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A Customer-Oriented Approach for Decision Support on New Product Development for ODM Clients

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Japan Advanced Institute of Science and Technology

Doctoral Dissertation

A Customer-Oriented Approach for Decision Support on New Product Development for ODM Clients

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Abstract

Due to a rising of online marketing, there are abundant of Original Design Manufacturer (ODM) clients existing in the market. To capture the market share, it is necessary for them to launch a customer-oriented product, which leads to the customer satisfaction and a success of the product at the end. In doing so, ODM clients need decision supports on their tasks to keep customers' focuses in all stages of the new product development (NPD) processes. However, ODM clients' tasks receive little attention in the literature and there is no decision support for ODM clients in NPD.

Motivated from these limitations, a customer-oriented linguistic approach for decision support on NPD for ODM clients is proposed in this study. The study focuses on three ODM clients' tasks for developing a new beverage product. Those tasks are 1) identifying customer-oriented product concept, 2) providing product specification to ODM manufacturers, and 3) screening an evaluation on go/no-go product. To support these three ODM clients' tasks, three models are developed.

For the first ODM clients' task, a model for prioritizing customer-oriented product concepts is developed so that a set of suitable product concepts is identified. In this model, a linguistic computation approach based on membership functions is applied to prioritize customer-oriented product concepts.

For the second ODM clients' task, a model for translating customer requirements to manufacturing requirements is introduced so that ODM clients are able to provide a product specification to their ODM manufacturers for supporting the manufacturing process. In this model, a linguistic computation based on term index is used to analyze customers' preferences on product characteristics.

For the third ODM clients' task, a model for evaluating customer-oriented product performance is developed so that ODM clients are able to screen go/no-go product. Here, the product performance is determined from the difference between the interval target linguistic terms and the interval perceived linguistic terms. In this model, a linguistic computation based on term index is used to analyze the interval perceived linguistic terms from customers.

The critical challenge in developing these three models is the loss of information from the approximation process in retranslating computed linguistic information to its initiated domain. Generally, the results of computing linguistic information do not match with their initial linguistic terms. Thus, the approximation process is needed to retranslate the computational linguistic results into their initial domain. However, the approximation process usually leads to the loss of information.This loss of information implies a lack of precision in the final results. Hence, it is important to develop models for supporting ODM clients' tasks that can avoid the loss of information during the evaluation processes. In this study, such an issue is the main concern in developing three models.

To demonstrate the effectiveness and applicability of the proposed models, a case study of developing a new soy milk beverage product is used. Consequently, all models show their abilities over the existing models. In summary, the effort in this study is to analyze linguistic information existed in ODM clients' tasks in order to provide a recommendation on NPD for ODM clients.

Keywords: Multiple criteria group decision making; Interval linguistic assessment; Probability distribution; Manhattan distance measure; New product development; ODM clients

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Sirin Suprasongsin

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Abbreviation and Terminology

Abbreviation	**Terminology**
DM	Decision Maker: The one who make a decision such as managers, shareholders, committee, etc.
NPD	New Product Development: It covers all processes ranging from product identification through product launching. In other words, it is a complete process bringing a product to the market.
ODM	Original Design Manufacturer: It is a company that designs and manufactures the actual product based on specification from its clients. It does not have its own brand product.
OEM	Original Equipment Manufacturer: It is a company that manufactured parts or equipments, which are markets by other companies, but it owns its brand product.
OBM	Original Brand Manufacturer: It is a company that sells an entire product made by a second company. It does not have its own brand product.
PLTS	Probabilistic Linguistic Term Set:
PULTS	Probabilistic Uncertain Linguistic Term Set:
RS	Respondent: The one who provides opinion on subject. In this thesis, it is the one who assess the questionnaire for gathering product perception on various aspects.
SD	Semantic Differential: It is a method mostly used in Kansei engineering technique.

Chapter 1

Introduction

In this chapter, a research background, a research motivation, a scope of work, a research goal, a research significance, and a research challenge are demonstrated. Finally, the structure of this thesis is presented.

1.1 Research background and Research motivation

A rising of online marketing increases an opportunity for Original Design Manufacturer (ODM) clients in expanding their sales and making an advertisement. Currently, there exists abundance of ODM clients in the market. To capture the market shares, a customer-oriented product is a key tool. The customer-oriented product is a product produced based on an understanding of customers' needs. Indicated by Ulrich and Eppinger [6], a company's success depends on the abilities to identify customer needs and to quickly create customer-oriented products. Generally, the customer-oriented product creates a customer satisfaction. Then, the satisfied customers create the customer loyalty, which leads to the steady stage of future cash flow. Finally, the cash flow will ensure the success of the company. The chain of value creation on customer-oriented product is presented in Figure 1.1.

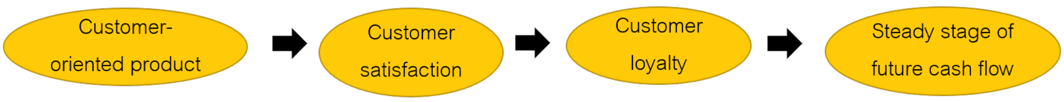

Figure 1.1: Value creation on customer-oriented product

However, it is difficult for ODM clients to research a whole process for a new customer-oriented product because it requires a high investment and specialties. Cooperation among organizations in supply chain, e.g. manufacturers, suppliers, and customers, may be a great strategy for ODM clients in developing a new customer-oriented product [7], [8].

A collaborative R&D network within organizations can be generally classified into three main modes based on their knowledge and specialty, which are Original Equipment Manufacturer (OEM), Original Design Manufacturer (ODM), and Original Brand Manufacturer (OBM). The knowledge flows among them are summarized in Table 1.1 [4].

OEM (Original Equipment Manufacturer) owns the brand name and markets the final products [9]. It manufactures the products that will be bought by a company and then sold under the purchasers brand name. OEM has a responsibility to produce the product they are assigned to make. The products have to meet the needs of the customers.

OBM (Original Brand Manufacturer) is a company that retails their own branded products that are either the entire products or component parts produced by a second company. They sell the goods under their own brand name in order to add value. The OBM will be responsible for everything including the production and development, supply chain, delivery and the marketing [10].

ODM (Original Design Manufacturer) is responsible for designing and manufacturing a product. ODM manufacturers sell the products that they design and produce to its clients, they do not sell directly to the market [10]. For example, HTC manufactures the Google Nexus One smartphone for Google. In ODM business, HTC acts as ODM manufacturer, while Google is an ODM clients [11], [12] .

From Table 1.1, ODM business consists of three parties, which are client, manufacturer, and supplier. Two main roles of ODM clients in new product development (NPD) are (1) providing product ideas to manufacturers for manufacturing a client-based product, and then (2) verifying a finished product. For example, a company has concepts for a 'new smart car' not only as fast, stable, and comfortable, but also as a driving trainer training the driving habits, i.e. economic drive, safe drive, etc. ODM clients have done the market research and know that they can market such a product with these concepts. Then, ODM clients provide their concepts to their contract ODM manufacturers to manufacture the actual product according to the given concepts. In some cases, ODM clients or ODM manufactures may outsource ODM suppliers for product development services, product designing services, etc, based on their own capabilities.

Table 1.1: An example of the distribution of tasks for new product development among OEM, ODM, and OBM [4]

Task for new product development	OEM			ODM			OBM		
	Client	Manufacturer	Supplier	Client	Manufacturer	Supplier	Client	Manufacturer	Supplier
1. Product idea	✓			✓			✓		
2. Electrical, Mechanical, Safety design	✓				✓			✓	
3. Design of modification, BOM producing		✓			✓			✓	
4. Concept, exterior design for parts			✓			✓			✓
5. Sample trying, mold development			✓			✓			✓
6. Sample design, RD test		✓			✓			✓	
7. Function verification	✓			✓				✓	
8. Pilot production		✓			✓			✓	
9. Market production		✓			✓			✓	

In summary, this section has discussed the characteristics of developing new product for ODM clients. Firstly, ODM clients need to provide product ideas to ODM manufacturers, and then verify the actual product from them.

These ODM clients' tasks involve with qualitative information and multiple attributes in evaluating customers' preferences and presenting them in the actual products. In MCDM problems with qualitative information, the main issues are how to represent and aggregate linguistic information. Fuzzy set theory proposed by Zadeh [13] is widely applied to deal with linguistic information. Basically, the results of computing linguistic information do not match with their initial linguistic terms. Thus, the approximation process is needed to retranslate the computational linguistic results into their initial domain. However, the approximation process usually leads to the loss of information. This loss of information implies a lack of precision in the final results. Hence, it is important to develop models for supporting ODM clients' tasks that can avoid the loss of information during the evaluation processes.

1.2 Scope of work

Despite the high growth rate of ODM clients, there are limited works developing the decision support models on new customer-oriented product development (NPD) for ODM clients. Taking this consideration into account, this research aims at proposing decision models for supporting ODM clients' tasks in developing the new customer-oriented product.

To scope the work, this research focuses only three tasks of ODM clients for developing a new Thai-tea soy milk beverage product. The three focused tasks are as follows.

1. Identifying customer-oriented product concepts

2. Providing product specification to ODM manufacturers

3. Screening an evaluation on go/no-go product

1.3 Research goal

The goal of this research is to develop decision models that can avoid the loss of information in linguistic computational processes for supporting three ODM clients' tasks in developing a new customer-oriented beverage product. To obtain this goal, three models are developed in support of three ODM clients' tasks as explained in details as follows.

1.3.1 Model 1

Task 1: Identifying customer-oriented product concept

To accomplish the first ODM clients' task, the proposed model prioritizes the customer-oriented product concepts. To do so, firstly, ODM clients provide the list of product concepts. Then, the target customers are asked to express their preferences on the product concepts from the list through a questionnaire survey using the interval linguistic terms. Next, the decision model is applied to analyze customers' preferences. Finally, a ranking of preferable product concepts is identified. The framework for ODM clients' task 1 is depicted in Figure 1.2.

1.3.2 Model 2

Task 2: Providing product specification to ODM manufacturers

To accomplish the second ODM clients' task, the proposed model translates customer requirements (CRs) on the beverage taste to manufacturing requirements (MRs). To do

Figure 1.2: A framework for Task 1

so, customers are first asked to provide their preferences on the product prototype based on the given aspects, i.e. sweetness degree, creamy degree, and Thai-tea smell degree, by using the questionnaire survey. Then, the differences on aspects between CRs and the product prototype are determined by the proposed model. Moreover, the proposed model is able to convert CRs to MRs by using some relative equations. Finally, the proposed decision model will encourage manufactures better understand customer needs by providing a technical product specification to ODM manufacturers. The framework for ODM clients' task 2 is depicted in Figure 1.3.

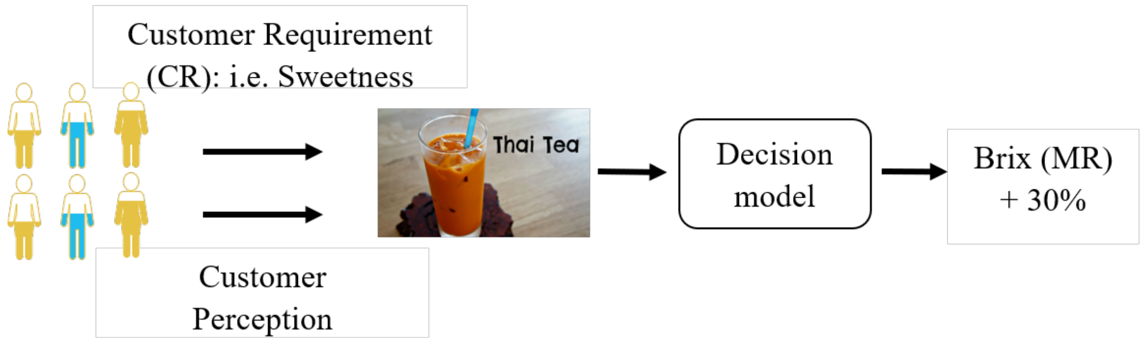

Figure 1.3: A framework for Task 2

1.3.3 Model 3

Task 3: Screening an evaluation of go or no-go product

To accomplish the last ODM clients' task for this research, the proposed model determines the fitness degree of the target product concepts and the perceived product concepts. Here, the target product concepts refer to the given concepts from ODM clients, while the perceived product concepts refer to the actual customers' perceptions on product concepts. To do so, two sets of linguistic information are gathered at the beginning by using a questionnaire survey.

- The first one, called 'Interval target linguistic terms ' , is gathered from ODM clients for targeting the product concepts.

- The second one, called 'Interval perceived linguistic terms ' , is collected from customers for assessing customers' perceptions on concepts from the actual product.

Having collected two sets of information, a decision model is applied to evaluate the difference between 'Interval target linguistic terms ' and 'Interval perceived linguistic terms ' . The differences are represented by the fitness degree. Obtaining the fitness degree can further support the decision on launching a new customer-oriented product. If the fitness degree passes the ODM clients' acceptable levels, it means that the actual product is able to reflect ODM clients' requirements, and it is ready to be launch to the market. The framework for ODM clients' task 3 is depicted in Figure 1.4.

Figure 1.4: A framework for Task 3

1.4 Research significance

New product development (NPD) project generally composes of many processes ranging from product-concept identification through product launch [14], [15]. As stated by Calatone [16], initially screening the product ideas significantly encourages managers to eliminate the risky product ideas at the beginning stage before high investment are made and opportunity cost incurred. In addition, Lin et al. [17] also indicated that initial screening the product ideas has a highest correlation with new product prior to commercialization resulting in resource consumption. Thus, a process of screening product ideas is a very important task in NPD project [18]. In practice, knowing what are the important product ideas may not enough to gain competitive advantages for NPD. It is also necessary to keep those ideas through product launch.

In short, the significances of this research can be summarized as the following points.

- The proposed models are able to smoothen the work flow between ODM clients and ODM manufacturers.
- The proposed models are able to support ODM clients' tasks.
- The proposed models are able to suggest a manufacturing department in specifying manufacturing requirements for manufacturing a product.
- The proposed models are able to support marketing department to (1) clarify the product identity, and (2) ensure the product concepts on the actual product.

1.5 Research challenge

The issue on identifying product ideas and keeping those product ideas through product launch have some challenges as the following.

- Product ideas are subjective and qualitative information, which are uncertain and ambiguous in nature. In other words, it is the customers' tacit knowledge. Thus, it is difficult to represent them as the explicit knowledge.
- It is a multiple criteria group decision making (MCGDM) problem. Thus, it is difficult to aggregate individual customers' opinions, and provide a compromised recommendation to ODM clients.
- Normally, there are some losses of information during the approximation process when several linguistic information are computed. It is also challenging in developing a model that can avoid those losses.

In this research, the challenges and difficulties addressed above will be alleviated. The proposed models are able to accomplish three focused ODM clients' tasks for developing new Thai-tea soy milk beverage product. The solutions importantly encourages ODM clients to make a further campaign, promotion, and other marketing strategies.

1.6 Overview of the Thesis

A structure of thesis is divided into six chapters, as illustrated in Figure , and are explained in details as follows.

- Chapter 1 describes the research background and research motivation. In the research background, the characteristics of new product development (NPD) for ODM clients are defined. Next, the scope of work in NPD for ODM clients' tasks is addressed. Then, the research goals, research significances and research challenges are presented. Finally, a thesis organization is provided.

- Chapter 2 presents a research background and some literature reviews on linguistic approaches for multiple criteria decision making problems including linguistic approaches based on approximation models and term-based models. In addition, other related knowledge are also recalled.

- Chapter 3 proposes a model for achieving ODM clients' task 1. Here, a linguistic approach based on approximation model is exploited. A new model called 3-tuple fuzzy linguistic model is proposed to prioritize the customer-oriented product concepts. Next, the normalization and aggregation processes for 3-tuple fuzzy linguistic model is introduced. Finally, a case study in a private company in Thailand is presented to show the applicability of the proposed model.

- Chapter 4 presents a model for achieving ODM clients' task 2. A new 3-tuple linguistic distance-based model is proposed to support decision on manufacturing a new customer-oriented product. The proposed model is based on linguistic term-index based approach. The effectiveness of the proposed model is presented through a case study in a private company in Thailand.

- Chapter 5 presents a model for achieving ODM clients' task 3. Similar to ODM clients' task 2, a 3-tuple linguistic distance based model is proposed to evaluate customer-oriented product performance. The proposed model is compared with the existing model to shows its effectiveness. In addition, the proposed model is also illustrated through a case study in a private company in Thailand.

- Chapter 6 contains some concluding remarks and suggestion for the future works.

Chapter 2

Background on fuzzy linguistic approaches

2.1 Linguistic decision making problems

In linguistic decision making problems, there are abundant decision models for representing, aggregating, and exploiting linguistic information. Stated by Rodriguez et al. [1] and Herrera et al. [19], a common decision resolution scheme consists of three main phases, as depicted in Figure 2.1.

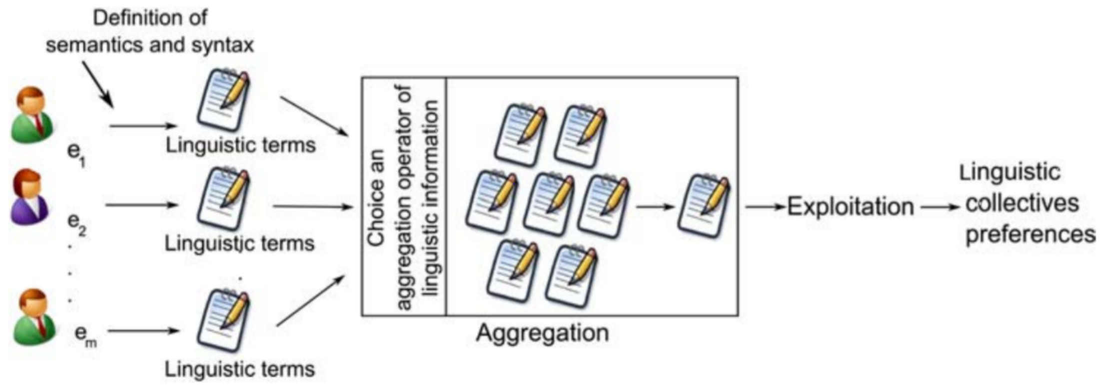

Figure 2.1: A linguistic decision making resolution scheme [1]

1. Selecting the linguistic term set with its semantics: It organizes the linguistic expression domain in which experts subjectively provide their linguistic assessment on criteria among several alternatives.

2. Developing the aggregation operator: It is about selecting the most suitable aggregation operator for aggregating linguistic information. A suitability of the aggregation operators depends on a data type and a problem identification.

3. Selecting the best alternative: In this phase, a ranking technique is assigned to select the best alternative from the linguistic collectives preferences.

In the next section, some linguistic computational approaches for aggregating linguistic information are reviewed.

2.2 Linguistic computation approaches

In linguistic computation approaches, a common problem is how to represent and aggregate linguistic information. So far, there are many proposed linguistic computation approaches in the literatures. In this research, only some linguistic computation approaches are focused and reviewed, as illustrated in Figure 2.2. From Figure 2.2, linguistic computation approaches can be classified into two folds:

1. An approach based on membership functions

2. An approach based on ordinal scales (term index)

For the rest of this chapter, these two approaches and their associated techniques are reviewed.

The approach based on membership functions is used for ODM clients' task 1, while the approach based on ordinal scales is used for ODM clients' tasks 2 and 3. It is because the problems for ODM clients' task1 and ODM clients' task 2,3 are formulated differently.

For ODM clients' task 1, translating linguistic terms into membership functions can handle the uncertainty more than ordinal scales since the arithmetic operation is needed in fusing information. For example, a respondent provides s_3, then s_3 can be represented as follows.

- Basing on membership functions; $s_3 : (0.25, 0.50, 0.75)$ (Triangular fuzzy numbers)

- Basing on ordinal scales; $s_3 : 3$ (Crisp value)

In this case, it can be noticed that representing s_3 by means of membership functions can handle uncertainty better than by means of ordinal scales because the minimum and maximum values of s_3 are also taken into account.

For ODM clients' tasks 2 and 3, the difference between two linguistic terms is determined. Linguistic terms are mapped as a point in a space. Then, the difference is determined corresponding to the coordinates. Mapping linguistic terms into a space can handle more uncertainty than translating them into numbers since numbers may not be appropriate to represent human being's perception. The perception of human being is naturally imprecision and vagueness. Thus, avoiding the interpretation of human being's perceptions by numbers can increase the efficiency of information fusion.

The approaches for each ODM client's task are depicted in Figure 2.3.

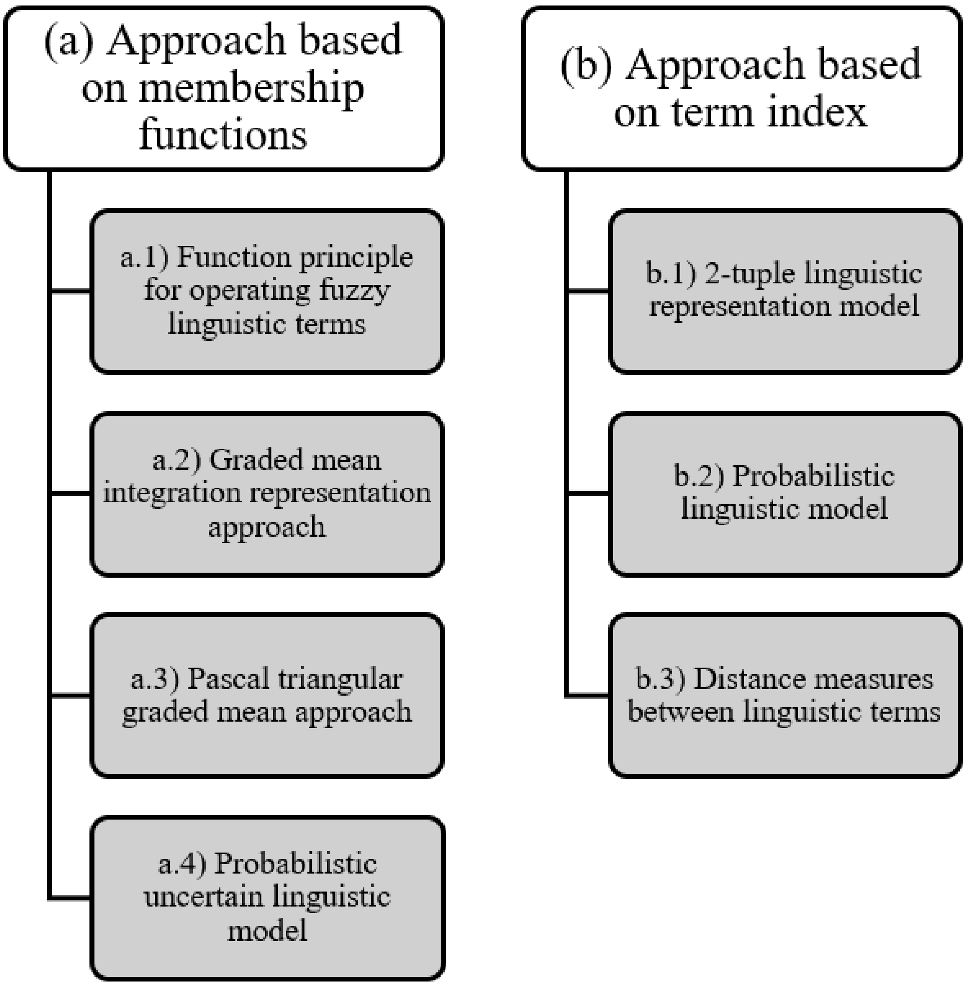

Figure 2.2: A flow diagram for the reviewed linguistic computation approaches

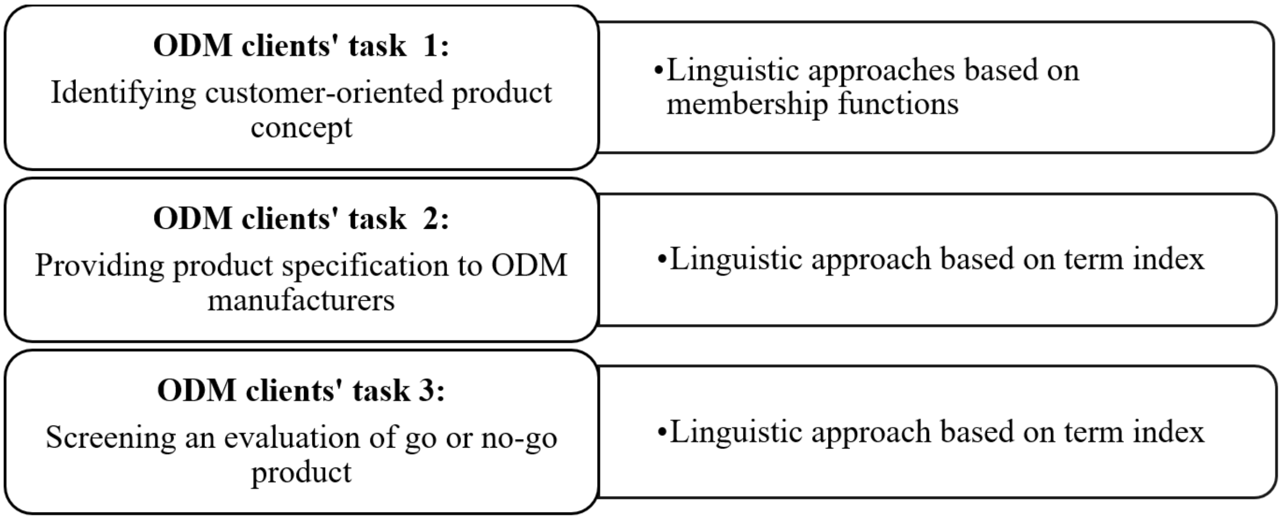

Figure 2.3: Approaches in developing models for ODM client's tasks

2.2.1 Linguistic computation approach based on membership functions and their techniques in developing models for ODM clients

The linguistic computational approach based on membership functions makes operations on the membership functions that supports the semantics of linguistic terms. It is developed based on a concept of the extension principle [20], [21]. Generally, the extension principle is a basic concept in the fuzzy sets theory [22]. It is used to generalize crisp mathematical concepts to fuzzy sets. However, the use of extended arithmetic based on the extension principle increases the vagueness of the results. The results are fuzzy numbers and may not match with any linguistic terms in the initiated linguistic domain. To deal with such a problem, the results may be approximated to a particular format or fuzzy number themselves [23]. However, it is important to note here that the approximation process generally lead to the loss of information, which may lead to invalid result at the end. Thus, the issue of how to manage the loss of information is the critical issue for the linguistic computation approach based on membership functions.

Next, some techniques used with the linguistic computation approach based on membership functions are reviewed. These techniques will be used for formulating decision models for ODM clients' tasks.

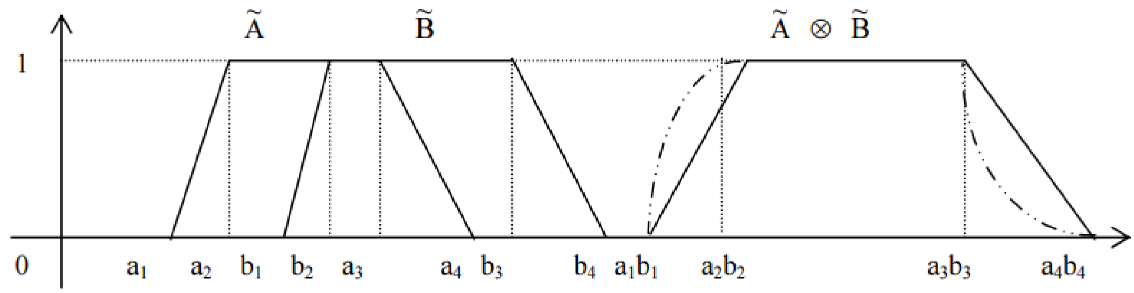

Figure 2.4: The multiplication of two membership functions under extension principle (.._..) and function principle (-) [2]

Function principle for operating fuzzy linguistic terms

Linguistic terms can be generally represented by membership functions, which are useful for representing the uncertainty. In 1975, Zadeh introduced a concept of extension principle for operating two membership functions [24]. Later in 1985, Chen [25] proposed a function principle, which is extended from the extension principle. The main difference is that the extension principle uses convolution to multiply membership functions, while the function principle uses pointwise product. By using pointwise multiplication, the function principle can handle more membership functions than the extension principle. The extension principle can multiply up to only four membership functions: $(\tilde{A} \otimes \tilde{B} \otimes \tilde{C} \otimes \tilde{D})$. In some problems, it may be necessary to consider more than four fuzzy information (membership functions). The difference on multiplication is graphically explained in Figure 2.4. The arithmetical operation under function principle can be defined as follows.

Definition 2.2.1. *[26] Let $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ be two triangular fuzzy numbers. Then, the fuzzy arithmetic operation can be defined as follows.*

1. *The addition of $\tilde{A}$ and $\tilde{B}$*
   $\tilde{A} + \tilde{B} = (a_1, a_2, a_3) + (b_1, b_2, b_3)$
   $= (a_1 + b_1, a_2 + b_2, a_3 + b_3)$

2. *The subtraction of $\tilde{A}$ and $\tilde{B}$*
   $\tilde{A} - \tilde{B} = (a_1, a_2, a_3) - (b_1, b_2, b_3)$
   $= (a_1 - b_1, a_2 - b_2, a_3 - b_3)$

3. The multiplication of $\tilde{A}$ *and* $\tilde{B}$ *is* $\tilde{A} \times \tilde{B} = (c_1, c_2, c_3)$

where $T = a_1b_1, a_1b_3, a_3b_1, a_3b_3$; $c_1 = min\ T$, $c_2 = a_2b_2$, $c_3 = max\ T$

However, if $a_1, a_2, a_3, b_1, b_2, b_3$ *are positive real numbers, then*

$\tilde{A} \times \tilde{B} = (a_1, a_2, a_3) \times (b_1, b_2, b_3)$

$= (a_1b_1, a_2b_2, a_3b_3)$

4. The division of $\tilde{A}$ *and* $\tilde{B}$ *is* $\frac{\tilde{A}}{\tilde{B}} = (c_1, c_2, c_3)$ *where* $T = \frac{a_1}{b_2}, \frac{a_1}{b_3}, \frac{a_3}{b_1}, \frac{a_3}{b_3}$

$c_1 = min\ T$, $c_2 = \frac{a_2}{b_2}$, $c_3 = max\ T$

However, if $a_1, a_2, a_3, b_1, b_2, b_3$ *are non-zero positive real numbers, then*

$\frac{\tilde{A}}{\tilde{B}} = (a_1, a_2, a_3) \div (b_1, b_2, b_3) = (\frac{a_1}{b_1}, \frac{a_2}{b_2}, \frac{a_3}{b_3})$

Graded mean integration representation approach

Naturally human beings better perceive a crisp value than fuzzy numbers. Thus, the final results of fuzzy operations are usually represented by a crisp value, instead of fuzzy numbers [27]. In 1998, Hsieh et al. [28] proposed a Graded Mean Integration Representation (GMIR) approach to defuzzify triangular fuzzy numbers into a crisp number [29]. For more details, see [30]. In 2006, Chen [31] introduced the properties of the representation of fuzzy numbers under extension principle by using GMIR approach. The GMIR approach can by generalized by the following formulation.

