Exploring the Correlation Between New Function Attributes Mined from Different Product Domains and Market Sales

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In order to satisfy various market needs and remain competitive in the marketplace, high technology industries create cross domain products that are differentiated from current product designs by integrating new function attributes from multiple product domains. However, given the vast number of candidate function attributes to select from, there is a fundamental challenge when searching for the appropriate function attributes to include in next generation products. This work quantifies the semantic similarities between descriptive design requirements and function attributes in order to identify new function attributes that have the highest similarity to each requirement. This work hypothesizes that there is a correlation between these new function attributes and increased product sales. The case study presented in this work tests this hypothesis in the mechanical transmission systems domain. This work analyses the impacts of products that contain different function attributes on actual product sales in the market. Transmission system function attributes and product sales data, including new electronic gear shifting systems from Shimano's bicycle division, are introduced in the case study. This case study reveals that the function attributes predicted by the method, increase the market sales of next generation products.

Keywords: Design Economics; Benefit/Cost Analysis; Mathematical Programming

1 Introduction

In order to satisfy market needs, companies actively seek to offer competitive and highly differentiated products (Alizon, Shooter, & Simpson, 2009; Kota, Sethuraman, & Miller, 2000; Pirmoradi, Wang, & Simpson, 2014). During the new product development process, product attributes are descriptors that represent a product's characteristics within its design requirements, such as function (e.g., representing the specific objectives of a product) and form (e.g., representing the physical configurations of a product) (Ghani, Probst, Liu, Krema, & Fano, 2006; Mukherjee & Hoyer, 2001; Rounds & Cooper, 2002). A design requirement is a logical representation of designers' purposes that is constructed in accordance with legislation and standards (Fox & Bilgic, 1996; Rounds & Cooper, 2002). A company may develop a new product by incrementally improving one or a few product attributes on the basis of limited design data relating to design requirements and previous product designs. In the presence of fierce market competition, these incremental improvements can erode a company's competitive edge in the market by making their products less distinct than products offered by competitors (Alizon et al., 2009; Leifer, O'Connor, & Rice, 2001; Yannou, Jankovic, Leroy, & Okudan Kremer, 2013). Consequently, companies seek to constantly differentiate products in order to remain competitive. A function attribute represents the operational purpose of design requirements, which are based on designers' understanding of customer needs (Guenov, 2008; Orfi, Terpenny, & Sahin-Sariisik, 2012; Umeda, Kondoh, Shimomura, & Tomiyama, 2005). Analysing a product's function attribute precedes the definition of other product attributes, such as form and material (Bohm & Stone, 2004; Bryant, Stone, McAdams, Kurtoglu, &

Campbell, 2005; Stone, Wood, & Crawford, 1999; Umeda et al., 2005). In the design community, methods have aimed to develop cross domain solutions by searching for product attributes across different engineering domains in order to solve complex engineering design problems (Cross, 1999; Danilovic & Browning, 2007). However, these methods are restricted to searching for design knowledge from the specific domains designers have an interest in or experience with, which potentially limits the competitiveness of next generation products.

Therefore, designers look for novel solutions during the initial steps of the design process by searching function attributes across product variants, product portfolios, and even across departments and organizations, in order to satisfy the continuously increasing variety of market needs (Tucker & Kang, 2012). Each year, more than 30,000 new consumer products are launched into the market, each with their own product attributes (Christensen, Cook, & Hall, 2005). The major challenge facing designers in the modern age is not a lack of product data, but the continuously increasing quantity and diversity of those data. Engineering design methods play a significant role in the product design process, as designers search and generate novel design solutions that address new and emerging customer preferences and market needs (Tuarob & Tucker, 2014, 2015a, 2015b; Tucker & Kim, 2008). Design methods that explore different product attributes have shown cross domain design synergies during the new product development process (Kang, Sane, Vasudevan, & Tucker, 2013; Kang & Tucker, 2015; Tucker & Kang, 2012). This work expands upon previous research by identifying new function attributes that have the potential to satisfy design requirements and increase product sales. Since designers across product domains may have different design and business objectives, the contributions of this work are limited to the exploration of novel functions for next generation mechanical transmission systems that have the potential to improve market sales. This work analyses the impact of implementing new function attributes in the development of next generation mechanical transmission systems by comparing actual market sales differences between products with new function attributes discovered by the method and products with function attributes discovered using existing product design methods. Future work will explore the validity of the method in domains beyond mechanical transmission systems, as more data is needed to generalize the findings beyond the domain explored in this work.

This paper is organized as follows. This section provides a concise motivation and background; section 2 describes works closely related to the method; section 3 presents a detailed description of the method; section 4 presents a case study that demonstrates the method with actual market sales data relating to new types of transmission systems (e.g., electronic gear shifting system) from a bicycle domain; the results of the case study are presented in section 5; and section 6 concludes the paper.

2 Literature review

This section reviews existing design methods relevant to the new product development process.

2.1 Product design based on customer needs analysis

Designers typically solicit feedback from current and potential customers during the creation of next generation product designs (Malen, 1996; Sullivan, Lee, Luxhoj, & Thannirpalli, 1994). Customer needs are defined as problems that customers intend to solve by purchasing products (Kurtadikar & Stone, 2003). In order to create next generation products that succeed in the market, designers focus on improving the attributes existing in the current product portfolio that are based on customer needs (Green, Rajan, & Wood, 2004). Techniques such as conjoint analysis (CA) quantify the probability of a customer's choice between each competitive product or product attribute (Moore, Louviere, & Verma, 1999; Olewnik & Lewis, 2007). Preferences pertaining to product attributes are gathered by collecting customer surveys. A utility function quantifies customer preferences between competitive products using collected product data. Discrete Choice Analysis (DCA) is a probabilistic choice model that predicts a customer's choice based on mutually exclusive, collectively exhaustive (MECE) alternative choices (Berry, 1994). In order to identify the most favored product across different expectation rates, the product design community has employed variations of the DCA model, such as multinomial logit (MNL), probit, nested logit, and ordered logit models (Hoyle, Chen, Ankenman, & Wang, 2009; Wassenaar, Chen, Cheng, & Sudjianto, 2005). The Quality Function Deployment (QFD) method aims to develop products that satisfy customer needs by identifying the interaction between customer needs and engineering metrics (EM) (Pullman, Moore, & Wardell, 2002). This interaction provides designers with functional engineering targets based on customer product preferences, which are obtained from customer surveys and focus groups (Green et al., 2004; Lowe, Ridgway, & Atkinson, 2000).

In order to optimize product attributes during next generation product design, designers employ data mining techniques in order to identify customers' choice patterns based on customer surveys (Kusiak & Smith, 2007; Lim, Liu, & Loh, 2012; Shao, Wang, Li, & Feng, 2005; Tucker & Kim, 2009). Semantic analysis techniques have been utilized to extract meaningful keywords from large scale product reviews in order to efficiently capture market needs (Tuarob & Tucker, 2013, 2014, 2015a, 2015b; Zhou, Jianxin Jiao, & Linsey, 2015).

Engineering designers quantify commonality across related products to mitigate product development costs associated with product differentiation. Each product can then be grouped into a product family, hereby sharing an underlying product design architecture (Orfi, Terpenny, & Sahin-Sariisik, 2011). Researchers measure and evaluate product complexity levels across product families in order to minimize costs while concurrently meeting market needs (Orfi et al., 2012). Clustering techniques have been used for market segmentation during the product family design process (Agard & Kusiak, 2004).

The aforementioned product design methods are limited to product attribute discovery in related product domains. However, discovering new product attributes from different products may provide vital information to engineering designers, who aim to create competitive next generation products, based on product differentiation. This work quantifies the semantic similarities between descriptive design requirements and function attributes in order to identify new function attributes that have the highest similarity values with each requirement. This work hypothesizes that there exists a correlation between these new function attributes discovered by the method presented in this paper and increased product sales.

