfaces simultaneously. The hierarchy perspective illustrates top-down and bottom-up approaches to modularity. The life cycle perspective represents modularity decisions based on different goals such as production, design and development, use, and retirement.

Due to the presence of many different possible perspectives, modularity can be defined as a bundle of product characteristics where different views emphasize different aspects [20]. As a consequence, methods aiming to offer more comprehensive understanding of the phenomena have started gaining attention from academia and from industry. For example, Tseng and Jiao [21] propose simultaneous assessments of different perspectives: functional, behavioral and structural views. They developed a Product Family Architecture (PFA) model involving both modularity and commonality issues [22]. Another example is a method assessing different product development phases (e.g. production, sales) simultaneously [23].

Despite the body of work in developing more comprehensive means for modularity shown above, there are a few research efforts that combine those modularity approaches with a practical and systematic modularization method [24]. Additionally, still those efforts address only single product design challenges. Such applications have not been examined and generalized designing product families and multiple platforms. This presents opportunities for creating approaches to manage and plan multiple modular product platforms from a more comprehensive view.

1.2 Research Problem

As discussed in Section 1.1.2 and demonstrated in Figure 3, modular products are created through substitution of add-on modules. The approach here permits the platform itself to be one of the several possible module combinations that are shared by a set of products [15].

A common approach to tackle the issue of finding the appropriate modular platform option (appropriate set of modules) is as an optimization exercise [15, 25]. Generally, such optimization approaches yield final configurations of modules, identification of the optimum degree of commonality, and optimum settings for the common modules as maximizing the level of meeting the requirements of each variant. The performance of the most optimum product and/or product platform architecture is assessed to underline its benefits. The existing optimization methods are beneficial in providing fast and quantitative optimal results. Unfortunately, they are difficult to modify to accommodate dynamic design requirements within the same product family (e.g., optimizing the products of the same family towards different numbers of modules) and their set-up requires specialized expertise. Additionally, the methods are not helpful for design teams to identify opportunities for improvement for non-optimal product variants and multiple platforms. This limits the existing optimization methods in being a practical application and easily adaptable to the real-time changes in product development strategies. For instance, Simpson [26] reports that few, if any, of the 40 optimization approaches identified have found their way into industrial applications or day-to-day use within industry.

An important question that must be addressed: *How can design teams be supported in designing product families along with distinctive product module definitions, and determining multiple product platforms and product variants?*

1.3 Research Purpose and Objectives

The purpose of this research is to develop and apply a generalized method to enable design teams to define distinctive product modules, multiple platform concepts, and optimal and non-optimal product variants. The goal is to support design teams in handling the complexity and the challenges of the development of modular product families during the product design stage.

1.4 Research Questions and Hypotheses

The following primary research question, supported by sub-questions, provides the basis and guides the research.

Primarily research question: ***how can a decision support approach from product module definition to the determination of platform alternatives (options) and product variants be integrated into product family design****?*

This research question is related directly to the principle objective of this study, which is to support design teams in determining of more than one platform concept during modular product family development. The primary question is divided into two sub-questions.

Q1: How can we support design teams to define distinctive product modules**?**

Hypothesis 1: Using the proposed research steps 1 through 3 in Chapter 3, critical design information in multiple characteristics can be identified and, then utilized for defining, generating, and distinguishing product modules.

Since Q1 is quite broad, the following three supporting questions and hypotheses will be used to verify Hypothesis 1.

Q 1.1: How can critical design information be identified and captured for creating product modules?
Q 1.2: How can the critical design information be utilized for defining product modules?
Q 1.3: How can the significant differences between modules can be determined and presented?

Sub-Hypothesis 1.1: A common market requirements motivated approach can be used to determine the critical product components. Additionally, functional relations and dependencies among the product components can be incorporated in defining product modules. QFD based tools can be adapted to capture such design knowledge.
Sub-Hypothesis 1.2: A data clustering approach can be utilized to define product modules by eliminating insignificant design variations in essence.
Sub-Hypothesis 1.3: Significant differences among the modules can be determined using non-parametric analysis methods. Design data mean vectors can be used to represent scaled module representations.

A second question will also be investigated in this study with a focus on defining modular product platform alternatives and product variants.

Q2: How can we support design teams to determine modular platform alternatives and product variants?

Hypothesis 2: Using the proposed research Step 4 in Chapter 3, product modules can be categorized according to their platformabilities (see Appendix), and then be utilized to detect potential platforms and product variants within the product families.

Product modules can be configured in many ways to define platform alternatives and product variants. This study aims to help designers understand design goals behind product module variants to construct platform alternatives and product variants. Below, Q2 is detailed in sub-questions to investigate Hypothesis 2 more precisely.

Question 2.1: How can design teams define a strategy for platforming arhictecture?
Question 2.2: How can design teams detect multiple potential platforms and product variants?

Sub-Hypothesis 2.1: Modularization driving factors analysis methods can be adapted to define module platformabilities to determine a platforming architecture strategy.
Sub-Hypothesis 2.2: A method to re-define (re-configure) existing products using the defined product modules can help detect module usage patterns in platform alternatives and product variants. Additionally, a design commonality prediction method can be developed to compare how generic existing or future product types are.

1.5 Overview of the Research Approach

The research approach aids design teams in achieving two major successive tasks; 1) defining distinctive product modules and 2) detecting multiple product platform concepts within the product families.

In order to support is the definition of distinctive product modules, a set of engineering decision management tools is proposed for identifying critical design information and their interactions. Similarities in the captured information within the product families are diagnosed though the application of a data clustering approach. The resulting clusters provide the basis of module definitions. Tools to define the distinctiveness of the modules are also provided.

In order to enable design teams to utilize the generated modules for detecting multiple product platform concepts within the product families, a module categorization method based on determining platformabilty is proposed. Observations of the distributions of these module types within the product families form the essence of the platform alternatives detection support in this research. Further, the results of the observations are captured in terms of module predictability scores to compute product variants' uniqueness within the product families.

1.6 Research Assumptions

This research approach is appropriate when the product design is known and mass design is applicable and is also the goal. It is most effective for analyzing large product groups for design commonalities across multiple design characteristics. Thus, another research assumption is that the selected product group is large enough for applying the proposed clustering approach. Statistically, the sample size is suggested not to be smaller than 35. The clustering algorithm used in this research is known being effective with very large data sets like 1000s.

In addition, feasible product similarities need to exist for proper application of the proposed clustering approach. Results of a clustering problem depend upon the selection of variables. The selection of "good" variables may come about with a fair bit of trial and error complemented with the analyst's intuition and background knowledge of the data set. Selection of "unwanted" variables leads to clusters that do not present an informative structure. An important step in any clustering is to select a distance measure, which will determine how the similarity of two elements is calculated. This will influence the shape of the clusters, as some elements may be close to one another according to one distance and further away according to another. A plain distance metric (Euclidean distance) is applied in this research.

Furthermore, it is assumed that products with insignificant differences across a set of selected design characteristics can be grouped in the same cluster where such insignificant differences do not create performance differences. In other words, performance differences within the products assigned to the same set of design group/cluster are assumed to be negligible.

Product component groups according to functional similarities provide a very important basis for defining product modularization in this research. The interactions between the product component groups are accepted to be insignificant, so that individual modularization search is applied to each product component group.

Furthermore, critical design information and interactions capture and collection is a crucial step in this research, since module and platform definitions closely depend on them. It is assumed that the collected design information reflects design team decisions and perceptions accurately and appropriately. It is also assumed that the collected design information is accurate, complete and appropriate for the proposed research method.

1.7 Research Contribution

This research provides a flexible and intuitive method for design decision support and design improvement in developing product variants from multiple platforms. By way of industrial case application study, this approach contributed in providing quick and less costly feedback in defining design modules and product variants. Additionally, the case application is a unique study in the field with the analysis of a large amount of product designs and the modularization of an integral design. Ultimately, this research will aid and enable platform thinking as business and product development concepts.

1.8 Overview of the Dissertation

An overview of the structure and chapters of the dissertation are shown in Figure 4. As shown, Chapter 1 provides the initial introduction for the data clustering based research method to support modular product family design.

Having laid the foundation by introducing the research questions and hypotheses for the work in Chapter 1, the next chapter contains a literature review of related research, highlighting strategies and methods in product family and platform design. Research areas that are reviewed include four major topics: (1) Major concepts in product family and platform planning are reviewed in Section 2.1. This helps communicate the relevant challenges and how the research community and industry address these challenges. This literature review provides a basis for the implemented platform architecture strategy selection in this research. (2) Section 2.2 summarizes existing modularity definitions and methods. The module identification matrix (MIM) is introduced in this section which is adapted for this research. (3) Section 2.3 reviews relevant engineering decision and platform evaluation methods. This section introduces the two decision making tools used in this research; quality functional deployment (QFD) and functional design structure matrix (DSM). In addition, the review on the product and platform evaluation methods provides a basis for the module predictability scoring method in this research. (4) Section 2.4 presents background information on data clustering techniques and their use in the product design field. It provides a basis for identifying the set of tools to classify product design data. Selected tools are namely principal component analysis (PCA), K-means clustering algorithm, Kruskal-Wallis test, and representative product selection.

The research approach is presented in Chapter 3. Since the research approach is applied to design a set of tire products to demonstrate the research method usefulness and feasibility, an introduction to the case study and tire product design is presented in Chapter 4. Research results and interpretations are presented in terms of the results of the tire case study in Chapter 5.

Chapter 6 is the final chapter in the dissertation and contains a summary of the dissertation, emphasizing the answers to the research questions and resulting research contributions. Finally, limitations translated into future work are discussed.

Additionally, a glossary is included for the definitions of the key concepts used in this research.

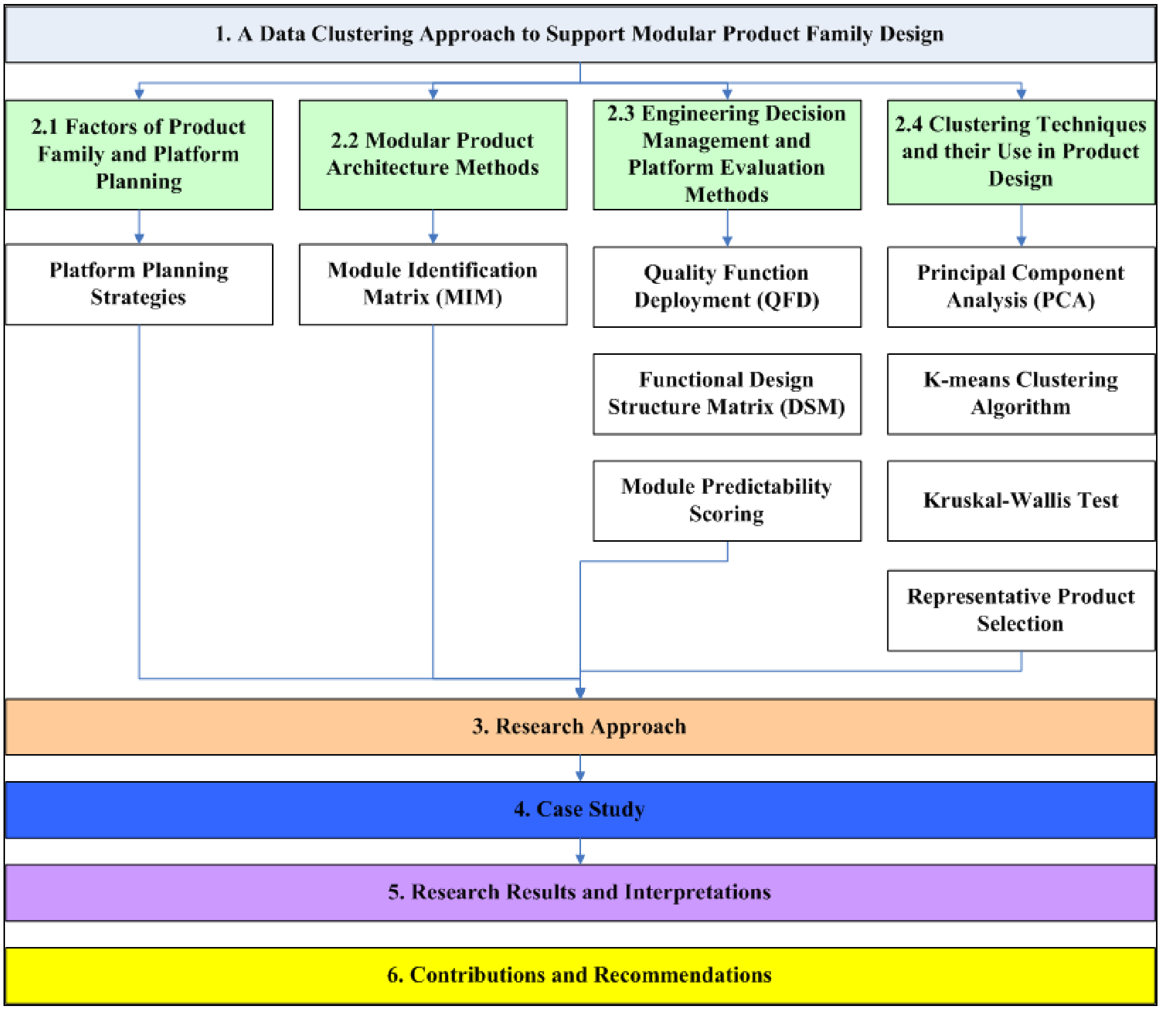


Figure 4: A pictorial overview of the dissertation

Chapter 2 : Literature Review

It is a difficult task for design teams and managers to maintain an adequate overview of product design process. This is particularly important for today's design process that companies include complex and challenging technical factors while offering several different product families (sets of related product offerings) simultaneously. In a product family development process, individual customization of products generally competes with the goal of maximizing commonality [14]. Also, it is easy to lose the balance between commonality and differentiation. For example, Audi had to retro-fit a tail-spoiler to its TT sports roadster to fix a rear wheel pressure problem. The cause of the problem was unexpected side-effects from the usage of a shared set of components [27]. All this calls for a systematic development and deployment of families of related products, also known as product family/platform planning. Product family/platform planning places a much higher demand on management of information of multiple types and from multiple sources [28].

Given the research focus on the support for redesigning product families, a review of relevant work is presented in this chapter. The topics and relevant hypotheses are divided into two major categories as follows:

1) Sections 2.3 and 2.4 provide background in order to support the development of a research approach to define distinctive product modules. Section 2.3 introduces engineering decision management tools to identify critical design information and their interactions. This supports sub-hypothesis 1.1. Section 2.4 discusses data clustering techniques and covers Hypotheses 1.2 and 1.3.
2) Sections 2.1 and 2.2 discuss product platforms and modularization from different aspects. They support the development of the platform alternative detection research method and cover sub-hypothesis 2.1. Section 2.3.2 presents evaluation methods for product and platform concepts. This supports sub-hypothesis 2.2 for the development of module predictability scoring approach in this research.

2.1 Factors of Product Family/Platform Planning

This section presents major product family and platform planning process concepts and their relationships. The section starts with an introduction of general concepts and principles of platform driven product development. Next, the major factors of the process and the challenges in planning products are presented.

2.1.1 Product Family/Platform Planning Concepts

A variety of definitions of a product platform can be found in the literature [29]:

- "a set of common components, modules, or parts from which a stream of derivative products can be efficiently developed and launched" [10]
- "a collection of the common elements, especially the underlying core technology, implemented across a range of products" [30]
- "the collection of assets [i.e., components, processes, knowledge, people, and relationships] that are shared by a set of products" [31]

Simpson et al [29] observe that product platforms have been defined diversely, ranging from general and abstract to being industry and product specific, while the meaning of platform differs in scope from product/artifact itself to a firm's value chain. As a robust platform can drive a winning business strategy for the company [9], defining the product platform within a company is perhaps one of the most challenging aspects of product family design [29]. Specifically, McGrath points out the need for clarification between platforms and products to avoid the confusion between platforms development and product development [30].

Regardless of the specific definition used, product families and platforms can offer a multitude of benefits when applied successfully. Sawhney [32] categorizes the benefits of platform thinking in six areas: speed, cost, design quality, coherence, referenceability, and option value. Reusing product platforms and component designs can dramatically reduce development time for new products from a common platform. Many sources reported that Black and Decker's power tools division launched one new product every week for several years after adopting platform thinking in its power tools division [33]. Additionally, shared designs and components reduce design costs. For example, reusing 35% of about 4 million lines of Microsoft Windows NT code from earlier versions of the platform significantly reduced its development cost [34]. Furthermore, the commonality in product and component designs can improve the design quality of new products, because the underlying platform has been thoroughly debugged and tested. It has reduced testing and certification of complex products such as aircraft [35], spacecraft [36, 37], and aircraft engines [37]. In terms of extending a firm's product offerings, an existing product platform management provides more logical and coherent extensions to related products, markets and geographical regions. Hewlett-Packard laser and inkjet printers are success stories of such coherent extension. Platform thinking can also improve marketing of new products to a set of customers that are logically related to the core customer base. The relatedness among customers of the core product and derivative products with good platform management can result in stronger brand advocacy. Finally, Sawhney [32] states that platform thinking and investments in product core technologies and designs represent a rich set of "call options" that a firm can use to exercise in a flexible and phased manner. An example is that GE products in the Indian appliance market enable GE to learn about the market ("a valuable call option") to enter into related businesses in India.

Despite its benefits, there are potential drawbacks and downsides of platform-based product development [38]. Too much commonality can adversely impact a brand's image. For example Volkswagen has been criticized for creating cars that are too similar [39]. Additional costs on product development can be experienced. Ulrich and Eppinger [31] found that developing a product platform can cost 2 to 10 times more than a single product. Gupta and Krishnan [40] found that sharing components across low-end and high-end products can increase unit variable costs due to over-designed low-end products. Technical problems might arise because of extreme utilization of the platform across the product family. For example, the Audi TT had unexpected technical difficulties at high speeds due to problems with the rear wheel down force, and the problems were attributed to the utilization of the A-platform [27].

Therefore, the key to a successful product family lies in properly balancing the inherent tradeoff between commonality and distinctiveness. This requires the establishment of a good understanding of the product family and platform planning assets and their interactions. The management framework [1] in Figure 5 captures the major components and drivers of platform development. The firm's current and new markets are shown at the top of the framework. Different levels of performance and price, company size or customer age are common separators to create tiers of niches within the target markets [9]. In Figure 5, platform options are sets of basic subsystems and interfaces from which product families can be derived to address one or more tiers of one or more market segments. A platform represents shared architecture within the products of a product family. The underlying core company capabilities for the common product architecture are summarized in terms of the market understanding, product technologies, production/process technologies, and distribution/services blocks in Figure 5. Common product architecture can be driven due to the commonalities across these groups of capabilities.

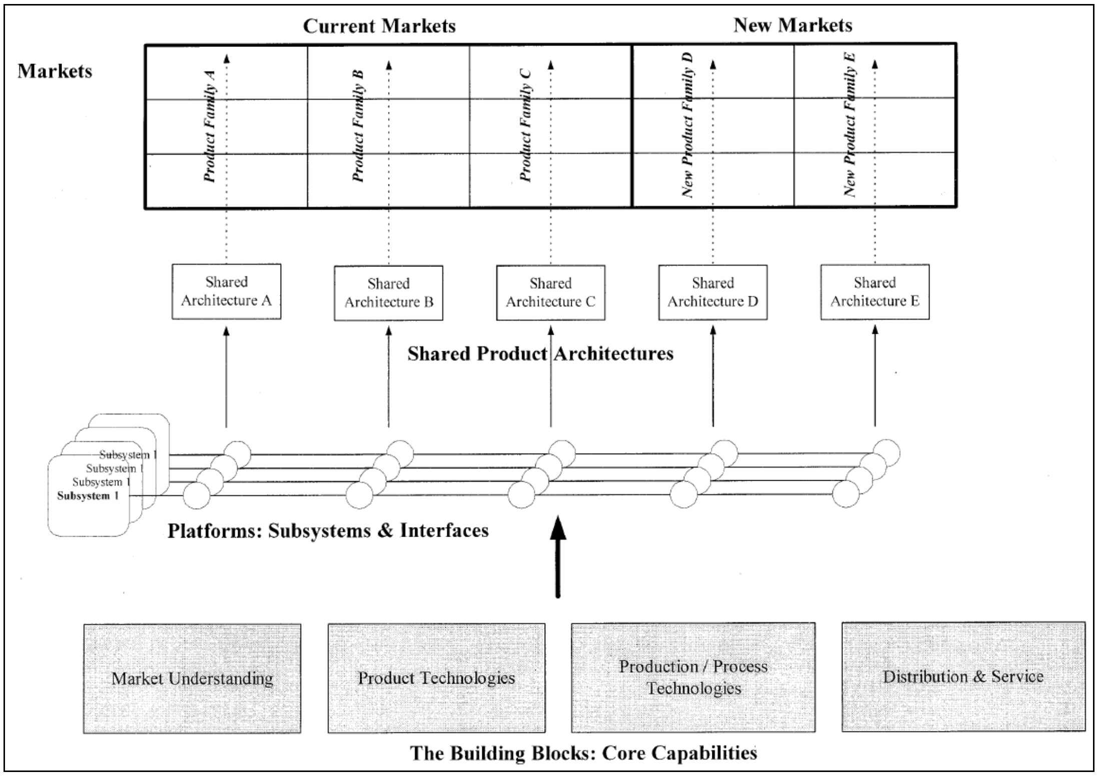


Figure 5: Platform framework [1]

2.1.2 Product Family/Platform Planning and Management

Recognizing the factors and the relations in product and product family design process in the previous section, the flowchart in Figure 6 presents product family/platform planning process [11]. As the process flowchart helps identify major process factors and their associations, it provides a unified and coherent view of the diverse literature prevalent in platform planning today. Figure 6 presents an overall process description for product family/platform planning.

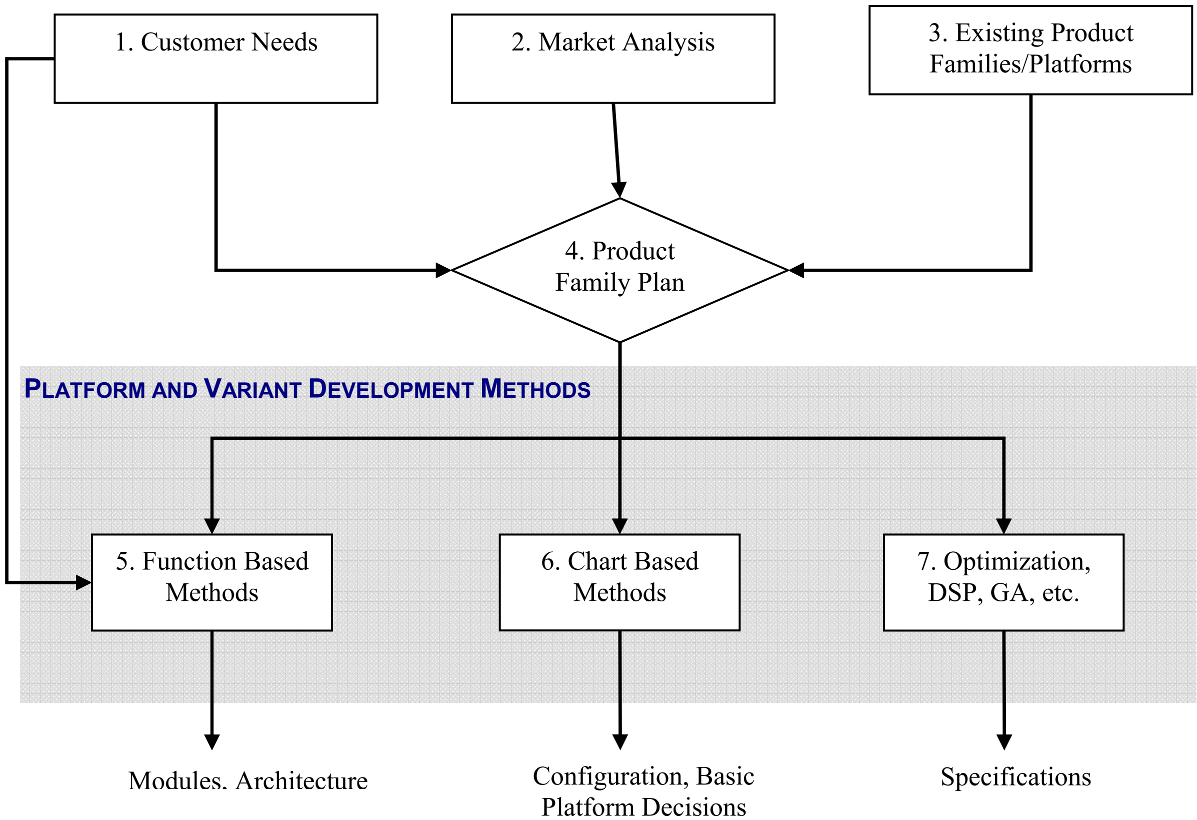


Figure 6: A platform planning process [11]

Approaches from both management and engineering fields have been incorporated in the platform planning process definition in Figure 6. The first three phases involve understanding the customer needs, the market and competitors, and the firms own products, platforms, and core competencies. Phase 4 involves planning details including strategy, products, features and specifications for the planned family. The next step involves actually developing architecture, or deciding on specification of platform and variant elements. Next, each of these phases is explained.

I. Customer Needs

Firms collect information on what customers need in a specific product. Each customer might have a slightly different perspective on how the product should be, and what its specifications should be. The only difference here is that since a product family is being planned (in opposite to single product planning), customer needs data should be collected from a wider segment of people, and should be representative of the whole market. Otto and Wood [41] prescribe a procedure in which the first step consists of data collection in which customers are surveyed for need target values. The product architecture is decided based on the survey results.

Also, customer needs are used to generate the function model of individual products of the family in case of a function based approach is used for platform development. Kurtadikar et al [42] proposed a function based and customer need motivated design method for conceptual design of product portfolios. In their work, customer needs are gathered using a survey technique. Base platform and potential differentiating modules are identified based on the calculated customer need frequency and weight parameters from the survey. Product architectures are drawn from variant functional models constructed by making alternative combinations of the based platform and differentiating modules.

II. Market Analysis

In order for the new products to do well in the market, it is essential that the company is in tune with market realities and trends. In today's fast changing, technology based marketplace, new innovations come and go all the time. Hence each company will have to do an extensive research on the market and determine the following details about competitors: number of competitors and market-share, products, features and specifications, technology, prices, and other important features. Essentially, benchmarking will have to be carried out for all the market segments. This is a prerequisite to platform planning as an overall view of the market conditions should be available to base decisions on the family of planned products.

The following method can be used to decide on product family specifications based on an overview of products competing in a market [11]:

- Identify market-segments in given market.
- Identify all commercially available products in all market segments and performance levels.
- Record features, specifications and price points.
- For a given feature, calculate mean and standard deviation of product specifications for each market segment.
- Tabulate the means and standard deviations.
- List out features or details in words if a numeric value is not possible.
- Based on customer surveys, identify mean and standard deviations of product specifications for features that customers expect in each market segment.
- Compare the two tables. Identify: untapped or over-exploited niches, in customer preferences tastes, etc.
- Carry out the above procedure calculating statistics for individual performance levels market-segments if market size is large, or if a sensitive analysis is desired.
- Decide on product features and specifications to design.

There are methods, for example the market segment grid [10] in Figure 7, to position prominent competitors in order to get an overview of the market . Additionally, graphical representations of information such as unit sales, price, and revenue can be used. Such representations show important financial data that is required while making decisions on whether or not to enter a given niche in a market segment. This gives the information required to make decisions based on profitability and market share.

III. Existing Products/Families/Platforms

A product family map [10] helps keep track of the creation and development of a platform. It consists of platforms, products and technologies of each generation in the product family's evolution, detailing corresponding technological or economic innovations. Sanderson and Uzumeri [43] developed a framework to help managers identify significant patterns that characterize their management of product models and families. In the framework, the pattern is obtained by investigating product-model and –family evolution which is described by the number of different types of products (the product variety) to rate of change.

IV. Product Family Plan

Once the firm has analyzed consumer needs, the market, and its own products, it is in a position to decide upon a strategy that will help it increase market share and revenues. In Figure 7, major market segments are arrayed horizontally. The vertical axis of the market segmentation grid reflects different tiers of price and performance. The first picture in Figure 7 shows a representation of horizontal leverage platform strategy. This strategy leverages a product platform, or one of its key elements, from one market niche to the next within a given tier of cost-performance. For example, Gillette Sensor-Excel razor systems for different shaving performance and cost market niches share the same razor cartridge as the razors' shape, color and the general design are different. In general, such a strategy is achieved by standardizing key subsystems (and their components), so that the shared systems can work with others with different performance. This requires careful subsystem design, since defects in shared subsystems will impact all the products serving the selected market niches. The middle picture in Figure 7 depicts another platform strategy in which the firm seeks to address a range of cost-performance tiers within a market segment with common product platforms. Such a strategy can be achieved by removing (scale down) or adding (scale up) certain functionalities or their technologies between the high-end and low-end products. Medical equipment suppliers, for example, tend to address the lower price-performance tiers first. Armed with modular platform designs, they can provide higher performance and functions based on the needs of hospitals and physicians. Lastly, Figure 7 shows a combination of horizontal leverage platform strategy with upward vertical scaling, also called as beachhead strategy. This strategy represents using a low-cost or/and performance platform for another market segment's low-end users, and then scaling up its performance characteristics. Hon Furniture Company provides a good example of the beachhead strategy. Hon made itself available for low-end market with products based on low-cost and modular platform architecture. As it developed it's serving capabilities in that broad market as creating seating and systems integrated furniture options from the same modular platform. Later, it penetrated upscale furniture niches.

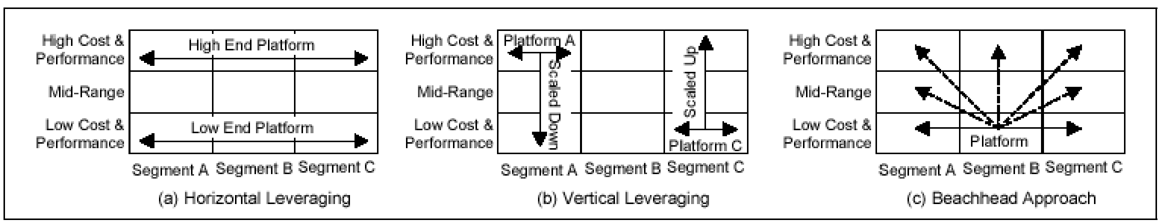


Figure 7: Platform strategies on a market segmentation grid [10]

Another important factor is that of competitors. Based on the firm's market analysis, it can choose to not enter into specific niches if they are unprofitable due to a strong hold by a competitor or too much competition. Similarly, if a niche has been under- serviced, the firm should focus on that. It is in this phase that differentiation or branding decisions can be made effectively. Some attributes of the product family are selected and given different values so that the products are differentiated from each other and also appeal to different kinds of customers. In case a firm maintains different brands in the same market, this is an ideal time to specify visual and performance cues and traits that set the brands apart. A modularity matrix [44] can be used for this purpose. A modularity matrix lists the possible functions from a family function structure as rows in the matrix, and then lists the possible products from that family as columns. The matrix allows the designer to consider different partitioning schemes for each product and for the portfolio as a whole.

V. Function-Based Product Family Design Methods

Referring again to Figure 6, phases (5), (6) and (7) correspond to the stage where overall specifications for the product family are converted into platform and differentiating modules, or into platform and differentiating feature specifications. Function-based methods involve the construction of a functional model of the proposed products and the creation of shared and variant modules. Two methods are presented here. One is a heuristic based method. The second is a visual, table-based method called the modularity matrix.

The first step of a heuristic based method is to create functional models of individual products. In order to do this, each customer requirements is converted into a statement (or statements) that involve flows and functions. These are agglomerated to form a monolithic block of functions and flows. To this, more functions are added in order for the model to be feasible and complete. This requires prior engineering knowledge. Function models of all the products in the family are agglomerated into one family functional model.

The modularity matrix [44] lists sub-functions from the family function diagram as rows in the matrix with possible products in the columns of the matrix. Each matrix element contains a specification value for the sub-function listed. If the specifications of a sub-function are common or similar across products, it can be shared as a common platform. Modules can be identified both at the individual product level and at the platform level.

VI. Chart Method [41]

This is a basic method which is used to determine design layouts and basic platform options for a product family. Table 1 shows the chart of a combination of configuration and platform options on the first two rows with the various criteria such as costs, visual appeal and ergonomics listed out on the second left column. The cells consist of a “score” which can be a positive, negative or zero. The option with the highest positive score wins.

Table 1: Chart for analysis of platform and family options [41]

	Product Family	Family 1			Family 2		
Evaluation Criteria	Platform Option	A	B	C	A	B	C
	Materials Cost	+	+	+	0	0	0
	Inventory Cost	–	0	+	–	–	–
	Visual Appeal	+	+	+	0	0	0
	Ergonomics	–	–	–	–	–	–
	TOTAL	0	1	2	-2	-2	-2

VII. Optimization, Decision Support Problem, and Other Methods

These methods usually involve techniques that are useful when the architecture of the product is known, and the design variables are being decided on. More often than not, the methods involve finding the optimal trade-off between certain design variables while operating under constraints such as cost and weight. More information related with decision support and optimization methods will be presented in Section 2.3.

Finally, the developed product platform/family planning chart in Figure 6 will support the construction of the methodology to support design teams in configuring modular platform-based product concepts. Additionally, it has been demonstrated above that it provides an organized means to investigate and communicate platform planning concepts.

2.2 Modular Product Architecting Methods

This section discusses modular platform and variant development methods in greater details. It will expand Step 5, 6, and 7 of the platform planning chart in Figure 6 with particular emphasis on modular product design. First, different approaches to define modularity in product planning are introduced. Then, different factors that influence the design of modules are presented. This is followed by the introduction of function-based approaches in identifying modules. Next, classification and identification of module interfaces are described. Finally, a description of how the reviewed methods will be incorporated into the development of the modeling environment proposed in this study.

A common approach for defining modules employs a systems approach [16, 45-47]. This perspective focuses on the high-level design of the system (modular design) and the interface designs that determine how components or subsystems (modules) work together. Blanchard and Fabrycky [19] define a system as composed of components, attributes, and relationships. In their definition, components are defined as the operating parts of a system consisting of input, process, and output. Attributes are the properties or discernible manifestations of the components, as relationships are defined as the links between the components and the attributes. Observing a similar approach applied to product design, the notions of “standardization” and “interchangeability” of components have been focused widely in the literature.

In addition to the systems perspective in defining modules, Fixson [20] defines two other viewpoints of modularity: the hierarchy and the lifecycle perspectives. The hierarchy perspective illustrates top-down and bottom-up approaches that result in different interpretations of modularity.

The life cycle perspective focuses on different goals and leads to different, often conflicting, module formations [20]. Each life phase sets different performance goals for the product. For this reason, a product that is optimized for one phase, is not necessarily optimal for others. The same phenomenon applies when developing optimal modularity as well.

Alternatively, Kreng and Lee have synthesized the identified goals of modular designs in the literature into 14 module drivers. The module drivers are presented in Table 31 found in Appendix F [31, 48, 49]: carryover, technology evolution, planned product changes, standardization of common modules, product variety, customization, flexibility in use, product development, product development management, styling, purchasing modularity components, manufacturability refinement and quality assurance, quick service and maintenance, product upgrading, and recycling, reuse, and disposal. Module drivers are linked to different functions of a company such as product development and design, production, after sales, etc. Although to date, the literature shows usage is limited to the design of a single product, the module drivers can be extremely beneficial in the development of product families and platforms. Such an approach can represent the objectives of finding the optimal modular product families, taking into consideration the company's specific needs in a simple manner. Therefore, we have integrated these module drivers into the proposed research approach for the concept configuration method.

As reported in Section 2.1.2, modules can also be identified in the functional domain. Functional representations have been commonly used to facilitate the systems approach to product family and platform architecting. Such a high level of abstraction (functions instead of components) allows allocation of functions and their interrelations to platforms without having physical structure and manufacturing constraints in mind. They are rooted in the engineering world and appear as one of the initial steps of the mental framework of the bottom-up approach [41]. Function structures describe a product or process in terms of functional elements that are required to achieve its overall function or purpose and functional interconnections [47, 50, 51]. This particular language is denoted as the functional basis and consists of two elements. One contains action verbs to describe function, while other one has nouns to describe flow. There has been a major effort of forming these information bases in a clear and standard way to improve design knowledge management and communication [52, 53]. Table 32 and Table 33 in Appendix F present the classified engineering functions and flows.

Function-based approaches to product modularization are used commonly. For example, Dahmus et al. [44] have proposed a function-based chart method to display the coordination between the product functions and the corresponding component solutions. The tool is called Modularity Matrix. Modularity Matrix shows the function allocation to the product components and supports the framework of the bottom-up approach. It lists the possible functions from a family function structure as rows in the matrix, and then lists the possible products from that family as columns. Each cell in the matrix contains a value that represents the function specification level required. The matrix allows the designer to consider different partitioning schemes for each product and for the portfolio as a whole.

Additionally, there are classification methods for modular product concepts in terms of the interfaces. For example, Strong et al [54] have developed a framework to classify the consumer phase of modularity (when the consumer can modify the product function by adding, subtracting, or substituting modules). They have developed the Modularity Type Matrix (MTM) which contains two types of interfaces—standard and unique—and a pair of architecture types—base and baseless. As standard interface allows any module to be attached to any interface on the product in question, unique interface requires a specific interface. Base architecture utilizes a base unit, as there is no base unit in baseless architecture.

As the MTM provides modularity interface categories from the use phase (customer phase) point of view, there exist other life cycle phases that a product has to run through. Each phase views different pieces of the interfaces. For example designers emphasize low functional interactions (where design phase modularity interfaces are essential), producers easy installation (where manufacturing phase modularity interfaces are critical), and meet product retirement regulations (where product retirement drivers have to be integrated). Similar interface categorizations can be used for the other product lifecycle phases. For example, Gershenson et al [55] cite the following modularity interaction types for documentation they found in the literature: physical, energy, information, material. The physical interactions include attachment (physical contacts, fixation and stops, fasteners, couplings, welds and the like), positioning (e.g. relative distance or angle between components, alignment including coaxial, collinear, parallel, perpendicular, and flush alignments), motion (cam-controlled objects, trajectory of joints, and end-efforts, etc.), containment (e.g. components contained in the same housing), and life-cycle issues (recycling, maintenance, retirement, etc.). The energy, information and material interactions include the need for energy, information or material transformation or exchange, respectively. These physical and structural constrains must be considered when components are grouped into modules. These constraints determine module compatibility within products and across product families. These constraints are crucial to be considered during design changes as well. Martin and Ishii [56] define a coupling index to indicate the strength of coupling between the components in a product. The stronger the coupling between components, the more likely a change in one will require a change in another one.

2.3 Engineering Decision Management and Platform Evaluation Methods

2.3.1 Engineering Decision Management Methods

As it has been discussed so far, it is quality of the decisions during product and business development that determine the quality of the result, the cost of the result, and how soon it is completed. Ullman [57] identifies ideal decision management as the determination of what to do next with the available information, making the best possible choice with known risk as a transparent part of the process, and documenting the results for distribution and reuse. Some indicators of poor decision management are late and over budget projects, poor stakeholder buy-in, unutilized expertise, low confidence in decisions, and unjustified, recorded, and reused decisions.

This section provides a brief review of selected decision management methods commonly used in the literature of modular product, platform and family development. It covers only the ones which are high likely to be used during the implementation of the presented research approach. The review includes Quality Function Deployment (QFD), Analytic Hierarchy Process (AHP), co-joint analysis, Multi-attribute Utility Theory (MAUT), and *Accord* decision making system which can handle the uncertainty and incompleteness in design knowledge. The first three methods (QFD, AHP, and conjoint analysis) are dominantly used for developing and discriminating the problem criteria. Robust Decision making system and judgmental modeling manage to capture the uncertainty, incompleteness, and inconsistency in design information during decision-making. This section aims to introduce the selected set of design decision management tools, as some of them will be used for the application of the proposed research methods.

QFD promises quality in meeting customer requirements, engineering principle deployment, criteria discrimination (very important-not important, wanted-unwanted), and alignment between "What is to be achieved" and "How is to be provided". Sivaloganathan et al. [58] have developed a design function deployment method which combines the benefits offered by QFD and computer-aided engineering. It provides a unique chart structure to store the information generated at different stages of the design process. Kreng and Lee [59] have used QFD to deploy the design of modular products in two major phases. Phase 1 is the exploration of design requirements, which combines customer needs, company development strategies, and designers' preference to select proper modular drivers (see Table 31 in Appendix F) through competitive analysis. In phase 2, modular product analysis and linear integer programming are used to establish final module configuration. They have demonstrated that designers can direct a new approach to establish product modules from the relative importance of those chosen modular drivers using an electrical consumer product. A similar module driver-based design strategy will be incorporated in the proposed method to configure modular families in this study. As the study of Kreng and Lee is limited with the design of a single product at a time, Martin and Ishii [56, 60] proposed a two phase-based QFD method to aid companies in developing product platform architectures. The first phase of the QFD is used to identify engineering metrics achieving the customer requirements as it includes the expected range of change in the customer requirements over platform life and the engineering target values from current market to planned future markets. In the second phase of QFD, identified engineering metrics in the first phase are matched with the components. A Generation Variety Index (GVI) for each component in the second phase of QFD is calculated based on the engineering expertise and judgment in estimating the cost of changing in the component to meet the most stringent future engineering metric target values in the first phase of QFD. Similarly, there are QFD applications to capture design information as comprehensive as possible. For example, Marsot [61] has developed a QFD-based methodology to integrate ergonomics at the design stage in a systematic manner.