Definition 2.2.2. *[28] Let assume that* L^{-1} *and* R^{-1} *are inverse functions of function L and R, respectively and the graded mean h-level of generalized fuzzy number* $A = (a_1, a_2, a_3 : w)$ *is* $\frac{h[L^{-1}(h)+R^{-1}(h)]}{2}$*. Then the defuzzified value P(A) based on the integral value of graded mean h-level can be defined using Eq. 2.1*

$$P(A) = \frac{\int_0^h [\frac{L^{-1}(h)+R^{-1}(h)}{2}]dh}{\int_0^w h\, dh} \tag{2.1}$$

where h is in between 0 *and* w, $0 < w \leq 1$*. The representation of fuzzy numbers can be formulated in eqs. 2.2 and 2.3. For example, assume that* $\tilde{A} = (a_1, a_2, a_3)$ *is triangular fuzzy numbers. Then,* $\tilde{A}$ *can be defuzzified by:*

$$P(A) = \frac{1}{2}\frac{\int_0^1 \int h[a_1 + h(a_2 - a_1) - h(a_3 - a_2)]dh}{\int_0^1 h\, dh} \tag{2.2}$$

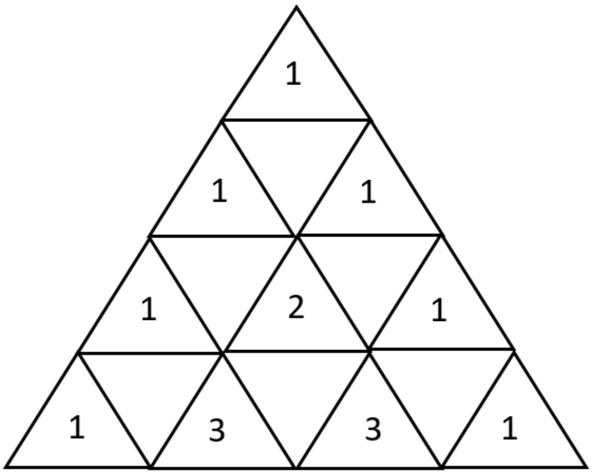

Figure 2.5: Coefficients of Pascal triangle numbers

$$P(A) = \frac{a_1 + 4a_2 + a_3}{6} \tag{2.3}$$

Pascal Triangular Graded Mean Approach

Similar to GMIR approach, pascal triangular graded mean approach is an alternative tool for defuzzifying fuzzy numbers to a crisp number [2]. It is extended from GMIR approach [28]. Due to their ease and ability in defuzzification, both approaches are applied in several research domains [26], [32], [33]. Basically, a concept of pascal triangle graded mean approach is taken from the coefficients of Pascal's triangle, as depicted in Figure 2.5. In this approach, the coefficients of Pascal triangle numbers are used as weights assigned for each fuzzy variable. The defuzzifying formula can be formulated as follows.

Definition 2.2.3. *[34] Let $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{C} = (c_1, c_2, c_3, c_4)$ are triangular fuzzy numbers and trapezoidal fuzzy number, respectively. Then the coefficient of fuzzy numbers from Pascal triangle numbers are described by the following equations:*

$$P(A) = \frac{a_1 + 2a_2 + a_3}{4} \tag{2.4}$$

$$P(C) = \frac{c_1 + 3c_2 + 3c_3 + c_4}{8} \tag{2.5}$$

Probabilistic linguistic model

Linguistic terms are usually more human-friendly than numbers in assessing the values on objects. Normally, they are finite and totally ordered. It can be generally defined in a form of linguistic term set, e.g. $S = \{s_1, s_2, \ldots, s_G\}$, where G is a cardinality of S. The semantics of terms can be represented by fuzzy numbers in the interval of $[0, 1]$, as described by membership functions [35], [36]. For example, a set of five symmetrical linguistic terms can be defined as follows:

$S = \{s_1 : Very\ Bad, s_2 : Bad, s_3 : Neutral, s_4 : Good, s_5 : Very\ Good\}$

where the triangular fuzzy numbers of a linguistic term set are defined by:

$$\begin{aligned} s_1 &= (0.00, 0.00, 0.25), \\ s_2 &= (0.00, 0.25, 0.50), \\ s_3 &= (0.25, 0.50, 0.75), \\ s_4 &= (0.50, 0.75, 1.00), \\ s_5 &= (0.75, 1.00, 1.00) \end{aligned}$$

Recently, Pang et al [5] proposed a probabilistic linguistic term set (PLTS) model aiming to deal with a multiple criteria group decision making problem, which corresponding to linguistic information. Their model can be formulated as follows.

Definition 2.2.4. *[5] Let $S = \{s_1, \ldots, s_g, \ldots, s_G\}$ be a set of linguistic terms.*

$$S(p) = \{s_g^k(p_k) \mid s_g \in S, p_k \geq 0\} \tag{2.6}$$

$$\sum_{k=1}^{K} p_k = 1 \tag{2.7}$$

where $s_g^k(p_k)$ is a linguistic term s_g^k associated with probabilistic linguistic p_k. g is an index of a linguistic term set S. $S(p)$ is the ordered probabilistic linguistic term set S. If r_g is a subscript of linguistic term s_g^k and $S(p)$ is arranged according to the value of r_g, then $s_g^k(p_k)$ is ordered in an descending order.

Example 2.2.1. *Suppose that 10 respondents participate in a film's performance evaluation. They provide their preferences by using linguistic terms, as shown below.*

$$S = \{\mathit{Extremely\ boring}(s_1), \mathit{very\ boring}(s_2), \mathit{boring}(s_3), \mathit{neutral}(s_4), \mathit{interesting}(s_5), \mathit{very\ interesting}(s_6), \mathit{extremely\ interesting}(s_7)\}$$

Four respondents feel that the film is 'Extremely interesting'$[s_7]$*. Two respondents think that the film is 'Interesting'*$[s_5]$*. Three respondents feel that it is 'Neutral'*$[s_4]$*. One respondent feel that it is 'Extremely boring '*$[s_1]$*. In this case, the probability of each linguistic term is as follow.*

$$S(p) = \{\langle [s_1], \tfrac{1}{10} \rangle, \langle [s_4], \tfrac{3}{10} \rangle, \langle [s_5], \tfrac{2}{10} \rangle, \langle [s_7], \tfrac{4}{10} \rangle\}$$

2.2.2 Linguistic computation approach based on ordinal scales (term index) and their techniques in developing models for ODM clients

In this approach, linguistic expressions are computed based on the indices of linguistic terms using an ordered structure of the linguistic term set to accomplish symbolic computation. Some useful techniques for computing linguistic information based on term index are discussed as follows.

2.2.3 2-tuple linguistic representation model

A 2-tuple linguistic representation model is first introduced by Herrera and Martinez [36] in 2000. It is proposed to deal with the loss of information, which usually occurs from an approximation process when retranslate the computed linguistic information to its initial linguistic domain [37], [38]. Since its introduction, this model is widely applied in many applications, e.g. engineering management [18], information filtering [39], group decision making [35], and product design [40], [41]. The 2-tuple linguistic representation model consists of two components [42]: (s_g, α).

1. s_g: It represents the linguistic term in set S.

2. α: It is a real number representing a symbolic translation parameter. It denotes a deviation of computed linguistic term from its closet linguistic term s_g, so that it can improve the accuracy of the linguistic computation.

Figure 2.6 shows the concept of 2-tuple representation: (s_g, α). From Figure 2.6, s_g is 'Medium ', and α is '0.25 '. The notions of 2-tuple representation model are further defined as follows.

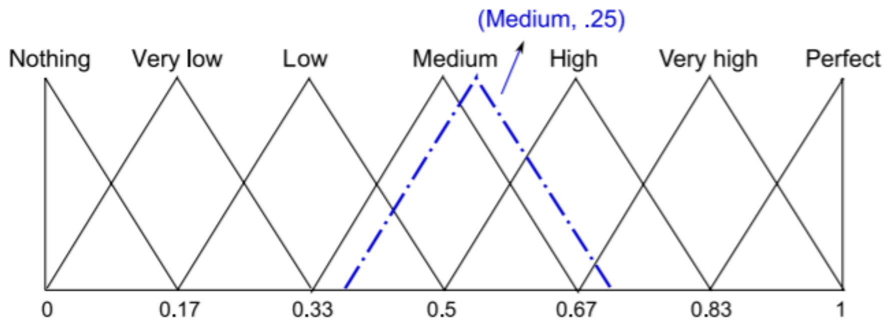

Figure 2.6: A 2-tuple representation model [1]

Definition 2.2.5. *[36], [43] Let $S = \{s_1, s_2, \ldots, s_G\}$ be a linguistic term set with cardinality G. $\beta \in [1, G]$ is the value representing the result of index aggregation operation in linguistic term set S. Then, a 2-tuple expressing the equivalent information to β is defined as:*

$$\Delta : [1, G] \longrightarrow S \times [-0.5, 0.5)$$

$$\Delta(\beta) = (s_i, \alpha), \text{ with} \begin{cases} s_i, & i = round(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases}$$

where s_i has the closest index label to β. α is the value of symbolic translation.

Example 2.2.2. *Suppose that $\beta = 3.1$ is the result of index aggregation operation in linguistic term set S. Then, the 2-tuple expressing the equivalent information to β is $(s_3, 0.1)$. It is also equivalent to $\Delta^{-1}(s_3, 0.1)$.*

2.2.4 Probabilistic uncertain linguistic model

In 2016, Pang et al [5] introduced a probabilistic linguistic model, as shown below.

Definition 2.2.6. *[5] Let $S = \{s_1, \ldots, s_g, \ldots, s_G\}$ be a set of linguistic terms, then the probabilistic linguistic model can be defined as:*

$$L(p) = \{L^n(p^n) | L^n \in S, p^n \geq 0, n = 1, 2, \ldots, N\} \tag{2.8}$$

where $L^n(p^n)$ is the linguistic term L^n associated with probability p^n, with $\sum_{n=1}^{N} p^n \leq 1$. N is the number of all different linguistic terms.

Later, in 2017, Lin et al. [44] extended Pang's model to allow respondents assess by more than one linguistic term. In other words, their model is able to deal with interval linguistic terms. Lin et al.'s probabilistic uncertain linguistic model can be defined as follows.

Definition 2.2.7. *[44] Let $S = \{s_1, s_2, \ldots, s_g\}$ be a set of linguistic terms.*

$S(p) = \{\langle [s^k, s'^k], p^k \rangle \mid p^k \geq 0,\ \ k = 1, 2, \ldots, K,\ \ \sum_{k=1}^{K} p^k \leq 1\}$

where $\langle [s^k, s'^k], p^k \rangle$ denotes the uncertain linguistic term $[s^k, s'^k]$, which are corresponding to its probabilistic linguistic value p^k. $s^k, s'^k \in S$ and $s^k \leq s'^k$

Remark 2.2.1. *If respondents are certain on their assessment, they provide only $[s^k]$. In contrast, if respondents hesitate or are uncertain on their assessment, they are allowed to assess by interval linguistic term $[s^k, s'^k]$.*

Example 2.2.3. *Suppose that 10 respondents are asked to express their impression on a hotel service by using linguistic term sets with cardinality $g = 7$ as defined below.*

$$S = \{\textit{extremely good, very good, good, neutral, bad, very bad, extremely bad}\}$$

Two respondents feel that the service is in between good and neutral $[s_3, s_4]$. Five respondents think that the service is very good $[s_2]$. One respondents feel that it is neutral $[s_4]$. Two respondents feels that it is extremely good $[s_1]$. Here, $S(p)$ can be written by

$$S(p) = \{\langle [s_1^1], \tfrac{2}{10} \rangle, \langle [s_2^2], \tfrac{5}{10} \rangle, \langle [s_3^3, s_4^3], \tfrac{2}{10} \rangle, \langle [s_4^4], \tfrac{1}{10} \rangle\}$$

Motivated by the above observations, in this study, an alternative approach to deal with multiple criteria group decision making problem under fuzzy environment is developed. The proposed alternative approach can handle with uncertainty effectively by providing a flexible method for respondents. The explanation is explained in the next section.

2.2.5 Distance measures between linguistic terms

Most of the previous works on distance measure between linguistic terms were done based on deviation degree [45] and similarity degree [46]. Recently, Rosello et al. [47] introduced a new distance measurement method, which was able to measure the distances in the space of qualitative assessment. The distances are defined from geodesic distance in a graph theory. Three main advantages over deviation and similarity degrees are 1) experts are able to judge different alternatives over different order-of magnitude spaces, 2) qualitative assessments can be made with imprecision, and 3) the distance concerns the number of change needed to move from one term to another [47]. In addition, Rosello et al's method also takes the confident levels of respondents into account. When a respondent is confident on his subjective opinion, he votes only one linguistic term. In contrast, when a respondent is not confident on his subjective opinion, he is able to vote by using linguistic term set $[s, s']$. Due to its essential advantages over existing methods, it is interesting to extend geodesic distance in determining the distances between linguistic terms.

Definition 2.2.8. *[3] [48] Distance between two linguistic terms is defined as the geodesic distance in the graph $G_{\mathbb{L}}$ (see Figure 2.7) with the injection $\psi : \mathbb{L} \longrightarrow \mathbb{Z}^2$ (see Figure 2.8). The distance is denoted by $d(\eta, \varsigma)$, where η and ς are linguistic vertices in a graph. If the weights of all vertices in the graph are equal, geodesic distance can be expressed as follows. Suppose $\eta = [s, s'] = (x, y)$ and $\varsigma = [(s)', (s')'] = (x', y')$.*

$$d(\eta, \varsigma) = d_{Manhattan}([s, s'], [(s)', (s')']) = d((x, y), (x', y')) = |x - x'| + |y - y'| \qquad (2.9)$$

Remark 2.2.2. *With the advantage of graph injection in Figure 2.8, the geodesic distance measure, which measures points in a space, can be viewed as the Manhattan distance measure, which measuring points in X-Y scales.*

Example 2.2.4. *Taking into account the distance between vertex $\eta = [l_1, l_3]$ and $\varsigma = [l_4, l_5]$, the shortest path can be computed as*

$$d(\eta, \varsigma) = d_{Manhattan}\psi(\eta), \psi(\varsigma) = d_{Manhattan}((2, 0), (4, 3)) = |2 - 4| + |0 - 3| = 5$$

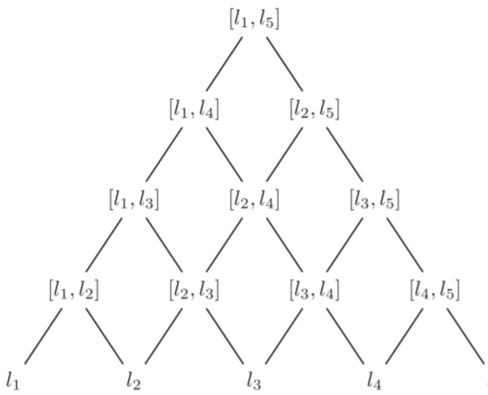

Figure 2.7: Graph representation of linguistic hierarchy corresponding to g=5 [3]

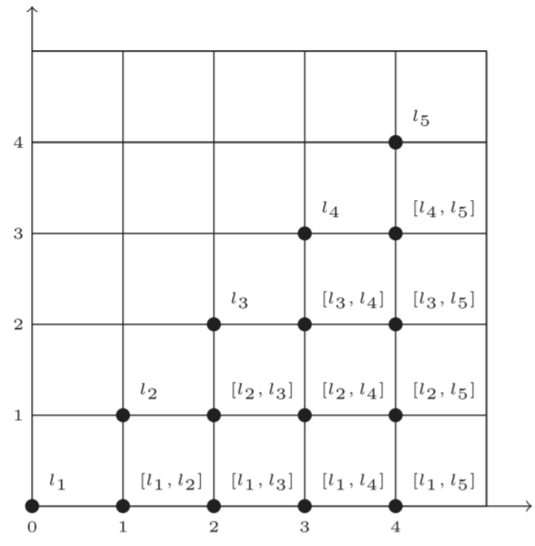

Figure 2.8: Injection $\psi : \mathbb{L} \longrightarrow \mathbb{Z}^2$ [3]

2.3 Summary

In this chapter, some related approaches, which will be used further in the thesis are recalled, including linguistic computation approach based on membership functions and linguistic computation approach based on term index. As mentioned above, this research aims at developing decision models for supporting ODM client's tasks.

Firstly, the linguistic computation approach based on membership functions and its corresponding techniques are comprehensively reviewed. The proposed model for supporting ODM client's task 1 will be developed based on this approach.

Secondly, the linguistic computation approach based on term index and its corresponding techniques are discussed because their applications will be further exploited to develop decision models for ODM client's task 2 and 3.

These approaches will be used to develop three customer-oriented models on new product development for supporting three ODM client's tasks. The proposed models will be discussed further in Chapters 3-5. An applicability and effectiveness of the proposed models are also presented through case studies from the Thai beverage company.

Chapter 3

Decision model for prioritizing customer-oriented product concepts

In this chapter, the first ODM clients' task is addressed. Firstly, the background and challenges of models developing for prioritizing a new customer-oriented product concepts are stated. In this model, a concept of probabilistic linguistic model [5] is comprehensively extended to this task. In addition, some conventional models and techniques of linguistic computation approach based on membership functions addressed previously in Chapter 2, are briefly analyzed, i.e. probabilistic linguistic model, and fuzzy operation rules. Next, a concept of the proposed model and its normalization process, and its aggregation process are explained. Then, the a new model is developed and illustrated through a case study. Some concluding remarks are also provided at the end of this chapter.

3.1 Model's background and its challenges

A Multiple criteria group decision making (MCGDM) is a common activity found in our daily life [49]. In a decision making process, people normally use linguistic terms, which are their natural language, such as 'Good', 'Attractive', 'Bad', etc, for expressing their mental perceptions [50]. This means that linguistic expressions are more in line with people's thinking habits [51]. However, linguistic expression is imprecise and uncertain in nature [52]. The issue of how to represent and aggregate them is challenging. This issue draws scholars' attentions to improve the effectiveness of computing linguistic terms for decades. In addition, since linguistic information is uncertain, a fuzzy set theory proposed by Zadeh [13], is usually applied to deal with it. Since its development, it has been extensively used for handling uncertain environment in various research domains, especially for decision making problem; [53], [54], [55], [56].

Up to now, many models have been proposed for dealing with MCGDM problems with fuzzy linguistic information. Delego et al. [57] focused on convex combination of linguistic labels. However, their results on linguistic interval numbers do not match with the initial linguistic levels, which leads to the loss of information [58]. To cope with the loss of information from an approximation process, Herrera and Martinez [36] proposed a 2-tuple fuzzy linguistic representation model. For more details on 2-tuple bases, see [42], [59], and [60]. Taking a different track, recently in 2016, Pang et al. [5] introduced a probabilistic linguistic term set (PLTS) model based on the idea that several possible linguistic terms with different weights may be considered at the same time (probabilities). Some new operational laws and aggregation operators for PLTS are also proposed. However, PLTS limits respondents to provide only one linguistic term for expressing their preference. To allow more flexibility for respondents' decision, Lin et al. [44] proposed a probabilistic uncertain linguistic term set (PULTS) model. The model allows respondents to provide more than one linguistic terms on their criteria assessment. Liu and You [61] extended the probabilistic linguistic term set (PLTS) and TODIM method (prospect theory-based method) to take respondent's cognitive behavior into account. For more related works on probabilistic linguistic-based group decision making models, see also [51], [62], and [63].

However, these existing probabilistic linguistic-based models assume that all respondents have an equal importance degree or indicate their importance degrees by a scalar value. Practically, respondents have different background, knowledge, culture, and specialization. For example, experts may have more importance degrees than general customers because they have more specific knowledge on that product than general customers. Moreover, the relative importances of respondents are also uncertain and imprecise [64]. Therefore, it is difficult to define them by a precise value.

In light of the above observation, it is necessary to develop a model considering three issues to improve the deficiencies in probabilistic linguistic-based models. The three issues can be briefly explained as follows.

- Respondents assess the criteria by a linguistic expression.
- Respondents have different relative importance. Their importance degrees are provided by linguistic expression.
- Linguistic terms have different importance degrees.

To improve the existing probabilistic linguistic-based model, a fuzzy linguistic model with the above three issues is proposed. Firstly, a symmetric triangular fuzzy number is used to represent the value of linguistic terms. We assume that a linguistic criterion assessment is provided with a probability distribution of the group respondents. In addition, we also assume that each respondent has different relative importances. Secondly, a normalization process, an aggregation process, and a defuzzifying process are proposed for processing the linguistic information in the 3-dimension fuzzy linguistic model. Thirdly, the applicability and advantages of the proposed model are shown through a case study from a beverage company in Thailand. Finally, the results are compared with the existing models.

3.2 3-dimension fuzzy linguistic representation model

In this section, a new concept called 3-dimension fuzzy linguistic representation is proposed. Then, the normalization, the aggregation process, and the defuzzifying process are investigated.

3.2.1 A concept of 3-dimension fuzzy linguistic representation

In some cases, respondents may prefer some of linguistic terms. Thus, the set of possible values may have a different relative importance resulting in the probability distribution. In addition, respondents may also have different importance degrees. Thus, information from each respondent (RS) can be represented by 3 dimensions:

$$\langle \text{ Linguistic assessment } (s_g), \text{ Respondent's weight } (w_k), \text{ Probabilistic linguistic } (p_g^k) \ \rangle$$

Taking these notation into account, we generally extend probabilistic linguistic model [5] and other existing models by the following definition.

Definition 3.2.1. *Let* $S = \{s_1, \ldots, s_g \ldots, s_G\}$ *and* $W = \{w_1, \ldots, w_k, \ldots, w_K\}$ *be two linguistic term sets.* p_g^k *is a scalar value. Then, the 3-dimension fuzzy linguistic information can be represented using 3 tuples as below.*

$$s(p)^k = \{\langle s_g^k, w_g^k, p_g^k \rangle \mid k = 1, 2, \ldots, K\} \tag{3.1}$$

where s_g^k *is a linguistic term* g *expressed by respondent* k*, and* w_g^k *is a linguistic term* g *for the importance degree of respondent* k*.* p_g^k *is the corresponding probability of* s_g *to the group decision making.*

3.2.2 A normalization of the 3-dimension fuzzy linguistic representation

In a group decision making, a probabilistic linguistic term set S is normalized by $\sum_{k=1}^{K} p_g^k = 1$. It means that a complete linguistic assessment information is provided, as exemplified in Example 2.2.1. p_g^k is normalized by the definition belows.

Definition 3.2.2. *Let* p_g^k *be a probability of linguistic term associated with linguistic term* s_g *and respondent* k*.*

$$p_g^k = p(s_g^k|S) = \frac{\sum_{k=1}^{K} |s_g|}{K} \tag{3.2}$$

Example 3.2.1. *Assume that three respondents vote* s_1*, while two respondents vote* s_2*. Thus, the probabilistic* p_1^k *and* p_2^k *can be defined below.*

$p_1^k = \frac{\sum_{k=1}^{K} |s_1|}{K} = \frac{3}{3+2} = \frac{3}{5} = 0.6$
$p_2^k = \frac{\sum_{k=1}^{K} |s_2|}{K} = \frac{2}{3+2} = \frac{2}{5} = 0.4$

and the total probabilistic linguistic term is

$\sum_{k=1}^{5} p_g^k = \sum_{k=1}^{5} p_1^k + p_2^k = 0.6 + 0.4 = 1.0$

3.2.3 Some aggregation operators for the 3-dimension fuzzy linguistic representation model

In this section, some aggregation operators for fusing linguistic information for 3-dimension fuzzy linguistic representation model is proposed. To do so, some operational rules of fuzzy numbers defined in definition 2.2.1 are used to compute the fuzzy numbers in the decision making process.

Definition 3.2.3. *Let $S = \{s_1, \ldots, s_g \ldots, s_G\}$ be a set of linguistic terms and $W = \{w_1, \ldots, w_k, \ldots, w_K\}$ be a set of respondents' weights. Note that W is assessed by s_g. A 3-dimension aggregation operator (Ω_{kj}) can be defined as follows.*

$$\Omega_{kj} = s_{gj}^k \times w_g^k \times p_{gj}^k \quad \forall k, j \tag{3.3}$$

where s_{gj}^k is a linguistic assessment of respondent k on criterion j. w_g^k is a linguistic weight of respondent k. $s_g \in S$ and $w_g \in W$. Each s_g and w_g consist of n fuzzy numbers; $s_g = (a_{g1}, a_{g2}, \ldots, a_{gn})$, $w_g = (b_{g1}, b_{g2}, \ldots, b_{gn})$. A notion of Ω_{kj} is further presented in Table 3.1. Ω_{kj} can be determined from the multiplication of fuzzy linguistic information.

Remark 3.2.1. *If $n = 3$, it is a triangular fuzzy numbers, while if $n = 4$, it is a trapezoidal fuzzy numbers.*

Table 3.1: A 3-tuple fuzzy linguistic matrix ($\hat{R_k}$) on criterion j, where $j = 1$

RS (d_k)	Linguistic assessment (s_g^k)			Linguistic weight (w_g^k)			Probability (p_g^k)	3-tuple aggregation for criterion 1 $\Omega_{kj} = \Omega_{k1} = s_{gj}^k \times w_g^k \times p_{gj}^k$
	(a_{g1}^k)	(a_{g2}^k)	(a_{g3}^k)	(b_{g1}^k)	(b_{g2}^k)	(b_{g3}^k)		
d_1	(a_{g1}^1)	(a_{g2}^1)	(a_{g3}^1)	(b_{g1}^1)	(b_{g2}^1)	(b_{g3}^1)	(p_g^1)	$\Omega_{11} = \langle (a_{g1}^1 \times b_{g1}^1 \times p_g^1), (a_{g2}^1 \times b_{g2}^1 \times p_g^1), (a_{g3}^1 \times b_{g3}^1 \times p_g^1) \rangle$
d_2	(a_{g1}^2)	(a_{g2}^2)	(a_{g3}^2)	(b_{g1}^2)	(b_{g2}^2)	(b_{g3}^2)	(p_g^2)	$\Omega_{21} = \langle (a_{g1}^2 \times b_{g1}^2 \times p_g^2), (a_{g2}^2 \times b_{g2}^2 \times p_g^2), (a_{g3}2 \times b_{g3}^2 \times p_g^2) \rangle$
$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
d_k	(a_{g1}^k)	$\ldots$	(a_{gn}^k)	(b_{g1}^k)	$\ldots$	(b_{gn}^k)	(p_g^k)	$\Omega_{kj} \langle (a_{gn}^k \times b_{gn}^k \times p_g^k), (a_{gn}^k \times b_{gn}^k \times p_g^k), (a_{gn}^k \times b_{gn}^k \times p_g^k) \rangle$

Example 3.2.2. *Assume that respondent $k = 1$ expresses his preference on criterion $j = 1$ using five linguistic levels ($G = 5$) with a triangular membership function ($n = 3$). He expresses his preference on criterion 1 by s_3 and his weight is s_4. Thus, his assessing information for criterion 1 can be represented by:*

- *His preference* (s^k_{gj})*:* $s^1_{31} = (0.25, 0.50.0.75)$

- *His weight* (w^k_g)*:* $s^1_4 = (0.50, 0.75, 1.00)$

In addition, if three out of ten respondents vote s_3 for criterion 1, then $p^k_{gj} = p^1_{31} = \frac{3}{10} = 0.3$*.*

Thus,

$\Omega_{11} = \langle(0.25 \times 0.50 \times 0.3), (0.50 \times 0.75 \times 0.3), (0.75 \times 1.00 \times 0.3)\rangle$

$\Omega_{11} = (0.0375, 0.1125, 0.2250)$

After obtaining the individual new linguistic assessment (Ω_{kj}) of each respondent k on criterion j, an average aggregation operator is used to aggregate all new linguistic assessment. By using function principle defined in definition 2.2.1, the fuzzy numbers can be aggregated by using an additive property.

Definition 3.2.4. *Let α_j be a total linguistic assessment from respondent k on j^{th} criterion .*

$$\alpha_j = \sum_{k=1}^{K} \Omega_{kj} \quad \forall j \tag{3.4}$$

3.2.4 Defuzzifying fuzzy numbers

Having obtained a collection of linguistic assessment Ω_{kj} of all criteria, a defuzzifying process is introduced in response to the ease of human perception. By using Pascal triangular graded mean approach described in definition 2.2.3, a scalar importance degree of each criterion is determined.

Definition 3.2.5. *Let $\tilde{A} = (a_1, a_2, a_3)$ be triangular fuzzy numbers for linguistic term s_g with $G = 5$. The defuzzified triangular fuzzy values (PAS) of $\tilde{A}$ is determined as follows.*

$$PAS_A = \frac{NOR_{\sum_{k=1}^{K}\Omega_{k1}} + 2 \times NOR_{\sum_{k=1}^{K}\Omega_{k2}} + NOR_{\sum_{k=1}^{K}\Omega_{k3}}}{4} \tag{3.5}$$

where $NOR_{\sum_{k=1}^{K}\Omega_{kj}}$ is a normalized total linguistic expression Ω_{kj}, derived from definition 3.2.6 below.

Definition 3.2.6. *Let $\hat{v_1}$,$\hat{v_2}$, $\hat{v_3}$ be the vector of multiplication result from Ω_{kj} of each respondent k on criterion j. Then, the normalization process for Ω_{kj} is defined as follows.*

$$NOR_{\sum_{k=1}^{K}\Omega_{kj}} = \{\frac{\hat{v_1}}{K \times 0.75}, \frac{\hat{v_2}}{K \times 1.00}, \frac{\hat{v_3}}{K \times 1.00}\} \tag{3.6}$$

where K is the total number of respondents and $(0.75, 1.00, 1.00)$ representing the triangular fuzzy numbers of linguistic term s_5 in set S ($G = 5$). If the cardinality G is greater or lower than 5, $(0.75, 1.00, 1.00)$ is changed to the corresponding fuzzy numbers of the highest linguistic term G.

