Definition of customer requirements, function requirements, and product structures based on big data and data mining methods

By

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A Thesis submitted to the Faculty of Graduate Studies of
The University of Manitoba
in partial fulfilment of the requirements of the degree of

DOCTOR OF PHILOSOPHY

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Abstract

Definition of customer requirements (CRs), function requirements (FRs), product structures (PSs) has significant impacts on product development. Traditional methods of defining CRs, FRs and PSs such as quality function deployment (QFD), expert evaluation and benchmarking highly rely on experience of experts and designers. This research proposes methods based on big data and data mining to improve accuracy and efficiency of decision-making in defining CRs, FRs, and PSs.

Online product customer comments are searched by a focused crawling method. Collected customer comments are filtered based on parts of speech and frequency of words. Filtered data are clustered into groups by an affinity propagation (AP) clustering method to define CRs. Importance rates (IRs) of CRs are then decided by integration of the importance-performance analysis and Kano model to balance conflict comments from different customers using a similarity matrix in the spectral clustering method.

FRs of a product are defined based on the function description of online products crawled using the focused crawling method. Minimum and maximum FR implementations of the product are decided by polynomial modeling and least square methods. IRs of FRs are defined by adjusting initial weight of FRs using the information entropy based on defined IRs of CRs. PSs are then defined based on relations of FRs and physical components in benchmarking products collected from online websites using WordNet hierarchy and association relation methods. By comparing performance of PSs using IRs of FRs and relations of FRs and PSs, the best PSs for meeting each FR are selected from potential design solutions using a pairwise comparison method.

The proposed methods are applied in design of upper limb rehabilitation devices to improve accuracy and efficiency in definitions of CRs, IRs of CRs, FRs implementation, IRs of FRs, and PSs. Results show that the methods can significantly improve quality of concept design in definitions of CRs, FRs, and PSs of product.

Acknowledgments

I would first like to express my deep and sincere gratitude to my supervisor Dr. Qingjin Peng for the support of my Ph.D. study. His guidance helped me all the time in preparing the research papers and writing my Ph.D. thesis. I got a lot of academic guidance as well as communication ability from Dr. Peng in the weekly group meeting. I could not complete my Ph.D. study without his excellent guidance.

I would also like to thank Dr. Ruppa Thulasiram and Dr. Xihui Liang for providing insightful comments and encouragement for my Ph.D. study. The valuable questions and comments incented me to widen my research from various perspectives. I would also like to thank my colleagues in the Virtual Manufacturing Lab: Hamid Fazeli, Rajiv Kumar Vashisht, Marwan Khalid, Bocheng Xu, Jing Guo, and Xiangwei Mou.

I wish to acknowledge that this research has been supported by the Discovery Grants from the Natural Sciences and Engineering Research Council (NSERC) of Canada, University of Manitoba Graduate Fellowships (UMGF), the Graduate Enhancement of Tri-Council Stipends (GETS) program from the University of Manitoba, and the Mitacs Accelerate program.

Finally, I am deeply thankful to my parents and my wife for their love, and support. My wife always encourages me when I face difficulties in my research or life. The research work and my Ph.D. thesis cannot be completed without the support of my family, advisor, and friends. I would like to thank everyone who helped me in my Ph.D. study.

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List of Abbreviations

A	Attractive quality
AHP	Analytic hierarchy process
ANNs	Artificial neural networks
ANOVA	analysis of variance
AP	Affinity propagation
CBOW	Continuous bag of words
CR	Customer requirement
CRs	Customer requirements
FBS	Function behavior structure
FRs	Function requirements
HoQ	House of Quality
I	Indifferent quality
ID	Importance degree
IPA	Importance performance analysis
IR	Importance rate
IRs	Importance rates
M	Must-be quality
NLTK	Natural Language Toolkit
O	One-dimensional quality
PAs	Physical attributes
POS	Part-Of-Speech
PSs	Product structures
QFD	Quality Function Deployment
R	Reverse quality
SD	Satisfaction degree
TOPSIS	Technique for the order preference by similarity to ideal solution
VSMs	Vector space models

Chapter 1 Introduction

1.1 Research background

Customer requirements (CRs) and function requirements (FRs) are used to define product specifications and structures in product design (Büyüközkan et al, 2004). Normally, CRs and importance rates (IRs) of CRs are decided based on different data sources such as the market survey, expert evaluation, and product customer reviews (Sousa-Zomer et al, 2017). FRs and IRs of FRs are then decided based on IRs of CRs (Alinezad et al, 2013). PSs can be finally determined based on FRs and IRs of FRs.

CRs present desires of customers for products (Jin et al, 2016). (Anderson & Fornell, 2020). CRs are used to guide designers to design products (Chong & Chen, 2010). CRs can be classified into different groups to define IRs of CRs (Xia & Wang, 2010) to describe the priority of CRs. Exiting methods to define IRs of CRs include the Kano model, importance performance analysis (IPA), and conjoint analysis (Carnevalli et al, 2010). The Kano model decides relations between the function implementation and customer satisfaction based on data of questionnaires (Dace et al, 2020). The IPA model uses factors such as the importance and satisfaction degree to determine CRs (Kuo et al, 2012). The conjoint analysis decides CRs using collected attributes of products such as features, functions, and benefits from the customer survey to estimate overall CRs (Green et al, 2001).

FRs provide product features to meet CRs (Franceschini et al, 2015). Generally, FRs describe the product behavior under some specific conditions. FRs are normally defined with product specifications (Nahm et al, 2013). FRs can be decided based on CRs using methods such as House of Quality (HoQ) and Analytic hierarchy process (AHP) to systematically transfer CRs into FRs (Kuo et al, 2012).

IRs of FRs describe the priority of FRs based on relations of FRs and CRs (Shrivastava, 2016). The AHP method can derive ratio scales from pairwise comparisons of FRs to define IRs of FRs using a matrix. IRs of FRs can also be decided in HoQ with different scores based on relations of FRs and CRs (Dace et al, 2020).

Product structures (PSs) can be finally determined based on FRs and IRs of FRs using benchmarking and Quality Function Deployment (QFD) methods. Benchmarking searches representative products in the market to find the best product structure for FRs (Casamayor et al, 2010). QFD helps forming product concepts using a design matrix to map FRs and PSs, which guides a recursive interaction to search design solutions. Different structural schemes can be searched based on product functions with appropriate components and formations to meet FRs (Meng et al, 2015). Design solutions are evaluated to find the best PSs (Chang et al 2017).

1.2 Identified research problems

Identified problems in the existing methods to decide CRs, IRs of CRs, FRs, IRs of FRs and PSs of product are as follows.

Existing methods to define CRs such as customer surveys require interviewing different customers to collect user needs of product, which is time-consuming. The accuracy of collected CRs is low as only limited customers can be approached. Exiting methods to define IRs of CRs such as the Kano model and IPA method are inaccurate because of some conflict requirements from different customers and need levels for IRs of CRs. These methods cannot combine different comments of customers. Average values of the product importance and performance are commonly used in definition of CRs, which ignores differences of customers. Effect of the function implementation is not considered in defining IRs of CRs.

Existing methods to define FRs include expert evaluation and conjoint analysis methods. The expert evaluation method defines FRs using a semantic scale built for each evaluation case separately via user interviews and product semantics. The conjoint analysis method uses consumer preferences to define product features in determining FRs. These methods can only provide qualitative solutions for implementation of FRs.

Existing methods to define IRs of FRs include House of Quality (HoQ) and Analytic hierarchy process (AHP) methods. HoQ is an analytical tool using different scores to describe the relevant degree of FRs and CRs. AHP derives ratio scales from pairwise comparisons between FRs to meet CRs. These methods use subjective ranking methods to assign weights of FRs based on experts' experience.

Existing methods to define PSs include benchmarking and QFD methods by transforming FRs into PSs based on IRs of FRs and relations of FRs and PSs. The QFD method transforms FRs into quantitative parameters to deploy functions in subsystems and component parts. Benchmarking searches product details and structures from existing products in the market. However, it is difficult to use these methods to decide specifications and structures to meet CRs accurately. Relations of FRs and design structures cannot be decided only using a design matrix.

1.3 Research objective and methods

Research objective of this thesis is the development of effective methods for decision-making in product development, especially in the concept design. Accuracy and efficiency are improved for the definition of CRs, IRs of CRs, FRs, IRs of FRs, and PSs. Five tasks are decided to achieve the research objective as follows.

1) Improvement of accuracy of the CRs definition based on online customer reviews of products using big data analysis.

2) Definition of IRs of CRs using integrated IPA and Kano models and spectral clustering based on different customer comments of products.

3) Definition of FRs using big data of online customer reviews and specifications of online products based on the slope of fitted curves.

4) Introduction of an objective method to improve accuracy of IRs of FRs using the information entropy and HoQ.

5) Development of an effective PSs definition method to decide the best PSs from potential product components using association relation and pairwise comparison methods.

1.4 Contents of the thesis

Contents of this thesis are shown in *Figure 1-1*. Chapter 1 introduces research backgrounds, problems, objectives and tasks, and contents of the thesis. Literature is reviewed in Chapter 2 to discuss related research. Chapter 3 introduces a CRs definition method based on online product customer reviews using the big data analysis. In Chapter 4, IRs of CRs are defined using integrated IPA and Kano models by spectral clustering based on different customer comments of products. A FRs implementation method is proposed using big data of online customer reviews and product specifications in Chapter 5. In Chapter 6, an objective definition of IRs of FRs is determined using the information entropy. A PSs definition method is developed based on relations of FRs and product specifications using an association relation method in Chapter 7, followed by Chapter 8 to summarize the research and future work.

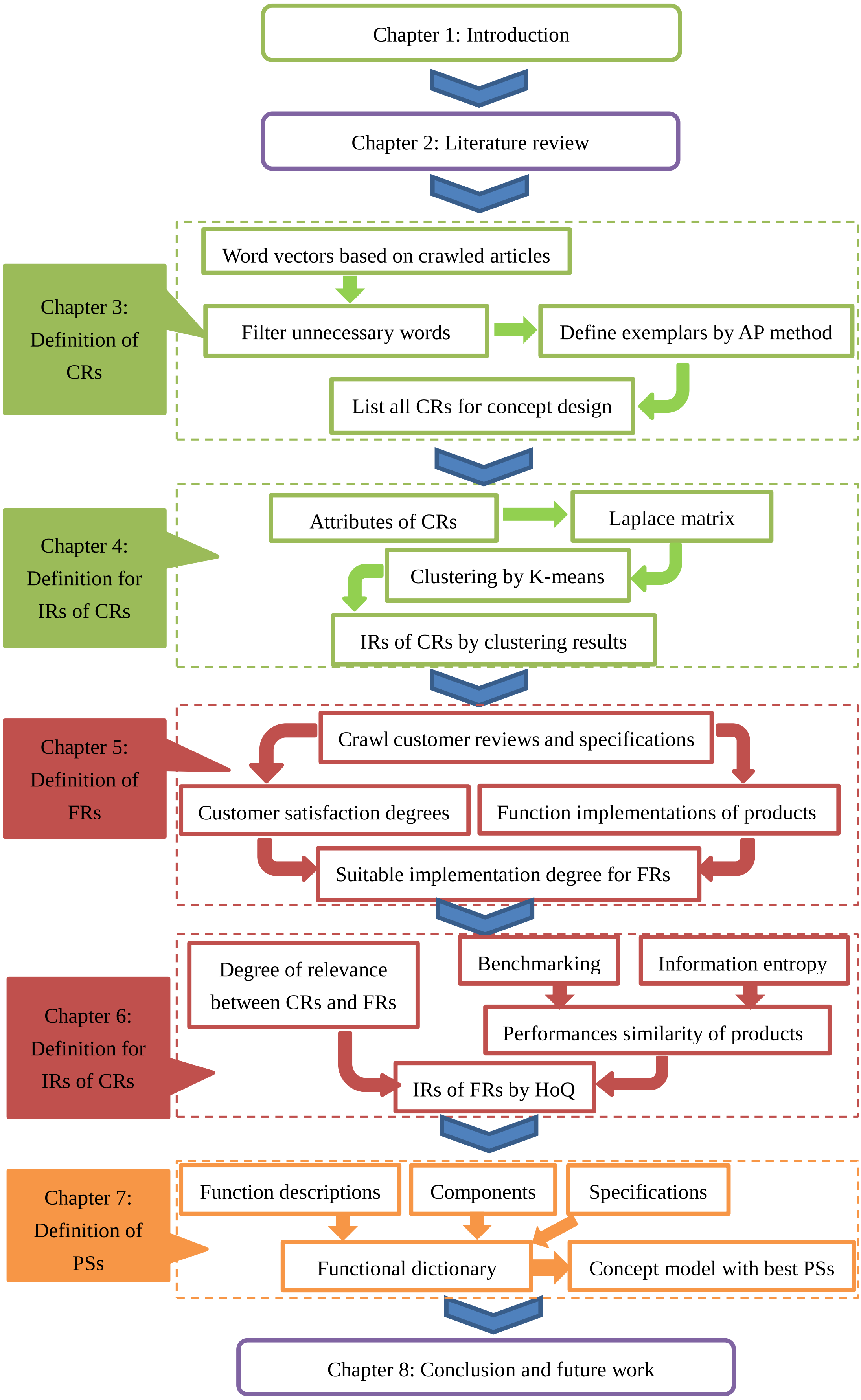


Figure 1-1 Contents of the thesis

Chapter 2 Literature review

Literature review investigates existing work and methods related to research problems of this thesis. Methods in definition of CRs, IRs of CRs, FRs, IRs of FRs, and PSs are discussed in Chapters 2.1 to 2.3. Methods of the big data, clustering, objective weighting, and relevance definition are reviewed from Chapters 2.4 to 2.7.

2.1 Methods in definition of CRs and IRs of CRs

Existing methods of the CRs definition include the affinity diagram and subjective grouping to transfer data of customer surveys into CRs.

The affinity diagram method identifies CRs by classifying collected customer comments from questionnaires into different levels of a dendrogram using a hierarchical clustering algorithm (Li et al, 2010). Similar customer comments are combined at the lowest level of the dendrogram to summary similar customer comments to generate a customer requirement (CR). Wu et al (2020) proposed a dendrogram with three levels to define CRs of the baby stroller based on customer comments using the affinity diagram method. Song et al (2013) combined the affinity diagram with pair-wise comparison method to analyze collected comments for the CRs definition in design of industrial products.

The subjective grouping method determines CRs based on grouping of customer comments from the expert evaluation using a similarity matrix. Grouping results of customer comments defined by experts are used in constructing the similarity matrix to cluster similar customer comments and define a CR for each cluster. Takai et al (2010) improved the subjective grouping method to determine CRs from customer comments using a co-occurrence matrix. Chen et al (2003) proposed a subjective grouping method to evaluate multicultural factors from elicited customer requirements for new product development.

The affinity diagram method requires the similarity comparison of collected comments by experts or designers. In addition, it is difficult to define different levels of the dendrogram accurately. The subjective grouping method requires a similarity matrix built by the expert for balancing conflict comments from different customers to decide CRs, which is also inaccurate. The existing methods are mainly based on manually collected customer comments to define CRs by experts, which may miss some important CRs as limited customers surveyed and knowledge of the experts. Big data methods such as the focused crawling and deep web crawling methods can collect a huge amount of online customer reviews, which offers an efficient method to define CRs.

Existing methods to define IRs of CRs include Kano model, IPA, and Kano-IPA model. The Kano model uses the degree of implemented functions of a product to identify five types of CRs that influence ultimate customer satisfactions to define IRs of CRs (Chaudha et al, 2011). Yadav et al (2013) proposed a sequential approach to define IRs of CRs based on the Kano model for incorporation of customer satisfaction with the CRs. Zhou et al (2019) proposed a fuzzy hierarchical Kano model to define IRs of CRs for personalized customized products.

The IPA model is a simple and effective technique to assist practitioners in identifying improvement priorities of a product, which can guide designers to define IRs of CRs. Product preference and importance of CRs from customer surveys can be considered in an IPA model. Deng et al (2008) proposed a back-propagation neural network method to define IRs of CRs based on the IPA model for critical service attributes, which improved the customer satisfaction for product service quality. Geng et al (2012) proposed an IPA approach to define IRs of CRs for evaluation of the product customer satisfaction using an artificial neural network method.

The Kano-IPA model combines different factors of CRs in Kano and IPA models to define IRs of CRs. Wu et al. (2010) identified key factors to increase customer satisfactions by integrating Kano and IPA models using improved questionnaires. Tontini et al. (2014) considered the impact of incremental innovations on customer satisfactions using a fusion method of IPA and Kano models. Deng et al. (2008) combined Kano and IPA models to manage resources by a partial correlation analysis.

In summary, the existing methods to define IRs of CRs have to divide CRs into many groups. Average values of the product importance and performance are used to evaluate comments of customers, which ignores differences of customers. The characters of CRs such as the satisfaction degree of CRs and actual implementation degree of CRs from different customers cannot be balanced to define accurate IRs of CRs. As clustering methods can identify groups of similar characters in a multivariate data sets, the clustering methods will be reviewed to find a suitable clustering method to group similar characters of CRs for IRs of CRs accurately.

2.2 Methods for definition of FRs and IRs of FRs

Existing methods to define FRs include expert evaluation and conjoint analysis. The expert evaluation defines FRs and FRs implementations from product descriptions and specifications by analyzing implemented product features and functions for accomplishing product tasks. Niu et al (2008) proposed an FRs definition method to extract and model FRs according to the linguistic characterization of domain actions by experts. Tseng et al (1998) defined FRs implementations by recognizing FRs patterns based on the expert evaluation of related products in the market.

The conjoint analysis is a market research approach to measure the value that consumers place on features of a product or service to determine FRs by combining real-life scenarios and statistical techniques. Lee et al (2006) proposed an improved conjoint analysis method to estimate FRs of a product by combining the static utility function model and price using a diffusion model. Sethuraman et al (2005) proposed an internet-based conjoint analysis method to define FRs using online data.

In summary, the existing methods to define FRs require experts to transfer CRs to intended behaviors for completing a task, which can only determine qualitative function implementations of FRs. Without an accurate definition of FRs, designers cannot improve product functions with negative customer sentiments and maintain product functions with positive customer sentiments. Semantic similarity methods in big data can determine similarity of sentences for function descriptions of products to define function implementation degree of collected products. Thus, it is necessary to review semantic similarity methods to find a suitable method to match function descriptions and implementation degrees to define quantitative FRs.

Existing methods of defining IRs of FRs include House of Quality (HoQ) and Analytic hierarchy process (AHP). HoQ is an efficient tool to define IRs of FRs based on relations of CRs and FRs defined by experts. Büyüközkan et al (2004) proposed a fuzzy analytic network method to decide IRs of FRs based on relations of CRs and FRs by combining HoQ and pairwise comparison matrix. Fung et al (2006) used an asymmetric fuzzy linear regression approach to estimate functional relations in defining IRs of FRs by integrating the least-squares regression and HoQ. Kuo et al (2009) applied a fuzzy group method of HoQ in product planning to define IRs of FRs, which reduced vagueness and uncertainty in balance of the environmental acceptability and overall customer satisfaction.

The AHP method uses relations between FRs to define IRs of FRs. Dabbagh et al (2016) proposed a prioritization method to define IRs of FRs by integrating prioritization and AHP methods. Lin et al (2008) integrated the AHP method and technique for the order preference by similarity to ideal solution (TOPSIS) to assist designers in defining IRs of FRs.

The existing methods of defining IRs of FRs require designers to build the pairwise matrix based on their experience in ranking relations of CRs and FRs, which is subjective.

2.3 Methods in definition of PSs

Existing methods to define PSs include QFD, Function behavior structure (FBS), and benchmarking. QFD applies the theory of inventive problem-solving and Kansei evaluation (Yang et al, 2019). It has been integrated with the fuzzy Delphi for collaborative product design and optimal selection of components (Wang et al, 2012).

FBS builds the link of FRs and PSs based on physical attributes derived from design objectives (Gero et al, 2007). FBS considers existing design solutions to improve product performances in various design domains. For example, FBS was applied in the evaluation of product concepts based on key FRs and structures (Dorst et al, 2005). It cannot effectively decide suitable structures to meet FRs.

Benchmarking searches advantages of existing products for the product improvement. By comparing different product performances in the market, the best solution from benchmarking products can be determined. Hosseinpour et al (2015) proposed a systematic benchmarking method for the sustainable product design. Germani et al (2010) developed an improved benchmarking method to define PSs based on co-design virtual environments for the collaborative product development.

The existing methods in defining PSs mainly collect product specifications and parameters manually. Only limited products in the market can be collected to compare the performance of products.

2.4 Methods of big data in defining CRs and FRs

With the increased number of customers on online shopping, a huge amount of customer reviews of products is available on webpages such as Amazon.com, BestBuy.com, and Alibaba.com (Qi et al, 2016). These online product reviews provide sufficient information to understand product performances to improve design of the product. These data can be collected online using big data methods such as the focused crawling and deep web crawling methods (Lee et al, 2008).

The focused crawling method collects data from webpages by prioritizing the crawl frontier and managing the hyperlink exploration. Tan et al. (2018) proposed a customer reviews collection method based on open-source data. A focused crawling method was used to filter links that were not related to topics. Alkalbani et al (2015) selected the appropriate website service using a focused crawling method to match users' requirements. The focused crawling method can selectively collect information of customer reviews from product webpages using a domain specific search engine. The method can assess the relevance of a target URL for the quality of required information before actually fetching the page.

The deep web crawling method can automatically extract a specific data set by downloading pages from websites. Zhao et al (2020) searched online customer purchase behaviors based on the semantic fuzziness using a deep web crawling method. Sharma et al (2010) proposed a deep web information retrieval method using an open framework to classify high dimensional and sparse data.

The deep web crawling method needs to collect all the information from the webpage, which increases the data crawling time. The focused crawling method can selectively search data for required information before actually fetching the page, which increases efficiency of the data collection. Using the focused crawling method in big data, online customer reviews can be collected to find CRs for product improvement.

Existing methods to define FRs cannot define quantitative FRs implementation, which influences designers to improve performance of product functions. Therefore, it is necessary to find an efficient method to guide designers to define accurate quantitative FRs implementation for product functions. Based on the collected online customer reviews and product function descriptions by the focused crawling method, sentences can be analyzed for semantic similarity to define quantitative FRs implementation. Thus, semantic similarity methods including the neural network, vector space modeling, and hierarchical semantic similarity can be used to define quantitative FRs implementation.

The neural network method uses a vector-based document representation to determine the similarity of two sentences by sentiment classification encoding. Tang et al. (2015) proposed a neural network model for continuous vector representations of documents with a variable length to classify the sentiment label of each document based on the similarity of two sentences. Socher et al. (2012) proposed a recursive neural network model to represent compositional vectors of sentences for the arbitrary syntactic type and length to form a matrix for capturing meaning changes of neighboring words in a sentence.

The vector space model determines the similarity of sentences using a cosine function and adopted WordNet database to determine semantic vectors using part-of-speech (POS) based on subspaces and raw data in expert systems. Lee (2011) proposed a sentence similarity definition method by defining the vector value via a WordNet similarity measure. Turney et al. (2010) proposed a vector space model of semantics based on Vector space models (VSMs) to determine the similarity of sentences.

The hierarchical semantic similarity method uses a confidence score to replicate the semantic equivalence between meanings of two sentences or words phases by various semantic relations of synonym sets. Qin et al. (2009) proposed a measure of the word semantic similarity by combining WordNet hierarchy and directed acyclic graph theory to improve accuracy of defining similarity between sentences. Li et al. (2006) determined the short sentence similarity by semantic and word order information implied in sentences.

Comparing with the neural network method and vector space model, the hierarchical semantic similarity method uses a directed acyclic graph to describe the distance of sentences and determine the similarity of sentences, it can decide the semantic similarity of sentences accurately. Therefore, the hierarchical semantic similarity method is selected in this research to match sentences of customer reviews to customer satisfaction degree and match sentences of product function descriptions to function implementation degree. Based on the defined customer satisfaction degree and function implementation degree, the quantitative FRs implementation can be defined.

2.5 Clustering methods in data mining to define IRs of CRs

The problem of existing methods in defining IRs of CRs is that characters of CRs such as customer satisfaction and implementation degrees of CRs from different customers cannot be balanced for the accurate CRs classification to define IRs of CRs. Clustering methods can combine different characters of CRs from conflict comments of customers to improve the IR accuracy of CRs.

Clustering methods use data mining techniques to classify data into different clusters based on some measures, which can be used to combine characters of conflict comments of customers to improve accuracy of IRs of CRs (Alvandi et al, 2012). Existing clustering methods include Fuzzy clustering, K-mean clustering, and spectral clustering.

Fuzzy clustering methods construct clusters with uncertain boundaries for the segmentation of data. Liu et al. (2009) proposed a modified fuzzy clustering method to classify various importance groups of CRs for certainty and precision of the CRs definition. Wang et al. (2011) divided customer quality requirements into a hierarchical structure by a fuzzy clustering method to determine weights of quality requirements for the accurate and reliable quality control. Jiang et al. (2010) proposed a fuzzy self-constructing clustering algorithm for reducing dimensionality of features to improve accuracy of text clustering. Gharib et al. (2010) proposed a fuzzy document clustering approach using the word sense disambiguation technique and WordNet lexical categories in the feature extraction process to improve the clustering quality. Fuzzy clustering methods can consider uncertainty of meaning of words to define clusters, which can improve clustering accuracy.

The K-mean clustering method is a vector quantization method to cluster words or texts into groups based on characters of the words. Alvandi et al. (2012) clustered customers based on their contributions to profitability in banking services using a K-mean clustering method. Ho et al. (2012) proposed a Genetic Algorithms (GA)-based K-mean algorithm to cluster customers for optimal solutions. Alghamdi et al. (2014) proposed a document representation model using the Bayesian vectorisation along with the K-mean to improve accuracy and efficiency of text clustering for high-dimensional data. Kasthuri et al (2014) analyzed the performance of information retrieval and extraction for Tamil language based on the iterative affix stripping stemmer using the K-mean clustering.