2.2 Product design based on functional models

In engineering design, a functional model is a structured representation of the standardized functions within the formalized design space. The functions are defined on a functional basis, which designers describe with standardized jargon (Stone & Wood, 2000). Discovering functions for next generation products allows fundamental explorations in product design and enables designers to explore function attributes that fit design requirements (Kurtoglu, Campbell, Arnold, Stone, & Mcadams, 2009; McAdams, Stone, & Wood, 1999). The functional model creates a product's architecture, where the architecture represents the product's functional structure. Designers have created functional architectures for next generation products on the basis of a functional model (Kurtoglu et al., 2009; Sangelkar & McAdams, 2013; Sen, Summers, & Mocko, 2010). A quantitative functional model that captures product functionality and customer requirements has been proposed (Stone et al., 1999). This model has created a product repository by assessing each product's function attributes on the basis of related customer requirements. Designers have combined functional models and TRIZ (a Russian term for the theory of inventive problem solving) to create next generation product design concepts by exploring interrelated patents within design requirements (Fu, Cagan, Kotovsky, & Wood, 2013; Liang & Tan, 2007). Since patents contain large-scale textual data sets, researchers have employed text mining techniques to search the functional attributes that are not only analogical to the design requirements, but are also included in structured formats (e.g., contradiction table, engineering parameters, inventive principles, and standard solutions defined from TRIZ theory) (Cascini & Russo, 2007; Liang, Tan, & Ma, 2008). Therefore, these approaches may support designers with 'reasonable' function attributes, which designers can cognitively retrieve. However, these methods are strongly based on the designers' analogies, and so they retrieve patents that are closely related to the designers' domains. The method presented in this work quantifies the relationships between design requirements and functional descriptions that are not limited to designers' domain knowledge. By comparing these quantified relationships, the method identifies function attributes that are from different domains and satisfies design requirements. Therefore, the method aims to provide designers with more efficient and insightful access in order to retrieve function attributes from different domain knowledge.

In a systems engineering context, EIA 632 has been established to standardize the systems functions (Martin, 2000). The ISO/IEC 15288 standard provides structured design frameworks for organizing system development projects (Arnold & Lawson, 2004). However, as the number of products continues to increase, designers are faced with the challenge of exploring novel function attributes that can lead to next generation products. To overcome these challenges, text mining techniques have been employed to extract function attributes from text-based product data, such as product technical descriptions (Ghani et al., 2006; Romanowski & Nagi, 2004). Researchers have extracted product function attributes from their functional descriptions through text mining techniques that can derive semantics from textual data sets (Kang et al., 2013; Tuarob & Tucker, 2014; Tucker & Kang, 2012; Tucker & Kim, 2011). In order to improve or differentiate product designs, the existing literature has focused on discovering function attributes from product descriptions and customer reviews. However, researchers have not demonstrated how their results impact real market sales. This work aims to provide designers with new function attributes for developing next generation products by identifying these attributes from different products that are not only novel to current generation products but will also increase market sales.

2.3 Product design based on different domain knowledge

Researchers have proposed design methods that develop novel engineering design solutions by discovering product attributes across multiple domains (Helms, Vattam, & Goel, 2009; Nagel, Nagel, Stone, & McAdams, 2010). In order to develop conceptual designs for new products, designers have employed design by analogy, which searches product attributes that meet customer requirements in multiple domains by comparing these attributes based on designers' product cognitions (Fu, Chan, et al., 2013). Designers have created novel design solutions by employing design by analogy techniques to search for new function attributes in unfamiliar product domains (Chan et al., 2011; Linsey et al., 2010). However, it is difficult to search for feasible attributes in other product domains, especially when there is a large difference between designers' knowledge and the product domain (Fu, Chan, et al., 2013;). In order to discover function attributes across multiple domains, researchers employ text mining techniques, such as WordTree and latent semantic analysis, to derive common parts from multiple product patents (Fu, Cagan, et al., 2013; Fu, Chan, et al., 2013; Linsey, Markman, & Wood, 2012). Because design by analogy provides multiple function attributes for next generation products, designers may find it challenging to identify which specific attribute may lead to designing next generation products. The method presented in this work predicts the candidate function attributes that can increase next generation product sales.

Bio-Inspired Design allows designers to take product attributes from nature and develop new design solutions for existing engineering design problems (Cheong, Chiu, Shu, Stone, & McAdams, 2011; French, 1994; Helms et al., 2009; Nagel et al., 2010; Vakili & Shu, 2001). In order to increase the bio-inspiration effects on the new product development process, researchers have presented rule-based models or have utilized text mining techniques (Cheong et al., 2011; Nagel et al., 2010). Cheong *et al*. have employed text mining techniques to search for meaningful function attributes from biological domains relevant to function attributes in engineering design (Cheong et al., 2011). Nagel *et al*. have generated design concepts by combining biological phenomena and engineering function attributes based on a function-based design model (Nagel et al., 2010). Vakili and Shu have proposed a rule-based model to identify suitable biological phenomena that could be related to a product's mechanical attributes (Vakili & Shu, 2001). Biological domain knowledge inspires designers to generate concepts that can solve engineering problems. Biologists try to understand designs in nature, while engineers generate designs by solving problems that appear in the physical world. Each domain has different viewpoints on design and uses different terminologies to investigate product attributes (Cheong et al., 2011; Helms et al., 2009; Nagel et al., 2010). These differences make it difficult for engineering designers to generate and discover inspiration between the biological domain and the engineering domain.

In engineering fields, bisociation aims to explore and analogize cross domain knowledge, which is shared knowledge across multiple domains, in order to search for creative information across multiple domains (Dubitzky, Tobias, Schmidt, & Berthold, 2012). The concept of bisociative design has been proposed to quantify previously unknown design synergies across engineering products (Tucker & Kang, 2012). In order to evaluate the degree of synergy between products, Tucker and Kang have presented a mathematical model that quantifies the similarities among product attributes (Tucker & Kang, 2012). Kang *et al.* have proposed a method that combines subassemblies from multiple End of Life (EOL) products and estimates a new product's value (Kang et al., 2013). Researchers in business have discovered that engineering companies can identify more entrepreneurial opportunities when the companies' decision makers explore bisociations across each individual's prior knowledge (Ko & Butler, 2002, 2006). However, the existing literature has only discovered product attributes across multiple domains that may lead to novel product design concepts. The method presented in this paper overcomes this limitation by searching for new function attributes across multiple product domains that meet design requirements and also contribute to an increase in sales.

2.4 Semantic analysis in product design

Semantic analysis techniques that discover knowledge from large-scale textual data sets have been proposed across a wide range of science and engineering disciplines. Utilizing these techniques, which mine statistically significant terms, in the science and engineering fields gives researchers access to an immense amount of textual data.

In the engineering design fields, semantic analysis techniques have been employed to extract product attributes from text-based product data, including customer feedback and product technical descriptions, in order to design products that better meet customers' needs (Ghani et al., 2006; Menon, Tong, Sathiyakeerthi, Brombacher, & Leong, 2003; Romanowski & Nagi, 2004). Researchers have extracted product *functions* from their *functional* descriptions, such as patents or official manuals, through text mining techniques that can derive semantics from textual data sets (Kang et al. 2013; Tucker and Kang 2012; Ghani et al. 2006; Tseng, Lin, and Lin 2007; Tuarob and Tucker 2014). For example, Menon et al. employed a vector space document representation technique to derive useful product development information from customer reviews (Menon et al., 2003). Tuarob and Tucker have collected 2.1×10^9 tweets in order to search for cell phone related knowledge and identify lead users and their product feature preferences through semantic analyses, which discovers potential product features for next generation cell phone designs (Tuarob & Tucker, 2015a). Tuarob and Tucker have analysed product favorability from large-scale social media data in order to improve next generation product design by adding or removing design features based on preferences (Tuarob & Tucker, 2015b). Zhou et al. have extracted latent customer needs from customer product reviews through semantic analysis, which identifies the hidden analogical reasoning of customers' preferences (Zhou et al., 2015). Gu et al. have employed a semantic reasoning tool to represent *functional* knowledge as function-cell pairs, where the cell is defined as a conceptual structure denoting the structure category that interacts with similar *functions* (Gu, Hu, Peng, & Li, 2012). Ghani et al. have extracted semantics as product attributes on the basis of textual product descriptions by employing a generative model with the expectation maximization (EM) technique (Ghani et al., 2006). Tucker and Kang have extracted semantics as *functions* and behaviors of products from textual descriptions to discover cross-domain knowledge among multiple product domains (Tucker & Kang, 2012).

While the results from the aforementioned works were limited to the same domain, the method introduced in this paper discovers potential attributes across multiple product domains. Furthermore, the analyses of product attributes presented in other works are categorized on the basis of experts' classifications, thereby limiting potential information that could improve current products. The method introduced in this paper aims to provide designers with candidate attributes across multiple product domains that meet design requirements.

In order to discover function attributes from multiple product domains, the Latent Dirichlet Allocation algorithm (LDA) is employed in this work. Comparing to other semantic analysis techniques which are presented in the aforementioned works (e.g. latent semantic analysis), the LDA algorithm has shown promising results on the basis of structured formats that describe products' functions in detail (e.g. patent, official description) (Anaya, 2011; Kang, 2016).

In the early stages of the product design and development process, automatic approaches or platforms have supported designers during each step in searching for next generation product attributes, as shown in Table 1. Step 3 focuses on retrieving the function attributes from product domains that designers are particularly interested in, which therefore potentially limits the competitiveness and market sales increase of next generation products.