3.3 An MCGDM evaluation model with 3-dimension fuzzy linguistic representation

In this section, a 3-dimension fuzzy linguistic evaluation model is proposed to determine the importance of criteria weights. For a criteria determination problem, suppose there are K respondents, $d_k = \{1, 2, \ldots, K\}$, responsible for assessing on J criteria, $c_j = \{1, 2, \ldots, J\}$. Then,

- Let $S^k = (s^k_{gj})_{m\times n}$ be the linguistic assessment matrix of k^{th} respondent. s^k_{gj} is the linguistic assessment with cardinality $g = 1, 2, \ldots, G$, provided by d_k on the assessment of c_j for prioritizing the importance of c_j.
- Let $W^k = (w^k_g)_{m\times n}$ be the respondents' weight matrix of k^{th} respondent. w^k_g is the linguistic weight given to d_k for his relative importance.
- Probabilistic linguistic term p^k_{gj} is also used to represent the probability of linguistic term s^k_{gj} associated with d_k on criterion c_j.

Based on these notations, the steps for the proposed evaluation model are summarized as follows.

Step 1. *Represent the linguistic assessment matrix $S^k = (s^k_{gj})_{m\times q}$ and the linguistic weight matrix $W^k = (w^k_g)_{m\times q}$ by a 3-tuple fuzzy linguistic matrix $\tilde{R}_k = (\tilde{r}^k_{gj})_{m\times q} =$*

$(\langle a_{gn}^k, b_{gn}^k, p_{gj}^k \rangle)_{m\times q}$, *where* a_{gn}^k *and* b_{gn}^k *represent the fuzzy triangular numbers in set* S^k *and* W^k, *respectively.*

The linguistic information can be transformed into their corresponding fuzzy numbers by using definition 2.2.7, which are symmetric fuzzy numbers. If an asymmetric fuzzy number is used, some additional mathematical operations need to be developed. For the probability distribution p_{gj}^k *of linguistic term* g *assessed by respondent* k *on criterion* j*, it is determined by definition 3.2.2.*

Step 2. *Aggregate linguistic assessment* S^k *and linguistic weight* W^k *of each* k^{th} *respondent on* j^{th} *criterion under function principle proposed by Chen [25], as addressed in definition 2.2.1. Note that the linguistic information is represented by fuzzy numbers. Then, with the use of definition 3.2.3, multiply the result of* S^k *and* W^k *by* p_{gj}^k*. Consequently, the new linguistic assessment* (Ω_{kj}) *of* k^{th} *decision maker on* j^{th} *criterion is obtained.*

$$\begin{aligned}\Omega_{kj} = \langle (\hat{v}_1 : a_{g1}^k \times b_{g1}^k \times p_g^k), (\hat{v}_2 : a_{g2}^k \times b_{g2}^k \times p_g^k),\\ (\hat{v}_3 : a_{g3}^k \times b_{g3}^k \times p_g^k) \rangle \quad \forall k, j, g\end{aligned} \tag{3.7}$$

Step 3. *Aggregate the linguistic assessment* Ω_{kj} *of all respondents* k *on* j^{th} *criterion by using aggregation laws from definition 2.2.1. The total linguistic assessment is defined as* α_j *by definition 3.2.4.*

$$\alpha_j = \sum_{k=1}^{K} \Omega_{kj} \quad \forall j \tag{3.8}$$

Step 4. *Normalize the total linguistic assessment* α_j *by using definition 3.2.6.*

$$\begin{aligned}NOR_{\alpha_j} &= NOR_{\sum_{k=1}^{K} \Omega_{kj}}\\ &= \{\frac{\hat{v}_1}{K \times 0.75}, \frac{\hat{v}_2}{K \times 1.00}, \frac{\hat{v}_3}{K \times 1.00}\}\end{aligned} \tag{3.9}$$

where $\hat{v}_1, \hat{v}_2$*, and* $\hat{v}_3$ *are the corresponding fuzzy numbers of* Ω_{kj}*.*

Step 5. *Defuzzify the normalized total linguistic assessment NOR_{α_j} by using Pascal triangular graded mean approach in definition 3.2.5. The importance degrees of criteria (PAS_j) are determined as follows.*

$$PAS_j = \frac{NOR_{\sum_{k=1}^{K}\Omega_{k1}} + 2 \times NOR_{\sum_{k=1}^{K}\Omega_{k2}} + NOR_{\sum_{k=1}^{K}\Omega_{k3}}}{4} \tag{3.10}$$

Note that in this case, triangular fuzzy numbers ($n = 3$) are used. If trapezoidal fuzzy numbers ($n = 4$) are used, then the corresponding coefficient is changed from 1:2:1 to 1:3:3:1.

Step 6. *Obtain a percentage of the importance weight (IM_j) by normalizing PAS_j. The normalizing equation is formulated as follows.*

$$IM_j = \frac{PAS_j}{\sum_{j=1}^{J} PAS_j} \tag{3.11}$$

3.4 A case study

3.4.1 Implementation of the proposed model

In this section, a case study is used to illustrate the applicability of the proposed model. A case study is taken from Wangsukjai export limited company [26]. The company wants to launch a new soy milk beverage product. To increase the product value, the company do a marketing survey by a questionnaire method. The questionnaire aims at prioritizing the relative importances of criteria.

Data collection

The company invites 30 respondents d_k ($k = 1, 2, \ldots, 30$) to prioritize the selected criteria for developing a new soy milk product. To encourage respondents' willingness, some tokens of participation are given to them. These respondents d_k have different importance degrees according to their frequencies of soy milk consumption, denoted as linguistic weight w_g^k, where g is an index in linguistic term set S ($g = 1, 2, \ldots, 5$). There are four selected criteria c_j ($j = 1, 2, \ldots, 4$), which are: (1) c_1 variety of flavor; (2) c_2 for a specific group; (3) c_3 health additive; and (4) added condiment. The linguistic assessment of respondents d_k on criterion j is denoted by s_{gj}^k, where g is an index in linguistic term set S ($g = 1, 2, \ldots, 5$). In addition, the probability distribution is used to define a different importance degree of the possible linguistic terms in set S. It is denoted as p_g^k.

The linguistic assessment s_{gj}^k and the respondents' weights w_g^k are provided in Table 3.2. Table 3.3 indicates the expression of linguistic terms and their corresponding triangular fuzzy numbers of w_g^k and s_{gj}^k. Next, the proposed model is used to prioritize criteria for increasing a value of the new soy milk product. The steps of the model are outlined as follows.

Steps

Step 1. *Transform the linguistic assessment (s_{gj}^k) in set S^k and the linguistic weight (w_g^k) in set W^k of decision maker k on criterion j, provided in Table 3.2 into the 3-tuple fuzzy linguistic representation $\tilde{R}_k = (\tilde{r}_{gj}^k) = (\langle a_{gn}^k, b_{gn}^k, p_{gj}^k \rangle)$, where a_{gn}^k and b_{gn}^k define the corresponding fuzzy triangular numbers in set S^k and W^k, respectively, as shown in Table 3.4. By eq. 3.2, p_{gj}^k of linguistic term g on criterion j is determined, as shown in Table 3.6, and their probability distributions are presented in Figure 3.1.*

Example 3.4.1. *From Table 3.2, a set of linguistic terms for assessing criteria c_1 to c_4 of d_1 can be interpreted as:*

$$\{s_5, s_2, s_5, s_3\} = \{(0.75, 1, 1), (0, 0.25, 0.5), (0.75, 1, 1), (0.25, 0.5, 0.75)\}$$

Step 2. *Sum Ω_{kj} by respondent k using eq. 3.8. Then, the total linguistic assessment α_j is obtained, as shown in Table 3.5; row 7.*

Step 3. *Aggregate linguistic assessment, linguistic weight, and probabilistic linguistic distribution by using eq. 2. We can obtain a collective linguistic assessment (Ω_{kj}) of k^{th} decision maker on j^{th} criterion, as shown in Table 3.5; rows 3 - 6.*

Example 3.4.2. *From Table 3.5, a collective linguistic assessment (Ω_{kj}) of d_1 on criterion 1 with w_3^1, s_{51}^1, and p_5^1 can be represented as:*

$$\begin{aligned}\Omega_{11} = \langle &(\hat{v}_1 : a_{31}^1 \times b_{51}^1 \times p_3^1), (\hat{v}_2 : a_{32}^1 \times b_{52}^1 \times p_5^1),\\ &(\hat{v}_3 : a_{33}^1 \times b_{53}^1 \times p_5^1)\rangle\\ = \langle &(0.25 \times 0.75 \times 0.17), (0.50 \times 1.00 \times 0.17),\end{aligned}$$

Table 3.2: Linguistic information of respondents d_k

Respondent (d_k)	Weight of respondent (w_g^k)	Criteria assessment (s_{gj}^k)			
		$c_1; j = 1$	$c_2; j = 2$	$c_3; j = 3$	$c_4; j = 4$
d_1	w_3	s_5	s_2	s_5	s_3
d_2	w_4	s_2	s_4	s_5	s_2
d_3	w_3	s_3	s_5	s_4	s_2
d_4	w_5	s_3	s_5	s_4	s_5
d_5	w_2	s_2	s_4	s_4	s_5
d_6	w_5	s_4	s_5	s_3	s_4
d_7	w_4	s_4	s_5	s_4	s_3
d_8	w_1	s_3	s_2	s_3	s_2
d_9	w_3	s_5	s_4	s_4	s_5
d_{10}	w_2	s_3	s_4	s_5	s_4
d_{11}	w_5	s_2	s_2	s_5	s_3
d_{12}	w_4	s_1	s_3	s_4	s_4
d_{13}	w_3	s_2	s_4	s_4	s_2
d_{14}	w_4	s_4	s_2	s_5	s_1
d_{15}	w_2	s_3	s_3	s_2	s_2
d_{16}	w_3	s_5	s_2	s_4	s_3
d_{17}	w_5	s_3	s_5	s_3	s_5
d_{18}	w_3	s_1	s_3	s_5	s_2
d_{19}	w_3	s_2	s_2	s_3	s_2
d_{20}	w_2	s_3	s_4	s_5	s_1
d_{21}	w_3	s_5	s_5	s_4	s_3
d_{22}	w_4	s_2	s_3	s_5	s_2
d_{23}	w_2	s_3	s_4	s_5	s_4
d_{24}	w_3	s_4	s_3	s_3	s_3
d_{25}	w_2	s_3	s_4	s_5	s_2
d_{26}	w_4	s_5	s_4	s_5	s_5
d_{27}	w_5	s_1	s_4	s_3	s_2
d_{28}	w_2	s_2	s_5	s_3	s_1
d_{29}	w_3	s_4	s_5	s_4	s_4
d_{30}	w_4	s_2	s_3	s_5	s_3

Table 3.3: A set of triangular fuzzy numbers for linguistic weight w_g^k and linguistic assessment s_{gj}^k

Label (s_g)	Linguistic information		Triangular fuzzy number
	Weight of respondent (w_g^k)	Criteria assessment (s_{gj}^k)	
s_1	Rarely	Unimportance weight	(0, 0, 0.25)
s_2	Slightly often	Weakly importance weight	(0, 0.25, 0.5)
s_3	Often	Moderately importance weight	(0.25, 0.5, 0.75)
s_4	Very often	Very importance weight	(0.5, 0.75, 1)
s_5	Extremely often	Extremely importance weight	(0.75, 1, 1)

Table 3.4: Triangular fuzzy numbers of (w_g^k) and (s_{gj}^k)

Respondent (d_k)	Weight (w_g^k)			(s_{g1}^k)				(s_{g2}^k)				(s_{g3}^k)				(s_{g4}^k)			
	a_{g1}^k	a_{g2}^k	a_{g3}^k	b_{g1}^k	b_{g2}^k	b_{g3}^k	p_g^k	b_{g1}^k	b_{g2}^k	b_{g3}^k	p_g^k	b_{g1}^k	b_{g2}^k	b_{g3}^k	p_g^k	b_{g1}^k	b_{g2}^k	b_{g3}^k	p_g^k
d_1	0.25	0.50	0.75	0.75	1.00	1	0.17	0.00	0.25	0.50	0.20	0.75	1.00	1.00	0.40	0.25	0.50	0.75	0.23
d_2	0.50	0.75	1.00	0.00	0.25	0.50	0.27	0.50	0.75	1.00	0.33	0.75	1.00	1.00	0.40	0.00	0.25	0.50	0.27
:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
d_{30}	0.5	0.75	1	0	0.25	0.5	0.27	0.25	0.5	0.75	0.20	0.75	1	1	0.40	0.25	0.5	0.75	0.23

Table 3.5: Importance weight (IM_j)

Respondent (d_k)	(s_{g1}^k); $j = 1$			(s_{g2}^k); $j = 2$			(s_{g3}^k); $j = 3$			(s_{g4}^k); $j = 4$		
	$a_{g1}^k b_{g1}^k p_g^k$	$a_{g2}^k b_{g2}^k p_g^k$	$a_{g3}^k b_{g3}^k p_g^k$	$a_{g1}^k b_{g1}^k p_g^k$	$a_{g2}^k b_{g2}^k p_g^k$	$a_{g3}^k b_{g3}^k p_g^k$	$a_{g1}^k b_{g1}^k p_g^k$	$a_{g2}^k b_{g2}^k p_g^k$	$a_{g3}^k b_{g3}^k p_g^k$	$a_{g1}^k b_{g1}^k p_g^k$	$a_{g2}^k b_{g2}^k p_g^k$	$a_{g3}^k b_{g3}^k p_g^k$
d_1	0.032	0.085	0.128	0.000	0.025	0.075	0.075	0.200	0.300	0.014	0.058	0.129
d_2	0.000	0.051	0.135	0.083	0.186	0.330	0.150	0.300	0.400	0.000	0.051	0.135
:	:	:	:	:	:	:	:	:	:	:	:	:
d_{30}	0.000	0.051	0.135	0.025	0.075	0.150	0.150	0.300	0.400	0.029	0.086	0.173
Total (α_j)	0.514	1.797	3.616	1.168	3.123	5.258	1.809	4.654	7.651	0.663	1.977	3.727
Normalized total linguistic assessment (NOR_{α_j})	0.023	0.080	0.161	0.052	0.139	0.234	0.080	0.207	0.340	0.029	0.088	0.166
Pascal (PAS_j)	0.086			0.141			0.209			0.093		
Importance weight (%) (IM_j)	16%			27%			40%			17%		

Table 3.6: Probability distribution p_{gj}^k

Criterion c_j	Linguistic term $s_g(g = 1, 2, \ldots, 5)$				
c_j	$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 5$
c_1	0.10	0.27	0.30	0.17	0.17
c_2	0.00	0.20	0.20	0.33	0.27
c_3	0.00	0.00	0.23	0.37	0.40
c_4	0.10	0.27	0.23	0.23	0.17

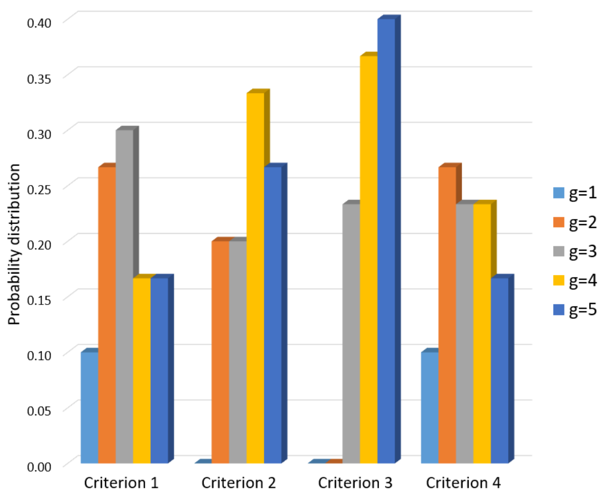

Figure 3.1: Probability distribution p_{gj}^k of linguistic term g on criterion j

$$(0.75 \times 1.00 \times 0.17)\rangle$$
$$= \langle 0.032, 0.085, 0.128\rangle$$

Example 3.4.3. *From Table 3.5, the total linguistic assessment α_j of criterion j can be represented as:*

$$\alpha_1 = \langle (0.032 + 0.000 + \cdots + 0.000),$$
$$(0.085 + 0.051 + \cdots + 0.051),$$
$$(0.128 + 0.135 + \cdots + 0.135)\rangle$$
$$= \langle 0.514, 1.797, 3.616\rangle$$

Step 4. *Normalize α_j by using eq. 3.9. Then, a normalized total linguistic assessment NOR_{α_j} is obtained, as shown in Table 3.5; row 8.*

Example 3.4.4. *From Table 3.5, the normalized total linguistic assessment NOR_{α_j} of criterion 1, with respect to 30 respondents, is equal to:*

$$NOR_{\alpha_1} = \{\tfrac{0.514}{30\times 0.75}, \tfrac{1.797}{30\times 1.00}, \tfrac{3.616}{30\times 1.00}\}$$
$$= \langle 0.023, 0.080, 0.161\rangle$$

Step 5. *Defuzzify NOR_{α_j} by using Pascal triangular graded mean approach in eq. 3.10. Then, PAS_j is obtained, which is a scalar value, as shown in Table 3.5; row 10.*

Example 3.4.5. *From Table 3.5, an importance degree PAS_j of criterion 1 is determined by*

$$PAS_1 = \tfrac{0.023+2\times 0.080+0.161}{4} = 0.086$$

Step 6. *Normalize PAS_j using eq. 3.11 to obtain the percentage of importance weight IM_j, which is represented by a scalar value (%), as shown in Table 3.5; row 10.*

Example 3.4.6. *From Table 3.5,the percentage of importance weight IM_j can be obtained by*

$$IM_1 = \tfrac{0.086}{0.528} = 16\%$$
$$IM_2 = \tfrac{0.141}{0.528} = 27\%$$
$$IM_3 = \tfrac{0.209}{0.528} = 40\%$$
$$IM_4 = \tfrac{0.093}{0.528} = 18\%$$

At this point, it is obvious that $IM_3 > IM_2 > IM_4 > IM_1$. Thus, $c_3 \succ c_2 \succ c_4 \succ c_1$.

3.4.2 Comparative study

To demonstrate an effectiveness of the proposed model, the proposed model is compared with the existing models, which are Pang et al.'s model [5] and Suprasongsin et al.'s model [26]. The comparative results of criteria weights obtained from each model are shown in Table 3.7.

Table 3.7: A comparative study

Model	Weight of criterion c_j				Ranking
	c_1	c_2	c_3	c_4	
Pang et al. [5]	17%	26%	39%	18%	$c_3 \succ c_2 \succ c_4 \succ c_1$.
Suprasongsin et al. [26]	21%	27%	30%	22%	$c_3 \succ c_2 \succ c_4 \succ c_1$.
Proposed model	16%	27%	40%	17%	$c_3 \succ c_2 \succ c_4 \succ c_1$.

From Table 3.7, it can be seen that all models rank the criteria weights in the same order: $c_3 \succ c_2 \succ c_4 \succ c_1$. However, if parameters are changed, the ranking may not be the same. Different models may provide different ranking and values of criteria weights. Thus, selecting a model critically affects the outcome. Models that consider more information are able to provide more general result. For example, the proposed model and Pang et al.'s model consider the probability distribution of linguistic terms. Their criteria weights are quite similar. In contrast, Suprasongsin et al.'s model does not consider the probability distribution of linguistic terms. Thus, its criteria weights are significantly different from the proposed model and Pang et al.'s model. In addition, the proposed model and Supransongsin et al.'s model consider linguistic information as fuzzy numbers, but Pang et al's model considers it as ordinal scales (crisp values). Thus, the proposed model and Supransongsin et al.'s model can handle uncertainty in linguistic assessment, while Pang et al.'s model cannot. The advantages of the proposed model over the existing models are summarized as follows.

- The proposed model has more advantages than Pang et al.'s model. It can handle the imprecision of linguistic assessment which are the nature of human beings. Assume that the linguistic computational process of linguistic assessment and probability distribution are as follows.

- Pang et al. [5] considers linguistic terms as ordinal scales (crisp value).

$$[s_3, (0.17)] = 3 \times 0.17 = 0.51$$

where s_3 is the linguistic assessment and 0.17 is the probability distribution of s_3 of the group assessment.

- For our proposed model, it considers linguistic terms as fuzzy numbers.

$$\begin{aligned}[s_3, (0.17)] &= (0.25, 0.5, 0.75) \times 0.17 \\ &= (0.0425, 0.085, 0.1275)\end{aligned}$$

where s_3 is the linguistic assessment and 0.17 is the probability distribution of s_3 of the group assessment.

Thus, the proposed model provides more complete information of respondents than Pang et al.'s model because they also provide the minimum and the maximum values of each criterion weight (0.0425 and 0.1275). These minimum and maximum values represent the imprecision of human beings.

- The proposed model considers more linguistic information than Suprasongsin et al.'s model [26]. Suprasongsin et al.'s model does not consider that linguistic terms have different important degrees. It considers only linguistic criteria assessments and linguistic respondents' weights, which are represented by fuzzy numbers. Consequently, its criteria weights are different from the proposed model.

In short, the proposed model is able to take three issues into account: probabilistic linguistic terms, linguistic criteria assessments, and linguistic respondents' weights. Finally, it provides more linguistic information than the comparative ones.

For further discussion, this information is also able to use in segmenting target customers. The way to segment customers by using fuzzy numbers of criteria weights was illustrated by Suprasongsin et al's model, 2017 [26]. Basically, its concept is based on the intersected area under a graph of the fuzzy number criteria weights (NOR_{α_j}) and the initial linguistic domain (s_g). The amount of intersected area, denoted by β, is used to judge whether a respondent will be included in the consumer segment or not. Suppose that β is less than 5% (cut-off point) of linguistic term (s_g), a respondent who provides a linguistic term s_g is segmented to that criterion k.

3.5 Concluding remarks

In this model, the 3-dimension fuzzy linguistic evaluation model for determining the criteria weights under uncertain environment is proposed. Fuzzy numbers are used to represent the linguistic information, which are linguistic criteria assessments from DMs and linguistic DM weights. In addition, the probabilistic linguistic terms are also employed to deal with different weights for different linguistic terms. To illustrate the applicability and the advantages of the proposed model, a case study is employed. The model aims at determining weights of product values (criteria) added for the new soy milk beverage product. The result shows that the proposed model provides an effective way to prioritize criteria weights, which can cope with uncertain linguistic information from criteria assessment, different decision makers, and different linguistic terms. The results are also compared with the existing models. It can be seen that the proposed model provides not only the same criteria ranking as other existing models, but also the additional information on fuzzy criteria weights, which can be used for further decision analysis such as classifying target customers.

Although the application focused in this model is mainly on determining criteria weight, it also can be applied to other problems such as project selection, supplier selection, and product selection, where linguistic terms are used in assessing information. I am also planning to extend the proposed model to deal with uncertain linguistic terms. In some situations, decision makers may not be sure to express their preferences by one linguistic term. In other words, they may have some hesitations on several linguistic terms. In this case, to increase the flexibility and the richness of linguistic expression, decision makers should be allowed to express their opinion by interval linguistic term. To do so, it is worth to study more on how 2-tuple fuzzy linguistic models and hesitant fuzzy linguistic models can be extended to deal with such issues. This is a direction for the future works on this model.

Chapter 4

Decision model for providing product specification to ODM manufacturers

In this chapter, the second ODM clients' task is addressed. Firstly, the background and challenges of models developing for translating customer requirements to manufacturing requirements are stated. In this model, a concept of manhattan distance measure is comprehensively extended to this task. In addition, some conventional models and techniques of linguistic computation approach based on ordinal scales addressed previously in Chapter 2, are briefly analyzed, i.e. manhattan distance measure, probabilistic uncertain linguistic terms. Next, a concept of the proposed model and its normalization process, and its aggregation process are explained. Then, the a new model is developed and illustrated through a case study. Some concluding remarks are also provided at the end of this chapter.

4.1 Model's background and its challenges

Customer satisfaction becomes a great concern to many firms throughout the world. Many firms use satisfaction as an indicator to evaluate the performance of products or services, including a firms future, because a high level of customer satisfaction leads to a high level of customer loyalty. Customer loyalty leads to the steady stage of the future cash flow [65].

In addition, customer satisfaction can also reduce the price elasticities because satisfied customers are willing to pay more on other products or services offered by the firm [66]. Hence, several firms try to develop a customer-oriented product in order to achieve a high customer satisfaction levels. To develop a customer-oriented product, a study of translating customer requirements (CRs) into manufacturing requirements (MRs) process is one of the major issues in the decision-making problems for new product development (NPD) areas [67].

Translating CRs to MRs is a multiple attributes group decision making (MAGDM) problem in nature. In MAGDM problems, how individual member expresses his/her opinion depends on the features describing attributes, and on their background, knowledge, culture, preference, and expertise [68]. Thus, there are some biases of heterogeneous members. To alleviate the biases, assigning the relative importances to each member is a common technique in MAGDM problems [69, 70]. So far, there exists various methods developed for determining relative importances of members. French [71] introduced the method based on the influence relations existing between members. Chen and Fan [72] proposed a method based on members levels in group decision. Xu [73] proposed a method based on the deviation measures between additive linguistic preference relation. In this paper, a reliability in attributes assessment is used to determine the relative importances of members.

In translating CRs to MRs, we may need to handle the linguistic information since it is frequently used to gather requirements from customers. However, dealing with the linguistic information is difficult because customer preferences or requirements are imprecise, subjective and dynamic in nature [74]. In addition, common techniques for handling linguistic information usually have an important deficiency on the loss of information, which implies a lack of precision at the final results. The deficiency usually appears because of the approximation used in the linguistic retranslation process. The retranslation process is used to translate the computed linguistic information to its initial domain for an ease of managers understanding [36].

To translate CRs to MRs, a Quality Function Deployment (QFD) is a common approach [44, 75], especially, for NPD context. See also [76–78]. It is a well-known management tool that provides a virtual process to help manufacturers focus on the CRs throughout a development cycle of the product or the process [79]. However, the conventional QFD approach requires many pairwise comparisons among CRs for ranking MRs [80–86]. Thus, QFD approach is not suitable for many CRs. In addition, there are many uncertainties arising from several assessments in QFD approach such as acquiring experts opinions, obtaining weighting customer requirements, and ranking manufacturing requirements. It is difficult to handle all these uncertainties.

Taking a different track, we extend a concept of manhattan distance measure and then propose a new evaluation model for translating CRs to MRs by taking uncertain linguistic assessment and heterogeneity of members into account. Manhattan distance measure is a technique in determining the differences between two linguistic variables. It can determine the differences between target linguistic variables and preferred linguistic variables. The preferred linguistic variables represent customers preferences or requirements, while target linguistic variables may represent companies desires. It is a useful technique since there is no approximation process in retranslating computed linguistic variables. Thus, it can avoid the loss of information occurring from the approximation in linguistic retranslation process. The characteristics and advantages of manhattan distance measure for computing linguistic information are summarized as follows [3]:

- The linguistic information is considered as term index. It is represented as a node in the grid (x-y scale) with a corresponding point.
- The distance between two nodes in the grid (x-y scale) is the number of edges in one of the shortest paths connecting them.
- It can avoid the loss of information from the approximation in linguistic retranslation process since linguistic information is represented by a node in space.
- It is capable of handling interval linguistic variables since they can be represented by nodes.

Basically, the concept of manhattan distance measure is that it represents linguistic terms as a corresponding point (vertex) in the x-y scale, and then measures the distance between two points. However, manhattan distance measure for linguistic terms normally considers only no polarity of linguistic assessment. The polarity refers to more (+) or less

(-) preferable on the reference point. For example, customers are asked to provide their preferences (Interval preferred linguistic terms) on the sweetness levels of the original Pepsi. Some customers prefer more sweetness degree (+), but others prefer less sweetness degree (-). In this case, a sweetness degree of the original Pepsi is the reference point (Interval target linguistic terms). A distance deviated from customers preferences to the reference point has two polarities. It does not mean that a higher sweet level is better than the lower one. The most suitable level depends on the fitness degree of customer preferences. Thus, to develop a customer-oriented Pepsi by using manhattan distance measure, it is necessary to consider how much more or less sweetness degree should be adjusted from the original Pepsis formula.

To overcome the deficiency of the conventional manhattan distance measure in its inability in handling a polar linguistic assessment, which usually exists in obtaining customer requirements or preferences, we propose a new technique called a polar manhattan distance measure. In addition, to present its applicability, an evaluation model with the polar manhattan distance measure is constructed for developing a new customer-oriented product by translating CRs to MRs. In this model, the respondents reliabilities are determined and assigned to alleviate the bias of respondents heterogeneity. To do so, customers are first asked to provide their requirements on product characteristics on a product prototype. Then, the linguistic difference between a node of customer preferences (Interval preferred linguistic terms) and a node of product prototype (Interval target linguistic terms) is determined. The linguistic difference refers to the differences between customer preferences and the attributes of the product prototype. Thus, the difference has the polar, which is more or less than the attributes of the product prototype. Finally, some aggregation operators and normalization processes are also developed to aggregate several individual opinions.

4.2 Polar manhattan distance measure

Conventionally, a manhattan distance measure for linguistic terms consider only the absolute distance from point to point in a grid. It does not consider the direction of linguistic difference. Thus, it is a non-polar by nature. In practice, there are many situations that the direction is necessary, especially in a domain of the customer requirements interpretation. For example, when we want to improve the existing product in several aspects, we want to know which direction of aspects that customers prefer the most. In this paper, the direction refers to the polarity of linguistic assessment and customers' requirements are a bipolar linguistic assessment.