The spectral clustering method uses a similarity matrix to extract important information of data. Wu et al. (2011) clustered customers based on their online shopping behaviours and service satisfaction using a spectral clustering method. Sagar et al. (2017) proposed a user segmentation model for user trajectories using a spectral clustering method. Chang et al. (2007) applied a spectral clustering technique to cluster customers in determining characters of loyal customers.

Comparing with other clustering methods, the spectral clustering method can process a huge amount of data easily because a similarity matrix can be used to extract important information and reduce the effect of useless information. In addition, the Laplace matrix in the spectral clustering method can combine categorical attributes and numerical attributes for clustering, which increases accuracy of clustering. Therefore, the spectral clustering method is selected in the proposed IR determination method to combine all the important factors to cluster CRs.

2.6 Weighting methods to define IRs of FRs

Existing weighting methods used in HoQ and AHP highly rely on experience of designers to define IRs of FRs based on IRs of CRs. Objective weighting methods include the information entropy, variance, and covariance. The information entropy defines the weight based on certain or uncertain factors of events. Chen et al. (2010) proposed a weighting method to solve multiple-attribute decision-making problems using an intuitionistic fuzzy information entropy method. Wang et al. (2009) developed a fuzzy objective weighting method using the entropy theory and closeness coefficient. Zou et al. (2006) defined weights of indicators for the water quality assessment using the information entropy.

Variance can define weights according to the degree of dispersion of data. Marín-Martínez et al (2010) proposed a weighting method using the reciprocal of variance and Monte Carlo simulation. Valliant et al. (2008) adjusted weights by the jackknife variance estimator by dropping groups of units, which has advantages of economizing on the computation time and file size. Covariance is also used in defining weights by two jointly distributed real-valued random variables. Stilp et al. (2012) applied shared versus unshared covariance to define the optimal weight for the correlation degree of data characters.

Comparing with other weighting methods, the information entropy can determine weights of FRs based on similarity of functions to search objective solutions for IRs of FRs.

2.7 Relevance methods to define PSs

Existing methods to define PSs only compare the performance of a few products in the market, which cannot determine accurate relations between FRs and PSs to define the best PSs. Thus, it is necessary to review relevance definition methods to find an accurate method to determine relations of FRs and PSs from collected products for defining PSs. Relations of FRs and existing PSs can support structure schemes in product concept design. Relevance definition methods include association relation, artificial neural network, and grey relational analysis.

The association relation method discovers significant relations of product attributes based on the frequency of structures that occur (Feng et al, 2016). Relations of FRs and design structures are defined based on the value of their connections (Sangelkar et al, 2012). PSs were improved based on an association relation mining and decision tree approach (Lee et al, 2012). The association relation method can determine relations of FRs and PSs based on the using frequency of structures in products.

Artificial neural networks (ANNs) can decide relations of design factors and PSs in the early stage of product design. For example, the cost of plastic injection molding was reduced by improved structures using ANNs (Tsai & Huang, 2017). ANNs can also improve product sustainability based on relations of design structures and environmental cost (Zhou et al, 2009).

The grey relational analysis describes relations of design factors (Hsiao et al, 2017). For example, optimal green decoration materials were qualitatively selected based on relations between the psychological satisfaction and interior environmental effect (Tian et al, 2018). The best design combination of product elements was proposed for matching a given product based on relations of product elements and images (Lai et al, 2005).

Comparing with other methods, the association relation method has a better performance to define relations of FRs and PSs for a quantitative result in determining the best PSs. ANNs require the support of sufficient product data. The grey relational analysis uses data of different PSs from collected products by user surveys, which reduces the solution accuracy. In addition, the association relation method can determine relations of PSs and FRs accurately based on the frequency of PSs used for meeting a FR in collected products. Therefore, the association relation method is selected to define relations of FRs and PSs for the best PSs.

2.8 Summary

For solving the problems defined in the literature review, methods of big data, clustering, weighting, and relevance definition are reviewed to determine suitable methods to define CRs, IRs of CRs, FRs, IRs of FRs, and PSs. The focused crawling method is selected to collect online customer reviews to define CRs. The hierarchical semantic similarity method is selected to match sentences of product function descriptions and function implementation degrees to define quantitative implementation of FRs. The spectral clustering method is selected to combine important factors to cluster CRs by combining categorical attributes and numerical attributes to defining IRs of CRs. The information entropy is selected to determine weights of FRs based on similarity of functions to search objective solutions for defining IRs of FRs. The association relation method is selected to determine relations of PSs and FRs accurately to define PSs in this research.

Chapter 3 Definition of customer requirements using big data

This chapter proposes a CRs definition method based on online customer product reviews using the big data. Word vectors are defined using a continuous bag of words (CBOW) model. Online customer reviews are searched by a crawling method and filtered by parts of the speech and frequency of words. Filtered words are then clustered into groups by an AP clustering method based on trained word vectors. Exemplars in clusters are finally used to define CRs. The proposed method is verified by case studies of product design. Results show the proposed method better performance to determine CRs compared to existing methods.

3.1 Proposed method

Raw data required are online articles and customer reviews of products. A flow chart of the proposed method is shown in *Figure 3-1*.

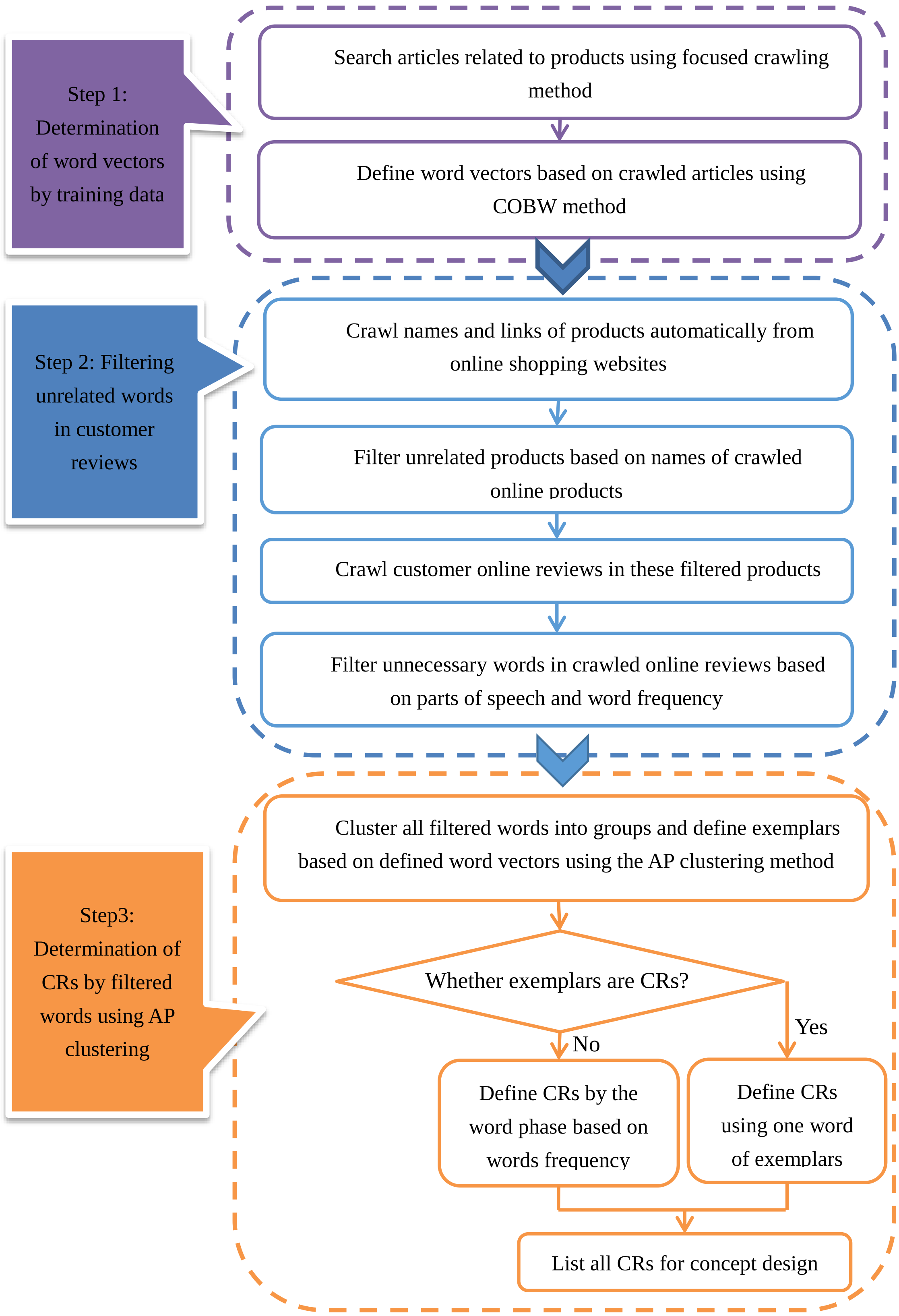


Figure 3-1 Proposed CRs definition method

3.1.1 Data collection and representation

Related review comments of a target product are searched online using the focused crawling method. Word vectors are defined to represent the data meaning based on the data set of text. Each word in the collected review comments is set as a target word for defining the word vector of the word. All collected words are trained using the CBOW model to decide the meaning of words based on words surrounding the target word. A CBOW model is used to efficiently represent the target word to generate a high-quality word vector in a context as shown in *Figure 3-2*. The CBOW model takes the context of each collected word as the input and predicts the word corresponding to the context. In *Figure 3-2*, the input layer uses one encoded vector to represent the total words V. The output layer is a word vector with N dimensions. The projection layer is represented by matrix W_p of size $V \times N$. Each row represents a word. By learning relations between pairs of words to update matrix W_p, word vectors in the output layer can be defined to represent the meaning of words.

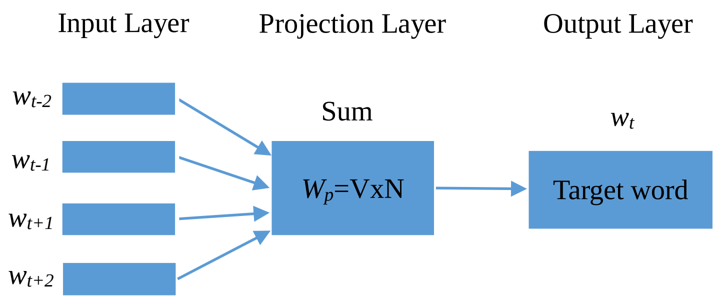


Figure 3-2 Word vectors definition by CBOW

A target word W_t is the altered word at position t in a sequence of training words in Eq. (3-1). W_t is represented by 2 words in front of the target word and 2 words after the target word.

$$W_t = \left(w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}\right) \tag{3-1}$$

After defining W_t, a word vector v_t in Eq. (3-2) is defined to describe the meaning of the t_{th} target word using a matrix of W_t. v_t is a representation word vector of the target word W_t.

$$v_t = \frac{1}{|W_t|}\sum_{i=1}^{|W_t|} v_i \tag{3-2}$$

To test performance of trained word vectors in describing similarity of words, the consistence of word vectors is evaluated for the similar meaning by the human intuition. If the word vectors cannot describe the similarity of words, more related data of the target product will be collected to train word vectors using the updated data set until the word vectors in the close distance are consistent with the similar meaning. Word vectors are then used to compare similarity of words in the following steps.

3.1.2 Determination of word vectors using collected data

For searching related products from online product websites, keywords are defined based on main functions of the product. The number of keywords is assigned from 1 to 5 based on complexity of products. Using keywords, product names and links of online products are collected from selected websites such as Amazon, Alibaba, and Best Buy using the focused web crawling method.

As the search engine may find unrelated products, these unrelated products are removed before crawling customer reviews. A filtering method is proposed based on similarity between keywords and names of crawled online products as follows.

$$\mathrm{F}_{xy} = \cos(x, y) = \frac{\vec{v}_x \cdot \vec{v}_y}{\sqrt{\vec{v}_x \cdot \vec{v}_x}\sqrt{\vec{v}_y \cdot \vec{v}_y}} \quad x \in (1, 2, ..., \mathrm{n}) \quad y \in (1, 2, ..., \mathrm{m}) \tag{3-3}$$

where, F_{xy} is a similarity value between keywords and words of the name for crawled products, $\vec{v}_x$ is the word vector of a keyword, $\vec{v}_y$ is the word vector of a crawled product name, n is the number of words in keywords, and m is the number of words in a crawled product name.

If n keywords are used, maximum value N_x for the most similarity word between the x_{th} keyword and a crawled product name is as follows.

$$\mathrm{N}_x = \mathrm{Max}\left[F_{xy}\right] \quad y \in (1, 2, ..., \mathrm{m}) \tag{3-4}$$

After searching N_x for n times using Eq. (3-4), values from N_1 to N_n are obtained. N_{Min} in Eq. (3-5) is the minimum value from N_1 to N_n. N_{Min} is defined to evaluate similarity between a target product and crawled products as follows.

$$N_{Min} = Min\left[N_1, N_2, \ldots, N_n\right] \tag{3-5}$$

$N_{standard}$ is used to evaluate similarity of a searched product with the target product. Values of $N_{standard}$ are set in a range from 0.35 to 0.50 according to the number of keywords. If N_{Min} is lower than $N_{standard}$, it means that the crawled product is not similar to the target product and should be filtered. After testing all crawled products, customer reviews in these filtered products are crawled as raw data to be used.

3.1.3 Filtering unrelated words from raw data

For using raw data, the punctuation in sentences of online customer reviews is filtered by normalization. In addition, all letters in the text are converted into lowercase to avoid the influence of word cases. A natural language toolbox, Natural Language Toolkit (NLTK) (Jafar et al, 2014), is used to split a paragraph into individual words based on the space character in a paragraph. Parts of speech are categories to describe a word according to its syntactic functions. There are eight types of words including noun, pronoun, verb, adjective, adverb, preposition, conjunction, and interjection. According to characters of these words, only nouns and adjectives are selected to describe product feelings and requirements. Part-Of-Speech (POS) Tagger is a piece of the software to read text for assigning words (Priyadarshi et al, 2020). Nouns and adjectives are selected in the raw data for defining CRs using POS Tagger.

The frequency of words F_w is used to filter unrelated words of nouns and adjectives. If a word appears only a few times in customer reviews, these words are treated as unrelated words. Minimum frequency F_{min} of words is proposed in Eq. (3-6).

$$F_{min} = \frac{N_c}{100} \tag{3-6}$$

where, N_c is the number of customers with comments. If a word has a lower frequency than F_{min}, this word is filtered from the data set.

Some nouns and adjectives may have little useful information to define CRs, such as “good” and “nice” are too general to define specific CRs, these words are also removed using an existing stop word data set with 851 words. Some nouns such as names of products and parts may be repeated many times, these words are also filtered. The left words are used for clustering in the next step.

3.1.4 Clustering filtered words using the AP clustering method

The punctuation in sentences is filtered by normalization from raw data of online customer reviews. The affinity propagation (AP) clustering method (Guan et al, 2010) clusters words into groups based on similarity of semantics in words by a mathematical distance. Each filtered word is represented by a word vector with m characters. The distance between two words (words *i* and *k*) is measured by the distance of word vectors as follows.

$$d(\mathrm{x}_i, x_k) = \|x_i - x_k\|_2 = \sqrt{(x_{i1}\text{-}x_{\mathrm{k}1})^2 + (x_{i2} - x_{k2})^2 + \cdots\cdots + (x_{im} - x_{km})^2} \tag{3-7}$$

Responsibility matrix R shows the fitness of word k as an exemplar for word *i* in Eq. (3-8). An exemplar is the best word that explains the other words in a cluster. A cluster only has one exemplar defined by a word.

$$R = [r(i,k)] \tag{3-8}$$

These responsibility values *r*(*i*,*k*) are determined based on similarity function *s*(*i*,*k*). For searching the shortest distance between x_i and x_k, the Euclidian distance is defined by using word vectors in Eq. (3-9), where x_i is the vector of word *i*,, x_j is the vector of word *j*. The responsibility is updated by Eq. (3-10).

$$s(i,k) = d(\mathrm{x}_i, x_k) \tag{3-9}$$

$$r(i,k) = s(i,k) + \max_{k' \neq k} \{a(i,k') + s(i,k')\} \tag{3-10}$$

Availability matrix *A* shows a suitable level of word *i* to choose word *k* as its exemplar. Initialization of the availability matrix is shown in Eq. (3-11), where n is the number of independent words for clustering.

$$A = a(i,k) = 0 \quad i,k \in \{1,2,\cdots\cdots,\mathrm{n}\} \tag{3-11}$$

Availabilities matrix $a(i,k)$ is updated using Eq. (3-12)

$$a(i,k) = \min\left\{0, r(k,k) + \sum_{i\neq i',k\neq k'} \{0, r(i',k)\}\right\} \tag{3-12}$$

Self-availability $a(k,k)$ is updated using Eq. (3-13), where i' and k refer to the row and column of the associated matrix.

$$a(k,k) = \sum_{i\neq i,k\neq k} \max\{0, r(i',k)\} \tag{3-13}$$

Criterion matrix $c(i,\ k)$ in Eq. (3-14) represents that each word in the criterion matrix is a simply sum of the availability matrix and responsibility matrix at that location, where *i* and *k* refer to the row and column of the associated matrix.

$$c(i,k) = a(i,k) + r(i,k) \tag{3-14}$$

The above steps from Eq. (3-8) to Eq. (3-14) are processed as a loop until the searching result remains unchanged. In order to avoid oscillation, an attenuation coefficient λ is proposed in the range of 0 to 1 based on the number of filtered words.

Responsibility matrix *R* and availability matrix *A* are updated for iterations as follows.

$$r_{t+1}(i,k) = (1-\lambda)r_{t+1}(i,k) + \lambda r_t(i,k) \tag{3-15}$$

$$a_{t+1}(i,k) = (1-\lambda)a_{t+1}(i,k) + \lambda a_t(i,k) \tag{3-16}$$

λ is assigned as 0.5 when the number of filtered words is lower than 100. λ is 0.7 when the number of filtered words is in the range of 101 to 500. λ is 0.9 when the number of filtered words is higher than 500.

Exemplar *p* is defined by maximizing the sum as follows.

$$p = \arg\max\{a(i,k) + r(i,k)\} \tag{3-17}$$

After iterations, the highest criterion value of each row in Eq. (3-14) is designated as the exemplar using Eq. (3-17). Rows that share the same exemplar are in the same cluster. Therefore, all the words with the same exemplar are clustered in a cluster.

3.1.5 CRs definition based on exemplars in clusters

After defining exemplars in each cluster, CRs are defined based on characters of exemplars. As words in a cluster have a similar meaning, all the words in the same cluster are summarized as one CR. An exemplar is the best word in the group to represent the meaning of all words in a cluster.

Words before or after exemplars are recorded to evaluate whether additional words are required to combine with exemplar for more clear information of CRs.

The percentage of i_{th} words before or after the d_{th} exemplar is represented by Eq. (3-18).

$$\mathrm{S}_d^i = \frac{P_i}{N_d} \tag{3-18}$$

where, N_d is the total frequency of the d_{th} exemplar in collected customer reviews. P_i is the frequency of the i_{th} word before or after the d_{th} exemplar.

$\mathrm{W}_{\mathrm{standard}}$ is defined in the range from 0.30 to 0.35 according to the total frequency of exemplar. W_d in Eq. (3-19) is the percentage of the highest frequency word before or after the d_{th} exemplar. If W_d is lower than $\mathrm{W}_{\mathrm{standard}}$, it means that the words before or after the exemplar are quite different. Therefore, all words in the group are defined by the exemplar directly.

$$\mathrm{W}_d = \mathrm{Max}\left|S_d^i\right| \tag{3-19}$$

However, additional words are added if W_d is higher than $\mathrm{W}_{\mathrm{standard}}$ because the additional words can provide more clear and accurate information for CRs. If an exemplar is an adjective, following nouns of the exemplar are collected as additional words. If an exemplar is a noun, previous adjectives and nouns are collected as additional words. The collected words with the highest frequency are selected to combine with the exemplar to define the word phase as CRs.

3.2 Case study

A case study is conducted to decide CRs for design of a passive upper limb rehabilitation device. Related product reviews and articles are crawled and collected as a data set to define word vectors. The collected data include articles of rehabilitation devices and patient recovery, and customer reviews of rehabilitation devices. The size of the collected data set is 1.25 GB. The number of dimensions for word vectors is defined as 300 based on the number of independent words. After filtering words with the frequency lower than 10, 15631 independent words are left in the data set.

Each word in collected articles is defined as a target word in turn. For example, the first sentence in a collected article is “Arm rehabilitation device is very high”. The third target word “device” in the first sentence W_3 is defined and shown in Eq. (3-20) using Eq. (3-1).

$$W_3 = \left(\overbrace{100000...0}^{15631}; \overbrace{010000...0}^{15631}; \overbrace{000100...0}^{15631}; \overbrace{000010...0}^{15631} \right) \tag{3-20}$$

After defining word vectors of all target words based on one-hot vectors, word vectors are trained to improve description of the meaning of words using Eq. (3-2). After verifying the accuracy of trained word vectors based on the meaning similarity of words, defined word vectors are used to describe similarity of words in customer reviews of passive upper limb rehabilitation devices. The size of defined word vectors is 25.1 MB.

Raw data of passive upper limb rehabilitation devices are collected based on names and links of related devices using the focused crawling method in webpages of Amazon and Alibaba. Keywords are defined as arm and rehabilitation based on functions of the target product. Web crawler tools are very popular as these tools have simplified and automated the entire crawling process and made the data crawling easy and accessible to users. For example, crawling tools such as Octoparse and Webcopy can automatically collect product names, product rankings, and product reviews from online shopping websites. By using these tools, 211 names and links of products are collected in Amazon and 76 products are collected from Alibaba.

By using Eqs. (3-3) to (3-5), 287 products are filtered into 125 products. These 125 products are used to collect raw data of customer reviews using the focused crawling method. There are 468 comments on the first product. Comments in total are 5635 for 125 products. Customer reviews found are shown in *Table 3-1*.

Table 3-1 Customer reviews from online product websites

Number	Ranking	Content of customer review comments
1	5 stars	Sling fabric is itchy and irritates my skin. It only works with very short arms. Even average arms won't get any wrist support.
……	……	……
468	3 stars	The length of this sling from elbow to hand is perfect for me. However, there was not enough support at the elbow as the bottom of the sling slopes.
……	……	……
5635	2 stars	Second time I've had shoulder surgery this year. The nylon sling the hospital provides is harsh on the neck and generally uncomfortable.

The size of the collected customer reviews for passive upper limb rehabilitation devices is 415 KB. The collected data are posted on an open access website (https://figshare.com/articles/dataset/customer_online_reviews_of_upper_limb_rehabilitation_devices_xlsx/13298429).

Punctuations in the reviews are filtered and sentences are transferred into individual words based on the space character. Words of customer reviews are filtered based on parts of speech using POS Tagger (Priyadarshi et al, 2020) and stop words introduced in Chapter 3.1.3. The frequency is defined as 56 using Eq. (3-6). Words with the frequency less than 56 times are filtered in the data set.

After filtering words, there are 79 words left. They are then clustered by the AP clustering method. The similarity of two words is measured by the distance of word vectors using Eq. (3-7). Responsibility matrix R is defined using Eqs. (3-8) to (3-10). Availability matrix A is determined using Eqs. (3-11) to (3-13). Criterion matrix $c(i,\ k)$ measures the sum of the availability matrix and responsibility matrix using Eq. (3-14).

In order to avoid oscillation, responsibility matrix R and availability matrix A are updated for iteration using Eqs. (3-15) and (3-16). The result of clustering groups is shown in the second column of *Table 3-2*. The exemplar of each group is defined by maximizing sum c(i,k) using Eq. (3-17) and shown in the third column of *Table 3-2*.

Table 3-2 Word clusters by the AP clustering method

	Words in each cluster	Words of exemplars	Number of words in each cluster
1	Flexibility, posture, adaptability, adjustable, adjustment, flexible, wear, tight,	flexible	8
2	Safe, safety, injury, dangerous, health, unsafe, protective, harmful, injured, pain, uncontrolled, wounded	safety	12
3	Light, heavy, lighter, weight, heavier, lightweight, weights	lightweight	7
4	Cheap, cheaper, expensive, affordable, money, price, discount, worth	price	8
5	Chemical, odors, odor, smell, disgusting, stimulating, mold,	smell	7
6	Supporting, strengthening, supports, assistance, support, supportive, aid, handle, help	support	9
7	Quality, durability, toughness, strength, durable, sturdy	durable	6
8	Comfort, comfortable, uncomfortable, comfy, cozy	comfort	5
9	Shaking, fastening, swinging, fastened, loose, shake,	Fastening	6
10	Size, large, larger, smaller, small, longer, short, fit, length, thickness, range	size	11
Total number of words			79

For deciding whether an exemplar can be used as a CR directly, words of exemplars are tested using Eqs. (3-18) and (3-19). $W_{standard}$ is defined as 0.3. If W_d is lower than 0.3, CRs are defined using exemplars directly. Meanwhile, 5 exemplars including flexible, smell, support, fastening and size cannot be used as CRs directly because W_1, W_5, W_6, W_9 and W_{10} in the second column of *Table 3-3* are higher than 0.3.

The last column in *Table 3-3* lists CRs defined by exemplar and top 3 words using the proposed method. Based on results of CRs defined by the proposed method, related functions and specifications can be decided for these CRs to improve customer satisfactions for the devices.