In addition to being incorporated in different stages of product and family development in many different modified forms, QFD has been also expanded to capture dynamically changing design information and relations and to integrate design information relations and generate design solutions. Adiano and Roth [62] used feedback loops to incorporate updated customer satisfaction data and dynamically link evolving requirements directly back into manufacturing and value chain processes. Updated customer requirements then "peg" the key parameters in statistical process control (SPC) charts. Similarly, Fung et al. [63] adopted the fuzzy inference technique to accommodate the possible imprecision and vagueness during Voice of Customer (VoC) interpretation. Also, Kim et al. [64] developed various models that allow a design team to reconcile tradeoffs among the major QFD components as well as the inherent fuzziness in the system by defining these components in crisp fuzzy way using multi-attribute value theory combined with fuzzy regression and fuzzy optimization theory. Verma et al. [65] presented an expert system extension to they fuzzy QFD methodology with the emphasis on the isolation of inconsistencies between customer articulation of functional requirements and the definition of system requirements and parameter target values. On the other hand, the quantum of benefits obtained from the use of QFD is proportional to the effectiveness of its use. Han et al. [66] developed a new comprehensive hierarchical framework for QFD planning process along with a zero-one goal programming model for the selection of design requirements.

AHP was designed to solve complex problems involving multiple criteria [67]. It allows decision-makers to specify their preferences using a verbal scale. This verbal scale can be very useful in helping a group or an individual to make a fuzzy decision. AHP is developed around three principles: the principle of constructing hierarchies, the principle of establishing priorities, and the principle of logical consistency [68]. The use of hierarchies helps to itemize the alternatives and attributes. Establishing priorities is based on pair-wise comparisons between the alternatives, one criterion at a time. For example, a problem with four alternatives and four criteria requires thirty two comparisons. Then, this data is reduced using a weighted average to find the ranking of the alternatives. The methods allows for checking consistency, the third principle.

Common application examples of AHP in the manufacturing literature include the generation of a set of design layout alternatives and a closeness relationship among planning departments of the alternatives. The user acceptability and confidence in the analysis provided by the AHP methodology is high when it is compared with other multi-attribute decision approaches [69]. The other benefits of AHP include the provision of a systematic way for subjective decision processes, serving sensitivity analysis, giving information about the evaluation criteria’s implicit weights, and providing better understanding and participation among the members of the decision-making group and hence a commitment to the chosen alternative. The literature suggests use of alternative scales (i.e., geometric scale), alternative techniques to estimate the priorities (e.g., eigenvector, logarithmic least squares) for some common shortcomings of AHP. Also AHP robustness can be verified by sensitivity analysis of weights.

Conjoint analysis decomposes overall measures of preference for hypothetical objects into the utility associated with different features or attribute levels making up that object [70]. Conjoint choice simulators use these individual level utilities along with descriptions of potential competitive products to estimate market shares for possible new product designs. One then searches this set of potential designs for the one that will best meet organizational objectives of sales, market share, profits, or cash flow [71]. Pullman [70] compared conjoint analysis and QFD in new product development. With conjoint analysis, they found that it was easier to compare the most preferred features (i.e., ones that maximized sales) to profit maximizing features and also to develop designs that optimize product line sales or profits. On the other hand, QFD was able to highlight the fact that certain engineering characteristics or design features had both positive and negative aspects. Rather than competing, we have viewed them as complementary approaches that should be conducted simultaneously; each providing feedback to the other. When the two approaches differed on the optimal level or importance of a feature, it appeared that conjoint analysis better captured customers' current preferences for product features while QFD captured what product developers thought would best satisfy customer needs.

Multi-Attribute Utility Theory (MAUT) is a commonly used method to provide analytical support to the decision-making process. Multi-attribute utility theory underlies a set of methods for making these choices (for example Pugh's method presented in Section 2.1.2, and Accord which will be presented later in this section is a probabilistic extension of it). All MAUT methods include defining the alternatives and relevant alternative attributes, evaluating each alternative on each attribute, assigning relative weights to the attributes to reflect preference, combining the attribute weights and evaluations to yield an overall satisfaction evaluation of each alternative, and performing sensitivity analysis and make a decision. Utility theory allows decision makers to give formalized preference to a space defined by the alternatives and criteria. For example, in one method, each alternative/criteria pair is given a score reflecting how well the alternative meets the criteria. The scores for each alternative are combined with measures of each criterion's importance (i.e. weight) to give a total utility for the alternative. Utility is a measure of preference for one alternative relative to another. A good introduction of this method is given in [72]. Traditional MAUT methods [73] were developed initially for individuals, but there are extensions for teams. A limitation of all MAUT methods is that information must be complete, consistent, certain and quantitative.

Rittel [74] has developed a decision-making model called IBIS. The IBIS model organizes the deliberation process that occurs during complex decision-making into a network of three data elements: Issues, Position, and Arguments. An Issue is an identified problem to be solved by deliberation. Each issue can have many Positions that are proposed solutions developed to resolve the issue. Each position can have any number of Augments that support or oppose that position. In the 1980s IBIS was applied and extended to support software design and information capture. Below, in Figure 8, Ullman [57] summarizes what is known about the information managed during decision-making, the activities used to develop and refine the information, and strategies used to manage the activities. In the model, each of the class information and their relationships are based on the IBIS model.

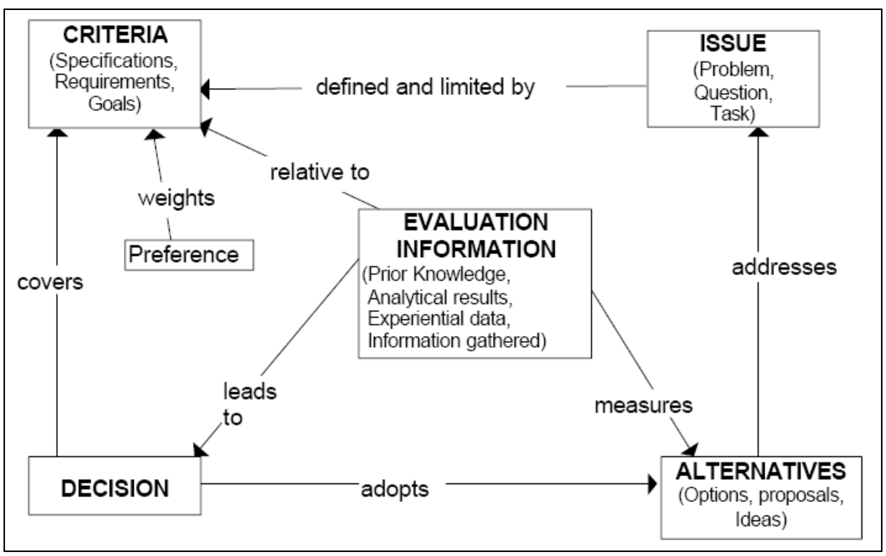


Figure 8: Decision-making information [57]

In Figure 8, an issue is defined and limited by the criteria used to measure its resolution. Issues are generally expressed as the desire to change, design, redesign, create, fix, develop, or choose an object which meets a number of stated and unstated criteria. Criteria limit solutions raised by an issue. The term “criterion” is used synonymously with “requirement”, “goal” or “specification” as all limit the space of acceptable solutions for the issue. There are two major parts to a criterion, the attribute of the alternative measured and a target value for the attribute. Each stakeholder has preference for how important s/he feels that each criterion is to the successful resolution of the issue. The combination of the criteria and the preference for them is often called the value model because their combination is used to measure or place a value on the alternatives.

An alternative is an option generated to address or respond to a particular issue. The goal of the decision-making is to find an alternative that the decision-makers agree to adopt. Alternatives are often called “options”, “ideas”, “proposals”, or “positions.” Any number of alternatives may be developed to resolve a design issue.

Evaluation information comprises the results of determining how well the alternatives resolve the issue. Evaluation is the activity of argumentation supported by information developed through prior knowledge, analysis, experimentation, or information gathering (e.g. expert advice). Argumentation measures alternatives with respect to criteria, and these arguments lead to agreements. A decision is the agreement to adopt an alternative(s) to resolve the issue. Decisions are dynamic; they may later be changed as criteria and preferences change, and as new alternatives are generated.

Using the model in Figure 8 and based on the relevant research in the literature, Ullman [57] has first identified the elements of the ideal decision support system and developed a method called Accord to meet the ideal. Accord uses a form of MAUT with probabilistic underpinnings. The method is an extension of MAUT, built on inference using Bayesian Networks [75]. This probabilistic methodology allows for calculating satisfaction and other results from inconsistent, incomplete, uncertain and evolving information. Accord supports the management of knowledge and confidence, necessary components of uncertain and evolving information for team decision-making. Similar effort to Accord, Yang et al. [76] have developed a prototype group decision-making system that is able to handle fuzziness and imprecision in the evaluation of decision alternatives. The developed system utilizes fuzzy systems theory to rank criteria and recommend an optimal decision alternative

2.3.2 Methods for Evaluating Product and Platform Concepts

As the previous section has presented examples of systematic decision-making processes in product and family development, this section presents three studies in identifying what actually to measure in product and platform concepts systematically. Presented concepts can potentially be used during the implementation of the presented research approach in this document. This section first introduces a user oriented product performance analysis approach of Cagan and Vogel [77]. Their approach can be used in assessing multiple product concepts for the same market grid which could be generated from many platform alternatives. Then, multi-criteria oriented product and product platform evaluation methods are discussed. These methods will help identify how to measure characteristics of product platform concepts which will be integrated into the effort of generating a single performance score.

Cagan and Vogel [77] have developed a user experience oriented approach to product performance analysis in terms of specifying attributes that contribute to a product's usefulness, usability, and desirability, and connect a product's features to those values. Fulfilling a fantasy by facilitating a more enjoyable way of doing something, a set of opportunities to add value to a product, called Value Opportunities (VOs), is defined. These seven Value Opportunity classes—emotion, aesthetics, identity, ergonomics, impact, core technology, and quality—each contribute to the overall experience of the product and relate to the value characteristics of useful, usable, and desirable. The ergonomics, core technology, and quality VOs address the satisfaction of the product during use, both immediate and long-term. Social and environmental impact, product identity, and aesthetics VOs each address lifestyle aspects of the consumer. The emotion VO connects most directly with the consumer's fantasy in using the product.

Considering the integration of multiple design drivers, goals, constraints, and their relationships into design of any artifact including product platforms, it is impossible to evaluate design concepts from a single perspective. In a general sense, designers' intention is to create product solutions, which are profitable for the company, and fulfilling customer requirements and other standards (i.e., safety, government and environment regulations) within a limited budget, development time, and manufacturing capacity. This requires a comprehensive and systematic product development processes and evaluation. Therefore, multi-criteria evaluation frameworks for screening product concepts are advised [2]. Ye et al [78] present a list of ten factors that affect product family design. These factors include customization, market life, technological innovation, family size, complexity, development time, service, and maintenance, environmental impacts, manufacturing cost, and product volume. Similarly, Otto and Holtta [2] proposed a framework of 19 metrics for multi-criteria product platform evaluation. The metrics are grouped into six categories: customer, variety, flexibility, complexity, organization, and after-sale. Both approaches strive to achieve a life-cycle product family development and evaluation strategy.

Following includes a short summary of commonly used evaluation techniques in the literature for determining, generating, and selecting robust design concepts from the life-cycle perspective. Presented techniques are not intended to be exhaustive, nor must every product and product family design account for all of them.

Pine [34] describes customization as a technique to deliver products in a product family that meet each unique customer's requirements. One *measurement of customization* is the number of unique products divided by the number of unique sets of customer requirements [78]. For example, a computer mouse family based on different sets of customer requirements such as left handed, right handed, wired/wireless, 2 buttons/3 buttons increases customer satisfaction [78]. However, customizable products, depending on the envelope of variety, may increase cost due to the need to have different life-cycle processes for each product. Otto and Holtta [2] present three metrics to measure how well a platform achieves the goal of easy enabling product variety: *carryover, common unit, and different specification* [2]. If a specific function can be incorporated into different products without change and no technology upgrades are expected, then the function should be isolated into a module [79]. To capture this, the following platform metric was created.

$$Y_{carryover} = 10\left(\frac{\#\,functions\_to\_carryover}{\#\,functions}\right)$$

If a function is shared by more than one product in a product family or used more than once in a single product it is called a common unit. Otta and Holtta [2] also created a scale given scores from 0 to 10 (0 requiring unique interface for each variant, 10 can be swapped into any variant with no changes) to identify the functions that distinguish each product variant. Mikkola and Gassmann [17] include similar metrics to drive a modularity function for the same evaluation purposes. Additionally, Holtta-Otta et al [80] introduce a method to help choose a common modules for platforms based on the Euclidian distance between the modules inputs and outputs. Among all, methods for commonality evaluation that generate *commonality indices* are seen the most frequently. A commonalty index is a metric to assess the degree of commonality within a product family based on the number of common components, the components costs, the manufacturing process, etc. [81]. *Different specification* means that there are more than one variation of a function or a module. Similar to the carryover metric, it is defined as a ratio of number of functions with different specification to number of functions [2]. The score for the product is the average of the modules' normalized scores.

If the essence of variety is to meet different customer requirements, to what extend a design concept meet the customer needs should also be measured. Ideally, a robust product should *add value* and *meet the customer requirement* [2]. To assess the former, Baldwin and Clark use a cost-worth approach for each module[46]. Ideally, the cost to worth ratio is one. If larger, the module's costs should be reduced; if lower, there is room for improvement in a module since a customer values it more that what it is worth. Similarly, Otto and Holtta [2] uses a scale of 10 based on a similar cost-worth approach. Additionally, they employed a modified Quality Function Deployment method to compare the product variant's ideal target on each requirement to what the platform can actually provide as presented below.

$$Y_{CR} = 10 \sum_{products} w_i \left(\frac{1}{M} \sum_{\mathrm{Re}\,quirement} (y-\tau)^2 \right)^{1/2}$$

Where w_i is the revenue weighted importance of product i, M is the number of requirements, y is the requirement level provided by the platform, and τ is the desired target for the requirement for the product variant.

Market life represents the time that one product family generation exists in the market [78]. A *measure of market life* can be calculated as the longest time a product from a particular generation of product family is marketed. Longer product family market life is likely to result in enhanced variety across a product family, satisfying more unique sets of customers.

The number of new technology applications across the life-cycle of product families can be used as a measure of innovation. Innovation can be pursued by implementing the existing technologies from other companies, and by developing completely new technologies [78]. Similarly, Otta and Holtta [2] present four metrics to assess how well the platform helps organization the development of the products in question and improves the development and production: *assembly ease, drive the organization, make-buy, and testing*. Based on the existing work of design-for-assembly (DFA) [82], an assembly metric for any module can be calculated as:

$$Y_{assembly} = \frac{3n}{\text{Assembly Time}}$$

where n is the number of modules in a product. For a *measure of drive the organization*, Otta and Holtta (2004) define an organizational alignment metric as extending the Design Structure Matrix (DSM) approach of Sosa et al [83]. This metric calculates the ratio of components in teams and components in modules to components in teams or components in modules. A scaled *metric for make-buy* assessment can be defined by dividing the number of outsourced components by number of components. Lastly, if a function needs separate testing, it should be isolated as a module. A scale measurement from 0 to 10, where 10 is direct measure of the flow in field conditions and 0 is no measurement done, is presented by Otta and Holtta [2].

Family size is the total number of different types of products in a product family [78]. While providing more product offerings satisfies a wider range of customers, a wider family size increases the complexity of design and manufacturing processes, and hence it increases cost.

Product family complexity is related to the amount of material, energy, and information needed to describe the products in the family [78]. Increasing the complexity of product may require more unique components and technologies. Otta and Holtta [2] assess the complexity by four metrics: *function and form alignment, redesign complexity, anti-synergy management, and alignment attachment distinction.* The *metric for function-form alignment*, a product is penalized if it has parts that are in more than one module. An example is a photocopier with a belt, where the belt is part of both the ink transfer module and the image transfer module. Also, modules whose parts are in more than one separate location are penalized. For example, an elevator where the control module has a user interface on the cab and a motor controller in the machine room. In the metrics, these two parameters (#parts in more than one module and #separate locations with the module's parts) are multiplied with separate difficulty weights. *Redesign complexity* score is calculated from the family function structure as the ratio of #intermodule interfaces to total redesign complexity weights is considered. One simple way of *assessing anti-synergies* is based on the interactions between the input and output flows of a module and their interactions with other modules' flows. To assess responses of a product against extreme requirement challenges throughout the development process, Otta and Holtta [2] present a metric, in which the new requirements of the architecture under development is compared with the requirements of the current model in the market.

Manufacturing companies need to compress *development time* to respond market quickly. Ulrich and Eppinger [31] define development time as the time required for the sequences of steps or activities, which an enterprise employs to conceive, design and commercialize.

Service and maintenance is what manufacturing companies provide to customers after the sale of a product [78]. The following three metrics evaluate how well the products will do after it has been sold to the customers and after customer is done using it: *reliability, service ease, and environmental friendliness* [2]. For *reliability*, common failure modes and effect analysis (FMEA) can be done to consider an opportunity to relax uniform failure mode assumption. Dahmus and Otto [84] derive rules for portioning a product based on service costs, using the service cost models of others. Their model shows that isolating two modules as two services module minimizes service costs. Otto and Holtta [2] use this principle to calculate a scale of 10. *Environmental friendliness* is another important factor to measure, as recycling as become increasingly important driver of modularity. Ye et al [78] describe environmental impacts as the influences on the environment caused by the materials and processes of a family of products during their complete life-cycle, for example, emission, waste, and energy consumption. The literature implies given scores from 0 to 4 (0 being worst) to different matter in different phases of a product's life-cycle [85].

Manufacturing cost is the total cost of the physical realization of the product from the design [78]. Boothroyd et al [82] suggest that the total manufacturing cost can be modeled as a combination of material costs, production costs, and purchase costs. Common cost analyses of product development include activity-based costing methods [86] and economies of substitution of components within a product or across product families techniques [87], [88].

Product volume is the total number of products across as a product family [78]. There are two ways to increase the production volume-increase the volume of each product in a family (increasing market share) or expand the number of different types of products in a family (increasing market size) [78].

2.4 Clustering Techniques and Their Use in Product Design

The research approach presented herein helps design teams generate product modules by defining product commonalities across multiple design dimensions. For this purpose, a clustering method is proposed. As presented above, it is common to tackle the issue of finding the appropriate modular platform options as an optimization exercise [15, 25]. Generally, such optimization approaches yield final configurations of modules, identification of the optimum degree of commonality, and optimum settings for the common modules as maximizing the level of meeting the requirements of each variant. The performance of the most optimum product and/or product platform architecture is assessed to underline its benefits. The existing optimization methods are beneficial in providing fast and quantitative optimal results. Unfortunately, they are difficult to modify to accommodate dynamic design requirements within the same product family (e.g., optimizing the products of the same family towards different numbers of modules) and their set-up requires specialized expertise. Additionally, the methods are really not helpful for design teams to identify opportunities for improvement for non-optimal product variants and multiple platforms. This limits the existing optimization methods in being a practical application and easily adaptable to the real-time changes in product development strategies.

In contrast, the proposed clustering method is believed to provide a more flexible, easy, and intuitive method to define product modules and platform alternatives. In clustering, relations among the input and output variables do not need to be well defined. Instead, a clustering algorithm looks for patterns for how data resemble each other in a given set of dimensions. Found patterns in data constitute constraints and relations among the variables. This also makes it easy to modify the clustering attributes. While the technique of clustering is not new, it remains strategic for many applications. The process involves classification of existing data such that the variation in the data in the same group is as low as possible and that between groups is very high. Therefore, it is intuitive and easy to deploy.

Clustering is the classification of objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait-often proximity according to some defined distance measure [33]. The major difference between clustering analysis and Analysis of Variance (ANOVA) is that clusters are predefined in ANOVA. Clustering analysis finds the clusters that would most likely resemble the data set subgroups itself from a selected perspective. In contrast, ANOVA identifies the variance between and within the given clusters.

Data clustering algorithms can be hierarchical or partitional (non-hierarchical) [33]. Hierarchical clustering is a way to investigate grouping in a data set, simultaneously over a variety of scales, by creating a cluster tree [89]. Hierarchical algorithms can begin with each element as a separate cluster and merge them into successively larger clusters (agglomerative) or can begin with the whole set and proceed to divide into successively smaller clusters (divisive). The partitional (non-hierarchical) typically partition the data into k clusters, where k is user defined number of clusters to be formed. In general these techniques work by selecting "k" initial partitions and then altering the memberships objects in those partitions to obtain better partitions.

An important step in any clustering is to select a distance measure, which will determine how the similarity of two elements is calculated. This will influence the shape of the clusters, as some elements may be close to one another according to one distance and further away according to another [33]. Common distance functions are Euclidean distance, Manhattan distance, and Chebyshev norm. Additionally, these distance metrics can be applied to construct clusters in different approaches: linkage-based methods, the centroid-based method, and nearest neighbor method (density-based method).

In addition to the type of clustering and the distance measurement technique, results of a clustering problem depend upon the selection of variables. The selection of "good" variables may come about with a fair bit of trial and error complemented with the analyst's intuition and background knowledge of the data set. Selection of "unwanted" variables leads to clusters that do not present an informative structure. Additionally, “goodness” of the clustering solution should be measured using various indices. This is an inexact science and requires some degree of subjectivity.

Data clustering has been used as the process of extracting valid, previously unknown, and easily interpretable information from large databases in order to improve and optimize engineering design and manufacturing process decisions [90, 91]. In the conceptual design stage, examples encourage using data clustering approaches to aid decision-making when selecting design concepts by extracting design knowledge and rules, clustering design cases, exploring interactively conceptual designs in large product development databases [91]. From the product family and platform development perspective, there are not many examples of data clustering techniques. Moon et al [92] describe a method for supporting product family design that consists of clustering design knowledge by their similarity based on functional features. The clustering result identifies the platform and its modules by a platform level membership function and classification. The method was applied to a case study involving a power tool family to determine a new platform. As the method application has not been expanded to large databases yet, its application is limited with defining single platform concept.

Chapter 3 : Approach and Methodology

The main research objective is to support product development teams in designing product families along with providing distinctive module and multiple platform concept definitions. The research is applicable for product families in which product varieties are accomplished by swapping product modules to address a set of market applications. Sets of modules that are shared by relative products define platform concepts.

For this research, a product module is defined as a collection of product components. A product component can include physical component(s), part(s) as well as design information/knowledge (i.e. tire tread design, mold design, and logical elements). A product component is defined by a set of its design characteristics. Such set may include geometric dimensions, material density, material flexibility, logical elements, and other characteristics like weight, look, etc.

According to the definitions above, a product module does not need to be a subassembly; it can include parts which cannot be detachable from each other. This could be the case for a module definition that includes both component material physical characteristics and component gauge dimensions. Such modules are referred to as integrated modules, as discussed in Chapter 2. The proposed research method is applicable when product modules are both subassembled as well as integrated.

The proposed research approach and methodology addresses the re-design of existing product families for the elimination of insignificant design differentiations. Mass design (common design as much as possible) should be the motivation of the re-design effort for this scenario.

An overview of the research approach and methodology is illustrated in the flow chart of Figure 9. It consists of 4 steps that a product design and development team would follow from, identifying common product performance areas to defining product modules and platform alternatives. This research is motivated by common market requirements.

Common market requirements, which customer groups in all target market segments demand for no extra price, need to be identified. The research assumption here is that such common customer requirements will help identify key product performance areas for developing and designing modular product families.

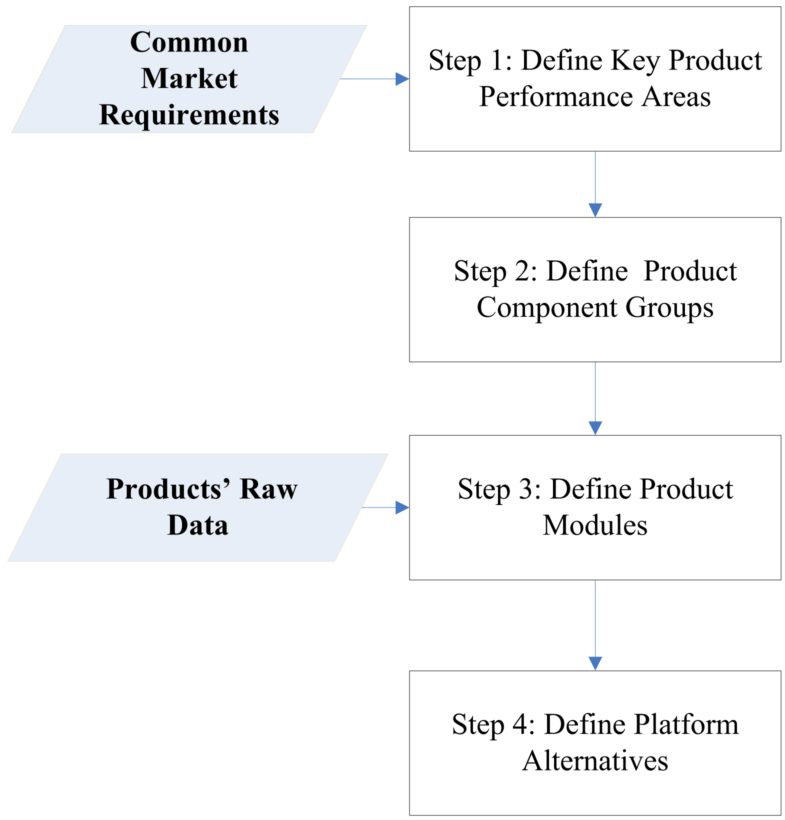


Figure 9: Research approach and methodology overview

Figure 10 displays the tools to support decision-making in the presented research approach. Quality Functional Deployment (QFD) based tools are used to identify the critical design information. For example, in Step 1, key product performance areas are determined by identifying the product performances critical to meet common customer requirements using a QFD matrix survey. Similarly, product components in Step 2 are the components vital to achieve the selected product performance areas, and they are determined using a QFD matrix. In Step 2, functional design structure matrix (DSM) is used to form the product component groups based on functional relations and dependencies among them. Another QFD based approach is used in Step 4; module identification matrix (MIM). This matrix is adapted to investigate the reasons for module variations.

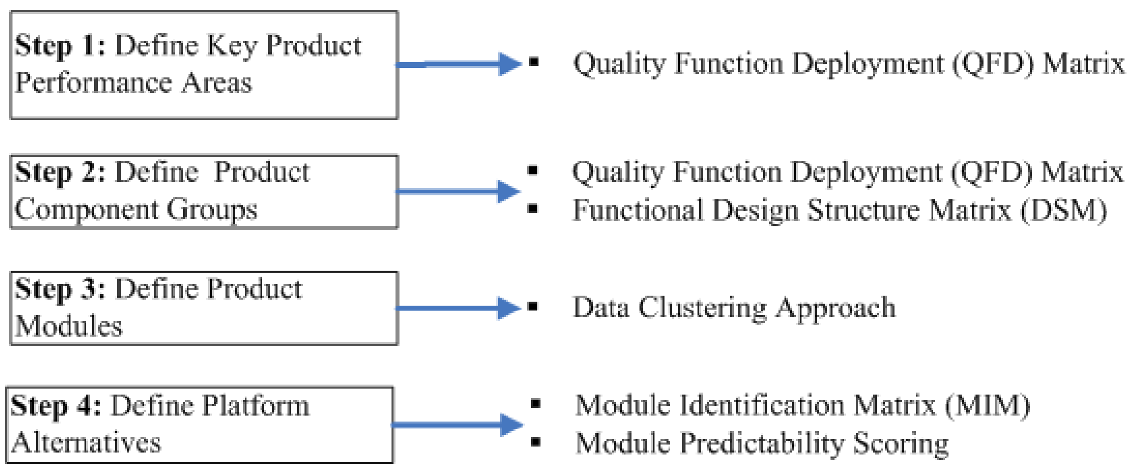


Figure 10: Research tools overview

Step 3 in

Figure 10 in, the data clustering approach includes a set of tools; a data refining method, a data discrimination method and a data clustering algorithm. In this research, product modules are generated by identifying design similarities across existing products using K-means, an unsupervised data clustering algorithm. Critical design characteristics, where the similarities will be searched for, are derived from the previously determined critical design information. Data refining is achieved using the adjusted approach of the principal component analysis (PCA). Additionally, similarities and differences among the generated product modules are investigated using the Kruskal-Wallis test in Step 3.

Once the modules are defined clearly, how they work with each other to derive product variants is investigated in Step 4. To achieve that, with the help of the adapted MIM, product modules are classified based on their platformabilities to define a platforming strategy. Module predictability scores in Step 4 are calculated based on how common a group of modules is in order to define a particular product variant when the platforming strategy is applied. For each platform alternative, a score is calculated to show its predicted uniqueness to generate products.

The remainder of this chapter provides a more detailed discussion of the steps of the research approach presented in Figure 9 and the use of the tools presented in Figure 10. In Section 3.1, common customer requirements for no extra price across target market segments are used to determine critical design information. QFD based approaches are used in Sections 3.1-3.4 to capture and manage the critical design information, their relations and dependencies to make decisions. Section 2.2 presents different definition perspectives to product modules. This information is adapted in Section 3.4 to define product platform architecture strategy. Section 2.4 pinpoints potential usages of data clustering approaches for designing product families as discussing requirements and steps of such methods. In this chapter, Section 3.3 introduces the data clustering technique employed in the research method to identify the product design information similarities within multiple product families to define product modules.

Additionally, in Section 3.5, the research hypotheses are revisited from Section 1.4, an outline for the strategy for verification and testing of the research hypotheses is discussed.

3.1 Step 1: Define Key Product Performance Areas

In this step, key product performance areas are identified for the targets of the platforming effort. As shown in Figure 10, a basic customer-requirements product-performances QFD matrix is used to identify key product performance areas linked to the common customer needs.

As an example, Table 2 presents a simplified QFD matrix for a vacuum cleaner. For the presented 5 customer requirements in Table 2 , vacuum power is the critical performance attribute, as the vacuum weight is found not as significant for the design. Therefore the design of the vacuum cleaner should be optimized around the vacuum power efficiency primarily.

Table 2: A simplified QFD matrix for a vacuum cleaner

Customer Requirements \ Performance attributes	Weight	Noise level	Power	Opening force (lid)
High suction performance			9	
Low price			9	
Low noise		9		
Easy maintenance				9
Easy storage	1			

The QFD approach presented in Table 2 is for the single product design problem. It is adapted to define key product performance areas for platforming problems in this research. The customer requirements are decided to be the common requirements across target market segments demand for no extra price. The research assumption here is that such common customer requirements will help identify key common product performance areas for developing and designing modular product families.

3.2 Step 2: Define Product Components Groups

Similar to Step 1, Step 2 uses a QFD approach to identify critical product components for product platform and family development. In Figure 9, product components such as physical components, component materials, design logic relations, etc. are identified to achieve the common customer requirements using a product-components product-performances QFD matrix. For the vacuum cleaner example, three components, chassis, motor and fan, are selected as the critical product components for vacuum power, key product performance feature identified in Step 1.

Furthermore, functional relations among the selected product components are determined using the design structure matrix (DSM) approach as demonstrated in Table 3. A list of functions commonly used in engineering fields is presented in Appendix F. DSM is a system modeling tool which can represent a larger number of system elements and their relationships in a compact way that highlights important patterns in the data (such as feedback loops and modules) [93]. Larses and Blackenfelt [94] identify four interaction types, spatial (S), energy (E), information (I) and material (M), in a functional DSM as demonstrated with the vacuum cleaner example in Table 3. In the example, selected vacuum cleaner components' interactions (interactions between the vacuum chassis, fan, and motor) are investigated in terms of these four types of interaction; S, E, I, and M as shown in Table 3. For the example, vacuum chassis, motor and fan are selected as the critical components and the found component interactions are presented in the functional DSM in Table 3. The vacuum cleaner chassis and motor have to be in a spatial proximity in the vacuum cleaner design as only the "S" box is filled in Table 3 to represent such interactions between them. Similarly, the motor and the fan are also joined by a spatial connection. However, Table 3 indicates another type of interaction between the motor and the fan. In addition to the required spatial proximity between them, electric current is transmitted from the motor to the fan as the "E" box is filled in Table 3 to represent such interaction.

Table 3: A simplified functional DSM for a vacuum cleaner

	Chassis		Motor		Fan	
Chassis	S	M	2		1	
	I	E				
Motor			S	M	1	
			I	E		2
Fan					S	M
					I	E

Additionally, the interactions are scored in the functional DSM. For example, the spatial interactions are given scores as follows: physical adjacency is necessary for functionality (+2), physical adjacency is beneficial, but not absolutely necessary for functionality (+1), physical adjacency does not affect functionality (0), physical adjacency causes negative effects but does not prevent functionality (-1), and physical adjacency must be prevented to achieve functionality (-2). For interactions of energy (E), information (I) and material (M) type, physical adjacency is represented as replaced energy transfer, information exchange, and material exchange respectively.

In this research, the functional DSM approach discussed above is proposed to define component groups by investigating the functional relations between them. As the interactions are assumed very high within each component group, they are assumed weaker among the groups. Thus, another research assumption is that the found product component groups can be treated independently for a clustering analysis to define product design modules in further research steps.

For the vacuum cleaner example, the key product functionality is found as vacuum power efficiency as demonstrated in Table 2 during the Step 1 discussions. From Table 3, motor and fan could be grouped together due to the necessary energy transfer for the vacuum power functionality and their similar spatial interactions with the chassis for the product functionality. Similarly, the chassis could form a single component group. As a result, two component groups could be defined for the vacuum cleaner example using the functional DSM, namely (1) motor and fan, and (2) chassis as displayed in Table 4.

The next step in the vacuum cleaner example requires investigating similarities across a set of vacuum cleaners in the motor and fan, and the chassis groups separately. From this, types of motor and fan, and chassis modules will be formed for the set of vacuum cleaners. To achieve this, these two component groups need to be defined in terms of their key design characteristics impacting the vacuum power efficiency (key product performance). As listed in Table 4, the following key design characteristics are speculated for the two vacuum cleaner component groups: motor power, motor weight, motor type, fan size, fan power, fan weight, chassis strength, chassis size, and chassis weight. These design characteristics form the original clustering attributes for the clustering approach to generate different types of motor-fan and chassis modules. The vacuum cleaners will be classified in terms of their similarities across motor power, weight, and type, fan power, weight, and size to define types of motor-fan modules and chassis strength, size and weight to define types of chassis modules.

Table 4: Speculated original clustering attributes for the vacuum cleaner example

Motor-fan component group original clustering attributes	*Chassis component group original clustering attributes*
Motor power Motor weight Motor type Fan power Fan weight Fan size	Chassis strength Chassis size Chassis weight

In a general view, each product component group from the functional DSM analysis is defined in terms of a set of unique critical design characteristics, referred as the original clustering attributes for the data clustering approach. Original clustering attributes can be product specifications, component dimensions, material physical characteristics, or logical elements (of electronic circuits), etc. As seen in the vacuum cleaner example, for instance, a total of two sets of original vacuum cleaner clustering attributes are defined: (1) motor power, weight, and type, and fan weight, power, and size, and (2) chassis strength, size, and weight. Original clustering attributes are relevant to the key platforming performance areas defined in Step 1.

The determination of the original clustering attributes is a very crucial sub-step in the presented research approach, since product modules will be determined solely based on similarities in these attributes. A cross-department consensus should be established to determine appropriate clustering attributes which are good representatives of component groups impacting the key performance areas. The construction and the number of clustering attributes can vary from one component group to another.

3.3 Step 3: Define Product Modules

In Step 3, types of product modules for each component group are defined by conducting an unsupervised clustering analysis, K-means cluster analysis. Clustering uses the original clustering attributes defined in Step 2. The research assumption is that products with indistinguishable differences in a set of clustering attributes can be grouped in the same cluster (module) where such existing differences do not create significant key performance differences. In other words, performance differences within the products assigned to the same set of design modules (clusters) are not distinctive enough.

K-means is an algorithm to cluster objects based on attributes into k partitions [95]. As shown in the formulation (1), focus of the algorithm is to minimize an objective function, in this case the squared error function

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} \left| x_j - \mu_i \right|^2 \qquad (1)$$

where there are k clusters S_i, $i = 1,2,..,k$ and μ_i is the centroid or mean point of all the points $x_j \in S_i$. In terms of performance, the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters. Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. Another main drawback of the algorithm is that it has to be provided the number of clusters (i.e. k) to find. Scaling of variables is an important consideration. If variables are measured on different scales (for example, one variable is expressed in dollars and another variable is expressed in years), results may be misleading. In such cases, variable standardization before performing the K-means cluster analysis should be considered. K-means is a simple algorithm that has been adapted to many problem domains.

Original clustering attributes (critical design characteristics), which will be actual product module attributes in this research, specific to each component group are already determined in Step 2. The clustering attributes are very crucial, since product modules will be determined solely based on similarities in these attributes. A research assumption is that products with insignificant differences across a set of clustering attributes (critical design characteristics) can be grouped in the same cluster (module) where such insignificant differences do not create value-adding performance differences. In other words, performance differences within the products assigned to the same set of design modules (clusters) are not significant.

The raw product data for the original clustering attributes must be pre-processed in order to suitably group the data based on these attributes. Principal component analysis (PCA) is used in this research to ensure that the variables used for the clustering stage are orthogonal. It serves the purpose of representing the data in a lower dimension. PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on [96]. PCA involves the computation of the eigenvalue decomposition or singular value decomposition of a data set, usually after mean centering the data for each attribute. This enables such a technique to work well even with datasets that contain outliers. The results of a PCA are usually discussed in terms of scores and loadings.

PCA is a popular technique in pattern recognition, but it is not optimized for class separability. Assuming a zero empirical mean (the empirical mean of the distribution has been subtracted from the data set), the reduced-space data matrix *Y* is determined by projecting the *X* data set into the reduced space defined by only the first *L* singular vector, W_L,

$$Y = W_L^T X = \Sigma_L V_L^T \tag{2}$$

The matrix *W* of singular vectors of *X* is equivalently the matrix *W* of eigenvectors of the matrix of observed covariances $C = XX^T$,

$$XX^T = W \Sigma \Sigma^T W^T \tag{3}$$

The eigenvectors with the largest eigenvalues correspond to the dimensions that have the strongest correlation in the data set. In this research, the cut off for the factors was chosen as 0.7 for the eigenvalues [97].

Furthermore, the factors obtained from the PCA are adjusted for the variance present in the original variable space. This is accomplished by standardizing the factors and then multiplying the standardized factors by the square root of eigenvalues [98]. In this way, each factor becomes an adjusted factor bringing a varying amount of influence in the clustering procedure. The influence exerted by each adjusted factor is dependent on the variance in the original variable space. In this research, K-means analysis is carried out on the adjusted factors, not the original clustering attributes determined in Step 2.

For the K-means analysis, the measure of dissimilarity is chosen to be the Euclidean distance. Several clustering solutions must be evaluated to find a suitable clustering solution. To a certain extent, the selection of a suitable clustering solution depends on the analyst's intuition about the data. In order to explain the separation of the clusters and validate the clusters in the original variables space (since the clustering is carried out on the factors obtained from the PCA) a non-parametric discriminant analysis, Kruskal-Wallis testing procedure is performed. The Kruskal-Wallis test is one-way analysis of variance by ranks. It tests the null hypothesis that multiple independent samples come from the same population. Unlike standard ANOVA, it does not assume normality, and it can be used to test ordinal variables.

Kruskal-Wallis method ranks all data from all groups together and assigns any tied values the average of the ranks [99]. The test statistics are given by;

$$K = (N-1)\frac{\sum_{i=1}^{g} n_i(\bar{r}_i - \bar{r})^2}{\sum_{i=1}^{g}\sum_{j=1}^{n_i}(r_{ij} - \bar{r})^2} \tag{4}$$

Where n_g is the number of observations in group g, r_{ij} is the rank (among all observations) of observation j from group i, N is the total number of observations across all groups, and $\bar{r}$ is the average of all the r_{ij} as shown in (5).

$$\bar{r}_i = \frac{\sum_{j=1}^{n_i} r_{ij}}{n_i} \tag{5}$$

After a correction for ties is applied, the p-value is approximated by

$$\Pr(\chi^2_{g-1} \geq K) \tag{6}$$

The null hypothesis of equal population medians would be rejected if $K \geq \chi^2_{g-1}$.

Result modules are defined in terms of their average clustering attributes as the differences between the modules are determined from the summary of Kruskal-Wallis test results. For Kruskal-Wallis, statistical differences between the modules for each original clustering attributes are tested for the 10% level in this research approach. To associate the module definitions with the existing product designs, a representative product for each module is investigated. A representative product represents the real data set which is ideally identical to the module definitions. It is determined by selecting product(s) whose distance to the module center is the least. This can be determined from the distributions of the product distances from their module centers. Products with the lowest distance in the distributions are selected as the representatives. Discrepancies between the characteristics of the representative products and the module definitions, if any, should be discussed for potential design improvement opportunities.

Here, abovementioned data clustering approach for product module definition is applied to the vacuum cleaner example. Applying this research step, vacuum cleaner motor-fan and chassis module types within 30 vacuum cleaners are determined and defined. Product modules are defined based on the similarities of the 30 vacuum cleaners across the original clustering attributes presented in Table 4 separately. In other words, design similarities between the 30 vacuum cleaners across motor weight, power, and types and fan power, weight, and size are investigated to define the types of motor-fan modules. Likewise, design similarities between the 30 vacuum cleaners across chassis strength, size, and weight are investigated to determine chassis module types.

To achieve successful module determination, the adjusted PCA approach is applied to eliminate highly correlated original clustering attributes within the 30 vacuum cleaners. Below, Figure 11 presents the resulting eigenvalues of the principal components extracted for the vacuum cleaner motor-fan group data set. As suggested earlier (principal components with the eigenvalues equal to or higher than 0.7), the motor-fan data set for the 30 vacuum cleaners can be represented in terms of the first two principal components in Figure 11, instead of using all 6 original clustering attributes. It is found that not all 6 clustering attributes are significantly different design dimensions within the 30 vacuum cleaners; so that the same data set can be represented in a lower dimension; 2 factors (first two principal components) from Figure 11.