Table 1 Exploring function attributes for new product development

Step 1. Identify customer requirements	Step 2. Establish design requirements	Step 3. Map requirements onto design specifications

- Voice Of Customer (VOC) - Requirement extraction models based on semantic analysis	- Consumer preference models - Consumer opinion mining models - Discrete Choice Analysis (DCA)	- Quality deployment (QFD) - Conjoint Analysis (CA)
(Gamon, Aue, Corston-oliver, & Ringger, 2005; Wei, Chen, Yang, & Yang, 2009; Yang, Wei, & Yang, 2009; Zhan, Loh, & Liu, 2009)	(Hoyle et al., 2009; Malen & Hancock, 1995a, 1995b; Petiot & Grognet, 2006)	(Huang & Mak, 1999; Pullman et al., 2002; X. (Luke) Zhang, Simpson, Frecker, & Lesieutre, 2012)

The method presented in Section 3 employs a topic model algorithm and a textual similarity measure to search for new function attributes that have the potential to increase next generation product sales from different product functions.

3 Method

This work quantifies the semantic similarities between descriptive design requirements and function attributes in order to identify new function attributes that have the highest similarity to each requirement. The hypothesis of this work is that there exists a correlation between these new function attributes which are discovered by the method presented in this paper, and increased product sales. The method summarized in Figure 1 outlines the steps towards testing this hypothesis. Collecting existing products' functional descriptions in a structured database allows designers to search for function attributes that can fit design requirements across different products. In order to identify which product's function attributes are closest to design requirements, Latent Dirichlet Allocation is employed in this research for analysing the semantic similarities between the product's functional descriptions and the described requirements.

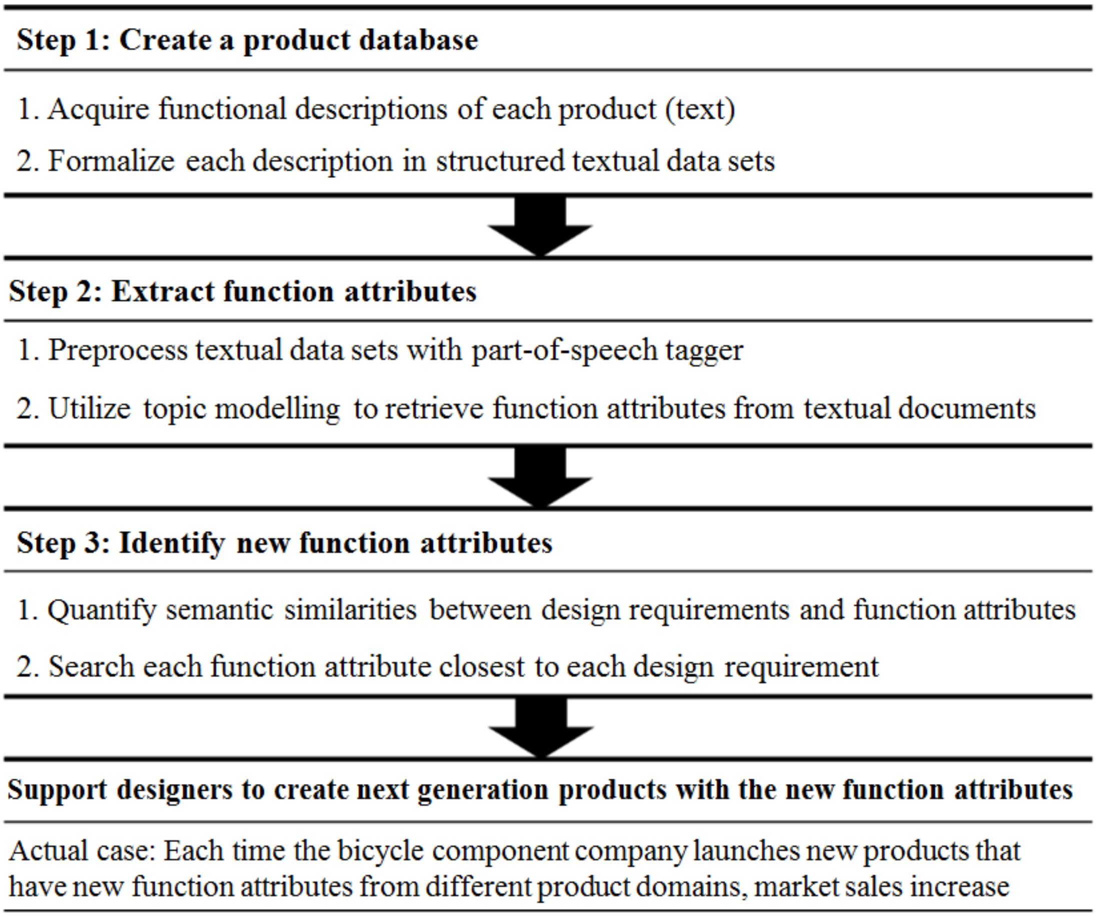


Figure 1 Flow chart of the method proposed in this work

The method aims to provide new function attributes that have the potential to increase next generation product market sales. In order to progress through each step of the method, the design data acquisition process is needed to create the database.

3.1 Step 1 Create a product database

The first step in the method is to create a database comprised of textual product specification data, as seen in Figure 2.

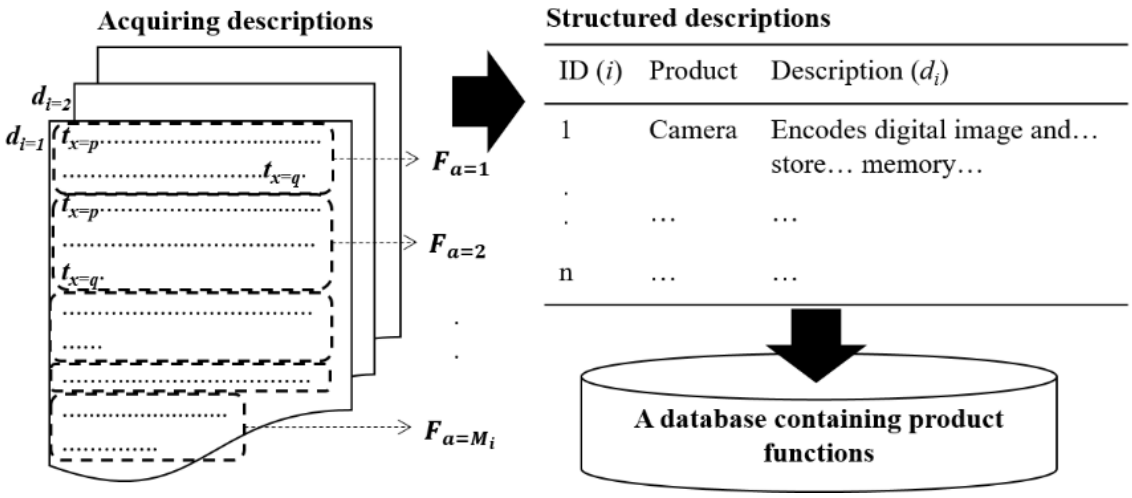


Figure 2 A database consisting of product functions

Data pertaining to a product's functions can be collected from the textual data that describes it, which can be found in official specification documents, technical manuals, or patents (Kang et al., 2013; Tucker & Kang, 2012). The collected data sets are integrated into one database with a structured format, as shown in Figure 2. It is assumed that each product has a unique identification number (ID) that will be used as the primary key for retrieving corresponding descriptions (d_i) in the method. Each description (d_i) is structured with the number of paragraphs (F_a), and these paragraphs are composed of textual terms (t_x) as the following representations.

- d_i: represents the textual description of product i
- t_x: represents the textual terms that exist in the textual description of product i
- F_a is the a^{th} function attribute (paragraph) in the functional description of product i.
- M_i : represents the number of functions of product i. This is the same as the number of paragraphs (specifications) in the product's functional description

The parameter F_a also indicates each function attribute that can found in the textual descriptions existing in the product database. For instance, let's assume product i=1 ($d_{i=1}$) has 27 function attributes ($M_{i=1}$ = 27; $F_{a=1}$, $F_{a=2}$, $F_{a=3}$, … $F_{a=27}$), then the first function attribute of the second product in the database ($d_{i=2}$) is described as $F_{a=28}$. Therefore, the total number of function attributes (F_a) is the sum of M_i , where i =1 to n and n represents the total number of products in the database.

Because engineering documents such as product functional descriptions are formally laid out, a paragraph of the description may contain one topic, which can be regarded as a function attribute (Nagle, 1996).