Table 3-3 CRs definition by exemplar

Exemplar	W in Eq. (3-19)	Top 3 words in front of exemplar			Final CRs
		1	2	3	
1. flexible	0.37	wear	movement	arm	CR.1 flexible wear
2. safety	0.21	none			CR.2 safety

3. lightweight	0.25	none			CR.3 lightweight
4. price	0.17	none			CR.4 price
5. smell	0.33	no	chemical	terrible	CR.5 no smell
6. support	0.39	arm	shoulder	elbow	CR.6 arm support
7. durable	0.25	none			CR.7 durable
8. comfort	0.16	none			CR.8 comfort
9. fastening	0.35	elbow	forearm	elbows	CR.9 elbow fastening
10. size	0.38	forearm	elbow	wrist	CR.10 forearm size

3.3 Verification of the CRs solution

CRs of a passive upper limb rehabilitation device defined by existing survey methods in literature (Callegaro et al, 2016) are compared to CRs from the proposed method. The results are shown in the second column of *Table 3-4*. CRs defined by the proposed method are shown in the last column of *Table 3-4.* Results of CRs comparisons by the survey method and proposed method are also shown in *Table 3-4.*

Comparing with the user survey method, the proposed method adds 3 CRs including CR.5 no smell, CR.9 elbow fastening, and CR.10 forearm size. In addition, 2 CRs with similar meaning in the survey method are combined into one CR in the proposed method. Adaptability and wearable are combined as one CR called flexible wear in the proposed method.

Table 3-4 CRs comparison by the existing method and proposed method

Number	CRs by existing methods	Comment for CRs by existing methods and proposed method	CRs by the proposed method
1	adaptability	CR.1 and CR.2 in the existing method is combined as a CR.	CR.1 flexible wear
2	wearable		
3	safety	Same CRs 2-4 and CRs 6-8 in the existing method and proposed method.	CR.2 safety
4	lightweight		CR.3 lightweight
5	price		CR.4 price
6	support the arm		CR.6 arm support
7	durability		CR.7 durable
8	comfortable		CR.8 comfort
9	easy operation	These 3 CRs in the existing method are removed from proposed method.	None
10	portability		
11	easy to store		
12	None	CR.5, CR.9 and CR. 10 in the proposed method are 3 CRs ignored by existing methods.	CR.5 no smell
13			CR.9 elbow fastening
14			CR.10 forearm size

For evaluating accuracy of CRs defined by the proposed method, online reviews of the product with the highest rating and lowest rating are analyzed. Customer reviews with one, two and three stars are defined as negative ratings. Customer reviews with four and five stars are defined as positive ratings. Negative and positive ratings in online reviews are used to verify the proposed method.

A product called Medical Support Strap for Broken & Fractured Bones has the highest rating 4.3. There are 175 satisfied customer reviews for this product in total. Percentages of satisfied customer reviews for each related CR are shown in *Table 3-5*.

In *Table 3-5*, there are more than 30% of satisfied customer reviews that are not included in CRs in the existing methods. In the proposed method, more than 95% of customer reviews are included in 10 CRs. All the 10 CRs from the proposed method have related positive customer reviews in the product with the highest rating. Therefore, the proposed CRs method can define CRs accurately to match positive customer reviews in the product.

Table 3-5 Satisfied reviews for the product with the highest rating

Existing method		Proposed method	
CRs	Rating	CRs	Rating
1. adaptability	3.5%	CR.1 flexible wear	6.0%
2. wearable	2.5%		
3. safety	6.5%	CR.2 safety	6.5%
4. lightweight	7.5%	CR.3 lightweight	7.5%
5. price	8.7%	CR.4 price	8.7%
6. support the arm	21.3%	CR.5 no smell	5.5%
7. durability	5.5%	CR.6 arm support	21.3%
8. comfortable	19.5%	CR.7 durable	5.5%
9. easy operation	0%	CR.8 comfort	19.5%
10. portability	1.5%	CR.9 elbow fastening	7.5%
11. easy to store	0%	CR.10 forearm size	9.5%
Not included	33.5%	Not included	3.0%

Online product reviews with the lowest rating are also analyzed to evaluate accuracy of CRs defined by the proposed method. A product called Soles Hinged Elbow Brace for Injury Recovery has the lowest average rating 2.9. There are 167 unsatisfied customer reviews for the product in total. Percentages of unsatisfied customer reviews for each related CR are shown in *Table 3-6*.

In *Table 3-6*, there are 53.8% of unsatisfied comments in the product with the lowest rating that are not considered in CRs from the existing method, because two important CRs of CR.9 elbow fastening and CR.10 forearm size are missed. In addition, there are very few unsatisfied comments for easy operation, portability, and easy to store. Some unnecessary and unimportant CRs are included in the exiting method. In the proposed method, only 6.3% of customer reviews cannot be found. Therefore, the proposed CRs definition method can find all the necessary CRs of the product, which shows the CRs definition accuracy compared to the existing method.

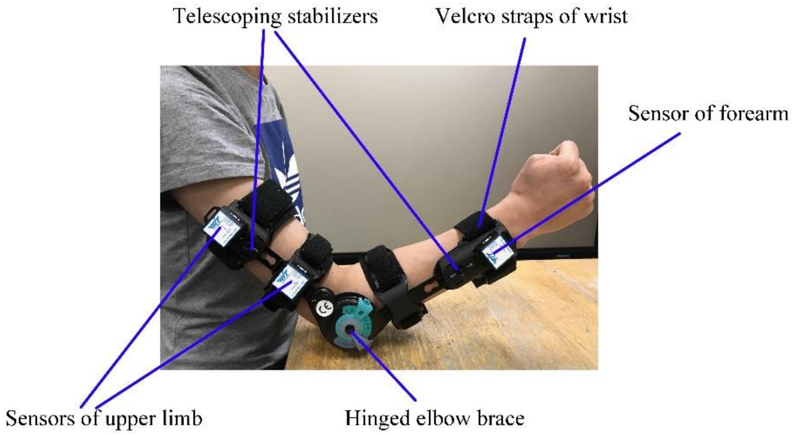
The product with the lowest rating called Soles Hinged Elbow Brace for Injury Recovery is shown in *Figure 3-3* (a). Specifications of tested rehabilitation devices in the third column of *Table 3-7* are from the product manuals. Required specifications for customers in the fourth column of *Table 3-7* are defined by an average value of specifications from the online collected products.

Table 3-6 Unsatisfied reviews for the product with the lowest rating

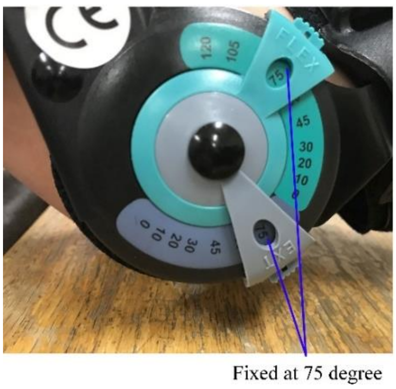
Existing method		Proposed method	
CRs	Rating	CRs	Rating
1. adaptability	3.8%	CR.1 flexible wear	5.9%
2. wearable	2.2%		
3. safety	5.5%	CR.2 safety	5.5%
4. lightweight	4.5%	CR.3 lightweight	4.5%
5. price	0.6%	CR.4 price	0.6%
6. support the arm	10.9%	CR.5 no smell	12.0%
7. durability	7.1%	CR.6 arm support	10.9%
8. comfortable	10.0%	CR.7 durable	7.1%
9. easy operation	1.0%	CR.8 comfort	10.1%
10. portability	0.6%	CR.9 elbow fastening	18.2%
11. easy to store	0%	CR.10 forearm size	18.8%
Not included	53.8%	Not included	6.3%

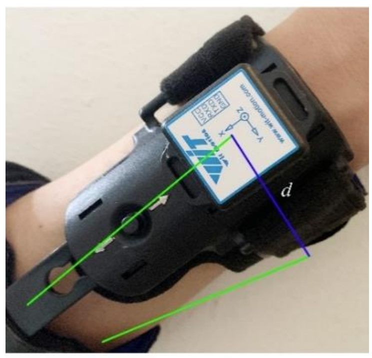
As all specifications of the product are not related to CR.9, an experiment is conducted to test CR.9. *Figure 3-3* (a) shows structures of the upper limb rehabilitation device. It can control the elbow range of motion to improve stability and recovery.

“Easy Hinge” can be used to control the elbow range of motion. Along with Velcro straps, each elbow brace features telescoping stabilizers to help patients finding the right stability and comfort level. The device can be used for the arm injuries recovery such as dislocations and fractures. In *Figure 3-3* (b), the hinged elbow brace should be fixed at 75 °to help patients with fractures or injuries to fix their arms for recovery. Two wireless motion sensors of upper arms are used to ensure that upper arms are fixed. One wireless motion sensor of forearm is used to measure displacement *d* of wrist in *Figure 3-3* (c) for testing the device stability. The motion sensor provides coordinate positions in x-y-z directions. The accuracy of the motion sensors is 0.01 mm. The acquisition frequency is 50 Hz. Based on two collected coordinate locations, the displacement of wrist *d* can be decided.



(a) Passive upper limb rehabilitation device





(b) Hinged elbow brace (c) Testing the wrist displacement of the existing device

Figure 3-3 Passive upper limb rehabilitation device for injury recovery

In *Figure 3-3* (c), if d is very low, it means that the device can meet CR.9 without any problem for the loose elbow structure. Movement angle θ of the hinged elbow brace can be measured by Eq. (3-21). Displacement d of wrist is defined by multiplying velocity of the motion sensor and movement time. l is length from elbow to the sensor of forearm.

$$\theta = \frac{360° d}{2\pi l} \tag{3-21}$$

Specifications and testing results for the passive upper limb rehabilitation device are shown in *Table 3-7*. Results show that the device cannot meet CR.5, CR.9 and CR.10. CR.5 no smell cannot be met in the device because the frame material is plastic with styrene which has a terrible smell. CR. 9 elbow fastening cannot be met because the maximum and average displacement of the fixed elbow structure are too high. CR.10 forearm size cannot be met because the device cannot reach the wrist and provide wrist support for 30% patients whose forearm is longer than 235 mm. These 3 CRs are ignored in the existing design of the product with the lowest rating. However, these 3 CRs can be found in the proposed method. If a product can be designed by using CRs defined by the proposed method, these 3 CRs can be met in the product to improve customer satisfactions significantly.

According to specifications and testing results in *Table 3-7*, designers ignored these necessary CRs including CR.5 no smell, CR.9 elbow fastening, and CR.10 forearm size in the design process. In the existing customer survey methods such as focus groups, CRs can only be defined based on the customer survey by designers. As the limited number of surveyed customers, CRs cannot be decided accurately. For example, CR.9 and CR.10 are difficult to be decided because some of their characters require feedbacks or comments from a large number of customers. The existing method can only consider a part of characters of the rehabilitation device.

Table 3-7 Specifications of passive upper limb rehabilitation devices

Product		Specifications of tested rehabilitation device	Required specifications for customers	Related CRs	Meet related CRs or not
	Frame material	Plastic with styrene	Health	CR.5	No
	Cover material	Cotton	Comfort	CR.8	Yes

	Whole size	500*80*90 mm	None	CR.1	Yes
	Length of forearm	180-235 mm	170-270 mm	CR.10	No
	Length of upper arm	170-230 mm	170-220 mm	CR.6&7	Yes
	Elbow angle	0-120 degree	0-120 degree	CR.2	Yes
	Diameter of forearm	50-180 mm	50-150 mm	CR.1&7	Yes
	Diameter of upper arm	50-180 mm	50-150 mm		Yes
	Price	115 US Dollar	Less than 300 US Dollar	CR.4	Yes
	Weight	0.53 kg	Lower than 3 kg	CR. 3	Yes
Testing	Displacement *d* of wrist movement	15.3 mm	0-2.0 mm	CR.9	No
	Angle θ of wrist movement	3.5 degree	0-1.0 degree		No

The proposed method can collect feedbacks and comments from a huge number of online customers, for example, comments of 5653 customers are collected in the case study. Therefore, the proposed CRs definition method can find the most common and important words from user comments to determine CRs accurately.

3.4 Summary

This chapter proposes a CR definition method based on the data crawling and AP clustering methods. Word vectors are determined using a CBOW method. After filtering online customer reviews using parts of speech and frequency of words, filtered words are clustered into groups by the AP clustering method. CRs are then defined by exemplars in each group and similarity between exemplars and general CRs. According to the case study and experiment of the passive upper limb rehabilitation device, advantages of the proposed method are verified in defining CRs effectively and accurately from online customer reviews.

Chapter 4 A spectral clustering method to define IRs of CRs

This chapter proposes a method to improve the definition accuracy of importance rates (IRs) of CRs. Based on customer comments of a product, IRs of CRs are defined using integrated IPA and Kano models by spectral clustering. A similarity matrix W is formed to balance the influence proportion between the IPA and Kano models considering comments of different customers for the product. The proposed method is compared to several existing methods in a case study of design of an active upper limb rehabilitation device. Results verify the proposed method.

4.1 Proposed method

Raw data used in the method include CRs and characters of CRs for Kano and IPA models. Collected raw data are normalized for eliminating the influence of dimensions. Categorical attributes in the Kano model are transferred to numerical attributes by integrating the current function implementation of CRs and categorical attributes of CRs in the Kano model. Conflict comments from different customers are processed using the analysis of variance (ANOVA) method and separated into different groups to show all important comments of customers.

A spectral clustering method is used to form a Laplace matrix to combine categorical attributes in the Kano model, numerical attributes of the importance degree, and customer satisfactions in the IPA model. CRs are clustered into 5 groups based on characters of CRs by the K-means method in a feature space. IRs of CRs are defined based on clustering results. Steps of the proposed method are shown in *Figure 4-1*.

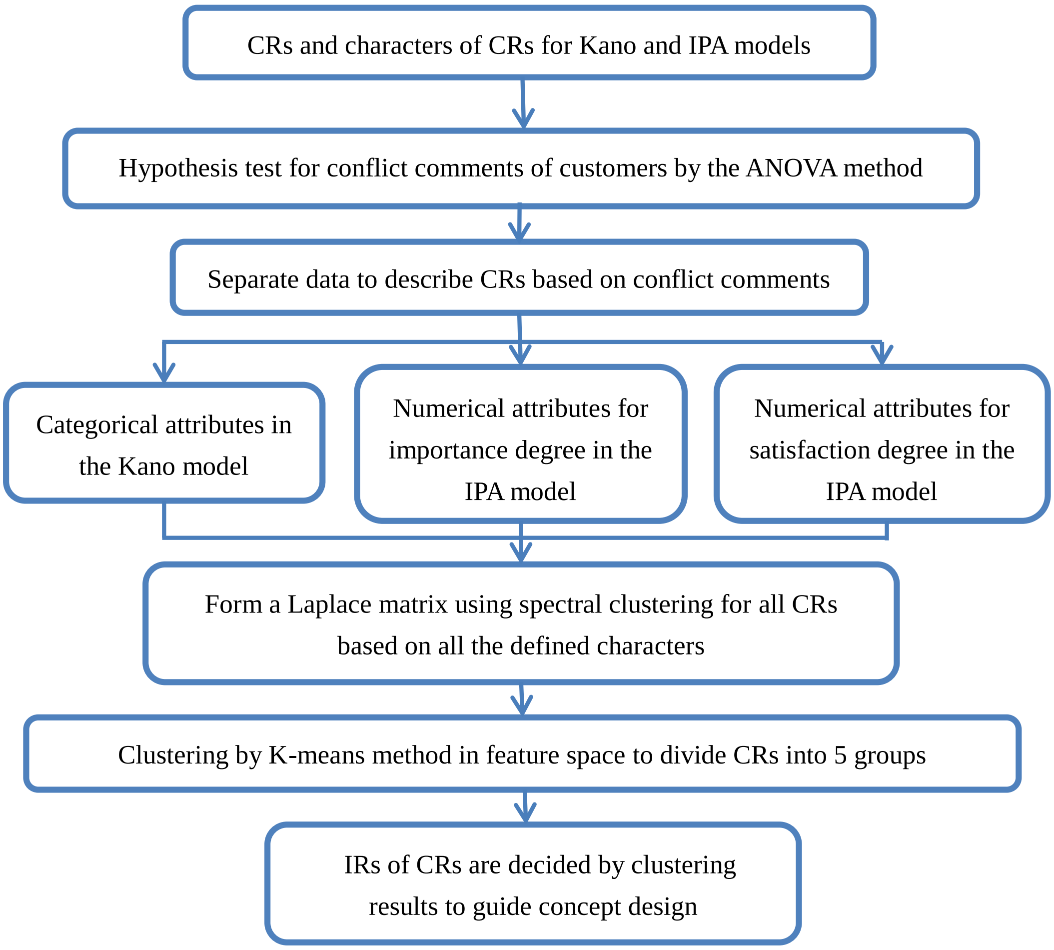


Figure 4-1 Proposed method of defining IRs of CRs

4.1.1 Data collection and transformation

Raw data are collected from literature based on requirements of Kano and IPA models as shown in *Table 4-1*.

Table 4-1 Raw data for Kano and IPA models

	Raw data collected	
1. Data for the Kano model	1.1 Description or comments from literature for the products have functions to meet a CR.	a. Customers need the product with the function
		b. It must have the function
		c. Customers are neutral
		d. Customers can live with the product included the function
		e. Customers need the product to remove the function
	1.2 Description or comments from literature for the product do not have functions to meet a CR.	a. Customers need the product without the function
		b. It must remove the function
		c. Customers are neutral
		d. Customers can live with the product without the function
		e. Customers need the product to add the function

	1.3 Function implementation degree of current products to meet a CR	a. Without any function to meet CRs (1 mark)
		b. Only the very basic function to meet CRs (2 mark)
		c. Functions meet CRs with some improvement space (3 mark)
		d. Functions meet CRs with little improvement required (4 mark)
		e. Functions fully meet CRs (5 mark)
2. Data for the IPA model	2.1 Importance degree (ID) of a CR	a. very importance (5 marks)
		b. importance (4 marks)
		c. normal (3 marks)
		d. unimportance (2 marks)
		e. very unimportance (1 mark)
	2.2 Satisfaction degree (SD) of a CR	a. very satisfaction (5 marks)
		b. satisfaction (4 marks)
		c. normal (3 marks)
		d. dissatisfaction (2 marks)
		e. very dissatisfaction (1 mark)

Based on data for the Kano model in *Table 4-1*, CRs are classified into 5 groups. Must-be Quality (M) is requirement of the customer expectation. One-dimensional Quality (O) attributes satisfaction when it is fulfilled, and dissatisfaction when it cannot be fulfilled. Attractive Quality (A) provides satisfaction when CRs are met fully, dissatisfaction when it is not fulfilled. Indifferent Quality (I) refers to aspects that are neither good nor bad, which results in neither customer satisfaction nor dissatisfaction. Reverse Quality (R) is a high degree of dissatisfaction when not all customers are alike. Based on data for the IPA model in *Table 4-1*, CRs are divided into 4 categories including the concentrating area for a mark of 5, keeping up good work for a mark of 4, low priority for a mark of 3, and possible overkill for a mark of 2.

For comparing data with different dimensions in Kano and IPA models, data in the IPA model are transferred into interval from 0 to 1 using Eq. (4-1).

$$x_{ij}^{n} = \frac{x'_{ij} - \min\limits_{1\le i\le n}\left\{x'_{ij}\right\}}{\max\limits_{1\le i\le n}\left\{x'_{ij}\right\} - \min\limits_{1\le i\le n}\left\{x'_{ij}\right\}} \quad (j = 1, 2, \ldots, h) \tag{4-1}$$

Values of CRs in the Kano model are also normalized. As categorical attributes cannot be directly used to search similarity, they are transferred into numerical attributes. As categories of O, I, and R are not influenced by the current function implementation degree of CRs, values for CRs in these 3 categories are directly defined based on classification results in Kano model. The value of O is assigned as “0.6” as the one-dimensional CRs can promote the product preference when CRs are satisfied. The value of I is defined as “0.2” when indifferent CRs cannot influence the customer satisfaction. The value of R is assigned as “0.1” because the reversed CRs can reduce the customer satisfaction.

Values for CRs in A and M groups are relative to the current function implementation degree of CRs. Based on the Kano model, values of categories A and M are proposed in Eqs. (4-2) and (4-3) as follows.

$$\begin{cases} \mathrm{V}_{\mathrm{A}}^{i} = \frac{1}{5}\times 5^{0.5x} \quad (x=1,2) \\ \mathrm{V}_{\mathrm{A}}^{i} = 2\times\frac{1}{5}^{0.2x} \quad (x=3,4,5) \end{cases} \tag{4-2}$$

$$\mathrm{V}_{\mathrm{M}}^{j} = 0.4+0.6\times\left(\frac{1}{5}\right)^{0.2x} \quad (x=1,2,3,4,5) \tag{4-3}$$

where, x is the current function implementation degree of CRs in product from 1 to 5.

$\mathrm{V}_{\mathrm{A}}^{i}$ is a value of the i_{th} CR in group A of the Kano model. Value of the i_{th} CR is higher if the product cannot provide a satisfied function (x is 1 or 2) to meet the i_{th} CR. Value of the i_{th} CR is lower if the product provides a satisfied function (x is 3, 4 or 5) to meet the i_{th} CR.

$\mathrm{V}_{\mathrm{M}}^{j}$ is a value of the j_{th} CR in group M of the Kano model. Value of the j_{th} CR is higher if the product cannot provide a satisfied function to meet the j_{th} CR (x is 1 or 2). Value of the j_{th} CR is lower if the product can provide a satisfied function to meet the j_{th} CR (x is 3, 4 or 5).

The average value of all customer responses in Kano and IPA models can be determined using results of data transformation from Eqs. (4-1), (4-2), and (4-3).

4.1.2 Hypothesis test by ANOVA for separating data to describe CRs

Data of the demographic and personal information such as customer background, expectation and preference on product can affect different customers to provide different opinions or comments for CRs. ANOVA is a statistical technique to check the significantly difference between data in two or more groups. It is used to analyze CRs in different conditions (Deng et al, 2008). Z score is used to test the data statistical significance by Eq. (4-4) to decide whether a null hypothesis should be accepted or rejected.

$$z=\left(x-\mu\right)/\sigma \tag{4-4}$$

where, z is the standard score (Z-score), x is the raw score of standardization, μ is the mean of data, σ is the standard deviation. Based on z value, the relation between p and z values is found using a Z-table in the reference (Deng et al, 2008).

The p-value is the probability that falsely rejects the null hypothesis. For a typical analysis, using standard $\alpha = 0.05$ cutoff, the null hypothesis is rejected when $p < 0.05$. The p value of customer data from each CR is calculated by Z-table.

If more than 30% of CRs related to the personal information are refused, raw data of describing CRs will be determined separately in Kano and IPA models because customers in different conditions have different comments for requirements of the product. Characters of CRs for defining IRs of CRs are shown in *Table 4-2. n* is the number of CRs for the product.

Table 4-2 Characters of CRs based on Kano and IPA models

	Kano model			IPA model					
CRs	1. Kano model of character 1	2. Kano model of character 2	3. Kano model of character k	4. ID for character 4	5. ID for character 5	6. ID for character h	7. SD for character 7	8. SD for character 8	9. SD for character m
CR.1	x_{11}	x_{12}	x_{1k}	x_{14}	x_{15}	x_{1h}	x_{17}	x_{18}	x_{1m}
CR.2	x_{21}	x_{22}	x_{2k}	x_{24}	x_{25}	x_{2h}	x_{27}	x_{28}	x_{2m}
CR.*n*	x_{n1}	x_{n2}	x_{nk}	x_{n4}	x_{n5}	x_{nh}	x_{n7}	x_{n8}	x_{nm}

4.1.3 Laplace matrix of the data

Based on data in *Table 4-2*, matrix *X* is formed to represent n CRs as shown in Eq. (4-5). Each CR has t attributes in Kano and IPA models.

$$X=\begin{bmatrix} v_1 \\ v_i \\ \vdots \\ v_n \end{bmatrix}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1t} \\ x_{i1} & x_{i2} & \cdots & x_{it} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nt} \end{bmatrix} \tag{4-5}$$

According to the graph theory in spectral clustering (Wang et al, 2018), an undirected weight similarity graph *G*= (*V*, *E*) is defined to compare similarity of CRs. For each CR, the character includes *t* factors: $v_i=\{x_{i1},x_{i2},\cdots,x_{it}\}$ ($i=1,2,\cdots,n$). Two vertices are connected by edge *E*. The length of the edge is defined by similarity w_{ij} between vertices v_i and v_j. Thus, the clustering problem is transformed into a graph partitioning problem of *G*.

Graph Laplace matrix *L* is defined in Eq. (4-6), where *L* is symmetric and positive semi-definite.

$$L=D-W \tag{4-6}$$

The similarity matrix *W* is calculated as follows.

$$W=(w_{ij}) \tag{4-7}$$

By combining Kano and IPA models, a similarity matrix *W* of the spectral clustering algorithm is formed as follows.

$$w_{ij}=\mathrm{c}\cdot w_s(v_i,v_j)+\mathrm{d}\cdot w_d(v_i,v_j)+\mathrm{f}\cdot w_e(v_i,v_j) \tag{4-8}$$

where, parameters c, d and f are used to represent the proportion of Kano and IPA models. As the same importance of Kano and IPA models is considered, the value of c for the Kano model is 0.5. Values of d and f for the IPA model are equal to 0.25, respectively.