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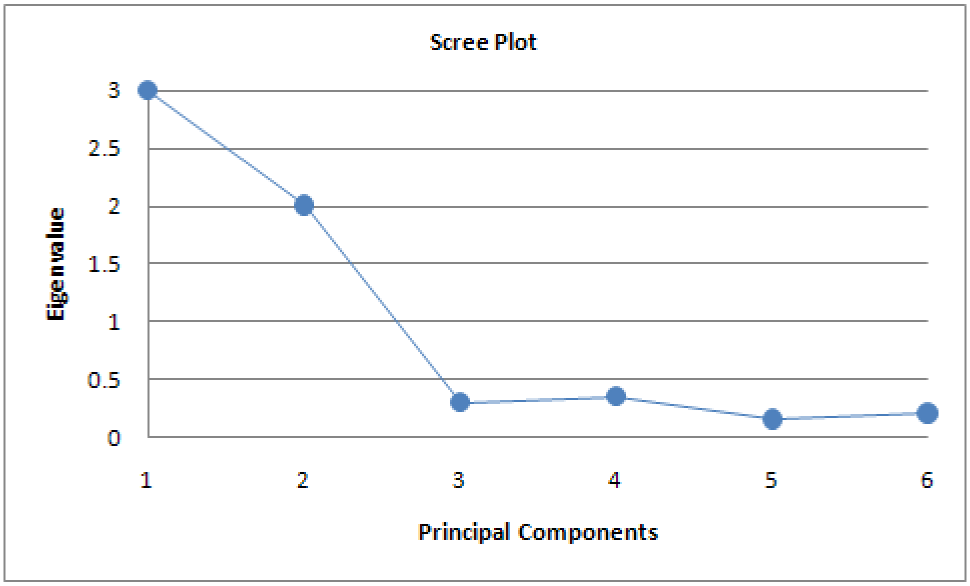


Figure 11: Resulting eigenvalues of the principal components for the vacuum cleaner motor-fan group

Table 5 shows the relations between the selected two factors from the PCA for the vacuum cleaner motor-fan group and the group's original clustering attributes. As shown in Table 5, Factor 1 is most highly correlated with motor and fan power. Motor power is a better representative, however, because it is less correlated with the second factor. Similarly, the second factor is most highly correlated with motor weight and type.

The results of the PCA for the motor-fan product component group show that 2 factors which are most highly correlated with motor weight, type, power, and fan power can explain a fair amount of the variability in the six original attributes, so the data set complexity can be reduced considerably for the following data clustering. Similarly, the PCA is carried out on the original clustering attributes of the second vacuum cleaner component group, the chassis group.

Table 5: Vacuum cleaner motor-fan group extracted factors-original clustering attributes matrix

Original clustering attribute	Factor1	Factor2
Motor power	0.957	0.1
Fan power	0.85	0.43
Fan weight	0.53	0.2
Motor weight	0.15	0.9
Motor type	0.03	0.85
Fan size	-0.53	-0.68

K-means clustering is carried out on the factors obtained from the PCA for the two vacuum product component groups separately. The resulting number of clusters for each component group indicates the suggested number of module types. For example, the clustering solution for the motor-fan product group results 5 clusters, which suggest 5 types of motor-fan modules across the 30 vacuum cleaners. Similarly, the clustering solution for the chassis component group results 3 clusters which suggest 3 types of chassis modules within the 30 vacuum cleaners.

Exact definition of each module type, however, is interpreted in terms of the product group's original clustering attributes. For instance, all 5 motor-fan module types as the clustering solution are interpreted in terms of this component group's original clustering attributes presented in Table 4; motor power, weight, and type, and fan size, power, and weight. In addition, the differences between the suggested module types for each original clustering attribute are determined by carrying out Kruskal-Wallis at the 10% level. Below, Table 6 shows the Kruskal-Wallis test results for the five vacuum cleaner motor-fan modules for all corresponding original clustering attributes. As presented by the table on the left upper corner of Table 6, motor-fan module 4 is unique in terms of its motor power, since the Kruskal-Wallis test results are all zero for the pair similarities of module 4 with the remaining 4 motor-fan modules. However, it is found that motor-fan module 1 is not significantly different from all the other modules, but most similar to module 3. In terms of their fan weight and size attributes, all 5 motor-fan modules are found significantly different from each other as presented in the corresponding tables in Table 6.

Table 6: Kruskal-Wallis test results for the suggested five vacuum cleaner motor-fan modules

Motor power	1	2	3	4	5
1	x	0.2	0.9	0	0.16
2		x	0.08	0	0.4
3			x	0	0.08
4				x	0
5					x

Fan power	1	2	3	4	5
1	x	0	0	0	0
2		x	0	1	1
3			x	0	0
4				x	1
5					x

Motor weight	1	2	3	4	5
1	x	0	0	0	0
2		x	0.37	0	0.37
3			x	0.04	0.171
4				x	0.002
5					x

Fan weight	1	2	3	4	5
1	x	0	0.05	0	0
2		x	0.03	0	0
3			x	0.02	0
4				x	0
5					x

Motor type	1	2	3	4	5
1	x	0	0	0	0
2		x	0.6	0	0.37
3			x	0.04	0.171
4				x	0.002
5					x

Fan size	1	2	3	4	5
1	x	0	0.05	0	0
2		x	0.03	0	0
3			x	0.02	0
4				x	0
5					x

Table 7 summarizes the found similarity relations among the five vacuum cleaner motor-fan modules in Table 6. The summary is achieved using a relative scale from low to high based on the module averages for each original clustering attribute as the Kruskal-Wallis test results are integrated at the same time. For example, the Kruskal-Wallis test results in Table 6 show that all five motor-fan modules are unique in their fan weight. Among the five, module 1 has the highest fan weight as the module 5 has the lowest fan weight. The remaining three motor-fan modules have unique fan weights between the two. Such relations are summarized as unique but according to relative average weight scale across the five modules in Table 7. On the other hand, module 2, 3, and 5 are not found different from each others in terms of the motor type in Table 6. Therefore these three modules are labeled with the same motor type scale in Table 7. Additionally, their motor type scale is found the lowest compared to the motor types of Module 1 and 4.

Table 7: Summary of the vacuum cleaner motor-fan module definitions

	Module 1	Module 2	Module 3	Module 4	Module 5
Motor weight	Low	Low Medium	Low	High	Low Medium
Motor type	High	Low	Low	Medium	Low
Motor power	Low	High	High	Medium	High
Fan weight	High	High Medium	Medium	Low Medium	Low
Fan size	Low	Low Medium	High	High Medium	Medium
Fan power	Low	High	Medium	High	High

The same module determination and definition approach is applied to the 3 vacuum cleaner chasses module types as well. Similarity relations among the 3 chassis modules are interpreted according to the 3 original clustering attributes presented in Table 4. Then, these relations are summarized in a table similar to Table 7 using the relative scale approach.

As discussed and demonstrated with the simplified vacuum cleaner example, Step 3 in this research is applied to determine and define the types of modules for each product component group from Step 2 separately. This is achieved by carrying out K-means clustering on previously treated design data sets using the PCA. Found module types are defined across corresponding sets of critical design characteristics, referred as original clustering attributes for the clustering approach.

3.4 Step 4: Define Platform Alternatives

A distinct differentiation should be defined for a solid basis for different modules and product platforms [100]. From the life cycle perspective [20], modularity decisions are based on different goals such as production, design and development, use, and retirement. Kreng and Lee [25, 48] have synthesized the identified goals of modular designs in the literature into 14 module drivers. The complete set of these 14 module drivers and their definitions are presented in Appendix F. These module drivers represent the number of driving forces for modularization within the product.

In this research, driving forces for the generated design modules in Step 3 are investigated within the product families. Based on the results of the investigation, a platforming architecture strategy is determined. Particularly, platformability of the modules are determined through investigating the modularization goals to decide how the modules should be swapped to derive product variants. To achieve this, the Module Indication Matrix (MIM) [48] is adapted. Originally, MIM is used to analyze technical solutions (components, etc.) regarding their reasons for being modules. Using MIM, product technical solutions are assessed against a set of module drivers to group them according to similarities in their relations to the module drivers. However, in this research, generated product modules are assessed against the set of module drivers to understand their platformabilities within the product families.

Figure 10 demonstrates how MIM is integrated into this research with the simplified vacuum cleaner example. In Figure 10, the total of 8 vacuum cleaner modules (5 motor-fan modules and 3 chassis modules) from the Step 3 discussions are assessed against the set of module drivers from [48] as the module drivers' definitions are presented in Table 8. As shown in Figure 10, the module drivers are grouped in 5, namely: development and design, variance, manufacturing, quality, purchase, and after-sale. Since this research focuses on modularity from the design perspective, only the first two relevant module driver groups are elaborated in Figure 10 within the highlighted area. Thus, neither the individual module drivers nor the scores of the assessment for the vacuum cleaner are presented for the other driver groups in Figure 10.

Module Driver	Module Group	Motor-Fan Modules	Chassis Modules
Development and design	Carryover	9	9
	Technology evolution		
	Planned design change	9	
Variance	Different specification		
	Styling	1	
Manufacturing		x	x
Quality		x	x
Purchase		x	x
Afer sale		x	x
	Total	**19**	**9**
	%	***68***	***32***

Figure 12: A simplified MIM for a vacuum cleaner

Table 8: Selected module drivers [25]

Module Driver	**Definition**
Carryover	A part or a subsystem of system of a product that most likely will not be exposed to any design changes during the life of the product platform
Technology Evolution	Parts that are likely to undergo changes as a result of changing customer demands and technology shift
Planned Product Changes	Parts of the product that the company intends to develop and change to fulfill certain customer demands better, or decrease production costs
Different Specifications	It refers to the range of product models produced within a particular time to meet the various market demand. Meanwhile, product variety should be obtained to adapt different specifications as well.
Styling	Providing variance by clustering typically visible parts of the product to underline product identity

From Figure 10, vacuum cleaners can be considered mature products with limited technical development and styling. From the total score row in Figure 10, the module profile for the vacuum cleaner shows that the 5 motor-fan modules have stronger and more modularization goals than the development and design, and variance perspectives. In this research, the stronger and the more relations that exist with the module drivers, the more likely there will be potential module variances. For example, different motor-fan modules are designed primarily to carry over some components within product families and to cut production cost as the planned design change. Similarly, different chassis modules are designed primarily due to component carry over. From the total scores in Figure 10, less different chassis modules are expected. There are stronger reasons to design more different motor-fan modules. Therefore, the 3 chassis modules are accepted to be more appropriate as platforming modules; highly platformable. Similarly, the 5 motor-fan modules are accepted to be more likely to generate different vacuum designs; less platformable.

From the above analysis, the platforming strategy illustrated in Figure 13 for vacuums can be considered viable. The platforming architecture strategy involves vacuum cleaners to share the chassis modules, as the vacuum cleaner differentiations should ideally be created by swapping the motor-fan modules. Figure 13 illustrates a platform alternative including chassis module1 to derive two types of vacuum cleaners by swapping motor-fan module1 with motor-fan module 2.

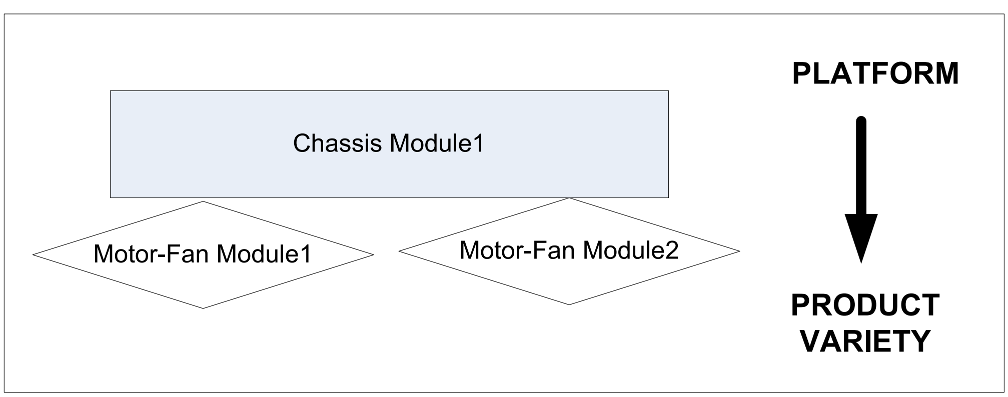


Figure 13: A pictorial representation of the platforming strategy for a vacuum cleaner family

Once a platforming architecture strategy is determined, actual numbers of platform alternatives and product types are determined next. This is achieved by re-defining the products using the generated modules from Step 3. Each product is redefined in terms of what module cluster it falls into according to the results of the clustering solutions. In the end, all products are defined in terms of a combination of the generated product modules. Re-defined products are divided according to their platform modules to observe existing platform alternatives. Then, the products are subdivided according to the shared modules to observe potential product types.

For the vacuum cleaner example, Table 9 presents the observed platform alternatives and redesigned vacuum cleaner variants by redefining the 30 vacuum cleaners using the 5 motor-fan and 3 chassis module types. As determined above, the chassis modules are decided to be the platforming modules. Since there are 3 types of chassis modules, there are 3 platform alternatives across the 30 vacuum cleaners. Table 9 shows that there are total of 12 (3/3/4 in the second row) vacuum cleaners sharing the chassis module 1, while the other 12 (5/4/3) vacuum cleaners share the chassis module 2 and the last 8 vacuum cleaners share the chassis module 3. In addition, the last row in Table 9 shows proposed vacuum cleaner variants which are derived from the 3 types of chassis platforms. Product variants are generated with different combinations of chassis and motor-fan modules. For example, 3 vacuum cleaner variants are proposed, as all three are derived from platform alternative I (chassis module 1) in combinations with motor-fan module 1, 2, and 3. Also 3 vacuum cleaner variants are proposed to be derived from platform alternative II (chassis module 2) in combinations with motor-fan module 1, 4, and 5. Lastly, there proposed 2 vacuum cleaner variants which are derived from platform alternative III (chassis module 3) in combinations with motor-fan module 2 and 5.

Table 9: Vacuum platform alternatives and variants

	Observed Platforms	**I**	**II**	**III**
	#of Vacuum Cleaners	*3/3/4*	*5/4/3*	*4/4*
Platform	Chassis Module	1	2	3
	Motor-fan Module	1/2/3	1/4/5	2/5

In addition to the distinctively defined platform alternatives and product variants, a variety of conclusions can be drawn from the proposed design variants in Table 9. The major one is the potential reduction in product numbers. For the results of the vacuum cleaner example in Table 9, a total of 8 vacuum types are proposed to cover the same design space defined by 30 vacuum cleaners. The presented research approach eliminates insignificant product varieties by declaring them the same with the clustering approach. This may deliver significant amounts of design reduction opportunities.

Lastly, commonality of the generated product modules within the product families are defined in terms of a prediction score computation. A module prediction score is defined as the ratio distribution of a module across the proposed product variants. For example, Table 9 shows that the chassis module 1 is proposed to be shared by 3 product variants out of the total of 8 product variants generated. Therefore, its prediction score is calculated as the ratio of 3 to 8; 0.375. Chassis module 2 has the same prediction score, 0.375, since it is also shared by 3 product variants out of 8. Chassis module 3 prediction score is however found lower, 0.25, since it is shared by only two product variants out of 8. These prediction scores of the chassis modules help understand how commonly each platform is used to derive product variants. In this case, platform I and II are used equally but more commonly than platform III. Among the 5 motor-fan modules, module 1, 2, and 5 are shared by two product variants, so that their prediction score is 0.25. The remaining motor-fan modules are unique to a single product variant. Their prediction score is therefore 0.125. As shown, module prediction scores help design teams understand general working patterns among the generated modules.

Below, Figure 14 summarizes the research steps with the outputs of the simplified vacuum cleaner example. Overall, the presented research approach helped the determination and identification of total of 8 vacuum cleaner modules and 3 platform alternatives as the platforming strategy is suggested to be optimized around the vacuum power performance. As the result of the presented modular product design and platform thinking, the vacuum cleaner variety is proposed to be reduced to 8 from 30.

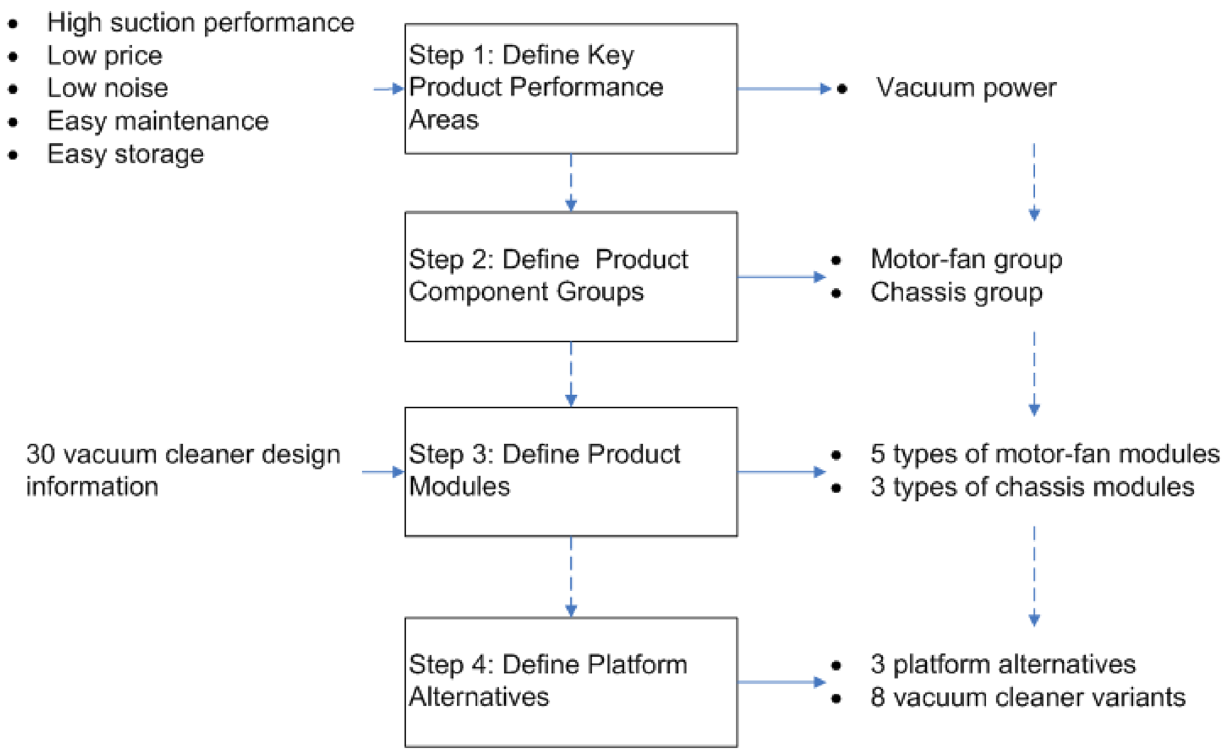


Figure 14: Vacuum cleaner example summary

3.5 Validation Strategy and Testing of the Research Hypotheses

As stated in Section 1.4, the following hypotheses are investigated in this dissertation in response to the research questions:

Hypothesis 1: Using the proposed research steps 1 through 3 in Chapter 3, critical design information in multiple characteristics can be identified and, then utilized for defining, generating, and distinguishing product modules.

To facilitate verification of Hypothesis 1, the following supporting sub-hypotheses are proposed:

Sub-Hypothesis 1.1: A common market requirements motivated approach can be used to determine the critical product components. Additionally, functional relations and dependencies among the product components can be incorporated in defining product modules. QFD based tools can be adapted to capture such design knowledge.
Sub-Hypothesis 1.2: A data clustering approach can be utilized to define product modules by eliminating insignificant design variations in essence.
Sub-Hypothesis 1.3: Significant differences among the modules can be determined using non-parametric analysis methods. Design data mean vectors can be used to represent scaled module representations.

These sub-hypotheses provide a basis for using common customer needs motivated decision making and data clustering approach to support defining distinctive product modules.

Hypothesis 2: Using the proposed research Step 4 in Chapter 3, product modules can be categorized according to their platformabilities, and then utilized to detect potential platforms and product variants.

To facilitate verification of Hypothesis 2, the following supporting sub-hypotheses are proposed:

Sub-Hypothesis 2.1: Modularization driving factors analysis methods can be adapted to define module platformabilities to determine a platforming architecture strategy.
Sub-Hypothesis 2.2: A method to re-define (re-configure) existing products using the defined product modules can help detect module usage patterns in platform alternatives and product variants. Additionally, a design commonality prediction method can be developed to compare how generic existing or future product types are.

These sub-hypotheses provide a basis for investigating modularization goals to support product module categorization. This motivates the determination of platform alternatives and product variants by searching the distributions of the modules within the product families by the defined categories.

As the hypotheses are addressed, the proposed method for integrating a decision support in designing product families along with distinctive product module and product variants definitions and multiple platform concepts is realized. The relationship between the hypotheses and the proposed research method is illustrated in Figure 15.

Addressing the sub-hypothesis 1.1 identified the activities for defining critical design information and the functional relations and dependencies among them. By applying customer-requirements product-performance QFD matrix, key product performances are determined. Motivated with the key product performances, critical product components are determined by applying the second QFD matrix. The relations and the dependencies between the critical product components are then investigated through the use of functional DSM.

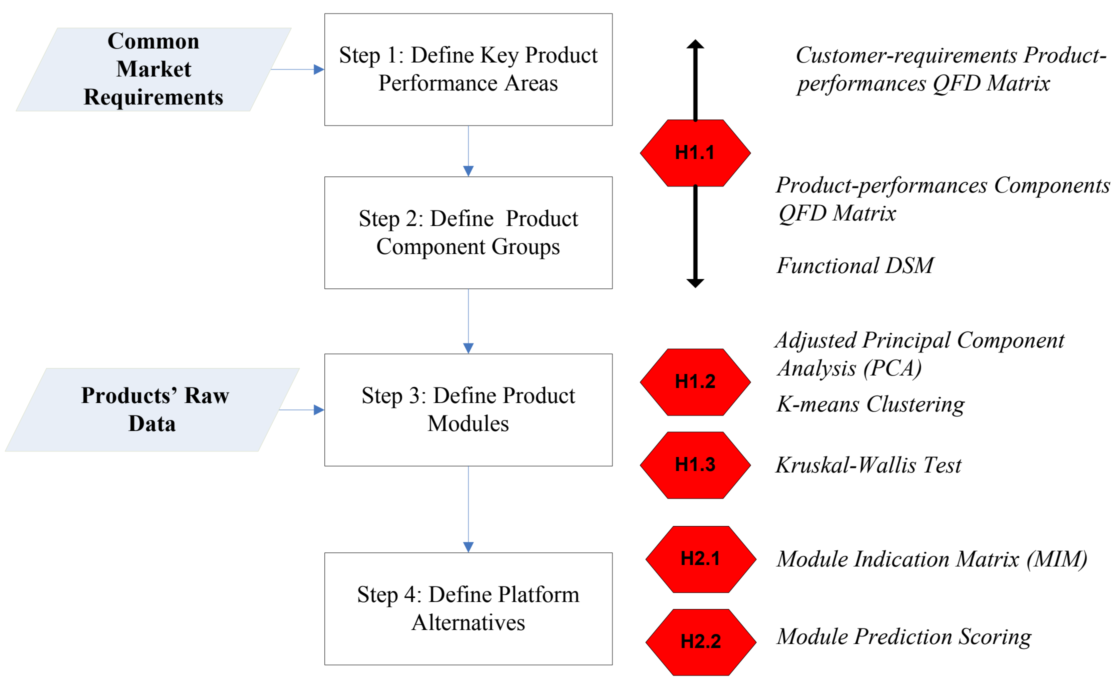


Figure 15: Relationship between sub-hypotheses and the proposed research approach

Sub-hypothesis 1.2 relates to identifying product modules which are defined as the groups of the critical product components using their critical design characteristics. Addressing this hypothesis provides a data clustering process to locate significant design variants within product families.

Sub-hypothesis 1.3 relates to testing the statistical significance of the product module differences. This is achieved through the use of Kruskal-Wallis tests, module mean vectors, and the representative products.

Addressing sup-hypothesis 2.1 provides a means to categorize product modules according to their platformabilities, MIM. This relates to defining the platforming architecture strategy. Applying the strategy, platform alternatives are observed by diagnosing the distributions of the determined module types within the product families, sub-hypothesis 2.2. This provides a module predictability scoring to evaluate resulting product variants' uniqueness.

To validate the proposed research method, an industry case study application is presented to demonstrate its usefulness and applicability; the design of 11 tire families (Chapter 5). Applying the proposed method, the tire families are modularized and redesigned, which demonstrates the method's usefulness in designing product families. Reduction in the design complexity is demonstrated, and the differences between the product variants are discussed. The applicability of the research approach is tested by verifying the results of the tire case study through extensive interviews with the experts at the tire company.

3.6 Summary and Preview

A method to facilitate the integration of a decision support approach for design teams in designing product families has been discussed. Detailed constituent elements of the proposed method are elaborated. In summary, the steps and tools presented in Table 10 are implemented in the proposed research.

The resulting method can help yield distinctive product modules and effective product platforms and variants for a set of product families. The next chapter provides an introduction to the industry case study of this procedure to product family design.

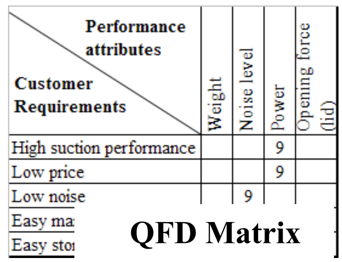
Table 10: Research approach and tools summary

<table>
<tr><th>Research Approach</th><th>Research Tools</th></tr>
<tr><td>

- Step 1: Define key product performance areas

</td><td>

- QFD Matrix



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- Step 2: Define product components groups

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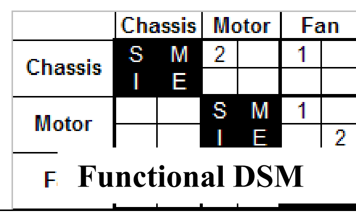
- QFD Matrix
- Functional DSM



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- Step 3: Define product modules

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- Adjusted PCA
- K-means clustering
- Kruskal-Wallis test
- Representative products

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- Step 4: Define platform alternatives

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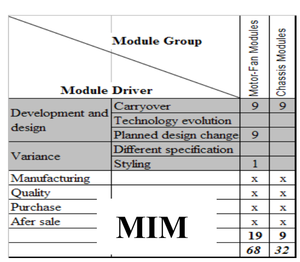
- MIM



- Module Predictability Scoring

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Chapter 4 : Case Study Introduction

The research approach to support product family designing is applied in a tire company, referred to as ABC. For the rest of this dissertation, the actual data is not disclosed; hence, letters and normalized/scaled data are used for illustrative purposes only as needed.

The research approach described in Chapter 3 is applied in defining tire design modules, and potential platform concepts within ABC's broad market replacement tire lines. All product lines of this study were chosen from the same tire brand. The selected tire brand includes a total of 11 sports/performance tire lines, 6 passenger tire lines, 18 light truck/SUV (including off-road tires) tire lines, and 3 winter tire lines in the 2007 product catalog. Different product categories focus on different tire performances in design; handling and maneuverability in sport/performance lines, wet and dry traction in passenger lines, and highway or off-road performance in light truck/SUV lines.

Using the proposed platforming approach, ABC identified tire design modules in terms of multiple design dimensions and potential platform concepts and product variants. In addition to design complexity reduction as an outcome, the presented research method provided ABC a new and effective, modular level, approach to define tire families.

4.1 Pneumatic Tires

A pneumatic tire can be defined as a complex reinforced rubber composite air container that carries the load [24]. The primary function of passenger car tire is to provide the interface between the vehicle and the road [101]. The rubber contact area for all four tires for a typical mid-size car is less than that of an 8.5x11 inch sheet of paper; each tire has a footprint area of about the same size of an average human's hand. Vehicle load causes tires to deflect until the average contact area pressure is balanced by the tires' internal air pressure. In addition, the ability of a vehicle to start, stop and turn corners results from friction between the road and the tires. Tire tread designs are needed to deal with the complex effects of weather conditions; dry, wet, snow-covered and icy surfaces. Another basic tire function is to absorb road irregularities. In effect, tires act as spring and damper system to absorb impacts and road surface irregularities under a wide variety of operation conditions.

A typical passenger tire contains a minimum of 20 components, 15 compounds, 10 fabrics, 5 steels, and 60 raw materials [102]. Figure 13 shows common tire components. The first inner component shown in Figure 13 is inner liner which is a thin, specially formulated compound laced on the inner surface of tubeless tires to improve air retention by lowering permeation outwards through the tire. Bead packages are bundles of rubber coated individual bronze plated bead wires and assure an air-tight fit with the wheel. Plies wrap around the bead wire bundles, pass radially across the tire and wrap around the bead bundle on the opposite side. Apex is applied on the top of the bead bundles to fill the void between the plies and the turned-up ply ends on the outside. Toe guard provides a layer of rubber between the plies and the wheel rim for resistance against chafing. Two steel belts are applied at opposite angles to one another on top of the plies under the tread area. They stabilize and strengthen the tread. Overlay components enhance shape stability at high speeds. The tread must provide the necessary grip or traction for driving, braking, and cornering, and the tread compound is specifically formulated to provide a balance between wear, traction, handling, and rolling resistance. Tire sidewall rubber serves to protect the plies from abrasion, impact and flex fatigue. The sidewalls also carry decorative treatments, sometimes include white or colored stripes or letter. The rubber compound is formulated to resist cracking due to environmental hazards such as ozone, oxygen, UV radiation, and heat.

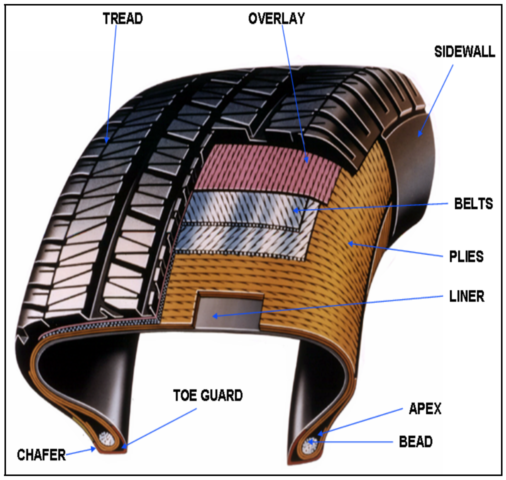


Figure 16: Common tire components and structure [103]

Each tire has its specifications printed on the tire's sidewall [23]. For example, rim diameter specifies (in inches) the wheel rim diameter the tire is designed for. Section width (tire width) is the width of the tire in millimeters (mm), measured from sidewall to sidewall. This measurement is for the tire when it is on its intended rim size. Aspect ratio tells the height of the tire as a percentage of the section width. The smaller the aspect ratio, the wider the tire in relation to its height. High performance tires usually have a lower aspect ratio than other tires, since tires with a lower aspect ratio provide better lateral stability. The load rating is a number that correlates to the maximum rated load for that tire. A letter for the maximum speed allowable for the tire is printed on a tire as well.

As shown in Figure 14, in tire manufacturing, raw materials (rubber, carbon black, chemicals, pigments, oils, fabrics, wire, etc.) are mixed in Banbury mixers. Tire components are prepared with extruding, calendaring, and cutting processes. Prepared components are assembled using tire building machines into one entity called (the picture in the middle of Figure 14), the green or unvolcanized tire. The green tire is converted into a finished product by curing (vulcanizing) it in a press (mold) under heat and pressure for a certain period of time. After curing, tires are inspected for balance and uniformity.

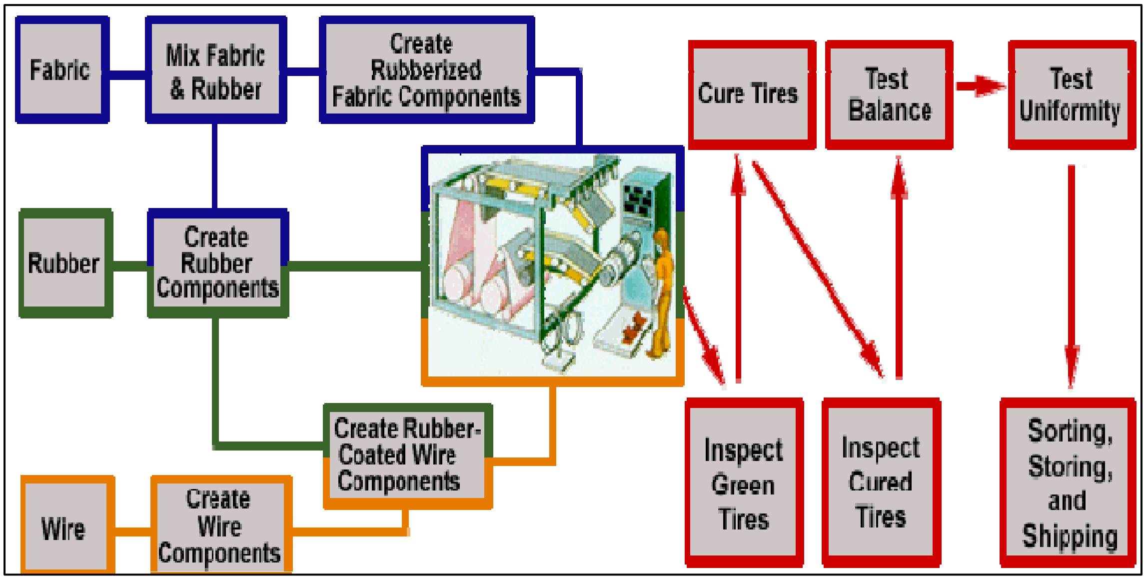


Figure 17: Overview of tire manufacturing process [101]

4.2 Tire Design Process

Figure 18 displays a tire design process chart adapted from [101]. Design goals and requirements generally include a list of product goals, including customer performance expectations, manufacturing requirements, internal company performance standards, and regulatory requirements. Based on the identified goals and requirements, tire design features are defined in terms of tread pattern, construction information, materials, and mold contour.

Example tread pattern design parameters include number of ribs and groove spacing. These affect the way water is eliminated to avoid hydroplaning. Percent void, shoulder slot size and orientation can all affect traction, handling, and water exit paths. Additionally, tread designs need to be acceptable aesthetically and to match the customer's perception of product performance.

Tire construction parameters affect body strength and are chosen based on manufacturing, engineering, and design criteria. Example construction parameters are number of plies, belt widths, belt tread crown angle, the location of the end of the turned-up ply, and ply stiffness.

Tread compounds are chosen to meet handling and traction requirements for wet, dry, and snow, but must have suitable wear potential and resistance to gravel hips and tearing. For example, subtread compounds and thickness are often determined by the rolling resistance imposed by the original equipment (OE) vehicle manufacturer. Bead filler compounds are chosen for controlling lower sidewall stiffness, based on ride and handling expectations.

Mold section width and outside diameter have an obvious impact on the dimensions of a finished tire. Mold profile items like tread, center, and shoulder radii and skid depth can also significantly affect tire performance.

Additionally, tire engineers use computer models and performance maps to help guide their selections and predict if performance targets will be met. Using an iterative process of design, construction and material choices, the engineer can reach a balance of compromises for each application.

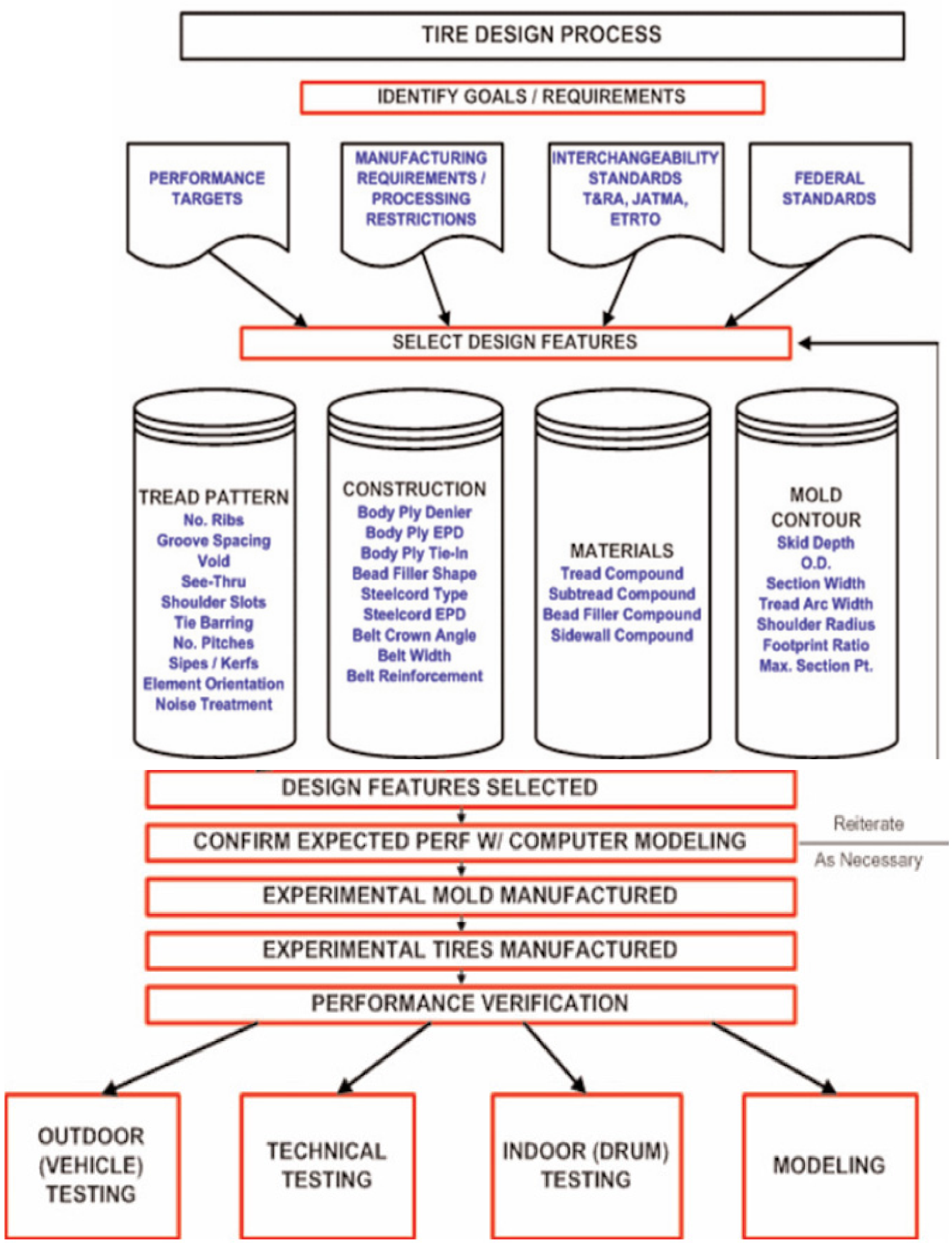


Figure 18: Tire design process [101]

4.3 Tire Performance Criteria

This section summarizes common tire performance test descriptions from [101].

Traditionally, outdoor tread wear rate tests involve sets of tires driven at prescribed speeds on a known course. Control of vehicle alignment, loads, and accelerations/deceleration rates are all critical to obtaining repeatable results. Irregular wear features can significantly shorten the service life or mileage potential of tires. While tread design and tire construction are influential, many external factors such as vehicle mis-alignment, vehicle suspension geometry, and driving factors such as high speed cornering, rapid acceleration or braking and underinflation of tires play significant roles in promoting irregular wear patterns.

Handling is a result of tire/vehicle interactions in response to various driver inputs. Handling tests are used by tire engineers or OE vehicle engineers as part of their approval process. Tires are evaluated for their response, stability, recovery linearity, on-center-feel, brake in turning, and other characteristics. Tests range from lane change maneuvers to maximum cornering capability. Also, closed course test tracks with a variety of curves can be used to compare lap times with experimental tire constructions.

For ride comfort, tires are evaluated for impact harshness over highway joints and railroad tracks, and for damping and bounce memory after road disturbances. They are also graded for road isolation, steering wheel oscillations, shake, vibration and other vehicle-specific features. For these tests, professional ride evaluators are used.

Patterns have tread elements of varying pitch lengths to prevent tires from generating identifiable tones. Professional evaluators rate coarse road noise transmitted through the tire from textured highway surface. They listen for growl, a low frequency noise noticed during low speed braking, and sizzle, a hissing sound on ultra-smooth surfaces.

Outdoor testing for tire endurance usually involves loading a vehicle to the maximum specified load and inflation, or more, and driving on a closed road course at a specified schedule of speeds. There are also indoor endurance tests with high speed tests with constant load but varying speeds.

Since tire rolling resistance can consume up to 25% of the energy required to drive at highway speeds, its tests are important for tire fuel economy measurements. Tests are indoor with precise instrumentation, calibration, speed control and equipment alignment for repeatable results.

The zone of contact with the road is a boundary region for tire design. This zone is called footprint or contact patch. The study of the tire footprint is a very complex matter. There are strong associations between the tire footprint and other properties of the tire, including tractions, tire/pavement interaction noise, ride over road irregularities, and wear. Visual tests, ink block printing, glass plate photography or video, stress, pressure sensitivity, and temperature in the footprint are only the several measurements used commonly in the tire industry. Depending on the tire application, there defined desired sets of footprint shape, temperature, pressure and stress.

4.4 Case Study Tires

To determine common market requirements in this application, results of a broad market tire customer survey are used. The survey was conducted for ABC to be able to segment the broad market customers in terms of their tire needs and requirements for product planning purposes. The survey had several components, for example vehicle uses, vehicle needs, effect of tires, scale importance, maximum difference preference scaling, willingness to pay, etc.

Using analysis of the maximum difference importance scores, ABC formed unique segments of customers. Each customer segment is defined in terms of a set of parameters, for example premium, cost of entry, less important features based willingness to pay and scale importance. For this case study, the focus was limited to the cost of entry features, since this was found to be most appropriate feature set when defining tire design commonalities. Cost of entry feature is important to customers. However, customers are not willing to pay much, if anything additional, for them. These features should be included in the price of the tire at no additional cost.

Among the formed customer segments, 4 customer segments are included for the case study. Based on the definitions of 4 broad market customer segments, 92 (67 mono ply tires and 25 double ply tires) replacement broad market tires from 11 North American tire lines were selected for the analysis. Tire specifications are displayed in Table 11. Tires only with 14, 15, 16, and 17 rim diameters are included. Tires (i.e. Light truck and SUV tires) with bigger rim diameters are excluded, since these tires are more of off-road market products than broad market tires. Additionally, aspect ratios dominantly for sports/performance and off-road tire applications are excluded.

The size of a tire is defined in terms of a combination of rim diameter, aspect ratio, and section width. Based on the discussions with ABC experts, the tire size differences across the selected 92 tires for this research application were decided to be appropriate to detect groups of design commonalities across the different sizes and product lines.