3.2 Step 2 Extract function attributes

In the context of engineering design, the topics of a product's functional description can be represented as the function attributes of the product. Since a functional description is usually written in natural language, it includes many terms that do not provide important information. Therefore, unnecessary terms, such as linking verbs and stop words (e.g., is, and, the, etc.), are eliminated in order to reduce noise (Munková Daša, Michal, & Martin, 2014; Murphy et al., 2014). In order to capture the function attributes from textual descriptions, all terms in the descriptions are tagged with a part-of-speech (POS) using the Stanford Log-linear POS Tagger (Toutanova & Manning, 2000). The functional descriptions can be replaced with triplet combinations (e.g., verb-noun-adjective/adverb) or subsets (e.g., noun-adjective, verb-adverb, etc.) of the combinations (W. Y. Zhang, Tor, Britton, & Deng, 2001). The National Institute of Standards and Technology (NIST) has developed standardized representation of function attributes in order to provide a common basis for the exchange of function attributes among individuals, teams, or software tools involved in product development (Hirtz, Stone, McAdams, Szykman, & Wood, 2002). A verb represents an action relating to a function attribute. A noun describes a target object (e.g., component) of the action. Additional function information is explained with complements (adjective/adverb) by describing how the action or object is performed.

After the preprocessing step, Latent Dirichlet Allocation (LDA) extracts the function attributes from the descriptions. LDA is a generative probabilistic model for compilations of text corpora, which can be regarded as functional descriptions with infinite mixtures over intrinsic topic groups (Blei, Ng, & Jordan, 2003). Each paragraph of the functional descriptions, such as patents, may represent its topic as each product's function attribute (Sheldon, 2009). In this work, the topics from the descriptions represent the products' function attributes. The LDA algorithm postulates that the description is a finite mixture of the number of functions and that each term's establishment is due to one of the functions from the description. LDA provides the mixing proportions of functions through a generative probabilistic model on the basis of the Dirichlet distribution, as shown in the following equation (1):

$$p(t_x|d_i) = \sum_{a=1}^{M_i} p(t_x|F_a)p(F_a|d_i) \tag{1}$$

Where,

- d_i: represents the textual description of product i
- t_x: represents the textual terms that can found in the textual description of product i
- F_a is the a^{th} function attribute (paragraph) in the functional description of product i
- M_i: represents the number of functions of product i

LDA extracts function attributes by computing a probability ($p(F_a|d_i)$) of a function (F_a) being a topic of a description (d_i), where each term retrieval probability $p(t_x| F_a)$ quantifies each function attribute being a keyword of a function (F_a). Each product's function is extracted with topic probabilities $p(F_a|d_i)$, as shown in Table 2.

Table 2 Extracted function attributes for product 1

ID(i)	Product	Function 1	Function 2	…	Function $M_{i=1}$
1	Camera	$p(F_{a=1}|d_{i=1})$	$p(F_{a=1}|d_{i=1})$	…	$p(F_{a=M1}|d_{i=1})$

Table 2 demonstrates a structural example of how each product's functions can be extracted. These function attributes represent the topics of each functional description in terms of contextual semantics. Each product's function attributes are extracted with fewer terms than its entire textual description. Therefore, the next section utilizes the acquired function attributes to discover new function attributes that have the potential to increase the market sales of next generation products.

3.3 Step 3 Identify new function attributes

Once each function attribute of product *i* is quantified by employing the LDA algorithm, designers can search for which product function attributes are closest to design requirements based on the following equation:

$$\mathrm{Sim}(F_r, F_a) = \frac{F_r \cap F_a}{F_r \cup F_a} \tag{2}$$

subject to,

$$F_r \in R \tag{3}$$

$$F_a \in A \tag{4}$$

$$\text{count}(A) = \sum_{i=1}^{n} M_i \tag{5}$$

where,

- F_r: represents each design requirement
- R: represents a set of the design requirements
- F_a: represents each function attribute discovered in the textual descriptions existing in the product database
- A: represents entire sets of the function attributes in the database
- M_i: represents a set of product i's function attributes
- n: represents the total number of products existing in the database

In the engineering design field, design requirements guide designers in compiling, organizing, and analysing function attributes that should be considered during the new product development process (Rounds & Cooper, 2002). The design requirements are described on the basis of a company's standards, such as ontologies, which are formal descriptions of engineering objects and their attributes, constraints, and relationships. This section of the method explores the semantical similarity between these requirements and the extracted function attributes from section 3.2. The similarity values are measured on a {0,1} scale, where 1 represents the highest similarity between the function attribute and the design requirement, and 0 represents completely unmatched function attribute to the design requirement.

In order to identify new function attributes that can be semantically matched with each requirement, the method iteratively processes a similarity measure (equation

(2)) for searching function attributes that have the maximum results with the requirements. The algorithm, as shown in Figure 3, logically describes this iteration process.

New function attribute identification algorithm

```
Input: Set of design requirements R // F_r ∈ R
       Set of function attributes A // F_a ∈ A
Output: Set of new function attributes // F_l ∈ L
int r, a, l
for (r=1; r<R+1; r++)
    F_l ← argmax (Sim (F_r, F_a))
    Add F_l to L
End
Return L;
```

Figure 3 Pseudo code of new function attribute identification algorithm

On the basis of each design requirement (F_r) and function attribute (F_a), this work compares similarity values between the requirements and attributes in order to search the maximum similarity value. Since each function attribute is comprised of terms, the algorithm may extract the same function attributes (e.g., the same terms, the same similarity value) for the new function attribute (F_l) that satisfies a certain function requirement. For instance, let the algorithm result in the same function attributes (e.g., hydraulic suspension) from product 1 (e.g., an aircraft) and product 2 (e.g., a car). The designer then needs to choose one of the attributes from the products, which operate in different ways. The method presented in this work reduces the above case by identifying the new function attribute (F_l) from the most similar product to the set of design requirements on the basis of each product's function sets. Equation (6) compares the entire functional similarity between a set of design requirements and the sets of each product's function attributes. Note that Equation (6) applies only if the algorithm

(Figure 3) results the same function attributes such as the ones mentioned above (e.g., hydraulic suspension from an aircraft and a car).

$$\mathrm{Sim}(R, F_{A_i}) = \frac{R \cap F_{A_i}}{R \cup F_{A_i}} \tag{6}$$

where,

- R: represents a set of the design requirements
- F_{A_i}: represents a set of product i's function attributes discovered from the method (referring to table 2, $F_{a=1\ldots,M1} \in F_{A_1}$)

The method selects a new function attribute, which is extracted from a product that has the highest similarity to the set of design requirements by Equation (6). Therefore, the method manages redundant data and maintains analogical function retrieval.

The method provides designers with new function attributes that are not only close to the requirements but are also different from current generation products. Therefore, the next generation product can remain competitive in the marketplace by satisfying market needs with new function attributes as well as differentiating these attributes from current products. To evaluate the research hypothesis, the next section demonstrates the method with actual market sales data and functional descriptions relating to each bicycle transmission system: electronic gear shifting systems as next generation products and wire tension bicycle transmission systems as current products.

4 Case study

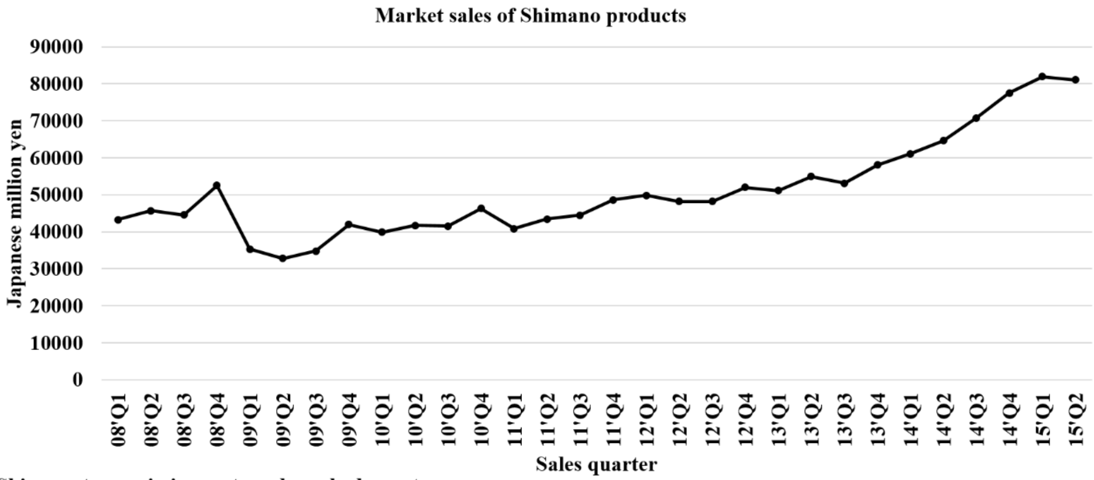
This section analyses each product's market sales data and functional descriptions collected from Shimano's bicycle component division. Shimano deals in bicycle transmission systems, with a 70% market share throughout the world (Yamada, 2014). The bicycle transmission systems domain, while a non-traditional application of study for design related research, represents a sizable market worth around $3.5bn in 2010 that is still growing globally (Yamada, 2014). Understanding and developing new bicycle transmission systems have been proposed in the engineering design community ranging from introductory level of mechanical engineering to intelligent transportation systems relating to a human's heart rate control (Corno, Giani, Tanelli, & Savaresi, 2015; Kosky, Balmer, Keat, & Wise, 2015). This case study introduces functional data and market sales of Shimano's products. This research discovers novel function attributes for the Shimano's new transmission systems and compares product sales between new systems and the old systems. The case study demonstrates each step of the method to test the hypothesis of this research. Shimano products are categorized in two types of transmission systems: automatic transmission systems, a traditional transmission systems. This company's innovation in product development has promoted the recent release of new types of automatic transmission systems (Di2) in the commercial market (Austen, 2009; Takeishi & Aoshima, 2006). The Di2 system uses electronic power to shift gears by sending digital signals rather than moving the gears with physical wire tension. In order to allow riders to focus on cycling (a common customer demand), Shimano designers applied new function attributes from products not related to a bicycle domain to develop a tension free transmission system (Mossman, 2005). The spec comparison between Di2 systems and non-Di2 systems is described below in Table 3.