Distance w_s is defined in Eq. (4-9) by categorical attributes of CRs based on k characters in the Kano model as follows.

$$w_s(v_i,v_j)=\begin{cases} \exp(-\dfrac{\|v_i^k-v_j^k\|^2}{2\sigma_s^2}) & i\neq j \\ 0 & i=j \end{cases} \quad (i,j=1,\ldots,n.) \tag{4-9}$$

$$\sigma_s=\frac{1}{K}\left(\frac{\sum\|v_i^k-v_j^k\|^2}{Max(\|v_i^k-v_j^k\|^2)}\right) \quad (i,j=1,\ldots,\mathrm{n}.) \tag{4-10}$$

where, *K* is the number of CRs.

Eq. (4-11) is formed as follows for distance w_d of numerical attributes of CRs based on h characters for importance degrees in the IPA model.

$$w_d(v_i, v_j) = \begin{cases} \exp(-\frac{\| v_i^h - v_j^h \|^2}{2\sigma_d^2}) & i \neq j \\ 0 & i = j \end{cases} \quad (i, j = 1, \ldots, n.) \tag{4-11}$$

$$\sigma_d = \frac{1}{K}\left(\frac{\sum \| v_i^h - v_j^h \|^2}{Max(\| v_i^h - v_j^h \|^2)} \right) \quad (i, j = 1, \ldots, n.) \tag{4-12}$$

Eq. (4-13) is formed for the distance w_e in numerical attributes of CRs based on m characters for satisfaction degree in the IPA model.

$$w_e(v_i, v_j) = \begin{cases} \exp(-\frac{\| v_i^m - v_j^m \|^2}{2\sigma_e^2}) & i \neq j \\ 0 & i = j \end{cases} \quad (i, j = 1, \ldots, n.) \tag{4-13}$$

$$\sigma_e = \frac{1}{K}\left(\frac{\sum \| v_i^m - v_j^m \|^2}{Max(\| v_i^m - v_j^m \|^2)} \right) \quad (i, j = 1, \ldots, n.) \tag{4-14}$$

A diagonal matrix D is formed in Eq. (4-15), where d_{ii} in matrix D is the sum of w_{ij} as shown in Eq. (4-16).

$$D = \begin{bmatrix} d_{11} & 0 & \cdots & 0 \\ 0 & d_{22} & \cdots & 0 \\ \cdots & \cdots & d_{ii} & \cdots \\ 0 & 0 & \cdots & d_{nn} \end{bmatrix} \tag{4-15}$$

$$d_{ii} = \sum_{i=1}^{n} w_{ij} \tag{4-16}$$

4.1.4 Clustering by the K-mean method in a feature space

A scale of 1 to 5 is used to represent the lowest to highest levels of importance of CRs based on 5 CR clusters obtained.

As the total number of clusters is 5, the 5 smallest eigenvalues of Laplace matrix L are used to build a feature space to cluster 5 groups. The K-mean method is used to cluster data into 5 clusters in the feature space. The fixed number of clusters can avoid the effect of scales and data orders in the K-mean method.

4.1.5 Definition of IRs of CRs based on clusters

Based on different function implementations, values of CRs in groups M and A of the Kano model are shown in *Figure 4-2*. IRs of CRs in the 5 clusters are shown in Table 4-3.

Importance rate (IR) determination rules are proposed in *Table 4-3*. IRs have 5 levels including very high, high, middle, low and very low. Rules are defined to ensure that a CR can be matched to one of the five levels. Based on clusters in *Table 4-3***,** if over 50% of CRs in each cluster are included in the same level, IRs of all CRs will be clustered in this level. If the percentage of CRs in any level is lower than 50%, the clustering is not successful because the value of CRs in these clusters cannot be defined based on clusters in *Table 4-3*. The raw data of CRs will be clustered again until a solution is found.

Figure 4-2 An improved Kano model

Table 4-3 IR determination based on clusters

Clusters	Category in Kano	Category in IPA	IRs of CRs
1. Very high IR	M1	Concentrate on	5
	M2	Concentrate on	
	A3	Concentrate on	
2. High IR	A2	Concentrate on	4
	O	Concentrate on	
	M2	Keep up good work	
	A2	Keep up good work	

3. Middle IR	M3	Keep up good work	3
	M3	Concentrate on	
	M1	Keep up good work	
	A3	Keep up good work	
	O	Keep up good work	
	M(M1,M2,M3)	Low priority	
4. Low IR	O	Low priority	2
	A(A1,A2,A3)	Low priority	
	M(M1,M2,M3)	Possible Overkill	
	O	Possible Overkill	
5. Very low IR	A(A1,A2,A3)	Possible Overkill	1
	I	Anyone in IPA model	
	R	Anyone in IPA model	

IRs of CRs provide guideline to improve customer satisfactions and remove unnecessary product functions.

4.2 Case study

A case study is conducted using the proposed method to decide IRs of CRs in the concept design of an active upper limb rehabilitation device. The design needs to meet requirements of different patients such as seriously injured and lightly injured patients. Existing rehabilitation devices in the market have problems of product function, structure, size, adaptability, portability, and price (Shi et al, 2019). These problems are caused by the low IRs accuracy of CRs in the product design stage. This case study improves accuracy of IRs of CRs using the proposed method. 13 CRs are used based on collected data of active upper limb rehabilitation devices from literature (Maciejasz et al, 2014) listed in *Table 4-4*.

Table 4-4 CRs of active upper limb rehabilitation devices

No.	CRs	No.	CRs
CR.1	Accurate movement	CR8	Reasonable price
CR.2.	Movement feedback	CR.9	Adaptability
CR.3	Automatic	CR.10	Portability
CR.4	Support the arm	CR.11	Safety
CR.5	Easy operation	CR.12	Material
CR.6	Interesting	CR.13	Quiet
CR.7	Light weight		

Raw data of active upper limb rehabilitation devices are collected from literature using the Kano and IPA models. Based on the literature of patients with arm injuries (Oujamaa et al, 2009), the required functions are defined for different kinds of patients with different characters such as expected cost, exercise location, frequency of rehabilitation exercise, and injured level. Based on the literature for the design of active upper limb rehabilitation devices (Maciejasz et al, 2014), the functions of ten popular devices in the market are determined. By comparing the required functions from different patients with the current functions of ten existing rehabilitation devices using *Table 4-1*, the raw data for Kano and IPA models are defined as shown in *Table 4-5*.

Table 4-5 Raw data of active upper limb rehabilitation devices

	Device 1							Device 2				…..
	Patients who used the device at home			Patients who used device at hospital			…..	Patients with serious injury			…..	…..
	Kano model	ID for IPA model	SD for IPA model	Kano model	ID for IPA model	SD for IPA model	…..	Kano model	ID for IPA model	SD for IPA model	…..	…..
CR.1	A	4	3	M	5	3	……	M	5	3	……	……
CR.2	M	5	4	M	5	4	……	M	5	4	……	……
CR.3	A	5	3	M	3	3	……	O	4	2	……	……
CR.4	O	4	2	M	5	3	……	M	5	2	……	……
CR.5	M	5	4	M	5	5	……	M	5	4	……	……
CR.6	M	1	2	A	1	2	……	A	1	3	……	……
CR.7	O	4	2	A	4	3	……	A	4	3	……	……
CR.8	O	5	4	A	5	4	……	O	5	4	……	……
CR.9	M	4	4	O	3	4	……	M	4	4	……	……
CR.10	M	5	3	M	4	3	……	O	4	3	……	……
CR.11	M	4	4	M	4	4	……	M	5	3	……	……
CR.12	M	5	5	M	5	5	……	M	5	5	……	……
CR.13	A	2	2	A	2	3	……	O	1	2	……	……

Data for the IPA model in *Table 4-5* are normalized using Eq. (4-1). Data for the Kano model in *Table 4-5* are transferred into numerical attributes based on Eqs. (4-2) and (4-3). Values of CRs in groups O, I and R are defined according to the improved

Kano model in *Figure 4-2*. The value of O is assigned as “0.6” as the one-dimensional CRs can promote the product preference when CRs are satisfied. The value of I is defined as “0.2” when indifferent CRs cannot influence the customer satisfaction. The value of R is assigned as “0.1” because the reversed CRs can reduce the customer satisfaction. All the classification results of groups M and A in the Kano model are transferred into numerical results using Eqs. (4-2) and (4-3).

A hypothesis test for the consistency of comments from patients with different characters such as injured duration/time, expected cost, exercise location, and injured level, in *Table 4-5* is conducted using Eq. (4-4) and Z-table in the AVOVA.

Results of the hypothesis test show that patients with different injured levels and using devices in different places have different comments for the CRs classification based on the Kano model. Patients with different injured levels in different places using devices have also different comments for ID of CRs and SD of CRs based on the IPA model. Thus, 12 attributes of CRs are defined in *Table 4-6*.

Table 4-6 12 attributes of CRs of active upper limb rehabilitation devices

CRs	Kano model				IPA model							
	1. Seriously injured patients	2. Lightly injured patients	3. Patients used at home	4. Patients used in hospital	5. ID for seriously injured	6. ID for lightly injured	7. ID for used at home	8. ID for used in hospital	9. SD for used at home	10. SD for used in hospital	11. SD for seriously injured	12. SD for lightly injured
CR.1	M	A	A	M	3.4	3.5	3.6	3.4	2.5	2.8	2.6	2.9
CR.2.	M	O	O	M	4.9	4.6	4.7	4.6	3.9	4.2	4.1	4.1
CR.3	M	O	A	M	4.1	2.9	4.6	2.6	2.6	2.7	2.3	2.6
CR.4	M	M	M	M	4.3	4.6	4.5	4.5	2.4	2.9	2.8	2.5
CR.5	M	M	M	M	4.8	4.4	4.6	4.6	4.1	4.5	4.3	4.5
CR.6	A	M	M	A	2.3	2.6	2.5	2.3	2.2	2.3	3.3	3.2
CR.7	A	O	O	A	3.3	3.4	3.3	3.3	2.5	2.6	2.6	3.6
CR.8	A	O	O	A	4.5	4.6	4.5	4.5	3.2	3.3	3.2	3.2
CR.9	M	M	M	O	4.3	4.0	4.3	2.9	4.2	4.1	4.2	4.2
CR.10	O	O	M	M	3.5	3.3	3.2	3.5	2.5	3.1	2.8	2.9
CR.11	M	M	M	M	4.2	4.0	4.1	4.1	4.2	4.3	4.3	4.3
CR.12	M	M	M	M	4.5	4.5	4.5	4.5	4.1	3.6	3.9	3.8
CR.13	O	A	A	A	1.3	1.5	1.8	1.7	2.1	2.6	2.3	2.5

The spectral clustering method divides CRs into 5 clusters. Based on data in *Table 4-6*, matrix X is formed to represent 13 CRs with 12 attributes using Eq. (4-5). Laplace matrix L is formed by a diagonal matrix D and similarity matrix W using Eq. (4-6).

Similarity matrix W is formed based on similarity of 13 CRs using Eqs. (4-7) and (4-8). The distance of 4 categorical attributes of 13 CRs in the Kano model is decided by Eq. (4-9). The distance of 4 numerical attributes of 13 CRs for ID in the IPA model is calculated using Eq. (4-11). The distance of 4 numerical attributes of 13 CRs for SD in the IPA model is decided by Eq. (4-13). Based on the result of similarity matrix W, a diagonal matrix D is formed using Eqs. (4-15) and (4-16).

According to the feature space built by the first 5 smallest eigenvalues, the K-mean method is used to cluster data in the feature space into 5 clusters. Using the IR determination rules in *Table 4-3*, 5 clusters are defined as follows.

$$P_1 = \{\mathrm{CR}_2, \mathrm{CR}_5, \mathrm{CR}_9, \mathrm{CR}_{11}\} \tag{4-17}$$

$$P_2 = \{\mathrm{CR}_6\} \tag{4-18}$$

$$P_3 = \{\mathrm{CR}_{13}\} \tag{4-19}$$

$$P_4 = \{\mathrm{CR}_1, \mathrm{CR}_3, \mathrm{CR}_8, \mathrm{CR}_{10}\} \tag{4-20}$$

$$P_5 = \{\mathrm{CR}_4, \mathrm{CR}_7, \mathrm{CR}_{12}\} \tag{4-21}$$

IRs of CRs in each group are determined and shown in Eq. (4-22).

$$\{P_1, P_2, P_3, P_4, P_5\} = \{3, 2, 1, 5, 4\} \tag{4-22}$$

4.3 Verification of the proposed method

For verifying the proposed method, three existing IRs methods including the Kano model, IPA model and combined IPA-Kano model are compared to the proposed IRs method in the case study. IRs of CRs for these methods are shown in *Table 4-7*.

Table 4-7 Comparison of the existing methods and proposed method

CRs	Kano model	IPA model	Existing combined IPA-Kano	Proposed IRs method
CR.1	A (3)	Low priority (3)	Chronic disease (2)	Very high IR (5)
CR.2.	O (4)	Keep good work (4)	Major weapon (4)	Middle IR (3)
CR.3	M (5)	Concentrate on (5)	Fatal (5)	Very high IR (5)
CR.4	M (5)	Concentrate on (5)	Fatal (5)	High IR (4)
CR.5	M (5)	Keep good work (4)	Survival (3)	Middle IR (3)
CR.6	M (5)	Possible overkill (2)	Fitness (1)	Low IR (2)
CR.7	O (4)	Low priority (3)	Defenseless (1)	High IR (4)
CR.8	A (3)	Concentrate on (5)	Defenseless (1)	Very high IR (5)
CR.9	M (5)	Keep good work (4)	Survival (3)	Middle IR (3)
CR.10	O (4)	Low priority (3)	Chronic disease (2)	Very high IR (5)
CR.11	M (5)	Keep good work (4)	Survival (3)	Middle IR (3)
CR.12	M (5)	Keep good work (4)	Survival (3)	High IR (4)
CR.13	A (3)	Low priority (3)	Chronic disease (2)	Very low IR (1)

Based on different IRs of CRs in *Table 4-7*, different IRs of FRs can be defined using HoQ in the QFD method to determine the design priority. Related rehabilitation devices in the market are then searched and selected (Maciejasz et al, 2014). Collected structures and functions of different devices are listed in *Table 4-8*.

Table 4-8 Comparisons of different solutions in the market

1. Devices based on the Kano model		2. Devices based on the IPA model	
CR.1	Motion sensor	CR.1	Motion sensor
CR.2	Force sensor	CR.2	Force sensor with closed loop control
CR.3	None	CR.3	Automatic record for displacement and force for patients' arm by sensors.
CR.4	6-DOF rehabilitation arm	CR.4	7-DOF rehabilitation arm
CR.5	5 different levels for all patients	CR.5	10 different levels for all patients
CR.6	3 different movement gestures	CR.6	15 different movement gestures
CR.7	110 kg	CR.7	160 kg
CR.8	$7,000-$8,000	CR.8	$15,000-$16,000
CR.9	3 different movement gestures	CR.9	5 different movement gestures
CR.10	2.1*2.1*2.3 m^3	CR.10	2.5*2.5*2.6 m^3
CR.11	Stop button	CR.11	Stop button
CR.12	Steel and plastic	CR.12	Steel and plastic
CR.13	Operation noise is about 45 DB	CR.13	Operation noise is about 40 DB
3. Device designed based on Kano-IPA model in the market		4. Device designed based on the proposed IRs definition method	

CR.1	Motion sensor	CR.1	Motion sensor
CR.2	Vision & Sound feedback	CR.2	Vision & Sound & Force feedback
CR.3	Automatic record only for displacement	CR.3	Automatic record for displacement & force for patients by sensors &screen
CR.4	5-DOF rehabilitation arm	CR.4	5-DOF rehabilitation arm
CR.5	5 different levels for all patients	CR.5	8 different levels for all patients
CR.6	10 gestures & virtual games	CR.6	15 gestures & virtual games
CR.7	70 kg	CR.7	65 kg
CR.8	$4,000-$5,000	CR.8	$3,000-$4,000
CR.9	10 gestures & virtual games	CR.9	15 gestures & virtual games
CR.10	1.5*1.5*1.6 m^3	CR.10	1.5*1.5*1.3 m^3
CR.11	Stop button	CR.11	Stop button
CR.12	Steel and plastic	CR.12	Steel and plastic
CR 13	Operation noise is about 35 DB	CR 13	Operation noise is about 30 DB

In the design based on IRs from the Kano model (Chaudha et al, 2011), the 6-DOF rehabilitation device only focuses on basic requirements. There are 7 Must-be requirements with 5 marks. Functions related to the basic requirements have good performance. However, all the attractive functions such as the movement feedback and automatic rehabilitation data record are not considered, which reduces competitiveness of the product.

In the device designed based on IRs from the IPA model (Deng et al, 2008), the IRs determination only focuses on two factors of the important and satisfaction degrees. Functions that are important and not satisfied can get the highest priority. However, some improvements of functions are difficult and costly, which causes problems for the device. For example, functions to meet CR.4 are improved by using 7-DOF arm based on the high IR of CR.4. However, the weight, size, and portability of the device are affected for fully meeting CR.4. Therefore, the design based on IRs from the IPA model cannot consider all important factors.

In the device designed based on IRs from the existing IPA-Kano method (Yin et al, 2016), the device performance is better than devices designed by the Kano and IPA models. The IPA-Kano method balances more important factors including the relation between function implement and customer satisfaction for CRs in the design. However, the IRs determination is not accurate if customers have conflict comments for the CRs. For example, CR.10 belongs to one-dimensional quality with the low important and satisfaction degree. According to the raw data, most of seriously injured patients believe that portability is not important for the device. Because they cannot complete the rehabilitation exercise by themselves and they do not need to take the device with them. However, most of light injured patients believe that portability is very important for rehabilitation because they can use the device at home. As 60 % of patients are seriously injured based on the collected data, the average value shows that CR 10 portability is not very important for patients. Because of the neglect of conflict comments from different customers, IR of CR.10 is not defined accurately.

For the device designed based on IRs from the proposed method, all the important factors are considered and balanced. With the accurate IRs, the existing design problems are solved and design advantages are maintained. For example, the adaptability is improved by providing more gestures of rehabilitation exercises and installing the device on a table. Meanwhile, the existing advantages such as the stable movement and light weight are remained. Therefore, the device designed by the proposed method has a better performance than other three existing devices.

As the proposed method can consider all the important factors to balance conflict comments of different customers, the proposed device has the highest customer satisfaction. The proposed method shows advantages to define IRs of CRs accurately compared to the existing IRs methods.

4.4 Summary

This chapter proposes a new method of defining IRs of CRs. CRs are classified by a spectral clustering method based on categorical attributes in the Kano model and numerical attributes in the IPA model. A Laplace matrix is designed to improve accuracy of the classification by considering conflict comments from different customers. Results of the CRs classification are used to define IRs of CRs.

For verifying the proposed method, four active upper limb rehabilitation devices are designed based on the existing and proposed method. The results show that the design based on IRs of CRs from the proposed method has the best performance to meet CRs.

Chapter 5 FRs implementation definition

This chapter proposes a method for the FRs implementation using big data of online customer reviews and product specifications. Comments of customer reviews are matched to CRs using a hierarchical semantic similarity method. Customer satisfaction degrees are defined based on emotional levels of adjectives and adverbs of customer comments using word vectors. The product function implementation degree is determined by specifications crawled from online products. Fitting curves are formed by defined customer satisfactions and function implementations using polynomial modeling and least square methods. Based on the slope of the fitted curves, the minimum and maximum FRs implementations are defined to guide a concept design process. The proposed method is applied in a case study of defining FRs implementations of passive upper limb rehabilitation devices. The design solution is verified by comparing with solutions of existing methods.

5.1 Proposed method

Raw data required for the proposed method include CRs, online customer reviews and product specifications crawled from online products. A flow chart of the proposed method is shown in *Figure 5-1*.

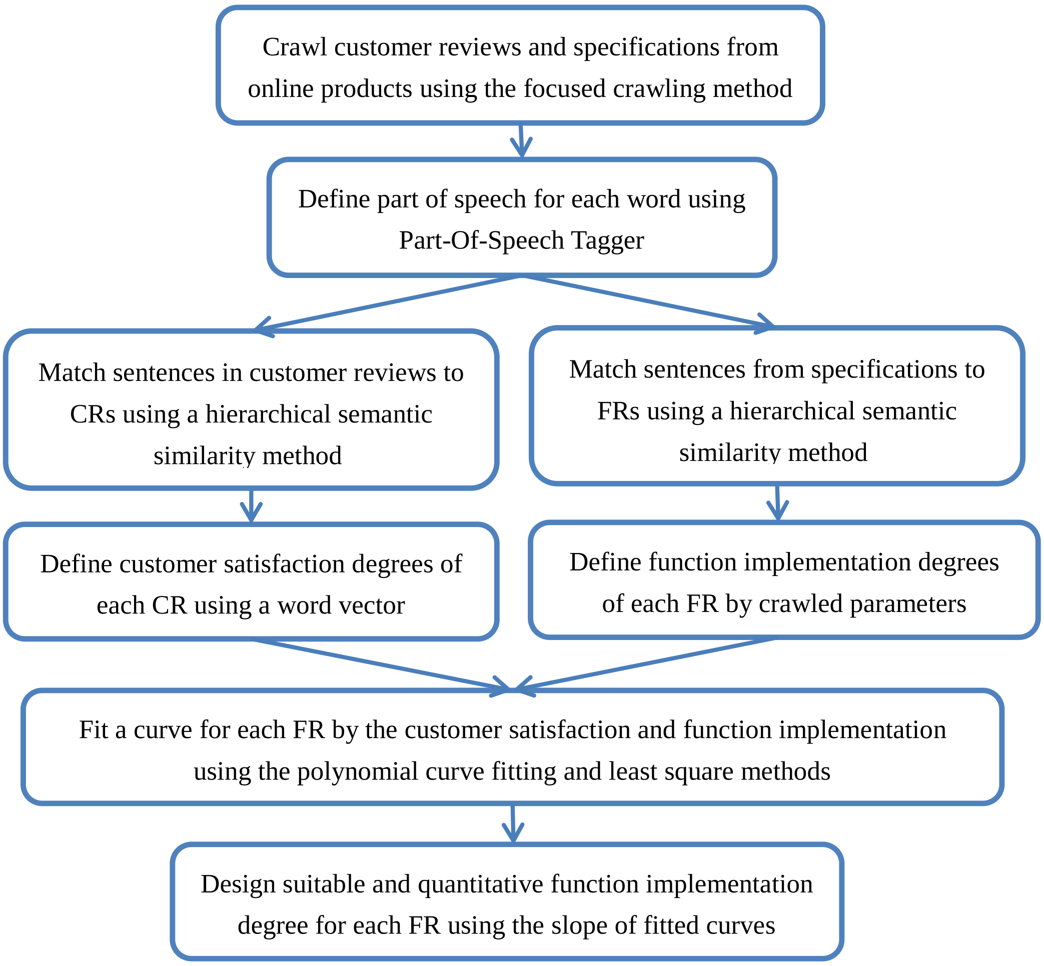


Figure 5-1 Proposed method of defining FRs implementation

5.1.1 Data collection and transformation

Customer reviews and specifications of target products are collected online using a focused crawling method in big data. The method can selectively retrieve information of customer reviews from product webpages using a domain specific search engine. It can assess the relevance of a target URL for the quality of required information before actually fetching the page. Ranking rates (1 to 5) of customers for the product can also be collected using the focused crawling method. Collected customer reviews are separated into different sentences based on commands of full stop in the paragraph. Parts of speech are used to describe a word in a sentence based on its syntactic function. By using POS Tagger, parts of speech for each sentence from collected customer reviews are marked.

5.1.2 Definition for customer satisfactions of CRs

There are two steps to define customer satisfactions of CRs, including matching each sentence to specific CRs using the WordNet hierarchy, and determining a numerical value to describe the customer satisfaction degree based on emotion and degree of a sentence from adjectives and adverbs.

A hierarchical method is used to match sentences with CRs based on the semantic similarity of sentences. WordNet (Chen et al, 2019) is a lexical database of short and general definitions for various semantic relations of synonym sets using hierarchical relations of nouns and verbs in a sentence. *Figure 5-2* illustrates the WordNet hierarchy based on a tree structure to take the best conceptual similarity value among all concept pairs as the word similarity. The tree structure is created to classify objects, places, concepts, events, properties, and relations into a taxonomic hierarchy. Based on the classification of words, the similarity can be represented by the number of steps in a taxonomic hierarchy based on words in a sentence of customer reviews and CRs, which can determine similarity between different customer reviews and CRs. In *Figure 5-2*, the similarity value between word b_3 and word b_7 is 3 as it takes 3 steps to move from word b_3 to word b_7.

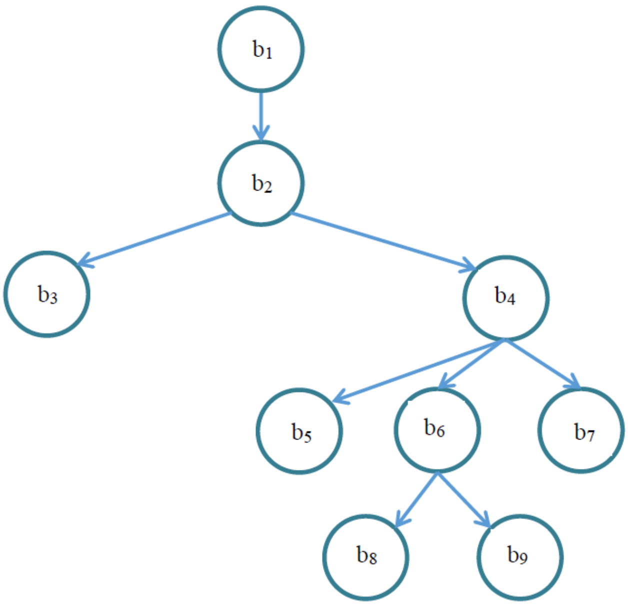


Figure 5-2 WordNet hierarchy

Using the WordNet hierarchy, each sentence is matched with a specific CR based on similarity of words in each sentence and words of a CR. Vector w_{jp}^{ir} for the j_{th} sentence of the r_{th} product compared to the p_{th} word of the i_{th} CR is represented as follows.

$$w_{jp}^{ir} = (v_{1jp}^{ir}, v_{2jp}^{ir}, \ldots, v_{mjp}^{ir}) \tag{5-1}$$

where, v_{mjp}^{ir} is a distance between the m_{th} word in the j_{th} sentence of the r_{th} product and the p_{th} word of the i_{th} CR using the data structure shown in *Figure 5-2*.