Table 11: Sample Tire Specifications

Number of Tire Lines	11
Number of Tires	92 (67 mono ply+25 double ply)
Included Tire Rim Diameters (inch)	14, 15, 16, 17
Included Aspect Ratios (%)	55, 60, 65, 70, 75
Included Section Widths (mm)	175, 185, 195, 205, 215, 225, 235, 255, 265, 275

Common market requirements in this case study are defined as the common cost of entry features across the 4 broad market customer segments. It is detected that there are 3 features that consumers across the 4 market segments find important, but expect to be included in the price of the tire at no additional cost, including; (1) strong/tough sidewall, (2) even tread wear, and (3) handling during everyday drive. These 3 features are used in Chapter 5 to define key tire performance areas for the proposed research method.

Chapter 5 : Research Results and Interpretations

This chapter discusses the research approach application in a tire case study. As discussed in Chapter 4, 92 (67 mono ply tires and 25 double ply tires) replacement broad market tires from 11 product lines were analyzed in the case study.

5.1 Applying Step 1: Define Key Product Performance Areas

In this step, platforming goals of the tire case study were determined. In essence, key product performances were determined to analyze how well a tire design meets with the commonly expected 3 customer needs—strong/tough sidewall, even treadwear, and handling during everyday drive.

In the case study, performance areas were defined in terms of measurable tire performance characteristics; ABC's existing tire performance tests. As presented in Appendix A, a 26x44 matrix format survey was designed to find out how a particular tire test relates to or predicts a customer need using one of the following 4 ratings; blank for unrelated, 1 for weak relation, 2 for medium relation, and 3 for strong relation. Six experts at ABC rated the relations among the selected tire tests list and the customer needs list.

Appendix A presents more information about the matrix survey structure and the survey results. Based on the survey results, tire tread wear, durability, and traction were selected as the key performance areas for this platforming effort.

5.2 Applying Step 2: Define Product Component Groups

In Step 2 for this case application, mainly 2 actions were held: (1) the determination of critical tire components for platforming, and (2) the identification of the functional interactions among the product components to form tire component groups, and the critical design characteristics as the original clustering attributes for the clustering analysis in the next step.

As the start of the determination of critical platforming tire components, major component types across the 92 tires were identified first: inner liner, (mono/double) ply, ply shoulder strips, beads, apex, chafer, toe guard, 2 belts, belt edge gumstrips, overlay, sidewalls, wedges, miniskirts, tread base, and tread cap. Although it is not a component like others, tread design was included as well. Then, using the tire-components tire-performance QFD matrix presented in Figure 31 in Appendix B, 9 tire component types out of these potential components were selected due to their relations with tire durability, traction, and tread wear: apex, beads, belts, chafer, sidewalls, toe guards, tread (cap and base together), tread design, and (mono and double) plies. These 9 design component types were decided to be modularized within the product families. ABC decided that the rest of the tire component types such as inner liner, belt edge gumstrips would be standardized later.

Additionally, selected tire components were grouped in terms of their functional interactions. These relations were defined based on components' functional resemblance in impacting tire durability, traction, and tread wear. Functional relations and dependencies between the 9 critical tire components across the 11 tire lines were investigated. Figure 19 displays simplified identified functional interactions between the product components.

Apex stiffens lower bead area and closes the gap between the ply turn-up and beads. As shown in Figure 19, these relations were defined necessary for physical adjacency (2), and beneficial but not necessary for functionality energy transfer (1) by the experts. Physical adjacency between sidewalls and chafer was indicated beneficial, but not absolutely necessary, for functionality (1). The experts indicated that toe guard protects chafer and this relation is necessary for energy transferring (2). Belts transfer driving forces to tread and similarly tread transfers driving forces to tread design. As they all were jugged necessary for energy transferring (2), the physical adjacency among them was indicated necessary for functionality (2). In this case no negative relations were considered, not because there are none, but rather because the technical concept is a conventional concept where the negative interactions are weak or easy to overcome, e.g., gumstrips are already included to protect belts.

GroupI		GroupII			Group III	GroupIV			
Apex	Beads	Chafer	Sidewalls	Toeguard	Ply	Belts	Tread	Tread Design	
S M I E	2 1				1 1				Apex
	S M I E				1 2				Beads
		S M I E	1 	 2	1 2				Chafer
			S M I E		1 2				Sidewalls
				S M I E	1 2				Toeguard
					S M I E	2 2			Ply
						S M I E	2 2	2 2	Belts
							S M I E	2 2	Tread
								S M I E	Tread Design

Interface types
S: Spatial
M: Material
I: Information
E: Energy

Interface strength
2: Necessary for functionality
1: Beneficial for functionality
0: Does not affect functionality
-1: Causes negative effects on functionality
-2: Must be prevented to achieve functionality

Figure 19: Functional DSM for broad market tire

Based on the defined functional interactions among the critical tire components for platforming in Figure 19, the following component groups were defined; Group I: apex and bead, Group II: chafer, toe guard, and sidewalls, Group III: ply, and Group IV: belts, tread, and tread design.

Group III was the only group with single component, ply, due to its multiple interactions with the other components. Apex stiffens ply, beads transfer forces and hold ply, and sidewalls, chafer, toe guard protect ply, and ply transfers driving forces to belts. Additionally, most of these relations (except the relationship between belts and ply) include physical adjacency beneficial, but not absolutely necessary, for the functionality.

Due to their similar interaction with ply and the interaction between them, apex and beads were grouped together in Group I. Because of the interactions between sidewalls and chaffer, and chaffer and toe guard, and their similar interaction with ply, chafer, toe guard, and sidewalls were grouped in Group II. Due to the strong relations among belts, tread and tread design, they were grouped in Group IV.

After determining the critical tire component groups for platforming, their critical design characteristics for platforming were selected. These characteristics formed the original clustering attributes for the clustering analysis in the next step. The experts indicated that the following types of tire component design characteristics impact tire durability, traction, and tread wear: 3 apex dimensions including apex material properties, 2 bead dimensions including type of bead, 2 chafer dimensions, 2 toe guard dimensions, 1 sidewall dimension (material only), (5 mono- and 11 double-) ply dimensions including material and reinforcement properties, 6 belt dimensions including material and reinforcement properties, 10 tread dimensions including material properties, and 2 tread design dimensions. In addition, tire size was identified as another critical characteristic to categorize tire designs for platforming. Tire size is defined in terms of 3 tire specifications; rim diameter, aspect ratio, and section width. These 3 specifications for each tire were also included.

As seen, the selected critical design characteristics are not only component dimensions (gauges, etc.) but also material physical properties, and (tread design) geometric parameters. In other words, the original clustering attributes included a variety of types. These clustering attribute types are not separable in terms of their impact on the key platforming tire performances, and critical in classifying tire design information to generate tire modules. Thus, tire modules defined in this case study were categorized as integrated modules.

The major output of this step was the original clustering attributes for functionally related critical tire component groups for platforming. This step was concluded with collecting data for the defined clustering attributes and tire size for the 92 tires.

5.3 Applying Step 3: Define Product Modules

In Step 3, the original tire clustering attributes were reduced for quality clustering analysis. Then, the data clustering approach was applied to define tire clusters. The result tire clusters defined actual tire modules across the original clustering attributes (critical design characteristics). Step 3 then was concluded with the investigation of the generated tire module combinations.

The original clustering attributes determined for each product component group in Step 2 were reduced by applying the principal component analysis (PCA) to obtain quality variables for clustering. The analysis was carried out for all 4 product component groups separately. SPSS 14.0 was used for the analysis [104]. Below Table 12 shows the number of original clustering attributes (critical design characteristics) defined in Step 2 for all tire component groups. It changes between 13 and 49 across the component groups. Table 12 also presents the number of factors from the PCA for each design component group. From the presented cumulative variance representations of the original data in Table 12, the reduced clustering attributes were still representing the original data variation very fairly.

Table 12: Tire component groups clustering attribute summary

Tire component groups		# of original clustering attributes	# of reduced clustering attributes (# of factors from PCA)	Factors' cumulative % variance representation of the original data
Group 1	Apex and Beads	16	5	91.89
Group 2	Chafer, Toe Guard, and Sidewalls	16	6	95.62
Group 3	Mono Ply	13	5	93.13
	Double Ply	22	5	92.85
Group 4	Belt, Tread, and Tread Design	49	9	91.96

The factors from the PCA in Table 12 were adjusted to show a varying amount of influence in the clustering stage based on the variance in the original variable space. As discussed in the previous chapter, the factors were standardized and then multiplied by the square root of their eigenvalues. In this way, each factor became an adjusted factor brining a varying amount of influence in the clustering procedure. All the adjusted PCA factor results and eigenvalue distributions of the original clustering attributes are presented in Appendix C.

As an example, Figure 20 shows 2D scatter plots for Group 1 (Apex+Beads) using the adjusted factors as axes. For Group 1, 5 principle component factors were identified. Each plot in Figure 20 only shows relations of adjusted factors pairs. As seen in Figure 20, heterogeneity exists in the data that is captured by the factors. Some natural partitions can be observed in the data representations in Figure 20, such as three data groups between the adjusted factor1 and 2, and two data groups between the adjusted factor1 and factor5. Exact number of partitions in entire 5 Group 1 factors cannot be determined from Figure 20 directly. In this research, the heterogeneity in data is removed by use of a scientific method of data partitioning, such K-means clustering.

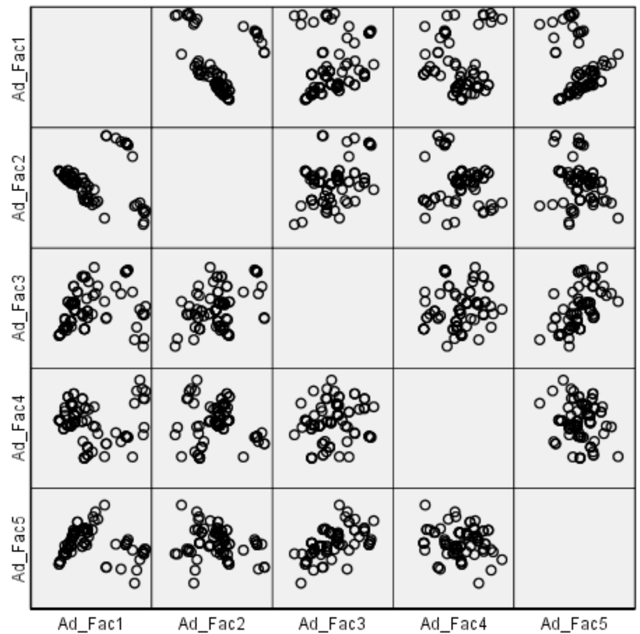


Figure 20: Pair scatter-plots of the adjusted principal components of Group 1

K-means clustering analysis was carried on the adjusted factors obtained from the PCA for the 4 tire component groups independently to generate tire modules. As discussed earlier in the research approach, the component groups were assumed to be functionally independent enough for separate modularization analyses. SPSS 14.0 was used for the clustering analysis [104]. With this selected technique of unsupervised classification, the tire design data determined the classes based on the adjusted factors. Classification of existing data such that the variation in the data in the same group was as low as possible and that between group was very high [98]. Resulting classes defined the tire modules. Using the clustering approach, tire modules were formed tight enough within themselves and as far away from each other as possible in terms of the selected original clustering attributes (critical design characteristics).

To ensure the classification efficiency, several clustering solutions were attempted with different cluster (tire module) numbers. Potential cluster numbers (potential module numbers) and final clustering solutions were determined mainly through discussion with experts at ABC. For discussion with experts, interpretations of all potential clustering solutions in terms of the component original clustering attributes were used. This provided a means to discuss the research outputs in terms of groups of products and their selected/critical design characteristics which the experts were very familiar and comfortable with. Potential clustering solutions were reduced to one or two most highly to be the final solutions with frequent discussions (2 or 3 30 minute long meetings per week) with groups of senior experts for about a month. Senior experts were helpful to flush out infeasible clustering solutions (potential tire modules) conveniently. For the remaining highly feasible tire module concepts, more meetings were held with larger and diverse expert groups. Different types of tire modules were discussed at those meetings depending on the focus product component expertise of the expert group. Such meetings were the ones where detail interpretations of each tire module were reviewed, and the final clustering solutions were determined.

Figure 21 shows the final clustering solutions for the entire component groups. As shown in Figure 21, 5 Group 1, 4 Group 2, 5 Group 3-mono ply, 4 Group 3-double ply, and 7 Group 4 tire modules were formed. Except Group 3, the total number of tires distributed within groups is 92 (total number tires). For Group 3, tires were pre-divided based on the number of ply component; there were 67 mono ply tires and 25 double ply tires. In Figure 21, the modules are presented according to the descending order of assigned tire numbers for the sake of easy representation. The assigned tire numbers to each module change from as low as 3 to as high as 29. ABC experts explained the resulting modules with the high assigned tire numbers, because of existing tire standardization efforts in place. For example, ABC standardized some tire toe guard and chafer (Group 2 elements) design characteristics in the past. However, these efforts never reached to the level of standardization of multiple design characteristics simultaneously. Presented data clustering approach in this thesis was able to locate the standardized design information as well as their working patterns with the other non-standardized design characteristics. For the modules defined by the lower number of assigned tires, such as 3 in Figure 21, ABC experts found the design differences recognizable enough for forming those modules. Additionally, distributions of the tire distances from their final classification module centers were discussed with the ABC experts to verify the final cluster compositions in Figure 21. These distributions are presented in box-plot graph format in

Apex D. These distributions helped design teams diagnose the variety within the modules. As shown in Apex D, all observed variability for each module was found within the reason.

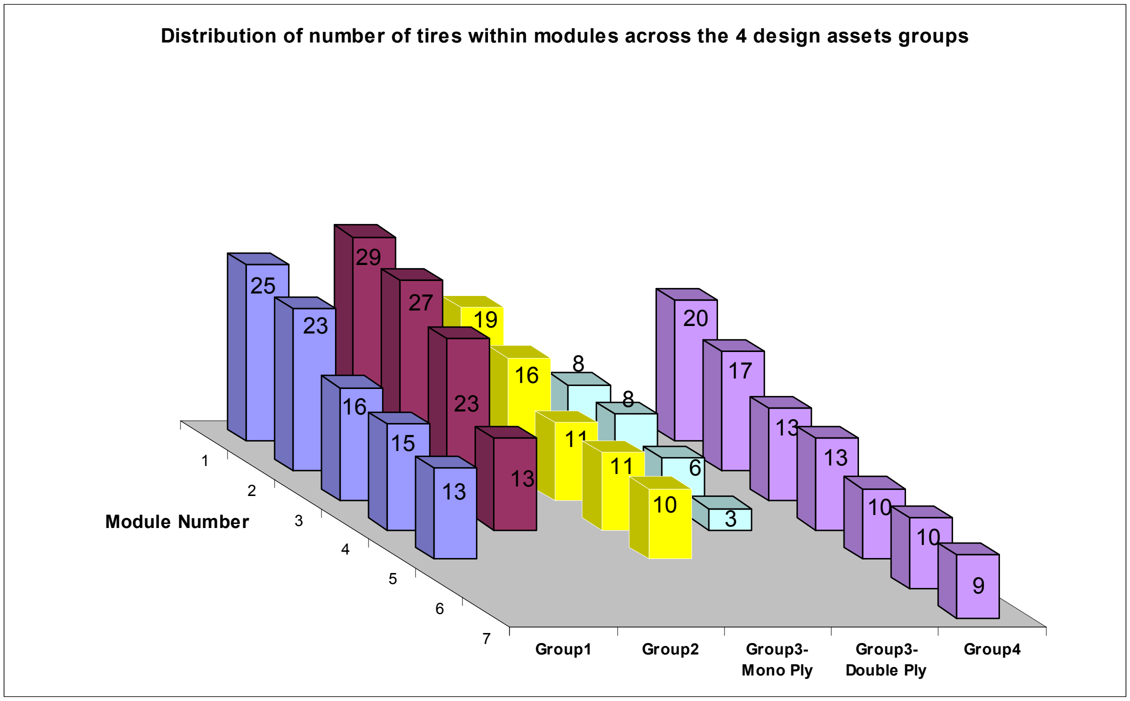


Figure 21: Tire module compositions

In order to analyze the composition of the modules and to understand the classification generated using the approach described in this thesis, the Kruskal-Wallis test was used. Each original clustering attribute types were considered a factor in this test. There were groups of original clustering attributes being the elements of the same type of design attribute. For example, tire component materials were defined using 6 physical characteristic lab test results which formed 6 original clustering attributes for the clustering analysis. Although each test result related to a critical property of the material, strong correlation existed between them, and these characteristics were reduced using the PCA for quality clustering. Similarly, after clustering, module compositions were diagnosed by the original clustering attribute types, instead of a diagnosis in terms of every single clustering attributes. In other words, module component material differences were diagnosed under the material original clustering attribute type, not for all 6 material physical lab test results individually. Statistical differences between the clusters for each original clustering attribute type were tested for the 10% level. Complete results of the tests for all tire component groups are presented in Appendix E. Based on the tests results, expected differences and similarities across the finalized modules were represented in terms of the mean vectors of the modules. Actual mean vectors were not disclosed here for proprietary reasons. Instead, relative scales from low to high average values for the original clustering attribute types were displayed.

Below Table 13 summarizes the clustering and the module composition analysis (by Kruskal-Wallis test) results for Group 1. As the result of the clustering analysis, 5 Group 1 modules were formed. Table 13 displays the differences/similarities between these modules across 6 original attribute types. These attribute types include 3 apex gauges, 1 bead gauge, 1 apex material and binary bead type. In Table 13, if two modules were found statistically not same at the 10% level for a particular original clustering attribute type as the summary of the Kruskal-Wallis test results, they were presented with their mean vector values of that original clustering attribute type. For example, in Table 13, module 1 was found significantly different than module 2 in Apex1 gauge as its average Apex1 value was higher. If the null hypothesis could not be rejected at the same confidence level for two modules for a particular original clustering attribute type, they were presented with the same average value level. For example, in Table 13, module 1 was found not different from module 3 in terms of Apex1 gauge based on the summary of the Kruskal Wallis test results, and thus they were represented with the same level of average value. Overall, there defined 5 Group 1 modules which could have been defined using 3 distinctive (low, medium, and high) values of Apex1 gauge. Current Apex1 variation within the 92 tires, on the other hand, was 7. As a result, it was found that these 7 Apex1 gauge values were not different as significantly as they were thought to be, when other critical design characteristics (in terms of original clustering attributes) and the functional similarities (in terms of design component groups) were considered. The relative scale from low to high provided a clear and simple way to describe the ideal distinctions between the modules across the original clustering attribute types.

Table 13: Summary of clustering results for Group 1

Original Clustering Attribute Type	Group 1 Module				
	1	2	3	4	5
Apex1	High	Medium	High	Low	Medium
Apex2	High	Medium	High Medium	Low	High Medium
Apex3	High	Low	Low	Medium	Low
Apex Material	High	Low	Medium	Low	Low
Bead1	High	Low Medium	High Medium	Low	Medium
Bead Type	Low	High	High	High	Low

As observed from Table 13, Module 1 is the only module with high values for all the original clustering attribute types, except the binary bead type. There is no module with all low original clustering types. The closest to the all low original clustering attribute type module is Module 4 with 4 low original clustering attribute types out of 6. Modules 2, 3, and 4 with the high bead type have values of medium, high, and low Apex1 gauge, respectively. These three modules show different combinations of the other clustering attribute types. Module 2 and 5 are two similar modules with two different bead types.

To associate the module definitions in Table 13 with the existing tire designs, a representative tire for each module was investigated. Identifying a representative tire is important to show that the module combinations in Table 13 present real tire original attribute type combinations. A representative tire for each module was determined by selecting tire(s) whose distance to the module center was the least. As mentioned before, distributions of the tire distances from their module centers are presented in box-plot graph format in Apex D. Tires with the lowest distance in those graphs in Apex D were selected as the module representative tires. In order to analyze whether the selected tires may be used as the representative tires of the modules, their actual original clustering attribute type values were compared with the mean vectors. The module definitions in Table 13 were found to be real and appropriate, since the module representative tires captured all but one—Apex2 gauge—faithfully. Thus, the presented clustering solution in Table 13 succeeded finding distinctive and significant Group 1 modules across the selected original clustering attributes. Module 2 representative tire had a lower value than the module average for Apex2 gauge, and it was the same value with Module 4's. Module 4 Apex2 gauge was indicated to be the low value, as Module 2 Apex2 gauge was expected to be medium value. In this case, the Module 2 representative tire failed to represent the expected Apex2 value faithfully. However, this was interpreted as a design improvement opportunity by some ABC experts. A tire with the presented original clustering attribute type combination for Module 2 in Table 13 was found value-added.

The same module description process was carried on for the rest of the tire component groups. A summary of the results are presented in the following paragraphs. ABC experts approved all the module definitions discussed below, and agreed that the representative tires presented good sets of design references for the generated tire modules.

Table 14 presents the results for Group 2. Modules are defined across 6 original clustering attribute types including 2 toe guard gauges, 2 chafer gauges, binary toe guard type, and sidewall material. It was proposed one of the toe guard gauges (Toe Guard1) be the same within the modules. Current variety in Toe Guard1 was 2, and it was proposed to be reduced to 1. Similarly, the existing 4 types of Toe Guard2 were proposed to be reduced to 3, namely: low, medium, and high as shown in Table 14. As the existing 2 types of toe guard and sidewall material, and 3 types of Chafer1 were kept the same, Chafer2 variety was proposed to be dropped to 2 from 3. The majority of the clustering attribute types of Group 2 were somewhat standardized by ABC. However, there was not any work on modular standardization based on component combinational working patterns. Such an approach helps understand the design reasoning and working relations better. This research approach helped diagnosis of such relations. For example, it was found that high toe guard type was never used with high sidewall material in contrast to the low toe guard type combinations of low and high sidewall materials. Or Module 1, 2, and 4 are the low Chafer2 and high Sidewall Material modules including all potential scales of the remaining original clustering attribute types. Module 3 is the only module with low Sidewall Material type. Except for two instances, identified representative tires captured the presented module combinations in Table 14 faithfully. Module 2 representative tire value had higher Toe Guard2 than the proposed medium value in

Table 14. Also, Module 3 representative tire had a higher Chafer1 value than the proposed low value in Table 14.

Table 14: Summary of clustering results for Group 2

Original Clustering Attribute Type	Group 2 Module			
	1	2	3	4
Toe Guard1	Standard	Standard	Standard	Standard
Toe Guard2	High	Medium	Medium	Low
Toe Guard Type	Low	High	Low	Low
Sidewall Material	High	High	Low	High
Chafer1	Medium	High	Low	High
Chafer2	Low	Low	High	Low

Table 15 and Table 16 show the summary of clustering results for Group 3. Five mono ply and 4 double ply modules were identified. Mono ply modules were defined in terms of ply angle, a ply gauge, ply material and ply strength. Similarly, double ply modules were defined in terms of the same types for the two plies. Ply strength represents the density of the wire embedded into ply components to increase the strength. With different wire densities, different ply strengths can be obtained using the same ply material.

Table 15: Summary of clustering results for Group 3-mono ply

Original Clustering Attribute Type	Group 3 Mono Ply Module				
	1	2	3	4	5
Ply1Angle	Standard	Standard	Standard	Standard	Standard
Ply1	High	High	High	Low	High
Ply1Material	High	High	Low	Low	Low
Ply1Strength	Medium	High	Medium	Low	Low

Table 16: Summary of clustering results for Group 3-double ply

Original Clustering Attribute Type	Group 3 Double Ply Module			
	1	2	3	4
Ply1Angle	Low	Low	High	Low
Ply1	Low	Low	High	Low
Ply1Material	Low	High	High	Low
Ply1Strength	Low	High	High	High
Ply2Angle	Low	Low	High	Low
Ply2	High	Low	High	Low
Ply2Material	High	Low	High	Low
Ply2Strength	High	Low	High	Low

For mono ply modules, ply angle was found standard as presented in Table 15, as it was categorized in 2 for double ply tires as shown in Table 16. For mono ply modules, low ply materials with low and medium strength levels, and high ply materials with high and medium strength levels were proposed. For double ply modules, however, low ply materials with low and high strength levels and high ply materials with high strength level were proposed. Additionally, only the first ply in double ply tires were expected to have the low material with high strength as displayed in Module 4 in Table 16. Generally speaking, production cost saving is the major reason to reduce number of plies in tires. One way to achieve this would be creating the additional ply material-strength combinations in Table 15, which were not used in double ply tires, such as low ply material with medium strength for mono ply module 3. Additionally, Module 2 is all high while Module 4 is all low modules to generate mono ply tires. Similarly, for double ply tires, there are Module 3 as all high and Module 4 as almost all low (except Ply1 strength). For both mono and double ply tires, existing material and material strength types were kept the same. Ply1 gauge variety was proposed to be dropped to 2 from 15 for mono ply tires and 12 for double ply tires. In addition, 2 Ply2 variations were proposed instead of 7. Mono ply representative tires captured the module definitions faithfully except 2 instances in Ply1 Strength. Module 1 representative tire had stronger ply strength than the expected (medium) and Module 3 representative tire had weaker ply than the expected (medium). The double ply representative tires had one instances different than what expected. Module 1 Ply2 Angle was higher than the expected (low).

Table 17 presents the summary of clustering results for Group 4. 7 Group 4 modules across 18 original clustering attribute types were formed. The original clustering attribute types includes 4 belt and 6 tread gauges, belt material and strength, 3 tread design geometric dimensions, 3 types of tread material. Belt4 and Tread3 gauges and Belt Strength were proposed to be standard for all modules, in contrast to existing 6 types of Belt4 gauges, 3 types of Belt Strength, and 11 types of Tread3 gauges within the 92 tires. Belt variety was proposed to be generated using 3 types of material and 3 types of Belt1, 2, and 3, but using the same Belt4 gauge and Belt Strength. Similarly tread differentiations were proposed to be created using the 5 tread gauges at the levels changing between 2 and 4, and the same Tread3 gauge across all modules. Module 2 has the all high tread gauges. Different tread design geometries were proposed to be created using 3 dimensions at 2 or 3 different levels. Once again, Module 2 has all high tread design geometric dimensions. Tire tread might contain different materials in its 3 regions: base, cap, and skirt. Table 17 presents the proposed tread material combinations for the generated 7 Group 4 modules. The representative tires failed to capture the presented module characteristics in 5 instances. Module 1 representative tire had lower Belt2 and higher Tread6 gauge than the expected values presented in Table 17. Module 6 representative tire had higher Tread2 and lower Tread Cap Material than the expected scales in Table 17. Similar to Module 1, Module 7 representative tire had lower Belt2 than the expected value in Table 17.

Table 17: Summary of clustering results for Group 4

Original Clustering Attribute Type	Group 4 Module						
	1	2	3	4	5	6	7
Belt1	High	High	Medium	High	Low	Medium	Low
Belt2	High	Low	Low	Low	High	Low	High
Belt3	High	High	Medium	High	Low	Medium	Low
Belt4	Standard	Standard	Standard	Standard	Standard	Standard	Standard
Belt Strength	Standard	Standard	Standard	Standard	Standard	Standard	Standard
Belt Material	High	High	Medium	Low	Medium	Medium	Medium
Tread1	High	High	Low	High	Low	Low	High
Tread2	High	High	High	High	High	Low	High
Tread3	Standard	Standard	Standard	Standard	Standard	Standard	Standard
Tread4	High	High	Medium	High	Low	Medium	Low Medium
Tread5	High	High	Medium	Medium	Low	Medium	Low Medium
Tread6	Low	High	Low	High	Low	Low	High
Tread Design1	Medium	High	Low	High	Low	Low	Medium
Tread Design2	High	High	Low	High	Medium	Low	Medium
Tread Design3	High	High	High	Low	High	High	High
Tread Base Material	Medium	Low	Medium	Low	Medium	High	Medium
Tread Cap Material	Low	High	Medium	High	High	High Medium	Low
Tread Skirt Material	High	Low	High	Low	High	High	High

Overall, a total of 25 modules were generated as presented in Table 18 below. Table 18 also displays current and proposed total number of variations in the original clustering attributes for each group in a scaled format for the confidentiality reasons (examples of the variation reductions were presented above when each group module combinations were discussed). Table 18 is presented to give an idea on the magnitude of the proposed total design complexity reduction. For example, currently a tire's belt, tread and tread design (Group 4) are defined in terms of a design dimension set (belt dimensions +tread dimensions+ tread design dimensions) from a total of 86* design values. However, this analysis proposed to define the same tire in terms of the same dimension set from only 25* values. This reduces the design complexity by a large amount.

Table 18: Tire case study results

		Number of modules	Current total variety*	Proposed total variety*
Group 1	Apex-Beads	5	13	7
Group 2	Chafer-Toe guard-Sidewall	4	15	4
Group 3	Mono Ply	5	21	5
	Double Ply	4	17	8
Group 4	Belt-Tread-Tread Design	7	86	25

*: Data is scaled for confidentiality reasons

In summary, in this step, modules for the 4 tire design groups were generated. Modules were determined clustering the 92 sample tires across multiple original clustering attributes of the 4 groups separately. Modules significant differences were ensured with the Kruskal-Wallis test. Module definitions were validated with determining the representative tires. ABC experts approved all the module definitions and the representative tires. Some failures of the representative tires were interpreted as design improvement opportunities. Next step presents how the generated tire modules were used to develop tire platform alternatives and product variants.

5.4 Applying Step 4: Define Platform Alternatives

An ABC expert rated the strength of the 5 module drivers of the product and design, and variance groups of Ericsson and Erixon [48] may have driven the variety across the tire module groups using the following scale: blank for no relation, 1 point for weak relation, 3 for medium relation, and 9 for strong relation.

Generally, carry over module driver refers to components and materials of a product that are desired not to be exposed to any design changes during the life of the product platform. Technology evolution module driver refers to material and structural product changes that result from changing technology shift. Examples would be changing bead type, usage of new tread fillers like silica. Planned product changes driver refers to the changes the company intends to carry out for production cost savings. Examples would be shifting from double ply to mono ply tire architecture, and usage of cheaper tread materials and modifying tread design geometry. Different specifications module driver refers to changes due to product application, such as passenger tires, performance tires versus off-road tires. Examples would be stiffer belts and apexes for one application tire to another. Styling module driver refers to changes connected to brand or trade-mark. Examples would be changing the sidewall material and marks, and tread design.

Figure 22 shows normalized total influences of the module drivers across the 4 tire module groups. Cumulatively, Group 4 modules were found to be influenced by the module driving factors the most and showed a big difference to the other groups' total relations with the module drivers. With more detailed analysis, variety within Group 4 modules were found strongly due to cost saving tread design (planned product changes) and new tread material for better tire performance (technology evolution). Additionally, belt design variations for different tire applications (different specifications) and tread design for noise reduction (styling) were among the important design reasons for the variety within Group 4. In contrast, in Figure 22, Group 2 shows the lowest cumulative relations with the module driving factors. Group 2 varieties were due to toe guard treatment (technology evolution) and sidewall material (styling). Similarly, variety in Group 1 were due to either cost saving or tire performance related apex material and bead type (planned product changes and different specifications). Group 3 module variants were due the differences in the ply number (planned product changes) and ply treatment for tire performances (different specifications).

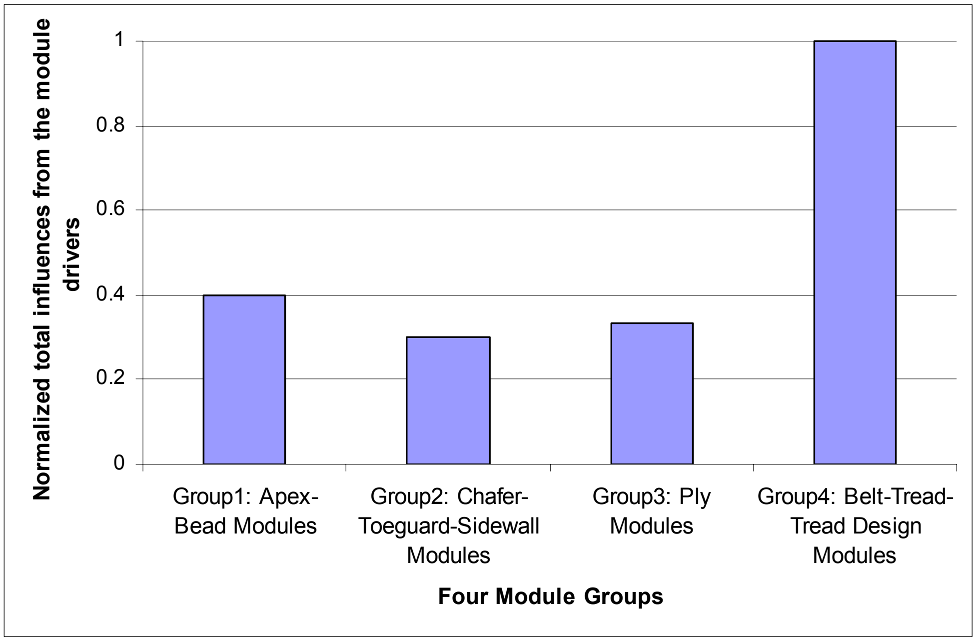


Figure 22: Normalized MIM results across the 4 module groups

Based on the observations in Figure 22, Group 2 modules were found to have the highest platformability, because of their relatively least total interactions with the major module driving factors. In this regard, Group 2 modules were followed by Group 3 (Ply) modules, Group 1 (Apex-Bead) modules, and Group 4 (Belt-Tread-Tread Design) modules, respectively.

With the help of the presented simple modularization driving factors analysis, the platforming architecture strategy was determined and presented in Figure 23. Platform alternatives were decided to be created with the module groups being influenced by the module drivers the least; Group 2 and Group 3 modules. As an example, in Figure 23, platform alternative1 consists of a double ply module (a Group 2 module) and a Group 3 module. Platform alternative2 has the same Group 2 module, but a different ply module (mono ply module 3). There are 6 products proposed to be derived from platform alternative1, while the product variety from platform alternative2 is 3.

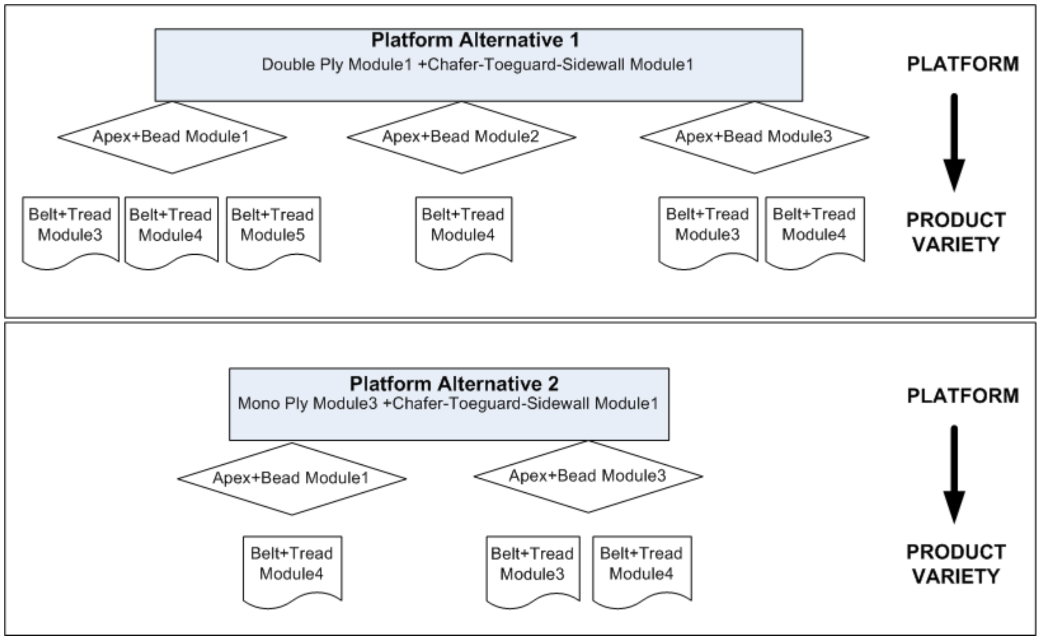


Figure 23: Examples of tire platform alternatives and product family planning strategy

In Figure 23, product differentiation was determined to channel using Group 1 (Apex+Bead) and Group 4 (Belt+Tread+Tread Design) modules. From left to right in the upper figure in Figure 23, the first 3 products share the same Apex+Bead module1, whereas next product uses Apex+Bead module 2 and last two product varieties share Apex+Bead module3. Products with different Apex+Bead modules are different in Apex+Bead module material or shape (technical developments) and stiffness for different tire applications (different specification) dominantly as discussed in Figure 22. On the other hand, differences in products derived from the same platform and sharing the same Apex+Bead module (for example differences between the first three product varieties of platform alternative 1 in Figure 23) are dominantly cost (planned product changes), tread material and tread design geometry (technical evolutions) (see Figure 22). Similarly, one product on the left of the bottom of Figure 23 derived from platform alternative2 differs from the other two products of this platform is dominantly cost (planned product changes), tread material and tread design geometry (technical evolutions). However, products of platform alternative2 differ from platform alternative1's products in terms of cost saving strategy in ply by reducing the number of ply from 2 to 1(planned product changes) dominantly and also serving different tire applications (i.e. performance versus passenger tires).

According to the determined platforming architecture strategy, the platform alternatives and product variants were observed as presented in Table 19 and Table 20. All 92 tires were re-defined in terms of what module groups they fell into as part of the clustering solutions. In other words, all tires were re-defined in terms of a combination of the four module groups defined in the earlier steps. Table 19 and Table 20 present observed platform alternatives and potential product variants for mono and double ply tires separately. Table 19 shows that there 12 observed mono ply platform types in the form of the following Group 2 (Chafer+Toeguard+Sidewall) and Group 3 (Mono Ply) modules combinations respectively; 1&1, 1&2, 1&3, 1&4, 1&5, 2&2, 2&4, 4&1, $&2, 4&3, 4&4, and 4&5. Similarly, Table 20 displays 8 double ply platforms; 1&2, 1&4, 2&2, 2&4, 3&1, 3&3, 4&2, and 4&4. Numbers of tires fell into different product types derived from the same platform are separated with "/" in the number of tires rows. For example, in Table 19, there were 3 product types derived from platform I as the results of the clustering solutions. There were 3 tires with the first product type, while there were 2 and 1 with the second and the third product types, respectively. Architectural differences between the 3 product types can also be seen. In Table 19, in addition to the Group 2 and Group 3 platform I modules, the 3 tires consist of Apex+Bead module 5 and Belt+Tread+Tread Design module 6. Next 2 tires have Apex+Bead module 4 and Belt+Tread+Tread Design module 3 while the single tire, grouped in the last product type derived from platform I, has Apex+Bead module 4 and Belt+Tread+Tread Design module 6.

Table 19: Observed mono ply tire platform alternatives and product types

	Observed Platforms	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
	# of Tires	*3/2/1*	*6/3/1/3*	*2/2/2*	*2/4/1*	*7/3/3*	*1*	*1*	*2/2*	*2*	*2/1/1/1*	*3*	*4/1/1*
Mono Ply Platforms	Chafer+Toeguard+Sidewall	1	1	1	1	1	2	2	4	4	4	4	4
	Mono Ply	1	2	3	4	5	2	4	1	2	3	4	5
	Apex+Bead	5/4/4	2/2/4/4	2/2/4	4/4/2	5/4/4	3	3	2/2	2	2/2/3/4	2	2/4/2
	Belt+Tread+Tread Design	6/3/6	6/3/3/6	6/3/6	3/6/6	6/3/6	3	5	6/7	6	3/6/3/5	6	6/5/3

Table 20: Observed double ply tire platform alternatives and product products

	Observed Platforms	I	II	III	IV	V	VI	VII	VIII
	#of Tires	*3/1*	*1/1*	*1/1/1*	*1/1*	*3*	*4/2*	*1*	*3/1*
Double Ply Platforms	Chafer+Toeguard +Sidewall	1	1	2	2	3	3	4	4
	Double Ply	2	4	2	4	1	3	2	4
	Apex+Bead	3/3	3/3	3/5/3	2/5	1	1/1	5	2/5
	Belt+Tread+Tread Design	3/6	6/3	7/1/1	3/1	4	2/4	3	7/6

In summary, it was found that 29 mono-ply product variants from 12 platform alternatives in Table 19 would be significantly different and sufficient to cover the current design space. Also, 15 double-ply product variants from 8 platform alternatives would be significantly sufficient to cover the existing design space. In other words, the same design variety created by the 92 tires was proposed to be generated with 44 (29+15) distinctive tire designs with well defined modules and platforms. The reader should note that this modularization scheme is not the only one that was possible within the context of partitioning design data using the clustering approach. However, the clustering solution chosen did result in modules that were significantly different along the several clustering attributes (critical design characteristics).

In addition, some design rules were identified by investigating how tire modules were distributed across proposed product types in Table 19 and Table 20. A predictability score for each module was calculated for mono and double ply tires separately. Module predictability was calculated as the ratio of the frequency of the module to the total frequencies of the same kind of modules across the corresponding proposed tire variants. For example, Figure 24 shows the predictability scores for Group 2 for the proposed mono ply and double ply product variants. As seen in Table 19, the proposed platform alternatives for mono ply tires include Group 2 module 1 for 16 of the proposed mono ply variants while module 2 and 4 are included by 2 and 11 types of mono ply tires, respectively. Accordingly, the predictability score for module 1, for example, is calculated as 0.55 as the ratio of the frequency it is observed across the proposed product variants (16) to the total frequency of all the Group 2 modules (29). Figure 24 shows that it is around twice more common to use Group 2 module 1 and module 4 for a mono ply product platform than using them for a double ply product platform. On the other hand, Group 2 module 3 is used only for double ply tire variants; therefore its predictability score for mono ply tires is zero. Additionally, it is about 4.7 times more likely to use Group 2 module 2 for double ply variants.