Table 3 Spec comparison between the Di2 systems and Shimano's non-Di2 systems.

parts	specs	Di2	non-Di2
PC interface 	It is a control system that contains a power source (battery) for the entire transmission system and converts electronic signals from each shifter and derailleur	electronic signal control	N/A
shifter 	It is lever that operates the gear switch	electronic signal control	manual tension control
derailleur (front) (rear) 	It is a chain drive system that shifts chains on a crankset (front derailleur) or sprockets (rear derailleur)	electronic signal control	manual tension control
wire 	It transmits interactive signals from each shifter to each derailleur	electronic signal control	manual tension control
crankset 	It is a power transfer system that converts human power to bicycle speed	identical	identical
sprockets 	It is a power transfer system converting human power to a rear wheel	identical	identical
chains 	It is a system of interlinking pins, plates, and rollers that transmits power from the crankset to sprockets	identical	identical

In order to test the hypothesis of this research, this section collects related patents, issued from 1976 onwards, as functional descriptions for each system, because according to The United States Patents and Trademark Office (USPTO), patents from 1976 onwards, contain the full contents (USPTO, 1994). Between 2008 and 2015, a total of forty two patents were found to be related to the Di2 systems, while a total of one hundred and forty two patents were found to be related to the non-Di2 systems. In the Di2 systems, Shimano designers cited twenty six patents relating to different product domains that introduced new function attributes, such as an automatic gear shift and an electronic switch. These function attributes were integrated into the design of the Di2 parts (Table 3) that differ from the non-Di2 systems.

Thirty five patents from different product domains are cited in the non-Di2 system relating patents. However, the technologies from these patents have not contributed to design the non-Di2 systems, which were launched in 2008. These patents have been cited for creating the initial versions of each system model, which could be considered next generation products in certain eras. For instance, Shimano Total Integration (STI) levers, which are still implemented in the current systems, were launched in 1990. Therefore, these thirty five patents are out of the scope of the analysis since they are not new attributes relating to systems designed between 2008 and 2015. Each patent relating to both systems (Di2 and non-Di2) are described in APPENDIX A and B. This work demonstrates that new function attributes from different product domains were employed to design the Di2 systems, whereas these attributes were not found in the non-Di2 systems. By comparing the market sales relating to each system, the above question is answered in section 5. Shimano’s actual sales data from 2008 to 2015 is demonstrated in Figure 4. From 2008 to 2015, Shimano has made 29 products, including 4 Di2 systems: DURA-ACE Di2, ULTEGRA Di2, XTR Di2, and ALFINE Di2. Each Di2 system has been categorized into different bicycle models. The Di2 systems for both DURA-ACE and ULTEGRA are developed for road cycling. Each XTR Di2 and ALFINE Di2 is built for mountain bikes and city bikes (for comfortable riding in daily life), respectively. The Di2 systems are developed for the top lines for each bicycle model (e.g., road, mountain, city). Note that several products have been launched in different years because of upgrades from earlier versions. For instance, the initial version of DURA-ACE Di2 was launched in Q3 2009, then the second version was launched in Q3 2013 with better functional performance than the previous one, such as being of lighter weight, fast gear shift mechanisms, etc. For similar reasons, traditional transmission systems were launched in different years. These products can be distinguished by serial numbers.



Shimano transmission systems launched quarters

Years	2008				2009				2010				2011				2012				2013				2014				2015	
quarters	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
DURA-ACE Di2							✓																✓							
ULTEGRA Di2															✓												✓			
XTR Di2																												✓		
ALFINE Di2																							✓							
105									✓																	✓				
XT									✓				✓																	✓
SLX									✓									✓												
XTR											✓																			
TIAGRA													✓																	✓
SORA						✓												✓												
TX																		✓								✓				
DURA-ACE			✓																✓											
LX																			✓											
DEORE																					✓									
ALTUS																					✓									
CLARIS									✓												✓									
ULTEGRA						✓															✓									
ALIVIO																										✓				
ZEE																		✓												
SAINT			✓															✓												
ACREA																														✓

Figure 4 Shimano's bicycle division market sales data (Shimano Inc, 2015b)

This case study demonstrates how the method presented in this work can search and identify novel functions, which have yet to be integrated into bicycle systems, in order to develop novel versions of Di2 systems. Electronic transmission systems are now launched in the market by major bicycle transmission industries; Shimano 50% market share; Campagnolo 40% market share; SRAM 10% market share (Yamada, 2014). Among these companies, Shimano is the first and the largest bicycle transmission company that launches the electronic transmission systems in the market. Searching new function attributes for creating next generation transmission systems (e.g., the Di2 systems) across multiple different domains challenges designers. The method in this work extracts new function attributes that have contributed to creating the Di2 systems by searching various function attributes from different products that are closest to the following design requirements (F_r). Note that the Di2 systems have already been launched in the market in accordance with design requirements, and therefore this case study retrieved these requirements from the Di2 systems' official specs (Shimano Inc, 2015a):

- $F_{r=1}$: Shift gears automatically
- $F_{r=2}$: Operate transmission electronically
- $F_{r=3}$: Electronic switch to change transmission
- $F_{r=4}$: Connect the system via electrical wire

4.1 Create a database of products

To perform the experiment, this research follows each step of the method (referring to Figure 1 of section 3). Since the gear shifting system is a subassembly of a bicycle, each data set in the database is also filled with subassemblies from multiple products, as shown in Table 4.

Table 4 A database containing the functions of each product (Beulich, Wagner, & Kirchberger, 2008; Blumer, 2009; Fischer, Esly, Berger, & Kimmig, 1999; D. Kim, 2009; D.-J. Kim, 2005; Okabe, Fukuoka, Yamauchi, & Nakamura, 2010; Prosperis, Sisto, & Borkowski, 2014; Solomon, Doczy, & Massaro, 2007; Svendsen, 2002; Tsai, 2009; Wagner, 2007)

ID(i)	Product	Description (d_i)
1	automotive transmission system (a)	US2002002641 A1: "A motor vehicle … transmission … automatic operating mode …"
2	automotive transmission system (b)	US5954178 A: "A control unit … transmission system in a motor vehicle … electric motor …"
3	automotive brake system (a)	US7219965 B2: " The first brake lever can be a hand brake lever … a foot brake lever …"
4	automotive brake system (b)	US7357464 B2: "The brake system assigned to the front wheel has a conventional design …"
5	phone camera system (a)	US7502558 B2: "An optical arrangement of an illuminating system for a camera according to…"
6	phone camera system (b)	US7585121 B2: "The camera module mainly includes a body and a turn member …"
7	tablet display system (a)	US20050030706 A1: "A tablet monitor includes a monitor main body … connector combining …"
8	tablet display system (b)	US20070097014 A1: "Electronic device comprises a computer-type device preferably …"
9	marine transmission system (a)	US20100248565 A1: "The boat includes a hull, …, water and a marine propulsion unit …"
10	marine transmission system (b)	US6123591 A: "A marine drive includes ... transmission and shifting … reverse drive …"
11	aircraft engine system (a)	US20090212156 A1: "The auxiliary power unit provides pneumatic or electric power to start…"
12	aircraft engine system (b)	US20140244133 A1: "Combustion turbines include a compressor, …, compressed airflow…"

The number of each product's function attributes (M_i) is quantified using the number of paragraphs in the collected descriptions: $M_{i=1}$ = 46, $M_{i=2}$ = 299, $M_{i=3}$ = 14, $M_{i=4}$ = 11, $M_{i=5}$ = 22, $M_{i=6}$ = 14, $M_{i=7}$ = 19, $M_{i=8}$ = 11, $M_{i=9}$ = 74, $M_{i=10}$ = 39, $M_{i=11}$ = 21, $M_{i=12}$ = 37

4.2 Extract function attributes from each product's functional descriptions

The collected descriptions are pre-processed by multiple natural language processing techniques. Stop words and linking verbs are removed for reducing noise. The POS tagger captures each term (e.g., verbs, nouns, adjectives, and adverbs) in the descriptions, and transfers each description into formalized textual data sets before performing LDA, as shown in Table 5. The pre-processing and function extraction processes are taken into account in step 2 of the method (Figure 1).