Let us make some clarifications on the differences between the bipolar assessment and the non-polar assessment. From Figure 4.1, it represents a non-polar assessment. Generally, people needs a higher quality of a medicine. No one wants a lower quality of medicine. Thus, the medicine is a non-polar assessment and the conventional manhattan distance measure can deal with this situation. In contrast, from Figure 4.2, it represents a bipolar assessment. It is about the desires or preferences of customers. Based on the Thai-tea product prototype, some want more sugar in it, while others prefer less sugar. In this case, the direction of customers' requirements should be considered. To deal with this case, a polar manhattan distance measure is proposed. It can be formulated as follows:

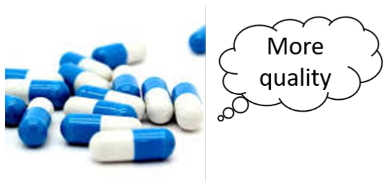

Figure 4.1: A non-polar assessment

Figure 4.2: A polar assessment

Definition 4.2.1. *Let $S = \{s_1, \ldots, s_g, \ldots, s_G\}$ be a set of linguistic terms. Distance between two linguistic terms is defined as the geodesic distance in the graph $G_{\mathbb{L}}$ (see Figure 2.7) with the injection $\psi : \mathbb{L} \longrightarrow \mathbb{Z}^2$ (see Figure 2.8). The distance is denoted by $d(\eta, \varsigma)$, where η is the reference vertex referring to the middle label of linguistic term set S: $\eta(s) = \frac{G+1}{2}$, and ς is the current vertex.*

- *s is the interval linguistic terms (Reference)*
- *s' is the interval linguistic terms (Preference)*
- *(x, y) and (x', y') are the corresponding points of s and s', respectively.*
- *(+) if the order of semantic level s (Reference) is less than of s' (Preference); $\eta(s) < \varsigma(s)$,*
- *(-) if the order of semantic level s (Reference) is greater than of s' (Preference); $\eta(s) > \varsigma(s)$*

$$\begin{aligned} d(\eta, \varsigma) &= \pm d_{PolarManhattan}([s, s'], [(s)', (s')']) \\ &= \pm d((x, y), (x', y')) = \pm|x - x'| + |y - y'| \end{aligned} \tag{4.1}$$

Example 4.2.1. *Let $S = \{s_1, s_2, \cdots, s_9\}$. Suppose that the reference vertex is $[s_5]$: $\eta(s) = \frac{9+1}{2} = 5$, which has a corresponding point at (4,4). The current vertex is $[s_2, s_3]$, which has a corresponding point at (2,1). Here, $5 > (\frac{2+3}{2})$. Thus, the total distance should have a negative sign (-). The total distance is computed by*

$$d(\eta, \varsigma) = \pm d_{PolarManhattan}((4, 4), (2, 1)) = -|(4 - 2) + (4 - 1)| = -5 \tag{4.2}$$

4.3 MCGDM model for encouraging manufacturing process on customer-oriented product

This section outlines the fuzzy multiple attributes group decision making (FMAGDM) problem for improving a product prototype based on customer preferences. To begin with, let us first denote some notations, which will be used in the further analysis. Let:

- $S = \{s_1, \cdots, s_g, \cdots, s_G\}$ be a set of linguistic terms
- $R = \{r_1, \cdots, r_n, \cdots, r_N\}$ be a set of respondents
- $F = \{f_1, \cdots, f_k, \cdots, f_K\}$ be a set of criteria

The model consists of three information assessed by interval linguistic terms in set S.

1. **Customer preferences provided by respondents**: They are used for indicating preferences of respondents denoted by x_{nk}. Here, x_{nk} is called Interval preferred linguistic terms.

2. **Product prototype setting provided by a company:** They are used as baseline for product design denoted by t_k. Here, t_k is called Interval target linguistic terms.

3. **Customer perceptions provided by respondents:** They are used for evaluating the change of customer perceptions when an attribute is adjusted at a time, denoted by $x_{nk'}$. This change is used for indicating the relationship among attributes.

Firstly, the required amount of each attribute to be adjusted with reference to the product prototype setting is determined by the difference between the customer preferences (x_{nk}) and the product prototype setting (t_k) using the proposed polar manhattan distance. In addition, the reliability weights of respondents on each attribute is also determined based on the customer preferences assessments. When his/her assessment (x_{nk}) is close to the majority assessment, he/she will gain a high weight since he/she is more reliable. In doing so, the reliability weight can alleviate the bias of subjective respondents. Moreover, in a general taste design, it is assumed that there are some effects on other attributes ($f_{k'}$), when the amount of attribute (f_k) is adjusted. To investigate this effect, the information of customer perception change is collected. Then, the effect of change on attributes is determined by the difference between the changes of customer perception $x_{nk'}$ and the center of linguistic terms in set S, ($\frac{G+1}{2}$), using the proposed polar manhattan distance. Let us explain more on the concept of effects on attribute changed by Figure 4.3. In Figure 4.3, when the amount of attribute $f_{K=1}$ is changed, then, there are some effects on attributes $f_{k'=2}$ and $f_{k'=3}$. Those effects are denoted by $h_{k'=2}^{k=1}$ and $h_{k'=3}^{k=1}$, respectively. Finally, the percentage adjustment to the product prototype is suggested by (1) the required amount of each attribute adjusted from the product prototype setting and (2) the relationship among attributes.

Based on these notations and information, the model for improving a new product prototype based on customer preferences is formulated as summarized in Figure 4.4 and the steps are explained in details as follows.

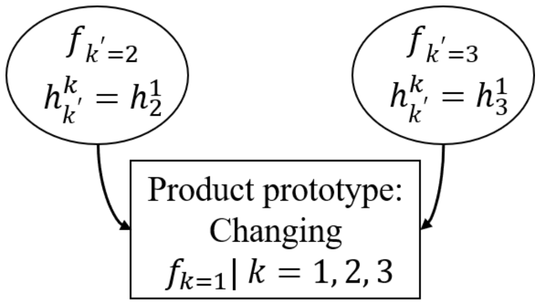

Figure 4.3: Notations of effects on an attribute changed: $f_{k=1}$

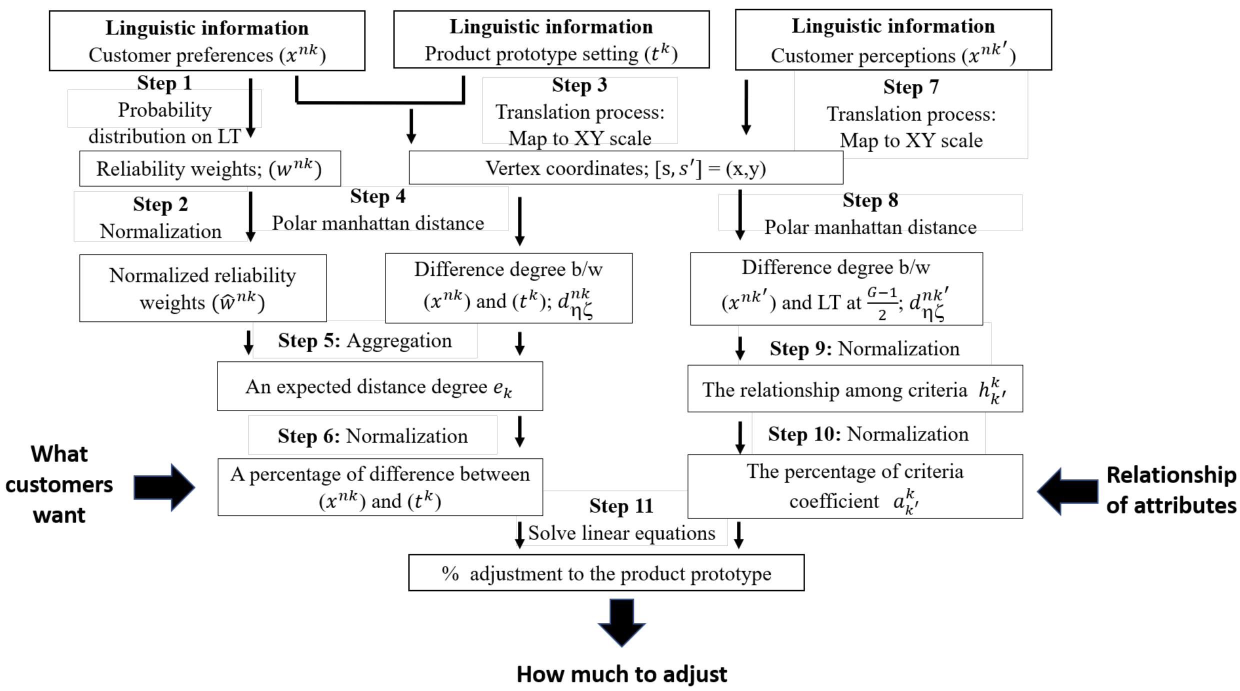

Figure 4.4: Steps of the proposed model 2

Step 1. *Determine the reliability weights of respondents. Respondents r_n express their preferences on attribute f_k by using interval preferred linguistic terms (x_{nk}), as depicted in Table 4.1. x_{nk} is an interval preferred linguistic term in $I^S, I^S = \{[s, s'] | s, s' \in S$ and $s \leq s'\}$. Then, x_{nk} is used to determine the reliability weights as follows.*

Let w_{nk} be a reliability weight of respondent n on attribute k, as shown in Table 4.2. Then, it can be determined by probability distribution using eq. 5.5.

$$w_{nk} = \frac{|\{r_{n'} | x_{n'k} = x_{nk}\}|}{N} \quad \forall n, k \tag{4.3}$$

Table 4.1: A matrix for RSs' expression

Respondents	Criteria				
	f_1	$\cdots$	f_k	$\cdots$	f_K
r_1	x_{11}	$\cdots$	x_{1k}	$\cdots$	x_{1K}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_n	x_{n1}	$\cdots$	x_{nk}	$\cdots$	x_{nK}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_N	x_{N1}	$\cdots$	x_{Nk}	$\cdots$	x_{NK}

Table 4.2: A matrix of reliability weight of RSs

Respondents	Criteria				
	f_1	$\cdots$	f_k	$\cdots$	f_K
r_1	w_{11}	$\cdots$	w_{1k}	$\cdots$	w_{1K}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_n	w_{n1}	$\cdots$	w_{nk}	$\cdots$	w_{nK}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_N	w_{N1}	$\cdots$	w_{Nk}	$\cdots$	w_{NK}

Step 2. *Normalize the reliability weights of respondents. In this step, w_{nk} is normalized to w_{nk} by using eq. 5.6.*

$$\hat{w}_{nk} = \frac{w_{nk}}{\sum_{n=1}^{N} w_{nk}} \quad \forall n, k \tag{4.4}$$

Step 3. *Map customer preferences of respondent n on attribute k (x_{nk}: interval preferred linguistic terms) and the product prototype setting on attribute k (t_k: interval target linguistic terms) into an XY scale as vertices with corresponding points. For example, assume that x_{11} is $[s_1, s_2]$. Then, the vertex coordinate is (1,0).*

Step 4. *Determine the difference between two interval linguistic terms ($d^{nk}_{\eta\varsigma}$) using the proposed polar manhattan distance defined in eq. 4.1. Since the difference between the product prototype and the customer preferences are evaluated, interval target linguistic terms (t_k) is at the middle of linguistic cardinality, which refers to no difference between the product prototype and the customer preferences.*

Step 5. *Determine the expected distance on each attribute k by aggregating a sum product of the normalized reliability weights w_{nk} and the difference of target and preferred linguistic terms ($d^{nk}_{\eta\varsigma}$).*

$$e_k = \sum_{n=1}^{N} \hat{w}_{nk} \times d^{nk}_{\eta\varsigma} \quad \forall k, \eta, \varsigma \tag{4.5}$$

Example 4.3.1. *Suppose that we want to measure the difference between interval target linguistic term $t_k(k = 1, 2, 3)$ and interval preferred linguistic term x_{nk} for attributes $f_k(k = 1, 2, 3)$. In this example, t_1, t_2 and t_3 are $[s_3]$. Three respondents are asked to provide their preferences on each attribute. The expected distance for attribute k (e_k) is obtained from eq. 4.5.*

- *For attribute 1 ($k = 1$), respondents 1, 2, and 3 vote $[s_2, s_3]$, $[s_4]$, and $[s_4]$, respectively. Thus, by eq. 4.5, the expected distance for* $f_1 = (\frac{0.333}{0.333+(2\times0.667)} \times (0+1)) + (\frac{0.667}{0.333+(2\times0.667)} \times (1+1)) + (\frac{0.667}{0.333+(2\times0.667)} \times (1+1)) = (0.2\times1) + (0.4\times2) + (0.4\times2) = 1.8.$
- *For attribute 2 ($k = 2$), respondents 1, 2, and 3 vote $[s_3, s_4]$, $[s_3]$, and $[s_3, s_5]$, respectively. Thus, by eq. 4.5, the expected distance for* $f_2 = (\frac{0.333}{3\times0.333} \times (1+1)) + (\frac{0.333}{3\times0.333} \times (0+0)) + (\frac{0.333}{3\times0.333} \times (2+0)) = (0.333\times2) + (0.333\times0) + (0.333\times2) = 1.332.$
- *For attribute 3 ($k = 3$), respondents 1, 2, and 3 vote $[s_3]$, $[s_2, s_3]$, and $[s_4, s_5]$, respectively. Thus, by eq. 4.5, the expected distance for* $f_3 = (\frac{0.333}{3\times0.333} \times (0+0) + (\frac{0.333}{3\times0.333} \times (0+1)) + (\frac{0.333}{3\times0.333} \times (2+1)) = (0.333\times0) + (0.333\times1) + (0.333\times3) = 1.332.$

Step 6. *Find the percentage of distance between x_{nk} and t_k by a normalization process.*

$$p_k = \frac{e_k}{Total\ distance} \quad \forall k \tag{4.6}$$

where the total distance is computed from $(G-1) \times 2$. G is the cardinality of linguistic term in set S. The total distance represents the total farthest distance from the lowest linguistic term to the highest linguistic term. If $G = 5$, then the farthest distance in X-axis of $s_1 : (0, 0)$ and $s_5 : (4, 0)$ is $|0 - 4| = 4$. For Y-axis, the farthest distance is also 4.

Taking Example 4 into account, $p_1 = \frac{1.8}{(5-1)\times 2} = (+)22.50\%$. It means that the group preference of attribute $k = 1$ is different from the product prototype by $(+)22.50\%$. It is important to note here that (p_k) has its direction. $(+)p_k$ means that respondents prefer the amount of attribute k to be higher than that of product prototype. $(-)p_k$ means that respondents prefer the amount of attribute k to be less than that of product prototype.

Step 7. *Map customer perception of respondent n on the change of attribute f_k and the product prototype setting (t_k) into an XY scale as vertices with the corresponding points. For example, assume that x_{11} is $[s_1, s_2]$. Then, the vertex coordinate is (1,0).*

The relationships among attributes are determined by linear equations. The input information is the customer perception of respondent n on the change of attribute f_k $(x_{nk'})$, as shown in Table 4.3. It has been assumed that when the amount of attribute f_k is changed, it may change customer perception on other attributes $f_{k'}$, where $f_k, f_{k'} \in F$ and $k \neq k'$. For the product prototype setting (t_k) noted in this step, it is always set at $\frac{G+1}{2}$. For example, $S = \{s_1, s_2, \ldots, s_7\}$, then the product prototype setting $t_k \forall k$ is $s_{\frac{7+1}{2}} = s_4$.

Step 8. *Determine the difference between two interval linguistic terms $(d^{nk'}_{\eta\varsigma})$ using the proposed polar manhattan distance defined in eq. 4.1. Since the difference between the product prototype and the customer preferences are evaluated, interval target linguistic terms (t_k) is at the middle of linguistic cardinality, which refers to no difference between the product prototype and the customer preferences.*

Step 9. *Determine the relationship among attributes f_k. It is determined by normalizing the differences between target (t_k) and perceived linguistic terms $(x_{nk'})$, as shown below.*

Table 4.3: The change of customer perception on attribute $f_{k'}$ when attribute f_k is changed

Respondent r_n	The change of customer perception on attribute $f_{k'}$ when attribute f_k is changed						
	$f_{k=1}$			$\cdots$	$f_{k=K}$		
	$f_{k'=2}$	$\cdots$	$f_{k'=K}$	$\cdots$	$f_{k'=1}$	$\cdots$	$f_{k'=K-1}$
r_1	x_{12}	$\cdots$	x_{1K}	$\cdots$	x_{11}	$\cdots$	$x_{1(K-1)}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_n	x_{n2}	$\cdots$	x_{nK}	$\cdots$	x_{n1}	$\cdots$	$x_{n(K-1)}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_N	x_{N2}	$\cdots$	x_{NK}	$\cdots$	x_{N1}	$\cdots$	$x_{N(K-1)}$

$$h^k_{k'} = \sum_{n=1}^{N} \frac{d^{nk'}_{\eta\varsigma}}{N} \quad \forall k \tag{4.7}$$

where $h^k_{k'}$ is the amount of perception change of attribute $f_{k'}$ on each attribute f_k, where $f_k, f_{k'} \in F$ and $k \neq k'$. $d^{nk'}_{\eta\varsigma}$ denotes the polar manhattan distance from point η (interval target linguistic terms) to point ς (interval perceived linguistic terms) on the XY scale.

Step 10. *Determine the attribute coefficients by normalizing the amount of relationship.*

$$a^k_{k'} = \frac{h^k_{k'}}{Total\ distance} \quad \forall k \tag{4.8}$$

where $a^k_{k'}$ is the attribute coefficient of attribute k' on attribute k. The total distance is computed from the cardinality of linguistic term set S, $(G-1) \times 2$. The total distance represents the total farthest distance from the lowest linguistic term to the highest linguistic term. In addition, if $a^k_{k'}$ has a negative sign $(-)$, it means that increasing the amount of attribute k weakens the level of attribute k'.

Example 4.3.2. *According to Table 3, respondents r_n are asked to provide their perception $(x_{nk'})$ when attribute k is changed from the product prototype. For example, respondents evaluate a product prototype based on three attributes $f_k(k = 1, 2, 3)$. Thus, there are two affected attributes $(f_{k'})$ for each attribute f_k, as illustrated in Figure 6. Then, we would like to know that when attribute k is changed, how much it will affect on customer*

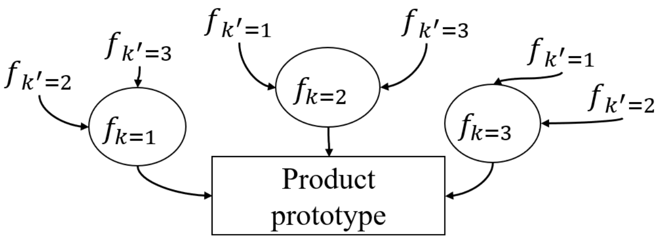

Figure 4.5: Product prototype with its attribites and its dependent attributes

perception on the other attributes ($f_{k'}$). Then, the difference between two interval linguistic terms ($d^{nk'}_{\eta\varsigma}$) is determined by using eq. 2. The product prototype setting ($t_k|k = 1, 2, 3$) is s_4, where $G = 7$.

Step 11. *Solve the relationship equation. Having obtained the attribute coefficient ($a^k_{k'}$) from step 10, a recommendation on manufacturing process to manufacturers is provided from the following equation.*

$$p_k = \Delta f_k + \sum_{k \neq k'}^{K} a^k_{k'} \Delta f^k_{k'} \ \forall k \tag{4.9}$$

where $f_k, f_{k'} \in F$ and $k \neq k'$. $a^k_{k'}$ is the attribute coefficient. Δf_k is the amount of change needed on attribute k. At the beginning, Δf_k is set to be 1 to obtain the attribute coefficient $a^k_{k'}$. Then, Δf_k is obtained from the percentage of distance between x_{nk} and t_k (p_k) in step 6.

Example 4.3.3. *From example 4.3.1, the relationship equations for criteria f_k are provided as follows.*

$$p_1 = \Delta f_1 + a^1_2 \Delta f^1_2 + a^1_3 \Delta f^1_3 \tag{4.10}$$

where the coefficient a^1_2, and a^1_3 are 0.15, and 0.23, respectively.

$$p_2 = \Delta f_2 + a^2_1 \Delta f^2_1 + a^2_3 \Delta f^2_3 \tag{4.11}$$

where the coefficient a^2_1, and a^2_3 are 0.07, and 0.11, respectively.

$$p_3 = \Delta f_3 + a^3_1 \Delta f^3_1 + a^3_2 \Delta f^3_2 \tag{4.12}$$

where the coefficient a_1^3, and a_2^3 are 0.13, and 0.09, respectively.

In example 4, p_1 is $22.50\%(+0.2250)$. *It means that customer prefers* 22.50% *more on attribute 1 than the product prototype. Thus, eq. 4.10 can be written as follows.*

$$p_1 = \Delta f_1 + 0.15\Delta f_2^1 + 0.23\Delta f_3^1 \tag{4.13}$$

$$0.2250 = \Delta f_1 + 0.15\Delta f_2^1 + 0.23\Delta f_3^1 \tag{4.14}$$

Then, the customer-oriented changes in the amount of f_1, f_2, and f_3 $(\Delta f_1, \Delta f_2, \Delta f_3)$ from its product prototype, are obtained. When the amount of change Δ of attributes is known, it is easier for manufacturers to develop a new customer-oriented product from its product prototype.

4.4 A case study

To illustrate an applicability of the proposed model, a case study from Wangsukjai export limited company, a Thai beverage company, is presented. It wants to help a manufacturer produce the new customer-oriented soy milk product by providing a recommendation regarding the proportion of soy milk's ingredients to its manufacturer. The proposed model with the proposed polar manhattan distance is used to analyze the data collected.

4.4.1 Data collection

4.4.2 Design of experiment

Two sets of data are collected from respondents: (1) customer preference on Thai tea characteristics (attributes) (x_{nk}), (2) the change of customer perception on adjusting an attribute at a time ($x_{nk'}$). To do so, respondents are asked to provide their opinions on six product prototypes, which are varied from a product baseline. They are grouped into three categories as shown in Figure 4.6. These categories are corresponding to three attributes, namely Thai tea smell, sweetness, and creamy. For example, if the product baseline consists of $X\%$ of Thai tea powder, $Y\%$ of sugar, and $Z\%$ of cream, then the components of attributes in varying attribute 1 (Category 1) are changed as follows.

- Prototype A.1 consists of $0.8X\%$ of Thai tea powder, $Y\%$ of sugar, and $Z\%$ of cream.

- Prototype A.2 consists of $1.2X\%$ of Thai tea powder, $Y\%$ of sugar, and $Z\%$ of cream.

In other word, A.1 is a product prototype when the amount of Thai-tea smell decreases. A.2 is a product prototype when the amount of Thai-tea smell increases. Hence, A.1 and A.2 can be viewed as the minimum and maximum boundaries of preferences for respondents in assessing their preference degrees on the Thai-tea smell attribute. In addition, respondents are also asked to assess their perception changed on sweetness and creamy of A.1 and A.2.

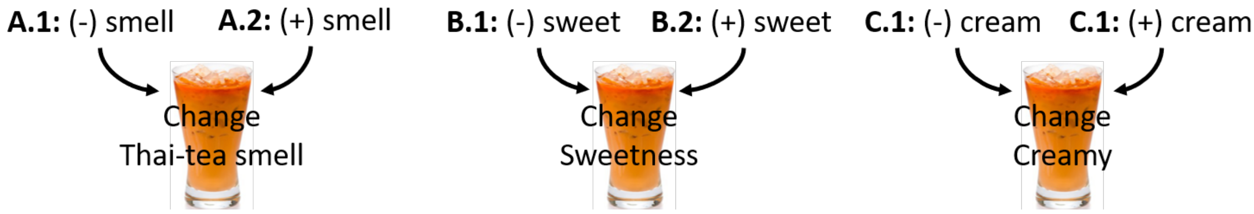

Figure 4.6: A diagram of six product prototypes

4.4.3 Gathering (1) customer preferences on Thai tea characteristics (attributes) (x_{nk})

In gathering customer preferences, respondents are asked to assess their preferences between A.1 (Weaker smell from the baseline) and A.2 (Stronger smell from the baseline) with linguistic terms $S_{Pref} = \{s_1, s_2, \ldots, s_9\}$ $(G = 9)$. The example question of gathering customer preferences on Thai tea smell is shown in Figure 4.7.

List	Characteristic	What Thai tea smell degree do you like?								
1	***Thai tea smell***	Would like to have a ***weaker*** smell than type A.1	Type A.1 is ***the right one!!***			At the middle ***between*** A.1 and A.2			Type A.2 is ***the right one!!***	Would like to have a ***stronger*** smell than type A.2
		( )	( )	( )	( )	( )	( )	( )	( )	( )

Figure 4.7: Question for gathering customer preferences on Thai tea smell

In Figure 4.7, when a respondent votes s_1, he/she prefers weaker Thai tea smell than A.1. This means that he/she prefers less than $0.8X\%$ of Thai tea powder of the product baseline. On the other hand, s_9 means that he/she prefers more than $1.2Y\%$ of Thai tea powder of the product baseline. When a respondent votes s_2 he/she prefers the proportion of Thai tea smell of A.1 the most. When he/she votes for s_5 he/she prefers the proportion of Thai tea smell of the baseline the most. Thus, customer preferences can be evaluated within a range of A.1 and A.2. In other words, A.1 and A.2 are the minimum and maximum boundaries.

4.4.4 Gathering (2) the change of customer perception on adjusting an attribute at a time ($x_{nk'}$)

In gathering customer preferences, respondents are asked to assess their perception on affected attributes with linguistic terms $S_{Perc} = \{s_1, s_2, \ldots, s_7\}$ ($G = 7$). The example questions of gathering customer perception on sweetness and creamy are shown in Figure 4.8.

List	Characteristic	Which one between A.1 or A.2 is **sweeter /more creamy**?						
2	***Sweetness***	A.1 is ***extremely*** sweeter	A.1 is ***much*** sweeter	A.1 is ***a bit*** sweeter	Not different	A.2 is ***a bit*** sweeter	A.2 is ***much*** sweeter	A.2 is ***extremely*** sweeter
		( )	( )	( )	( )	( )	( )	( )
3	***Creamy***	A.1 is ***extremely*** more creamy	A.1 is ***much*** more creamy	A.1 is ***a bit*** more creamy	Not different	A.2 is ***a bit*** more creamy	A.2 is ***much*** more creamy	A.2 is ***extremely*** more creamy
		( )	( )	( )	( )	( )	( )	( )

Figure 4.8: Question for gathering customer perception on affected attributes

In Figure 4.8, when a respondent vote s_1 for a sweetnesss attribute, he/she feels that the sweetness level of A.1 and A.2 is different and A.1 is extremely sweeter. It also infers that decreasing the amount of Thai tea smell decreases the sweetness level. When a respondent vote s_4, he/she feels that the sweetness level of A.1 and A.2 is not different and changing the degree of Thai tea smell does not affect the perception of sweetness level. Respondents opinions on 1) customer preferences (x_{nk}) and 2) customer perception ($x_{nk'}$) are shown in Figure 4.4 - 4.5.

4.4.5 A result of applying the proposed model

Tables 4.4 - 4.5 present the linguistic assessments of respondents. Tables 4.6 - 4.7: columns 2-4 show a relative importance of respondent n on attribute k , which is obtained by eqs.

Table 4.4: Linguistic assessment provided by respondents on each formula

Rspondent r_n	Changing $f_{k=1=\text{Thai tea}}$			Changing $f_{k=2=\text{Sweet}}$			Changing $f_{k=3=\text{Creamy}}$		
	Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)		Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)		Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)	
	Thai tea	Sweet	Creamy	Sweet	Thai tea	Creamy	Creamy	Thai tea	Sweet
r_1	s_1	s_3	s_6	s_9	s_5	s_5	s_6	s_4	s_4
r_2	s_1	s_6	s_3	s_8, s_9	s_6	s_7	s_9	s_4	s_6
r_3	s_6, s_7	s_5, s_6	s_2	s_9	s_5	s_1, s_2	s_8	s_6	s_6
r_4	s_8	s_4	s_4	s_5	s_8	s_4	s_7	s_4	s_4
r_5	s_7, s_8	s_4	s_4	s_8, s_9	s_4	s_4	s_7, s_8	s_4	s_4
r_6	s_3	s_3	s_1	s_5	s_4	s_4	s_8	s_4	s_4
r_7	s_5	s_3	s_1	s_6, s_7	s_4	s_1, s_2	s_3, s_5	s_3	s_5
r_8	s_8	s_4	s_6	s_2	s_4	s_4	s_5	s_3	s_3
r_9	s_3	s_3	s_3	s_8	s_1	s_7	s_5, s_6	s_4	s_3
r_{10}	s_4	s_2	s_2	s_2	s_4	s_3	s_2	s_1	s_2
r_{10}	s_4	s_2	s_2	s_2	s_4	s_3	s_2	s_1	s_2
r_{11}	s_5	s_3	s_3	s_5	s_3	s_3	s_5	s_1	s_3
r_{12}	s_3	s_2	s_3	s_5	s_4	s_3	s_4	s_2	s_3
r_{13}	s_2	s_4	s_4	s_2	s_3	s_2	s_1	s_2	s_3
r_{14}	s_5	s_5	s_5	s_8	s_5	s_3	s_8	s_4	s_5
r_{15}	s_8	s_3	s_3	s_5	s_2	s_2	s_5	s_2	s_2
r_{16}	s_8, s_9	s_5	s_4	s_8	s_1	s_6	s_7	s_3	s_5
r_{17}	s_9	s_6	s_7	s_7	s_5	s_7	s_9	s_5	s_5
r_{18}	s_1	s_4	s_4	s_5	s_4	s_4	s_5	s_4	s_4
r_{19}	s_8	s_2	s_4	s_8	s_4	s_5	s_5, s_6	s_4	s_4
r_{20}	s_8	s_3	s_5	s_8	s_3	s_5, s_6	s_5	s_3	s_3
r_{21}	s_1	s_3	s_4	s_5	s_4	s_4	s_5	s_4	s_4
r_{22}	s_1	s_5	s_3	s_9	s_4	s_5	s_8	s_4	s_5
r_{23}	s_5	s_4	s_4	s_8	s_2	s_2	s_5	s_4	s_4
r_{24}	s_8	s_3	s_4	s_3	s_7	s_6	s_9	s_4	s_3
r_{25}	s_1	s_5	s_4	s_8	s_4	s_6	s_2	s_4	s_5
r_{26}	s_1	s_4	s_1	s_5	s_5	s_5	s_6	s_4	s_4
r_{27}	s_3, s_4	s_4	s_1	s_5	s_5	s_5	s_6	s_4	s_4

Table 4.5: Linguistic assessment provided by respondents on each formula (Cont)