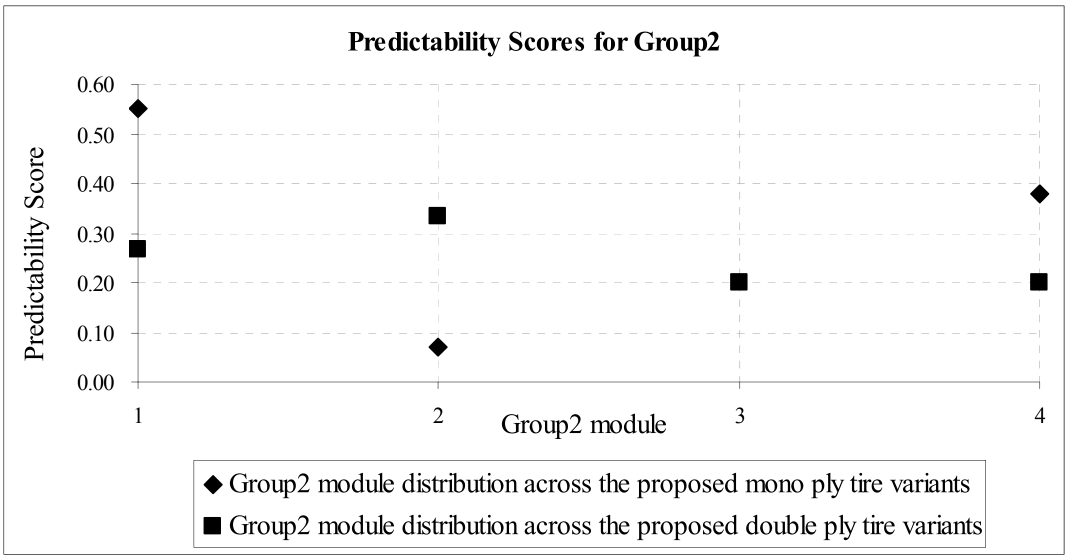


Figure 24: Group 2 predictability scores

As discussed above, the second module group forms the proposed tire platforms in Table 19 and Table 20 is Group 3. Modules of Group 3 are not comparable across the two kinds of platform alternatives due to their incomparable architectural differences. However, it is still useful to compute their predictability scores within their own kind to observe the commonality of the modules within the platform alternatives. Figure 25 shows that all 5 modules of Group 3 are utilized very similarly within the proposed mono play tire variants. In contrast, module2 and module4 double plies are more than twice on average common compared to the remaining 2 double ply modules.

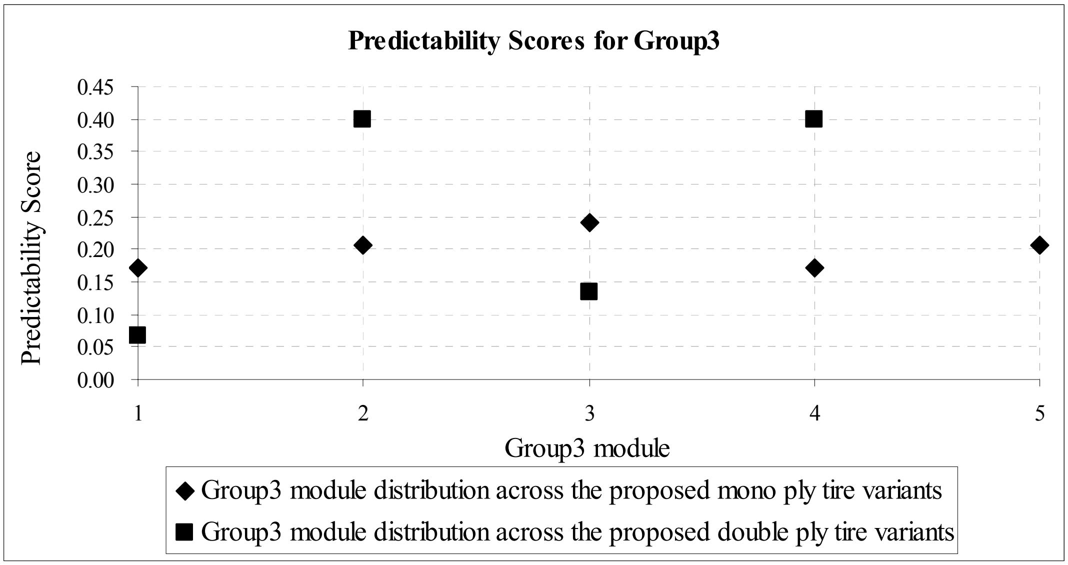


Figure 25: Group 3 predictability scores

As determined earlier, Group 1 modules are utilized as one means to derive tire variants from the proposed platform alternatives in Table 19 and Table 20. Below, Figure 26 presents the predictability scores for Group 1 modules. Module 1 is utilized to derive mono ply products only, while module 4 is used for only mono ply tire designs. In addition, it is about 4 times more common to use module3 and module5 for generating double ply tires. Module 2, on the other hand, is a more (about 3.45 times) common module for mono ply tire designs.

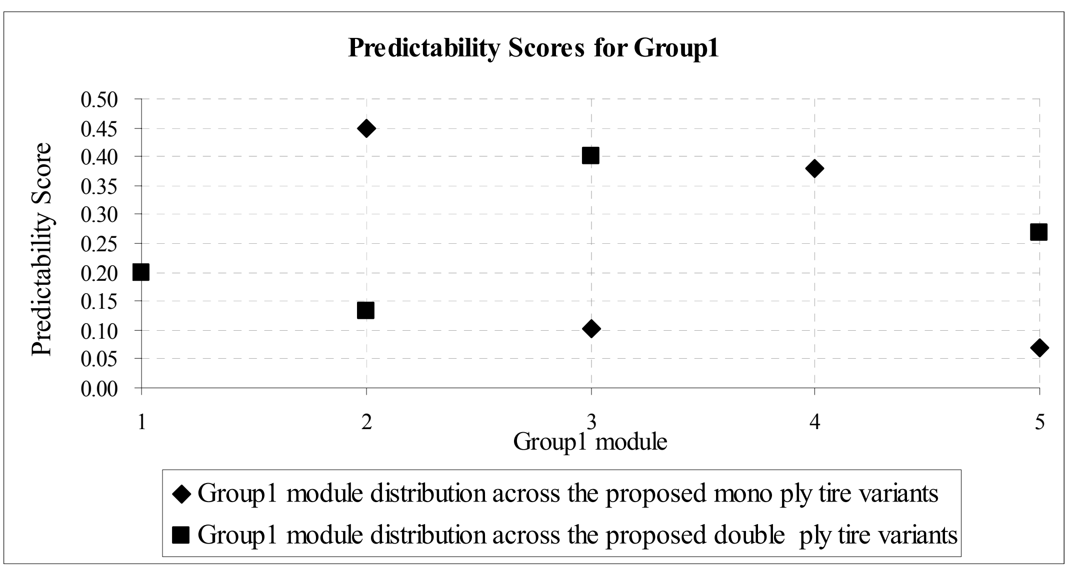


Figure 26: Group 1 predictability scores

Another tire derivation means from the platforms is using the Group 4 modules. Among the second types of Group 4 modules, module1 and module2 are utilized to derive double ply tires only. Similarly, module5 is solely used in mono ply tire designs. Utilizations of module3, module4, and module7 show very similar patterns for the both types of tire variants. Module6 is more commonly used for mono ply tire designs.

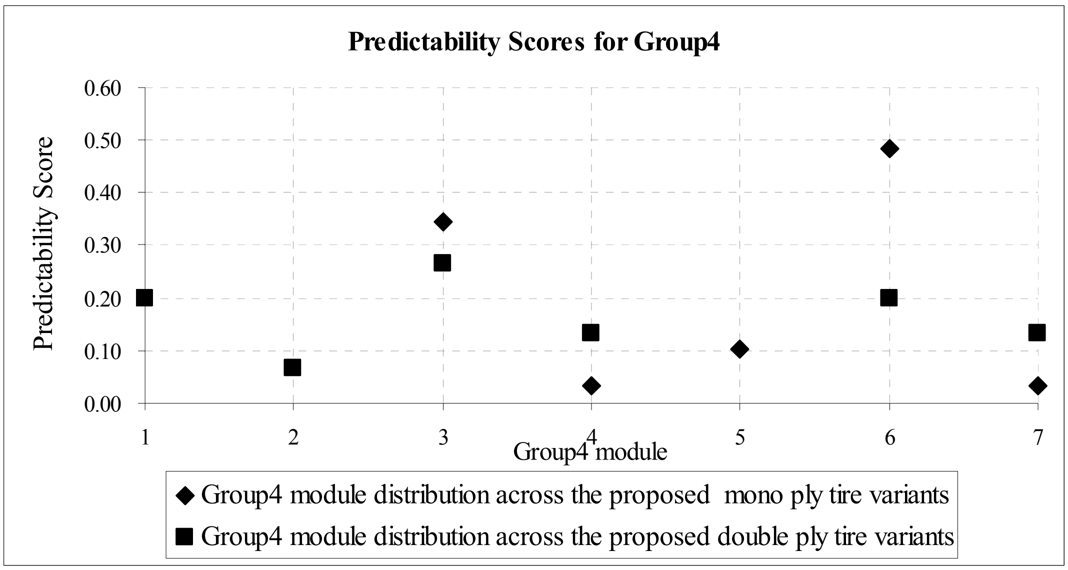


Figure 27: Group 4 predictability scores

As demonstrated above, the predictability score approach can be used to investigate module use patterns among proposed product variants. It can also help select modules for new product concepts as well as identify design improvements by utilizing modules with low predictability scores. In addition, relative commonality scores can be computed using the module predictability scores for the proposed product variants and platforms. For example, the commonality score for platform I in Table 19 is 0.0935 as the multiplication of Group 2 module1 and Group 3 module1 predictability scores. This platform is 6 times more common than platform VI within the proposed mono ply tires. Similarly, platform II, III and V in Table 19 are found to be the most generic platforms for mono ply architecture, as platform VI and VII are the least. Furthermore, platform I, II, III, and IV are the most generic double-ply platforms. The least common double ply platforms are platform V and VI.

Presented module predictability scores provided some precision on how general the generated modules are and how generic is a combination of the four modules in tire architecture. Among the generated 4 product types from mono ply platform III in Table 19, the product types with Group 1 module 2 and Group 4 module 6 are the most generic architecture. The same observations can be expanded to all product types to analyze the product architecture predictability. Additionally, predictabilities of new product concepts can be computed in the similar way.

The presented integral modular tire design approach provided valuable insight that would not have been available without the approach.

5.5 Summary and Preview

To identify similar design information for defining product modules and platform alternatives, several QFD based design decision management tools, a data clustering approach and process, and a commonality differentiation approach in terms of module prediction scores were incorporated into the proposed method to facilitate product family design as summarized in Figure 28. A case study for redesign of 11 tire lines, total of 92 broad market tires, was used to demonstrate the usefulness and applicability of the proposed method.

Critical tire design information and their interactions were identified through Step 1 and 2 as the case study outputs for these steps are presented in Figure 28. Tire modules were generated and their differences were identified in Step 3. Using the generated tire modules, product platforms were determined within the 11 product lines in Step 4. Using the module predictability scores, uniqueness of the generated design concepts (modules, product variants, and platforms) were defined in Step 4.

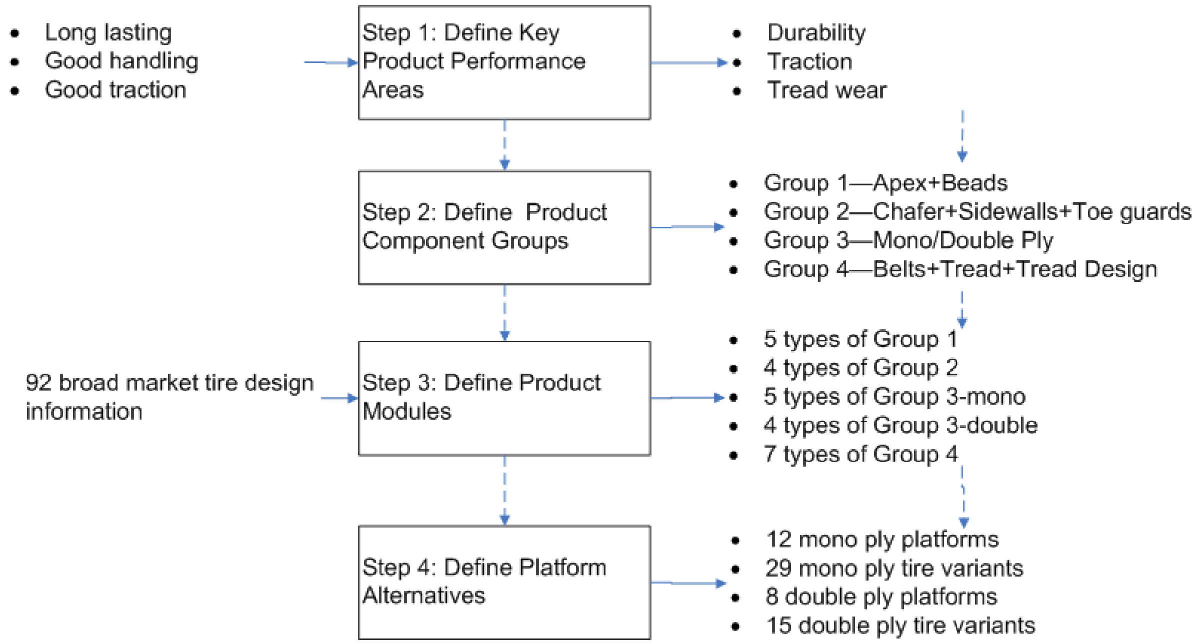


Figure 28: Research and the case study summary

In addition to communicating with many ABC experts during the case study application, the application results were presented for different departments at ABC. Engineers and directors indicated that each of the presented research approach was helpful as a framework for determining and defining distinctive tire modules, platform alternatives and product variants.

Chapter 6 : Contributions and Recommendations

In this dissertation, a method to support design teams in determining product platform alternatives and product variants along with distinctive product module definitions has been developed and tested. Section 6.1 reviews the research objectives and the proposed research approach, concluding with answers to the research questions posed in Chapter 1. The resulting contributions and limitations of the research are then summarized in Section 6.2. Concluding remarks are given in Section 6.3 along with opportunities for future research.

6.1 Research Summary

As stated in Chapter 1, the principal objective in this dissertation is to incorporate a decision support method for defining platform alternatives along with distinctive product modules and product variants. For this purpose, several QFD based tools are used to determine critical design information; product components and their critical characteristics. Relations and dependencies between the product components also are defined using the function based DSM. K-means clustering type is used to define product modules by optimizing multiple design differences across product families. The clustering is supported by the adjusted PCA approach and the significant difference test, Kruskal-Wallis. Kruskal-Wallis test is used to define the significant differences between the product modules. Relative differences across the modules are presented with the module mean values. Furthermore, potential reasons for the observed module variety are investigated by adapting the MIM. Based on the information drawn from the MIM, modules are categorized according to their platfomabilities. Distributions of the platform modules within the product families are searched for platform alternatives. Similar search is carried on for the other types of modules for product variants. Based on the search results, module predictability scores are calculated to show the commonality of the observed module combinations.

In summary, the resulting research method yields a means to locate and eliminate insignificant design complexities. The proposed method is tested with a tire case study application including 92 tires from 11 product lines. The proposed method provided valuable insight that would not have been available without the approach in a fast (1 month after data collection) and flexible manner.

Two major lessons learned from the application follow.

- The proposed method provided support design teams for product modules and platform design decision-makings based on reducing insignificant design information varieties. Particularly, data clustering facilitated an intuitive and flexible environment for the experts' participation to finalize clustering solutions. It was intuitive for the experts to make decision using the overall characteristics of the generated product groups which they are very familiar with. It was flexible, fast and easy to try and communicate alternative solutions with the experts.
- The application of the proposed method to the industry case study showed need for consistent, reliable, and complete information from different aspects of the conceptual design stage (e.g., engineering information, marketing information, material information). The proposed method can facilitate the integration of such information. For example, one of the QFD tools provides a frame of reference through which customer needs and product performance information can work together. However, more practical ways for these tools need to be developed and incorporated into the proposed method.

In particular, the use of this method to support product platforming and product modularization is introduced and exploited in the context of the following motivating research questions.

Q1: How can we support design teams to define distinctive product modules?

Hypothesis 1: Using the proposed research steps 1 through 3 in Chapter 3, critical design information in multiple characteristics can be identified and utilized for defining, generating, and distinguishing product modules.

Q2: How can we support design teams to determine modular platform alternatives and product variants?

Hypothesis 2: Using the proposed research Step 4 in Chapter 3, product modules can be categorized according to their platformabilities, and then utilized to detect potential platforms and product variants.

These two hypotheses are affirmed. Based on the results of the case application in Chapter 5, the proposed research steps were shown to be effective in defining product modules and utilizing them to determine platform alternatives and propose product variants. For instance, Section 5.3 presents the summaries of clustering results for the defined 4 product component groups. These summaries provide scaled module definitions across the identified critical design characteristics, as module differences were decided based on the results of the non parametric discriminant analysis. Furthermore, Section 5.4 illustrates the resulting platforming architecture strategy and presents the observed platform module combinations and the module combinations deriving the product variants. The following questions and sub-hypotheses are also addressed.

Q 1.1: How can critical design information be identified and captured for creating product modules?
Q 1.2: How can the critical design information be utilized for defining product modules?
Q 1.3: How can the significant differences between modules can be determined and presented?

Sub-Hypothesis 1.1: A common customer needs motivated approach can be used to determine the critical product components. Additionally, functional relations and dependencies among the components can be incorporated in defining product modules. QFD based tools can be adapted to capture such design knowledge.
Sub-Hypothesis 1.2: A data clustering approach can be utilized to define product modules by eliminating insignificant design variations in essence.
Sub-Hypothesis 1.3: Significant differences among the modules can be determined using non-parametric analysis methods. Design data mean vectors can be used to represent scaled module representations.

As motivated in Section 2.1.2 through an incorporation of customer need frequency and weight parameters information in conceptual design of product portfolios, costumer needs motivated methods permit designers to define valued-adding design goals. Section 5.1 uses common customer needs demanded for no extra price to define design goals. The design goals are defined in terms of a set of product performances. QFD described in Section 2.3.1 is effectively used to capture relational information and manage engineering decisions. Section 5.2 uses a QFD based data capturing method that permits design teams to define the product components based on their relations with the design goals. Section 5.2 also uses the functional DSM, essentially QFD based, to investigate relations and dependencies between the product components. This leads design teams to group product components to search for product modules separately.

As motivated in Section 2.4 through a comparison with optimization exercises, clustering methods can provide fast, easy, intuitive and flexible means to define design data commonalities. Section 5.3 uses the clustering approach including adjusted PCA and K-means algorithm to reduce the total number of critical design information variations from 152 to 49 on a scaled form for confidentiality reasons. Also, the clustering approach helps design teams define 25 modules.

Furthermore, Section 5.3 locates module significant differences by utilizing the summaries of the Kruskal-Wallis test results on the generated modules. Section 5.3 also demonstrates how module mean vectors can present scaled module definitions. This allow easy to review and understand module descriptions for design teams. Additionally, Section 5.3 helps design teams identify representative products for each generated module to validate the module descriptions.

Question 2.1: How can design teams define a strategy for platforming arhictecture?
Question 2.2: How can design teams detect multiple potential platforms and product variants?

Sub-Hypothesis 2.1: Modularization driving factors analysis methods in the literature can be adapted to define module platformabilities to determine a platforming architecture strategy.
Sub-Hypothesis 2.2: A method to re-define (re-configure) existing products using the defined product modules can help detect module usage patterns in platform alternatives and product variants. Additionally, a design commonality prediction method can be developed to compare how generic existing or future product types are.

As motivated in Sections 2.2 and 2.3.2 through categorization and measurement efforts to define solid basis for product modules, module drivers allow design teams identify goals of modular designs in a systematic manner. Section 3.5 adapts MIM to define reasons for being modules in terms of a set of modularization factors. Section 5.4 defines platformability scores for component groups based on their relations to the modularization factors. This helps designers determine two module types as platform modules. Section 5.4 diagnoses the distributions of the platforming modules within the product families and identifies a total of 20 platform alternatives. Designers define product variants by investigating the non-platform modules' distributions within the product families. Section 5.4 proposes 44 product variants. The ratio of the frequency of the module to the total frequencies of the same kind of modules is defined as the predictability score. Section 5.4 for example utilizes the predictability scores for detecting 7 of the 20 platforms as the most generic platform concepts within the product families.

6.2 Contributions and Limitations of the Research

This research has contributed to re-designing product families and platforms through a method for defining distinctive product modules. Through the case application presented in Chapter 5, the research contributions are realized in such way that a set of product families are redesigned to effective families of products derived from multiple platform concepts.

One of the contributions of this research lies in its simplicity and the use of non-parametric techniques to define product modules. Classification is a good approach and intuitive for this purpose. Design information can easily be modified to reflect dynamic design requirements. The method can be used to simulate different module definitions and corresponding product platform and family concepts. Different module numbers and types can be easily tried for different design strategies.

The proposed method contributes to the product development of many companies that frequently ask where to start and how much benefit can be obtained from platform-based product design. For example, an engineering team can determine product variants by well defined product modules and predictability scores to improve the effectiveness of product families. Hence, the adoption of the method support the development processes for identifying opportunities for improvement for non-optimal product family and platform concepts.

A basic requirement for the proposed method to be applicable to support designing product families and platforms is the complete and accurate product-specific design information. Similarly, captured design knowledge is required to reflect design team decisions and perceptions accurately and appropriately. However, all product data and knowledge is not always available, accurate, unbiased or complete, so that design data always has uncertainty associated with it.

Furthermore, the proposed research method is very sensitive to the selection of data clustering type, distance measurement technique, and variables. Their selection may come about with a fair bit of trial and error complemented with the analyst's institution and background knowledge of the products and the techniques. This is an inexact science and requires some degree of subjectivity.

The research method is motivated by the common customer requirements and functional interaction similarities of the design information. Mis-estimating this information might lead to incorrect module definitions since design teams can misjudge their effects on the product family design. Thus, careful attention needs to be paid to measure common customer requirements and to define the design information functional interactions.

6.3 Opportunities for Future Research

The issue of selecting a good clustering solution is a non-trivial one. Clustering must be performed such that it is valid and statistically rigorous. There is some subjectivity involved when selecting a good clustering solution. This research presents guidelines about choosing a clustering solution to support product family support; however, it may still require investigation of different clustering approaches. For future study, fuzzy clustering technique is planned to be investigated. Fuzzy clustering might give a clearer understanding of the underlying structure of the data by uncovering information that would have been lost in hard clustering.

This research method can be expanded as a future product module and platform alternative prediction tool with the implementation of a dynamic clustering technique. Unlike the static clustering techniques, dynamic clustering techniques can approximate future cluster centers using motion models. Such an approach can be useful to analyze product platform and family evolutions and develop dynamic design strategies accordingly.

Product performance analyses are needed to measure the performance sensitivity among different module combinations to create product variants. Such sensitivity analyses can support to realize the benefits of module and platform alternatives. Similarly, a cost analysis approach needs to be included for a more complete design analysis.

Furthermore, contributions of this research can be expanded to designing new product families. This research helps teams in understanding existing designs from the modular architecture perspective. As demonstrated earlier, product variants are defined in terms of product module collections. As this brings a simple but effective means to understand the differences between the existing product variants, it can support the generation of new product and product family concepts. For example, new combinations of the existing modules can be proposed as new product concepts. Similarly, existing modules can be modified, i.e. scaled up or down performance or cost wise, to support new product family concepts. However, such applications will be meaningful with the expansion of this research with the integration of product performance and cost information. Product performance and cost information should be included in the definitions of modules to provide more complete trade-offs for comparing different module designs or collections of module designs.

On product innovation, the presented module determination and definition approach in this research can be combined with product function-based approaches. Similar to identifying product modules based on design similarities, product function modules can be defined as grouping strongly related functions. Reasoning systems can be developed to link the design modules (focus of this research) and such function modules. This can support innovative product design as providing all potential function and design module pairs for human designers. Similarly, product customers and product use scenarios can be grouped in customer and product use modules, respectively. Customer, product use, and design modules can be linked to provide product design from multiple perspectives.

In addition to abovementioned extension of this research on product design learning and innovation, its contributions can be extended to product design, development, and manufacturing process controlling as well. As discussed in the literature review chapter, modular product architecture is found very helpful for global product development

(GPD) in which development of complete subsystems or components is to be carried out by teams in different locations. Without clearly defined modularity, more intense collaboration across design interfaces is necessary. As this research addresses the determination and definitions of product design modules and platform alternatives in an intuitive and flexible means, it is anticipated to be beneficial for applications of GPD business strategies. Due to its flexibility and simplicity, this research promotes the identification of value-added design assets and the related processes in a practical manner. In addition, this research approach is oriented around the identification of insignificant design variations and their eliminations by grouping them in design modules. Such potential design complexity reduction approach is anticipated to promote identification of related non-value adding development and manufacturing processes. All these opportunities can extend lean thinking and principles into companies' product design and development processes.

Glossary

Common Customer Needs for Platforming: Common needs which customer groups in all target market segments demand for no extra price.

Component Design Characteristics: A collection of design specifications to identify a product component. The collection may include geometric dimensions, material physical properties, logical design elements, and other specifications like weight, look, etc. Critical design characteristics are the component's features with strong impacts on the key product performance areas for platforming.

Design Structure Matrix (DSM): A system modeling tool which can represent a large number of system elements and their relationships in a compact way that highlights important patterns in the data.

Integral Product Platform: In general, it is a single part, which will be shared across the product family being developed. In integral product architectures, a one-to-one mapping between functional elements and physical components of a product is nonexistent, and interfaces shared between the components are coupled, or highly interdependent.

Key/Target Product Performance Areas for Platforming: Product performance features which are strongly linked to the common customer needs. The key product performance areas are used to determine the key design assets for the product modularization.

K-means Clustering: An algorithm to cluster objects based on attributes into k partitions. Focus of the algorithm is to minimize the total intra-cluster variance. The measure of dissimilarity is the Euclidean distance.

Kruskal-Wallis test: A non-parametric disciminant analysis. It is one-way analysis of variance by ranks. It does not assume normality and it can be used to test ordinal variables.

Market Segmentation Grid: A matrix arraying major market segments horizontally where the vertical axis reflects different tiers of price and performance.

Modular Product Family: A group of related products in which product varieties are accomplished by swapping product modules (collections of product components) to address a set of market applications.

Modular Product Platform: A set of common modules (collections of product components) which is implemented across a range of products. Platform concepts are determined by investigating the distributions of the highly platformable modules across the products.

Modularity Matrix: A matrix lists the possible functions from a family function structure as rows and the possible products from that family as columns. The matrix allows the designer to consider different partitioning schemes for each product and for the portfolio as a whole.

Module Drivers: Goals of modular designs. Module drivers represent the number of driving forces for modularization within the product.

Module Indication Matrix (MIM): A matrix to analyze technical solutions regarding their reasons for being modules. Using MIM, product technical solutions are assessed against a set of module drivers to group them according to similarities in their relations to the module drivers.

Module Predictability Score: The ratio of the use frequency of a module to the total use frequencies of the same kind of modules across the products.

Original Clustering Attributes: A set of critical product component design characteristics as the basis for determining, defining, and interpreting product modules with using the proposed data clustering approach.

Platformability: It is a relative measure to categorize product module groups. The measurement is based on the relations of the product module groups with a set of module drivers. Module groups in multiple and strong relations with the module driver set are defined to be relatively less platfomable groups, compared to the modules with less and weak relations with the module driver set.

Principal Component Analysis (PCA): An orthogonal linear transformation that transforms the date to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA involves the computation of the eigenvalue decomposition or singular value decomposition of a data set, usually after mean centering the data for each attribute.

Product Component: A product's design assets which may be a physical component, part as well as design information/knowledge. Product component is defined by a set of design characteristics.

Product Components Group: A group of product components in strong functional interactions with each other. The functional interactions within the component group are assumed to be more dominant than the interactions among the groups.

Product Modularity: A bundle of product characteristics where different views emphasize different aspects.

Product Module: A collection of product components. It is the clustering solution based on the selected product components' critical design characteristics.

Appendix A: Step 1 QFD Matrix Survey and Results

A 26X44 matrix formatted survey was designed for Step 1. A snapshot of the over all survey is presented in Figure 29. In the survey, 26 customer needs were grouped in 9 as shown in rows in Figure 29. The 9 customer needs groups include low cost, long lasting, good traction, good handling, good ride, quite, looks good, basic functions, and important controls. Similarly, 44 tire performance tests were grouped in 8 as shown in columns in Figure 29. The 8 tire performance tests groups include measurement, D.O.T., durability, traction, aesthetics, tread wear, miscellaneous, and field evaluation. More information about the performance tests can be found in Section 4.3. Due to its size, the survey was divided and distributed in 8 pages for reading convenience as demonstrated with the 4 sections of A and B in Figure 29.

Using the survey in Figure 29, 6 experts identified the relations between the customer needs and the tire performance tests using one of the following 4 ratings; blank for unrelated, 1 for weak relation, 2 for medium relation, and 3 for strong relation.

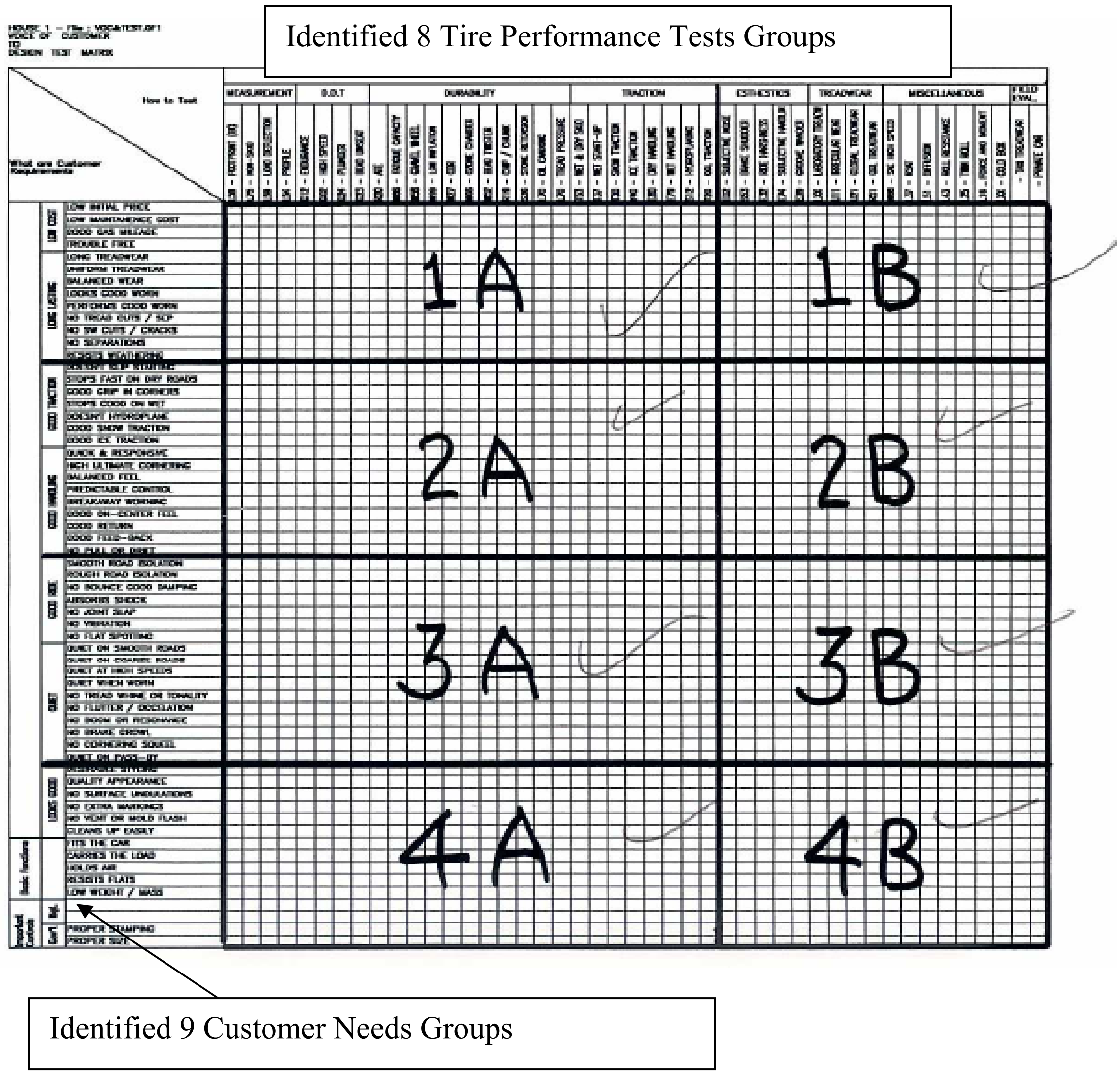


Figure 29: A snapshot from the customer-needs tire-performance tests QFD survey

The survey results are summarized in Figure 30. For this study, the survey results were analyzed based on the total responses for the relations between the tire performance tests groups and the customer needs groups. Figure 30 shows the customer needs groups in the x-axis and the normalized tire performance tests groups' relations to the customer needs groups in the y-axis. Figure 30 displays a relative appropriateness for each performance tests group to measure the list of customer needs groups in term of normalized relative percentage based on the survey results. For example, the experts indicated that the tread wear performance tests are appropriate to measure how well the design meets with the long lasting, good handling, good ride, and quite customer needs. It is also affiliated with measuring some of the remaining customer needs, for example low cost, basic functions, and looks good, but not as strongly. Thus, tread wear tests can be said inappropriate to drive conclusions about how well tire design meets with these customer requirements.

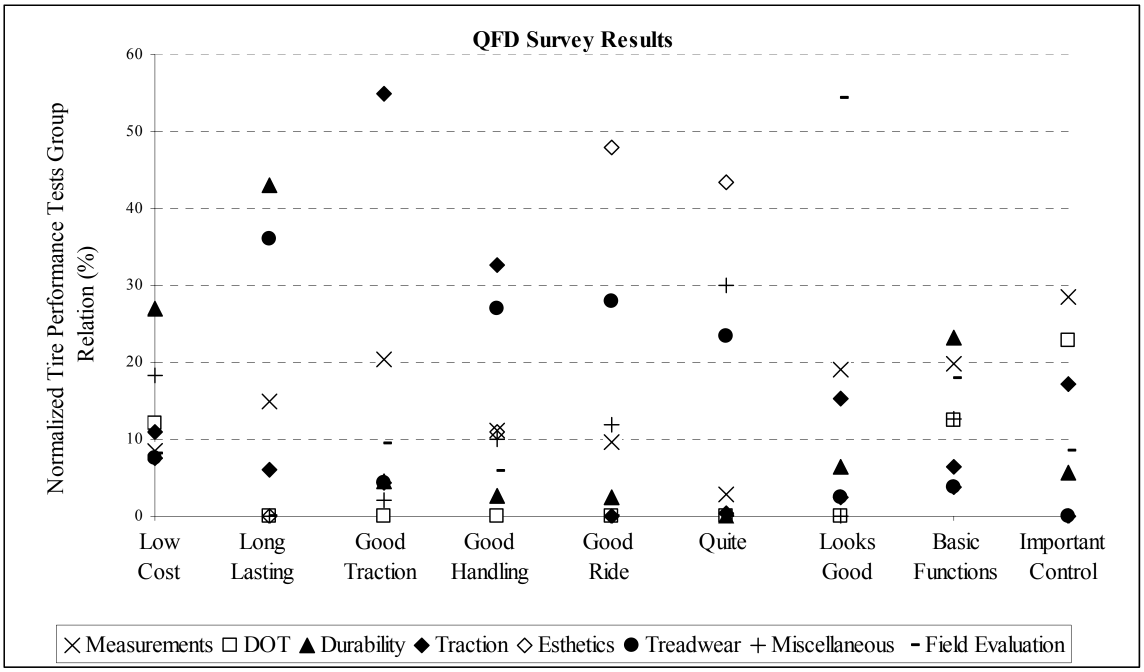


Figure 30: Results of QFD survey for Step 1

In the survey, the low cost customer needs group are defined in terms of items like low initial price and maintenance cost, good gas mileage, etc. Figure 30 shows that durability tests are found distinctively more appropriate to measure how well tire is meeting with such design requirements. The second appropriate measurements include the D.O.T., traction, aesthetics, tread wear, and measurement tests.

Examples for defining long lasting are long, uniform, balanced tread wear, good performance at worn status, resisting weathering, etc. From the survey results in Figure 30, durability and tread wear can be said to be the most appropriate tests for measuring such design requirements. Furthermore, except the measurement and traction tests, the remaining test groups are found completely inappropriate while designing for the customer requirements.

Good traction definition includes items like no slipping, no hydroplaning, good grip in cornering, fast stopping on dry roads, etc. The traction group is found distinctively the most related, as the measurement tests are the most appropriate one among the remaining groups for tire design around good traction requirements.

Good handling requirements include balanced feel, predictable control, good feedback, no pull or drift during driving, etc. Traction and tread wear tests are appropriate when the design is optimized for such requirements. Also, it can be said that the measurements and miscellaneous tests groups are more appropriate compared to the rest of the performance test groups.

Good ride requirements include smooth road isolation, good damping, no flat spotting, etc. As displayed in Figure 30, the esthetics is found the most appropriate test group when optimizing the design for such requirements. It is followed by the tread wear tests. Among the remaining test groups, the miscellaneous and measurement tests are found more appropriate for designing for good ride. Similarly, the esthetics, miscellaneous, and tread wear tests are appropriate for designing quite tires. The quite tire requirements include no tread whine or tonality, no boom or resonance, quite on pass-by, etc.

The looks good group is defined as tire design with desirable styling, quality appearance, no extra markings, and cleans up easily, etc. In Figure 30, the measurements and durability tests are found the most appropriate ones while optimizing the design for such requirements.

The basic functions relate to tire design which fits the car, caries the load, holds air, etc. The durability, measurements, and field evaluations are the most appropriate design evaluations for such requirements.

Lastly, the measurements, D.O.T, and traction tests groups are the appropriate when the important controls are evaluated in tire design. The important controls include proper stamping, proper size, etc.

For the case study, the selected 3 common customer requirements fall in the long lasting, good traction, and good handling customer needs groups in the QFD survey. From Figure 30, the experts selected durability, tread wear, and traction as the key goals for the platforming effort.

Appendix B: Step 2 QFD Matrix and Results

Below Figure 31 shows a simplified version of the tire-components tire-performance areas QFD matrix. The figure is not detailed due to company confidentiality requirements. Figure 31 highlights the interactions between the three selected tire performance tests (durability, tread wear, and traction) in Step 2 and the major tire component types, as not aiming to display the interactions with the other performance tests. As displayed in Figure 31, following 9 tire design components were selected as the critical tire components for this platforming effort; ply, belt, bead, apex, chafer, toe guard, sidewall, tread, and tread design. The remaining components' interactions with the key performance areas were not found as significant. These components would be standardized later.

	Ply	Bead	Apex	Chafer	Toeguard	Sidewall	Belt	Tread (Base+Cap)	Tread Design	Inner Liner	Overlay	Mini Skirt	Ply Shoulder Strips	Belt Edge Gumstrips
Durability	X	X	X	X	X	X	X	X		x	x	x	x	x
Tread Wear	X		X				X	X	X		x			
Traction								X	X					
Measurement							X		X					
Esthetics						x			X					
....														

Figure 31: Simplified tire component performance QFD matrix

Appendix C: Step 3 Module Definitions

Table 21 below shows adjusted PCA factor results for Group 1 (Apex-Bead). The original clustering attributes of Group 1 is 16 including the critical design characteristics listed in Table 22. Conducted PCA reduced the variable number to 5 factors. The scree plot in Figure 32 shows the distribution of the Eigen values of the 16 original clustering attributes. Table 22 shows the load distributions of the clustering attributes across the extracted five factors. From Table 22, the first factor is most highly correlated with five of the 8 apex material physical features (Apexmaterial1, 4, 5, 7, and 8), Apex2 and 3, and Bead1. The second factor is most highly correlated with another apex material physical feature, Apexmaterial6. As Apex1 is a good representative of the third factor, factor 4 is correlated with Aspect_ratio the most. Factor 5 is most correlated with Apex1 and Apexmaterial2.