Table 5 Pre-processed functional descriptions

ID (i = 1 to 12)	Product	Preprocessed description (n: noun, v: verb, adj: adjective, adv: adverb)
1	automotive transmission system (a)	wheels (n) vehicle (n) driven (verb), …, device (n) functionally (adv), …”
⋮	⋮	⋮
12	aircraft engine system (b)	Combustion (n) turbine (n) include (v) compressor (n), …, compressed (adj) …”

Given the functional descriptions of the 12 products, the method extracts each product’s function attributes, as shown in Figure 5. Based on each number of paragraphs in the collected descriptions, LDA extracts more than 600 function attributes from the entire function descriptions (A): $\text{count}(A) = \sum_{i=1}^{n} M_i$ = 607, referring to equation (5), where $M_{i=1}$ = 46, $M_{i=2}$ = 292, $M_{i=3}$ = 14, $M_{i=4}$ = 11, $M_{i=5}$ = 22, $M_{i=6}$ = 14, $M_{i=7}$ = 19, $M_{i=8}$ = 11, $M_{i=9}$ = 74, $M_{i=10}$ = 39, $M_{i=11}$ = 21, $M_{i=12}$ = 37.

ID	Product	$F_{a=1}$: operating transmission automatically	$F_{a=2}$: changing switch automatically	…	$F_{a=46}$: select manually driver
1	automotive transmission system (a)	$P(F_{a=1}\|d_{i=1})$ = 0.273	$P(F_{a=2}\|d_{i=1})$ = 0.209	…	$P(F_{a=46}\|d_{i=1})$ = 0.001

⋮

ID	Product	$F_{a=571}$: include operational turbine	$F_{a=572}$: corresponds residual rotor	…	$F_{a=607}$: transfers independent gas
12	aircraft engine system (b)	$P(F_{a=571}\|d_{i=12})$ = 0.227	$P(F_{a=572}\|d_{i=12})$ = 0.19	…	$P(F_{a=607}\|d_{i=12})$ = 0.002

Figure 5 Extracted function attributes from each product

After LDA extracts each function attribute from each product, this research aggregates each function into a set of function attributes (referring to equation (2)): product$_{i=1}$'s first function is represented with $F_{a=1}$ … product$_{i=12}$'s the last function is represented with $F_{a=607}$.

4.3 Identify new function attributes for the Di2 system

Searching for the closest function attributes (F_a) to the design requirements (F_r) is the final step (Step 3 in Figure 1) of the method presented in this research. In order to identify the new function attributes for the Di2 system, the method quantifies the semantic similarities (equation (2)) between each product's function attribute and design requirements.

The new function attributes implemented to create the Di2 systems are identified from patents related to each automotive transmission system (a) and (b) (ID: 1 and 2, referring to Table 4) by searching the maximum similarity values across 2428 values (F_a: 607 × F_r: 4) with the new function attribute algorithm (Figure 3) and equation (6) in section 3.3. Table 6 describes each similarity value between the identified function attributes and the requirements.

Table 6 Identified new function attributes for the Di2 system

F_l (F_a) product (ID) F_r	$F_{l=1}$ ($F_{a=53}$): automatically transmit gears 2	$F_{l=2}$ ($F_{a=59}$): operates transmission electronic 2	$F_{l=3}$ ($F_{a=2}$): changing switch automatically 1	$F_{l=4}$ ($F_{a=205}$): connects transmitting wires 2
$F_{r=1}$: shifts gear automatically	0.667	0	0.333	0
$F_{r=2}$:operates transmission electronically	0.333	1	1	0.333
$F_{r=3}$: electronical switch change	0	0.333	0.667	0

$F_{r=4}$: connects electrical wire	0	0.333	0	0.667

Referring to Table 6, each design requirement corresponds with each function attribute from product 1 and 2: Sim ($F_{r=1}, F_{a=53}$) = 0.667, Sim ($F_{r=2}, F_{a=59}$) = 1, Sim ($F_{r=3}, F_{a=2}$) = 0.667, and Sim ($F_{r=4}, F_{a=205}$) = 0.667. The function description (US20020026841) of automotive transmission system (a) was referenced in Shimano's patent (US6682087) to develop the transmission control system for the Di2 systems (Takeda, 2004). The function description (US5954178) of automotive transmission system (b) was referenced in Shimano's patent (US8282519) to design the electronic derailleur for selecting multiple gears to change speed in the Di2 systems (Ichida & Fujii, 2012). In order to verify the feasibility of the method presented in section 3, this research analysed 42 patents closely related to Shimano's electronic transmission systems by processing the same steps shown in this case study. Since the Di2 systems have already been launched into the market, design requirements that have been used for creating certain functions for these systems can be found in the description section of each patent, which explains the objects of the invention. Although some inventions related to the Di2 systems were patented back in the 1990s, the actual product was commercialized in 2009. Competitors such as Campagnolo, who also developed an electronic transmission system in the past (1992), launched a product (EPS) similar to the Di2 in 2012 (Campagnolo Corp, 2012). This occurred due to fact that related technologies that met the function attributes were not advanced enough in the past. For instance, electronic parts (e.g., batteries, computing systems, motors) that can be fitted to bicycles had low mechanical and electronic performance (Campagnolo Corp, 2012).

5 Results and discussion

Comparing the collected function descriptions (patents) related to each transmission system (e.g., the Di2 and non-Di2 systems launched since 2008) shows that the Di2 systems have been designed with function attributes from other product domains, whereas non Di2 systems have been created with bicycle-related function attributes.

Table 7Number of patents that are related to each system

Products launched since 2008	Di2	Non-Di2
number of related patents	42	132
number of other product domain patents that have been cited in the related patents	26	0

Referring to section 4, 35 patents from different product domains were discovered from the non-Di2 system relating patents. However, these other product domain patents were employed for designing each initial version of the non-Di2 systems, which were created before 2008. Since these patents are not in the scope of this work, the actual result for the case study indicates that no patent has been cited for designing the recent versions of non-Di2 systems (e.g., launched since 2008). The 26 patents (referring to Table 7) have been discovered from 11 patents among the 42 patents related to the Di2 systems, as shown in Table 8.

Table 8 Non-bicycle domain patents that are related to the Di2 system

Di2 patents	Different product domain patents cited by Di2 patents
US6835148	US4922424
US7874567	US6480761, US20050200606
US7651423	US4391159, US4520907, US4817463, US5004077, US5832784
US8286529	US6498474, US7104152
US20060183584	US4790202, US6357313
US20070191159	US5407101
US8282519	US5180959, US5954178
US6741045	US4638496, US5424709, US5952914, US642644
US7980974	US4928206, US5903440, US6842325, US6909405, US2005001404

US6682087	US20020026841
US7306531	US5025563

The method presented in this research identifies new function attributes for the Di2 systems from 19 patents among these 26 patents (referring to Table 8): US4922424, US6480761, US4391159, US4817463, US5004077, US5832784, US7104152, US4790202, US6357313, US5407101, US5180959, US5954178, US5424709, US5952914, US4928206, US5903440, US6909405, US2005001404, US5025563. This research includes 10 patents that are unrelated to the Shimano case (referring to Table 4). From a total of 11 experiments, the method did not select any of these patents. Therefore, this research shows that the method has 73.08% accuracy when benchmarked against the actual Shimano case.

Since this work presents feasible results compared to the actual Shimano case, which has been shown to be effective for developing a new product, the following sections discuss next generation products' impacts on an increase in market sales.