Rspondent r_n	Changing $f_{k=1=\text{Thai tea}}$			Changing $f_{k=2=\text{Sweet}}$			Changing $f_{k=3=\text{Creamy}}$		
	Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)		Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)		Focused attribute (x_{nk})	Other attributes ($x_{nk'}$)	
	Thai tea	Sweet	Creamy	Sweet	Thai tea	Creamy	Creamy	Thai tea	Sweet
r_{28}	s_8	s_4	s_1	s_4	s_5	s_4	s_5	s_4	s_6
r_{29}	s_4	s_5	s_5	s_7, s_8	s_2	s_5	s_5	s_3	s_4
r_{30}	s_6	s_5	s_4	s_8	s_4	s_4	s_8, s_9	s_5	s_5
r_{31}	s_6	s_4, s_5	s_2	s_8	s_2	s_3	s_9	s_3	s_6
r_{32}	s_7	s_3	s_2	s_7	s_4	s_6	s_7	s_3	s_2
r_{33}	s_8	s_2	s_4	s_2	s_7	s_3	s_8	s_3	s_4
r_{34}	s_5	s_4	s_7	s_5	s_2	s_6	s_7	s_5	s_4
r_{35}	s_1	s_4	s_4	s_5	s_5	s_4	s_6	s_5	s_4
r_{36}	s_4	s_2	s_5	s_4	s_3	s_5	s_6	s_3	s_5
r_{37}	s_7	s_3	s_3	s_4	s_4	s_2	s_7	s_4	s_3
r_{38}	s_5	s_2	s_4	s_5	s_4	s_7	s_2	s_2	s_2
r_{39}	s_8	s_3	s_3	s_6	s_5	s_5	s_6	s_5	s_3
r_{40}	s_5, s_6	s_3	s_2	s_4, s_5	s_4	s_5	s_7	s_4	s_4
r_{41}	s_1	s_7	s_5	s_2	s_7	s_5	s_4	s_4	s_1
r_{42}	s_6	s_4	s_4	s_8	s_4	s_4	s_6	s_5	s_5
r_{43}	s_1, s_2	s_5, s_6	s_2, s_3	s_6, s_7	s_4	s_4	s_5	s_4	s_4
r_{44}	s_7, s_8	s_2, s_3	s_4	s_7, s_8	s_4	s_5, s_6	s_6, s_7	s_4	s_4
r_{45}	s_7	s_3	s_3	s_8	s_4	s_6	s_6, s_7	s_4	s_4
r_{46}	s_8	s_2	s_3	s_9	s_7	s_6	s_2	s_4	s_5
r_{47}	s_1	s_4	s_4	s_8	s_3	s_2	s_9	s_7	s_5
r_{48}	s_1	s_5	s_5	s_5	s_5	s_5	s_6	s_5	s_5
r_{49}	s_4	s_2	s_1	s_8	s_7	s_6	s_2	s_4	s_5
r_{50}	s_7	s_3	s_2	s_7	s_5	s_5	s_6	s_5	s_5
r_{51}	s_3	s_3	s_4	s_7	s_9	s_4	s_8	s_5	s_6
r_{52}	s_8	s_3	s_4	s_8	s_4	s_4	s_5	s_4	s_2
r_{53}	s_3	s_6	s_2	s_8	s_5	s_5	s_5	s_3	s_2
r_{54}	s_9	s_3	s_4	s_8	s_2	s_5	s_6	s_6	s_3
r_{55}	s_3, s_4	s_4	s_2	s_7	s_4	s_4	s_7, s_8	s_3	s_4
r_{56}	s_4	s_2	s_3	s_5	s_6	s_4	s_5	s_3	s_5
r_{57}	s_8	s_3	s_2	s_5, s_6	s_4	s_6	s_3, s_4	s_4	s_4

5.5 - 5.6 in steps 1 - 2. The results from the polar manhattan distance measure of step 4 are represented in columns 5-7 in Tables 4.6 - 4.7, while columns 8-10 represent the results of the expected distances e_k obtained from eq. 4.5 in step 5, as computed below.

$$e_1 = \sum_{n=1}^{N} \hat{w}^{n1} \times d_{\eta\varsigma}^{n1} = -0.3409 \tag{4.15}$$

$$e_2 = \sum_{n=1}^{N} \hat{w}^{n2} \times d_{\eta\varsigma}^{n2} = 2.9683 \tag{4.16}$$

$$e_3 = \sum_{n=1}^{N} \hat{w}^{n3} \times d_{\eta\varsigma}^{n3} = 1.5180 \tag{4.17}$$

Then, the percentages of differences between the target and preferred linguistic terms are determined from eq. 4.6 in step 6, where the total distance is $((9-1) \times 2 = 16)$.

$$p_1 = \frac{e_1}{16} = \frac{-0.3409}{16} = -2.1305\% \tag{4.18}$$

$$p_2 = \frac{e_2}{16} = \frac{2.9683}{16} = 18.5519\% \tag{4.19}$$

$$p_3 = \frac{e_3}{16} = \frac{1.5180}{16} = 9.4873\% \tag{4.20}$$

Next, the differences between target and perceived linguistic term ($d_{\eta\varsigma}^{nk'}$) are determined by using eq. 4.1. Tables 4.8 - 4.9 show the results of $d_{\eta\varsigma}^{nk'}$ for dependent attributes for step 8. By using $d_{\eta\varsigma}^{nk'}$, the relationship among attributes is determined by eq. 4.1 in step 9. The results of $h_{k'}^{k}$ are presented as follows.

$$h_2^1 = \sum_{n=1}^{N} \frac{d_{\eta\varsigma}^{n2}}{57} = -0.667 \tag{4.21}$$

$$h_3^1 = \sum_{n=1}^{N} \frac{d_{\eta\varsigma}^{n3}}{57} = -1.140 \tag{4.22}$$

, and for h_1^2, h_3^2, h_1^3, and h_2^3 are 0.579 0.912 -0.351 0.000, respectively. Then, the attributes coefficients are determined by using eq. 4.8 in step 10.

$$a_2^1 = \frac{h_1^1}{12} = \frac{-0.667}{12} = -5.556\% \tag{4.23}$$

$$a_3^1 = \frac{h_2^1}{12} = \frac{-1.140}{12} = -9.503\% \tag{4.24}$$

, and for a_1^2, a_3^2, a_1^3, and a_2^3, are 4.825%, 7.602%, -0.029%, and 0 %. These attributes coefficients $a_{k'}^k$ will be used as components in the relationship equation 4.9 in step 11, as shown below.

For criterion 1: $f_k = f_1$,

$$p_1 = \Delta f_1 - 0.05556\Delta f_2^1 - 0.09503\Delta f_3^1 \tag{4.25}$$

For criterion 2: $f_k = f_2$,

$$p_2 = 0.04825\Delta f_1^2 + \Delta f_2 + 0.07602\Delta f_3^2 \tag{4.26}$$

For criterion 3: $f_k = f_3$,

$$p_3 = -0.029\Delta f_1^3 - 0\Delta f_2^3 + \Delta f_3 \tag{4.27}$$

Then, $\Delta f_1, \Delta f_2, \Delta f_3$ in eqs. 4.25 - 4.27 are substituted by the percentage of preferred adjustment p_k obtained from step 6: $p_1 = -2.130\%$, $p_2 = 18.552\%$, and $p_3 = 9.487\%$. Then, eqs. 4.25 - 4.27 are changed to be eqs. 30-32, respectively.

For criterion 1: $f_k = f_1$,

$$-0.02130 = \Delta f_1 - 0.05556\Delta f_2^1 - 0.09503\Delta f_3^1 \tag{4.28}$$

For criterion 2: $f_k = f_2$,

$$0.18552 = 0.04825\Delta f_1^2 + \Delta f_2 + 0.07602\Delta f_3^2 \tag{4.29}$$

For criterion 3: $f_k = f_3$,

$$0.09487 = -0.029\Delta f_1^3 - 0\Delta f_2^3 + \Delta f_3 \tag{4.30}$$

The results of $\Delta f_1, \Delta f_2, \Delta f_3$ are $-0.00237, 0.17843, 0.094801$, respectively. Finally, the manufacture is suggested to adjust the amount of ingredients (attributes) at -0.237% (f_1), 17.84% (f_2), and 9.48% (f_3). For the product prototype, if the proportion of ingredient 1 is 100 ml, then the suggested proportion is 99.763 ml.

It is interesting to notice that when the relationship among attributes is considered, the amount of percent adjustment between customer preference without attributes relationship (p_k) and the needed change Δf_k is different. This difference significantly proves that when the amount of attribute is adjusted, it affects the perception on other attributes.

To validate the result, the new product prototype with the suggested proportions should be implement. Then, respondents are asked to assess the questionnaire survey based on the new prototype again. If the percentage of differences between customer preferences and the product prototype (p_k) is less than the acceptable level of the company, a product prototype is successfully improved.

4.4.6 Conclusion and future work

In this chapter, an alternative approach for recommending the manufacturing process is proposed. Evaluations are considered on an ordinal scale. Firstly, customers are asked to provide their preferences on given criteria. In addition, to obtain the relationship among criteria, they are also asked to evaluate their feeling on the change of criteria. Then, the proposed model is applied to the data. Consequently, the model provides a recommendation to manufacturers, which can be further used in manufacturing a new-customer oriented product. The practical results lead us to prove that the model is useful in real-life managerial decision making. In addition, the proposed model is also able to reduce the loss of information since there is no approximation process from retranslating linguistic information into the general format.

For future work, it is interesting to extend the proposed polar manhattan distance measure to the case where different individuals may prefer to express their preferences by different linguistic term sets. In other words, a multiple granularity linguistic information in MCGDM problems is our of interest. Moreover, the proposed model can be extended to use with an asymmetric linguistic term, which normally happens in the real situation. These issues are our focuses in the future.

Table 4.6: Weight $\hat{w}^{nk}$, Distance $d^{nk}_{\eta\varsigma}$, and $\hat{w}^{nk} \times d^{nk}_{\eta\varsigma}$

Respondents r_n	Weight $\hat{w}^{nk}$ (Step 2)			Distance $d^{nk}_{\eta\varsigma}$ (Step 4)			$\hat{w}^{nk} \times d^{nk}_{\eta\varsigma}$ (Step 5)		
	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3
r_1	0.028	0.004	0.026	-8.000	8.000	2.000	-0.224	0.030	0.053
r_2	0.028	0.004	0.012	-8.000	7.000	8.000	-0.224	0.026	0.096
r_3	0.003	0.004	0.014	3.000	8.000	6.000	0.008	0.030	0.086
r_4	0.031	0.026	0.014	6.000	0.000	4.000	0.183	0.000	0.058
r_5	0.005	0.004	0.002	5.000	7.000	4.000	0.025	0.026	0.010
r_6	0.013	0.026	0.014	-4.000	0.000	6.000	-0.051	0.000	0.086
r_7	0.015	0.004	0.002	0.000	3.000	-2.000	0.000	0.011	-0.005
r_8	0.031	0.009	0.031	6.000	-6.000	0.000	0.183	-0.056	0.000
r_9	0.013	0.030	0.005	-4.000	6.000	0.000	-0.051	0.179	0.000
r_{10}	0.013	0.009	0.012	-2.000	-6.000	-6.000	-0.025	-0.056	-0.072
r_{11}	0.015	0.026	0.031	0.000	0.000	0.000	0.000	0.000	0.000
r_{12}	0.013	0.026	0.005	-4.000	0.000	-2.000	-0.051	0.000	-0.010
r_{13}	0.003	0.009	0.002	-6.000	-6.000	-8.000	-0.015	-0.056	-0.019
r_{14}	0.015	0.030	0.014	0.000	6.000	6.000	0.000	0.179	0.086
r_{15}	0.031	0.026	0.031	6.000	0.000	0.000	0.183	0.000	0.000
r_{16}	0.003	0.030	0.014	7.000	6.000	4.000	0.018	0.179	0.058
r_{17}	0.005	0.009	0.012	8.000	4.000	8.000	0.041	0.037	0.096
r_{18}	0.028	0.026	0.031	-8.000	0.000	0.000	-0.224	0.000	0.000
r_{19}	0.031	0.030	0.005	6.000	6.000	1.000	0.183	0.179	0.005
r_{20}	0.031	0.030	0.031	6.000	6.000	0.000	0.183	0.179	0.000
r_{21}	0.028	0.026	0.031	-8.000	0.000	0.000	-0.224	0.000	0.000
r_{22}	0.028	0.004	0.014	-8.000	8.000	6.000	-0.224	0.030	0.086
r_{23}	0.015	0.030	0.031	0.000	6.000	0.000	0.000	0.179	0.000
r_{24}	0.031	0.002	0.012	6.000	-4.000	8.000	0.183	-0.007	0.096
r_{25}	0.028	0.030	0.012	-8.000	6.000	-6.000	-0.224	0.179	-0.072
r_{26}	0.028	0.026	0.026	-8.000	0.000	2.000	-0.224	0.000	0.053
r_{27}	0.005	0.026	0.026	-3.000	0.000	2.000	-0.015	0.000	0.053
r_{28}	0.031	0.006	0.031	6.000	-2.000	0.000	0.183	-0.011	0.000
r_{29}	0.013	0.004	0.031	-2.000	5.000	0.000	-0.025	0.019	0.000
r_{30}	0.008	0.030	0.002	2.000	6.000	7.000	0.015	0.179	0.017
r_{31}	0.008	0.030	0.012	2.000	6.000	8.000	0.015	0.179	0.096
r_{32}	0.010	0.009	0.014	4.000	4.000	4.000	0.041	0.037	0.058
r_{33}	0.031	0.009	0.014	6.000	-6.000	6.000	0.183	-0.056	0.086
r_{34}	0.015	0.026	0.014	0.000	0.000	4.000	0.000	0.000	0.058
r_{35}	0.028	0.026	0.026	-8.000	0.000	2.000	-0.224	0.000	0.053
r_{36}	0.013	0.006	0.026	-2.000	-2.000	2.000	-0.025	-0.011	0.053
r_{37}	0.010	0.006	0.014	4.000	-2.000	4.000	0.041	-0.011	0.058
r_{38}	0.015	0.026	0.012	0.000	0.000	-6.000	0.000	0.000	-0.072
r_{39}	0.031	0.002	0.026	6.000	2.000	2.000	0.183	0.004	0.053
r_{40}	0.003	0.002	0.014	1.000	-1.000	4.000	0.003	-0.002	0.058

Table 4.7: Weight $\hat{w}^{nk}$, Distance $d^{nk}_{\eta\varsigma}$, and $\hat{w}^{nk} \times d^{nk}_{\eta\varsigma}$ (Cont)

Respondents r_n	Weight $\hat{w}^{nk}$ (Step 2)			Distance $d^{nk}_{\eta\varsigma}$ (Step 4)			$\hat{w}^{nk} \times d^{nk}_{\eta\varsigma}$ (Step 5)		
	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3	Attribute 1: f_1	Attribute 2: f_2	Attribute 3: f_3
r_{41}	0.028	0.009	0.005	-8.000	-6.000	-2.000	-0.224	-0.056	-0.010
r_{42}	0.008	0.030	0.026	2.000	6.000	2.000	0.015	0.179	0.053
r_{43}	0.003	0.004	0.031	-7.000	3.000	0.000	-0.018	0.011	0.000
r_{44}	0.005	0.004	0.002	5.000	5.000	3.000	0.025	0.019	0.007
r_{45}	0.010	0.030	0.002	4.000	6.000	3.000	0.041	0.179	0.007
r_{46}	0.031	0.004	0.012	6.000	8.000	-6.000	0.183	0.030	-0.072
r_{47}	0.028	0.030	0.012	-8.000	6.000	8.000	-0.224	0.179	0.096
r_{48}	0.028	0.026	0.026	-8.000	0.000	2.000	-0.224	0.000	0.053
r_{49}	0.013	0.030	0.012	-2.000	6.000	-6.000	-0.025	0.179	-0.072
r_{50}	0.010	0.009	0.026	4.000	4.000	2.000	0.041	0.037	0.053
r_{51}	0.013	0.009	0.014	-4.000	4.000	6.000	-0.051	0.037	0.086
r_{52}	0.031	0.030	0.031	6.000	6.000	0.000	0.183	0.179	0.000
r_{53}	0.013	0.030	0.031	-4.000	6.000	0.000	-0.051	0.179	0.000
r_{54}	0.005	0.030	0.026	8.000	6.000	2.000	0.041	0.179	0.053
r_{55}	0.005	0.009	0.002	-3.000	4.000	5.000	-0.015	0.037	0.012
r_{56}	0.013	0.026	0.031	-2.000	0.000	0.000	-0.025	0.000	0.000
r_{57}	0.031	0.004	0.002	6.000	1.000	-3.000	0.183	0.004	-0.007

Table 4.8: Distance $d_{\eta\varsigma}^{nk'}$ (Step 8)

Respondent r_n	Distance $d_{\eta\varsigma}^{nk'}$ of affected attribute $f_{k'}$					
	For $f_k = f_1$: $f_{k'}^k = f_2^1$	For $f_k = f_1$: $f_{k'}^k = f_3^1$	For $f_k = f_2$: $f_{k'}^k = f_1^2$	For $f_k = f_2$: $f_{k'}^k = f_3^2$	For $f_k = f_3$: $f_{k'}^k = f_1^3$	For $f_k = f_3$: $f_{k'}^k = f_2^3$
r_1	-2.000	4.000	2.000	2.000	0.000	0.000
r_2	4.000	-2.000	4.000	6.000	0.000	4.000
r_3	3.000	-4.000	2.000	-5.000	4.000	4.000
r_4	0.000	0.000	8.000	0.000	0.000	0.000
r_5	0.000	0.000	0.000	0.000	0.000	0.000
r_6	-2.000	-6.000	0.000	0.000	0.000	0.000
r_7	-2.000	-6.000	0.000	-5.000	-2.000	2.000
r_8	0.000	4.000	0.000	0.000	-2.000	-2.000
r_9	-2.000	-2.000	-6.000	6.000	0.000	-2.000
r_{10}	-4.00	-4.000	0.000	-2.000	-6.000	-4.000
r_{11}	-2.000	-2.000	-2.000	-2.000	-6.000	-2.000
r_{12}	-4.000	-2.000	0.000	-2.000	-4.000	-2.000
r_{13}	0.000	0.000	-2.000	-4.000	-4.000	-2.000
r_{14}	2.000	2.000	2.000	-2.000	0.000	2.000
r_{15}	-2.000	-2.000	-4.000	-4.000	-4.000	-4.000
r_{16}	2.000	0.000	-6.000	4.000	-2.000	2.000
r_{17}	4.000	6.000	2.000	6.000	2.000	2.000
r_{18}	0.000	0.000	0.000	0.000	0.000	0.000
r_{19}	-4.000	0.000	0.000	2.000	0.000	0.000
r_{20}	-2.000	2.000	-2.000	3.000	-2.000	-2.000
r_{21}	-2.000	0.000	0.000	0.000	0.000	0.000
r_{22}	2.000	-2.000	0.000	2.000	0.000	2.000
r_{23}	0.000	0.000	-4.000	-4.000	0.000	0.000
r_{24}	-2.000	0.000	6.000	4.000	0.000	-2.000
r_{25}	2.000	0.000	0.000	4.000	0.000	2.000
r_{26}	0.000	-6.000	2.000	2.000	0.000	0.000
r_{27}	0.000	-6.000	2.000	2.000	0.000	0.000
r_{28}	0.000	-6.000	2.000	0.000	0.000	4.000
r_{29}	2.000	2.000	-4.000	2.000	-2.000	0.000

Table 4.9: Distance $d_{ij}^{nk'}$ (Step 8) (Cont)

Respondent r_n	Distance $d_{\eta\varsigma}^{nk'}$ of affected attribute $f_{k'}$					
	For $f_k = f_1$: $f_{k'}^k = f_2^1$	For $f_k = f_1$: $f_{k'}^k = f_3^1$	For $f_k = f_2$: $f_{k'}^k = f_1^2$	For $f_k = f_2$: $f_{k'}^k = f_3^2$	For $f_k = f_3$: $f_{k'}^k = f_1^3$	For $f_k = f_3$: $f_{k'}^k = f_2^3$
r_{30}	2.000	0.000	0.000	0.000	2.000	2.000
r_{31}	1.000	-4.000	-4.000	-2.000	-2.000	4.000
r_{32}	-2.000	-4.000	0.000	4.000	-2.000	-4.000
r_{33}	-4.000	0.000	6.000	-2.000	-2.000	0.000
r_{34}	0.000	6.000	-4.000	4.000	2.000	0.000
r_{35}	0.000	0.000	2.000	0.000	2.000	0.000
r_{36}	-4.000	2.000	-2.000	2.000	-2.000	2.000
r_{37}	-2.000	-2.000	0.000	-4.000	0.000	-2.000
r_{38}	-4.000	0.000	0.000	6.000	-4.000	-4.000
r_{39}	-2.000	-2.000	2.000	2.000	2.000	-2.000
r_{40}	-2.000	-4.000	0.000	2.000	0.000	0.000
r_{41}	6.000	2.000	6.000	2.000	0.000	-6.000
r_{42}	0.000	0.000	0.000	0.000	2.000	2.000
r_{43}	3.000	-3.000	0.000	0.000	0.000	0.000
r_{44}	-3.000	0.000	0.000	3.000	0.000	0.000
r_{45}	-2.000	-2.000	0.000	4.000	0.000	0.000
r_{46}	-4.000	-2.000	6.000	4.000	0.000	2.000
r_{47}	0.000	0.000	-2.000	-4.000	6.000	2.000
r_{48}	2.000	2.000	2.000	2.000	2.000	2.000
r_{49}	-4.000	-6.000	6.000	4.000	0.000	2.000
r_{50}	-2.000	-4.000	2.000	2.000	2.000	2.000
r_{51}	-2.000	0.000	9.000	0.000	2.000	4.000
r_{52}	-2.000	0.000	0.000	0.000	0.000	-4.000
r_{53}	4.000	-4.000	2.000	2.000	-2.000	-4.000
r_{54}	-2.000	0.000	-4.000	2.000	4.000	-2.000
r_{55}	0.000	-4.000	0.000	0.000	-2.000	0.000
r_{56}	-4.000	-2.000	4.000	0.000	-2.000	2.000
r_{57}	-2.000	-4.000	0.000	4.000	0.000	0.000

Chapter 5

Decision model for screening an evaluation of go or no-go product

In this chapter, the third ODM clients' task is addressed. Firstly, the background and challenges of models developing for screening an evaluation of go or no-go product are stated. In this model, the concepts of manhattan distance measure and probabilistic uncertain linguistic terms are comprehensively extended to this task. In addition, some conventional models and techniques of linguistic computation approach based on ordinal scales addressed previously in Chapter 2, are briefly analyzed. Next, a concept of the proposed model and its normalization process, and its aggregation process are explained. Then, the a new model is developed and illustrated through a case study conducted in a beverage company in Thailand.

5.1 Model's background and its challenges

Since respondents naturally evaluate the NPD performance by linguistic expression based on their subjective perceptions and individual experiences, there exists the occurrence of uncertainty, impreciseness, and fuzziness from linguistic transformation processes. Consequently, it leads to the information loss during the evaluation process. Thus, it is necessary to develop an evaluation model for determining the NPD performance in support of firms' decision making.

In assessing respondents' subjective opinions, kansei engineering is usually used as a translating technology of people's psychological feeling for a product to design elements [87]. Since its success introduction, it is applied in various industries, especially in a new product development domain [85], [88]. However, there are yet limited works applying the kansei-based model to existing products [89]. In addition, although a semantic differential (SD) method [90] normally works together with the kansei-based models in many decision making problems, most of them aim at achieving the highest or the lowest semantic levels of kansei features (Monotonicity). In fact, there is a case that the highest or the lowest semantic levels are not the best solution. For example, suppose that linguistic term set $S = \{s_1, s_2, s_3, s_4, s_5\}$. Mr.A wants to drink a cup of coffee at room temperature (s_3). Thus, if it is too hot (s_5) or too cold (s_1), he does not prefer. In this case, to achieve his highest satisfaction level, it is necessary to transform the semantic level(s) of his preference on kansei feature into target semantic level (s_3) for making his customized coffee.

Due to the needs of capturing target semantic levels and evaluating NPD performance observed above, we propose a new model focusing on the NPD performance evaluation using kansei data by taking the distance semantic levels of firm-specified preference and people's perception on kansei features of the beverage packaging design into consideration. The evaluation would be helpful for further marketing and recommendation purpose.

Until now, there are many fuzzy linguistic approaches dealing with respondents' uncertainties in assessing data [91], [92], [93], [94]. With an ability to avoid information distortion and losing during the linguistic information process, 2-tuple linguistic model have been extensively used in group decision making problems [95]. Chen and Tai [96] measured the intellectual capital performance based on 2-tuple fuzzy linguistic information. Wang [97] considered multi-granularity linguistic variables in his 2-tuple-based model to evaluate the supply performance in dynamic environment on product-oriented strategy. Wang [80] presented a 2-tuple fuzzy linguistic computation model in evaluating NPD performance for a high-technological company in Taiwan. Taking a different track, Pang et al. [5] recently introduced a probabilistic linguistic term set (PLTS) model based on the idea that several possible linguistic terms may have different weights. Lin et al. [44] extended Pang et al.'s model by allowing respondents to provide more than one linguistic terms on their criteria assessment, called probabilistic uncertain linguistic term set (PULTS) model. Liu and You [61] also extended PLTS and TODIM method (prospect theory-based method) to take respondent's cognitive behavior into account, see more PLTS details on [51], [62], and [63].

However, those mentioned models do not concern about the fitness degree of linguistic levels between target and perceived Kansei features. As Zadeh [24] presented the concept of linguistic variable, the linguistic 2-tuple model assumes an order relation consistency on the qualitative scale treated as the linguistic term set of a linguistic variable. Thus, it is possible that we can measure the distance between two linguistic terms on the same initiated linguistic domain by using the 2-tuple linguistic-based model.

Stated by Liao et al [46], there are many types of distance and similarity measures between linguistic terms set such as Hamming distance measure, Euclidean distance measure, and Hausdroff distance measure [98], [99], [100]. Although, aforementioned techniques do not yet consider the distance between target levels and perceived levels on Kansei features, they inspire us to develop a linguistic distance-based model to deal with uncertainty over two linguistic terms.

To improve the existing model, a 3-tuple linguistic distance-based representation model with kansei data is proposed. Th proposed model is consisted of three tuples, i.e. (1) the ansei assessment on object, (2) the relative importance of respondents, and (3) the deviation degree from target-perceived linguistic terms. The related knowledge used for this models are 2-tuple linguistic approach, a probability distribution and Manhattan distance measure.

5.2 A 3-tuple linguistic distance-based model

In this section, a concept of 3-tuple linguistic distance-based representation model is first defined. Then, the computation processes for 3-tuple linguistic distance-based model are proposed.

5.2.1 Concept of a 3-tuple linguistic distance-based model

In this model, we extend and redefine a concept of the two tuples (s_g, α) from the conventional 2-tuple linguistic representation model for tackling with a new product's go/no-go screening. Moreover, the 3^{rd} tuple is also added to represent the respondents' reliability weights to alleviate the bias in group decision making problem.

The previous 1^{st} tuple is used to define a linguistic terms (s_g) assessed by respondents. Now, it is used to represent the perception of respondents on attributes, as denoted by *Interval Perceived Linguistic Terms (IPLTs)*, ($[s_g, s'_g]$). For the 2^{nd} tuple, it is previously used to define the difference between the computed linguistic information and its closet linguistic term s_g. Here, it is redefined as a symbolic symbol expressing the difference between two interval linguistic terms. Lastly, as mentioned above, the 3^{rd} tuple is used to denote the respondents' reliability weights. In short, each respondent assessment contains three information, which are represented by tuples as follows.

$$r_m : \langle x^{mk}(1^{st}tuple), \alpha_{\eta\varsigma}^{mk}(2^{nd}tuple), p^{mk}(3^{rd}tuple)\rangle$$

where m and k are indice for a set of respondents and a set of criteria, respectively. Now, let us explain how to obtain x^{mk}, $\alpha_{\eta\varsigma}^{mk}$, and p^{mk} by the computational process shown below.

5.2.2 Computational process

Let:

- $S = \{s_1, \dots, s_g, \dots, s_G\}$ be a set of linguistic terms
- $R = \{r_1, \dots, r_m, \dots, r_M\}$ be a set of respondents
- $F = \{f_1, \dots, f_k, \dots, f_K\}$ be a set of criteria.

From these notations, we then define an interval perceived linguistic terms (IPTLs) (x^{mk}), a difference between two interval linguistic terms ($\alpha_{\eta\varsigma}^{mk}$), and a respondent's reliability weight (p^{mk}), and represent them as 3-tuple information representation for respondents.

Definition 5.2.1. *The Interval Perceived Linguistic Terms (IPLTs) represents the perception or feeling of respondents m on product concept k. IPLTs is denoted by x^{mk}, with $x^{mk} \in I^S$.*

$$I^S = \{[s_g, s'_g] | s_g, s'_g \in S \ \& \ s_g \leq s'_g\} \tag{5.1}$$

Table 5.1: Perception on criteria f_k assessed by respondents r_m is defined by interval perceived linguistic terms (IPLTs) x^{mk}

Respondents R	Criteria F				
	f_1	$\dots$	f_k	$\dots$	f_K
r_1	x^{11}	$\dots$	x^{1k}	$\dots$	x^{1K}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_m	x^{m1}	$\dots$	x^{mk}	$\dots$	x^{mK}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
r_M	x^{M1}	$\dots$	x^{Mk}	$\dots$	x^{MK}

where I^S associates with interval linguistic terms in S. With this linguistic representation, it implies that a respondent r_m uses x^{mk} for expressing their perception on product f_k. The notation of x^{mk} is depicted in Table 5.1.

By exploiting the IPLTs (x^{mk}), we then propose approaches to compute the difference between two interval linguistic terms ($\alpha_{\eta\varsigma}^{mk}$) and the reliability weights of respondents (p^{mk}) , as the following.

As mention above, a new product is screened by the difference of two interval linguistic terms ($\alpha_{\eta\varsigma}^{mk}$); (1) IPLTs ($x^{mk}$) given by respondents, (2) the interval target linguistic terms (t^k) given by a firm. When the degree of fit between x^{mk} and t^k passes a firm acceptable level, a product can be launched to the market. For example, the firm needs an 'Extremely attractive' packaging design (t^k). Thus, the firm expects that customers should perceive that the packaging is 'Extremely attractive' (x^{mk}). In this case, if x^{mk} matches with t^k, then it means that the packaging is successfully designed as firm expected.

To determine the degree of fit, we borrow the concepts of linguistic distance degree from a 2-tuple linguistic-based model [36] and a manhattan distance measure. In the conventional 2-tuple linguistic-based model, there are two components indicating the computed linguistic term (s_g) and the difference of the computed linguistic term and the initial linguistic description (α). From this definition, we initiate an idea of measuring difference between two interval linguistic terms (x^{mk} and t^k). To do so, we first redefine a concept of a former parameter α to be a difference between x^{mk} and t^k, which is redenoted as $\alpha_{\eta\varsigma}^{mk}$.

$\alpha_{\eta\varsigma}^{mk}$ is computed with the help of geodesic distance in a graph theory [3]. In the graph theory, the linguistic information is mapped to a vertex coordinator, as depicted in Table 5.2. Having obtained a vertex coordinator matrix, $\alpha_{\eta\varsigma}^{mk}$ is simply computed by the following definition.