The similarity between of the j_{th} sentence of the r_{th} product and all the words of the i_{th} CR is determined as s_j^{ir} in Eq. (5-2).

$$s_j^{ir} = \sum_{p=1}^{p} \frac{v_{1jp}^{ir} + v_{2jp}^{ir} + \ldots + v_{mjp}^{ir}}{\sqrt{(v_{1jp}^{ir})^2 + (v_{2jp}^{ir})^2 + \ldots + (v_{mjp}^{ir})^2}} \tag{5-2}$$

The minimum value $\mathrm{sim}(jr)$ of s_j^{ir} in the j_{th} sentence of the r_{th} product is defined using Eq. (5-3).

$$\mathrm{sim}(jr) = \min[s_j^{ir}] \tag{5-3}$$

where, the minimum value of s_j^{ir} means that the sentence is related to the i_{th} CR compared to other CRs. When $s_j^{ir} = \mathrm{sim}(jr)$, the j_{th} sentence of the r_{th} product N_j^r is matched with the i_{th} CRs using Eq. (5-4).

$$N_j^r = i \tag{5-4}$$

After matching each sentence to a specific CR, the customer satisfaction degree is determined by emotion and degree of a sentence from adjectives and adverbs. The value of adverb is used to describe the degree of a sentence and to define the level of sentiment for the sentence. Degrees of all adverb words are divided into 5 levels by 5 standard words including 5 (extreme), 4 (very), 3 (more), 2 (quite), and 1 (little). Word vector similarity S_{jg} between a_j^r and v_g is defined as follows.

$$S_{jg} = \cos(a_j^r, v_g) = \frac{a_j^r \cdot v_g}{\sqrt{a_j^r \cdot a_j^r}\sqrt{v_g \cdot v_g}} \quad g \in (1,5) \tag{5-5}$$

where, v_g is a word vector of the 5 standard words, g is a value of 5 standard words from 5 to 1, and a_j^r is a word vector of adverb in the j_{th} sentence of the r_{th} product.

The maximum value of similarity $\mathrm{adv}(jr)$ for adverbs in the j_{th} sentence of the r_{th} product is defined using Eq. (5-6).

$$\mathrm{adv}(jr) = \max\left[S_{jg}\right] \tag{5-6}$$

When $S_{jg} = \mathrm{adv}(jr)$, a_j^r is defined as follows.

$$a_j^r = g \tag{5-7}$$

where, a_j^r is a value of adverb to describe degree of the j_{th} sentence of the r_{th} product. If there is no adverb in the j_{th} sentence of the r_{th} product, a_j^r is 1.

The value of adjective words is used to describe emotions of a sentence, which can determine positive and negative attitudes of customers. As an adjective word may have positive and negative attitudes for different CRs, a value of adjective words is defined from -1 to 1 using customer ranking of a product. The adjective words are defined as a numerical value based on the crawled customer reviews. If h_j^r is a rank from a customer for the j_{th} sentence of the r_{th} product, e_j^r can be represented as a value of adjective words in the j_{th} sentence of the r_{th} product using Eq. (5-8). The range of h_j^r is from 1.0 to 5.0 according to the ranking of customers. 5.0 means that customers are very satisfied for a product, and 1.0 means that customers are very unsatisfied for a product. Eq. (5-8) is used to adjust the value range of adjective words from 1.0~5.0 into -1.0~1.0.

$$e_j^r = \frac{h_j^r - 3}{2} \tag{5-8}$$

Customer satisfaction degree y_j^r for the j_{th} sentence of the r_{th} product is defined by the related value of noun words and value of adjective words as follows.

$$y_{\mathrm{j}}^r = a_{\mathrm{j}}^r \times e_{\mathrm{j}}^r \tag{5-9}$$

where, a_j^r is a value of adverb in the j_{th} sentence of the r_{th} product. e_j^r is a value of adjective words in the j_{th} sentence of the r_{th} product.

The original data record the j_{th} sentence of the r_{th} product from the m_{th} customer. The overall customer satisfaction degree for the m_{th} customer of the r_{th} product can be decided as follows.

$$CS_m^r = \frac{\sum_{j\in m}^{N(m)} y_j^r}{N(m)} \tag{5-10}$$

where, CS_m^r is the average value of customer satisfaction degree for the m_{th} customer of the r_{th} product defined by all the sentences of comments from the m_{th} customer of the r_{th} product. $N(m)$ is the number of sentences commented from the m_{th} customer of the r_{th} product.

Error E_m between CS_m^r and R_m^r is defined as follows. R_m^r is ranking rates (1 to 5) defined by the m_{th} customer of the r_{th} product.

$$E_m = \frac{\left| R_m^r - CS_m^r \right|}{5} \tag{5-11}$$

The average value of the customer satisfaction degree defined by the proposed method is compared with ranking rates (1 to 5) defined by each customer online to filter the misleading or fake online customer review. If the error is greater than 15%, the online customer review is deleted from the dataset. If the error between overall rankings defined by divided sentences and ranking by the customer is lower than 15%, the online customer review is saved in the dataset for following uses. Based on the filtered online customer review, the accuracy of the customer satisfaction degree of CR in each sentence can be improved based on the WordNet hierarchy method.

By using the filtered online customer reviews, Satisfaction degree z^{ri} of the i_{th} CR for the r_{th} product is defined as follows.

$$z^{ri} = \frac{\sum y_n^r}{n} \tag{5-12}$$

where, y_r^n is the customer satisfaction degree in n sentences of the r_{th} product. n is the number of sentences related to CR_i for the r_{th} product in the filtered online customer reviews dataset.

Therefore, each collected sentence can be matched to a specific CR using the WordNet hierarchy based on Eqs. (5-1) to (5-4), a numerical value is determined for the customer satisfaction degree based on the emotion and degree of a sentence from adjectives and adverbs using Eqs. (5-5) to (5-12).

5.1.3 Function implementation degree of each collected product

There are two steps to define the function implementation degree of a product including matching the product specification with a CR and deciding a numerical value of describing the function implementation based on the product specification. Crawled specifications from online products including function descriptions and parameters in *Table 5-1* are used to determine the function implementation degree related to CRs of a product. The function description in *Table 5-1* is used to match the specification with a CR. FRs are defined by function descriptions of products from sellers in the online shopping website using the focused crawling method. Parameters of product specifications are used to define the function implementation degree of the product.

Table 5-1 Function and parameters crawled from online products

Number	Function description	Range of Parameters
1	FR1	D1
2	FR2	D2
3	FR3	D3
……	……	……
n	FRn	Dn

Similarity between FRs and CRs is used to match function descriptions from crawled specifications with CRs using the hierarchical semantic similarity method.

A vector w_k^i is represented by the k_{th} FR compared to the p_{th} word of the i_{th} CR as follows.

$$w_{kp}^{i}=(v_{1kp}^{i},v_{2kp}^{i},...,v_{mkp}^{i}) \tag{5-13}$$

where, v_{mkp}^{i} is a distance between the m_{th} word of the k_{th} FR and the p_{th} word of the i_{th} CR using the data structure shown in *Table 5-1*.

Similarity of the k_{th} FR and all the words of the i_{th} CR for the r_{th} product is decided using Eq. (5-14).

$$s_{kr}^{i}=\sum_{p=1}^{p}\frac{v_{1kp}^{i}+v_{2kp}^{i}+...+v_{mkp}^{i}}{\sqrt{(v_{1kp}^{i})^{2}+(v_{2kp}^{i})^{2}+...+(v_{mkp}^{i})^{2}}} \tag{5-14}$$

The minimum value of each FR is defined as follows.

$$\text{sim}(k)=\min[s_{kr}^{i}] \tag{5-15}$$

When $s_{kr}^{i}=\text{sim}(k)$, the k_{th} FR of the r_{th} product is matched with the i_{th} CR in *Table 5-1* using Eq. (5-16).

$$N_{k}^{r}=i \tag{5-16}$$

Based on the result of N_{k}^{r} in Eq. (5-16), each crawled specification is matched with a CR. Function implementation degree F_{ir} for the r_{th} product of CR$_i$ is decided as follows.

$$F_{ir}=-\frac{10\left|v^{ir}-v_{ide}^{i}\right|}{\left|v_{ide}^{i}-v_{wor}^{i}\right|}+5 \tag{5-17}$$

where, v^{ir} is a value of the specification such as dimension, degree and weight in the r_{th} product of CR$_i$. v_{ide}^{i} is the best specification which fully meets CR$_i$ in all crawled products. v_{wor}^{i} is the worst value of specifications with the worst performance for meeting CR$_i$ in all crawled products.

The range of F_{ir} in Eq. (5-17) is from -5 to 5. 5 represents that the specification value of a product is equal to the value of the best specification in all crawled products, so the product has the best FR implementation to meet a CR. 0 represents that the product function to meet a CR is in the intermediate level of all products. -5 represents that the specification value of a product is equal to the value of the worst specification in all crawled products, so the product has the worst FR implementation to meet a CR.

5.1.4 Determination of quantitative FRs implementations using fitting curves

Based on defined customer satisfaction degrees and function implementation degrees, quantitative FRs implementations can be defined using polynomial fitting and least square methods.

For a CR, there are *i* data points (x_i, y_i) for representing *i* products, where x_i is the function implantation degree for the i_{th} product of a CR, y_i is the satisfaction degree for the i_{th} product of a CR, and *m* is the largest exponent of *x* for fitting function in Eq. (5-18). A curve defined by Eq. (5-18) is fitted by minimizing the sum of squared deviations using Eq. (5-19).

$$P(x_i) = a_0 + a_1 x + a_2 x^2 + ...+ + a_m x^m = \sum_{i=0}^{m} a_i x^i \tag{5-18}$$

$$\mathrm{I} = \sum_{i=1}^{m} \left[P\left(x_i\right) - \mathrm{y}_i \right]^2 \quad i = 1, 2, ..., m \tag{5-19}$$

After the fitting curve is formed, data points in the curve are used to evaluate the product performance. *x* value in each point represents a function implementation of the product, *y* value in each point represents an average satisfaction degree of a CR for the product. The data mean is calculated using Eq. (5-20).

$$\bar{K}(x_i) = \frac{K_1 + K_2 + ...K_{x_i}}{i} \tag{5-20}$$

where, K_{x_i} is the derivative of function $P(x_i)$ at point x_i. $\bar{K}(x_i)$ is the average increase rate of the customer satisfaction degree when the function implementation degree is increased. The value of $\bar{K}(x_i)$ represents the average importance of CRs because the importance of a CR is higher when increasing the function implementation can improve the customer satisfaction degree.

Standard deviation S_k of i data points (x_i, K_{x_i}) represents the distribution of slope K_{x_i} in Eq. (5-20). S_k is calculated using Eq. (5-21). S_k can be used to decide the linear or nonlinear relationship of the increased rate of customer satisfaction and the increased function implementation.

$$S_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(K_{x_i} - \bar{K}_{x_i})^2} \tag{5-21}$$

The change rate of K_{x_i} is defined as follows.

$$D_{x_i} = K_{x_i+1} - K_{x_i} \tag{5-22}$$

The gap of average customer satisfaction growth rate d_i between the low function implementation and high function implementation is calculated using Eq. (5-23).

$$d_i = (D_{x_{0.5i}} + \ldots + D_{x_i}) - (D_{x_1} + \ldots + D_{x_{0.5i}}) \tag{5-23}$$

Based on changes of the curve slope and Kano model, CRs can be classified into 5 categories including Must-be quality (M), One-dimensional quality (O), Attractive quality (A), Indifferent quality (I), and Reverse quality (R). The CRs classification by fitting curves is defined as shown in *Table 5-2*.

Table 5-2 CRs classification by fitting curves

	Mean of K in Eq. (5-20)	Standard of K in Eq. (5-22)	Gap of d_i in Eq. (5-23)	CRs classification result
1	Higher than 0.1	Higher than 1.0	Higher than 0	M
2	Higher than 0.1	Lower than 1.0	\	O
3	Higher than 0.1	Higher than 1.0	Lower than 0	A
4	-0.1 to +0.1	\	\	I
5	Lower than -0.1	\	\	R

The mean of K in Eq. (5-20), standard of K in Eq. (5-21) and gap of d_i in Eq. (5-23) show characters of a curve such as the slope and change of the slope, which describes the relationship between the function implementation and customer satisfaction. If the curve slope for a CR is higher than 0.1 and the standard of slope K is lower than 1.0, the customer satisfaction has a positive linear relationship with the increase of the function implementation, and the CR is in the O group.

If the curve slope of a CR is higher than 0.1, the standard of slope K is lower than 1.0 and gap of d_i is higher than 0, it means that the customer satisfaction degree has a rapid increase in the beginning and slow increase later when the function implementation increases, and the CR is in M group. If the curve slope of a CR is higher than 0.1, the standard of slope K is higher than 1.0 and gap of di is lower than 0, the customer satisfaction has a slow increase at beginning and rapid increase later when the function implementation increases, and the CR is in the A group.

If the curve slope of a CR is lower than -0.1, the customer satisfaction will be decreased when the function implementation increases and the CR is defined in the R group. If the curve slope of a CR is between -0.1 to 0.1, the customer satisfaction will not have difference when the function implementation increases or decreases, and the CR is in the I group.

Rate f_i is a percentage of products with functions related to CRs in A group compared to the total number of products. Rate f_i is decided as follows.

$$f_i = \frac{p_i}{r} \tag{5-24}$$

where, P_i is the number of products that meet the minimum function implementation degree for CRi, and r is the number of total products.

A guideline of the quantitative FRs implementations to meet each CR in *Table 5-3* is defined based on CRs classification results in *Table 5-2* to determine the best function implementations of a product.

Table 5-3 Guideline for quantitative FRs implementations

CRs in groups	FRs implementations requirement		
	Must have it or not	Minimum requirement	Maximum requirement
M	Yes	K is lower than 0.1	No need to increase
O	Yes	When y=3	As better as possible
A	Yes (f_i >0.3), No (f_i <0.3)	When y=4	As better as possible
I	Remove related functions	/	/
R	Remove related functions	/	/

For CRs in group M, the customer satisfaction is constant after the basic function of a CR is met. Thus, it requires to provide a basic function to meet CRs and there is no need to continually increase functions related to CRs in group M. For CRs in the O group, the customer satisfaction can steadily increase when the function implementation increases. Thus, it requires to provide functions to meet CRs and continually improves functions related to CRs in the O group if possible.

For CRs in the A group, the customer satisfaction can increase when the function of a CR is fully met. If more than 30% percentage of existing products have functions related to a CR in the A group, it requires functions to fully meet CRs in the A group. Functions related to CRs in R and I groups should be removed because the function implementations of these CRs can reduce the customer satisfaction of the product.

Based on the guideline of FRs implementations in *Table 5-3,* the best quantitative FRs implementations are defined to improve the design of a product.

5.2 Case study

A case study is conducted to decide the FRs implementation of passive upper limb rehabilitation devices using the proposed method. Based on the definition of CRs in Chapter 3, there are 10 CRs for passive upper limb rehabilitation devices including CR.1 flexible wear, CR.2 safety, CR.3 lightweight, CR.4 price, CR.5 no smell, CR.6 arm support, CR.7 durable, CR.8 comfort, CR.9 elbow fastening and CR.10 forearm size (Shi et al, 2021).

Passive upper limb rehabilitation devices help patients to recover injured arms by fixing injured arm with a special gesture and providing accurate movement direction in daily exercises. By online searching upper limb rehabilitation devices, 19 rehabilitation devices were found on Webpages of Amazon and Alibaba. Online customer reviews and product specifications of these 19 rehabilitation devices are collected using the focused crawling method. There are 3653 online customer reviews in total for these rehabilitation devices. The data size of the collected online customer reviews and specifications is 3.5 MB.

The online reviews of these products are analyzed using the focused crawling method. The review comments are divided into sentences based on commands. Each sentence is matched with a CR. For example, the sentence “This upper arm recovery device is pretty light" is the collected review comment from the second sentence in the first collected product. The sentence has 5 words that are nouns and adjectives. Vector w_{21}^{11} is defined to compare the sentence with the word of CR.1 using Eq. (5-1) as follows.

$$w_{21}^{11} = (3, 7, 1, 3, 5) \tag{5-25}$$

The value of N_2^1 is 3 based on Eqs. (5-2) to (5-4), Therefore, the sentence "This upper arm recovery device is pretty light", is matched with CR.3 lightweight. The value of adverb word "pretty" a_2^1 is calculated as 3 using similarity of word vectors based on Eqs. (5-5) to (5-7). Value e_2^1 of adjective word "light" is calculated as 1 using Eq. (5-8). The customer satisfaction degree y_2^1 is decided as 3 using Eq. (5-9).

Based on Eqs. (5-9) to (5-11), inaccurate or conflicted online customer reviews are filtered. The accuracy of the customer satisfaction degree of CR defined by each sentence based on the WordNet hierarchy method is improved.

There are 6 sentences in the review comment related to CR.3 for the first product in the filtered online customer reviews. These 6 sentences are used to define the customer satisfaction degree. Therefore, the average customer satisfaction degree of CR.3 for the first product z^{13} is defined as follows using Eq. (5-12).

$$z^{13} = \frac{y_2^1 + y_7^1 + y_{15}^1 + y_{22}^1 + y_{36}^1 + y_{52}^1}{6} = -1.5 \tag{5-26}$$

All the average customer satisfaction degrees of 19 products for 10 CRs are defined using Eq. (5-12) by the same process. After determining the average customer satisfaction degree of each CR for each product, the product function implementation degree can be defined by crawled parameters for each product. For example, FRs and parameters of the product crawled for the first product are shown in Table 5-4.

Table 5-4 Specifications of the crawled first product

Number	FRs	parameters in a product
FR.1	Joint movement angle	0 °-125 °
FR.2	Safety	Stop button
FR.3	Weight	0.7kg
FR.4	Price	138 US dollar
FR.5	Material	Phthalate
FR.6	Structure	Elbow brace
FR.7	Durable material	Aviation, aluminum, alloy,
FR.8	Cover of product	Cotton
FR.9	Adjustable mobility	0-120 degree
FR.10	The length of forearm	17-26 cm

Function descriptions in *Table 5-4* are matched with CRs shown in *Table 5-5* using Eqs. (5-13) to (5-16). Based on crawled parameters of all products, the best and worst parameters of the products are defined in *Table 5-5*.

Table 5-5 Best and worst parameters from all products

CRs	Related parameters for describing FRs	Definition of *x*	
		Best	worst
CR.1	Maximum adjustable strap degree (°)	110	60
CR.2	Safety structure (level)	10	0
CR.3	Weight (Kg)	0.3	5.3
CR.4	Price of the product (USD)	35	116
CR.5	Smell of Material	10	0
CR.6	Elbow brace structure	10	0
CR.7	Strength of material	10	0
CR.8	Cover of material	10	0
CR.9	Adjustable mobility degree (°)	0-120	0-60
CR.10	Range for length of forearm (cm)	17-26	19-23

Based on the best and worst parameters of the products, function implementation degrees of each product F_{ir} are defined using Eq. (5-17). Results of the function implementation and customer satisfaction degree for CR.3 are shown in *Table 5-6*, where x is the function implementation degree of CR.3 for each product. The range of x is from -5 to 5. 5 represents that the product has the best function implementation for meeting a CR. 0 represents that the function implementation of a CR for the product is in the intermediate level of all products. -5 represents that the product has the worst function implementation of a CR. y is the average customer satisfaction degree of CR.3 for each product. The range of y is from -5 for the lowest satisfaction degree to 5 for the highest satisfaction degree.

Table 5-6 Function implementation and customer satisfaction degree for CR.3

Number	1	2	3	4	5	6	7
x	-4.7	-3.3	-0.3	2.3	-4.5	3.5	3.7
y	-1.5	1.6	2.8	3.1	-1.3	3.0	3.1
Number	8	9	10	11	12	13	14
x	-4.6	-4.1	-1.5	-0.5	1.5	1.7	3.6
y	-1.6	1.0	2.0	2.4	2.8	2.9	3.0
Number	15	16	17	18	19		
x	3.8	3.6	4.6	-5.0	5.0		
y	3.0	2.9	3.0	-1.7	3.1		

Based on *Table 5-6*, a curve is fitted by minimizing the sum of squared deviations using Eqs. (5-18) and (5-19) to represent relations of the function implementation and customer satisfaction of CR.3 as follows.

$$P(x_i) = 2.6 + 0.19x + 0.034x^2 - 0.001x^3 - 0.004x^4 + 0.0006x^5 \qquad (5\text{-}27)$$

The mean value of slope $\bar{K}(x_i)$ for the curve in Eq. (5-27) is 3 from Eq. (5-20). S_k of CR.3 in Eq. (5-27) is 0.3 from Eq. (5-21). The gap of the average customer satisfaction growth rate between the low function implementation and high function implementation d_i is 1 based on Eqs. (5-22) and (5-23). By using Eqs. (5-18) to (5-23), 10 fitting curves of 10 CRs for relations between the function implementation and customer stratification degree are formed as shown in *Figure 5-3*, *Figure 5-4*, and *Figure 5-5*.

Four CRs including CR.2, CR.3, CR.5 and CR.6 in *Figure 5-3* belong to the M group. *Figure 5-3* shows that when CRs in this group are not met, customers are very dissatisfied for the product. When CRs in this group are fully met, customers are just neutral for the product.

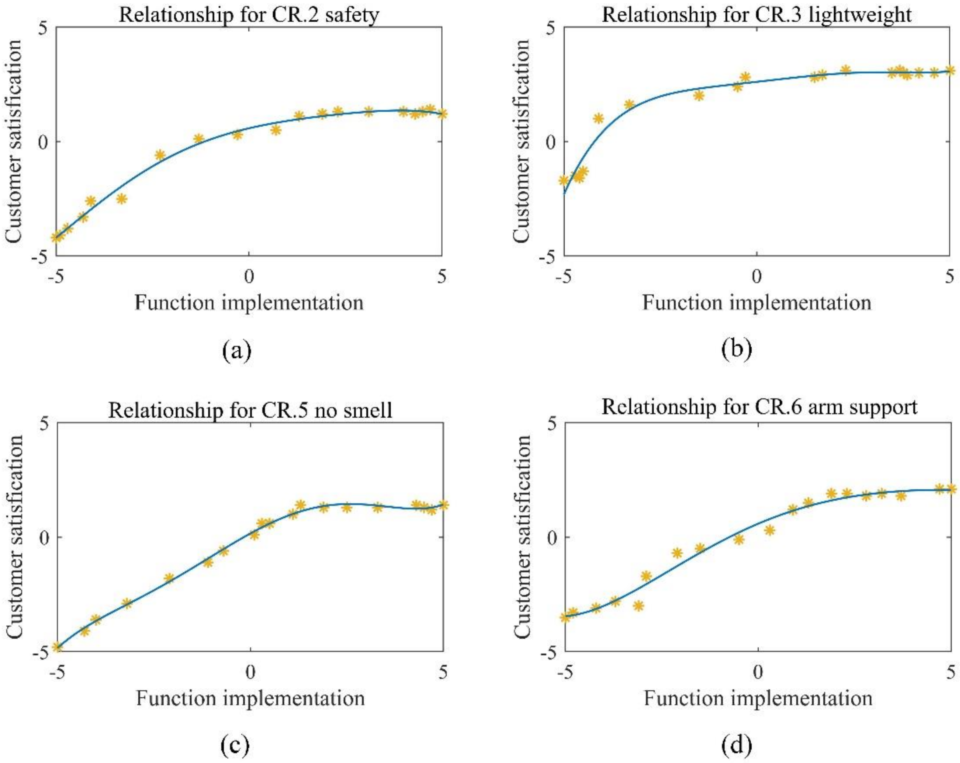


Figure 5-3 CRs in the M group

Four CRs including CR.1, CR.4, CR.7 and CR.8 in *Figure 5-4* belong to the O group. *Figure 5-4* shows that CRs in this group have a linear relation between the function implementation and customer satisfaction.