5.1 Exploring the Correlation between Market Sales and New Product Attributes

In order to test the hypothesis of this research, this section utilizes the market sales variation between each system launch quarter and the next quarter. Please note that Shimano produces bicycle transmission systems. Therefore, most of the sales proceeds come from bicycle assembly companies (e.g., business to business model) such as Trek, Giant, and Specialized, which results in financial transactions during the next fiscal quarter from the product sales period.

The Di2 systems were launched in 5 quarters from 2008 to 2015 (referring to Figure 4). In order to analyse the correlation between the Di2 systems launch and market sales, this research quantifies the sales difference from each quarter, as shown in Table 9. Each period relating to the Di2 system launch is highlighted with asterisks: 09'Q4-Q3, 11'Q4-Q3, 13'Q4-Q3, 14'Q3-Q2, and 14'Q4-Q3.

Table 9 Sales difference between each quarter

period	**sales difference (Japanese million yen)**	**period**	**sales difference (Japanese million yen)**
08'Q2-Q1	2366	**12'Q1-11'Q4**	1213
08'Q3-Q2	-1053	**12'Q2-Q1**	-1611
08'Q4-Q3	7912	**12'Q3-Q2**	27
09'Q1-08'Q4	-17182	**12'Q4-Q3**	3737
09'Q2-Q1	-2511	**13'Q1-12'Q4**	-831
09'Q3-Q2	1940	**13’Q2-Q1**	3836
09'Q4-Q3	7257 *	**13'Q3-Q2**	-1882
10'Q1-09'Q4	-2079	**13'Q4-Q3**	4999 *
10'Q2-Q1	1750	**14'Q1-13'Q4**	2965
10'Q3-Q2	-116	**14'Q2-Q1**	3613
10'Q4-Q3	4699	**14'Q3-Q2**	6067 *
11'Q1-10'Q4	-5454	**14'Q4-Q3**	6790 *
11'Q2-Q1	2658	**15'Q1-14'Q4**	4422
11'Q3-Q2	990	**15'Q2-Q1**	-878
11'Q4-Q3	4145 *		

Compared to other periods, which launched traditional bicycle transmission systems (e.g., 3 different products were launched in 10’Q2) or nothing (e.g. 10’Q4), market sales increased in all of the periods related to the Di2 systems launch. Furthermore, only the Di2 systems were launched in these quarters: 09’Q3, 11’Q3, 13’Q3, 14’Q2, and 14’Q3. Table 10 summarizes the sales variation impacts of the Di2 systems.

Table 10 Sales comparison between the Di2 system launch periods and the other periods

	likelihood of sales decrease (%)	likelihood of sales increase (%)	average sales increase (Japanese million yen)
periods relating to the Di2 systems launch	0	100	5851.6
periods not relating to the Di2 systems launch	41.667	58.333	355.458

5.2 Statistical Verification of the Correlation Between Radical Sales Increase and the Introduction of New Function Attributes from Different Product Domains

The Di2 systems are innovative products that represent competition with emerging technologies (e.g., electric bicycles). Therefore, the manufacturer will receive a higher market valuation than traditional transmission systems that represent competition with the existing dominant designs/redesigns (Pardue, Higgins, & Biggart, 2000). Although there exists a correlation between launching the Di2 systems and increased sales of Shimano’s bicycle products as shown in Table 10 in section 5.1, the Di2 system launch periods need to show higher sales increase than the traditional transmission system launch periods. By analysing the differences in sales across the periods with the Box-and-Whisker plot and deviation analysis, this research reveals a correlation between the Di2 systems and radical market sales increases.

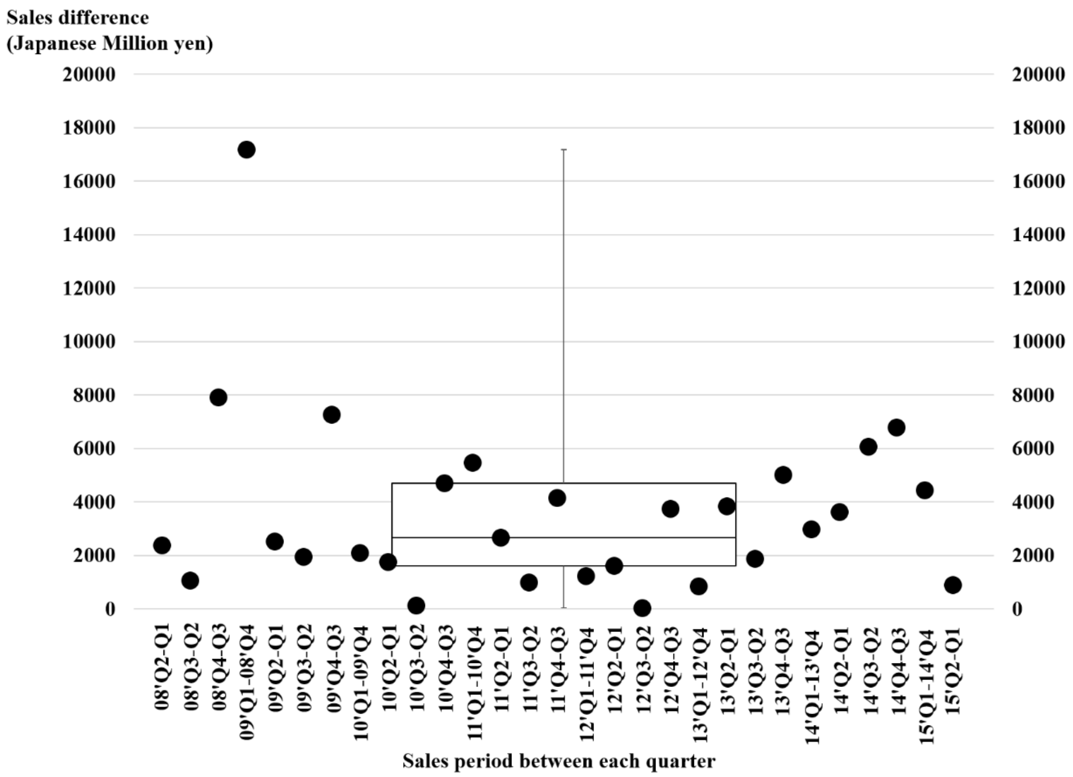


Figure 6 Box-and-Whisker plot on sales difference

In statistics, the values that are higher than the upper limit of the box (e.g., 4699 in Figure 6) are identified as the top 25% across the entire values in the Box and Whisker plot. This research explores each sales difference value that overwhelms the upper limit of the box, which presents a radical increase in market sales. Please note that the difference between each market sales value represents absolute numbers, since this plot is employed for analysing the amount of sales difference. Therefore, each period 09’Q1-08’Q4 (actual difference value: -17182) and period 11’Q4-Q3 (actual difference value: -5454) is not considered as a radical market increase period.

The market sales radically increased in each period 08’Q4-Q3 (7912), 09’Q4-Q3 (7527), 10’Q4-Q3 (4699), 13’Q4-Q3 (4999), 14’Q3-Q2 (6067), and 14’Q4-Q3 (6790), respectively.

Table 11 Radical sales increase comparison between the Di2 system launch periods and the other periods based on a Box and Whisker plot

	likelihood of radical market sales increase (%)
periods related to the Di2 systems launch	80
periods not related to the Di2 systems launch	8.333

Table 11demonstrates that the Di2 systems have larger impacts on a radical sales increase than the other products. In terms of the Di2 system launch period, 4 of the 5 (80%) periods related to the radical sales increase periods (09'Q4-Q3, 13'Q4-Q3, 14'Q3-Q2, 14'Q4-Q3), while periods not related to the Di2 systems launch were related 2 over 24 (8.333%) to the radical sales increase periods (08'Q4-Q3, 10'Q4-Q3).

Analysing sales deviation across the periods also verifies the existence of a correlation between Di2 systems and radical increased market sales, as shown in Figure 7.