Table 5.2: Vertex coordinators of linguistic term set S, $G = 7$

x-axis	y-axis						
	0	1	2	3	4	5	6
0	s_1						
1	s_1, s_2	s_2					
2	s_1, s_3	s_2, s_3	s_3				
3	s_1, s_4	s_2, s_4	s_3, s_4	s_4			
4	s_1, s_5	s_2, s_5	s_3, s_5	s_4, s_5	s_5		
5	s_1, s_6	s_2, s_6	s_3, s_6	s_4, s_6	s_5, s_6	s_6	
6	s_1, s_7	s_2, s_7	s_3, s_7	s_4, s_7	s_5, s_7	s_6, s_7	s_7

Definition 5.2.2. *In the x-y scale, η and ς are the vertex coordinators of interval target linguistic terms (t^k) and interval perceived linguistic terms (x^{mk}), respectively. A distance between two vertices in the martix is determined by teh manhattan distance measure.*

$$\alpha_{\eta\varsigma}^{mk} = d(\eta, \varsigma) = d((x, y), (x', y')) = |x - x'| + |y - y'| \tag{5.2}$$

Example 5.2.1. *Assume that at criterion 1, the interval target linguistic variable is $[s_1, s_2]$ and the interval perceive linguistic variable of decision maker 1 is $[s_3, s_4]$. In this case, $\eta = (1, 0)$ and $\varsigma = (3, 2)$, as illustrated in Table 5.2.*

$$\begin{aligned} \alpha_{(1,0),(3,2)}^{11} &= d([s_1, s_2], [s_3, s_4]) \\ &= d((1, 0), (3, 2)) = |1 - 3| + |0 - 2| = 4 \end{aligned} \tag{5.3}$$

Now, let see how can we determine the reliability weights of respondents (p^{mk}) by using IPLTs (x^{mk}).

Table 5.3: 3-tuples decision matrix, $r_m = \langle x^{mk}, \alpha^{mk}_{\eta\varsigma} \rangle$, p^{mk}

Criterion	Target LTs	Respondents														
f_k	t^k	r_1			...			r_m			...			r_M		
f_1	t^1	x^{11}	$\alpha^{11}_{\eta\varsigma}$	p^{11}	...	...	...	x^{m1}	$\alpha^{m1}_{\eta\varsigma}$	p^{m1}	...	...	...	x^{M1}	$\alpha^{M1}_{\eta\varsigma}$	p^{M1}
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
f_k	t^k	x^{1k}	$\alpha^{1k}_{\eta\varsigma}$	p^{1k}	...	...	...	x^{mk}	$\alpha^{mk}_{\eta\varsigma}$	p^{mk}	...	...	...	x^{Mk}	$\alpha^{Mk}_{\eta\varsigma}$	p^{Mk}
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
f_K	t^K	x^{1K}	$\alpha^{1K}_{\eta\varsigma}$	p^{1K}	...	...	...	x^{mK}	$\alpha^{mK}_{\eta\varsigma}$	p^{mK}	...	...	...	x^{MK}	$\alpha^{MK}_{\eta\varsigma}$	p^{MK}

As respondents normally have different levels of knowledge, background, culture, and specialization on a particular criterion [101]. They are not expected to have a sufficient expertise to comment on all aspects of product without bias [70]. To alleviate the bias, the relative importances are usually assigned to each respondent. Basically, the weights are either given or determined from the available data [102], [103].

In this study, the reliability weights of respondents denoted as p^{mk} is obtained from x^{mk}, which is given by respondents themselves. Basically, the idea is that when a judgment of the respondent is close to the majority assessment, it can infer that his/her judgment is more reliable than others. Thus, p^{mk} is related to a probability distribution of x^{mk}, which can be computed by the following definition.

Definition 5.2.3. *The interval probabilistic linguistic variable $X(p)$*

$$X(p) = \{X^n(p^n) | X^n \in I^S, p^n \geq 0, n = 1, 2, \ldots, N\} \tag{5.4}$$

where $X^n(p^n)$ is the interval linguistic term X^n, with $X^n \in I^S$, associated with the probability p^n, and N is the number of all different linguistic term in $X(p)$. It can be noted that:

- *If $\sum_{n=1}^{N} p^n = 1$, then there is a complete information of probabilistic distribution of all possible linguistic term in S.*
- *If $\sum_{n=1}^{N} p^n < 1$, then there is an incomplete information of probabilistic distribution of all possible linguistic term in S.*
- *If $\sum_{n=1}^{N} p^n = 0$, then the information is completely unknown.*

Definition 5.2.4. *The reliability weights of respondents are determined from the probability distribution of a group assessment, which can be defined as follows.*

$$p^{mk} = \frac{|\{r^{m'}|x^{m'k} = x^{mk}\}|}{M} \quad \forall m, k \tag{5.5}$$

After obtaining p^{mk}, a normalization process is required to normalize the weights so that the total weight is equal to 1.

$$\hat{p}^{mk} = \frac{p_{mk}}{\sum_{m=1}^{M} p_{mk}} \quad \forall m, k \tag{5.6}$$

Example 5.2.2. *Suppose that there are ten respondents (RSs) vote for criterion 1. RSs 1-5 vote [s_2]. RSs 6-7 vote [s_2, s_3] and RSs 8-10 vote [s_1]. Then, RS 6 will have a reliability weight for criterion 1 as:*

$$p^{61} = \frac{2}{10} = 0.2 \tag{5.7}$$

Thus, RSs 1-5 will have a reliability weight for criterion 1 = 0.5. RSs 6-7 = 0.2 and RSs 8-10 = 0.3.

Example 5.2.3. *According to Example 5.2.2, p^{61} can be normalized as follows.*

$$\begin{aligned} \hat{p}^{61} = \frac{p^{61}}{\sum_m p^{m1}} &= \frac{0.2}{(0.5 \times 5) + (0.2 \times 2) + (0.3 \times 3)} \\ &= \frac{0.2}{3.8} = 0.053 = 5.3\% \end{aligned} \tag{5.8}$$

In other words, it means that RS 6 has a reliability weight (p^{mk}) = 5.3 % on criterion 1.

In summary, the 3-tuple linguistic distance based representation model consists of three information for each respondents, which are the IPLTs, the difference between two linguistic terms, and the reliability weights, as depicted in Table 5.3. It can also be concluded as tuples: $\langle x^{mk}, \alpha^{mk}_{\eta\varsigma}, p^{mk} \rangle$.

5.3 MCGDM model for screening a new product's go/no-go

The new product screening is based on the idea that a firm satisfies when respondents are able to perceived a criterion at the given target levels of linguistic terms. Suppose that respondents $r_m(m = 1, 2, \ldots M)$ are responsible for assessing on criteria $f_k(k = 1, 2, \ldots, K)$. Then,

- Let x^{mk} be an interval perceived linguistic terms (IPLTs) in linguistic term set S; $S = \{s_1, \ldots, s_g, \ldots, s_G\}$, provided by r_m in assessing f_k.

$$x^{mk} = \{[s_g^k, {s'}_g^k] | s_g, s'_g \in S\} \quad \forall m, k \tag{5.9}$$

- Let t^k be an interval target linguistic terms (ITLTs) in linguistic term set S; $S = \{s_1, \ldots, s_g, \ldots, s_G\}$ on criterion f_k provided by a firm.

$$t^k = \{[s_g^k, {s'}_g^k] | s_g, {s'}_g \in S\} \quad \forall k \tag{5.10}$$

Based on these notations and assumptions, the procedures for a proposed model can be proceeded as follows. In the first step, the reliability weights of respondents are determined. They are represented by the probabilistic distribution over linguistic term set. Secondly, the difference between IPLTs and ITLTs are measured. Thirdly, the degree of fit denoted by the expected distance, is calculated by using arithmetic mean operator. Lastly, a new product is screened according to the acceptable satisfaction level of a firm. The flow diagram of the proposed model is illustrated in Figure 5.1. Now let us further explain the proposed model step by step as follow.

Step 1. *Deriving the reliability weight of each respondent on each criterion*

From the matrix of individual assessment shown in Table 5.1, the probabilistic distributions of criterion k around linguistic expression x^{mk} are computed by using eq. 5.5, as defined in Definition 5.2.4.

$$p^{mk} = \frac{|\{r^{m'} | x^{m'k} = x^{mk}\}|}{M} \quad \forall m, k$$

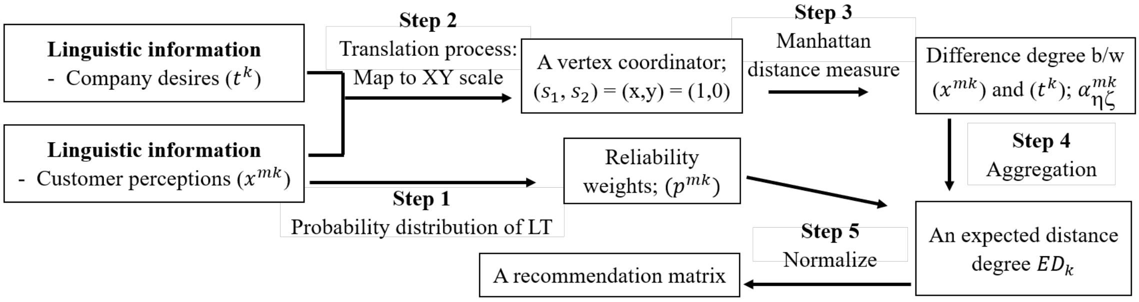

Figure 5.1: Procedures for the proposed 3-tuple linguistic distance-based evaluation model

Then, by using eq. 5.6, p^{mk} is normalized so that the sum of p^{mk} of each criterion k is equal to 1.

$$\hat{p}^{mk} = \frac{p_{mk}}{\sum_{m=1}^{M} p_{mk}} \quad \forall m, k$$

Step 2. *Measuring the difference between IPLTs and ITLTs*

The linguistic difference $\alpha^{mk}_{\eta\varsigma}$ is measured by eq. 5.2.

$$\alpha^{mk}_{\eta\varsigma} = d(t^k, x^{mk}) = d(\eta, \varsigma) = d((x, y), (x', y')) = |x - x'| + |y - y'|$$

After obtaining $\alpha^{mk}_{\eta\varsigma}$, all linguistic information can be represented in the proposed 3-tuple linguistic distance representation model, as $r_m : \{\langle x^{mk}, \alpha^{mk}_{\eta\varsigma}, p^{mk}\rangle | k = 1, 2, \ldots, K\}$.

Step 3. *Determining the expected distance degree of kansei features*

With the use of conventional arithmetic operation, the expected distance ED_k on criterion k is determined by multiplying p^{mk} by $\alpha^{mk}_{\eta,\varsigma}$.

$$ED_k = \sum_{m=1}^{M} p^{mk} \times \alpha^{mk}_{\eta,\varsigma} \quad \forall k \tag{5.11}$$

Step 4. *Screening a new product's go/no-go*

When the expected distance degrees ED_k are less than the firm's threshold (TH); $ED_k \leq TH$, it implies that the actual product is able to reflect criterion k. In addition, when all $ED_k \leq TH$, it represents that the product has enough performance to be launched to the market since it is able to reflect all of target criteria. In contrast, if any ED_k is greater than TH, the product is not yet ready to be launched. In addition, the inferior *criterion k has to be reproduced or redesigned. To screen the products, firstly, the acceptable level β must be provided by the firm, e.g. $\beta = 5\%, 10\%, 15\%$. Then, the threshold is computed by the following equation.*

$$TH = \beta \times (G - 1 \times 2) \tag{5.12}$$

where G is the cardinality of linguistic term set S. $(G - 1 \times 2)$ represents the total distance of x-axis and y-axis in $\mathbb{Z}^2$.

5.4 A case study on Thai-tea soy milk beverage

In this section, a case study taken from Wangsukjai export limited company, Thailand, is used to illustrate how the 3-tuple linguistic distance-based evaluation model developed previously works in practice.

A firm is an Original Design Manufacturing (ODM)'s client. ODM is one of the cooperation modes in a supply chain for the Research and Development (R&D)'s project in NPD. In practice, a firm needs to provide their product concepts to its contract ODM manufacturer. Then, ODM manufacturer will produce an actual product according to concepts given by a firm. Finally, a firm needs to validate the actual product by screening whether it is able to reflect the given firm's concepts or not.

To increase the advantage competitiveness of the company and to capture a potential health market in Thailand. A firm decided to expand its product line by developing a new Thai-tea soy milk beverage product. In this study, we focus on designing a packaging for the new Thai-tea soy milk beverage product. Its launching decision is depending on the 3-tuple linguistic distance-based evaluation in screening a new product. A kansei questionnaire method is used to gather opinions in evaluating at what level respondents can perceive the target product concepts provided by the firm. The firm satisfies when respondents can perceive product concepts at the same level(s) as its given target level(s). The framework of the new product's go/no-go screening evaluation model for Thai-tea soy milk packaging design is graphically described in Figure 5.2.

Figure 5.2: Framework of a new product's go/no-go screening

5.4.1 Data collection

In a new product screening's process, the data is collected through a workshop conducted. The workshop is necessary since it congregates target customers. Moreover, we can also improve a quality of the data by ensuring that target customers understand how to do the questionnaire. Finally, some tokens of participation are given to the participated target customers to encourage their willingness in assessing the questionnaire. There were sixty one target customers (respondents) participated in this evaluation. Eleven product concepts were selected for packaging design evaluation. The product concepts were identified by kansei features, and assessed by means of linguistic terms in set S. There are two sets of input data collected.

- Data collected from ODM client: The interval target linguistic terms (ITLTs); (t^k).
- Data collected from respondents: The interval perceived linguistic terms (IPLTs); (x^{mk}).

More descriptions on how to obtain ITLTs and IPLTs are explained below.

Designing a questionnaire

Kansei features are applied to represent the product concepts $f_k (k = 1, 2, \ldots, 11)$. They are often used to express people's psychological feeling on products [87]. It has been successfully applied to product design process in various industries such as food and drink, packaging, automotive, etc [104], [105], [89]. In this study, kansei features are first selected by the firm. They are defined by a bipolar pair of opposing as exemplified belows. [106] Let:

- $F = \{f_1, \ldots, f_k, \ldots, f_K\}$ be a set of kansei features selected

- $W = \{< w_k^+, w_k^- > | k = 1, 2, \ldots, K\}$ be a set of bipolar pair of opposing

For example, f_1 is the color theme on the packaging. The bipolar pair of kansei words corresponding to f_1 is $\{<$ soft color (w_1^+), energetic color $(w_1^-) >\}$.

Having obtained kansei features (f_k), a semantic differential (SD) method with G-point scales [107] is used to design a questionnaire for gathering kansei data as illustrated in Figure 5.3. The questionnaire is also presented in Table 5.4.

F_k

w_K^+	s_1	...	s_G	w_K^-

Figure 5.3: G-point scale for gathering kansei data

Gathering ITLTs and IPLTs

With the use of questionnaire, the firm was asked to evaluate its desirable scales on selected kansei features (f_k) by means of linguistic terms; ITLTs (t^k). Then, respondents were asked to provide their perception on kansei features (f_k) by means of linguistic terms; IPLTs (x^{mk}).

Kansei assessment database

Now, in the kansei assessment database, it consists of t^k and x^{mk}. From Table 5.4, when the interval perceived linguistic terms x^{mk} (✓) is close to the interval target linguistic terms t^k (•), it means that the ODM manufacture successfully designs a packaging. In addition, when respondents hesitate in selecting in which degree, they can check ✓ in all hesitated degrees. These respondents also have different reliability weights on each kansei feature (f_k) according to their close assessment to the majority assessment, denoted as p^{mk}. The linguistic term set S used in this study is defined by

$$S = \{\text{Extremely}(w_k^+), \text{Much}(w_k^+), \text{Less}(w_k^+), \text{Neutral}, \text{Less}(w_k^-), \text{Much}(w_k^-), \text{Extremely}(w_k^-)\}$$

where w_k^+ and w_k^- are the opposing bipolar pair of kansei feature f_k.

Table 5.4: An evaluation form evaluating product concepts for packaging design

f_k	Left Kansei word (w_k^+)	s_1	s_2	s_3	s_4	s_5	s_6	s_7	Right Kansei word (w_k^-)
		Extremely	Much	Less	Neutral	Less	Much	Extremely	
Packaging (coloring, layout, font size, and motto)									
1	***Attractive*** A product can induce us to touch, look back, and read its article on the package, within 5 minutes.	•					✓		***Unattractive*** A product can not induce us to touch, look back, and read its article on the package, within 5 minutes.
2	***Simple*** The font and character on the packaging are easy to read.		•	•				✓	***Detailed*** The font and character on the packaging are not easy to read.
3	***Clean*** A color of background is apparently different from the color of word. In other words, the word is not merged with the background, e.g., Black and White	•	✓						***Dirty*** A color of background is apparently different from the color of word. In other words, the word is merged with the background, e.g., Red and Orange
4	***Soft color*** The colors of this family are usually described {near neutral}, {milky}, {desaturated}, and {lacking strong chromatic content. In addition, it also evokes the feeling of romantic and happiness.		• ✓	•					***Energetic color*** The colors of this family usually represent sunshine, and other light playful feelings.
5	***Providing health related graphics*** An infographic available on the package induces us to think that if we drink this product, we will be healthy	•			✓				***Not providing health related graphics*** An infographic available on the package does not induce us to think that if we drink this product, we will be healthy
...	...								...
11	***Feeling full*** After reading a product description, consumers feel full.		✓	•					***Feeling not full*** After reading a product description, consumers feel not full.

5.4.2 Result of the proposed model's implementation

Once the Kansei assessment database has been built, the proposed 3-tuple linguistic distance-based model is used to screen the new product's go/no-go. The steps are outlined as follows.

Step 1. *Deriving the reliability weight of each respondent on each criterion*

By using eqs. 5.5 and 5.6, the reliability weights of respondents on each kansei feature (f_k) are derived. Their individual linguistic assessments are provided in Tables 5.5 - 5.6. The results are presented in Tables 5.7 - 5.8.

Example 5.4.1. *For respondent r_1, his linguistic assessment on kansei feature f_1 is $[s_3]$:x^{11}. The probability distribution over linguistic terms $[s_3]$ on f_1 is derived by using eq. 5.5.*

$$p^{11} = \tfrac{14}{61} = 0.2295$$

Then, p^{11} is normalized by using eq. 5.6.

$$\hat{p}^{11} = \tfrac{p^{11}}{\sum_{m=1}^{61} p^{mk}} = \tfrac{0.2295}{10.3443} = 0.0222 = 2.22\%$$

Consequently, the reliability weight of respondent 1 on kansei feature 1, which is 0.0022, is indicated in Table 5.7: column 2, row 3.

Step 2. *Measuring the difference between IPLTs and ITLTs*

The firm provides a set of ITLTs for eleven kansei feature as:

$$t^k = \{[s_1], [s_2, s_3], [s_1], [s_2, s_3], [s_1], [s_1], [s_1], [s_1, s_2], [s_2, s_3], [s_2, s_3], [s_3]\}$$

The manhattan distance measure addressed in eq. 5.2 is utilized to determine the difference of t^k and x^{mk}. The result are shown in Tables 5.9 - 5.11. Note that the vertex coordinator of linguistic term with cardinality $G = 7$ is provided in Table 5.2.

Example 5.4.2. *For respondent r_1, his linguistic assessment on criterion f_1 is $[s_3] : x^{11}$. Thus, the difference degree $\alpha^{11}_{\eta\varsigma}$ can be determined by*

$$\alpha^{11}_{\eta\varsigma} = d(t^1, x^{11}) = d((0, 0), (2, 2)) = |0 - 2| + |0 - 2| = 4$$

Table 5.5: Linguistic assessment by respondents x^{mk} $(r_1 - r_{45})$

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_1	$[s_3]$	$[s_2]$	$[s_1]$	$[s_3]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_2]$
r_2	$[s_3, s_4]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_3, s_4]$	$[s_1]$	$[s_2]$	$[s_1, s_2]$	$[s_5, s_6]$	$[s_2, s_3]$	$[s_4]$
r_3	$[s_2, s_3]$	$[s_3]$	$[s_1, s_2]$	$[s_1, s_2]$	$[s_3]$	$[s_1]$	$[s_2]$	$[s_2, s_3]$	$[s_5]$	$[s_1, s_2]$	$[s_5]$
r_4	$[s_3, s_4]$	$[s_3, s_4]$	$[s_5]$	$[s_1]$	$[s_4]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_7]$	$[s_1]$	$[s_3]$
r_5	$[s_3, s_4]$	$[s_4, s_5]$	$[s_1, s_2]$	$[s_1]$	$[s_6, s_7]$	$[s_5, s_6]$	$[s_2, s_3]$	$[s_3, s_4]$	$[s_6, s_7]$	$[s_2, s_3]$	$[s_2, s_3]$
r_6	$[s_2]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$
r_7	$[s_4, s_5]$	$[s_4]$	$[s_4]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_2, s_3]$	$[s_3, s_4]$	$[s_4]$	$[s_4, s_5]$	$[s_3, s_4]$	$[s_3, s_4]$
r_8	$[s_4]$	$[s_6]$	$[s_3]$	$[s_2]$	$[s_4, s_5]$	$[s_2]$	$[s_1]$	$[s_1, s_2]$	$[s_5, s_6]$	$[s_1, s_2]$	$[s_4]$
r_9	$[s_3]$	$[s_1]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_1]$	$[s_1]$	$[s_1]$	$[s_2]$	$[s_2]$	$[s_2]$
r_{10}	$[s_3, s_4]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_7]$	$[s_2]$	$[s_2]$
r_{11}	$[s_3]$	$[s_7]$	$[s_4]$	$[s_5]$	$[s_4]$	$[s_4]$	$[s_5]$	$[s_4]$	$[s_2]$	$[s_7]$	$[s_4]$
r_{12}	$[s_3]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_4]$	$[s_3]$	$[s_2]$	$[s_2]$
r_{13}	$[s_4, s_5]$	$[s_4]$	$[s_4]$	$[s_1, s_2]$	$[s_5]$	$[s_6, s_7]$	$[s_3, s_4]$	$[s_4]$	$[s_3, s_4]$	$[s_3]$	$[s_2]$
r_{14}	$[s_5]$	$[s_6]$	$[s_4]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_4]$	$[s_7]$	$[s_3]$	$[s_2]$
r_{15}	$[s_3, s_4]$	$[s_3]$	$[s_5]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_3, s_4]$	$[s_7]$	$[s_1]$	$[s_2, s_3]$
r_{16}	$[s_4, s_5]$	$[s_5]$	$[s_5, s_6]$	$[s_3]$	$[s_5, s_6]$	$[s_3, s_4]$	$[s_1]$	$[s_4]$	$[s_5]$	$[s_1]$	$[s_4, s_5]$
r_{17}	$[s_4, s_5]$	$[s_5]$	$[s_5, s_6]$	$[s_6]$	$[s_5]$	$[s_5, s_6]$	$[s_6]$	$[s_4]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_4]$
r_{18}	$[s_2, s_3]$	$[s_2]$	$[s_1, s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_4]$	$[s_4, s_5]$	$[s_4, s_5]$	$[s_4]$
r_{19}	$[s_3, s_4]$	$[s_3, s_4]$	$[s_3, s_4]$	$[s_1]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_2, s_3]$	$[s_3]$
r_{20}	$[s_2, s_3]$	$[s_1]$	$[s_2, s_3]$	$[s_1, s_2]$	$[s_3, s_4]$	$[s_1]$	$[s_1]$	$[s_2, s_3]$	$[s_2, s_3]$	$[s_1, s_2]$	$[s_2]$
r_{21}	$[s_3]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_5]$	$[s_1]$	$[s_2]$	$[s_5]$	$[s_4]$	$[s_4]$	$[s_5]$
r_{22}	$[s_3]$	$[s_5]$	$[s_3]$	$[s_3]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_5]$	$[s_5]$	$[s_2]$	$[s_2]$
r_{23}	$[s_3]$	$[s_2]$	$[s_5]$	$[s_1]$	$[s_3]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_4]$	$[s_2]$	$[s_3]$
r_{24}	$[s_3, s_4]$	$[s_4]$	$[s_4, s_5]$	$[s_2]$	$[s_4]$	$[s_3]$	$[s_3]$	$[s_4]$	$[s_4]$	$[s_3]$	$[s_4]$
r_{25}	$[s_3, s_4]$	$[s_4, s_5]$	$[s_3, s_4]$	$[s_3, s_4]$	$[s_2, s_3]$	$[s_2, s_3]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_3]$	$[s_2]$	$[s_4, s_5]$
r_{26}	$[s_3, s_4]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3, s_4]$	$[s_2, s_3]$	$[s_2]$	$[s_4]$
r_{27}	$[s_3, s_4]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3, s_4]$	$[s_1]$	$[s_3]$	$[s_4]$	$[s_4]$	$[s_2]$	$[s_2]$
r_{28}	$[s_2, s_3]$	$[s_3]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_4, s_5]$	$[s_3]$	$[s_2]$	$[s_2, s_3]$	$[s_5, s_6]$	$[s_5]$
r_{29}	$[s_3]$	$[s_5]$	$[s_5]$	$[s_4]$	$[s_4]$	$[s_6]$	$[s_2]$	$[s_4]$	$[s_7]$	$[s_1]$	$[s_4]$
r_{30}	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_5]$
r_{31}	$[s_5]$	$[s_4]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_3]$	$[s_5]$	$[s_3]$
r_{32}	$[s_3, s_4]$	$[s_3, s_4]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_3, s_4]$	$[s_2, s_3]$	$[s_1, s_2]$	$[s_1, s_2]$	$[s_2, s_3]$	$[s_2, s_3]$	$[s_2, s_3]$
r_{33}	$[s_3]$	$[s_4]$	$[s_3, s_4]$	$[s_2]$	$[s_4]$	$[s_5]$	$[s_4]$	$[s_4]$	$[s_5, s_6]$	$[s_4]$	$[s_4]$
r_{34}	$[s_3]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_4]$	$[s_3]$	$[s_2]$	$[s_5]$	$[s_6]$	$[s_5]$	$[s_3]$
r_{35}	$[s_4, s_5]$	$[s_3, s_4]$	$[s_5]$	$[s_3]$	$[s_1]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_4, s_5]$	$[s_3]$	$[s_4]$

Table 5.6: Linguistic assessment by respondents x^{mk} $(r_{46} - r_{61})$

Respondent	Product concept f_k									
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_{36}	$[s_4, s_5]$	$[s_5]$	$[s_4]$	$[s_2]$	$[s_4]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_6]$	$[s_1]$	$[s_2]$
r_{37}	$[s_2]$	$[s_1]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_3]$	$[s_2]$
r_{38}	$[s_4, s_5]$	$[s_4, s_5]$	$[s_4]$	$[s_3, s_4]$	$[s_4, s_5]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_4, s_5]$	$[s_1]$	$[s_4]$
r_{39}	$[s_4]$	$[s_6]$	$[s_5]$	$[s_2]$	$[s_4, s_5]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_6]$	$[s_1]$	$[s_3]$
r_{40}	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_1]$	$[s_1]$	$[s_1]$	$[s_3]$	$[s_3]$	$[s_2]$	$[s_2]$
r_{41}	$[s_7]$	$[s_5]$	$[s_5]$	$[s_4]$	$[s_4]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_4]$	$[s_4]$	$[s_4]$
r_{42}	$[s_3]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_4]$	$[s_2]$	$[s_6]$	$[s_6]$	$[s_2]$	$[s_2]$
r_{43}	$[s_2]$	$[s_2]$	$[s_6]$	$[s_5]$	$[s_5]$	$[s_1]$	$[s_2]$	$[s_4]$	$[s_7]$	$[s_2]$	$[s_5]$
r_{44}	$[s_3, s_4]$	$[s_5]$	$[s_3]$	$[s_4]$	$[s_3]$	$[s_6]$	$[s_4]$	$[s_3]$	$[s_6]$	$[s_2]$	$[s_4]$
r_{45}	$[s_5]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_1]$	$[s_4]$	$[s_2]$	$[s_3]$	$[s_5]$	$[s_1]$	$[s_3]$
r_{46}	$[s_3, s_4]$	$[s_5, s_6]$	$[s_2, s_3]$	$[s_4, s_5]$	$[s_4, s_5]$	$[s_5, s_6]$	$[s_2, s_3]$	$[s_4, s_5]$	$[s_7]$	$[s_1]$	$[s_2, s_3]$
r_{47}	$[s_3, s_4]$	$[s_4, s_5]$	$[s_2, s_3]$	$[s_1]$	$[s_5, s_6]$	$[s_3, s_4]$	$[s_2, s_3]$	$[s_3, s_4]$	$[s_5, s_6]$	$[s_1]$	$[s_3, s_4]$
r_{48}	$[s_4]$	$[s_2]$	$[s_3]$	$[s_4]$	$[s_4]$	$[s_3]$	$[s_4]$	$[s_4]$	$[s_6]$	$[s_4]$	$[s_4]$
r_{49}	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_4]$	$[s_3]$
r_{50}	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_4]$	$[s_2]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_2]$	$[s_3]$
r_{51}	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_4]$	$[s_2]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_2]$	$[s_3]$
r_{52}	$[s_2]$	$[s_4]$	$[s_3]$	$[s_2]$	$[s_4]$	$[s_4]$	$[s_4]$	$[s_4]$	$[s_6]$	$[s_2]$	$[s_4]$
r_{53}	$[s_7]$	$[s_2]$	$[s_4]$	$[s_1]$	$[s_7]$	$[s_7]$	$[s_1]$	$[s_4]$	$[s_7]$	$[s_7]$	$[s_4]$
r_{54}	$[s_2]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_1]$	$[s_1]$
r_{55}	$[s_3]$	$[s_2]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_2]$
r_{56}	$[s_3]$	$[s_2, s_3]$	$[s_2]$	$[s_3]$	$[s_3]$	$[s_5]$	$[s_4]$	$[s_3]$	$[s_5]$	$[s_2]$	$[s_5]$
r_{57}	$[s_6]$	$[s_6]$	$[s_5]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_5]$	$[s_1]$	$[s_3]$	$[s_2]$
r_{58}	$[s_4, s_5]$	$[s_5]$	$[s_3]$	$[s_2, s_3]$	$[s_4]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_2]$	$[s_1]$	$[s_1]$
r_{59}	$[s_3, s_4]$	$[s_5]$	$[s_4, s_5]$	$[s_2]$	$[s_1, s_2]$	$[s_3]$	$[s_1, s_2]$	$[s_2, s_3, s_4]$	$[s_5]$	$[s_2, s_3]$	$[s_4]$
r_{60}	$[s_3]$	$[s_3]$	$[s_4, s_5]$	$[s_1, s_2]$	$[s_2]$	$[s_4, s_5]$	$[s_2, s_3]$	$[s_3, s_4, s_5]$	$[s_3, s_4]$	$[s_1, s_2]$	$[s_3, s_4]$
r_{61}	$[s_4]$	$[s_3]$	$[s_3, s_4]$	$[s_1]$	$[s_2]$	$[s_3]$	$[s_2]$	$[s_4]$	$[s_3, s_4]$	$[s_3]$	$[s_4]$

Table 5.7: Reliability weights of respondents p^{mk} ($r_1 - r_{27}$)