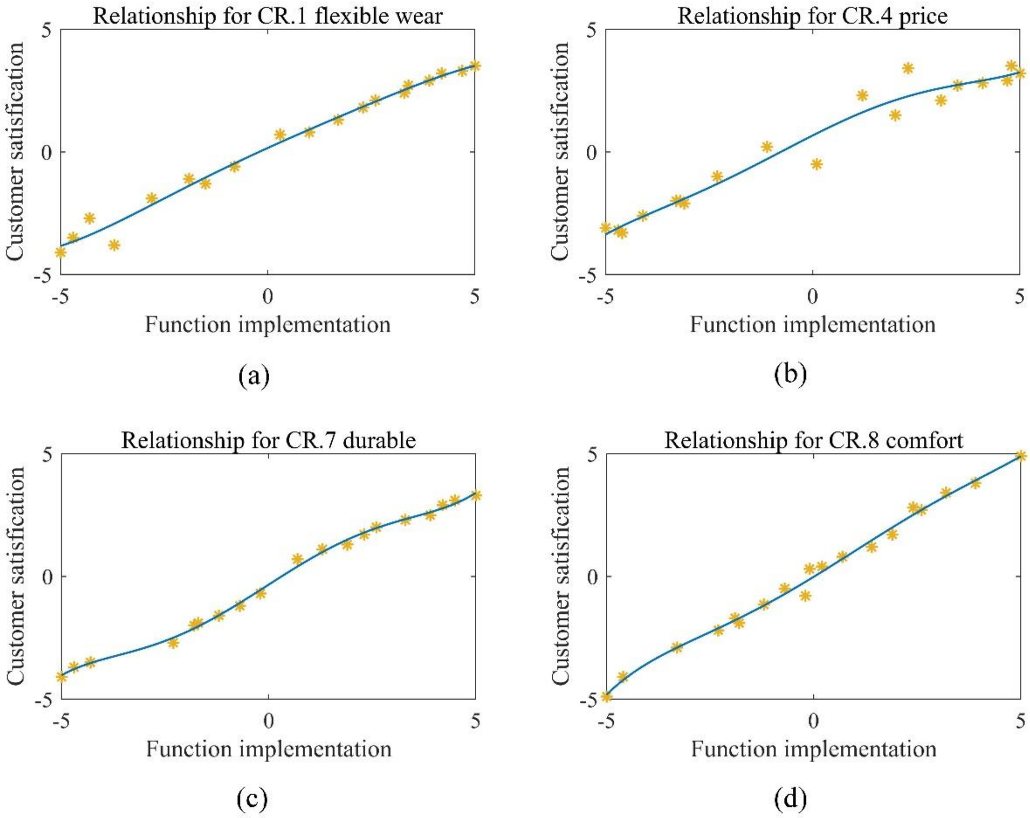


Figure 5-4 CRs in the O group

Two CRs including CR.9 and CR.10 in *Figure 5-5* belong to the A group. *Figure 5-5* shows that customers are very satisfied for the product if the function implementation of related CRs in this group can be fully achieved.

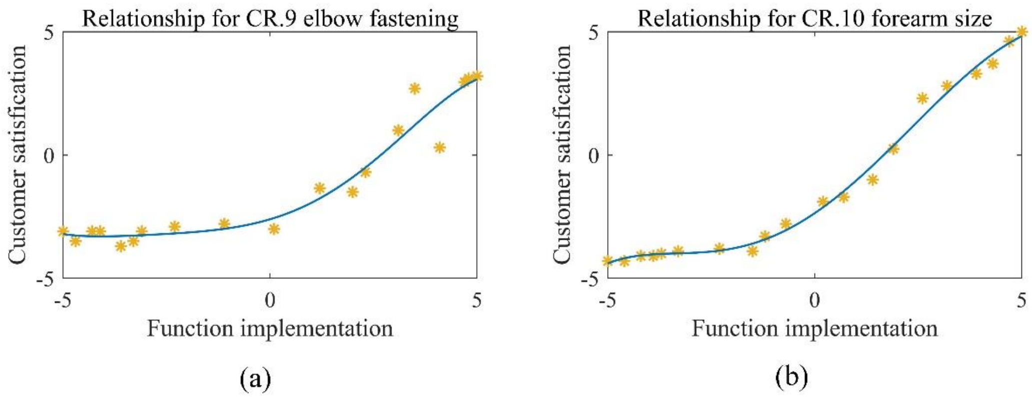


Figure 5-5 CRs in the A group

The percentage of products for functions related to CR.9 and CR.10 in the A group compared to the total number of products is calculated in Eqs. (5-28) and (5-29) using Eq. (5-24). As f_9 is lower than 0.3, functions related CR.9 can be removed if it is conflicted with other CRs. As f_{10} is higher than 0.3, functions related CR.10 must be maintained in the concept design.

$$f_9 = 0.16 \tag{5-28}$$

$$f_{10} = 0.58 \tag{5-29}$$

Based on *Table 5-3*, the minimum and maximum FRs implementations are defined in *Table 5-7*.

Table 5-7 Minimum and maximum FRs implementations

CRs	CRs classification	Must have it or not	FRs	Related parameters for describing FRs	Minimum FRs implementations	Maximum FRs implementations
CR.1	O	Yes	FR.1	Adjustable strap degree (°)	80	130
CR.2	M	Yes	FR.2	Safe structure	Metal frame	None
CR.3	M	Yes	FR.3	Weight (Kg)	1.8	None
CR.4	O	Yes	FR.4	Price of the product (USD)	100	35
CR.5	M	Yes	FR.5	Smell of Material	Synthetic plastic	None
CR.6	M	Yes	FR.6	Structure of elbow	Elbow brace	None
CR.7	O	Yes	FR.7	Life of product (year)	2	5
CR.8	O	Yes	FR.8	Material of arm cover	Cotton	Fabric
CR.9	A	No	FR.9	Adjustable mobility degree (°)	1.5	0.5
CR.10	A	Yes	FR.10	Range for length of forearm (cm)	230 mm	270mm

The product should be designed to meet the minimum requirement of FRs for CR.2, CR.3, CR.5, and CR.6 in the M group. Further improvement is not needed for the function implementation related to CRs in the M group. The function related to CR1, CR4, CR7, and CR.8 in the O group should meet the minimum requirement at first and then improve the function implementation as much as possible. The function implementation related to CR.9 in the A group can be removed if it conflicts with other CRs because very less crawled products have this function and customers are not dissatisfied when the product do not have the function related to CR.9. The FRs implementation related to CR.10 in the A group should meet the minimum requirement because most of crawled products have functions related to CR.10.

5.3 Verification for proposed method

For verifying the effectiveness of the proposed FRs implementation definition method, existing FRs implementation definitions are compared to the proposed FRs implementation method in design of a passive upper limb rehabilitation device.

5.3.1 FRs implementation defined by the existing Kano model and IPA model

The Kano model requires collecting questionnaires from the customer survey to define relations between CRs and FRs for the FRs implementation. The IPA model defines the FRs implementation by questionnaires using relations between weights of the importance for FRs and current customer satisfaction of CRs. FRs implementations defined by Kano and IPA models are shown in *Table 5-8*.

Table 5-8 FRs implementations defined by Kano and IPA models

CRs	FRs implementation by the Kano model		IPA model	FRs implementation by the IPA model
CR.1	O	As better as possible	C	Improve function implementation
CR.2	M	Must meet basic need	K	Keep current function implementation
CR.3	M	Must meet basic need	K	Keep current function implementation
CR.4	O	As better as possible	P	Reduce function implementation
CR.5	M	Must meet basic need	K	Keep current function implementation
CR.6	M	Must meet basic need	C	Improve function implementation
CR.7	O	As better as possible	L	Improve function implementation if possible
CR.8	O	As better as possible	K	Keep current function implementation
CR.9	A	Add it if possible	C	Improve function implementation
CR.10	A	Add it if possible	C	Improve function implementation

The FRs implementation result by the Kano model in *Table 5-8* can only provide a qualitative analysis result. For example, FRs implementations related to CRs in the M group should meet the basic need. FRs implementations related to CRs in the O group should be improved as much as possible. FRs implementations related to CRs in the A group should be added if possible. FRs implementations related to CRs in I and R groups should be removed. However, FRs implementation results by the Kano model only provide a trend to increase or reduce the FRs implementation of a CR rather than an accurate guide for the FRs implementation.

The FRs implementation result by the IPA model in *Table 5-8* can only guide designers to improve or reduce FRs implementations of related CRs in different groups. FRs implementations related to CRs in the C group should be improved. FRs implementations related to CRs in the K group should be maintained compared to surveyed products. FRs implementations related to CRs in the L group should be improved when they do not conflict with other CRs. FRs implementations related to CRs in the P group can be reduced. However, CRs classification results by the IPA model cannot provide an accurate guideline for product design to determine FRs implementations.

The existing FRs implementations definition methods require questionnaires of customers. It is time-consuming to collect survey questionnaires and transfer data to the CRs classification manually. For meeting the solution accuracy, more than 200 questionnaires may be required from customers in different conditions (Yadav et al, 2013).

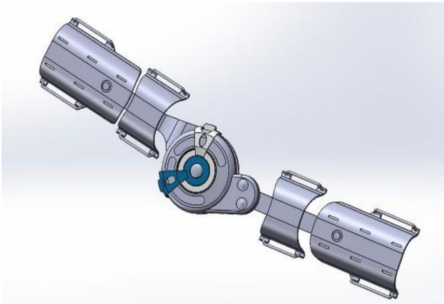
The proposed method can define quantitative FRs implementations accurately and efficiently. FRs implementations related to CRs in the M group should meet the minimum function requirement. It is unnecessary to improve the FRs implementations if it already met the minimum function requirement. FRs implementations related to CRs in the O group should meet the minimum function requirement when the customer satisfaction degree is equal to 3. In addition, the FRs implementation should be improved if possible. FRs implementations related to CRs in the A group should be added if most of crawled products include functions related to CRs in this group. FRs implementations related to CRs in I and R groups should be removed.

5.3.2 Design solutions by the existing methods and proposed method

For verifying the proposed FRs implementations definition method, design solutions based on the Kano model, IPA model, and proposed method are searched. *Figure 5-6* shows different design solutions of the passive upper limb rehabilitation devices based on different CRs classifications.

(a) Design solution by Kano model

(b) Design solution by IPA model



(c) Design solution by proposed method

Figure 5-6 Design solutions of passive upper limb rehabilitation devices

Based on results of the proposed FRs implementation method in *Table 5-7* and the existing methods in *Table 5-8,* specifications of three passive upper limb rehabilitation devices are identified as shown in *Table 5-9*.

Table 5-9 Specifications for passive upper limb rehabilitation devices

FRs	Design specification to meet FRs	Specifications by Kano model	Specifications by IPA model	Specifications by proposed method
FR.1	Whole size	600*200*130 mm	550*70*50 mm	500*80*90 mm
	Diameter of forearm	110-170 mm	50-230 mm	100-165 mm
FR.2	Frame structure	Welding	Assembling	Assembling
FR.3	Weight	1.55 Kg	3.55 Kg	0.55 Kg
FR.4	Price	155 US dollar	355 US dollar	115 US dollar
FR.5	Irritating odor materials	None	None	None
FR.6	Length of upper arm	220 mm	190-220 mm	170-230 mm
	Frame material	Steel	Metal	Plastic
FR.7	Frame component	2 parts	9 parts	8 parts
FR.8	Cover material	Cotton	None	Cotton
	Elbow movement angle	None	0-90 degree	0-120 degree
FR.9	Elbow fastening angle	0-0.5 degree	0-5.0 degree	0-1.5 degree
FR10	Length of forearm	210 mm	210-215 mm	180-235 mm

Performances of passive upper limb rehabilitation devices designed by two existing methods and the proposed method are compared based on specifications in *Table 5-9*. Specifications defined by the proposed method include the smaller size, lightweight, and less material required compared to specifications defined by the Kano model and IPA model. The proposed solution can meet all the FRs accurately. For example, the range of the forearm length defined by the proposed method is 180-235 mm which can meet FR.10 for adults and children with different arm lengths.

Using the Kano model, designers can only get the qualitative FRs implementations to determine specifications of related FRs, which affects the accuracy for the product FRs implementations and reduces the customer satisfaction. For example, the forearm length defined by the Kano model is 210 mm, which cannot meet FR.10 for users with different arm lengths.

The design solution by the IPA model cannot provide an accurate FRs implementations for product specifications. The IPA model collects the customer satisfaction for each FR and importance of each FRs based on a specific product. The accuracy of the FRs implementations highly depends on selected benchmarking products, which reduces the accuracy of specifications. In addition, designers can only adjust the FRs implementations based on the selected benchmarking products because results of questionnaires are only based on customer comments on these specific products. For example, the range for the forearm length defined by the IPA model is 210-215 mm based on the benchmarking devices and FRs. The device can only meet FR.10 for adults with the standard height from 170 to 180 cm.

Comparing with the existing methods, the proposed FRs implementations method has a better performance in defining product specifications. For example, the proposed method can determine the minimum requirement of FRs to meet CRs in the M group. Based on the proposed method, the plastic frame of the rehabilitation device can meet the minimum requirement of strength for safety. Further improvement is not needed for the FRs implementations related to CRs in the M group because customers cannot have more satisfaction for the further function improvement. Therefore, the proposed method provides a higher accuracy to determine the FRs implementations compared to the existing methods.

In addition, the proposed method collects raw data online automatically, which improves efficiency of the FRs implementations definition significantly. Existing methods such as Kano and IPA models require complex questionnaires, which is time-consuming and inaccurate. The proposed method has advantages on both accuracy and efficiency for the FRs implementation definition.

5.4 Summary

This chapter proposes a new FRs implementation method based on the sentence meaning of the collected customer reviews and specifications using the word vector. The function implementation of products is defined based on specifications of crawled products. The customer satisfaction is decided based on the meaning of sentences. The function implementation is determined by the semantic similarity. A fitting curve is formed by the customer satisfaction degree and function implementation degree using the polynomial fitting and least-square methods. Based on the slope of the fitting curve, the minimum and maximum FRs implementations are defined to guide the design process. The proposed method can be applied for products with available online sale information such as electric devices, household appliances and vehicles.

Chapter 6 An objective weighting method for defining IRs of FRs

This chapter proposes an objective method to define IRs of FRs using information entropy and benchmarking methods. The degree of relevance between CRs and FRs is decided by the AHP method. The information entropy and benchmarking methods are integrated to define similarity of performances for selected benchmarking products to meet a FR. IRs of FRs are then defined based on the performance similarity of selected benchmarking products and degree of relevance between CRs and FRs using HoQ. The proposed method is verified in a case study of designing an active upper limb rehabilitation device. Results show that the proposed method has improved weighting accuracy of FRs in concept design.

6.1 Proposed method

A flowchart of defining IRs of FRs is shown in *Figure 6-1*. Raw data required include CRs, IRs of CRs, and FRs.

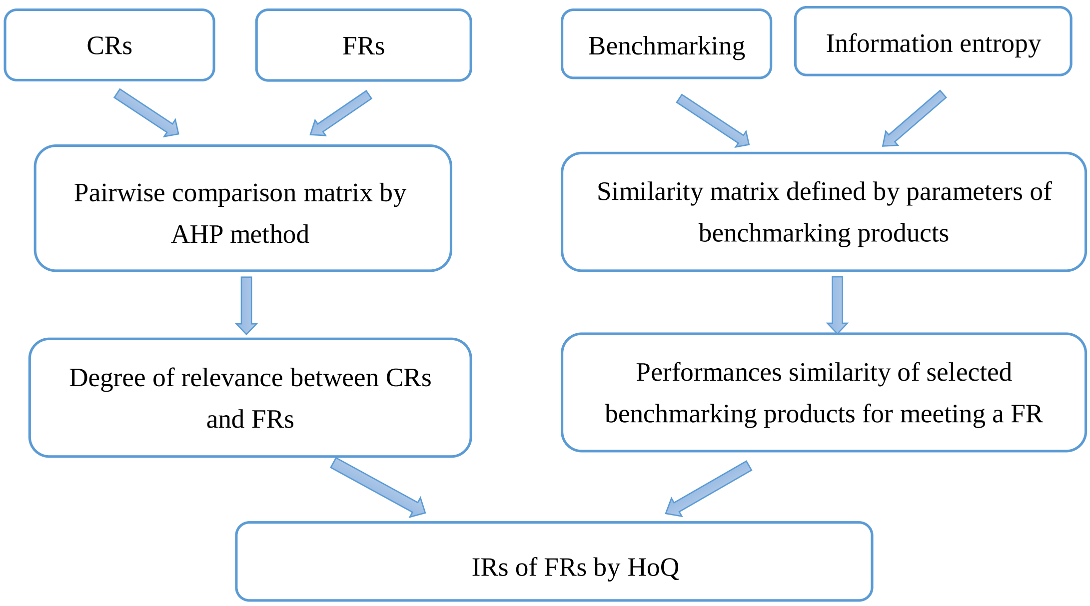


Figure 6-1 Proposed method of defining IRs of FRs

6.1.1 Degree of relevance between CRs and FRs by the AHP method

Based on the AHP method, the performance of FRs for meeting a CR is compared using *Table 6-1*.

Table 6-1 Determination method for relevance between CRs and FRs

Value	Description
1	j_{th} FR and k_{th} FR have the same contribution for meeting a CR.
3	j_{th} FR has a slightly higher contribution than k_{th} FR for meeting a CR.
5	j_{th} FR has a higher contribution than k_{th} FR for meeting a CR.
7	j_{th} FR has a strongly higher contribution than k_{th} FR for meeting a CR.
9	j_{th} FR has an absolutely higher contribution than k_{th} FR for meeting a CR.
2,4,6,8	Intermediate value of adjacent importance

The comparison of performance between the j_{th} FR and k_{th} FR for meeting a CR is defined as a_{jk}. A vector c_{ij} is formed to define the degree of relevance between CRs and FRs using Eq. (6-1).

$$c_{ij} = \sum_{k=1}^{m} a_{jk} \Big/ m \tag{6-1}$$

where, c_{ij} is the degree of relevance between the i_{th} CR and the j_{th} FR. m is the total number of FRs.

Based on the defined degree of relevance between CRs and FRs, matrix $\boldsymbol{A}$ is built as follows.

$$\mathbf{A} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \cdots & \cdots & c_{ij} & \cdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix} \tag{6-2}$$

where, n is the total number of CRs and m is the total number of FRs.

6.1.2 Performances similarity of benchmarking products

Benchmarking and information entropy methods are integrated to determine performances similarity of benchmarking products to meet each FR. Matrix **X** in Eq. (6-3) is built based on the parameters and performances for implementing m FRs in t selected benchmarking products.

$$\mathbf{X} = (x_{ij})_{m\times t} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1t} \\ x_{21} & x_{22} & \cdots & x_{2t} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mt} \end{pmatrix} \tag{6-3}$$

where, t is the number of benchmarking products selected in the market.

For comparing performance of different functions in benchmarking products, the information entropy E_i is defined to describe similarity of performances for benchmarking products to meet the i_{th} FR using Eqs. (6-4) and (6-5).

$$E_i = -K\sum_{j=1}^{t} P_{ij} \ln P_{ij}, \ \ K = 1/\ln t \tag{6-4}$$

A probability function P_{ij} is determined by parameters as follows.

$$P_{ij} = x_{ij} \Big/ \sum_{j=1}^{t} x_{ij} \tag{6-5}$$

Results of information entropy E_i in Eq. (6-4) are transferred into interval from 0 to 1 for normalization as follows.

$$k_i = \frac{E_i - \min\limits_{-1 \le i \le n}\{E_i\}}{\max\limits_{1 \le i \le n}\{E_i\} - \min\limits_{1 \le i \le n}\{E_i\}} \ \ (i = 1, 2, \ldots, \mathrm{m}) \tag{6-6}$$

Normalized result **k** for performances similarity of selected benchmarking products for meeting each FR are as follows.

$$\mathbf{k} = (k_1, \cdots, k_i, \cdots, k_m)^{\mathrm{T}} \tag{6-7}$$

6.1.3 IRs of FRs using HoQ

The IRs of FRs are then defined based on performances similarity of selected benchmarking products to meet a FR and degree of relevance between CRs and FRs using HoQ in *Table 6-2.*

Table 6-2 Definition of IRs of FRs using HoQ

CRs	IRs of CRs	FRs			
		FR_1	FR_2	FR_j	FR_m
CR_1	d_1	c_{11}	c_{12}	c_{1j}	c_{1m}
CR_2	d_2	c_{21}	c_{22}	c_{2j}	C_{2m}
CR_i	d_i	c_{i1}	c_{i2}	c_{ij}	c_{im}
CR_n	d_n	c_{n1}	c_{n2}	c_{nj}	c_{nm}
IRs of FRs		f_1	f_2	f_j	f_m

IRs of FRs are then calculated by similarity of selected benchmarking products for meeting each FR and degree of relevance between CRs and FRs using Eq. (6-8).

$$f_j = k_j \bullet \sum_{i=1}^{n} c_{ij} \bullet d_i \tag{6-8}$$

where, f_j is IR of the j_{th} FR. c_{ij} is the degree of relevance between the i_{th} CR and the j_{th} FR. d_i is IR of the i_{th} CR. k_j is similarity of performances for benchmarking products to meet the j_{th} FR.

f_j in Eq. (6-8) is normalized as follows.

$$r_j = f_j \Big/ \sum_{i=1}^{m} f_j \tag{6-9}$$

Normalized IRs of FRs are then obtained as follows for the priority of concept design.

$$\mathbf{r} = (\mathrm{r}_1, r_2, \cdots, r_m)^{\mathrm{T}} \tag{6-10}$$

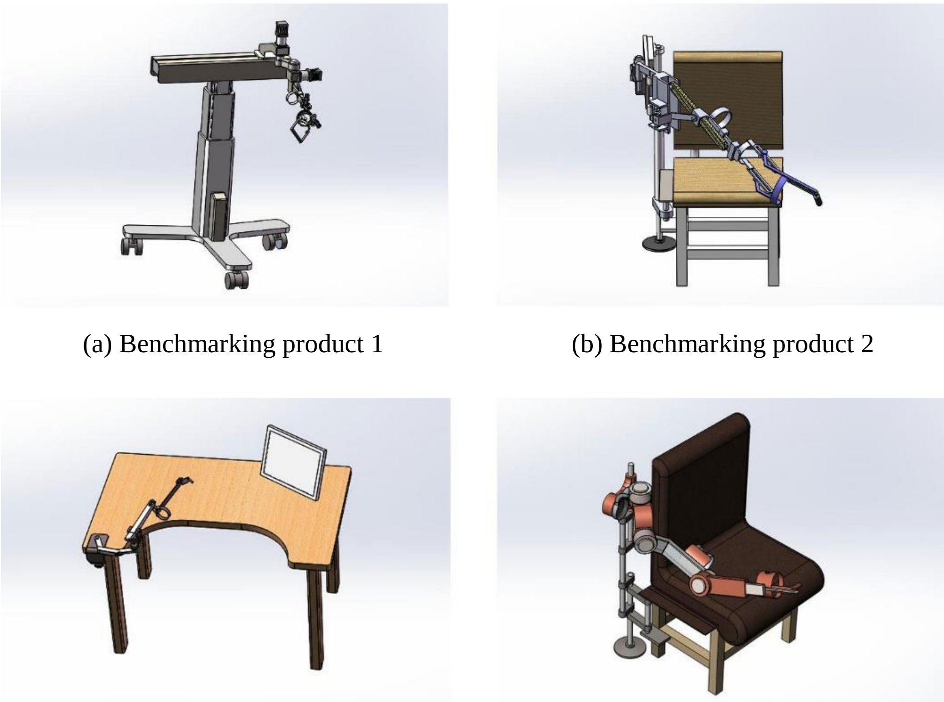
6.2 Case study

A case study is conducted for determining IRs of FRs in design of an active upper limb rehabilitation device to verify the proposed method. Relations of FRs and CRs of active upper limb rehabilitation devices are shown in *Table 6-3*. CRs and IRs of CRs are defined based on the results in Chapter 4. CRs for active upper limb rehabilitation devices include accurate movement CR.1, movement feedback CR.2, automatic CR.3, support arm CR.4, easy operation CR.5, interesting CR.6, light weight CR.7, reasonable price CR.8, adaptability CR.9, portability CR.10, safety CR.11, material CR.12, and quiet CR.13. IRs of CRs defined in Chapter 4 are shown in the second column of *Table 6-3*. FRs are defined based on collected function descriptions of active upper limb rehabilitation devices from literature (Maciejasz et al, 2014). 10 FRs include sensor selection FR.1, motor selection FR.2, interactive function FR.3, adjustable height and length FR.4, suitable material FR.5, flexible movement structure FR.6, portable design FR.7, lightweight design FR.8, displacement limit FR.9, and degree of freedom design FR.10.

The degree of relevance between CRs and FRs of active upper limb rehabilitation devices is defined in Eq. (6-11) by Eqs. (6-1) and (6-2) using the AHP method.

$$\mathbf{A}=\begin{bmatrix} 0.31 & 0.09 & 0 & 0.10 & 0 & 0.10 & 0 & 0.04 & 0.05 & 0.31 \\ 0.35 & 0.07 & 0.26 & 0 & 0 & 0 & 0 & 0.10 & 0.05 & 0.17 \\ 0.23 & 0.10 & 0.13 & 0.05 & 0 & 0.20 & 0.05 & 0.12 & 0.08 & 0.04 \\ 0.06 & 0 & 0 & 0.14 & 0 & 0.49 & 0.10 & 0 & 0.05 & 0.16 \\ 0.15 & 0.02 & 0 & 0.27 & 0 & 0.15 & 0 & 0.38 & 0 & 0.03 \\ 0 & 0 & 0.51 & 0 & 0 & 0.15 & 0.10 & 0.11 & 0 & 0.13 \\ 0 & 0 & 0 & 0.06 & 0.06 & 0.12 & 0.33 & 0.38 & 0 & 0.05 \\ 0.07 & 0.03 & 0.05 & 0.16 & 0.02 & 0.03 & 0.23 & 0.33 & 0.01 & 0.08 \\ 0.02 & 0.01 & 0.05 & 0.39 & 0 & 0.08 & 0.25 & 0.05 & 0.02 & 0.14 \\ 0 & 0 & 0 & 0.06 & 0 & 0 & 0.61 & 0.15 & 0.05 & 0.06 \\ 0.05 & 0.02 & 0 & 0.12 & 0 & 0.02 & 0.15 & 0.14 & 0.33 & 0.17 \\ 0 & 0 & 0 & 0.03 & 0.53 & 0 & 0.24 & 0.16 & 0.01 & 0.03 \\ 0 & 0.55 & 0 & 0 & 0.23 & 0 & 0 & 0 & 0 & 0.22 \end{bmatrix} \tag{6-11}$$

Four popular rehabilitation devices in the market are selected as benchmarking products in *Figure 6-2*.



(a) Benchmarking product 1 (b) Benchmarking product 2

(c) Benchmarking product 3 (d) Benchmarking product 4

Figure 6-2 3D models of benchmarking products.