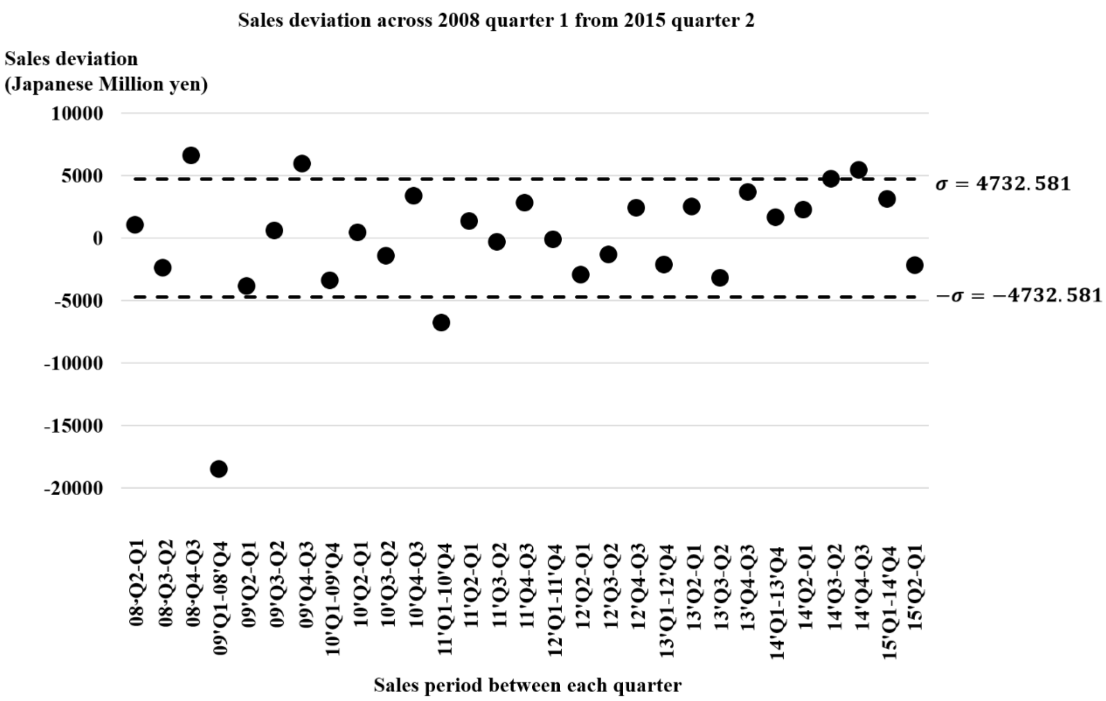


Figure 7 Sales difference deviation analysis from 2008 to 2015

The standard deviation (σ) of the sales difference is quantified as 4732.581, as shown in Figure 7. In statistics, the standard deviation is a measure that quantifies the amount of variation. This research explores each deviation value that overwhelms the positive standard deviation, hereby identifying a radical increase in market sales. The market sales radically increased in each period 08'Q4-Q3 (6608.931), 09'Q4-Q3 (5953.931), 14'Q3-Q2 (4763.931), and 14'Q4-Q3 (5486.931), respectively.

Table 12 Radical sales increase comparison between the Di2 system launch periods and the other periods based on deviation analysis

	likelihood of radical market sales increase (%)
periods related to the Di2 systems launch	60
periods not related to the Di2 systems launch	4.167

Table 12 demonstrates that the Di2 systems have a larger impact on radical sales increase than the other products. In terms of the Di2 system launch period, 3 of the 5 (60%) periods related to the radical sales increase periods (09'Q4-Q3, 14'Q3-Q2, 14'Q4-Q3), while periods not related to the Di2 systems launch were related 1 over 24 (4.167%) to the radical sales increase periods (08'Q4-Q3).

Although this paper is limited in developing mechanical transmission systems for the bicycle gear systems, the method presents novel function attributes from different product domains. The highest Di2 system (Dura-Ace Di2 9070) is around $3000 (USD) whereas the price of the highest traditional transmission system (Dura-Ace 9000) from the same manufacturer (Shimano) is less than half of the Di2 system (approximately $1200). In terms of functional aspects, the significant difference between each system is whether using electronic power or not for changing gears. Comparing to the Di2 systems and other products in Shimano, including the high-end goods for the traditional transmission systems (e.g., Dura-Ace and Ultegra), this research shows that there exists a correlation between the novel functions discovered and an increase in markets sales. The method presented in this work identifies new function attributes from different product domains that have contributed to develop the Di2 systems. Therefore, the method supports designers to search and discover new function attributes for mechanical transmission systems in the bicycle business.

6 Conclusions and future work

This work includes an extensive literature review of research in the engineering design methods relevant to the early stages of the new product development process. The literature review has shown that engineering design methods continue to introduce more automated approaches that explore next generation products' function attributes from product domains that designers are particularly interested in. Although the existing approaches have greatly affected product designs, results from these approaches will limit the competitiveness and market sales of next generation products. Semantic analyses have been employed in the engineering design field to extract function attributes from customer reviews and functional descriptions. This work explores function attributes from multiple products' function descriptions and quantifies the semantic similarities between design requirements and the extracted function attributes. To support designers in identifying function attributes for creating next generation products, this work extracts new function attributes that are semantically closest to the design requirements. In order to analyse the impact of new function attribute implementations on market sales, this work conducts a case study by performing the method with actual market sales data and patents related to different types of transmission systems from Shimano's bicycle component division.

The case study demonstrates that launching next generation products (the Di2 systems) is correlated to an increase in sales, compared to selling traditional products (non-Di2 systems). In the engineering design field, investigating small mechanical transmission systems, such as bicycle components, have been employed for understanding and creating cross domain products ranging from introductory level of mechanical artifacts to sophisticated transportation systems that employ function attributes from multiple product domains. In terms of bicycle transmission systems, the Di2 systems represent competition with emerging technologies by using electronic powers for automatic gear changing/trimming, hereby creating higher market valuation than traditional transmission systems. Actual market sales data from Shimano shows that launching innovative products (e.g., the Di2 systems) that operate new function attributes (e.g., electronic gear shifting function) correlates to increased market sales. By analysing functional descriptions related to each system, this study discovers that the Di2 systems have been designed with new function attributes from different product domains, whereas non-Di2 systems' functions were incrementally improved. Therefore, designers need to actively search for new function attributes, which results in developing competitive and highly differentiated designs for next generation products.

The method in this research achieves comparable results to Shimano's actual new product development practice by identifying function attributes for the Di2 system implementations. In order to satisfy the design requirements, including customer preferences and market needs, designers may search limited data or rely on their own knowledge. This research verifies that function attributes identified by text mining techniques are feasible to implement as new function attributes for next generation products. Future work will explore the validity of the method in domains beyond mechanical transmission systems.

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Appendix A. Patents relating to the Di2 systems

US20060183584	US8137223
US20070191159	US8241158
US20070207885	US8282519
US5653649	US8286529
US6015159	US8360909
US6073061	US8882122
US6227068	US8998756
US6367833	USRE41782
US6682087	
US6725143	
US6740003	
US6741045	
US6774771	
US6834876	
US6835148	
US6866279	
US6877755	

US6899649
US6979009
US7243937
US7247108
US7264256
US7290458
US7306531
US7399244
US7467567
US7547263
US7651423
US7704173
US7805268
US7874567
US7900946
US7980974
US8025597

Appendix B. Patents relating to the non-Di2 systems

US 7100471	US 7677998	US 5860880	US20070135249
US 7228756	US 7722486	US 5624335	US7722489
US 5701786	US 7438658	US20040163486	US20060058133
US 5203213	US 5246405	US20050109148	US20080305902
US 5020387	US 7651424	US20080295636	US20080026888
US 20150094179	US 7361110	US20020139218	US8007383
US 20070129193	US 6287228	US20020139637	US8025598
US 20070265122	US 20080103000	US20040144193	US20080096706
US 20150210353	US 20060194660	US7824287	US7396304
US 5073151	US 20060058135	US7967709	US7318784
US 5087226	US 20050192141	US6039665	US7189172
US 5192248	S 20040116222	US6176798	US 4755162
US 5954604	US 5518456	US5893299	US6419602
US 5904072	US 4610644	US5988016	US6470767
US 6014913	US6135905	US5845543	US6482115
US 5819600	US 5836844	US5852954	US20020033066

US 6058803	US 5695421	US5907980	US20020033067
US 20050217417	US 6290621	US6145184	US 7437969 B2
US 20060112780	US 7665384	US20070241530	US 7721621 B2
US 7527277	US 5085621	US7240585	US 8549955 B2
US 6443032	US 6340338	US7472626	US20060070479
US 5085620	US 6341538	US20030172771	US20070137386
US 7438657	US 4229987	US20050039570	US20080295635
US 20040127314	US 20070202978	US20070298920	US6792825
US 5620384	US 5682794	US7014584	US20030000333
US 5779581	US 6155132	US5496222	US 6393939
US 6234927	US 6647823	US6962544	US6276885,
US 6099425	US 5829313	US20030100393	US6415684
US 6923740	US 7152497	US20040166973	US 8375824
US 5624336	US 5617761	US7186194,	US20080314185
US 7081058	US 20070068312	US20040157690,	
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Biographical Sketches

Sungwoo Kang was a Ph.D. candidate in the department of Industrial and Manufacturing Engineering at The Pennsylvania State University when he conducted this research. His research is focused on developing text mining and natural language processing methods that enhance the product design search process by automatically searching for design-related knowledge.

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