Table 21: Group 1 (Apex+Beads) adjusted factors

Adjusted Factor1	Adjusted Factor2	Adjusted Factor3	Adjusted Factor4	Adjusted Factor5
0.673927	-0.8318	3.020634	0.962507	1.359857
1.884045	4.787869	-0.7118	-1.34058	-1.54549
-1.62515	0.487774	0.369748	1.046006	0.40799
2.911612	4.521107	1.623238	-0.65406	-0.10618
-1.3262	0.037308	0.439869	0.428371	0.596467
-1.41361	0.152618	0.403312	0.457451	0.447089
-1.7691	0.707212	0.335264	1.104945	0.113323
-0.00234	-2.08386	-0.64866	-2.04405	0.807489
-1.65082	0.580722	0.410489	1.076654	0.266801
-2.04113	1.157677	0.507264	1.589458	-0.09178
-1.73267	-0.03932	-0.90115	-0.21575	-0.21409
-0.34653	-1.91476	-1.47186	-2.2264	-0.02604
-2.50064	0.548578	-1.49266	-0.41001	-0.67343
-2.85081	0.997969	-1.85946	0.103874	-1.19374
-1.38848	-0.20843	-0.07795	-0.03338	0.619438
-2.09785	0.176613	-1.28564	-0.19377	-0.40032
-0.02744	-1.72282	-0.1674	-1.55322	0.63514
-0.54736	0.355952	2.35478	1.46445	0.716304
-1.73267	-0.03932	-0.90115	-0.21575	-0.21409
-2.9691	1.124459	-1.93468	0.132154	-1.34722
-2.09785	0.176613	-1.28564	-0.19377	-0.40032
-2.19659	0.235461	-1.56627	-0.1542	-0.7406
-1.38848	-0.20843	-0.07795	-0.03338	0.619438

-0.34653	-1.91476	-1.47186	-2.2264	-0.02604
-0.02744	-1.72282	-0.1674	-1.55322	0.63514
3.937676	4.026651	2.682027	-0.88206	-0.12328
4.055931	3.900182	2.757251	-0.91035	0.030201
4.174213	3.773693	2.832476	-0.93863	0.18367
-1.45004	0.899151	1.639723	1.778131	0.774497
-0.31015	-0.07215	2.347603	0.845247	0.896591
-1.53256	0.454232	0.485713	1.048375	0.42027
-1.41361	0.152618	0.403312	0.457451	0.447089
-1.06942	-0.01649	1.226505	0.639807	1.280612
3.937676	4.026651	2.682027	-0.88206	-0.12328
-1.41361	0.152618	0.403312	0.457451	0.447089
-1.73267	-0.03932	-0.90115	-0.21575	-0.21409
-1.3262	0.037308	0.439869	0.428371	0.596467
-2.85081	0.997969	-1.85946	0.103874	-1.19374
-0.34653	-1.91476	-1.47186	-2.2264	-0.02604
-2.09785	0.176613	-1.28564	-0.19377	-0.40032
-1.69307	0.628927	0.316861	1.168896	0.096526
-0.48892	-1.47384	-0.51637	-1.19754	0.862765
-0.58102	-0.92466	-0.36406	0.044752	-0.24014
0.472612	-2.40814	-0.39459	-1.84587	0.789859
0.564693	-1.96735	0.96412	-0.23536	1.607138
0.801229	-2.22033	1.114569	-0.29193	1.914085
0.088023	-0.49148	1.967583	0.805283	0.356475
-0.11278	-0.80993	0.73835	0.103806	-0.15123
-1.31248	-0.28671	-0.09636	0.030573	0.602641
-1.31248	-0.28671	-0.09636	0.030573	0.602641
-0.58102	-0.92466	-0.36406	0.044752	-0.24014
-2.37656	0.826263	-0.71959	0.691857	-0.21159
1.945762	4.765508	-0.63448	-1.339	-1.5373
4.634694	2.610257	1.224797	-2.16356	-0.47286
-1.69369	-0.18832	-1.29155	-0.15014	-0.5852
1.738542	-3.79084	0.532748	-2.14241	2.338126
1.039161	-2.03755	1.659642	-0.70618	1.452632
-2.85081	0.997969	-1.85946	0.103874	-1.19374
-2.9691	1.124459	-1.93468	0.132154	-1.34722
-2.09785	0.176613	-1.28564	-0.19377	-0.40032
-2.50064	0.548578	-1.49266	-0.41001	-0.67343
3.937676	4.026651	2.682027	-0.88206	-0.12328
4.055931	3.900182	2.757251	-0.91035	0.030201
-2.04113	1.157677	0.507264	1.589458	-0.09178
-1.45004	0.899151	1.639723	1.778131	0.774497
-0.54736	0.355952	2.35478	1.46445	0.716304
-1.65082	0.580722	0.410489	1.076654	0.266801
-1.06942	-0.01649	1.226505	0.639807	1.280612
-2.33508	0.604696	-1.27846	0.42543	-0.58061
-2.36021	0.965739	-0.79719	0.91626	-0.75296
-0.23412	-0.15044	2.3292	0.909199	0.879794

-1.73267	-0.03932	-0.90115	-0.21575	-0.21409
-1.38848	-0.20843	-0.07795	-0.03338	0.619438
-0.00234	-2.08386	-0.64866	-2.04405	0.807489
-0.34653	-1.91476	-1.47186	-2.2264	-0.02604
3.443584	4.160085	1.092443	-1.21111	-1.65366
5.391202	-2.19474	-0.03687	2.628398	-1.06601
5.771819	-3.11038	-0.45009	1.490063	-0.5599
5.8901	-3.23687	-0.37486	1.461783	-0.40643
-2.85081	0.997969	-1.85946	0.103874	-1.19374
-1.69307	0.628927	0.316861	1.168896	0.096526
-2.09785	0.176613	-1.28564	-0.19377	-0.40032
-1.73267	-0.03932	-0.90115	-0.21575	-0.21409
-1.31248	-0.28671	-0.09636	0.030573	0.602641
-0.02744	-1.72282	-0.1674	-1.55322	0.63514
-1.41361	0.152618	0.403312	0.457451	0.447089
5.072143	-2.3867	-1.34133	1.9552	-1.7272
5.983228	-3.00232	0.18161	1.924334	-0.4253
5.833349	-4.21796	-2.16778	-0.32145	-0.71497
5.652866	-2.80877	-0.36768	2.080986	-0.58672
5.740222	-4.45249	-2.72425	-0.784	-0.6961
4.846909	-2.51921	-2.24694	1.18192	-2.53391

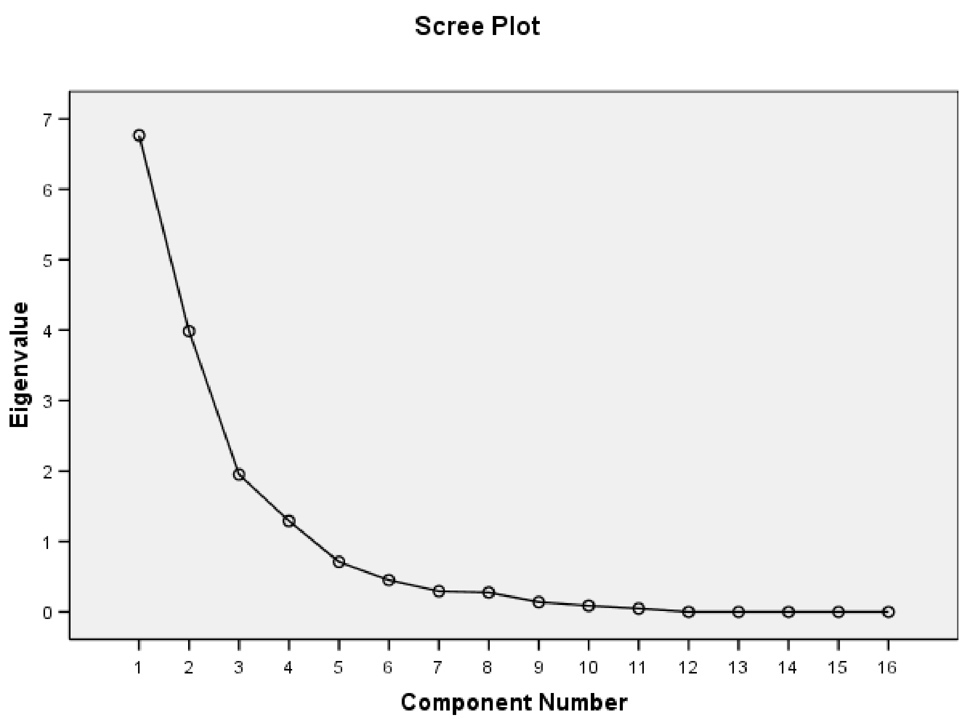


Figure 32: Group 1 (Apex+Beads) eigenvalue distribution

Table 22: Group 1 component matrix

Group 1: Apex+Beads Component Matrix[a]

	Component				
	1	2	3	4	5
Rim_diameter	.458	-.608	-.006	-.535	.101
Section_width	.688	-.542	.177	-.074	.260
Aspect_ratio	.236	.437	.568	.524	-.014
Apex1	.490	-.068	.655	.204	.429
Apex2	.770	-.345	.191	-.187	-.102
Apex3	.711	-.539	-.069	.268	-.046
Apexmaterial1	.813	-.246	-.309	.346	-.214
Apexmaterial2	.384	.524	-.599	.080	.440
Apexmaterial3	-.463	-.698	-.344	.365	.185
Apexmaterial4	.727	.299	-.550	.204	.183
Apexmaterial5	.797	.572	-.009	-.120	-.126
Apexmaterial6	.550	.794	-.024	-.243	.067
Apexmaterial7	.739	.640	.023	-.170	-.099
Apexmaterial8	.844	-.227	-.176	.288	-.312
Bead1	.805	-.215	.407	.009	.031
Beadtype	-.540	.583	.233	.299	-.021

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 23 below shows adjusted PCA factor results for Group 2 (Chafer+Toe guard+Sidewalls). The original clustering attributes of Group 2 is 16 including the critical design characteristics listed in Table 24. Conducted PCA reduced the variable number to 6 factors. The scree plot in Figure 33 shows the distribution of the Eigen values of the 16 original clustering attributes. Table 24 shows the load distributions of the clustering attributes across the extracted six factors. From Table 24, the first factor is most highly correlated with five of the 8 sidewalls material physical features (Sidewallmaterial1, 2, 3, 5, and 6). Section_width and Toeguard1 are good representatives of the second factor. Factor 3 is most highly correlated with Chafer2 and Aspect_ratio. As Toeguard2 is good representative for factor 4, the fifth factor is highly correlated with Toeguard3. Factor 6 does not have any good representative clustering attribute; it is found correlated with Rim_diameter and Toeguard3 weakly.

Table 23: Group 2 (Chafer+Toe guard+Sidewalls) adjusted factors

Adjusted Factor1	Adjusted Factor2	Adjusted Factor3	Adjusted Factor4	Adjusted Factor5	Adjusted Factor6
0.544215	0.932004	2.500155	0.329805	2.758529	1.429137
1.838808	0.819381	0.067338	-3.24299	2.339799	0.28976
1.277557	0.447354	1.009449	-1.42217	-1.13114	-0.24916
1.073509	0.791928	1.360479	-0.95141	-0.82918	0.116917
1.0821	0.995078	0.661611	-0.94267	-0.99567	0.209971
0.805191	-0.70055	0.205861	0.830802	0.161319	0.070408
1.095864	-1.43732	0.511163	0.243312	0.091921	-0.49311
0.436543	0.631522	-1.45463	1.543753	-0.16832	0.924425
1.094615	-0.40034	0.881039	-0.91086	-0.94611	-0.53988
1.276398	-0.98155	1.494809	-1.13558	-0.64747	-0.8417
1.218281	-0.02027	-1.1661	-0.25066	0.183798	0.144873
0.65807	0.260982	-2.25613	0.964849	0.205679	0.615118
1.130526	-1.05698	-1.33706	0.152655	0.434918	-0.25022
1.325983	-1.60471	-0.98922	-0.32685	0.299434	-0.70936
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
1.035339	-0.86795	-1.29451	0.260637	0.368832	-0.14584
0.523138	0.239342	-0.79831	1.427031	0.064242	0.726985
0.865715	-1.26991	2.011529	0.813466	-0.1156	-0.27685
1.218281	-0.02027	-1.1661	-0.25066	0.183798	0.144873
1.42117	-1.79375	-1.03177	-0.43483	0.36551	-0.81374
1.035339	-0.86795	-1.29451	0.260637	0.368832	-0.14584
1.130526	-1.05698	-1.33706	0.152655	0.434918	-0.25022
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
0.65807	0.260982	-2.25613	0.964849	0.205679	0.615118
0.523138	0.239342	-0.79831	1.427031	0.064242	0.726985
0.575072	-0.53316	1.706227	1.400955	-0.04619	0.286661
0.479885	-0.34413	1.748776	1.508948	-0.11228	0.391047
0.384698	-0.15508	1.791338	1.616931	-0.17836	0.495434
0.960932	-1.45894	1.96898	0.705483	-0.04953	-0.38124
0.670258	-0.72219	1.663678	1.292972	0.019882	0.182274
0.90549	-1.05924	0.596261	0.459277	-0.04024	-0.28433
0.805191	-0.70055	0.205861	0.830802	0.161319	0.070408
0.583663	-0.33001	1.007359	1.409695	-0.21268	0.379714
0.575072	-0.53316	1.706227	1.400955	-0.04619	0.286661
0.805191	-0.70055	0.205861	0.830802	0.161319	0.070408
1.218281	-0.02027	-1.1661	-0.25066	0.183798	0.144873
1.0821	0.995078	0.661611	-0.94267	-0.99567	0.209971
1.325983	-1.60471	-0.98922	-0.32685	0.299434	-0.70936
0.65807	0.260982	-2.25613	0.964849	0.205679	0.615118
1.035339	-0.86795	-1.29451	0.260637	0.368832	-0.14584
1.095864	-1.43732	0.511163	0.243312	0.091921	-0.49311
0.523138	0.239342	-0.79831	1.427031	0.064242	0.726985
1.312219	0.827674	-0.83877	-1.51282	-0.78815	-0.00628
0.808639	2.138118	-1.04144	-0.3377	-1.25922	0.959601

0.592165	2.339009	0.193008	-0.02233	-1.90086	1.018543
0.401791	2.71707	0.278106	0.19363	-2.03302	1.227316
1.073509	0.791928	1.360479	-0.95141	-0.82918	0.116917
1.113254	1.002599	-0.05479	-1.30559	-0.75382	0.109437
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
1.312219	0.827674	-0.83877	-1.51282	-0.78815	-0.00628
1.793266	-0.28716	-0.61856	-2.31628	-0.72539	-0.77857
1.838808	0.819381	0.067338	-3.24299	2.339799	0.28976
0.829656	1.598259	1.371204	-0.13644	3.343434	1.795524
1.407406	0.638643	-0.88132	-1.62081	-0.72207	-0.11067
0.079964	7.79238	-0.37063	3.237353	0.022265	-5.16096
0.711906	1.982905	1.431285	0.343208	2.869037	2.093497
1.325983	-1.60471	-0.98922	-0.32685	0.299434	-0.70936
1.42117	-1.79375	-1.03177	-0.43483	0.36551	-0.81374
1.035339	-0.86795	-1.29451	0.260637	0.368832	-0.14584
1.130526	-1.05698	-1.33706	0.152655	0.434918	-0.25022
0.575072	-0.53316	1.706227	1.400955	-0.04619	0.286661
0.479885	-0.34413	1.748776	1.508948	-0.11228	0.391047
1.276398	-0.98155	1.494809	-1.13558	-0.64747	-0.8417
1.05484	-0.61101	2.296307	-0.55667	-1.02147	-0.5324
0.865715	-1.26991	2.011529	0.813466	-0.1156	-0.27685
1.094615	-0.40034	0.881039	-0.91086	-0.94611	-0.53988
0.677601	0.517922	1.334687	0.147537	-1.18462	0.228567
1.230796	-1.41568	-0.94666	-0.21887	0.233358	-0.60497
1.317392	-1.80786	-0.29034	-0.33559	0.465919	-0.80241
0.670258	-0.72219	1.663678	1.292972	0.019882	0.182274
1.218281	-0.02027	-1.1661	-0.25066	0.183798	0.144873
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
0.436543	0.631522	-1.45463	1.543753	-0.16832	0.924425
0.65807	0.260982	-2.25613	0.964849	0.205679	0.615118
1.385794	2.565686	0.931222	-0.38669	4.443001	-2.74568
-8.5015	-0.69712	1.595425	-1.15533	0.051223	-0.55954
-8.87877	0.431816	0.633804	-0.45111	-0.11193	0.201417
-8.97396	0.62086	0.676353	-0.34312	-0.17801	0.305803
1.325983	-1.60471	-0.98922	-0.32685	0.299434	-0.70936
1.095864	-1.43732	0.511163	0.243312	0.091921	-0.49311
1.035339	-0.86795	-1.29451	0.260637	0.368832	-0.14584
1.218281	-0.02027	-1.1661	-0.25066	0.183798	0.144873
1.090691	1.198214	-0.03727	-0.93393	-1.16214	0.303024
0.523138	0.239342	-0.79831	1.427031	0.064242	0.726985
0.805191	-0.70055	0.205861	0.830802	0.161319	0.070408
-8.36657	-0.67548	0.137607	-1.6175	0.19267	-0.67141
-8.98255	0.417711	1.375221	-0.35186	-0.01153	0.212741
-9.12108	1.582391	-1.78563	-0.20908	-0.13365	0.850505
-9.33478	-1.24418	0.852468	0.415942	-0.07557	-0.52599
-9.6688	0.468222	-2.65625	1.038237	-0.06221	0.570912
-8.80163	-2.00464	-1.22603	-0.58631	1.006144	-0.99862

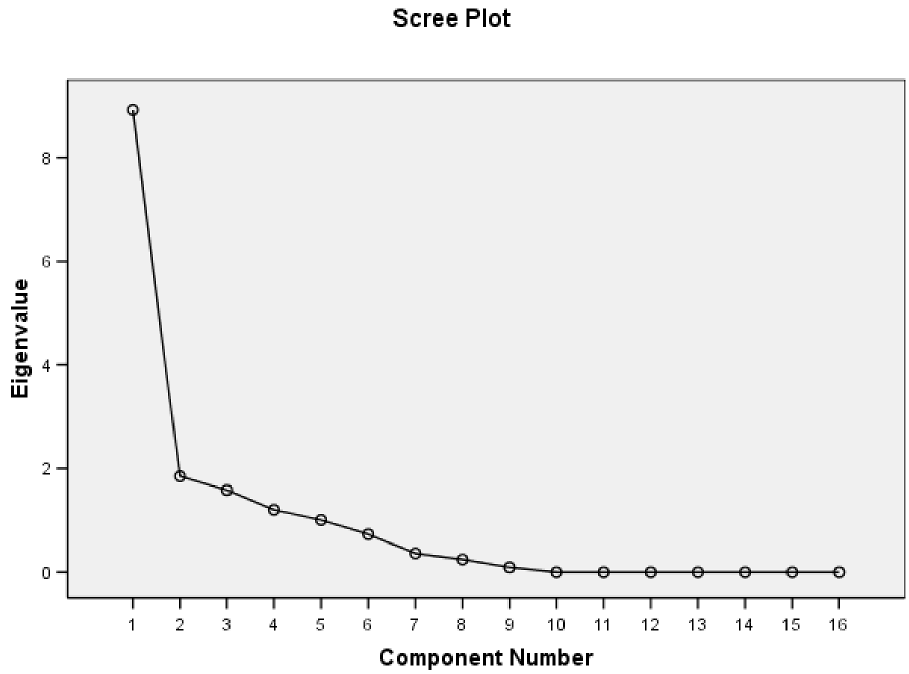


Figure 33: Group 2 (Chafer+Toe guard+Sidewalls) eigenvalue distribution

Table 24: Group 2 component matrix

Group 2: Chafer+Sidewalls+Toe guard Component Matrix[a]

	Component					
	1	2	3	4	5	6
Rim_diameter	-.449	.564	-.337	.399	.101	.298
Section_width	-.660	.587	.124	.271	-.149	.204
Aspec_ratio	-.026	-.274	.888	-.010	.163	-.079
Toeguard1	.024	.618	.007	.261	.201	-.713
Toeguard2	-.128	-.518	-.188	.623	.431	.058
Toeguard3	.112	.327	.216	-.298	.811	.216
Sidewall_material1	.993	.036	.012	.102	-.015	.032
Sidewall_material2	.993	.036	.012	.102	-.015	.032
Sidewall_material3	.993	.036	.012	.102	-.015	.032
Sidewall_material4	-.993	-.036	-.012	-.102	.015	-.032
Sidewall_material5	.993	.036	.012	.102	-.015	.032
Sidewall_material6	.993	.036	.012	.102	-.015	.032
Sidewall_material7	-.993	-.036	-.012	-.102	.015	-.032
Sidewall_material8	-.993	-.036	-.012	-.102	.015	-.032
Chafer1	.524	.556	.068	-.422	-.073	.099
Chafer2	-.300	.193	.760	.405	-.238	.137

Extraction Method: Principal Component Analysis.

a. 6 components extracted.

Table 25 below shows adjusted PCA factor results for Group 3 (Mono Ply). The original clustering attributes of Group 2 is 12 including the critical design characteristics listed in Table 26. Conducted PCA reduced the variable number to 5 factors. The scree plot in Figure 34 shows the distribution of the Eigen values of the 12 original clustering attributes. Table 26 shows the load distributions of the clustering attributes across the extracted five factors. From Table 26, the first factor is most highly correlated with four out of five ply material physical features (Ply_material1, 2, 3, and 4) and Ply_strength1. Section_width, Ply2, and Rim_diameter are good representatives of factor 2. Factor 3 is most highly correlated with Ply_strength2, as Ply1 is a good representative of the fourth factor. Aspect_ratio defines factor 5 the best.

Table 25: Group 3 (Mono Ply) adjusted factors

Adjusted Factor1	Adjusted Factor2	Adjusted Factor3	Adjusted Factor4	Adjusted Factor5
-2.24468	-1.30413	-0.84042	-1.73133	-0.0005
-1.63574	-0.2514	1.175635	1.10062	0.761907
-1.60256	0.259513	1.80862	0.425411	1.572592
-2.14809	0.787092	0.295895	0.123661	1.399755
-1.7043	0.393002	1.278516	-0.3878	0.577762
-1.64467	-2.35188	0.009167	0.179546	-0.12731
-1.0529	2.610887	1.808767	-1.32034	-1.57423
-2.09394	-1.86329	-0.94014	0.91987	0.692441
-2.08169	-2.99343	-0.57815	-0.30899	1.229883
-2.25213	0.607926	-0.6908	1.029102	0.021579
-2.32651	2.211355	-1.0697	0.780328	-0.76306
-1.83221	-0.51081	-0.18711	0.920623	-1.26459
-1.78277	-1.25106	0.152463	-0.66691	-0.77012
-1.73304	1.194042	1.091331	-1.47431	0.146974
-2.27879	0.113088	-0.91029	0.713175	-0.24675
-2.25625	2.146856	-0.08801	-0.7331	0.482924
-0.84134	-0.96563	3.013851	-0.0241	0.766719
-2.24536	0.718408	-0.42794	-0.30387	0.271578
-2.28554	-1.57133	-0.99715	-1.37095	-0.29396
-2.27879	0.113088	-0.91029	0.713175	-0.24675
-2.31234	-0.40183	-1.27332	1.32396	-0.66853
-1.74214	1.045578	0.738107	0.316871	-0.18896
-2.33308	2.104322	-1.32435	2.071639	-1.00524
-2.26494	2.00529	-0.4248	0.974762	0.162612
3.304932	-2.54728	0.148748	-0.48066	0.79694
3.222816	0.106313	0.913598	2.107036	0.971323
3.242757	0.062859	0.913788	0.00586	0.907225
3.163504	0.440763	0.478396	1.048125	0.228112
3.19293	0.980496	0.804677	0.822538	0.598003
-1.70915	0.313589	1.089584	0.570281	0.398074
-2.24388	0.74258	-0.37043	-0.59545	0.326261
-0.90893	0.47361	2.531582	-0.34541	-0.06534
-2.25951	-1.08684	-0.80231	-0.93006	-0.04907
-1.84235	2.167993	0.172576	-0.41445	-1.21068
-1.79655	0.038641	0.258048	-0.10671	-0.76467
3.236887	-2.07969	-0.25702	-1.09213	0.03084
-2.26113	2.067444	-0.27694	0.224966	0.303236
1.890092	0.672057	-2.32188	-0.67574	0.97962
-2.21465	1.27885	-0.05236	-0.77939	0.688338
-2.21402	1.289211	-0.02772	-0.90436	0.711772
3.129493	0.362024	-0.07799	-1.18647	-0.47766
-1.04031	-2.15323	0.982968	-1.3397	-1.93424
3.094124	-1.51381	-0.90757	1.092432	-1.28212
-2.24808	-0.11994	-0.69855	-1.95182	0.090335

-1.03345	-1.61439	0.924081	1.183484	-1.99852
-2.29866	-1.7854	-1.50646	1.211668	-0.77833
1.84582	0.624296	-2.24382	-0.9093	0.858564
-1.06428	-0.5703	1.307385	-0.89465	-1.80551
-0.84653	-3.37252	1.501463	0.013375	-0.38363
-2.05993	-2.76228	-0.79449	1.819172	1.11766
-2.08009	-0.64525	0.794594	0.36167	2.247429
3.259059	-1.84165	-0.45691	0.952729	-0.06576
3.192711	0.977032	0.796467	0.864196	0.590188
3.126315	-0.47024	0.138633	-1.78927	-0.31239
3.196496	-2.61469	-0.76356	0.445367	-0.54441
3.224733	0.137382	0.987525	1.732133	1.041635
3.109553	0.771136	0.129214	-0.6459	-0.41631
3.135388	1.252164	0.315851	-0.16335	-0.17924
3.055625	2.859701	-0.14906	0.22299	-1.06265
3.025011	2.208841	-0.64398	1.104773	-1.57595
3.09604	-1.02377	-0.22051	-1.39706	-0.71353
3.235188	-2.10731	-0.32272	-0.75889	-0.03166
3.072922	0.114023	-0.47636	0.995963	-1.05182
1.875245	1.164015	-1.91754	-1.13489	1.228455
1.903191	1.679577	-1.64876	-1.06889	1.543654
3.093978	2.12362	0.288433	-0.15873	-0.37684
3.17049	0.554709	0.749474	-0.3265	0.485926

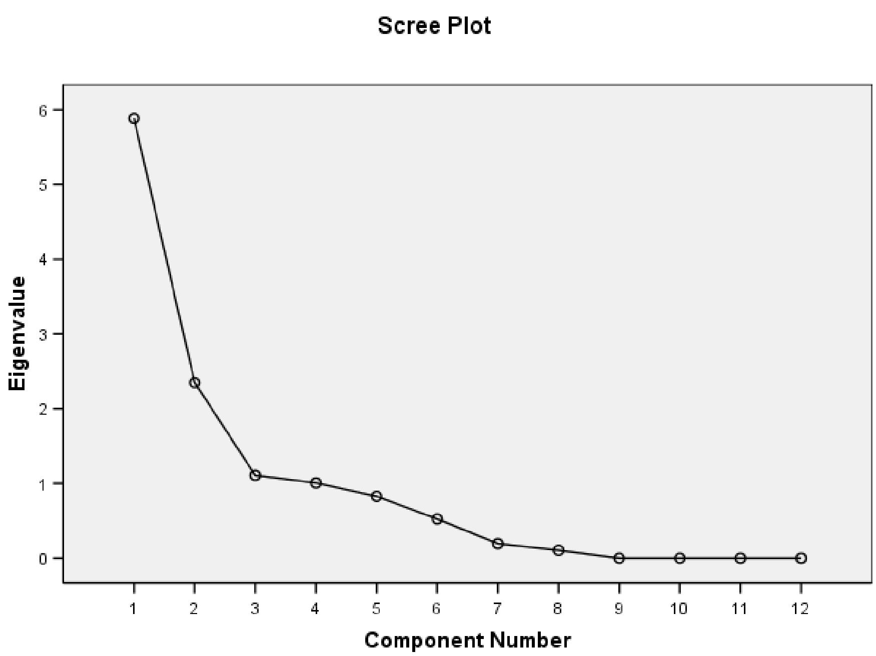


Figure 34: Group 3 (Mono Ply) eigenvalue distribution

Table 26: Group 3-Mono component matrix

Group 3: Mono Ply Component Matrix[a]

	Component				
	1	2	3	4	5
Rim_diameter	-.070	.902	-.044	.118	-.143
Section_width	.101	.792	.253	.113	.318
Aspect_ratio	.142	-.565	.416	.234	.631
Ply1	-.012	-.121	-.198	.957	-.163
Ply2	-.045	.723	.330	.087	.141
Ply_material1	.981	.058	-.168	-.012	.074
Ply_material2	.981	.058	-.168	-.012	.074
Ply_material3	.981	.058	-.168	-.012	.074
Ply_material4	.981	.058	-.168	-.012	.074
Ply_material5	-.981	-.058	.168	.012	-.074
Ply_strength	.783	-.137	.445	.022	-.324
Plyt_strength	.652	-.128	.617	.033	-.359

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 27 below shows adjusted PCA factor results for Group 3 (Double Ply). The original clustering attributes of Group 3 is 22 including the critical design characteristics listed in Table 28. Conducted PCA reduced the variable number to 5 factors. The scree plot in Figure 35 shows the distribution of the Eigen values of the 22 original clustering attributes. From Table 28, the first factor is most highly correlated with the four ply2 material physical characteristics (ply1_material1, 2, 3, and 4) and the two ply2 strength characteristics. Four ply1 material physical characteristics are good representatives of factor 2. Section_width is the best representative for factor 3. Factor 4 is most highly correlated with the two ply1 strength features, as Ply2 is the best representative for factor 5.

Table 27: Group 3 (Double Ply) adjusted factors

Adjusted Factor1	Adjusted Factor2	Adjusted Factor3	Adjusted Factor4	Adjusted Factor5
-3.13358	-2.2185	-0.37262	-0.20772	-1.8569
-2.29907	2.644109	1.347332	-0.04653	-0.83557
-2.08994	2.58262	1.456698	0.11746	-0.95174
-1.98995	2.499265	1.665271	0.144166	-0.89182
-1.83456	2.831889	0.406629	0.390215	-1.41303

-1.77169	1.198101	-0.01157	-3.17515	-0.90857
-2.09045	-1.76894	-0.02948	1.298479	2.248643
-2.09569	-1.97401	0.559531	1.089578	2.704364
-1.94985	-1.07821	-1.58362	2.377408	0.723749
-3.03959	-1.25154	0.44516	1.205899	-0.22144
-1.38508	1.938396	-3.30838	-2.38234	0.381873
-1.08678	-2.71029	2.919736	-0.96717	1.706821
-1.43717	2.644552	-1.35726	-1.052	2.241778
-3.54272	-2.1698	-0.18331	-0.4058	-1.77725
-3.18889	-1.27185	1.201117	1.555287	-0.63225
-1.75033	3.108182	-2.16077	0.034149	1.232446
4.04021	1.525778	-0.49381	1.293173	-0.783
4.241541	0.991115	0.638996	0.108908	0.368209
4.553553	1.04159	0.193481	0.293258	0.202065
4.093231	1.425132	-0.52933	1.047257	-0.50051
4.603381	1.106346	0.329152	0.656998	-0.19977
4.498363	0.460115	1.320078	-1.34713	1.787516
3.334212	-3.57784	-2.00239	0.730905	-1.16924
2.527564	-4.6169	1.758463	-2.672	-0.24488
2.793274	-3.35932	-2.2091	-0.08731	-1.2115

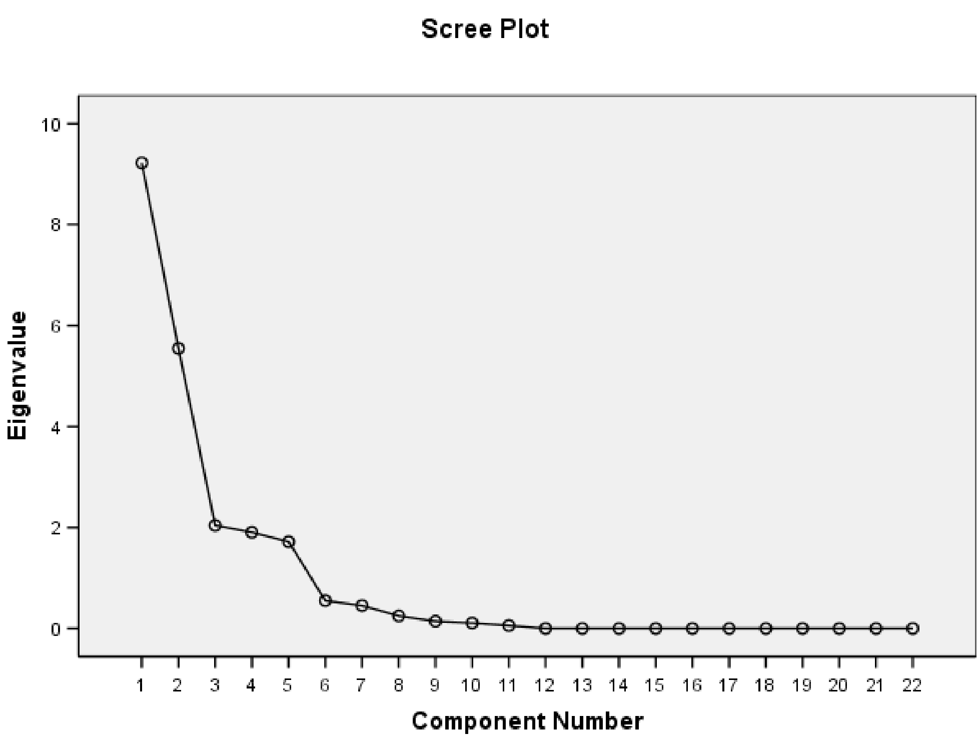


Figure 35: Group 3 (Double Ply) eigenvalue distribution

Table 28: Group3-Double component matrix

Group 3: Double Ply Component Matrix[a]

	Component				
	1	2	3	4	5
Rim_diameter	.458	-.170	.433	-.386	-.522
Section_width	.533	-.385	.524	.133	-.258
Aspect_ratio	-.192	.460	-.497	.081	.549
Ply1	.478	.178	-.520	.027	.180
Ply1Angle	.586	.144	-.437	.466	-.440
Ply2	.253	-.252	.430	.080	.744
Ply1_material1	.282	.932	.091	-.197	-.028
Ply1_material2	.282	.932	.091	-.197	-.028
Ply1_material3	.282	.932	.091	-.197	-.028
Ply1_material4	.282	.932	.091	-.197	-.028
Ply1_material5	-.282	-.932	-.091	.197	.028
Ply1_strength1	.013	.491	.434	.731	.081
Ply1_strength2	.013	.491	.434	.731	.081
Ply2Angle	.586	.144	-.437	.466	-.440
Ply3	.915	-.137	-.160	.116	.149
Ply2_material1	.975	-.125	-.038	-.048	.113
Ply2_material2	.975	-.125	-.038	-.048	.113
Ply2_material3	.975	-.125	-.038	-.048	.113
Ply2_material4	.975	-.125	-.038	-.048	.113
Ply2_material5	-.975	.125	.038	.048	-.113
Ply2_strength1	.927	-.222	.146	-.037	.038
Ply2_strength2	.927	-.222	.146	-.037	.038

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Table 29 below shows adjusted PCA factor results for Group 4 (Belt+Tread+Tread Design). The original clustering attributes of Group 4 is 49 including the critical design characteristics listed in Table 30. Conducted PCA reduced the variable number to 9 factors. The scree plot in Figure 36 shows the distribution of the Eigen values of the 49 original clustering attributes. From Table 30, the first factor is most highly correlated with five tread cap material physical features, Tread_Design2, Tread4, and three tread skirt material physical features. Seven tread base material physical characteristics are good representatives of factor 2 as factor 3 is highly correlated with Section_width. Four belt material physical features are representatives of factor 5, while factor 6 is correlated with the belt1 and 2 angles. Tread6, 3, and 2 are representatives of factor7, 8, and 9, respectively.

Table 29: Group 4 (Belt+Tread+Tread Design) adjusted factors

Adjusted Factor1	Adjusted Factor2	Adjusted Factor3	Adjusted Factor4	Adjusted Factor5	Adjusted Factor6	Adjusted Factor7	Adjusted Factor8	Adjusted Factor9
-0.67897	0.666747	0.070504	1.005979	0.094745	0.181218	0.051574	-0.08177	-0.17687
-0.4993	0.735629	0.497139	0.730939	1.266705	-0.18539	-0.4897	0.399784	0.000151
-0.60234	0.733861	0.273287	0.810347	0.836667	0.042341	-0.37112	0.200929	0.378684
-0.19838	-0.94348	0.58242	0.823617	-0.45948	-0.97488	-1.51967	-0.82795	1.041047
-0.42282	0.87003	0.064246	-0.66448	0.518438	0.434676	-0.16636	0.439839	0.392663
-0.4573	0.840872	0.153392	-0.81493	0.8534	-0.25938	-0.23464	0.696101	0.460017
-0.57589	0.746144	-0.19628	-0.55042	-0.15416	0.049463	0.424714	0.380532	0.066141
-0.42211	0.933792	0.02841	-0.72501	0.672197	-0.61306	-0.90218	-0.25182	-0.49205
-0.59994	0.773789	-0.55464	-0.39127	-0.4988	0.530177	-1.19915	0.458961	-1.66248
-0.01027	-0.80682	0.589837	-0.62649	-0.80768	-0.91958	-0.2785	-1.06358	1.188319
-0.51907	0.941331	-0.0116	-0.53246	-0.65154	-0.36511	0.656955	0.84725	0.543355
-0.35783	0.876421	0.253753	-0.72116	0.874083	-0.09966	-0.33249	0.406865	-0.42542
-0.45644	0.864859	0.131776	-0.76131	0.54332	0.017671	1.433856	-0.75914	2.306146
-0.04694	-0.80439	0.326231	-0.60924	-0.849	-0.79418	-1.68444	-0.5476	0.237983
-0.38663	0.71914	0.142423	-0.69201	0.171609	0.912616	3.399754	-0.91715	2.799415
0.079039	-0.92087	0.58168	-0.49958	-1.15612	-0.3516	0.473292	-1.17721	-0.23652
-0.55059	0.799137	0.296008	0.713651	1.095046	-0.52197	-1.04338	-0.15469	0.26405
-0.36523	-1.42367	0.369634	0.633635	0.173713	-0.65238	-0.18652	-0.45152	0.457847
-0.74649	0.62937	-0.26136	0.998917	-0.06719	0.327612	-0.45687	-0.13257	-0.02012
-0.60969	0.739795	0.274167	0.810984	0.824091	0.027316	-0.37781	0.163374	0.402416
-0.64972	0.667052	-0.02534	1.019806	-0.16041	0.58057	0.676728	-0.80121	-0.0398
-0.12687	-0.92814	0.605882	0.759557	-0.46779	-0.54905	-1.12392	-1.39833	1.277711
-0.08668	-0.86232	0.327573	-0.74001	-0.69055	-1.01275	-1.13438	-0.30917	1.443715
-0.15465	-1.07909	0.714336	1.095285	-0.96927	-0.60127	-0.0625	-0.45114	0.002631
-0.13192	-1.06863	0.800712	1.027565	-0.75982	-0.75598	-0.32452	-0.42584	-0.19655
-0.46297	0.870061	-0.00117	-0.82585	0.810118	-0.87376	-0.69065	0.184487	0.090814
-0.39795	0.922993	0.038488	-0.73357	0.716615	-0.48741	-0.87589	-0.11594	-0.38257
-0.08853	-1.14718	0.614908	-1.16947	0.915239	-2.353	-0.6989	-0.6503	-0.0825
-0.42362	0.869858	0.064171	-0.66375	0.518907	0.430787	-0.17151	0.44875	0.392715
-0.35438	0.86492	0.24037	-0.71496	0.876885	-0.1689	-0.33366	0.412025	-0.62404
-0.44947	0.864605	0.028367	-0.64207	0.465404	0.149124	-0.20796	0.279319	-0.08627
-0.48869	0.792035	-0.27107	-0.43396	-0.51957	0.706277	0.851737	-0.69417	-0.52854
0.085697	-0.93553	0.504276	-0.43036	-1.32213	0.044718	0.524074	-0.8752	-0.0846
-0.54168	0.789119	-0.2048	-0.42953	-0.31276	0.06772	0.194217	-0.12714	-1.05767
-0.57612	0.755522	-0.49524	-0.46214	-0.40729	0.548664	-0.26906	0.034598	-0.3515
-0.02993	-0.81578	0.34877	-0.63728	-0.80284	-0.75772	-1.3336	-0.67052	0.715827
0.166065	-0.79458	1.038463	-0.54648	-0.48889	-1.12965	-0.07109	-0.47721	-0.40112
-0.07437	-1.66146	-0.02864	-1.02666	0.366409	0.047158	0.69998	1.720539	0.082807
0.408683	-1.94877	-5.16266	0.17852	0.3058	0.623227	0.503035	-2.13944	-0.76601
0.021573	-1.28211	-0.45793	-0.51943	-1.49246	1.060304	-0.29622	0.503427	0.055169
0.641498	-0.62627	-4.35006	0.543454	-1.22775	-1.55156	0.605207	4.008896	1.026633
-0.12603	-1.98271	0.234134	0.829536	0.944445	1.992776	1.090489	-1.50053	-2.27828
0.028319	-0.96135	0.412404	-0.52923	-1.56377	-0.8567	0.133325	1.157609	-0.33566
0.279604	-1.57589	-0.08191	-0.78553	0.91451	4.11489	-0.97143	1.442085	1.965904
0.302762	-1.61197	-0.07886	-0.95452	1.031394	4.314618	-0.36387	1.264482	2.92933