Based on the function performance of four benchmarking products, matrix $\boldsymbol{X}$ is formed using Eq. (6-3). Specifications of FR.4, FR.8, FR.9, and FR.10 are found from these products directly. For example, details of FR.8 for lightweight design of four benchmarking products are 180, 110, 25, and 150kg, respectively. Details of FR.1, FR.2, FR.3, FR.5, FR.6, and FR.7 are defined by 5 different levels from 1 to 5 according to the performance of benchmarking products for these FRs. When values are close to each other in a row of the matrix, performances of functions in four benchmarking products are similar.

Based on Eqs. (6-4) to (6-7), normalized results for the performances similarity of selected benchmarking products to meet each FR are defined as follows.

$$\mathbf{k} = (0.092, 0.147, 0.074, 0.109, 0.054, 0.102, 0.058, 0.043, 0.212, 0.110)^{T} \quad (6\text{-}12)$$

Based on the HoQ method, IRs of FRs are defined as shown in *Table 6-3* using the function similarity of selected benchmarking rehabilitation devices and degree of relevance between CRs and FRs. IRs of CRs are shown in the second column in *Table 6-3*.

Table 6-3 IRs of FRs for active upper limb rehabilitation devices

CRs	IRs of CRs	FRs									
		FR.1	FR.2	FR.3	FR.4	FR.5	FR.6	FR.7	FR.8	FR.9	FR.10
CR.1	5	0.31	0.09	0	0.10	0	0.10	0	0.04	0.05	0.31
CR.2	3	0.35	0.07	0.26	0	0	0	0	0.10	0.05	0.17
CR.3	5	0.23	0.10	0.13	0.05	0	0.20	0.05	0.12	0.08	0.04
CR.4	4	0.06	0	0	0.14	0	0.49	0.10	0	0.05	0.16
CR.5	3	0.15	0.02	0	0.27	0	0.15	0	0.38	0	0.03
CR.6	2	0	0	0.51	0	0	0.15	0.10	0.11	0	0.13
CR.7	4	0	0	0	0.06	0.06	0.12	0.33	0.38	0	0.05
CR.8	5	0.07	0.03	0.05	0.16	0.02	0.03	0.23	0.33	0.01	0.08
CR.9	3	0.02	0.01	0.05	0.39	0	0.08	0.25	0.05	0.02	0.14
CR.10	5	0	0	0	0.06	0	0	0.61	0.15	0.05	0.06
CR.11	3	0.05	0.02	0	0.12	0	0.02	0.15	0.14	0.33	0.17
CR.12	4	0	0	0	0.03	0.53	0	0.24	0.16	0.01	0.03
CR.13	1	0	0.55	0	0	0.23	0	0	0	0	0.22
IRs of FRs		0.460	0.295	0.211	0.557	0.145	0.524	0.495	0.326	0.507	0.596

By using Eq. (6-8), IRs of FRs for active upper limb rehabilitation devices are defined in the last row of *Table 6-3*. Based on Eq. (6-9) and Eq. (6-10), IRs of FRs are normalized as follows.

$$\mathbf{r} = (0.112, 0.072, 0.051, 0.135, 0.035, 0.127, 0.121, 0.079, 0.123, 0.145)^{\mathrm{T}} \quad (6\text{-}13)$$

Based on normalized IRs of FRs, the design priority can be decided accurately for the design sequence to meet FRs.

6.3 Verification of the proposed method

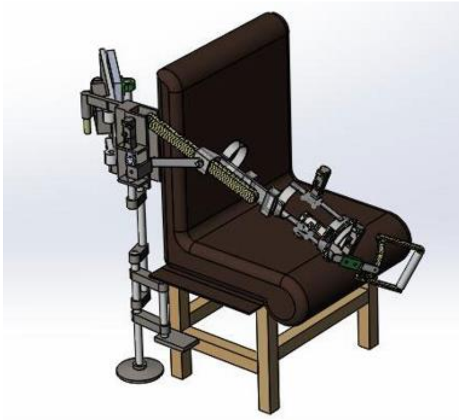
For verifying the proposed method, two active upper limb rehabilitation devices defined by existing IRs of FRs definition method and proposed IRs of FRs method are compared for the performance analysis. In the existing method, IRs of FRs for active upper limb rehabilitation devices are defined based on relations between CRs and FRs from experts ranking using the HoQ method (Zhang et al, 2017). IRs of FRs defined by existing and proposed methods are shown in *Table 6-4*.

Table 6-4 IRs of FRs defined by existing and proposed methods

FRs		IRs of FRs defined by the existing method	IRs of FRs defined by the proposed method
FR.1	sensor selection	0.109	0.112
FR.2	motor selection	0.032	0.072
FR.3	interactive function	0.062	0.051
FR.4	adjustable height and length	0.111	0.135
FR.5	suitable material	0.053	0.035
FR.6	flexible movement structure	0.112	0.127
FR.7	portable design	0.192	0.121
FR.8	lightweight design	0.165	0.079
FR.9	displacement limit	0.052	0.123
FR.10	degree of freedom design	0.113	0.145

Based on defined IRs of FRs, the design priority of the devices can be decided. Design priorities are used to find the best design structure and components from the benchmark devices (Maciejasz et al, 2014). Design solutions by existing and proposed methods are shown in *Figure 6-3*.

(a) Design by the existing method



(b) Design by proposed method

Figure 6-3 Design solutions by existing and proposed IRs of FRs methods

Parameters of two active upper limb rehabilitation devices are defined as shown in *Table 6-5*. Data of two devices include basic characters, adjustment range, and target customers of devices as shown in *Table 6-5*. Basic characters are the total cost, number of components, weight, and degree of freedom. Cost includes costs of raw materials, manufacturing, assembling, packing, distributing of the product. The total number of components is decided based on structures of devices. The device weight is decided based on the material density and volume. Adjustable parameters are height, upper arm length, and lower arm length.

Table 6-5 Parameters of two active upper limb rehabilitation devices

	Parameters of active upper limb rehabilitation devices	Design by the existing method	Design by the proposed method
Basic characters	Total cost (US Dollar)	2950	1290
	Number of components	45	83
	Weight (Kg)	35	145
	Degree of freedom	3	5
Adjustment range	Adjusted range of height for the whole device (cm)	0-41	0-60
	Adjusted range of upper arm length (cm)	20-30	10-40
	Adjusted range of lower arm length (cm)	20-30	10-35
Target customers	Whether can be used for seriously injured patients?	No	Yes
	Whether can be used for children?	No	Yes

Comparing with the device designed by the existing method, the device designed by the proposed method has the better performance for many FRs including the adjustable height, adjustable length, degree of freedom, and flexible movement structure to meet requirements of most users in rehabilitation. For example, the device in *Figure 6-3* (b) designed using the proposed method provides a large upper arms adjustment range from 10 to 40 cm, which can meet both adults and children. The device in *Figure 6-3* (a) designed using the existing method can only provide the adjustment range of upper arms from 20 to 30 cm, which can only be used by adults.

In addition, the device in *Figure 6-3* (b) designed by the proposed method has 5 degrees of freedom for the active exercise. The device in *Figure 6-3* (a) designed by the existing method only has 3 degrees of freedom, which cannot provide an accurate movement in rehabilitation to meet the need of seriously injured patients.

Therefore, the device in *Figure 6-3* (a) designed using the existing IRs of FRs method cannot meet requirements of most users. Performances of benchmarking products are ignored in weighting FRs. The proposed method improves the design solution by improving weights of FRs.

6.4 Summary

This chapter presents a method for defining IRs of FRs using the information entropy and benchmarking method. The degree of relevance between CRs and FRs is decided by the AHP method. The information entropy and benchmarking methods are integrated to define similarity of performances for selected benchmarking products to meet a FR, which improves the accuracy and objectiveness for defining IRs of FRs. Design of active upper limb rehabilitation devices in the case study verifies the proposed method compared to solutions from the existing IRs of FRs definition method.

Chapter 7 Definition of product structures based on WordNet hierarchy and association relation

This chapter proposes a method of the product structures (PSs) definition based on relations of product functions and physical structures using the WordNet hierarchy and association relation method. Physical attributes (PAs) of product functions are searched based on similarity of FRs and functions of existing product components. Suitable product components are selected based on PAs of product components to meet FRs. Relations between PSs and FRs are defined by the association relation to decide the best structure from all the potential solutions using a pairwise comparison method. The proposed method is verified in a case study of design for upper limb rehabilitation devices.

7.1 Proposed method

Data required for the method include FRs, IRs of FRs, and specifications of related products. FRs are defined based on CRs of the target product. IRs of FRs are decided based on the function importance of the product. Product specifications are collected by a focused crawling method. The focused crawling method collects data by searching product specifications and parameters based on product descriptions in the product sales webpage. A flowchart of the proposed method is shown in *Figure 7-1*.

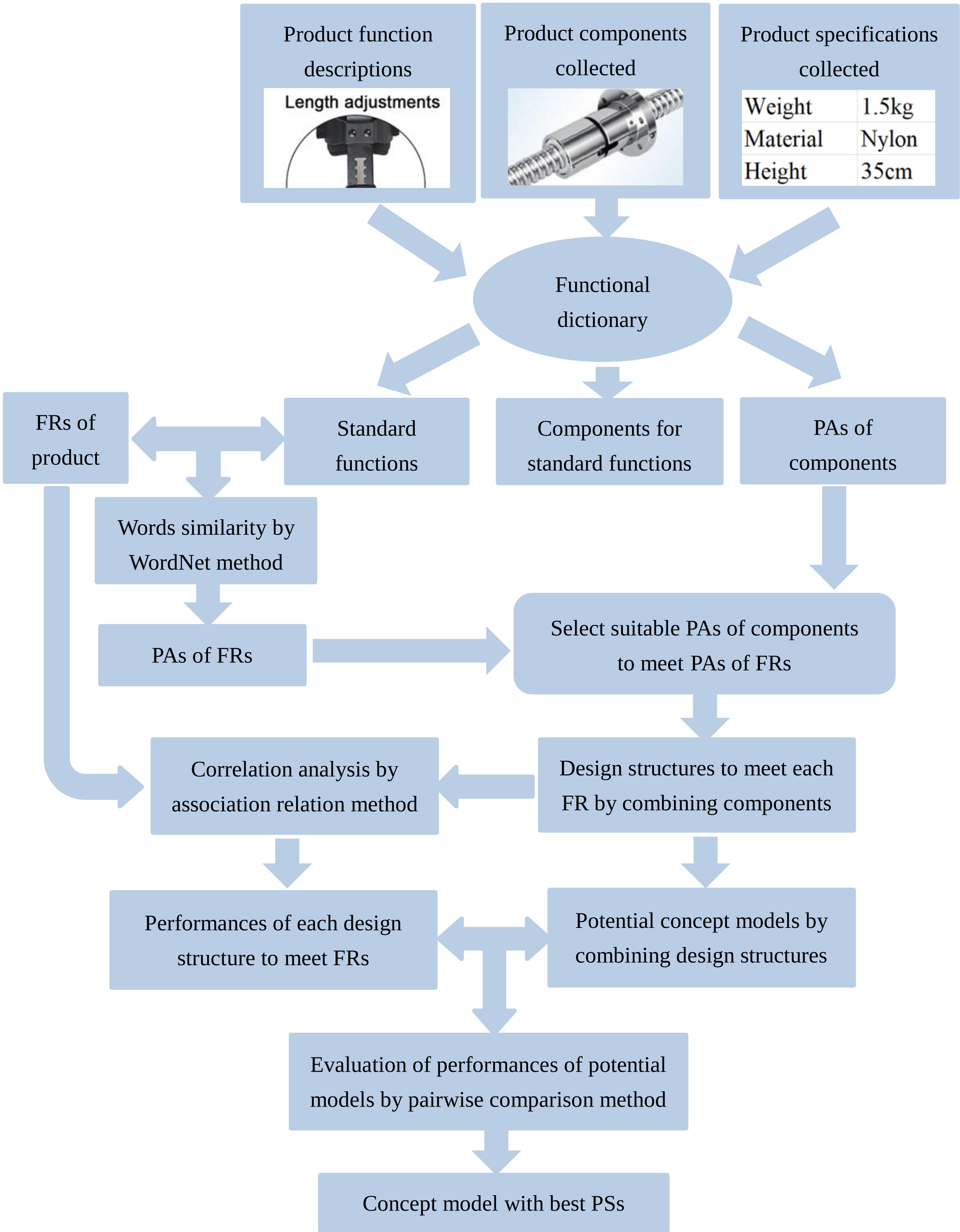


Figure 7-1 Proposed method of defining PSs

7.1.1 Definition for PAs of FRs

For defining required PAs to describe FRs, a functional dictionary is created based on descriptions and specifications of products from the product online information as shown in *Table 7-1*. Function descriptions of products with online information are defined as standard functions of the products. Based on structures of collected products, components of the products are defined to meet standard functions. PAs of components such as material and size are defined as physical characters based on specifications and parameters of these components to describe these standard functions. There are numerical and categorical product attributes. Results of PAs such as specific values of product size and velocity are defined by specifications of collected products. These standard function descriptions, PAs of product components, and PAs from collected products are shown in *Table 7-1*.

Table 7-1 PAs of standard functions from collected products

No.	Standard function description	Components to meet function	Type of PAs	PAs of components		Results of PAs		
						Product 1	……	Product m
1	Drive arm	Servo motor	Categorical attributes	1	Type	Closed loop	……	Closed loop
				…	……	……	……	……
				p	Material	Steel	……	Steel
			Numerical attributes	1	Size	35*40*40 mm	……	55*50*50 mm
				…	……	……	……	……
				q	Power	30 W	……	50 W
		Stepping motor	Categorical attributes	1	Type	Open loop	……	Open loop
				…	……	……	……	……
				p	Material	Steel	……	Steel
			Numerical attributes	1	Size	55*60*60 mm	……	75*80*80 mm
				…	……	……	……	……
				q	Power	50 W	……	60 W
i	……	……	……	…	……	……	……	……
n	……	……	……	…	……	……	……	……

In *Table 7-1*, words of standard function descriptions in the functional dictionary represent specific functions. The functional vocabulary provides product PAs such as size, length, and velocity to describe a function. Each function category in the library corresponds to some commonly used PAs to describe attributes of functions.

Categorical attributes in functions provide types of components such as type of a motor or a bearing. Numerical attributes of functions provide measuring ranges of product components such as size of a part and torque of a motor.

Based on the WordNet hierarchy (Ahsaee et al, 2014), words of standard functions are matched with words of FRs based on their similarity in the defined functional vocabulary to determine PAs of FRs. For example, if there are m words for the j_{th} FR, its vector w_j^i compared to the i_{th} word of standard functions can be represented as follows.

$$w_j^i = (v_{1j}^i, v_{2j}^i, \ldots, v_{mj}^i) \tag{7-1}$$

where, v_{mj}^i is a distance between the m_{th} word of the j_{th} FR and the i_{th} word of its standard function in the functional vocabulary library. The similarity between words of the j_{th} FR and the i_{th} word for the standard function in *Table 7-1* is determined as s_j^i in Eq. (7-2).

$$s_j^i = \frac{v_{1j}^i + v_{2j}^i + \ldots + v_{mj}^i}{\sqrt{(v_{1j}^i)^2 + (v_{2j}^i)^2 + \ldots + (v_{mj}^i)^2}} \tag{7-2}$$

The minimum value of s_j^i for the j_{th} FR is defined as follows.

$$\mathrm{sim}(j) = \min[s_j^i] \tag{7-3}$$

where, the j_{th} FR is related to the i_{th} word for the standard function in the functional vocabulary library.

When $s_j^i = \mathrm{sim}(j)$, the i_{th} standard function can be used to meet the j_{th} FR in *Table 7-1* using Eq. (7-4). Thus, product categorical and numerical attributes for the i_{th} standard function in *Table 7-1* are selected to meet the j_{th} FR as follows.

$$V_j = i \tag{7-4}$$

FRs are then matched with the i_{th} standard function in *Table 7-1*. Product categorical and numerical attributes in the i_{th} standard function are used to describe required characters of product components for a FR. Numerical PAs describe characters of FRs. Categorical PAs are types of FRs to describe characters of FRs.

Results of PAs to meet FRs are defined based on CRs.

For selecting suitable design components from all the potential design components to meet a function, results of PAs of FRs are compared with PAs of product components to determine suitable design components. Ranges of numerical values of PAs for product components are compared with numerical values of PAs of FRs using Eqs. (7-5) and (7-6) as follows.

$$V_{\min}^{jk} \geq V_{\min}^{sk} \tag{7-5}$$

$$V_{\max}^{jk} \leq V_{\max}^{sk} \tag{7-6}$$

where, $V_{\min}^{jk}$ is the minimum value of the k_{th} numerical attribute to meet the j_{th} FR. $V_{\min}^{sk}$ is the minimum value of the k_{th} numerical attribute in the s_{th} collected product component. $V_{\max}^{jk}$ is the maximum value of the k_{th} numerical attribute to meet the j_{th} FR. $V_{\max}^{sk}$ is the minimum value of the k_{th} numerical attribute in the s_{th} collected product component. If the s_{th} collected product component meets Eqs. (7-5) and (7-6), numerical attributes of the s_{th} product component meet requirements of the j_{th} FRs.

Categorical PAs of product components are also matched with categorical PAs of FRs. Categorical PAs of the j_{th} FR are compared with categorical PAs of the s_{th} product component to meet categorical PAs of FRs using Eq. (7-7).

$$\begin{cases} \mathrm{z}^{j} = 1;\ \text{if } \mathrm{C}^{j} = Q^{s} \\ \mathrm{z}^{j} = 0;\ \text{if } \mathrm{C}^{j} \neq Q^{s} \end{cases} \tag{7-7}$$

where, C^{j} is a categorical physic attribute of the j_{th} FR. Q^{s} is a categorical physic attribute of the s_{th} product components.

When categorical PAs of the s_{th} product component are the same as categorical PAs of the j_{th} FR, a value 1 will be returned to z^{j}. It indicates that the s_{th} product component meets categorical PAs of the j_{th} FR in Eq. (7-7). When categorical PAs of the s_{th} product component are different from categorical PAs of the j_{th} FR, a value 0 is returned to z^{j}. It shows that the s_{th} product component cannot meet categorical PAs of the j_{th} FR.

If a product component meets Eq. (7-7), the product component matches categorical PAs of the related FR. Product components that meet both numerical PAs based on Eqs. (7-5) and (7-6) and categorical PAs based on Eq. (7-7) can meet related FRs. Thus, these potential product components are selected for related FRs.

Based on selected potential product components, a design structure is decided by one product component or several combined product components to meet a FR. After suitable design structures are decided for all FRs, these design structures are combined to form product concepts as potential design solutions.

7.1.2 Correlation analysis between FRs and design structures

As different design structures may meet a FR, the performance of different design structures should be evaluated for the best structure to meet a FR. Design structures and FRs are linked by an association relation method to evaluate the performance of design structures. Relations define contributions of design structures to the implementation of FRs as follows.

$$Sup(\mathrm{X}_i^j) = \frac{Sum(\mathrm{X}_i^j)}{N} \tag{7-8}$$

where, $Sup(\mathrm{X}_i^j)$ is a rate of the j_{th} design structures occurred in collected products. X_i^j represents that the i_{th} collected product has the j_{th} design structure. $Sup(\mathrm{X}_i^j)$ represents the total number of collected products with the j_{th} design structure. N is the total number of collected products online.

$Sup(\mathrm{Y}_k)$ is defined for a rate of collected products that meet requirements of the k_{th} FR as follows.

$$Sup(\mathrm{Y}_k) = \frac{Sum(\mathrm{Y}_k)}{N} \tag{7-9}$$

where, $Sum(\mathrm{Y}_k)$ is the total number of collected products that meet requirements of the k_{th} FR.

$Sup(\mathrm{X}_i^j \cup \mathrm{Y}_k)$ is defined as a rate for the total number of collected products that have the i_{th} design structure to meet the j_{th} FR as follows.

$$Sup(\mathrm{X}_i^j \cup \mathrm{Y}_k) = \frac{Sum(\mathrm{X}_i^j) + Sum(\mathrm{Y}_k)}{N} \tag{7-10}$$

$\mathrm{L}(\mathrm{X}_i^j \Rightarrow \mathrm{Y}_k)$ is used to represent the correlation degree of the i_{th} design structure to implement the j_{th} FR as follows.

$$\mathrm{L}(\mathrm{X}_i^j \Rightarrow \mathrm{Y}_k) = \frac{Sup(\mathrm{X}_i^j \cup \mathrm{Y}_k)}{Sup(\mathrm{X}_i^j) \times Sup(\mathrm{Y}_k)} \tag{7-11}$$

Based on the correlation degree, a value can be determined for a positive or negative effect of a structure for a FR. A positive relation between the i_{th} design structure and the j_{th} FR can be decided if $\mathrm{L}(\mathrm{X}_i^j \Rightarrow \mathrm{Y}_k)$ is greater than 1.0, and vice versa.

The correlation degree between FRs and design structures can determine the influence between design structures and FRs. The result is used to evaluate the performance of potential concepts for defining the best design structures to meet FRs.

7.1.3 Determination of the best design structures using pairwise comparisons

Based on defined potential concepts and relations between design structures and FRs, a pairwise comparison is proposed to search the best design structure.

Matrix X is defined for comparing performances of conceptual models to meet each FR as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mk} \end{bmatrix} \tag{7-12}$$

$$x_{ij} = \sum_{i=1}^{k} \mathrm{lift}(\mathrm{X}_i^j \Rightarrow \mathrm{Y}_k) \tag{7-13}$$

where, x_{ij} represents performance of the i_{th} conceptual model to meet the j_{th} FR.

Based on IR of a FR, a pairwise comparison matrix is formed in Eq. (7-14).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1k} \\ r_{21} & r_{22} & \cdots & r_{2k} \\ \cdots & \cdots & r_{ij} & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mk} \end{bmatrix} \tag{7-14}$$

where, r_{ij} is defined based on IR of a FR and performance of the i_{th} concept. v_j is IR of the j_{th} FR.

$$r_{ij} = v_j \times x_{ij} \tag{7-15}$$

D_i is defined as a distance between the i_{th} concept and the best structure to meet the FR in all potential models as follows.

$$D_i = \sqrt{\sum_{j=1}^{k} (r_{ij} - r_j^+)^2} \quad i = 1, 2, \ldots, m \tag{7-16}$$

where, r_j^+ represents the best design structure to meet the j_{th} FR.

$$r_j^+ = \mathrm{Max}\left[r_{ij} \right] \tag{7-17}$$

The overall weight w_i of the i_{th} concept model is defined as follows.

$$w_i = \frac{D_i}{\sum_{i=1}^{n} D_i} \tag{7-18}$$

The weight of each potential concept is defined in Eq. (7-19).

$$W = \left[w_1 \quad w_2 \quad \ldots \quad w_n \right] \tag{7-19}$$

A smaller w_i means a better performance of the design structures in the i_{th} concept model to meet all FRs. Therefore, design structures in a concept model with the lowest value in Eq. (7-19) are selected to define PSs of a product.

7.2 Case study

PSs of the active upper limb rehabilitation device are developed using the proposed method. FRs and IRs of FRs for active upper limb rehabilitation devices are based on the result in Chapter 6 (Shi et al, 2020). There are 10 FRs listed in *Table 7-2*.

Table 7-2 FRs of upper limb rehabilitation devices

FRs		IRs of FRs
FR.1	sensor selection	0.112
FR.2	motor selection	0.072
FR.3	interactive function	0.051
FR.4	adjustable height and length	0.135
FR.5	suitable material	0.035
FR.6	flexible movement structure	0.127
FR.7	portable design	0.121
FR.8	lightweight design	0.079
FR.9	displacement limit	0.123
FR.10	degree of freedom design	0.145

Related devices such as arm and leg rehabilitation devices are searched from the product online sales website. PAs of standard functions from these rehabilitation devices are defined in *Table 7-3*.

Table 7-3 PAs of standard functions from collected rehabilitation devices

No.	Words of standard functions	Components to meet functions	Type of PAs	Name of PAs	Results of PAs		
					1st product	……	7th product
1	Drive arm	Servo motor	Categorical attributes	Type	Closed loop	……	Closed loop
				Material	Steel	……	Steel
			Numerical attributes	Size	35*40*40 cm	……	55*50*50mm
				Accuracy	0.5 mm	……	1.5 mm
				Torque	50 N*m	……	70 N*m
				Power	30 W	……	50 W
		Stepping motor	Categorical attributes	Type	Open loop	……	Open loop
				Material	Steel	……	Steel
			Numerical attributes	Size	55*60*60mm	……	75*80*80 mm
				Accuracy	2.5 mm	……	3.5 mm
				Torque	60 N*m	……	80 N*m
				Power	50 W	……	60 W
		……	……	……	……	……	……
...	……	……	……	……	……	…...	……
176	Support axis ……	Bearing	Categorical attributes	Type	Deep groove	……	Angular contact
				Material	Steel	……	Steel
			Numerical attributes	Force	2500 N	……	3500 N
				Diameter	20mm	……	30mm
				Speed	200 r/s	……	300 r/s
		……	……	……	……	…...	……

Based on the WordNet hierarchy (Ahsaee et al, 2014), words of standard functions in the functional vocabulary library of *Table 7-1* are matched with words of 10 FRs based on their similarities. For example, the similarity between words of FR.4 and the first word of standard functions is defined based on Eqs. (7-1) and (7-2) as follows.

$$s_4^1 = \frac{v_{14}^1 + v_{24}^1 . + v_{31}^1}{\sqrt{(v_{14}^1)^2 + (v_{24}^1)^2 + (v_{34}^1)^2}} = 0.07 \tag{7-20}$$

Based on Eqs. (7-3) and (7-4), FR.4 is matched with the 27_{th} standard function "adjustment" of functions in Table 3 as follows.

$$V_4 = 27 \tag{7-21}$$

Based on PAs in the 27_{th} standard function "adjustment" in *Table 7-3*, 5 categorical attributes and 5 numerical attributes are defined as shown in the first row and fourth row of *Table 7-4* using the functional dictionary of *Table 7-3*. Five categorical attributes include continuity, direction, characteristics, movement, and reciprocity. Five numerical attributes are range, speed, accuracy, load, and size. Results of the five categorical attributes in the second and third rows are defined based on current CRs for meeting FR.4 in the market. Results of the five numerical attributes in the fifth and sixth rows are also defined based on current CRs for meeting FR.4 in the market.