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_1	0.0222	0.0317	0.0124	0.0142	0.0066	0.0154	0.0066	0.0105	0.0054	0.0191	0.0217
r_2	0.0238	0.0317	0.0290	0.0142	0.0066	0.0416	0.0285	0.0045	0.0108	0.0213	0.0029
r_3	0.0063	0.0072	0.0062	0.0051	0.0133	0.0416	0.0285	0.0030	0.0162	0.0059	0.0087
r_4	0.0238	0.0058	0.0166	0.0142	0.0216	0.0154	0.0285	0.0060	0.0216	0.0191	0.0145
r_5	0.0238	0.0058	0.0062	0.0142	0.0015	0.0024	0.0044	0.0075	0.0027	0.0213	0.0058
r_6	0.0158	0.0317	0.0124	0.0283	0.0282	0.0130	0.0120	0.0105	0.0108	0.0264	0.0043
r_7	0.0127	0.0087	0.0145	0.0039	0.0083	0.0024	0.0033	0.0315	0.0135	0.0015	0.0043
r_8	0.0063	0.0058	0.0186	0.0283	0.0083	0.0154	0.0120	0.0045	0.0108	0.0059	0.0029
r_9	0.0222	0.0058	0.0124	0.0283	0.0133	0.0416	0.0120	0.0060	0.0108	0.0264	0.0217
r_{10}	0.0238	0.0058	0.0290	0.0142	0.0282	0.0416	0.0285	0.0150	0.0216	0.0264	0.0217
r_{11}	0.0222	0.0014	0.0145	0.0026	0.0216	0.0032	0.0011	0.0315	0.0108	0.0029	0.0260
r_{12}	0.0222	0.0317	0.0290	0.0283	0.0282	0.0416	0.0120	0.0315	0.0216	0.0264	0.0217
r_{13}	0.0127	0.0087	0.0145	0.0051	0.0066	0.0007	0.0033	0.0315	0.0108	0.0103	0.0217
r_{14}	0.0048	0.0058	0.0145	0.0142	0.0282	0.0154	0.0120	0.0315	0.0216	0.0103	0.0217
r_{15}	0.0238	0.0072	0.0166	0.0283	0.0282	0.0416	0.0285	0.0075	0.0216	0.0191	0.0058
r_{16}	0.0127	0.0130	0.0041	0.0142	0.0033	0.0016	0.0120	0.0315	0.0162	0.0191	0.0029
r_{17}	0.0127	0.0130	0.0041	0.0013	0.0066	0.0024	0.0011	0.0315	0.0108	0.0029	0.0260
r_{18}	0.0063	0.0317	0.0062	0.0283	0.0282	0.0416	0.0285	0.0315	0.0135	0.0029	0.0260
r_{19}	0.0238	0.0058	0.0104	0.0142	0.0282	0.0416	0.0120	0.0075	0.0135	0.0213	0.0145
r_{20}	0.0063	0.0058	0.0062	0.0051	0.0066	0.0416	0.0120	0.0030	0.0108	0.0059	0.0217
r_{21}	0.0222	0.0317	0.0124	0.0283	0.0066	0.0416	0.0285	0.0060	0.0216	0.0088	0.0087
r_{22}	0.0222	0.0130	0.0186	0.0142	0.0133	0.0154	0.0285	0.0060	0.0162	0.0264	0.0217
r_{23}	0.0222	0.0317	0.0166	0.0142	0.0133	0.0416	0.0285	0.0150	0.0216	0.0264	0.0145
r_{24}	0.0238	0.0087	0.0062	0.0283	0.0216	0.0049	0.0066	0.0315	0.0216	0.0103	0.0260
r_{25}	0.0238	0.0058	0.0104	0.0039	0.0015	0.0024	0.0033	0.0030	0.0216	0.0264	0.0029
r_{26}	0.0238	0.0317	0.0290	0.0283	0.0282	0.0154	0.0285	0.0075	0.0108	0.0264	0.0260
r_{27}	0.0238	0.0317	0.0290	0.0283	0.0066	0.0416	0.0066	0.0315	0.0216	0.0264	0.0217

Table 5.8: Reliability weights of respondents p^{mk} ($r_{28} - r_{61}$)

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_{28}	0.0063	0.0072	0.0186	0.0283	0.0282	0.0016	0.0066	0.0105	0.0108	0.0015	0.0087
r_{29}	0.0222	0.0130	0.0166	0.0051	0.0216	0.0016	0.0285	0.0315	0.0216	0.0191	0.0260
r_{30}	0.0158	0.0317	0.0290	0.0142	0.0282	0.0416	0.0120	0.0105	0.0216	0.0088	0.0087
r_{31}	0.0048	0.0087	0.0290	0.0142	0.0282	0.0154	0.0066	0.0150	0.0216	0.0029	0.0145
r_{32}	0.0238	0.0058	0.0104	0.0026	0.0066	0.0024	0.0022	0.0045	0.0108	0.0213	0.0058
r_{33}	0.0222	0.0087	0.0104	0.0283	0.0216	0.0016	0.0077	0.0315	0.0108	0.0088	0.0260
r_{34}	0.0222	0.0317	0.0124	0.0283	0.0216	0.0049	0.0285	0.0060	0.0189	0.0029	0.0145
r_{35}	0.0127	0.0058	0.0166	0.0142	0.0066	0.0154	0.0285	0.0060	0.0135	0.0103	0.0260
r_{36}	0.0127	0.0130	0.0145	0.0283	0.0216	0.0154	0.0285	0.0060	0.0189	0.0191	0.0217
r_{37}	0.0158	0.0058	0.0290	0.0283	0.0282	0.0049	0.0285	0.0150	0.0216	0.0103	0.0217
r_{38}	0.0127	0.0058	0.0145	0.0039	0.0083	0.0154	0.0077	0.0315	0.0135	0.0191	0.0260
r_{39}	0.0063	0.0058	0.0166	0.0283	0.0083	0.0154	0.0066	0.0150	0.0189	0.0191	0.0145
r_{40}	0.0158	0.0317	0.0290	0.0142	0.0066	0.0416	0.0120	0.0150	0.0216	0.0264	0.0217
r_{41}	0.0032	0.0130	0.0166	0.0051	0.0216	0.0154	0.0077	0.0315	0.0216	0.0088	0.0260
r_{42}	0.0222	0.0317	0.0290	0.0142	0.0133	0.0032	0.0285	0.0015	0.0189	0.0264	0.0217
r_{43}	0.0158	0.0317	0.0021	0.0026	0.0066	0.0416	0.0285	0.0315	0.0216	0.0264	0.0087
r_{44}	0.0238	0.0130	0.0186	0.0051	0.0133	0.0016	0.0077	0.0150	0.0189	0.0264	0.0260
r_{45}	0.0048	0.0317	0.0186	0.0283	0.0066	0.0032	0.0285	0.0150	0.0162	0.0191	0.0145
r_{46}	0.0238	0.0014	0.0062	0.0026	0.0083	0.0024	0.0044	0.0030	0.0216	0.0191	0.0058
r_{47}	0.0238	0.0058	0.0062	0.0142	0.0033	0.0016	0.0044	0.0075	0.0108	0.0191	0.0043
r_{48}	0.0063	0.0317	0.0186	0.0051	0.0216	0.0049	0.0077	0.0315	0.0189	0.0088	0.0260
r_{49}	0.0158	0.0317	0.0290	0.0283	0.0282	0.0154	0.0285	0.0150	0.0216	0.0088	0.0145
r_{50}	0.0158	0.0317	0.0290	0.0142	0.0216	0.0154	0.0285	0.0315	0.0216	0.0264	0.0145
r_{51}	0.0158	0.0317	0.0290	0.0142	0.0216	0.0154	0.0285	0.0315	0.0216	0.0264	0.0145
r_{52}	0.0158	0.0087	0.0186	0.0283	0.0216	0.0032	0.0077	0.0315	0.0189	0.0264	0.0260
r_{53}	0.0032	0.0317	0.0145	0.0142	0.0015	0.0007	0.0120	0.0315	0.0216	0.0029	0.0260
r_{54}	0.0158	0.0317	0.0186	0.0142	0.0282	0.0154	0.0285	0.0105	0.0216	0.0191	0.0043
r_{55}	0.0222	0.0317	0.0124	0.0283	0.0133	0.0154	0.0285	0.0105	0.0216	0.0264	0.0217
r_{56}	0.0222	0.0014	0.0290	0.0142	0.0133	0.0016	0.0077	0.0150	0.0162	0.0264	0.0087
r_{57}	0.0016	0.0058	0.0166	0.0283	0.0282	0.0154	0.0285	0.0060	0.0054	0.0103	0.0217
r_{58}	0.0127	0.0130	0.0186	0.0013	0.0216	0.0154	0.0285	0.0105	0.0108	0.0191	0.0043
r_{59}	0.0238	0.0130	0.0062	0.0283	0.0015	0.0049	0.0022	0.0015	0.0162	0.0213	0.0260
r_{60}	0.0222	0.0072	0.0062	0.0051	0.0282	0.0016	0.0044	0.0015	0.0108	0.0059	0.0043
r_{61}	0.0063	0.0072	0.0104	0.0142	0.0282	0.0049	0.0285	0.0315	0.0108	0.0103	0.0260

Table 5.9: Difference between two linguist terms (t^k and x^{mk}); $\alpha^{ok}_{\eta\varsigma}$ of $r_1 - r_{23}$

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_1	4	1	0	1	0	2	4	1	3	3	2
r_2	5	1	2	3	5	0	2	0	6	0	2
r_3	3	1	1	2	4	0	2	2	5	2	4
r_4	5	2	8	3	6	2	2	1	9	3	0
r_5	5	4	1	3	11	9	3	4	8	0	1
r_6	2	1	0	1	2	0	0	1	1	1	4
r_7	7	3	6	2	7	3	5	5	4	2	1
r_8	6	7	4	1	7	2	0	0	6	2	2
r_9	4	3	0	1	4	0	0	1	1	1	2
r_{10}	5	3	2	1	2	0	2	3	9	1	2
r_{11}	4	9	6	5	6	6	8	5	1	9	2
r_8	6	7	4	1	7	2	0	0	6	2	2
r_9	4	3	0	1	4	0	0	1	1	1	2
r_{10}	5	3	2	1	2	0	2	3	9	1	2
r_{11}	4	9	6	5	6	6	8	5	1	9	2
r_{12}	4	1	2	1	2	0	0	5	1	1	2
r_{13}	7	3	6	2	8	11	5	5	2	1	2
r_{14}	8	7	6	1	2	2	0	5	9	1	2
r_{15}	5	1	8	1	2	0	2	4	9	3	1
r_{16}	7	5	9	1	9	5	0	5	5	3	3
r_{17}	7	5	9	7	8	9	10	5	2	4	2
r_{18}	3	1	1	1	2	0	2	5	4	4	2
r_{19}	5	2	5	3	2	0	0	4	4	0	0
r_{20}	3	3	3	2	5	0	0	2	0	2	2
r_{21}	4	1	0	1	8	0	2	7	3	3	4
r_{22}	4	5	4	1	4	2	2	7	5	1	2
r_{23}	4	1	8	3	4	0	2	3	3	1	0

Table 5.10: Difference between two linguist terms (t^k and x^{mk}); $\alpha_{\eta\varsigma}^{ok}$ of $r_{24} - r_{48}$

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_{24}	5	3	7	1	6	4	4	5	3	1	2
r_{25}	5	4	5	2	3	3	5	6	1	1	3
r_{26}	5	1	2	1	2	2	2	4	0	1	2
r_{27}	5	1	2	1	5	0	4	5	3	1	2
r_{28}	3	1	4	1	2	7	4	1	0	6	4
r_{29}	4	5	8	3	6	10	2	5	9	3	2
r_{30}	2	1	2	1	2	0	0	1	3	3	4
r_{31}	8	3	2	1	2	2	4	3	1	5	0
r_{32}	5	2	5	4	5	3	1	0	0	0	1
r_{33}	4	3	5	1	6	8	6	5	6	3	2
r_{34}	4	1	0	1	6	4	2	7	7	5	0
r_{35}	7	2	8	1	0	2	2	1	4	1	2
r_{36}	7	5	6	1	6	2	2	1	7	3	2
r_{37}	2	3	2	1	2	4	2	3	1	1	2
r_{38}	7	4	6	2	7	2	6	5	4	3	2
r_{39}	6	7	8	1	7	2	4	3	7	3	0
r_{40}	2	1	2	3	0	0	0	3	1	1	2
r_{41}	12	5	8	3	6	2	6	5	3	3	2
r_{42}	4	1	2	1	4	6	2	9	7	1	2
r_{43}	2	1	10	5	8	0	2	5	9	1	4
r_{44}	5	5	4	3	4	10	6	3	7	1	2
r_{45}	8	1	4	1	0	6	2	3	5	3	0
r_{46}	5	6	3	4	7	9	3	6	9	3	1
r_{47}	5	4	3	3	9	5	3	4	6	3	1
r_{48}	6	1	4	3	6	4	6	5	7	3	2

Table 5.11: Difference between two linguist terms (t^k and x^{mk}); $\alpha^{ok}_{\eta\varsigma}$ of $r_{49} - r_{61}$

Respondent	Product concept f_k										
r_m	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
r_{49}	2	1	2	1	2	2	2	3	1	3	0
r_{50}	2	1	2	3	6	2	2	5	3	1	0
r_{51}	2	1	2	3	6	2	2	5	3	1	0
r_{52}	2	3	4	1	6	6	6	5	7	1	2
r_{53}	12	1	6	3	12	12	0	5	9	9	2
r_{54}	2	1	4	1	2	2	2	1	1	3	4
r_{55}	4	1	0	1	4	2	2	1	1	1	2
r_{56}	4	0	2	1	4	8	6	3	5	1	4
r_{57}	10	7	8	1	2	2	2	7	3	1	2
r_{58}	7	5	4	0	6	2	2	1	1	3	4
r_{59}	5	5	7	1	1	4	1	3	5	0	2
r_{60}	4	1	7	2	2	7	3	5	2	2	1
r_{61}	6	1	5	3	2	4	2	5	2	1	2

Step 3. *Determining the expected distance degree of kansei features*

By using eq. 5.11, the expected distance degree of product concepts can be computed. The results are presented in Tables 5.12: column 2.

Example 5.4.3. *For product concept f_1, the expected distance degree can be computed as follow.*

$$ED_1 = \sum_{m=1}^{61} p^{m1} \times \alpha_{\eta\varsigma}^{m1} = (0.0222 \times 4) + (0.0238 \times 5) + \cdots + (0.0063 \times 6) = 4.4865$$

Step 4. *Screening a new product's go/no-go*

Consequently, the succession of the packaging design is determined by a threshold, which is corresponding to the firm's acceptable level (β). A higher β refers to the higher expectation of the firm. The evaluation result with adjustable β is shown in Table 5.12: columns 4-11. In addition, the ranking of the best and worst product concepts are also defined, as depicted in Table 5.12: column 3.

Moreover, Table 5.12 also shows that when β is equal to 45%, the finished product pass all standard levels, and is ready to be launched. However, if the firm sets β between 0% − 40%, some kansei features have to be redesigned. For example, when $\beta = 30$, the kansei features f_1, f_3, f_5, f_8, and f_9 need to be redesigned.

Example 5.4.4. *If the firm sets the acceptable level β at 10%, then threshold can be computed by eq. 5.12.*

$$TH = 0.10 \times (7 - 1 \times 2) = 1.2$$

When all expected distance degree passes the referred threshold, it means the ODM manufacturer succeeds in customizing a packaging design because the packaging can reflect the target product concepts. In this case, for β = 10%, only f_6 passes the firm's expectation. Thus, other inferior product concepts $f_1 - f_5$ and $f_7 - f_{11}$ need to be redesigned.

5.4.3 Comparison and discussion

In the previous part, we have applied the 3-tuple linguistic distance-based model to a case of Wangsukjai export limited company for a new packaging's go/no-go screening. To

Table 5.12: Expected distance degree (ED_k), Ranking, and Threshold with adjustable β

Product concept (f_k)	Expected distance	Ranking	Threshold							
			$\beta = 10\%$ (1.2)	$\beta = 15\%$ (1.8)	$\beta = 20\%$ (2.4)	$\beta = 25\%$ (3.0)	$\beta = 30\%$ (3.6)	$\beta = 35\%$ (4.2)	$\beta = 40\%$ (4.8)	$\beta = 45\%$ (5.4)
f_1	4.4865	11	Not pass	Not pass	Not Pass	Not Pass	Not Pass	Not Pass	Not Pass	Pass
f_2	1.8658	5	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass
f_3	3.7101	7	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass
f_4	1.4273	2	Not pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
f_5	3.8026	8	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass
f_6	0.9802	1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
f_7	2.0865	6	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass
f_8	4.2444	9	Not pass	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass
f_9	4.3639	10	Not pass	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass
f_{10}	1.6162	3	Not pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
f_{11}	1.8104	4	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass

present an effectiveness of the proposed model, let us analyze the results obtained from the proposed model to the results obtained from Pang et al.'s model [5].

It is worth to note here that the differences from our proposed model and Pang et al.'s model can obviously be noticed from Step 1: *Deriving the reliability weight of each respondent on each criterion.* For latter steps, our proposed model and Pang et al.'s model are the same. Now, let us explain how Pang et al.'s model apply to this problem, as shown step by step below.

Step 1. *Determine probability distribution p^k of linguistic term over S from linguistic assessments x^{mk} in Tables 5.5 - 5.6. Unlike the proposed model, the probabilistic linguistic p^k depends only on criterion k. In other words, respondents has the same importance degree. Table 5.13; 2^{th} tuple presents a group probabilistic linguistic expression on product concept f_k.*

Step 2. *Determine the difference between two linguistic terms (x^{mk}) and (t^k) $\alpha_{\eta\varsigma}$ by using manhattan distance measure. The results are shown in Table 5.13; 3^{rd} tuple.*

Step 3. *Determine the expected distance degrees of each criterion k by multiplying p^k_{gn} with $\alpha_{\eta\varsigma}$. The comparative results of expected distance degrees are shown in Table 5.14.*

Table 5.13: Results of comparative model (Pang et al.'s model) [5]

Product concept (f_k)	Representation of linguistic information on product concept f_k: $\langle x^{mk}, p^k, \alpha_{\eta\varsigma} \rangle$
f_1	$\{\langle [s_2^1], \frac{10}{61}, 2\rangle, \langle [s_2^1, s_3^1], \frac{4}{61}, 3\rangle, \langle [s_3^1], \frac{14}{61}, 4\rangle, \langle [s_3^1, s_4^1], \frac{15}{61}, 5\rangle, \langle [s_4^1], \frac{4}{61}, 6\rangle,$ $\langle [s_4^1, s_5^1], \frac{8}{61}, 7\rangle, \langle [s_5^1], \frac{3}{61}, 8\rangle, \langle [s_6^1], \frac{1}{61}, 10\rangle, \langle [s_7^1], \frac{2}{61}, 12\rangle\}$
f_2	$\{\langle [s_1^2], \frac{4}{61}, 3\rangle, \langle [s_2^2], \frac{22}{61}, 1\rangle, \langle [s_2^2, s_3^2], \frac{1}{61}, 0\rangle, \langle [s_3^2], \frac{5}{61}, 1\rangle, \langle [s_3^2, s_4^2], \frac{4}{61}, 2\rangle, \langle [s_4^2], \frac{6}{61}, 3\rangle,$ $\langle [s_4^2, s_5^2], \frac{4}{61}, 4\rangle, \langle [s_5^2], \frac{9}{61}, 5\rangle, \langle [s_5^2, s_6^2], \frac{1}{61}, 6\rangle, \langle [s_6^2], \frac{4}{61}, 7\rangle, \langle [s_7^2], \frac{1}{61}, 9\rangle\}$
f_3	$\{\langle [s_1^3], \frac{6}{61}, 0\rangle, \langle [s_1^3, s_2^3], \frac{3}{61}, 1\rangle, \langle [s_2^3], \frac{22}{14}, 2\rangle, \langle [s_2^3, s_3^3], \frac{3}{61}, 3\rangle, \langle [s_3^3], \frac{9}{61}, 4\rangle, \langle [s_3^3, s_4^3], \frac{5}{61}, 5\rangle,$ $\langle [s_4^3], \frac{7}{61}, 6\rangle, \langle [s_4^3, s_5^3], \frac{3}{61}, 7\rangle, \langle [s_5^3], \frac{8}{61}, 8\rangle, \langle [s_5^3, s_6^3], \frac{2}{61}, 9\rangle, \langle [s_6^3], \frac{1}{61}, 10\rangle\}$
f_4	$\{\langle [s_1^4], \frac{11}{61}, 3\rangle, \langle [s_1^4, s_2^4], \frac{4}{61}, 2\rangle, \langle [s_2^4], \frac{22}{14}, 1\rangle, \langle [s_2^4, s_3^4], \frac{1}{61}, 0\rangle, \langle [s_3^4], \frac{11}{61}, 1\rangle,$ $\langle [s_3^4, s_4^4], \frac{3}{61}, 2\rangle, \langle [s_4^4], \frac{4}{61}, 3\rangle, \langle [s_4^4, s_5^4], \frac{2}{61}, 4\rangle, \langle [s_5^4], \frac{2}{61}, 5\rangle, \langle [s_6^4], \frac{1}{61}, 7\rangle\}$
f_5	$\{\langle [s_1^5], \frac{4}{61}, 0\rangle, \langle [s_2^5], \frac{1}{61}, 2\rangle, \langle [s_2^5, s_3^5], \frac{17}{61}, 3\rangle, \langle [s_3^5], \frac{8}{61}, 4\rangle, \langle [s_3^5, s_4^5], \frac{4}{61}, 5\rangle, \langle [s_4^5], \frac{13}{61}, 6\rangle,$ $\langle [s_4^5, s_5^5], \frac{5}{61}, 7\rangle, \langle [s_5^5], \frac{4}{61}, 8\rangle, \langle [s_5^5, s_6^5], \frac{2}{61}, 9\rangle, \langle [s_6^5, s_7^5], \frac{1}{61}, 11\rangle, \langle [s_7^5], \frac{1}{61}, 12\rangle\}$
f_6	$\{\langle [s_1^6], \frac{16}{61}, 0\rangle, \langle [s_2^6, s_3^6], \frac{19}{61}, 3\rangle, \langle [s_3^6], \frac{3}{61}, 4\rangle, \langle [s_3^6, s_4^6], \frac{6}{61} \rangle, \langle [s_4^6], \frac{4}{61}, 6\rangle, \langle [s_4^6, s_5^6], \frac{2}{61}, 7\rangle,$ $\langle [s_5^6], \frac{2}{61}, 8\rangle, \langle [s_5^6, s_6^6], \frac{3}{61}, 9\rangle, \langle [s_6^6], \frac{2}{61}, 10\rangle, \langle [s_6^6, s_7^6], \frac{1}{61}, 11\rangle, \langle [s_7^6], \frac{1}{61}, 12\rangle\}$
f_7	$\{\langle [s_1^7], \frac{11}{61}, 0\rangle, \langle [s_1^7, s_2^7], \frac{2}{61}, 1\rangle, \langle [s_2^7], \frac{26}{14}, 2\rangle, \langle [s_2^7, s_3^7], \frac{4}{61}, 3\rangle, \langle [s_3^7], \frac{6}{61}, 4\rangle,$ $\langle [s_3^7, s_4^7], \frac{3}{61}, 5\rangle, \langle [s_4^7], \frac{7}{61}, 6\rangle, \langle [s_5^7], \frac{1}{61}, 8\rangle, \langle [s_6^7], \frac{1}{61}, 10\rangle\}$
f_8	$\{\langle [s_1^8], \frac{4}{61}, 1\rangle, \langle [s_1^8, s_2^8], \frac{3}{61}, 0\rangle, \langle [s_2^8], \frac{7}{61}, 1\rangle, \langle [s_2^8, s_3^8], \frac{2}{61}, 2\rangle, \langle [s_2^8, s_4^8], \frac{1}{61}, 3\rangle, \langle [s_2^8, s_5^8], \frac{1}{61}, 5\rangle,$ $\langle [s_3^8], \frac{10}{61}, 3\rangle, \langle [s_3^8, s_4^8], \frac{5}{61}, 4\rangle, \langle [s_4^8], \frac{21}{61}, 5\rangle, \langle [s_4^8, s_5^8], \frac{2}{61}, 6\rangle, \langle [s_5^8], \frac{4}{61}, 7\rangle, \langle [s_6^8], \frac{1}{61}, 9\rangle\}$
f_9	$\{\langle [s_1^9], \frac{2}{61}, 3\rangle, \langle [s_2^9], \frac{4}{61}, 1\rangle, \langle [s_2^9, s_3^9], \frac{4}{61}, 0\rangle, \langle [s_3^9], \frac{8}{61}, 1\rangle, \langle [s_3^9, s_4^9], \frac{4}{61}, 2\rangle, \langle [s_4^9], \frac{8}{61}, 3\rangle,$ $\langle [s_4^9, s_5^9], \frac{5}{61}, 4\rangle, \langle [s_5^9], \frac{6}{61}, 5\rangle, \langle [s_5^9, s_6^9], \frac{4}{61}, 6\rangle, \langle [s_6^9], \frac{7}{61}, 7\rangle, \langle [s_6^9, s_7^9], \frac{1}{61}, 8\rangle, \langle [s_7^9], \frac{8}{61}, 9\rangle\}$
f_{10}	$\{\langle [s_1^{10}], \frac{13}{61}, 3\rangle, \langle [s_1^{10}, s_2^{10}], \frac{4}{61}, 2\rangle, \langle [s_2^{10}], \frac{18}{61}, 1\rangle, \langle [s_2^{10}, s_3^{10}], \frac{5}{61}, 0\rangle, \langle [s_3^{10}], \frac{7}{61}, 1\rangle, \langle [s_3^{10}, s_4^{10}], \frac{1}{61}, 2\rangle,$ $\langle [s_4^{10}], \frac{6}{61}, 3\rangle, \langle [s_4^{10}, s_5^{10}], \frac{2}{61}, 4\rangle, \langle [s_5^{10}], \frac{2}{61}, 5\rangle, \langle [s_5^{10}, s_6^{10}], \frac{1}{61}, 6\rangle, \langle [s_7^{10}], \frac{2}{61}, 9\rangle\}$
f_{11}	$\{\langle [s_1^{10}], \frac{3}{61}, 4\rangle, \langle [s_2^{10}], \frac{15}{61}, 2\rangle, \langle [s_2^{10}, s_3^{10}], \frac{4}{61}, 1\rangle, \langle [s_3^{10}], \frac{10}{61}, 0\rangle,$ $\langle [s_3^{10}, s_4^{10}], \frac{3}{61}, 1\rangle, \langle [s_4^{10}], \frac{18}{61}, 2\rangle, \langle [s_4^{10}, s_5^{10}], \frac{2}{61}, 3\rangle, \langle [s_5^{10}], \frac{6}{61}, 4\rangle\}$

Table 5.14: A comparative result of expected distance degree, ranking, and threshold with adjustable β from Pang et al.'s model [5]

Product concept (f_k)	Expected distance	Ranking	Threshold							
			$\beta = 10\%$ (1.2)	$\beta = 15\%$ (1.8)	$\beta = 20\%$ (2.4)	$\beta = 25\%$ (3.0)	$\beta = 30\%$ (3.6)	$\beta = 35\%$ (4.2)	$\beta = 40\%$ (4.8)	$\beta = 45\%$ (5.4)
f_1	4.93443	11	Not pass	Not pass	Not Pass	Not Pass	Not Pass	Not Pass	Not Pass	Pass
f_2	2.77049	5	Not pass	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass
f_3	4.19672	9	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass
f_4	1.91803	2	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass
f_5	4.52459	10	Not pass	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass
f_6	3.36066	6	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass	Pass
f_7	2.70492	4	Not pass	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass
f_8	3.72131	7	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass
f_9	4.14754	8	Not pass	Not pass	Not pass	Not pass	Not pass	Pass	Pass	Pass
f_{10}	2.19672	3	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass
f_{11}	1.88525	1	Not pass	Not pass	Pass	Pass	Pass	Pass	Pass	Pass

Step 4. *Screen a new product's go/no-go by using adjustable β. The results are presented in Table 5.14.*

According to Table 5.14, it can be noticed that the result of thresholds is the same as the result obtained from our proposed model in Table **??**, while the results of expected distance degree and rankings are different. This is basically due to Pang et al.'s model assumed that the reliability weight of respondents is the same for all criteria.

However, it should emphasize here that the reliability weights obtained from Pang et al.'s model may lead to a double count issue in MCGDM problems. Here, the double count issue is a situation where respondents' weights are computed twice. For example, suppose that there are five respondents. Three of them vote for s_5. Two of them vote for s_2. Thus, if each respondent has an equal importance, then a group assessment may be around s_4. There is no need for computing the probability distribution of linguistic terms in set S such as $\frac{3}{5}$ for s_5 and $\frac{2}{5}$ for s_2, because a group assessment complies with the individual assessments' aggregation. Thus, when respondents have the same importance degree, obtaining a probability distribution is a double count event and it is an unnecessary procedure.

5.5 Concluding remark

In this activity, we proposed the 3-tuple linguistic distance-based model for a new product's go/no-go screening. Linguistic assessment is used as a tool to obtain the psychological feeling of a firm and target customers on product at several perspectives (kansei features). The workshop were conducted to enhance the quality of data collected. To develop a model, firstly, a reliability weights of respondents are determined by means of the probability distribution. Secondly, the difference between the interval target linguistic terms (ITLTs) and the interval perceived linguistic terms (IPLTs) is determined by an exploitation of the 2-tuple linguistic representation model and the manhattan distance measure. Then, the expected distance between ITLTs and IPLTs is determined. Lastly, the screening process of a new product's go/no-go is investigated by comparing a firm's acceptable level to the expected distance. The case study shows the applicability of the proposed model, and the results are compared with the conventional model.

This model also accomplishes the concerning issues addressed at the beginning of this paper.

- It is able to handle uncertainties of respondents in their linguistic assessments by using interval linguistic terms.
- It is able to handle the loss of information in linguistic aggregation by representing the linguistic term as a symbolic symbol in the space and then aggregating them as points in the space.
- The biolar linguistic assessments are considered here.
- The target-oriented linguistic terms are considered here.

Moreover, the major advantages of the proposed model to an ODM client can be summarized as follows.

- It smoothens the cooperation between the ODM client and its contract ODM manufacturer.
- It screens out the inferior product concepts, which significantly reduce unnecessary investments and opportunity costs.

- It supports further marketing strategy.

Although the application focused in this paper is mainly on screening the new product's go/no-go, it is also interesting to apply the proposed model for other product evaluating problems, where ensuring the product specification is of interest. We are also planning to extend the proposed model to deal with multi-granular linguistic term sets and incomplete data in evaluation process, for making it applicable to more complex situations in NPD context. Thus, it is worth to study more on how 3-tuple linguistic distance-based model can extend to deal with such issues. This is a direction for our future work.