0.352503	-1.97614	-4.5116	1.425195	1.665851	-0.41263	-0.48522	-1.62379	-0.02825
-0.02091	-0.96301	0.310325	-0.76827	-1.0935	-1.19456	-0.39138	1.700317	1.254846
-0.03738	-1.13103	-0.23531	-0.62428	-1.00443	0.136309	-0.98979	0.477084	0.705288
0.014648	-0.91459	0.311366	-0.65235	-1.24747	-1.11633	-0.61742	1.208855	0.267305
-0.01877	-1.6246	0.429286	-0.82758	0.234729	-0.20897	1.531381	1.811931	-1.09518
0.19695	-1.58048	1.945096	0.496523	2.031039	0.669835	1.597428	3.652342	-0.0135
-0.09298	-1.82579	0.652118	0.688832	1.182131	0.313035	0.660844	0.301382	-2.2853
0.408377	-1.71189	1.578338	0.008711	4.860398	1.370526	-0.82313	-1.07533	-0.72544
-0.45002	0.544832	-0.00254	-1.48324	2.796352	-2.03642	-0.16693	-0.1625	0.011754
-0.09383	-1.32842	0.742166	-1.07175	0.054047	-1.72611	4.304532	-2.93924	2.895131
-0.70047	0.690673	-0.08279	0.940974	0.189884	0.139687	-0.47572	-0.18861	0.194196
-0.74792	0.612251	-0.14865	1.14532	-0.35509	0.315861	0.342324	-0.16983	-0.46727
-0.64484	0.691648	-0.41544	-0.41108	-0.60399	0.184106	0.715465	0.29247	-0.22426
-0.56654	0.826568	-0.38689	-0.4528	-0.25834	0.137143	-0.98709	0.148242	-1.45249
-0.54267	0.712445	-0.37941	-0.30529	-0.9314	0.9154	1.191414	-0.62942	-1.16636
-0.5101	0.827289	0.380249	0.65344	1.28098	-0.4836	-1.05753	-0.1225	0.643864
-0.71552	0.686223	-0.10676	0.954592	0.156105	-0.04137	-0.4936	-0.30341	-0.12964
-0.59996	0.767794	-0.35576	-0.61195	-0.06497	-0.03546	-0.10707	0.254306	0.351769
-0.7587	0.539884	-0.17972	1.217149	-0.59578	0.61793	0.780634	0.005094	-0.6699
-0.63983	0.724159	0.228156	0.951459	0.334391	-0.08665	0.022469	-0.20986	-0.11591
-0.76461	0.529196	-0.23688	1.212513	-0.63313	0.846009	0.731907	0.088825	-0.3611
-0.37176	0.947995	0.104655	-0.7815	0.877115	-0.59723	-0.91834	-0.14951	-0.24286
-0.51024	0.752778	-0.36505	-0.3762	-0.71222	0.916005	0.919907	-0.60074	-0.64217
-0.55255	0.668637	-0.48263	-0.29057	-1.04182	1.203122	1.275419	-0.50407	-0.92201
-0.51656	0.819771	-0.29868	-0.53164	-0.12423	0.50511	-0.26469	0.053481	0.10281
-0.08651	-1.00417	0.99624	1.001851	-0.53555	-1.14171	-0.29714	-0.60941	-0.40651
0.108648	-0.8711	0.798459	-0.48147	-0.82579	-0.63888	-0.06942	-0.29117	-0.25299
-0.17177	-0.9546	-0.22498	-0.33084	-1.74483	0.140344	-2.24479	0.252385	-1.00583
-0.32794	-1.10278	0.074421	1.043988	-1.31541	-0.19684	-1.18679	-0.60379	0.916587
-0.52432	0.693578	0.539254	1.031414	0.446941	-0.21413	0.754491	-0.00718	-0.95359
-0.36629	0.820157	0.293711	-0.42144	0.084503	-0.09682	0.92235	0.097546	-1.43518
-0.7536	0.61665	-0.35066	1.029733	-0.22358	0.781153	-0.21237	0.018156	0.735344
-0.75758	0.613612	-0.35845	1.034786	-0.23049	0.723086	-0.2231	0.003024	0.628501
-0.69785	0.684201	-0.68632	-0.48528	-0.57126	0.114058	0.092933	0.166975	0.053185
-0.62818	0.734735	-0.64415	-0.39436	-0.65419	0.526715	-0.09141	-0.09357	-0.39086
-0.78723	0.558395	-0.32451	1.167552	-0.54343	0.608118	0.298652	-0.05125	-0.33604
0.110617	-1.23771	1.48622	-0.61322	-0.05644	-1.94193	2.235614	2.177817	-2.89265
2.360717	0.394205	0.315348	2.866436	-0.41246	-0.37148	0.842593	0.271598	-0.30863
3.142912	1.037613	0.038477	-1.30116	-0.56511	0.554826	0.807107	-0.91138	-0.78454
2.569107	0.599683	0.895718	2.537243	0.817266	-0.73848	0.114161	0.557414	1.045365
3.215346	1.143933	-0.18637	-1.80923	0.662601	0.013271	-1.53853	-0.9443	0.594385
3.250703	1.184216	0.281562	-1.63093	0.499777	-0.09596	-0.67111	-0.78203	-0.21594
2.799636	0.694909	-1.07751	-1.12329	-1.44938	1.26829	-0.60386	0.761249	-0.59438
2.418876	0.44607	0.138517	2.850053	-0.35878	0.145735	0.095685	-0.01969	-0.12041
2.48855	0.541835	0.732098	2.623635	0.572661	-0.67858	-0.05804	0.946422	0.928273
3.176399	1.034311	0.343092	-1.25036	-0.55416	0.539509	1.190238	-0.70301	-1.38232

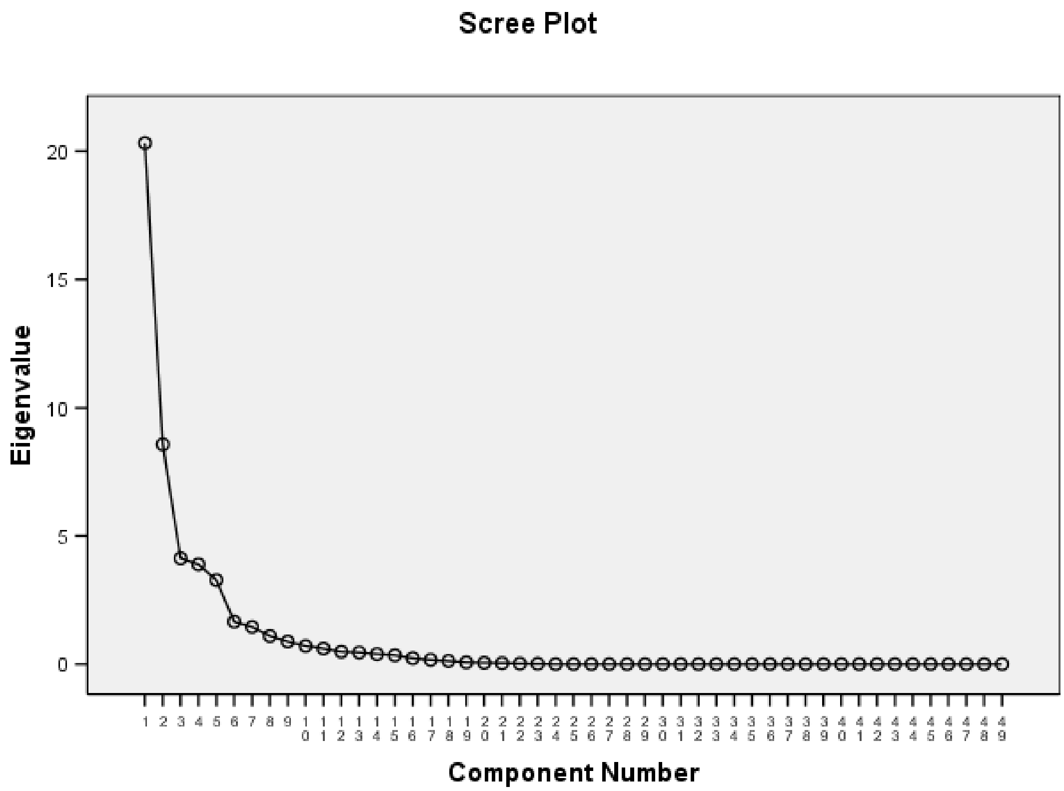


Figure 36: Group 4 (Belt+Tread+Tread Design) eigenvalue distribution

Table 30: Group 4 component matrix

Component Matrix[a]

	Component								
	1	2	3	4	5	6	7	8	9
Rim_diameter	.431	.141	.544	.100	.367	-.282	-.190	.096	-.044
Section_width	.659	.117	.579	.124	.204	-.218	.105	.018	-.010
Aspect_ratio	.037	-.241	-.067	.113	-.546	.290	.547	.004	-.235
Belt1_1	.393	.396	.623	.143	.278	-.341	-.090	-.154	.063
Belt1_Angle	.088	-.415	-.152	.170	.697	.315	-.109	-.200	-.044
Bel2_1	.393	.396	.623	.143	.278	-.341	-.090	-.154	.063
Belt2_Angle	.034	-.321	.122	.212	.574	.407	-.161	-.469	-.146
Belt_strength	.527	.234	-.159	.114	-.102	.137	-.115	-.158	-.302
Belt_material1	-.698	-.252	-.096	.567	-.069	-.056	.005	.078	.124
Belt_material2	-.434	-.184	-.126	.863	-.070	-.021	-.046	-.018	.055
Belt_material3	-.476	-.196	-.124	.840	-.071	-.026	-.040	-.006	.065
Belt_material4	-.517	-.207	-.122	.812	-.072	-.031	-.034	.007	.075
Belt_material5	-.266	-.133	-.127	.912	-.063	-.002	-.065	-.061	.017
Tread1	.420	-.163	.441	.160	.366	.374	.041	.342	.109
Tread2	.549	-.339	.213	.065	.250	.374	.063	.457	.116
Tread3	-.020	-.030	.161	-.062	.039	.000	.645	-.289	.621
Tread4	.740	.177	.325	.295	-.211	.000	.277	.019	-.222
Tread5	.143	.321	.561	.336	-.352	-.042	.283	.077	-.183
Tread6	.512	-.024	.220	-.007	.246	.514	-.103	.065	.208
Tread_Design1	.673	-.115	.283	.140	.135	-.074	.111	.124	-.087
Tread_Design2	.809	-.255	.087	.065	.230	.106	.040	.242	-.073
Tread_Design3	-.632	-.053	-.011	.126	-.044	-.276	-.253	.396	.067
Tread_Base_material1	-.587	.758	-.121	.035	.206	.041	.091	.089	-.013
Tread_Base_material2	-.572	.730	-.181	.019	.215	.010	.105	.157	.013
Tread_Base_material3	.520	-.816	.045	-.068	-.188	-.084	-.074	.003	.047
Tread_Base_material4	-.534	.798	-.117	.048	.204	.049	.092	.079	-.017
Tread_Base_material5	-.587	.772	-.073	.048	.196	.065	.080	.034	-.033
Tread_Base_material6	-.588	.771	-.074	.047	.197	.065	.080	.035	-.033
Tread_Base_material7	-.581	.775	-.079	.048	.198	.063	.081	.040	-.031
Tread_Base_material8	-.579	.778	-.065	.051	.195	.070	.078	.025	-.037
Tread_Base_material9	.541	-.781	-.027	-.076	-.168	-.113	-.053	.080	.074
Tread_Cap_material1	.738	.402	-.422	.016	-.124	.005	-.148	.060	.138
Tread_Cap_material2	.719	.427	-.331	.051	-.181	.117	-.186	.096	.062
Tread_cap_material3	-.114	.559	.328	-.023	-.575	.275	-.318	.007	.146
Tread_cap_material4	.754	.132	-.576	.016	.163	-.147	.000	-.011	.082
Tread_cap_material5	.770	-.002	-.537	.040	.258	-.177	.089	.022	.025
Tread_cap_material6	.832	.037	-.474	.062	.211	-.134	.080	.046	.008
Tread_cap_material7	.851	.269	-.417	.049	.023	-.059	-.051	-.027	.080
Tread_cap_material8	.651	-.228	-.493	.049	.394	-.228	.215	.112	-.043
Tread_cap_material9	.397	.645	.097	-.003	-.482	.143	-.281	-.098	.220
Tread_skirt_material1	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001
Tread_skirt_material2	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001
Tread_skirt_material3	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001
Tread_skirt_material4	.939	.269	-.028	.131	-.074	.031	.009	-.027	-.001
Tread_skirt_material5	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001
Tread_skirt_material6	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001
Tread_skirt_material7	.939	.269	-.028	.131	-.074	.031	.009	-.027	-.001
Tread_skirt_material8	.939	.269	-.028	.131	-.074	.031	.009	-.027	-.001
Tread_skirt_material9	-.939	-.269	.028	-.131	.074	-.031	-.009	.027	.001

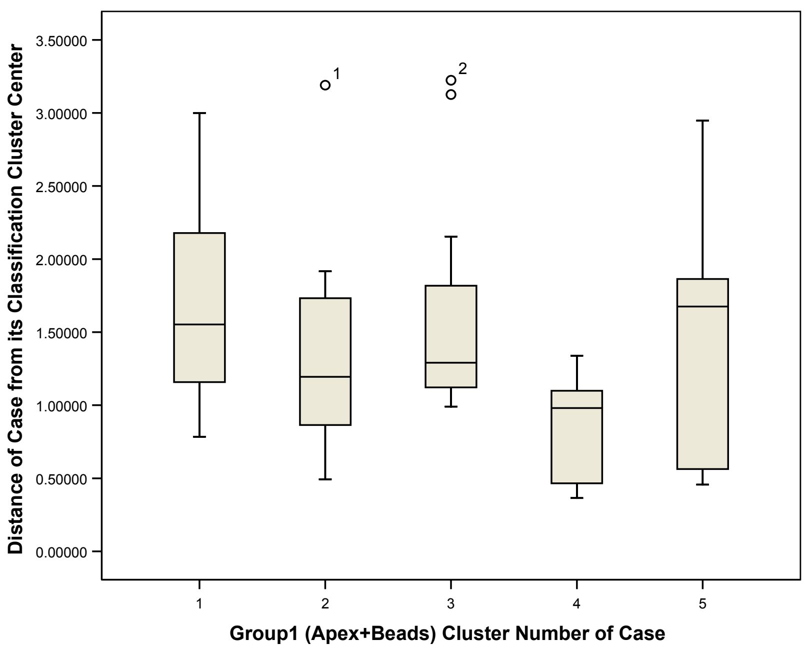
Extraction Method: Principal Component Analysis.

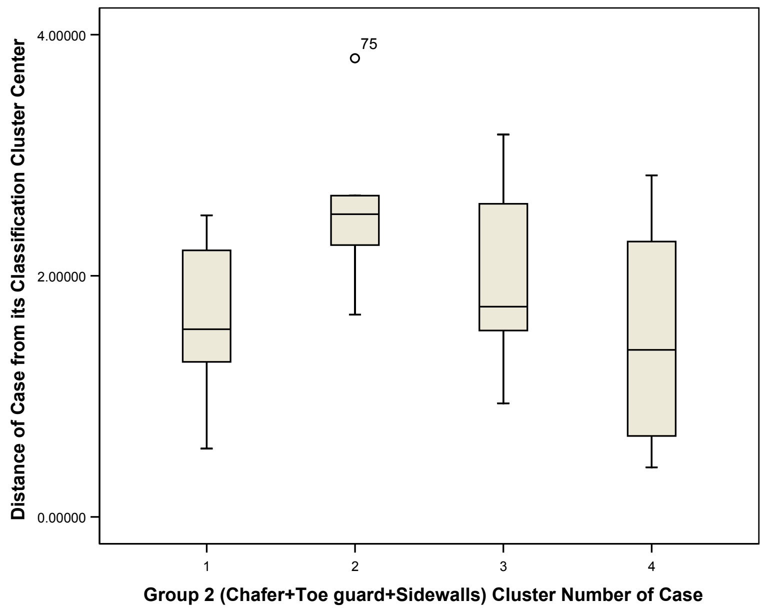
a. 9 components extracted.

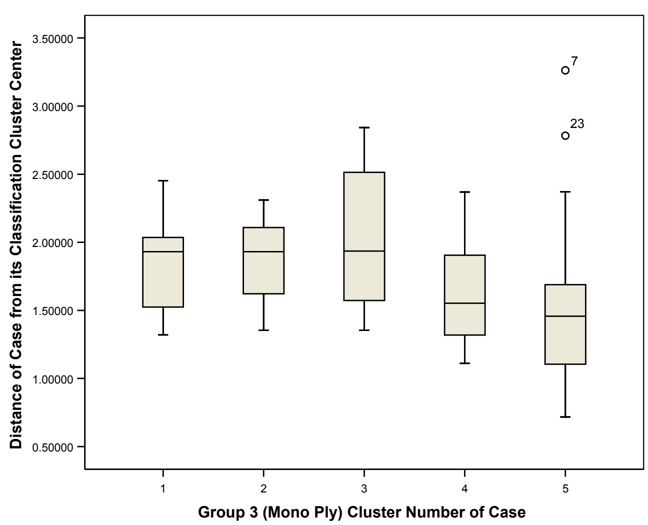
Appendix D: Step 3 Module Representative Product Selection

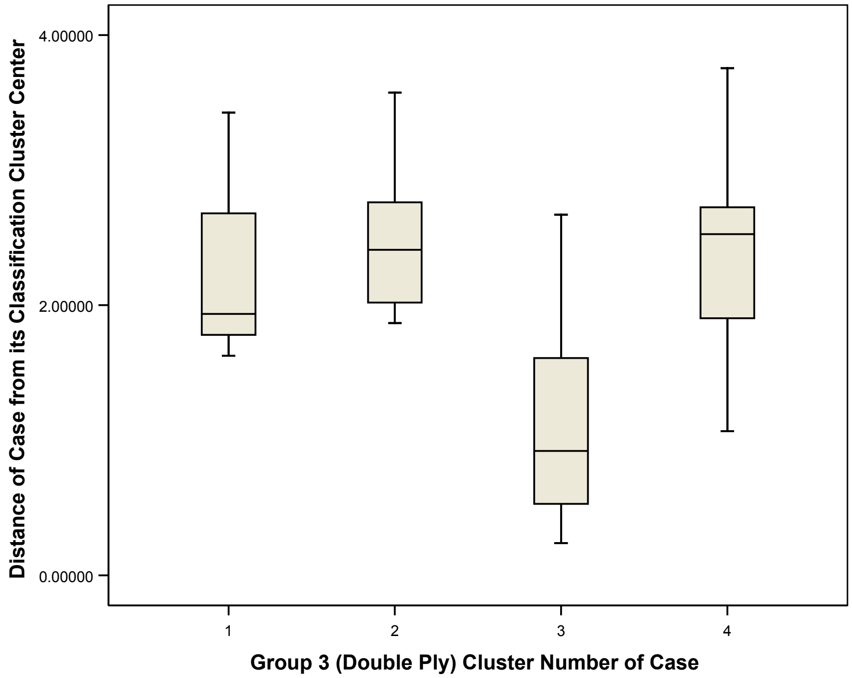
This section presents distributions of tire distances from their classification module centers. In the case study, presented graphs were used as a tool to diagnose the similarities within defined tire modules. There observed some variability within the clusters, but all the distances are within the reason.

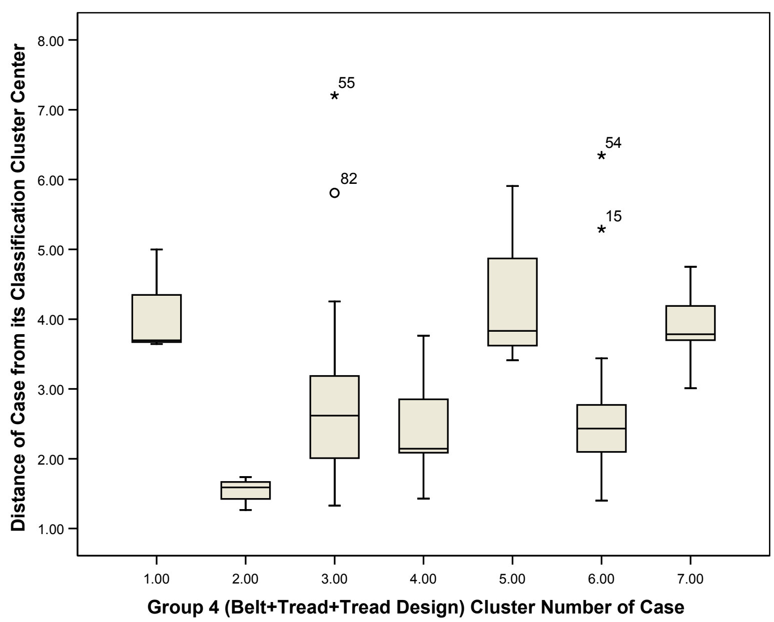
Below, the graphs show the median, quartiles, and outliers and extreme values for a scale variable. The interquartile range (IQR) is the difference between the 75th and 25th percentiles and corresponds to the length of the box. The line included in the box represents the median. Outliers are values between 1.5 IQR's and 3 IQR's from the end of a box. Extremes are values more than 3 IQR's from the end of a box.




4.00000
2.00000
0.00000
75
1
2
3
4
Distance of Case from its Classification Cluster Center
Group 2 (Chafer+Toe guard+Sidewalls) Cluster Number of Case


3.50000
3.00000
2.50000
2.00000
1.50000
1.00000
0.50000
7
23
1
2
3
4
5
Distance of Case from its Classification Cluster Center
Group 3 (Mono Ply) Cluster Number of Case


Distance of Case from its Classification Cluster Center
4.00000
2.00000
0.00000
1
2
3
4
Group 3 (Double Ply) Cluster Number of Case


Distance of Case from its Classification Cluster Center
8.00
7.00
6.00
5.00
4.00
3.00
2.00
1.00
55
82
54
15
1.00
2.00
3.00
4.00
5.00
6.00
7.00
Group 4 (Belt+Tread+Tread Design) Cluster Number of Case

Appendix E: Step 3 Module Differences

1. Group 1 Kruskal Wallis Test Results

Below, the sets of tables present the Kruskal Wallis test results for the defined 5 Group 1 modules across 5 (3 Apex gauge+ 1 Apex material +1 Bead gauge) critical design characteristic types (original clustering attributes). Bead type was not included since it was binary.

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	1	13	26.11
	2	25	20.91
	Total	38	
Apex2	1	13	38.00
	2	25	17.50
	Total	38	
Apex3	1	13	38.00
	2	25	17.50
	Total	38	
Bead1	1	13	37.50
	2	25	17.63
	Total	38	
Apex Material	1	13	38.00
	2	25	17.50
	Total	38	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	1.586	26.559	24.984	22.197	37.000
Df	1	1	1	1	1
Asymp. Sig.	.208	.000	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	1	13	10.33
	3	15	10.64
	Total	28	
Apex2	1	13	16.00
	3	15	6.00
	Total	28	
Apex3	1	13	16.00
	3	15	6.00
	Total	28	
Bead1	1	13	12.50
	3	15	8.86
	Total	28	
Apex Material	1	13	16.00
	3	15	6.00
	Total	28	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	.016	18.000	17.257	3.827	19.000
df	1	1	1	1	1
Asymp. Sig.	.899	.000	.000	.050	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	1	13	27.00
	4	23	12.39
	Total	36	
Apex2	1	13	28.00
	4	23	12.00
	Total	36	
Apex3	1	13	28.00
	4	23	12.00
	Total	36	
Bead1	1	13	28.00
	4	23	12.00
	Total	36	
Apex Material	1	13	28.00
	4	23	12.00
	Total	36	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	17.354	28.800	21.005	22.147	31.000
df	1	1	1	1	1
Asymp. Sig.	.000	.000	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	1	13	14.94
	5	16	11.03
	Total	29	
Apex2	1	13	20.00
	5	16	8.00
	Total	29	
Apex3	1	13	20.00
	5	16	8.00
	Total	29	
Bead1	1	13	20.00
	5	16	8.00
	Total	29	
Apex Material	1	13	20.00
	5	16	8.00
	Total	29	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	1.984	21.600	18.131	18.500	23.000
df	1	1	1	1	1
Asymp. Sig.	.159	.000	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	2	25	21.31
	3	15	28.23
	Total	40	
Apex2	2	25	19.46
	3	15	33.95
	Total	40	
Apex3	2	25	23.79
	3	15	20.55
	Total	40	
Bead1	2	25	19.90
	3	15	32.59
	Total	40	
Apex Material	2	25	17.50
	3	15	38.00
	Total	40	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	2.913	13.832	.799	8.575	38.000
df	1	1	1	1	1
Asymp. Sig.	.088	.000	.371	.003	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	2	25	39.90
	4	23	12.89
	Total	48	
Apex2	2	25	31.68
	4	23	25.04
	Total	48	
Apex3	2	25	34.44
	4	23	20.96
	Total	48	
Bead1	2	25	37.53
	4	23	16.39
	Total	48	
Apex Material	2	25	29.00
	4	23	29.00
	Total	48	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	39.715	5.030	12.182	25.180	.000
df	1	1	1	1	1
Asymp. Sig.	.000	.025	.000	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	2	25	26.09
	5	16	22.53
	Total	41	
Apex2	2	25	19.99
	5	16	36.37
	Total	41	
Apex3	2	25	23.99
	5	16	27.30
	Total	41	
Bead1	2	25	20.06
	5	16	36.20
	Total	41	
Apex Material	2	25	25.00
	5	16	25.00
	Total	41	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	.833	18.301	.781	14.405	.000
df	1	1	1	1	1
Asymp. Sig.	.361	.000	.377	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	3	15	28.18
	4	23	12.39
	Total	48	
Apex2	3	15	27.91
	4	23	12.52
	Total	48	
Apex3	3	15	21.86
	4	23	15.41
	Total	48	
Bead1	3	15	24.86
	4	23	13.98
	Total	48	
Apex Material	3	15	29.00
	4	23	12.00
	Total	48	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	20.389	26.695	4.359	10.054	33.000
df	1	1	1	1	1
Asymp. Sig.	.000	.000	.037	.002	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	3	15	16.32
	5	16	11.43
	Total	31	
Apex2	3	15	13.32
	5	16	13.63
	Total	31	
Apex3	3	15	11.55
	5	16	14.93
	Total	31	
Bead1	3	15	17.77
	5	16	10.37
	Total	31	
Apex Material	3	15	21.00
	5	16	8.00
	Total	31	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	2.940	.051	1.871	6.441	25.000
df	1	1	1	1	1
Asymp. Sig.	.086	.822	.171	.011	.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

Ranks

	Cluster Number of Case	N	Mean Rank
Apex1	4	23	13.46
	5	16	28.77
	Total	39	
Apex2	4	23	12.52
	5	16	30.20
	Total	39	
Apex3	4	23	15.43
	5	16	25.73
	Total	39	
Bead1	4	23	12.00
	5	16	31.00
	Total	39	
Apex Material	4	23	19.50
	5	16	19.50
	Total	39	

Test Statistics(a,b)

	Apex1	Apex2	Apex3	Bead1	Apex Material
Chi-Square	19.228	31.526	9.795	29.316	.000
df	1	1	1	1	1
Asymp. Sig.	.000	.000	.002	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Cluster Number of Case

2. Group 2 Chafer-Sidewall-Toe Guard Kruskal Wallis Test Results

Below, the sets of tables present the Kruskal Wallis test results for the defined 4 Group 2 modules across 6 (2 Toe guard gauge+ 2 Chafer gauge +1 Sidewall material+ 1 Toe guard type) critical design characteristic types (original clustering attributes). Decision about the toe guard type was not made based on this analysis, since this variable is binary. It was easier to include toe guard information than excluding from the data file for the analysis.

Ranks

	Module	N	Mean Rank
Toeguard1	1.00	29	28.50
	2.00	13	33.25
	Total	42	
Toeguard2	1.00	29	31.00
	2.00	13	12.00
	Total	42	
Toeguardtype	1.00	29	26.00
	2.00	13	42.00
	Total	42	
SidewallMaterial	1.00	29	29.00
	2.00	13	29.00
	Total	42	
Chafer1	1.00	29	26.79
	2.00	13	38.00
	Total	42	
Chafer2	1.00	29	28.87
	2.00	13	30.08
	Total	42	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	8.500	35.871	42.000	.000	19.712	.034
df	1	1	1	1	1	1
Asymp. Sig.	.004	.000	.000	1.000	.000	.854

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Toeguard1	1.00	29	30.50
	3.00	23	30.50
	Total	52	
Toeguard2	1.00	29	35.00
	3.00	23	5.00
	Total	52	
Toeguardtype	1.00	29	30.50
	3.00	23	30.50
	Total	52	
SidewallMaterial	1.00	29	35.00
	3.00	23	5.00
	Total	52	
Chafer1	1.00	29	32.29
	3.00	23	20.33
	Total	52	
Chafer2	1.00	29	28.46
	3.00	23	42.06
	Total	52	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	.000	52.000	.000	52.000	10.298	5.308
df	1	1	1	1	1	1
Asymp. Sig.	1.000	.000	1.000	.000	.001	.021

a Kruskal Wallis Test
b Grouping Variable: Modul

Ranks

	Module	N	Mean Rank
Toeguard1	1.00	29	38.50
	4.00	27	38.50
	Total	56	
Toeguard2	1.00	29	51.00
	4.00	27	13.00
	Total	56	
Toeguardtype	1.00	29	38.50
	4.00	27	38.50
	Total	56	
SidewallMaterial	1.00	29	38.50
	4.00	27	38.50
	Total	56	
Chafer1	1.00	29	30.23
	4.00	27	55.38
	Total	56	
Chafer2	1.00	29	36.21
	4.00	27	43.18
	Total	56	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	.000	56.000	.000	.000	33.575	1.928
df	1	1	1	1	1	1
Asymp. Sig.	1.000	.000	1.000	1.000	.000	.165

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Toeguard1	2.00	13	8.75
	3.00	23	7.50
	Total	36	
Toeguard2	2.00	13	8.75
	3.00	23	7.50
	Total	36	
Toeguardtype	2.00	13	12.50
	3.00	23	5.00
	Total	36	
SidewallMaterial	2.00	13	12.50
	3.00	23	5.00
	Total	36	
Chafer1	2.00	13	12.00
	3.00	23	5.33
	Total	36	
Chafer2	2.00	13	6.33
	3.00	23	9.11
	Total	36	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	1.500	.401	14.000	14.000	9.333	1.607
df	1	1	1	1	1	1
Asymp. Sig.	.221	.527	.000	.000	.002	.205

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Toeguard1	2.00	13	18.08
	4.00	27	15.50
	Total	40	
Toeguard2	2.00	13	24.33
	4.00	27	14.00
	Total	40	
Toeguardtype	2.00	13	28.50
	4.00	27	13.00
	Total	40	
SidewallMaterial	2.00	13	16.00
	4.00	27	16.00
	Total	40	
Chafer1	2.00	13	16.92
	4.00	27	15.78
	Total	40	
Chafer2	2.00	13	14.58
	4.00	27	16.34
	Total	40	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	4.167	18.419	30.000	.000	.144	.223
df	1	1	1	1	1	1
Asymp. Sig.	.041	.000	.000	1.000	.704	.637

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Toeguard1	3.00	23	17.50
	4.00	27	17.50
	Total	50	
Toeguard2	3.00	23	30.00
	4.00	27	13.00
	Total	50	
Toeguardtype	3.00	23	17.50
	4.00	27	17.50
	Total	50	
SidewallMaterial	3.00	23	5.00
	4.00	27	22.00
	Total	50	
Chafer1	3.00	23	7.00
	4.00	27	21.28
	Total	50	
Chafer2	3.00	23	22.39
	4.00	27	15.74
	Total	50	

Test Statistics(a,b)

	Toeguard1	Toeguard2	Toeguardtype	SidewallMaterial	Chafer1	Chafer2
Chi-Square	.000	33.000	.000	33.000	17.412	3.678
df	1	1	1	1	1	1
Asymp. Sig.	1.000	.000	1.000	.000	.000	.055

a Kruskal Wallis Test
b Grouping Variable: Module

3. Group 3 Mono Ply Kruskal Wallis Test Results

Below, the sets of tables present the Kruskal Wallis test results for the defined 5 Group 3 mono ply modules across 3 (1 gauge +1 material+ 1 material treatment characteristics) critical design characteristic types (original clustering attributes). Ply angle type was not included since it was the same for all the tires.

Ranks

	Module	N	Mean Rank
Ply1	1.00	10	13.50
	2.00	17	13.50
	Total	26	
Ply1Material	1.00	10	13.50
	2.00	16	13.50
	Total	26	
Ply1Strength	1.00	10	10.30
	2.00	16	15.50
	Total	26	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	.000	.000	7.273
df	1	1	1
Asymp. Sig.	1.000	1.000	.007

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	1.00	10	9.25
	3.00	11	12.59
	Total	21	
Ply1Material	1.00	10	16.50
	3.00	11	6.00
	Total	21	
Ply1Strength	1.00	10	10.50
	3.00	11	11.45
	Total	21	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	1.536	20.000	.156
df	1	1	1
Asymp. Sig.	.215	.000	.693

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	1.00	10	15.20
	4.00	11	7.18
	Total	21	
Ply1Material	1.00	10	16.50
	4.00	11	6.00
	Total	21	
Ply1Strength	1.00	10	13.70
	4.00	11	8.55
	Total	21	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	8.927	20.000	4.582
df	1	1	1
Asymp. Sig.	.003	.000	.032

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	1.00	10	13.75
	5.00	19	15.66
	Total	29	
Ply1Material	1.00	10	24.50
	5.00	19	10.00
	Total	29	
Ply1Strength	1.00	10	19.40
	5.00	19	12.68
	Total	29	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	.358	28.000	5.470
df	1	1	1
Asymp. Sig.	.550	.000	.019

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	2.00	16	13.34
	3.00	11	14.95
	Total	27	
Ply1Material	2.00	16	19.50
	3.00	11	6.00
	Total	27	
Ply1Strength	2.00	16	16.50
	3.00	11	10.36
	Total	27	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	.274	26.000	8.538
df	1	1	1
Asymp. Sig.	.600	.000	.003

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	2.00	16	16.16
	4.00	11	10.86
	Total	27	
Ply1Material	2.00	16	19.50
	4.00	11	6.00
	Total	27	
Ply1Strength	2.00	16	19.50
	4.00	11	6.00
	Total	27	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	3.035	26.000	24.632
df	1	1	1
Asymp. Sig.	.081	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	2.00	16	17.63
	5.00	19	18.32
	Total	35	
Ply1Material	2.00	16	27.50
	5.00	19	10.00
	Total	35	
Ply1Strength	2.00	16	27.00
	5.00	19	10.42
	Total	35	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	.040	34.000	27.708
df	1	1	1
Asymp. Sig.	.841	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	3.00	11	15.18
	4.00	11	7.82
	Total	22	
Ply1Material	3.00	11	11.50
	4.00	11	11.50
	Total	22	
Ply1Strength	3.00	11	15.82
	4.00	11	7.18
	Total	22	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	7.316	.000	11.045
df	1	1	1
Asymp. Sig.	.007	1.000	.001

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	3.00	11	18.00
	5.00	19	14.05
	Total	30	
Ply1Material	3.00	11	15.50
	5.00	19	15.50
	Total	30	
Ply1Strength	3.00	11	22.55
	5.00	19	11.42
	Total	30	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	1.453	.000	13.176
df	1	1	1
Asymp. Sig.	.228	1.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1	4.00	11	6.64
	5.00	19	20.63
	Total	30	
Ply1Material	4.00	11	15.50
	5.00	19	15.50
	Total	30	
Ply1Strength	4.00	11	15.45
	5.00	19	15.53
	Total	30	

Test Statistics(a,b)

	Ply1	Ply1Material	Ply1Strength
Chi-Square	18.190	.000	.001
df	1	1	1
Asymp. Sig.	.000	1.000	.978

a Kruskal Wallis Test
b Grouping Variable: Module

4. Group 3 Double Ply Kruskal Wallis Test Results

Below, the sets of tables present the Kruskal Wallis test results for the defined 4 Group 3 double ply modules across 8 (4 gauge +2 material+ 2 material treatment characteristics) critical design characteristic types (original clustering attributes). Ply angle type was included as well.

Ranks

	Module	N	Mean Rank
Ply1Angle	1.00	3	7.17
	2.00	8	5.56
	Total	11	
Ply1	1.00	3	6.00
	2.00	8	6.00
	Total	11	
Ply1Material	1.00	3	2.00
	2.00	8	7.50
	Total	11	
Ply1Strength	1.00	3	3.00
	2.00	8	7.13
	Total	11	
Ply2Angle	1.00	3	7.17
	2.00	8	5.56
	Total	11	
Ply2	1.00	3	10.00
	2.00	8	4.50
	Total	11	
Ply2Material	1.00	3	10.00
	2.00	8	4.50
	Total	11	
Ply2Strength	1.00	3	10.00
	2.00	8	4.50
	Total	11	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Material	Ply1Strength	Ply2Angle	Ply2	Ply2Material	Ply2Strength
Chi-Square	.681	.000	10.000	4.500	.681	9.778	10.000	10.000
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	.409	1.000	.002	.034	.409	.002	.002	.002

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1Angle	1.00	3	4.00
	3.00	6	5.50
	Total	9	
Ply1	1.00	3	2.17
	3.00	6	6.42
	Total	9	
Ply1Material	1.00	3	2.00
	3.00	6	6.50
	Total	9	
Ply1Strength	1.00	3	2.00
	3.00	6	6.50
	Total	9	
Ply2Angle	1.00	3	4.00
	3.00	6	5.50
	Total	9	
Ply2	1.00	3	4.17
	3.00	6	5.42
	Total	9	
Ply2Material	1.00	3	5.00
	3.00	6	5.00
	Total	9	
Ply2Strength	1.00	3	5.00
	3.00	6	5.00
	Total	9	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Material	Ply1Strength	Ply2Angle	Ply2	Ply2Material	Ply2Strength
Chi-Square	2.000	4.940	8.000	8.000	2.000	.439	.000	.000
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	.157	.026	.005	.005	.157	.508	1.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1Angle	1.00	3	7.17
	4.00	8	5.56
	Total	11	
Ply1	1.00	3	5.50
	4.00	8	6.19
	Total	11	
Ply1Material	1.00	3	6.00
	4.00	8	6.00
	Total	11	
Ply1Strength	1.00	3	3.00
	4.00	8	7.13
	Total	11	
Ply2Angle	1.00	3	7.17
	4.00	8	5.56
	Total	11	
Ply2	1.00	3	9.33
	4.00	8	4.75
	Total	11	
Ply2Material	1.00	3	10.00
	4.00	8	4.50
	Total	11	
Ply2Strength	1.00	3	9.50
	4.00	8	4.69
	Total	11	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Material	Ply1Strength	Ply2Angle	Ply2	Ply2Material	Ply2Strength
Chi-Square	.681	.099	.000	4.500	.681	5.624	10.000	6.563
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	.409	.753	1.000	.034	.409	.018	.002	.010

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1Angle	2.00	8	5.63
	3.00	6	10.00
	Total	14	
Ply1	2.00	8	6.13
	3.00	6	9.33
	Total	14	
Ply1Material	2.00	8	7.50
	3.00	6	7.50
	Total	14	
Ply1Strength	2.00	8	6.75
	3.00	6	8.50
	Total	14	
Ply2Angle	2.00	8	5.63
	3.00	6	10.00
	Total	14	
Ply2	2.00	8	4.50
	3.00	6	11.50
	Total	14	
Ply2Material	2.00	8	4.50
	3.00	6	11.50
	Total	14	
Ply2Strength	2.00	8	4.50
	3.00	6	11.50
	Total	14	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Material	Ply1Strength	Ply2Angle	Ply2	Ply2Material	Ply2Strength
Chi-Square	5.417	2.057	.000	1.625	5.417	11.805	13.000	13.000
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	.020	.151	1.000	.202	.020	.001	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1Angle	2.00	8	8.50
	4.00	8	8.50
	Total	16	
Ply1	2.00	8	8.00
	4.00	8	9.00
	Total	16	
Ply1Material	2.00	8	12.50
	4.00	8	4.50
	Total	16	
Ply1Strength	2.00	8	8.50
	4.00	8	8.50
	Total	16	
Ply2Angle	2.00	8	8.50
	4.00	8	8.50
	Total	16	
Ply2	2.00	8	8.00
	4.00	8	9.00
	Total	16	
Ply2Material	2.00	8	8.50
	4.00	8	8.50
	Total	16	
Ply2Strength	2.00	8	8.00
	4.00	8	9.00
	Total	16	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Material	Ply1Strength	Ply2Angle	Ply2	Ply2Material	Ply2Strength
Chi-Square	.000	.179	15.000	.000	.000	1.000	.000	1.000
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	1.000	.672	.000	1.000	1.000	.317	1.000	.317

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Ply1Angle	3.00	6	10.00
	4.00	8	5.63
	Total	14	
Ply1	3.00	6	10.00
	4.00	8	5.63
	Total	14	
Ply1Material	3.00	6	11.50
	4.00	8	4.50
	Total	14	
Ply1Strength	3.00	6	8.50
	4.00	8	6.75
	Total	14	
Ply2Angle	3.00	6	10.00
	4.00	8	5.63
	Total	14	
Ply2	3.00	6	11.33
	4.00	8	4.63
	Total	14	
Ply2Material	3.00	6	11.50
	4.00	8	4.50
	Total	14	
Ply2Strength	3.00	6	11.00
	4.00	8	4.88
	Total	14	

Test Statistics(a,b)

	Ply1Angle	Ply1	Ply1Materia l	Ply1Strengt h	Ply2Angle	Ply2	Ply2Materia l	Ply2Strengt h
Chi-Square	5.417	3.783	13.000	1.625	5.417	10.079	13.000	9.750
Df	1	1	1	1	1	1	1	1
Asymp. Sig.	.020	.052	.000	.202	.020	.001	.000	.002

a Kruskal Wallis Test
b Grouping Variable: Module

5. Group 4 Belts-Tread-Tread Design Kruskal Wallis Test Results

Below, the sets of tables present the Kruskal Wallis test results for the defined 7 Group 4 modules across 18 (4 Belt gauge + 1 Belt material+ 1 Belt material treatment+ 6 Tread gauge+ 3 Tread Design geometric dimension+ 3 Tread material characteristics) critical design characteristic types (original clustering attributes).