Table 7-4 PAs of FR.4

Categorical attributes		Continuity	Direction	Characteristics	Movement	Reciprocity
	Horizontal adjustment	Continue	Horizontal	Linear	Double	Double
	Vertical adjustment	Continue	Vertical	Linear	Double	Double
Numerical attributes		Range	Speed	Accuracy	Load	Size
	Horizontal adjustment	0.1-1.0m	0.1-1.0m/s	1.0-5.0mm	500N	20*10cm
	Vertical adjustment	0.1-1.5m	0.1-0.3m/s	2.0-5.0mm	2500N	50*20cm

All the potential product components to meet each FR are searched. For example, all the potential design components to meet FR.4, adjustable height and length, are found as shown in *Figure 7-2* by searching related components in *Table 7-3*.

Figure 7-2 Potential product components for meeting FR.4

Numerical attributes of potential product components to meet FR.4 are shown in *Table 7-5*. By using Eqs. (7-5) and (7-6), design components a, b, c, d, and e are selected to meet numerical attributes of FR.4 for the vertical adjustment. Design components e and f are selected to meet numerical attributes of FR.4 for the horizontal adjustment of the device.

Table 7-5 Numerical attributes of potential product components for meeting FR.4

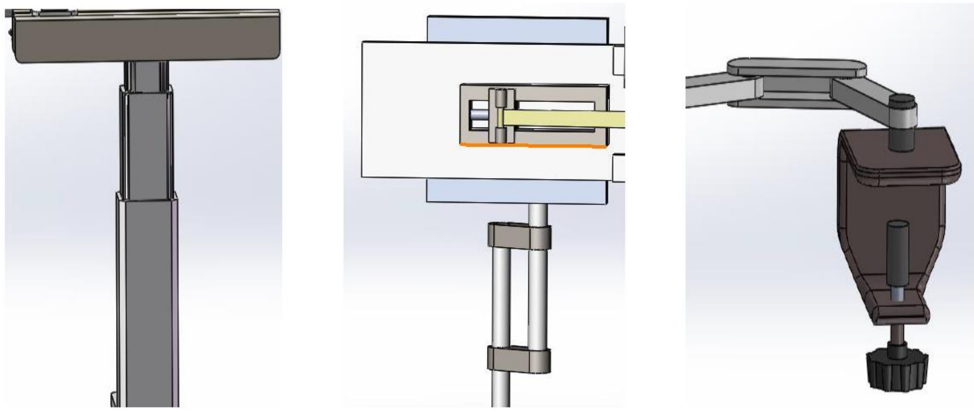
Numerical attributes (a to c)	Name of product components	a	b	c
	Load capacity	0-5000N	0-6000N	0-2000N
	Size	30*10cm	10*20cm	10*10cm
	Transmission distance	0-200cm	0-300cm	0-150cm
	Accuracy	1.5-8.0 mm	0.5-5.0 mm	0.1-2.0 mm
	Speed	0.1-0.5 m/s	0.1-0.3 m/s	0.1-0.5m/s
Numerical attributes (d to e)	Name of product components	d	e	f
	Load capacity	0-2000N	0-3000N	0-1000N
	Size	10*20 cm	10*20cm	8*8cm
	Transmission distance	0-150cm	0-150cm	0-70cm
	Accuracy	0.5-2.0 cm	0.5-1.0 cm	0.5-1.5 cm
	Speed	0.1-0.6m/s	0.1-1.5m/s	0.1-1.5m/s

Categorical attributes of potential product components to meet FR.4 are shown in *Table 7-6*. By using Eq. (7-7), suitable product components are defined for the vertical adjustment for FR.4. For all values 1 in a column, the related product components can meet categorical attributes of a FR. Therefore, Components b, d, and e can meet categorical attributes of the vertical adjustment for FR.4. Components a, b, c, e, and f can meet categorical attributes of the horizontal adjustment for FR.4. Therefore, suitable design components for vertical adjustment are b, d, and e, and suitable product components for horizontal adjustment are e and f.

Table 7-6 Categorical attributes of potential product components for meeting FR.4

Name of categorical attributes for vertical adjustment in FR.4	PAs of FR.4	Components					
		a	b	c	d	e	f
Continuity of movement	Continue	1	1	1	1	1	1
Rate characteristics of movement	Linear	1	1	1	1	1	1
Reciprocity of movement	Double	1	1	1	1	1	0
Load for axial direction	Vertical	0	1	0	1	1	1
Direction of movement	Double	1	1	1	1	1	1
Name of categorical attributes for horizontal adjustment in FR.4	PAs of FR.4	Components					
		a	b	c	d	e	f
Continuity of movement	Continue	1	1	1	1	1	1
Rate characteristics of movement	Linear	1	1	1	1	1	1
Reciprocity of movement	Double	1	1	1	1	1	1
Axial direction	Horizontal	1	1	1	0	1	1
Direction of movement	Double	1	1	1	1	1	1

Based on compatibility between vertical and horizontal adjustment components, three suitable structures I, II, and III to meet FR.4 are found as shown in *Figure 7-3*. Structure I is formed by vertical adjustment component e and horizontal adjustment component e. Structure II has vertical adjustment component d and horizontal adjustment component e. Structure III uses vertical adjustment component b and horizontal component f.



Structure I Structure II Structure III

Figure 7-3 Design structure solutions for FR.4

Related design structures to meet the other 9 FRs are decided by the same process. All the suitable design structures of geometrical and material characteristics to meet FRs are defined and stored. After checking the compatibility between all the design structures to meet 10 FRs, the suitable design structures are combined for conceptual models. In the end, design structures for 12 potential models are formed for the concept design solution in *Table 7-7*.

Table 7-7 Design structures of 12 potential models

Models	Design structures						
	Sensor selection	Motor selection	Exercise feedback	Adjustment structure	Material	Base	DOF
1	Displacement	Servo	Sound	II	Metal& Plastic	Fixed frame	3
2	Angle	Stepping	Force	I	Metal	Guide	6
3	Contact	Servo	Vision	III	Metal	Wheels	4
4	Displacement	Servo	Sound& vision	II	Metal& Plastic	Fixed frame	5
5	Contact	Stepping	Sound	I	Plastic	Wheels	3
6	Angle	Servo	Force	III	Metal	Wheels	6
7	Contact	Stepping	Vision	III	Plastic	Guide	4
8	Displacement	Servo	Sound& vision	II	Metal& Plastic	Screw bolt	5
9	Contact	Servo	Force	I	Metal	Wheels	6
10	Displacement	Stepping	Sound& vision	II	Metal& Plastic	Screw bolt	3
11	Contact	Stepping	vision	III	Plastic	Guide	5
12	Angle	Servo	Force	II	Metal	Wheels	5

These potential concepts in *Table 7-7* are further evaluated to decide the best concept as the final design solution as follows.

For searching the best concept model from 12 potential concept models, performances of different solutions are evaluated to meet FRs using relations between FRs and design structures of rehabilitation devices.

There are 235 rehabilitation devices collected from the product online website. Product specifications of these 235 rehabilitation devices are searched by the focused crawling method from the product online shopping website. The performance of the most popular existing rehabilitation device is used as a benchmark product (Maciejasz et al, 2014). The performance of each FR for each collected product can be defined based on values of the structure specifications. If a product from online websites has a better performance for a FR than the benchmark product, the value is defined as 1. Otherwise, the value is assigned as 0. Results are shown in *Table 7-8*.

Table 7-8 FRs evaluations of active upper limb rehabilitation devices

Device #	Performance evaluation of FRs									
	FR.1	FR.2	FR.3	FR.4	FR.5	FR.6	FR.7	FR.8	FR.9	FR.10
1	1	0	1	0	1	1	1	1	1	1
2	0	1	0	1	1	1	0	1	0	1
3	0	1	0	1	0	0	1	0	0	0
4	1	0	1	0	1	0	1	1	1	0
5	0	1	0	0	0	1	1	0	1	1
6	1	0	1	1	1	1	0	1	0	1
7	0	1	1	0	1	0	1	1	0	0
8	1	1	1	1	0	1	0	0	1	1
…	…	…	…	…	…	…	…	…	…	…
235	1	1	1	1	0	1	1	1	1	0

The correlation degree of structures and FRs is defined using Eq. (7-11). For example, $L(X_2^{10} \Rightarrow Y_4)$ in Eq. (7-22) is formed by Eqs. (7-8) to (7-11), which shows that the second design solution contributes FR.4 for height and length adjustments significantly.

$$L(X_2^{10} \Rightarrow Y_4) = \frac{0.90}{0.25} = 3.6 \tag{7-22}$$

Correlation degrees of three adjustment structures and each FR are listed in *Table 7-9* for the support level of an adjustment structure for a FR. For example, 10 relations between adjustment structure II and 10 FRs are formed. Structure II can improve the performance of FR.4 adjustment height and length significantly (3.6, strong), FR.6 flexible movement greatly (2.5, strong), but a negative influence on FR.8 lightweight (0.7, weak). In addition, there are not relations between adjustment structure II for other 7 FRs including FR.1, FR.2, FR.3, FR.5, FR.8, FR.9, and FR.10.

Table 7-9 Correlation degrees of FRs and adjustment structures

Adjustment structures	Correlation degree L									
	FR.1	FR.2	FR.3	FR.4	FR.5	FR.6	FR.7	FR.8	FR.9	FR.10
Structure I	0.9	1.1	1.0	1.4	1.0	2.1	1.0	1.0	1.1	1.0
Structure II	1.0	1.0	1.0	3.6	1.0	2.5	1.0	0.7	1.0	1.0
Structure III	1.0	1.0	1.0	1.6	1.0	3.9	0.7	0.7	1.0	1.0

Based on Eqs. (7-8) to (7-11), all the relations between FRs and design structures are used to evaluate the performance of potential concept models. *Table 7-9* shows that structure II has the highest contribution to meet FR.4 and structure III has the highest contribution to meet FR.6. These relations can determine the influence of structures for FRs, which can evaluate the performance of potential concept models to select the best design solution.

Based on the 12 potential concept solutions and relations between FRs and design structures, a pairwise comparison matrix is built to search the best concept of upper limb rehabilitation devices. The performance of potential concepts to meet 10 FRs is used as the design objective for the pairwise comparison. IRs of FRs are assigned based on data (Shi et al, 2020) as follows.

$$\mathrm{FRs} = \begin{bmatrix} 0.112 & 0.072 & 0.051 & 0.135 & 0.035 & 0.127 & 0.121 & 0.079 & 0.123 & 0.145 \end{bmatrix} \tag{7-23}$$

A pairwise comparison matrix for the concept comparison is formed using Eqs. (7-12) to (7-15) as follows.

$$X = \begin{bmatrix} 3.5 & 2.6 & 7.5 & 5.3 & 3.5 & 8.4 & 3.6 & 1.4 & 2.1 & 3.2 \\ 5.3 & 1.6 & 1.6 & 3.3 & 5.4 & 3.2 & 7.5 & 3.5 & 5.3 & 2.3 \\ 4.3 & 3.5 & 3.6 & 5.4 & 3.3 & 4.6 & 4.5 & 6.3 & 4.2 & 1.2 \\ 2.1 & 4.3 & 2.5 & 6.4 & 6.8 & 2.4 & 3.1 & 2.3 & 2.1 & 2.2 \\ 3.6 & 2.7 & 3.3 & 1.2 & 4.2 & 6.7 & 5.7 & 1.1 & 3.2 & 2.6 \\ 7.6 & 5.3 & 2.5 & 5.5 & 1.2 & 8.1 & 3.1 & 6.6 & 5.5 & 7.7 \\ 5.5 & 2.1 & 5.5 & 4.8 & 7.8 & 9.5 & 8.5 & 7.3 & 7.6 & 5.2 \\ 4.3 & 6.5 & 6.5 & 3.2 & 6.5 & 1.5 & 3.6 & 8.1 & 4.5 & 3.2 \\ 2.5 & 3.2 & 3.4 & 4.5 & 4.2 & 6.3 & 1.2 & 4.3 & 5.3 & 1.2 \\ 1.7 & 6.7 & 2.6 & 7.3 & 8.2 & 5.3 & 2.5 & 1.3 & 5.5 & 3.3 \\ 7.6 & 7.2 & 7.5 & 3.2 & 7.5 & 6.2 & 3.1 & 6.6 & 1.2 & 4.5 \\ 2.4 & 3.3 & 5.2 & 4.2 & 1.2 & 2.6 & 5.2 & 7.6 & 8.8 & 6.5 \end{bmatrix} \tag{7-24}$$

By using Eqs. (7-16) to (7-19), performances of these 12 potential models are decided as shown in Eq. (7-25). Results show that the fourth potential concept model has the lowest value 0.053, which indicates the best performance for the active upper limb rehabilitation device. The performance ranking of the 12 models is defined in Eq. (7-25).

$$\mathrm{W} = \left[0.135, 0.067, 0.071, 0.053, 0.058, 0.092, 0.077, 0.069, 0.101, 0.092, 0.075, 0.110\right]^T \tag{7-25}$$

Therefore, the fourth concept model shown in *Table 7-10* has the best structures by comparing 12 potential models.

Table 7-10 The concept model of the device with the best design structures

FRs	Design structures for the best concept model
FR.1	Sound & vision sensor
FR.2	Servo motor
FR.3	Sound & vision & Force feedback
FR.4	Vertical adjustment: Telescopic rod Horizontal adjustment: Slide way
FR.5	Base: Steel; Arm: plastic
FR.6	Foldable rod
FR.7	Wheels of base
FR.8	Plastic material for arm; Hollow rod
FR.9	Limit switch
FR.10	5 DOF (Shoulder flexion; Shoulder rotation; Elbow flexion; Forearm pronation; Wrist flexion)

The rehabilitation device designed by the proposed method in *Table 7-10* has 5 DOF to balance the movement accuracy and cost. The type of vertical movement for the height adjustment is a telescopic rod to balance the adjustment range and lightweight. The concept design solution can define the best PSs for the best overall performance in all the potential models.

7.3 Verification of the proposed method

For verifying the proposed method, active upper limb rehabilitation devices designed by existing methods are compared to the device designed by the proposed PSs definition method.

Device A shown in *Figure 7-4* (a) is the best active upper limb rehabilitation device sold from Alibaba. The type of height adjustment in rehabilitation device A is a slider way. Device B shown in *Figure 7-4* (b) is the best active upper limb rehabilitation device sold from Hocoma. Hocoma is one of the most famous online websites for selling rehabilitation devices. The height adjustment structure is defined by a slider way structure.

(a) Device A in the market (b) Device B in the market

Figure 7-4 Benchmark devices A and B

Structures of devices A and B are defined by collected specifications from sellers online as shown in *Table 7-11*.

Table 7-11 Structures of active upper limb rehabilitation devices in the market

FRs	Structures of devices in the market	
	Device A	Device B
FR.1	Non-contact displacement sensor	Angle displacement sensor
FR.2	Stepping motor	Servo motor
FR.3	Force feedback	Sound & Force feedback
FR.4	Vertical adjustment: Telescopic rod Horizontal adjustment: Slide & guide	Vertical adjustment: Slide way Horizontal adjustment: Linkage
FR.5	Base: Steel; Arm: plastic	Base: Steel; Arm: Steel
FR.6	Adjustable rod	Adjustable linkage
FR.7	Wheels of base	Wheels of base
FR.8	Aluminum material for arm	Aluminum material for arm
FR.9	Limit switch	Limit switch
FR.10	4 DOF (Shoulder flexion; Shoulder rotation; Elbow flexion; Wrist flexion)	6 DOF (Shoulder flexion; Shoulder rotation; Elbow flexion; Forearm pronation; Wrist flexion; Wrist deviation)

Device A has problems for meeting FR.2, FR.8, and FR.10. The adjustment structure is not suitable for the rehabilitation exercise. Although device A can provide enough adjustment ranges to complete the exercise, the size and weight of the device are increased seriously, which affects the device performance. In addition, the motor selection to meet FR.2 in device A is a stepping motor, which influences the movement accuracy for the exercise. Device A has a problem of the DOF selection. 4 DOF structures cannot provide an accurate trajectory for human daily actions, which cannot provide rehabilitation movements for patients smoothly and accurately.

Device B has problems for meeting FR.4, FR.8, and FR.10. The structure of device B is very complex because of 6 DOF, which increases manufacturing cost. However, the movement accuracy of device B in rehabilitation exercises is similar to devices with 5 DOF. In addition, the size of device B is very large because its linkages are not retractable to meet patients with different heights. Therefore, device B cannot meet the requirement of rehabilitation exercises.

The model designed by the proposed method has a better performance for the arm recovery because it has a better structure to complete rehabilitation exercises. It meets all FRs compared to other devices. The model designed by the proposed method has 5 DOF for the arm to complete rehabilitation exercises accurately. For example, adjustment structures of the proposed model include a telescopic rod for the vertical adjustment and a slide way for the horizontal adjustment, which balances different FRs such as lightweight and portable requirements.

By using the association relation method, relations of design structures and FRs are considered accurately to search the best design structures solution from all potential concept models for defining PSs of the device. Therefore, the upper limb rehabilitation device designed by the proposed method has the best performance compared to the existing devices.

7.4 Summary

This chapter proposes a PSs definition method using WordNet hierarchy and association relation methods. PAs of FRs are defined based on similarity of FRs and standard functions of existing product components using the WordNet hierarchy. By searching suitable product components to meet attributes of FRs using the knowledge database of mechanical components, different potential concepts can be formed for potential design solutions. The product performance to meet each FR is evaluated based on relations between FRs and design structures using an association relation method. Several design structures of potential concept models are further evaluated to select the best design structures of concept model for defining PSs of a product by a pairwise comparison method. The proposed PSs definition method is verified in a case study of design for an active upper limb rehabilitation device.

Chapter 8 Conclusion and future work

8.1 Research summary

A new CR definition method is proposed based on the data crawling and AP clustering method. Word vectors are determined using the CBOW method. After filtering online customer reviews using parts of speech and frequency of words, filtered words are clustered into groups by the AP clustering method. CRs are then defined by exemplars in each group and similarity between exemplars and general CRs. According to the case study and experiment of the upper limb rehabilitation device, the proposed method is verified for defining CRs effectively and accurately from online customer reviews.

A new IRs of CRs determination method is proposed to meet CRs by a spectral clustering method based on categorical attributes in the Kano model and numerical attributes in the IPA model. A Laplace matrix is designed to improve accuracy of the classification by considering conflict comments from different customers to define IRs of CRs. For verifying the proposed method, four upper limb rehabilitation devices are designed based on IRs of CRs using three existing IRs determination methods and the proposed method. Results show that the design of rehabilitation devices based on IRs of CRs from the proposed method has the best function for completing the rehabilitation exercise.

A new FRs implementation method is proposed based on sentence meaning using the word vector. The function implementation of products is defined based on specifications of crawled products. The customer satisfaction is decided based on the meaning of sentences. The function implementation is determined by the semantic similarity. A fitting curve is formed by the customer satisfaction degree and function implementation degree using the polynomial fitting and least-square methods. Based on the slope of the fitting curve, the minimum and maximum function implementations are defined to guide a concept design. The proposed method can be applied for products with available online sale information such as electric devices, household appliances, and vehicles.

An objective weighting method is proposed for defining IRs of FRs using information entropy, HoQ, and benchmarking methods. The degree of relevance between CRs and FRs is decided by the AHP method. The information entropy and benchmarking methods are integrated to define similarity of performances of selected benchmarking products to meet a FR, which improves the accuracy and objectiveness in defining IRs of FRs. Design of rehabilitation devices in the case study verifies the proposed method compared to solutions from the existing weighting method.

A PSs definition method is developed using WordNet hierarchy and association relation methods. PAs of FRs are defined based on similarity of FRs and standard functions of existing product components using the WordNet hierarchy. By searching suitable design structures to meet attributes of FRs using the knowledge database of mechanical components, different potential concepts are formed for potential design solutions. The product performance to meet each FR is evaluated based on relations between FRs and design structures using an association relation method. Potential concept models are further evaluated to select the best design structures of the concept model to define PSs of a product by a pairwise comparison method. The proposed method is verified in a case study of design for an active upper limb rehabilitation device.

8.2 Research contributions

This research proposes big data-based methods to improve the accuracy and efficiency of decision-making in defining CRs, FRs, and PSs. Research contributions are as follows.

- For the CRs definition: 1) Efficiency of defining CRs is improved by automatically collecting a huge amount of online customer reviews from the product sales webpage using the focused crawling method. 2) Accuracy of defining CRs is improved by combining different online comments from customers for an exemplar to represent the meaning of all the words in a cluster using the AP clustering method. 3) The proposed IRs of CRs definition method can determine CRs to best match the consumer interests.

- For the IRs of CRs definition: 1) Efficiency of defining IRs of CRs is improved by clustering CRs automatically using a spectral clustering method. 2) Accuracy of defining IRs of CRs is improved by combining different comments of customers from Kano and IPA models using a similarity matrix in the spectral clustering method. 3) Customer satisfaction is improved in the product design using the accurate IR of CRs.
- For the FRs implementation: 1) A curve formula is formed to determine relationships between the customer satisfaction and function implementation by combining the hierarchical semantic similarity and polynomial fitting methods, which defines the quantitative trend of customer satisfaction based on the function implementation accurately. 2) Based on the defined relation between customer satisfaction and function implementation, the best quantitative function implementation is determined to meet each FR.
- For the IRs of FRs definition. 1) The performance of FRs for meeting a CR is compared to define degree of relevance between CRs and FRs using the AHP method. 2) An accurate and objective weighting method is proposed based on the information entropy and benchmarking products. 3) The information entropy and benchmarking methods are integrated to define the performance similarity of benchmarking products to meet a FR.
- For the PSs definition. 1) By using the focused crawling method, a huge amount of product structures and specifications is efficiently collected from online products to build a functional dictionary for selecting suitable design components to meet different FRs. 2) PAs of FRs are determined based on similarity of FRs and functions of existing product structures using the WordNet hierarchy, which can accurately and efficiently define required parameters to meet FRs. 3) Based on IRs of FRs defined by customer reviews, potential design schemes are evaluated and compared by a pairwise comparison method to define design structures to meet FRs with high IRs. 4) Relations between structure schemes and FRs are defined by the association relation method to determine the best design solution from potential schemes in the concept design process.

8.3 Future work

The future work will consider the automatic analysis of online customer reviews for defining CRs, FRs, and PSs and optimization of different design factors for determining IRs of CRs and IRs of FRs. Based on the integrity, authority, and consistency of collected data, unrelated customer reviews will be filtered automatically to further improve the accuracy of raw data from online customer reviews. The filtered customer reviews will be analyzed automatically to define CRs and FRs based on the meaning similarity between collected customer reviews and characters of products by a deep reinforcement learning method. PSs of products will be defined automatically by searching patents of related products without assistance of the expert.

The effect of different design factors from Kano and IPA models will be determined based on relations between design factors and CRs to further improve the accuracy for the proposed IRs of CRs method. In addition, the influence of different design factors for performances of benchmarking products will be determined to further improve the accuracy for the proposed IRs of FRs method.

Papers published and accepted during this research

Following paper relates to contents of Chapter 3.

1. Yanlin Shi, Qingjin Peng. Definition of customer requirements in big data using word vectors and affinity propagation clustering. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 235(5), 2021, 1279-1291. https://doi.org/10.1177/09544089211001776.

Following papers relate to contents of Chapter 4.

2. Yanlin Shi, Qingjin Peng. A spectral clustering method to improve importance rating accuracy of customer requirements in QFD. The International Journal of Advanced Manufacturing Technology, 107, 2020, 2579–2596. DOI: 10.1007/s00170 -020-05204-1.

3. Yanlin Shi, Qingjin Peng. A VR based user interface for the upper limb rehabilitation. Procedia CIRP 78, 2018, 115-120. DOI: 10.1016/j.procir.2018.08.311.

Following paper relates to contents of Chapter 5.

4. Yanlin Shi, Qingjin Peng. Enhanced Customer Requirement Classification for Product Design using Big Data for Improved Kano Model. Advanced Engineering Informatics, 49, 2021. https://doi.org/10.1016/j. aei.2021.101340.

Following papers relate to contents of Chapter 6.

5. Yanlin Shi, Qingjin Peng, Jian Zhang. An Objective Weighting Method of Function Requirements for Product Design Using Information Entropy. Computer-Aided Design & Applications, 17(5), 2020, 966-978. https://doi.org/10. 14733/ cadaps.2020.966-978.

6. Yanlin Shi, Qingjin Peng. Improved Benchmarking Method Using Kinematics Analysis in Design of an Upper Limb Exoskeleton Rehabilitation Device. ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. https://doi.org/10.1115/DETC2018-85465.

Following paper relates to contents of Chapter 7.

7. Yanlin Shi, Qingjin Peng. Trajectory planning of rehabilitation exercise using an integrated reward function in reinforcement learning. Computer-Aided Design &

Applications, 19(5), 2022, 1042-1054. https://doi.org/10.14733/cadaps.2022.1042-1054.

8. Yanlin Shi, Qingjin Peng. Conceptual design of product structures based on WordNet hierarchy and association relation. Journal of Intelligent Manufacturing (Revision has been submitted under review).

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