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	3.67
	2.00	10	4.25
	Total	19	
Belt2	1.00	9	5.33
	2.00	10	3.00
	Total	19	
Belt3	1.00	9	3.67
	2.00	10	4.25
	Total	19	
Belt4	1.00	9	5.33
	2.00	10	3.00
	Total	19	
BeltStrength	1.00	9	3.50
	2.00	10	4.38
	Total	19	
BeltMaterial	1.00	9	4.00
	2.00	10	4.00
	Total	19	
Tread1	1.00	9	5.33
	2.00	10	3.00
	Total	19	
Tread2	1.00	9	5.33
	2.00	10	3.00
	Total	19	
Tread3	1.00	9	4.00
	2.00	10	4.00
	Total	19	
Tread4	1.00	9	2.00
	2.00	10	5.50
	Total	19	
Tread5	1.00	9	3.67
	2.00	10	4.25
	Total	19	
Tread6	1.00	9	4.00
	2.00	10	4.00
	Total	19	
TreadDesign1	1.00	9	2.00
	2.00	10	5.50
	Total	19	
TreadDesign2	1.00	9	3.33

	2.00	10	4.50
	Total	19	
TreadDesign3	1.00	9	5.67
	2.00	10	2.75
	Total	19	
TreadBaseMaterial	1.00	9	6.00
	2.00	10	2.50
	Total	19	
TreadCapMaterial	1.00	9	2.00
	2.00	10	5.50
	Total	19	
TreadSkirtMaterial	1.00	9	6.00
	2.00	10	2.50
	Total	19	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	.135	3.111	.135	3.111	.750	.000
df	1	1	1	1	1	1
Asymp. Sig.	.714	.078	.714	.078	.386	1.000

	Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
Chi-Square	3.111	3.111	.000	4.500	.125	.000	6.000
df	1	1	1	1	1	1	1
Asymp. Sig.	.078	.078	1.000	.034	.724	1.000	.014

	TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
Chi-Square	.500	3.182	6.000	6.000	6.000
df	1	1	1	1	1
Asymp. Sig.	.480	.074	.014	.014	.014

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	18.50
	3.00	17	13.44
	Total	26	
Belt2	1.00	9	22.67
	3.00	17	12.92
	Total	26	
Belt3	1.00	9	18.50
	3.00	17	13.44
	Total	26	
Belt4	1.00	9	22.67

	3.00	17	12.92
	Total	26	
BeltStrength	1.00	9	16.00
	3.00	17	13.75
	Total	26	
BeltMaterial	1.00	9	22.50
	3.00	17	12.94
	Total	26	
Tread1	1.00	9	25.67
	3.00	17	12.54
	Total	26	
Tread2	1.00	9	25.50
	3.00	17	12.56
	Total	26	
Tread3	1.00	9	13.50
	3.00	17	14.06
	Total	26	
Tread4	1.00	9	24.67
	3.00	17	12.67
	Total	26	
Tread5	1.00	9	19.67
	3.00	17	13.29
	Total	26	
Tread6	1.00	9	18.67
	3.00	17	13.42
	Total	26	
TreadDesign1	1.00	9	20.50
	3.00	17	13.19
	Total	26	
TreadDesign2	1.00	9	25.33
	3.00	17	12.58
	Total	26	
TreadDesign3	1.00	9	13.50
	3.00	17	14.06
	Total	26	
TreadBaseMaterial	1.00	9	14.00
	3.00	17	14.00
	Total	26	
TreadCapMaterial	1.00	9	5.50
	3.00	17	15.06
	Total	26	
TreadSkirtMaterial	1.00	9	14.00
	3.00	17	14.00
	Total	26	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	1.113	7.637	1.113	7.637	.565	5.216
df	1	1	1	1	1	1
Asymp. Sig.	.292	.006	.292	.006	.452	.022

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
10.418	10.109	.029	6.215	1.741	1.180	3.018
1	1	1	1	1	1	1
.001	.001	.864	.013	.187	.277	.082

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
6.889	.015	.000	6.563	.000
1	1	1	1	1
.009	.903	1.000	.010	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	4.00
	4.00	13	4.80
	Total	22	
Belt2	1.00	9	6.17
	4.00	13	3.50
	Total	22	
Belt3	1.00	9	4.00
	4.00	13	4.80
	Total	22	
Belt4	1.00	9	6.17
	4.00	13	3.50
	Total	22	
BeltStrength	1.00	9	2.00
	4.00	13	6.00
	Total	22	
BeltMaterial	1.00	9	7.00
	4.00	13	3.00
	Total	22	
Tread1	1.00	9	6.17
	4.00	13	3.50
	Total	22	
Tread2	1.00	9	6.17
	4.00	13	3.50
	Total	22	
Tread3	1.00	9	4.50
	4.00	13	4.50

	Total	22	
Tread4	1.00	9	2.17
	4.00	13	5.90
	Total	22	
Tread5	1.00	9	5.17
	4.00	13	4.10
	Total	22	
Tread6	1.00	9	3.67
	4.00	13	5.00
	Total	22	
TreadDesign1	1.00	9	2.00
	4.00	13	6.00
	Total	22	
TreadDesign2	1.00	9	3.67
	4.00	13	5.00
	Total	22	
TreadDesign3	1.00	9	6.50
	4.00	13	3.30
	Total	22	
TreadBaseMaterial	1.00	9	7.00
	4.00	13	3.00
	Total	22	
TreadCapMaterial	1.00	9	2.00
	4.00	13	6.00
	Total	22	
TreadSkirtMaterial	1.00	9	7.00
	4.00	13	3.00
	Total	22	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	.200	3.810	.200	3.810	7.000	7.000
df	1	1	1	1	1	1
Asymp. Sig.	.655	.051	.655	.051	.008	.008
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
3.810	3.810	.000	4.408	.360	.591	7.000
1	1	1	1	1	1	1
.051	.051	1.000	.036	.549	.442	.008

TreadDesign2	TreadDesign3	TreadBaseMat erial	TreadCapMate rial	TreadSkirtMate rial
.562	3.319	7.000	7.000	7.000
1	1	1	1	1
.453	.069	.008	.008	.008

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	5.00
	5.00	10	2.00
	Total	19	
Belt2	1.00	9	3.17
	5.00	10	3.83
	Total	19	
Belt3	1.00	9	5.00
	5.00	10	2.00
	Total	19	
Belt4	1.00	9	3.67
	5.00	10	3.33
	Total	19	
BeltStrength	1.00	9	3.50
	5.00	10	3.50
	Total	19	
BeltMaterial	1.00	9	4.50
	5.00	10	2.50
	Total	19	
Tread1	1.00	9	5.00
	5.00	10	2.00
	Total	19	
Tread2	1.00	9	4.67
	5.00	10	2.33
	Total	19	
Tread3	1.00	9	3.50
	5.00	10	3.50
	Total	19	
Tread4	1.00	9	5.00
	5.00	10	2.00
	Total	19	
Tread5	1.00	9	5.00
	5.00	10	2.00
	Total	19	
Tread6	1.00	9	4.00
	5.00	10	3.00
	Total	19	
TreadDesign1	1.00	9	4.50
	5.00	10	2.50
	Total	19	
TreadDesign2	1.00	9	5.00
	5.00	10	2.00
	Total	19	
TreadDesign3	1.00	9	3.67
	5.00	10	3.33

		N	Mean Rank
	Total	19	
TreadBaseMaterial	1.00	9	3.00
	5.00	10	4.00
	Total	19	
TreadCapMaterial	1.00	9	2.00
	5.00	10	5.00
	Total	19	
TreadSkirtMaterial	1.00	9	3.50
	5.00	10	3.50
	Total	19	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	3.857	.202	3.857	.049	.000	2.500
df	1	1	1	1	1	1
Asymp. Sig.	.050	.653	.050	.825	1.000	.114

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
4.355	2.402	.000	3.857	3.971	.429	2.400
1	1	1	1	1	1	1
.037	.121	1.000	.050	.046	.513	.121

TreadDesign2	TreadDesign3	TreadBaseMat erial	TreadCapMate rial	TreadSkirtMate rial
3.857	.051	1.000	4.500	.000
1	1	1	1	1
.050	.822	.317	.034	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	28.50
	6.00	20	25.31
	Total	29	
Belt2	1.00	9	28.50
	6.00	20	24.49
	Total	29	
Belt3	1.00	9	28.50
	6.00	20	25.31
	Total	29	
Belt4	1.00	9	28.50
	6.00	20	24.49
	Total	29	
BeltStrength	1.00	9	29.00
	6.00	20	25.28
	Total	29	

BeltMaterial	1.00	9	29.00
	6.00	20	24.57
	Total	29	
Tread1	1.00	9	29.00
	6.00	20	24.12
	Total	29	
Tread2	1.00	9	29.00
	6.00	20	24.01
	Total	29	
Tread3	1.00	9	25.50
	6.00	20	25.50
	Total	29	
Tread4	1.00	9	29.00
	6.00	20	24.04
	Total	29	
Tread5	1.00	9	29.00
	6.00	20	24.98
	Total	29	
Tread6	1.00	9	29.00
	6.00	20	25.07
	Total	29	
TreadDesign1	1.00	9	29.00
	6.00	20	24.38
	Total	29	
TreadDesign2	1.00	9	29.00
	6.00	20	24.00
	Total	29	
TreadDesign3	1.00	9	22.17
	6.00	20	25.71
	Total	29	
TreadBaseMaterial	1.00	9	2.00
	6.00	20	27.00
	Total	29	
TreadCapMaterial	1.00	9	3.00
	6.00	20	26.94
	Total	29	
TreadSkirtMaterial	1.00	9	25.50
	6.00	20	25.50
	Total	29	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	.138	22.218	.138	22.218	.509	4.319
df	1	1	1	1	1	1
Asymp. Sig.	.710	.000	.710	.000	.476	.038
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1

10.958	29.00	.000	7.925	1.020	.677	7.298
1	1	1	1	1	1	1
.001	.000	1.000	.005	.313	.411	.007

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
8.338	.199	29.000	29.00	.000
1	1	1	1	1
.004	.655	.000	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	1.00	9	7.00
	7.00	13	3.00
	Total	22	
Belt2	1.00	9	4.67
	7.00	13	4.40
	Total	22	
Belt3	1.00	9	7.00
	7.00	13	3.00
	Total	22	
Belt4	1.00	9	4.67
	7.00	13	4.40
	Total	22	
BeltStrength	1.00	9	6.00
	7.00	13	3.60
	Total	22	
BeltMaterial	1.00	9	6.50
	7.00	13	3.30
	Total	22	
Tread1	1.00	9	5.50
	7.00	13	3.90
	Total	22	
Tread2	1.00	9	5.67
	7.00	13	3.80
	Total	22	
Tread3	1.00	9	4.50
	7.00	13	4.50
	Total	22	
Tread4	1.00	9	6.67
	7.00	13	3.20
	Total	22	
Tread5	1.00	9	6.50
	7.00	13	3.30
	Total	22	

Tread6	1.00	9	3.67
	7.00	13	5.00
	Total	22	
TreadDesign1	1.00	9	4.50
	7.00	13	4.50
	Total	22	
TreadDesign2	1.00	9	7.00
	7.00	13	3.00
	Total	22	
TreadDesign3	1.00	9	4.83
	7.00	13	4.30
	Total	22	
TreadBaseMaterial	1.00	9	4.50
	7.00	13	4.50
	Total	22	
TreadCapMaterial	1.00	9	3.50
	7.00	13	5.10
	Total	22	
TreadSkirtMaterial	1.00	9	4.50
	7.00	13	4.50
	Total	22	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	5.250	.025	5.250	.025	2.520	4.200
Df	1	1	1	1	1	1
Asymp. Sig.	.022	.875	.022	.875	.112	.040

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
.960	1.204	.000	3.801	3.278	.556	.000
1	1	1	1	1	1	1
.327	.273	1.000	.051	.070	.456	1.000

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
5.060	.095	.000	1.400	.000
1	1	1	1	1
.024	.759	1.000	.237	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	2.00	10	25.25
	3.00	17	12.71
	Total	27	

Belt2	2.00	10	16.50
	3.00	17	14.17
	Total	27	
Belt3	2.00	10	25.25
	3.00	17	12.71
	Total	27	
Belt4	2.00	10	16.50
	3.00	17	14.17
	Total	27	
BeltStrength	2.00	10	19.00
	3.00	17	13.75
	Total	27	
BeltMaterial	2.00	10	23.00
	3.00	17	13.08
	Total	27	
Tread1	2.00	10	25.50
	3.00	17	12.67
	Total	27	
Tread2	2.00	10	25.00
	3.00	17	12.75
	Total	27	
Tread3	2.00	10	14.00
	3.00	17	14.58
	Total	27	
Tread4	2.00	10	26.50
	3.00	17	12.50
	Total	27	
Tread5	2.00	10	25.25
	3.00	17	12.71
	Total	27	
Tread6	2.00	10	21.38
	3.00	17	13.35
	Total	27	
TreadDesign1	2.00	10	26.50
	3.00	17	12.50
	Total	27	
TreadDesign2	2.00	10	26.50
	3.00	17	12.50
	Total	27	
TreadDesign3	2.00	10	6.38
	3.00	17	15.85
	Total	27	
TreadBaseMaterial	2.00	10	2.50
	3.00	17	16.50
	Total	27	
TreadCapMaterial	2.00	10	26.50
	3.00	17	12.50

	Module	N	Mean Rank
	Total	27	
TreadSkirtMaterial	2.00	10	2.50
	3.00	17	16.50
	Total	27	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	8.160	.750	8.160	.750	3.150	6.611
df	1	1	1	1	1	1
Asymp. Sig.	.004	.386	.004	.386	.076	.010

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
11.550	10.464	.039	10.105	8.056	3.298	11.859
1	1	1	1	1	1	1
.001	.001	.844	.001	.005	.069	.001

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
9.942	4.903	27.000	15.709	27.000
1	1	1	1	1
.002	.027	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	2.00	10	3.88
	4.00	13	5.90
	Total	23	
Belt2	2.00	10	5.00
	4.00	13	5.00
	Total	23	
Belt3	2.00	10	3.88
	4.00	13	5.90
	Total	23	
Belt4	2.00	10	5.00
	4.00	13	5.00
	Total	23	
BeltStrength	2.00	10	3.13
	4.00	13	6.50
	Total	23	
BeltMaterial	2.00	10	7.50
	4.00	13	3.00
	Total	23	
Tread1	2.00	10	5.00
	4.00	13	5.00
	Total	23	

Tread2	2.00	10	5.00
	4.00	13	5.00
	Total	23	
Tread3	2.00	10	5.00
	4.00	13	5.00
	Total	23	
Tread4	2.00	10	6.75
	4.00	13	3.60
	Total	23	
Tread5	2.00	10	5.88
	4.00	13	4.30
	Total	23	
Tread6	2.00	10	3.75
	4.00	13	6.00
	Total	23	
TreadDesign1	2.00	10	5.00
	4.00	13	5.00
	Total	23	
TreadDesign2	2.00	10	4.00
	4.00	13	5.80
	Total	23	
TreadDesign3	2.00	10	6.50
	4.00	13	3.80
	Total	23	
TreadBaseMaterial	2.00	10	5.00
	4.00	13	5.00
	Total	23	
TreadCapMaterial	2.00	10	5.00
	4.00	13	5.00
	Total	23	
TreadSkirtMaterial	2.00	10	5.00
	4.00	13	5.00
	Total	23	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	1.236	.000	1.236	.000	5.000	8.000
df	1	1	1	1	1	1
Asymp. Sig.	.266	1.000	.266	1.000	.025	.005
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
.000	.000	.000	3.068	.767	2.813	.000
1	1	1	1	1	1	1
1.000	1.000	1.000	.080	.381	.094	1.000

TreadDesign2	TreadDesign3	TreadBaseMat erial	TreadCapMate rial	TreadSkirtMate rial

.968	2.215	.000	.000	.000
1	1	1	1	1
.325	.137	1.000	1.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	2.00	10	5.50
	5.00	10	2.00
	Total	20	
Belt2	2.00	10	2.50
	5.00	10	6.00
	Total	20	
Belt3	2.00	10	5.50
	5.00	10	2.00
	Total	20	
Belt4	2.00	10	3.50
	5.00	10	4.67
	Total	20	
BeltStrength	2.00	10	4.38
	5.00	10	3.50
	Total	20	
BeltMaterial	2.00	10	5.00
	5.00	10	2.67
	Total	20	
Tread1	2.00	10	5.50
	5.00	10	2.00
	Total	20	
Tread2	2.00	10	4.50
	5.00	10	3.33
	Total	20	
Tread3	2.00	10	4.00
	5.00	10	4.00
	Total	20	
Tread4	2.00	10	5.50
	5.00	10	2.00
	Total	20	
Tread5	2.00	10	5.50
	5.00	10	2.00
	Total	20	
Tread6	2.00	10	4.88
	5.00	10	2.83
	Total	20	
TreadDesign1	2.00	10	5.50
	5.00	10	2.00
	Total	20	

TreadDesign2	2.00	10	5.50
	5.00	10	2.00
	Total	20	
TreadDesign3	2.00	10	3.25
	5.00	10	5.00
	Total	20	
TreadBaseMaterial	2.00	10	2.50
	5.00	10	6.00
	Total	20	
TreadCapMaterial	2.00	10	4.50
	5.00	10	3.33
	Total	20	
TreadSkirtMaterial	2.00	10	2.50
	5.00	10	6.00
	Total	20	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	4.582	5.600	4.582	.622	.750	3.200
df	1	1	1	1	1	1
Asymp. Sig.	.032	.018	.032	.430	.386	.074

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
6.000	.622	.000	4.582	4.582	1.715	5.478
1	1	1	1	1	1	1
.014	.430	1.000	.032	.032	.190	.019

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
4.500	1.212	5.600	.622	6.000
1	1	1	1	1
.034	.271	.018	.430	.014

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	2.00	10	30.00
	6.00	20	24.83
	Total	30	
Belt2	2.00	10	26.50
	6.00	20	25.96
	Total	30	
Belt3	2.00	10	30.00
	6.00	20	24.83
	Total	30	
Belt4	2.00	10	26.50

	6.00	20	25.96
	Total	30	
BeltStrength	2.00	10	30.00
	6.00	20	25.28
	Total	30	
BeltMaterial	2.00	10	30.00
	6.00	20	24.77
	Total	30	
Tread1	2.00	10	30.00
	6.00	20	24.47
	Total	30	
Tread2	2.00	10	30.00
	6.00	20	24.04
	Total	30	
Tread3	2.00	10	25.00
	6.00	20	26.09
	Total	30	
Tread4	2.00	10	30.00
	6.00	20	24.00
	Total	30	
Tread5	2.00	10	30.00
	6.00	20	24.02
	Total	30	
Tread6	2.00	10	30.00
	6.00	20	25.05
	Total	30	
TreadDesign1	2.00	10	30.00
	6.00	20	24.00
	Total	30	
TreadDesign2	2.00	10	30.00
	6.00	20	24.00
	Total	30	
TreadDesign3	2.00	10	7.00
	6.00	20	27.62
	Total	30	
TreadBaseMaterial	2.00	10	2.50
	6.00	20	28.00
	Total	30	
TreadCapMaterial	2.00	10	30.00
	6.00	20	24.00
	Total	30	
TreadSkirtMaterial	2.00	10	2.50
	6.00	20	28.00
	Total	30	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	3.786	.085	3.786	.085	3.564	5.609
df	1	1	1	1	1	1
Asymp. Sig.	.052	.770	.052	.770	.059	.018

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
9.766	30.00	.090	12.297	12.417	2.665	16.346
1	1	1	1	1	1	1
.002	.000	.764	.000	.000	.103	.000

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
10.900	8.201	30.000	28.800	30.000
1	1	1	1	1
.001	.004	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	2.00	10	7.50
	7.00	13	3.00
	Total	23	
Belt2	2.00	10	3.50
	7.00	13	6.20
	Total	23	
Belt3	2.00	10	7.50
	7.00	13	3.00
	Total	23	
Belt4	2.00	10	3.50
	7.00	13	6.20
	Total	23	
BeltStrength	2.00	10	6.75
	7.00	13	3.60
	Total	23	
BeltMaterial	2.00	10	7.00
	7.00	13	3.40
	Total	23	
Tread1	2.00	10	4.00
	7.00	13	5.80
	Total	23	
Tread2	2.00	10	4.50
	7.00	13	5.40
	Total	23	
Tread3	2.00	10	5.00
	7.00	13	5.00

	Total	23	
Tread4	2.00	10	7.50
	7.00	13	3.00
	Total	23	
Tread5	2.00	10	7.50
	7.00	13	3.00
	Total	23	
Tread6	2.00	10	4.13
	7.00	13	5.70
	Total	23	
TreadDesign1	2.00	10	7.50
	7.00	13	3.00
	Total	23	
TreadDesign2	2.00	10	7.50
	7.00	13	3.00
	Total	23	
TreadDesign3	2.00	10	4.25
	7.00	13	5.60
	Total	23	
TreadBaseMaterial	2.00	10	2.50
	7.00	13	7.00
	Total	23	
TreadCapMaterial	2.00	10	7.50
	7.00	13	3.00
	Total	23	
TreadSkirtMaterial	2.00	10	2.50
	7.00	13	7.00
	Total	23	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.261	3.200	6.261	3.200	3.675	5.120
df	1	1	1	1	1	1
Asymp. Sig.	.012	.074	.012	.074	.055	.024

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
1.829	.343	.000	6.154	6.261	.747	8.000
1	1	1	1	1	1	1
.176	.558	1.000	.013	.012	.387	.005

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
6.050	.563	8.000	6.857	8.000
1	1	1	1	1
.014	.453	.005	.009	.005

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	3.00	17	13.19
	4.00	13	23.70
	Total	30	
Belt2	3.00	17	14.58
	4.00	13	17.00
	Total	30	
Belt3	3.00	17	13.19
	4.00	13	23.70
	Total	30	
Belt4	3.00	17	14.58
	4.00	13	17.00
	Total	30	
BeltStrength	3.00	17	12.50
	4.00	13	27.00
	Total	30	
BeltMaterial	3.00	17	17.50
	4.00	13	3.00
	Total	30	
Tread1	3.00	17	12.71
	4.00	13	26.00
	Total	30	
Tread2	3.00	17	12.81
	4.00	13	25.50
	Total	30	
Tread3	3.00	17	15.10
	4.00	13	14.50
	Total	30	
Tread4	3.00	17	12.58
	4.00	13	26.60
	Total	30	
Tread5	3.00	17	14.46
	4.00	13	17.60
	Total	30	
Tread6	3.00	17	12.50
	4.00	13	27.00
	Total	30	
TreadDesign1	3.00	17	12.50
	4.00	13	27.00
	Total	30	
TreadDesign2	3.00	17	12.50
	4.00	13	27.00
	Total	30	
TreadDesign3	3.00	17	17.06

	4.00	13	5.10
	Total	30	
TreadBaseMaterial	3.00	17	17.50
	4.00	13	3.00
	Total	30	
TreadCapMaterial	3.00	17	12.50
	4.00	13	27.00
	Total	30	
TreadSkirtMaterial	3.00	17	17.50
	4.00	13	3.00
	Total	30	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.482	.933	6.482	.933	18.044	14.746
df	1	1	1	1	1	1
Asymp. Sig.	.011	.334	.011	.334	.000	.000

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
13.533	12.246	.048	11.390	.569	12.128	14.097
1	1	1	1	1	1	1
.000	.000	.826	.001	.451	.000	.000

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
12.015	8.752	28.000	18.004	28.000
1	1	1	1	1
.001	.003	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	3.00	17	15.31
	5.00	10	3.50
	Total	27	
Belt2	3.00	17	12.50
	5.00	10	26.00
	Total	27	
Belt3	3.00	17	15.31
	5.00	10	3.50
	Total	27	
Belt4	3.00	17	13.50
	5.00	10	18.00
	Total	27	
BeltStrength	3.00	17	13.75

	5.00	10	16.00
	Total	27	
BeltMaterial	3.00	17	13.98
	5.00	10	14.17
	Total	27	
Tread1	3.00	17	14.38
	5.00	10	11.00
	Total	27	
Tread2	3.00	17	13.77
	5.00	10	15.83
	Total	27	
Tread3	3.00	17	14.13
	5.00	10	13.00
	Total	27	
Tread4	3.00	17	15.38
	5.00	10	3.00
	Total	27	
Tread5	3.00	17	15.44
	5.00	10	2.50
	Total	27	
Tread6	3.00	17	14.00
	5.00	10	14.00
	Total	27	
TreadDesign1	3.00	17	13.92
	5.00	10	14.67
	Total	27	
TreadDesign2	3.00	17	13.15
	5.00	10	20.83
	Total	27	
TreadDesign3	3.00	17	14.17
	5.00	10	12.67
	Total	27	
TreadBaseMaterial	3.00	17	13.50
	5.00	10	18.00
	Total	27	
TreadCapMaterial	3.00	17	12.50
	5.00	10	26.00
	Total	27	
TreadSkirtMaterial	3.00	17	14.00
	5.00	10	14.00
	Total	27	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.058	13.060	6.058	1.451	.565	.002
df	1	1	1	1	1	1

Asymp. Sig.	.014	.000	.014	.228	.452	.963
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
.916	.305	.140	6.695	7.453	.000	.031
1	1	1	1	1	1	1
.339	.581	.708	.010	.006	1.000	.861

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
2.505	.106	8.000	13.020	.000
1	1	1	1	1
.113	.745	.005	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	3.00	17	31.85
	6.00	20	36.12
	Total	37	
Belt2	3.00	17	32.58
	6.00	20	35.74
	Total	37	
Belt3	3.00	17	31.85
	6.00	20	35.12
	Total	37	
Belt4	3.00	17	32.58
	6.00	20	34.74
	Total	37	
BeltStrength	3.00	17	35.58
	6.00	20	36.21
	Total	37	
BeltMaterial	3.00	17	34.46
	6.00	20	36.79
	Total	37	
Tread1	3.00	17	35.00
	6.00	20	36.51
	Total	37	
Tread2	3.00	17	30.85
	6.00	20	33.52
	Total	37	
Tread3	3.00	17	36.94
	6.00	20	35.52
	Total	37	
Tread4	3.00	17	35.50
	6.00	20	36.26
	Total	37	
Tread5	3.00	17	32.42

	Module	N	Mean Rank
	6.00	20	36.83
	Total	37	
Tread6	3.00	17	32.77
	6.00	20	35.65
	Total	37	
TreadDesign1	3.00	17	30.77
	6.00	20	33.56
	Total	37	
TreadDesign2	3.00	17	30.50
	6.00	20	33.70
	Total	37	
TreadDesign3	3.00	17	34.21
	6.00	20	36.91
	Total	37	
TreadBaseMaterial	3.00	17	12.50
	6.00	20	28.00
	Total	37	
TreadCapMaterial	3.00	17	32.60
	6.00	20	36.73
	Total	37	
TreadSkirtMaterial	3.00	17	36.00
	6.00	20	36.00
	Total	37	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	1.478	5.058	1.478	5.058	.038	.288
df	1	1	1	1	1	1
Asymp. Sig.	.224	.025	.224	.025	.846	.591

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
.147	6.661	.248	.022	1.265	.968	2.948
1	1	1	1	1	1	1
.701	.010	.618	.881	.261	.325	.086

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
1.729	.318	30.000	4.992	.000
1	1	1	1	1
.189	.573	.000	.025	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	3.00	17	16.85
	7.00	13	6.10

	Total	30	
Belt2	3.00	17	13.33
	7.00	13	23.00
	Total	30	
Belt3	3.00	17	16.85
	7.00	13	6.10
	Total	30	
Belt4	3.00	17	13.33
	7.00	13	23.00
	Total	30	
BeltStrength	3.00	17	16.08
	7.00	13	9.80
	Total	30	
BeltMaterial	3.00	17	15.31
	7.00	13	13.50
	Total	30	
Tread1	3.00	17	12.63
	7.00	13	26.40
	Total	30	
Tread2	3.00	17	12.79
	7.00	13	25.60
	Total	30	
Tread3	3.00	17	15.21
	7.00	13	14.00
	Total	30	
Tread4	3.00	17	15.38
	7.00	13	13.20
	Total	30	
Tread5	3.00	17	16.85
	7.00	13	6.10
	Total	30	
Tread6	3.00	17	12.94
	7.00	13	24.90
	Total	30	
TreadDesign1	3.00	17	13.65
	7.00	13	21.50
	Total	30	
TreadDesign2	3.00	17	13.33
	7.00	13	23.00
	Total	30	
TreadDesign3	3.00	17	15.38
	7.00	13	13.20
	Total	30	
TreadBaseMaterial	3.00	17	15.00
	7.00	13	15.00
	Total	30	
TreadCapMaterial	3.00	17	15.90

	7.00	13	10.70
	Total	30	
TreadSkirtMaterial	3.00	17	15.00
	7.00	13	15.00
	Total	30	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.752	9.518	6.752	9.518	4.097	.288
df	1	1	1	1	1	1
Asymp. Sig.	.009	.002	.009	.002	.043	.592

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
14.369	12.399	.232	.280	6.918	8.566	4.740
1	1	1	1	1	1	1
.000	.000	.630	.596	.009	.003	.029

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
5.340	.297	.000	2.750	.000
1	1	1	1	1
.021	.586	1.000	.097	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	4.00	13	6.00
	5.00	10	2.00
	Total	23	
Belt2	4.00	13	3.00
	5.00	10	7.00
	Total	23	
Belt3	4.00	13	6.00
	5.00	10	2.00
	Total	23	
Belt4	4.00	13	4.00
	5.00	10	5.33
	Total	23	
BeltStrength	4.00	13	6.00
	5.00	10	2.00
	Total	23	
BeltMaterial	4.00	13	3.00
	5.00	10	7.00
	Total	23	
Tread1	4.00	13	6.00

	5.00	10	2.00
	Total	23	
Tread2	4.00	13	5.00
	5.00	10	3.67
	Total	23	
Tread3	4.00	13	4.50
	5.00	10	4.50
	Total	23	
Tread4	4.00	13	6.00
	5.00	10	2.00
	Total	23	
Tread5	4.00	13	5.80
	5.00	10	2.33
	Total	23	
Tread6	4.00	13	6.00
	5.00	10	2.00
	Total	23	
TreadDesign1	4.00	13	6.00
	5.00	10	2.00
	Total	23	
TreadDesign2	4.00	13	6.00
	5.00	10	2.00
	Total	23	
TreadDesign3	4.00	13	3.30
	5.00	10	6.50
	Total	23	
TreadBaseMaterial	4.00	13	3.00
	5.00	10	7.00
	Total	23	
TreadCapMaterial	4.00	13	5.00
	5.00	10	3.67
	Total	23	
TreadSkirtMaterial	4.00	13	3.00
	5.00	10	7.00
	Total	23	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	5.000	6.667	5.000	.741	7.000	6.667
df	1	1	1	1	1	1
Asymp. Sig.	.025	.010	.025	.389	.008	.010
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
7.000	.741	.000	5.000	3.801	5.316	6.563
1	1	1	1	1	1	1
.008	.389	1.000	.025	.051	.021	.010

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
5.060	3.319	6.667	.741	7.000
1	1	1	1	1
.024	.069	.010	.389	.008

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	4.00	13	22.80
	6.00	20	24.77
	Total	33	
Belt2	4.00	13	27.00
	6.00	20	26.45
	Total	33	
Belt3	4.00	13	22.80
	6.00	20	24.77
	Total	33	
Belt4	4.00	13	27.00
	6.00	20	26.45
	Total	33	
BeltStrength	4.00	13	30.00
	6.00	20	24.00
	Total	33	
BeltMaterial	4.00	13	3.00
	6.00	20	29.00
	Total	33	
Tread1	4.00	13	34.50
	6.00	20	24.59
	Total	33	
Tread2	4.00	13	29.50
	6.00	20	24.05
	Total	33	
Tread3	4.00	13	25.50
	6.00	20	26.61
	Total	33	
Tread4	4.00	13	30.00
	6.00	20	24.00
	Total	33	
Tread5	4.00	13	31.50
	6.00	20	25.97
	Total	33	
Tread6	4.00	13	30.00
	6.00	20	24.00
	Total	33	
TreadDesign1	4.00	13	30.00

	6.00	20	24.00
	Total	33	
TreadDesign2	4.00	13	30.00
	6.00	20	24.00
	Total	33	
TreadDesign3	4.00	13	6.40
	6.00	20	28.64
	Total	33	
TreadBaseMaterial	4.00	13	3.00
	6.00	20	29.00
	Total	33	
TreadCapMaterial	4.00	13	30.00
	6.00	20	24.00
	Total	33	
TreadSkirtMaterial	4.00	13	3.00
	6.00	20	29.00
	Total	33	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.514	.106	6.514	.106	24.556	16.957
df	1	1	1	1	1	1
Asymp. Sig.	.011	.744	.011	.744	.000	.000
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
11.715	26.353	.113	14.970	.698	14.335	19.500
1	1	1	1	1	1	1
.001	.000	.737	.000	.404	.000	.000

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
13.365	11.271	31.000	33.333	31.000
1	1	1	1	1
.000	.001	.000	.000	.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	4.00	13	8.00
	7.00	13	3.00
	Total	26	
Belt2	4.00	13	4.00
	7.00	13	7.00
	Total	26	
Belt3	4.00	13	8.00
	7.00	13	3.00

	Total	26	
Belt4	4.00	13	4.00
	7.00	13	7.00
	Total	26	
BeltStrength	4.00	13	8.00
	7.00	13	3.00
	Total	26	
BeltMaterial	4.00	13	3.00
	7.00	13	8.00
	Total	26	
Tread1	4.00	13	4.50
	7.00	13	6.50
	Total	26	
Tread2	4.00	13	5.00
	7.00	13	6.00
	Total	26	
Tread3	4.00	13	5.50
	7.00	13	5.50
	Total	26	
Tread4	4.00	13	8.00
	7.00	13	3.00
	Total	26	
Tread5	4.00	13	6.90
	7.00	13	4.10
	Total	26	
Tread6	4.00	13	6.00
	7.00	13	5.00
	Total	26	
TreadDesign1	4.00	13	8.00
	7.00	13	3.00
	Total	26	
TreadDesign2	4.00	13	8.00
	7.00	13	3.00
	Total	26	
TreadDesign3	4.00	13	3.50
	7.00	13	7.50
	Total	26	
TreadBaseMaterial	4.00	13	3.00
	7.00	13	8.00
	Total	26	
TreadCapMaterial	4.00	13	8.00
	7.00	13	3.00
	Total	26	
TreadSkirtMaterial	4.00	13	3.00
	7.00	13	8.00
	Total	26	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	6.988	3.857	6.988	3.857	8.036	8.333
df	1	1	1	1	1	1
Asymp. Sig.	.008	.050	.008	.050	.005	.004

	Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
Chi-Square	2.250	.417	.000	7.075	2.306	.310	9.000
df	1	1	1	1	1	1	1
Asymp. Sig.	.134	.519	1.000	.008	.129	.577	.003

	TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
Chi-Square	6.902	4.472	9.000	8.036	9.000
df	1	1	1	1	1
Asymp. Sig.	.009	.034	.003	.005	.003

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	5.00	10	3.33
	6.00	20	26.91
	Total	30	
Belt2	5.00	10	19.00
	6.00	20	24.00
	Total	30	
Belt3	5.00	10	3.33
	6.00	20	26.91
	Total	30	
Belt4	5.00	10	23.33
	6.00	20	25.00
	Total	30	
BeltStrength	5.00	10	29.00
	6.00	20	25.28
	Total	30	
BeltMaterial	5.00	10	24.33
	6.00	20	25.57
	Total	30	
Tread1	5.00	10	19.50
	6.00	20	25.88
	Total	30	
Tread2	5.00	10	22.67
	6.00	20	25.04
	Total	30	
Tread3	5.00	10	25.50
	6.00	20	25.50

	Total	30	
Tread4	5.00	10	2.33
	6.00	20	26.98
	Total	30	
Tread5	5.00	10	2.00
	6.00	20	27.00
	Total	30	
Tread6	5.00	10	22.67
	6.00	20	25.68
	Total	30	
TreadDesign1	5.00	10	23.17
	6.00	20	25.01
	Total	30	
TreadDesign2	5.00	10	19.00
	6.00	20	24.00
	Total	30	
TreadDesign3	5.00	10	21.17
	6.00	20	25.78
	Total	30	
TreadBaseMaterial	5.00	10	2.00
	6.00	20	27.00
	Total	30	
TreadCapMaterial	5.00	10	19.00
	6.00	20	24.00
	Total	30	
TreadSkirtMaterial	5.00	10	25.50
	6.00	20	25.50
	Total	30	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	7.528	27.476	7.528	4.164	.509	.029
df	1	1	1	1	1	1
Asymp. Sig.	.006	.000	.006	.041	.476	.865

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1
.982	4.552	.000	8.158	8.446	.122	1.449
1	1	1	1	1	1	1
.322	.033	1.000	.004	.004	.727	.229

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
8.338	.337	28.958	27.476	.000
1	1	1	1	1
.004	.561	.000	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	5.00	10	3.50
	7.00	13	5.10
	Total	23	
Belt2	5.00	10	5.00
	7.00	13	4.20
	Total	23	
Belt3	5.00	10	3.50
	7.00	13	5.10
	Total	23	
Belt4	5.00	10	4.33
	7.00	13	4.60
	Total	23	
BeltStrength	5.00	10	6.00
	7.00	13	3.60
	Total	23	
BeltMaterial	5.00	10	4.83
	7.00	13	4.30
	Total	23	
Tread1	5.00	10	2.00
	7.00	13	6.00
	Total	23	
Tread2	5.00	10	3.00
	7.00	13	5.40
	Total	23	
Tread3	5.00	10	4.50
	7.00	13	4.50
	Total	23	
Tread4	5.00	10	2.67
	7.00	13	5.60
	Total	23	
Tread5	5.00	10	2.50
	7.00	13	5.70
	Total	23	
Tread6	5.00	10	2.17
	7.00	13	5.90
	Total	23	
TreadDesign1	5.00	10	2.83
	7.00	13	5.50
	Total	23	
TreadDesign2	5.00	10	4.00
	7.00	13	4.80
	Total	23	
TreadDesign3	5.00	10	4.67
	7.00	13	4.40

		N	Mean Rank
	Total	23	
TreadBaseMaterial	5.00	10	5.33
	7.00	13	4.00
	Total	23	
TreadCapMaterial	5.00	10	7.00
	7.00	13	3.00
	Total	23	
TreadSkirtMaterial	5.00	10	4.50
	7.00	13	4.50
	Total	23	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	.851	.267	.851	.030	2.520	.156
df	1	1	1	1	1	1
Asymp. Sig.	.356	.606	.356	.863	.112	.693

Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign 1
5.600	1.867	.000	2.754	3.733	4.462	3.810
1	1	1	1	1	1	1
.018	.172	1.000	.097	.053	.035	.051

TreadDesign2	TreadDesign3	TreadBaseMat erial	TreadCapMate rial	TreadSkirtMate rial
.202	.024	1.667	5.385	.000
1	1	1	1	1
.653	.877	.197	.020	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Ranks

	Module	N	Mean Rank
Belt1	6.00	20	28.79
	7.00	13	5.00
	Total	33	
Belt2	6.00	20	24.98
	7.00	13	30.80
	Total	33	
Belt3	6.00	20	28.79
	7.00	13	5.00
	Total	33	
Belt4	6.00	20	24.98
	7.00	13	30.80
	Total	33	
BeltStrength	6.00	20	27.63
	7.00	13	15.90
	Total	33	

BeltMaterial	6.00	20	26.96
	7.00	13	22.20
	Total	33	
Tread1	6.00	20	24.35
	7.00	13	26.70
	Total	33	
Tread2	6.00	20	24.05
	7.00	13	29.50
	Total	33	
Tread3	6.00	20	26.61
	7.00	13	25.50
	Total	33	
Tread4	6.00	20	26.94
	7.00	13	22.40
	Total	33	
Tread5	6.00	20	28.78
	7.00	13	5.10
	Total	33	
Tread6	6.00	20	24.56
	7.00	13	24.70
	Total	33	
TreadDesign1	6.00	20	24.64
	7.00	13	24.00
	Total	33	
TreadDesign2	6.00	20	24.00
	7.00	13	30.00
	Total	33	
TreadDesign3	6.00	20	26.98
	7.00	13	22.00
	Total	33	
TreadBaseMaterial	6.00	20	29.00
	7.00	13	3.00
	Total	33	
TreadCapMaterial	6.00	20	27.91
	7.00	13	13.20
	Total	33	
TreadSkirtMaterial	6.00	20	26.50
	7.00	13	26.50
	Total	33	

Test Statistics(a,b)

	Belt1	Belt2	Belt3	Belt4	BeltStrength	BeltMaterial
Chi-Square	11.355	23.086	11.355	23.086	5.806	.640
Df	1	1	1	1	1	1
Asymp. Sig.	.001	.000	.001	.000	.016	.424
Tread1	Tread2	Tread3	Tread4	Tread5	Tread6	TreadDesign1

14.544	26.225	.113	.456	12.824	8.683	11.170
1	1	1	1	1	1	1
.000	.000	.737	.500	.000	.003	.001

TreadDesign2	TreadDesign3	TreadBaseMaterial	TreadCapMaterial	TreadSkirtMaterial
13.365	.577	31.000	19.970	.000
1	1	1	1	1
.000	.448	.000	.000	1.000

a Kruskal Wallis Test
b Grouping Variable: Module

Appendix F: Modular Drivers and Product Functions Definitions

Table 31: Module drivers [25]

Module Driver	Definition
Carryover	A part or a subsystem of system of a product that most likely will not be exposed to any design changes during the life of the product platform
Technology Evolution	Parts that are likely to undergo changes as a result of changing customer demands and technology shift
Planned Product Changes	Parts of the product that the company intends to develop and change to fulfill certain customer demands better, or decrease production costs
Standardization of Common Modules	Parts carrying functions required by all customers are possible candidates for common unit modules. It implies large production volumes.
Product Variety	It refers to the range of product models produced within a particular time to meet the various market demand. Meanwhile, product variety should be obtained to adapt different specifications as well.
Customization	Firms produce specific product in response to designated customer's requirements by different modules, which should be differentiate from product variety.
Flexibility in Use	Firms can rearrange or add some modules to achieve the desired and/or additional functions without drastically changing the whole product infrastructure.
Product Development Management	Concurrent engineering tends to rearrange design task into correlated subs-tasks by identifying interfaces and relationships among modules to substantially reduce developing lead-time.
Styling	Providing variance by clustering typically visible parts of the product to underline product identity
Purchasing Modularity Components	System purchasing means purchasing standard modules from vendors instead of buying individual parts. This black-box engineering implies that vendors take the responsibilities of manufacturing, development, and quality; therefore it's possible for customer to obtain high purchasing flexibility and better service.
Manufacturability Refinement and Quality Assurance	Modules with similar manufacturing processes are grouped to a family, which can reduce production cost effectively, utilize machines efficiently, and also assure quality easily.
Quick Service and Maintenance	Different components of a product process different maintenance frequencies and requires different skills to repair. By grouping components into modules, fault analysis, and maintenance can be easily facilitated.
Product Upgrading	Designing a module to allow upgrading offers for customer to change the product in future.
Recycling, Reuse, and Disposal	Constructing modules to meet growing environmental regulations and customer preferences for "green" products.

Table 32: Engineering functions [51]

Class (Primary)	Secondary	Tertiary	Correspondents
Connect	Couple		Associate, connect
		Join	Assemble, fasten
		Link	Attach
	Mix		Add, blend, coalesce, combine, pack
Convert	Convert		Condense, crate, decode, differentiate, digitize, encode, evaporate, generate, integrate, liquefy, process, solidify, transform
Support	Stabilize		Steady
	Secure		Constrain, hold, place, fix
	Position		Align, locate, orient
. .	… …	… …	… …

Table 33: Engineering flows [51]

Class (Primary)	Secondary	Tertiary	Correspondents
Material	Human		Hand, foot, head
	Gas		Homogeneous
	Liquid		Incompressible, compressible, homogeneous
	Solid	Object	Rigid-body, elastic-body, widget
		Particulate	
		Composite	
	Plasma		
	Mixture	… … …	… … …
Energy	Acoustic Human … …	… … … …	… … … …
Signal	. .	… …	… …

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