Chapter 6

Conclusion

In this thesis, some basic knowledge about decision making and linguistic information were recalled and discussed. Linguistic computation approaches based on membership functions and term index were mainly focused. In addition, a 2-tuple linguistic representation model, manhattan distance measure, and probabilistic uncertain linguistic term set were studied in detail to pave the way for proposing 3-dimension fuzzy linguistic based model, 3-tuple linguistic distance based model, and a prioritized manhattan distance based model. These three proposed models were used as decision supports for three ODM clients' tasks, which were,

1. Identifying customer-oriented product concepts
2. Providing product specification to ODM manufacturers
3. Screening an evaluation on go/no-go product

Three case studies were used to explain the applicability and effectiveness of the proposed model.

6.1 The main contribution

1. Proposed a 3-tuple linguistic distance based model.

   In many linguistic based decision making problems, most of them aim at achieving the highest semantic levels of a linguistic term set, not some levels in between.

However, there are some cases that achieving some levels in between can satisfy respondents more than the highest one. Thus, a 3-tuple linguistic distance based model is proposed to determine the distance degree between the target linguistic term (Goal) and the perceived linguistic term (Actuality) so that the degree of fitness can be identified. Other sub-contributions are as follows.

- The notion of 3-tuple linguistic distance based model is generalized and presented .
- Some aggregation operators are developed for the proposed model. With the use of these aggregation operators, the model is able to deal with multiple criteria group decision making problems.

2. Proposed a polaritized manhattan distance measure.

   Considering that a manhattan distance measure does not considered the direction or the distance polarity (+/-), while the distance polarity appears commonly in a bipolar linguistic assessment such as increasing or decreasing, left or right, simple or complex. In some cases, it cannot be conclude that increasing is better than decreasing. It depends on their preferences. Motivated from its limitation and concerns, a polaritized manhattan distance measure is developed. The significant idea is to introduce the direction (+) and (-) into the algorithm of manhattan distance measure so that it can indicate the direction of the distance result. Other sub-contributions includes:

   - A general notion of the polaritized manhattan distance measure, which can be further applied in other applications is proposed.
   - The aggregation and normalization processes for modeling a 3-tuple linguistic based model with the polaritized manhattan distance measure, are proposed.

3. Proposed a novel approach for determining relative importance of respondents.

   In practice, a bias of heterogeneous respondents is alleviated by assigning weights to them. Generally, there is an uncertainty occurring during assignment since linguistic assessments are uncertain and vague in nature. To avoid such an uncertainty, a novel approach for determining relative importance of respondents is proposed. The key concept of the proposed model is based on the assumption that when people provide their opinions close to the majority, it means that they are reasonable and reliable. Other sub-contributions are as follows.

- Some aggregation operators are developed for the proposed model to deal with multiple criteria group decision making.

6.2 Contribution to knowledge science

Three decision models developed in this research systematically encourage ODM clients in developing a new customer-oriented product. They provide the new ways of modeling customers' opinions and preferences regarding linguistic expressions, which represent individual tacit knowledge in making a decision. In addition, the aggregation linguistic algorithms proposed in this research are used to incorporate individual opinions to a group consensus. Moreover, the finding also provides competitive advantages and knowledge created for ODM clients in new product development project. Thus, the tacit knowledge can be explicit by a new product as shown in Figure 6.1. In addition, this study can be illustrated by a SECI model as shown in Figure 6.2.

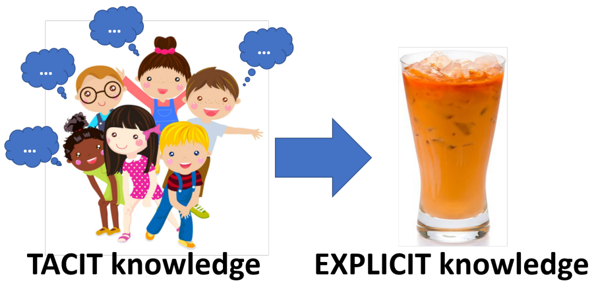

Figure 6.1: TACIT knowledge → EXPLICIT knowledge

6.3 Direction for future work

In this research, decision models on new product development context for ODM clients are proposed. However, it is of interest to apply the proposed model in other practical applications such as in supplier selection, product selection, etc, where information exists in linguistic expression. In addition, the proposed decision models are basically based

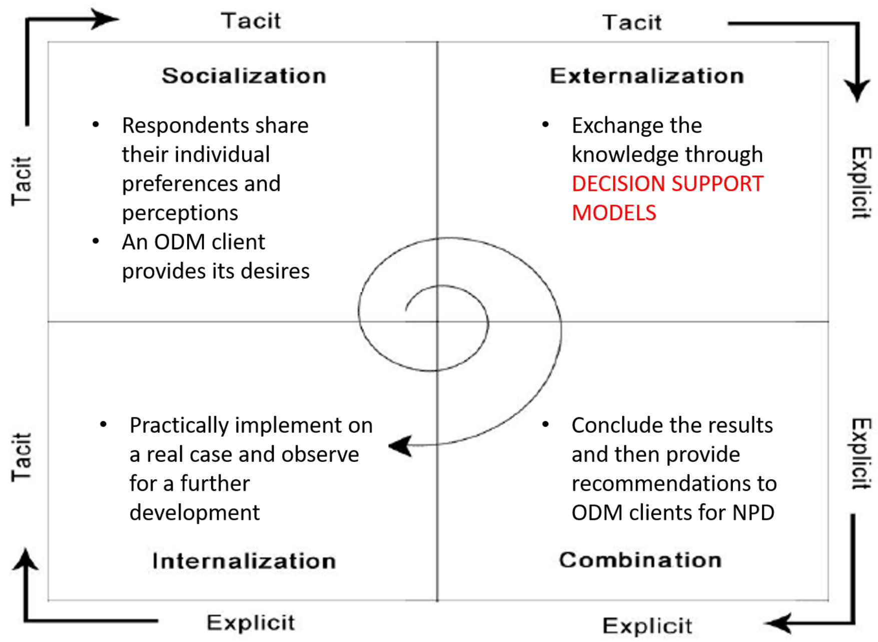

Figure 6.2: The work illustrated by SECI model

on single linguistic term sets. It is also interesting to extend the proposed models to a case of multiple granularity linguistic information for managing information assessed by different linguistic term sets, together with its application in a decision making problem with heterogeneous information sources.

Moreover, the aggregation operators proposed for the developed models are all linear. In practice, there are some cases that linear additive assumption is not applicable. For example, dependent criteria have a relationship among them. Thus, it is also of interest to develop some non-additive or non-linear aggregation operators for the models developed in this research. The issues mentioned above are the direction of my future research.

Appendix A

Questionnaire on customer-oriented evaluation for ODM clients in support of ODM clients' activity 1

In this appendix, I will present a questionnaire designed for evaluating customer preferences on product concepts provided by ODM clients. It consists of two main parts: a respondents' information and an evaluation on customer preference on soymilk's concepts.

A.1 A general information of respondents for ODM client's activity 1 (Part 1)

In this part, respondents are asked to select the answer from the choice provided, as shown in Figure A.1

A.2 An evaluation on customer-oriented product concept for Thai-tea beverage product (Part 2)

In this part, respondents have to select the value added in soymilk. In assessing the questionnaire, if they hesitate in selecting ✓ in which degrees, they can select all the hesitated degree.

Please select the answer from the choice provided

1. Gender: ☐ Male ☐ Female
2. What is your consumption frequency? ***(Please select all that apply)***

   ☐ Extremely often (> once a day)

   ☐ Very often (5-8 times a week)

   ☐ Moderate (2-5 times a week)

   ☐ Slightly often (2-7 times a month)

   ☐ Rarely (< 1 once a month)
3. Which segment(s) are you? ***(Please select all that apply)***

   ☐ Taste-conscious segment ☐ Dieter segment

   ☐ Health-conscious segment ☐ Natural-lover segment

Figure A.1: A general information of respondents for ODM client's activity 1

Figure A.2: An evaluation on customer-oriented product concept for Thai-tea beverage product

Product concept (Value added)	Unimportance weight	Weakly importance weight	Moderate importance weight	Very importance weight	Extremely importance weight
Variety of flavor					
For a specific group					
Health additive					
Added condiment					

Appendix B

Questionnaire on customer-oriented evaluation for ODM clients in support of ODM clients' activity 2

This questionnaire aims at gathering customer preferences on product characteristics. There are two parts. The first part describes about respondents' information, while the second part gathers information about respondent preferences on product characteristics.

B.1 A general information of respondents for ODM client's activity 2 (Part 1)

Respondents have to select the answer from the choice provided, as shown in Figure B.1.

B.2 An evaluation on customer-oriented taste for Thai-tea beverage product (Part 2)

In this part, respondents are asked that "What characteristics do you want Thai-tea soymilk to be? ". They have to evaluate their feeling degree to three characteristics on three formulas. Three formulas are called Formula A, Formula B , and Formula C. Three characteristics are Thai-tea smell, Sweetness, and Creamy.

Please select the answer from the choice provided

1. Gender ☐ Male ☐ Female
2. What is your consumption frequency? ***(Please select all that apply)***

   ☐ Extremely often (> once a day)

   ☐ Very often (5-8 times a week)

   ☐ Moderate (2-5 times a week)

   ☐ Slightly often (2-7 times a month)

   ☐ Rarely (< 1 once a month)
3. Which segment(s) are you? ***(Please select all that apply)***

   ☐ Taste-conscious segment ☐ Dieter segment

   ☐ Health-conscious segment ☐ Natural-lover segment
4. With comparing to the sweetness of original Pepsi's taste, what sweetness degree do you like the most?

   ☐ I extremely like the sweetness degree less than the sweetness of original Pepsi's taste.

   ☐ I like the sweetness degree less than the sweetness of original Pepsi's taste.

   ☐ I like the sweetness degree as the same as the sweetness of original Pepsi's taste.

   ☐ I like the sweetness degree more than the sweetness of original Pepsi's taste.

   ☐ I extremely like the sweetness degree more than the sweetness of original Pepsi's taste.

Figure B.1: A general information of respondents for ODM client's activity 2

List	Characteristic	What Thai tea smell degree do you like?								
1	***Thai tea smell***	Would like to have a ***weaker*** smell than type A.1	Type A.1 is ***the right one!!***			At the middle ***between*** A.1 and A.2			Type A.2 is ***the right one!!***	Would like to have a ***stronger*** smell than type A.2
		( )	( )	( )	( )	( )	( )	( )	( )	( )

List	Characteristic	Which one between A.1 or A.2 is **sweeter** /**more creamy**?						
2	***Sweetness***	A.1 is ***extremely*** sweeter	A.1 is ***much*** sweeter	A.1 is ***a bit*** sweeter	Not different	A.2 is ***a bit*** sweeter	A.2 is ***much*** sweeter	A.2 is ***extremely*** sweeter
		( )	( )	( )	( )	( )	( )	( )
3	***Creamy***	A.1 is ***extremely*** more creamy	A.1 is ***much*** more creamy	A.1 is ***a bit*** more creamy	Not different	A.2 is ***a bit*** more creamy	A.2 is ***much*** more creamy	A.2 is ***extremely*** more creamy
		( )	( )	( )	( )	( )	( )	( )

Figure B.2: An evaluation form of formula A

List	Characteristic	What sweetness degree do you like?								
1	***Sweetness***	would like to have a ***less sweet*** degree than type B.1	Type B.1 is ***the right one!!***			At the middle ***between*** B.1 and B.2			Type B.2 is ***the right one!!***	would like to have a ***more sweet*** degree than type B.2
		( )	( )	( )	( )	( )	( )	( )	( )	( )

List	Characteristic	Which one between B.1 or B.2 has a **stronger smell** / is **more creamy**?						
2	***Thai tea smell***	B.1 has an ***extremely*** stronger smell	B.1 has a ***much*** stronger smell	B.1 has ***a bit*** stronger smell	Not different	B.2 has ***a bit*** stronger smell	B.2 has a ***much*** stronger smell	B.2 has an ***extremely*** stronger smell
		( )	( )	( )	( )	( )	( )	( )
3	***Creamy***	B.1 is ***extremely*** more creamy	B.1 is ***much*** more creamy	B.1 is ***a bit*** more creamy	Not different	B.2 is ***a bit*** more creamy	B.2 is ***much*** more creamy	B.2 is ***extremely*** more creamy
		( )	( )	( )	( )	( )	( )	( )

Figure B.3: An evaluation form of formula B

List	Characteristic	What creamy degree do you like?								
1	***Creamy***	Would like to have a ***less creamy*** degree than type C.1	Type C.1 is ***the right one!!***			At the middle ***between*** C.1 and C.2			Type C.2 is ***the right one!!***	Would like to have a ***more creamy*** degree than type C.2
		( )	( )	( )	( )	( )	( )	( )	( )	( )

List	Characteristic	Which one between C.1 or C.2 has a **stronger smell** / is **sweeter**?						
2	***Thai tea smell***	C.1 has an ***extremely*** stronger smell	C.1 has a ***much*** stronger smell	C.1 has ***a bit*** stronger smell	Not different	C.2 has ***a bit*** stronger smell	C.2 has a ***much*** stronger smell	C.2 has an ***extremely*** stronger smell
		( )	( )	( )	( )	( )	( )	( )
3	***Sweetness***	C.1 is ***extremely*** sweeter	C.1 is ***much*** sweeter	C.1 is ***a bit*** sweeter	Not different	C.2 is ***a bit*** sweeter	C.2 is ***much*** sweeter	C.2 is ***extremely*** sweeter
		( )	( )	( )	( )	( )	( )	( )

Figure B.4: An evaluation form of formula C

Appendix C

Questionnaire on customer-oriented evaluation for ODM clients in support of ODM clients' activity 3

In this section, a questionnaire is designed for evaluating customer perception on the actual product designed by ODM manufactures, with respect to various criteria. The objective of this questionnaire is to evaluate the fitness degree of the interval target linguistic term and the interval perceived linguistic term on the actual product.

The questionnaire consists of two main parts. In the first part, a personal information of respondents is gathered. Then, in the second part, respondents are asked to provide their perception on the actual product.

C.1 A general information of respondents for ODM client's activity 3 (Part 1)

In this part, respondents are asked to select the answer from the choice provided, as shown in Figure C.1.

Please select the answer from the choice provided

1. Gender: ☐ Male ☐ Female
2. What is your consumption frequency? ***(Please select all that apply)***

   ☐ Extremely often (> once a day)

   ☐ Very often (5-8 times a week)

   ☐ Moderate (2-5 times a week)

   ☐ Slightly often (2-7 times a month)

   ☐ Rarely (< 1 once a month)
3. Which segment(s) are you? ***(Please select all that apply)***

   ☐ Taste-conscious segment ☐ Dieter segment

   ☐ Health-conscious segment ☐ Natural-lover segment

Figure C.1: A general information of respondents for ODM client's activity 3

C.2 An evaluation on customer perception on packaging design regarding criteria (Part 2)

In this part, respondents are asked to select all the levels that they think the product belongs to. In assessing the evaluation, if they hesitate in selecting in which degree, they can check '✓' in all hesitated degrees. Note that v_1 represents the highest degree that close to Left Kansei word, while v_7 is otherwise.

Figure C.2: An evaluation on customer perception on packaging design regarding criteria

f_k	Left Kansei word (w_k^+)	s_1	s_2	s_3	s_4	s_5	s_6	s_7	Right Kansei word (w_k^-)
		Extremely	Much	Less	Neutral	Less	Much	Extremely	
Packaging (coloring, layout, font size, and motto)									
1	***Attractive*** A product can induce us to touch, look back, and read its article on the package, within 5 minutes.								***Unattractive*** A product can not induce us to touch, look back, and read its article on the package, within 5 minutes.
2	***Simple*** The font and character on the packaging are easy to read.								***Detailed*** The font and character on the packaging are not easy to read.

Figure C.3: An evaluation on customer perception on packaging design regarding criteria (Cont)

f_k	Left Kansei word (w_k^+)	s_1 Extremely	s_2 Much	s_3 Less	s_4 Neutral	s_5 Less	s_6 Much	s_7 Extremely	Right Kansei word (w_k^-)
Packaging (coloring, layout, font size, and motto)									
3	***Clean*** A color of background is apparently different from the color of word. In other words, the word is not merged with the background, e.g., Black and White								***Dirty*** A color of background is apparently different from the color of word. In other words, the word is merged with the background, e.g., Red and Orange
4	***Soft color*** The colors of this family are usually described {near neutral}, {milky}, {desaturated}, and {lacking strong chromatic content. In addition, it also evokes the feeling of romantic and happiness.								***Energetic color*** The colors of this family usually represent sunshine, and other light playful feelings.
5	***Providing health related graphics*** An infographic available on the package induces us to think that if we drink this product, we will be healthy								***Not providing health related graphics*** An infographic available on the package does not induce us to think that if we drink this product, we will be healthy
6	***Family product*** This product is for all ages. Everyone can consume.								***Customized product*** This product is not for all ages. Only someone can consume.
7	***Available for everyday life*** Consuming a product everyday does not affect health concern or cause any disease.								***Not available for everyday life*** Consuming a product everyday may cause some bad effect on health. Should consume it only few days a week.
8	***Feeling slim*** After reading a product description, customers can feel that if they consume a product, they can reduce their weights.								***Feeling fat*** After reading a product description, customers can feel that if they consume a product, they will gain weights.
9	***Smooth*** After reading a product description, consumers feel that there is nothing left on the tongue. They do not have to drink a water immediately.								***Sand-like texture*** After reading a product description, consumers feel that there is something left on the tongue. They have to drink a water immediately.
10	***Concentrated*** After reading a product description, consumers feel that they drink a concentrated soy milk.								***Diluted*** After reading a product description, consumers feel that they drink a clear drinking water.
11	***Feeling full*** After reading a product description, consumers feel full.								***Feeling not full*** After reading a product description, consumers feel not full.

Bibliography

[1] R. M. Rodríguez and L. Martínez, "An analysis of symbolic linguistic computing models in decision making," *International Journal of General Systems*, vol. 42, no. 1, pp. 121–136, 2013.

[2] C. H. Hsieh, "Optimization of fuzzy production inventory models," *Information sciences*, vol. 146, no. 1-4, pp. 29–40, 2002.

[3] E. Falcó, J. L. García-Lapresta, and L. Roselló, "Allowing agents to be imprecise: A proposal using multiple linguistic terms," *Information Sciences*, vol. 258, pp. 249–265, 2014.

[4] Y. Guo, "Collaborative innovation and collaborative mode for design chain," in *Computational Intelligence and Design (ISCID), 2011 Fourth International Symposium on*, vol. 2, pp. 137–140, IEEE, 2011.

[5] Q. Pang, H. Wang, and Z. Xu, "Probabilistic linguistic term sets in multi-attribute group decision making," *Information Sciences*, vol. 369, pp. 128–143, 2016.

[6] S. Eppinger and K. Ulrich, *Product design and development*. McGraw-Hill Higher Education, 2015.

[7] L. Y. Lu and C. Yang, "The r&d and marketing cooperation across new product development stages: An empirical study of taiwan's it industry," *Industrial marketing management*, vol. 33, no. 7, pp. 593–605, 2004.

[8] G. Martin and F. Schirrmeister, "A design chain for embedded systems," *Computer*, vol. 35, no. 3, pp. 100–103, 2002.

[9] J. Gao, Y. Yao, V. C. Zhu, L. Sun, and L. Lin, "Service-oriented manufacturing: a new product pattern and manufacturing paradigm," *Journal of Intelligent Manufacturing*, vol. 22, no. 3, pp. 435–446, 2011.

[10] L. Hammond, "What is the difference between oem, obm and odm?," 2015.

[11] B. Niu, Y. Wang, and P. Guo, "Equilibrium pricing sequence in a co-opetitive supply chain with the odm as a downstream rival of its oem," *Omega*, vol. 57, pp. 249–270, 2015.

[12] Phones-review, "Can htc desire outgun google nexus one?," 2010.

[13] L. A. Zadeh, "Fuzzy sets," *Information and control*, vol. 8, no. 3, pp. 338–353, 1965.

[14] R. G. Cooper and E. J. Kleinschmidt, "An investigation into the new product process: steps, deficiencies, and impact," *Journal of product innovation management*, vol. 3, no. 2, pp. 71–85, 1986.

[15] S. Greenstein, "Outsourcing and climbing a value chain," *IEEE Micro*, vol. 25, no. 5, pp. 84–84, 2005.

[16] R. J. Calantone, C. A. Benedetto, and J. B. Schmidt, "Using the analytic hierarchy process in new product screening," *Journal of Product Innovation Management*, vol. 16, no. 1, pp. 65–76, 1999.

[17] C.-T. Lin and C.-T. Chen, "A fuzzy-logic-based approach for new product go/nogo decision at the front end," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 34, no. 1, pp. 132–142, 2004.

[18] V.-N. Huynh and Y. Nakamori, "A linguistic screening evaluation model in new product development," *IEEE Transactions on Engineering Management*, vol. 58, no. 1, pp. 165–175, 2011.

[19] F. Herrera and E. Herrera-Viedma, "Linguistic decision analysis: steps for solving decision problems under linguistic information," *Fuzzy Sets and systems*, vol. 115, no. 1, pp. 67–82, 2000.

[20] D. Dhouib, "An extension of macbeth method for a fuzzy environment to analyze alternatives in reverse logistics for automobile tire wastes," *Omega*, vol. 42, no. 1, pp. 25–32, 2014.

[21] A. Jiménez, A. Mateos, and P. Sabio, "Dominance intensity measure within fuzzy weight oriented maut: An application," *Omega*, vol. 41, no. 2, pp. 397–405, 2013.

[22] D. J. Dubois, *Fuzzy sets and systems: theory and applications*, vol. 144. Academic press, 1980.

[23] H.-B. Yan, T. Ma, and V.-N. Huynh, "On qualitative multi-attribute group decision making and its consensus measure: A probability based perspective," *Omega*, vol. 70, pp. 94–117, 2017.

[24] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoningi," *Information sciences*, vol. 8, no. 3, pp. 199–249, 1975.

[25] S.-H. Chen, "Operations on fuzzy numbers with function principal," 1985.

[26] S. Suprasongsin, V.-N. Huynh, and P. Yenradee, "An alternative fuzzy linguistic approach for determining criteria weights and segmenting consumers for new product development: A case study," in *International Symposium on Knowledge and Systems Sciences*, pp. 23–37, Springer, 2017.

[27] T. J. Ross, *Fuzzy logic with engineering applications*. John Wiley & Sons, 2009.

[28] S.-H. Chen and C. H. Hsieh, "Graded mean representation of generalized fuzzy numbers," PROCEEDING OF CONFERENCE ON FUZZY THEORY AND ITS APPLICATIONS, 1998.

[29] C.-C. Lo, D.-Y. Chen, C.-F. Tsai, and K.-M. Chao, "Service selection based on fuzzy topsis method," in *IEEE 24th International Conference on Advanced Information Networking and Applications Workshops (WAINA)*, pp. 367–372, IEEE, 2010.

[30] C.-C. Chou, "The canonical representation of multiplication operation on triangular fuzzy numbers," *Computers & Mathematics with Applications*, vol. 45, no. 10-11, pp. 1601–1610, 2003.

[31] S. H. Chen, S. T. Wang, and S. M. Chang, "Some properties of graded mean integration representation of lr type fuzzy numbers," *Tamsui Oxford Journal of Mathematical Sciences*, vol. 22, no. 2, p. 185, 2006.

[32] S. H. Chen and S. M. Chang, "Optimization of fuzzy production inventory model with unrepairable defective products," *International Journal of Production Economics*, vol. 113, no. 2, pp. 887–894, 2008.

[33] S. Suprasongsin, P. Yenradee, *et al.*, "Optimization of supplier selection and order allocation under fuzzy demand in fuzzy lead time," in *International Symposium on Knowledge and Systems Sciences*, pp. 182–195, Springer, 2016.

[34] S. K. Babu and R. Anand, "Statistical optimization for generalised fuzzy number," *International Journal of Modern Engineering Research*, vol. 3, no. 2, pp. 647–651, 2013.

[35] F. Herrera and L. Martínez, "A model based on linguistic 2-tuples for dealing with multigranular hierarchical linguistic contexts in multi-expert decision-making," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 31, no. 2, pp. 227–234, 2001.

[36] F. Herrera and L. Martínez, "A 2-tuple fuzzy linguistic representation model for computing with words," *IEEE Transactions on fuzzy systems*, vol. 8, no. 6, pp. 746–752, 2000.

[37] R. Degani and G. Bortolan, "The problem of linguistic approximation in clinical decision making," *International Journal of Approximate Reasoning*, vol. 2, no. 2, pp. 143–162, 1988.

[38] F. Herrera and L. Martinez, "The 2-tuple linguistic computational model: advantages of its linguistic description, accuracy and consistency," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 9, no. supp01, pp. 33–48, 2001.

[39] E. Herrera-Viedma, F. Herrera, L. Martınez, J. C. Herrera, and A. López, "Incorporating filtering techniques in a fuzzy linguistic multi-agent model for information gathering on the web," *Fuzzy sets and Systems*, vol. 148, no. 1, pp. 61–83, 2004.

[40] M. Li, "The extension of quality function deployment based on 2-tuple linguistic representation model for product design under multigranularity linguistic environment," *Mathematical Problems in Engineering*, vol. 2012, 2012.

[41] M. Li, "The method for product design selection with incomplete linguistic weight information based on quality function deployment in a fuzzy environment," *Mathematical Problems in Engineering*, vol. 2013, 2013.

[42] L. Martı, F. Herrera, *et al.*, "An overview on the 2-tuple linguistic model for computing with words in decision making: Extensions, applications and challenges," *Information Sciences*, vol. 207, pp. 1–18, 2012.

[43] H. Zhu, J. Zhao, and Y. Xu, "2-dimension linguistic computational model with 2-tuples for multi-attribute group decision making," *Knowledge-Based Systems*, vol. 103, pp. 132–142, 2016.

[44] M. Lin, Z. Xu, Y. Zhai, and Z. Yao, "Multi-attribute group decision-making under probabilistic uncertain linguistic environment," *Journal of the Operational Research Society*, pp. 1–14, 2017.

[45] Z. Xu, "Deviation measures of linguistic preference relations in group decision making," *Omega*, vol. 33, no. 3, pp. 249–254, 2005.

[46] H. Liao, Z. Xu, and X.-J. Zeng, "Distance and similarity measures for hesitant fuzzy linguistic term sets and their application in multi-criteria decision making," *Information Sciences*, vol. 271, pp. 125–142, 2014.

[47] L. Roselló, M. Sánchez, N. Agell, F. Prats, and F. A. Mazaira, "Using consensus and distances between generalized multi-attribute linguistic assessments for group decision-making," *Information Fusion*, vol. 17, pp. 83–92, 2014.

[48] L. Roselló, F. Prats, N. Agell, and M. Sánchez, "Measuring consensus in group decisions by means of qualitative reasoning," *International Journal of Approximate Reasoning*, vol. 51, no. 4, pp. 441–452, 2010.

[49] F. Herrera, S. Alonso, F. Chiclana, and E. Herrera-Viedma, "Computing with words in decision making: foundations, trends and prospects," *Fuzzy Optimization and Decision Making*, vol. 8, no. 4, pp. 337–364, 2009.

[50] L. A. Zadeh, "Fuzzy logic= computing with words," *IEEE transactions on fuzzy systems*, vol. 4, no. 2, pp. 103–111, 1996.

[51] Y. Zhang, Z. Xu, H. Wang, and H. Liao, "Consistency-based risk assessment with probabilistic linguistic preference relation," *Applied Soft Computing*, vol. 49, pp. 817–833, 2016.

[52] L. A. Zadeh, "Soft computing and fuzzy logic," *IEEE software*, vol. 11, no. 6, pp. 48–56, 1994.

[53] F. J. Cabrerizo, J. M. Moreno, I. J. Pérez, and E. Herrera-Viedma, "Analyzing consensus approaches in fuzzy group decision making: advantages and drawbacks," *Soft Computing*, vol. 14, no. 5, pp. 451–463, 2010.

[54] H. Tian, J. Li, F. Zhang, Y. Xu, C. Cui, Y. Deng, and S. Xiao, "Entropy analysis on intuitionistic fuzzy sets and interval-valued intuitionistic fuzzy sets and its applications in mode assessment on open communities," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 22, no. 1, pp. 147–155, 2018.

[55] T. Hasuike and H. Katagiri, "An objective formulation of membership function based on fuzzy entropy and pairwise comparison," *Journal of Intelligent & Fuzzy Systems*, vol. 32, no. 6, pp. 4443–4452, 2017.

[56] T. Takeda, Y. Sakai, S. Kobashi, K. Kuramoto, and Y. Hata, "Foot age estimation system from walking dynamics based on fuzzy logic," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 18, no. 4, pp. 489–498, 2014.

[57] M. Delgado, J. L. Verdegay, and M. A. Vila, "On aggregation operations of linguistic labels," *International journal of intelligent systems*, vol. 8, no. 3, pp. 351–370, 1993.

[58] H.-B. Yan, V.-N. Huynh, and Y. Nakamori, "A probabilistic model for linguistic multi-expert decision making involving semantic overlapping," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8901–8912, 2011.

[59] V.-N. Huynh, C. H. Nguyen, and Y. Nakamori, “Medm in general multi-granular hierarchical linguistic contexts based on the 2-tuples linguistic model,” in *Granular Computing, 2005 IEEE International Conference on*, vol. 2, pp. 482–487, IEEE, 2005.

[60] G. Wei and X. Zhao, “Some dependent aggregation operators with 2-tuple linguistic information and their application to multiple attribute group decision making,” *Expert Systems with Applications*, vol. 39, no. 5, pp. 5881–5886, 2012.

[61] P. Liu and X. You, “Probabilistic linguistic todim approach for multiple attribute decision-making,” *Granular Computing*, vol. 2, no. 4, pp. 333–342, 2017.

[62] Y. Zhai, Z. Xu, and H. Liao, “Probabilistic linguistic vector-term set and its application in group decision making with multi-granular linguistic information,” *Applied Soft Computing*, vol. 49, pp. 801–816, 2016.

[63] X. Zhang and X. Xing, “Probabilistic linguistic vikor method to evaluate green supply chain initiatives,” *Sustainability*, vol. 9, no. 7, p. 1231, 2017.

[64] J. M. Merigo and G. Wei, “Probabilistic aggregation operators and their application in uncertain multi-person decision-making,” *Technological and Economic Development of Economy*, vol. 17, no. 2, pp. 335–351, 2011.

[65] K. Matzler and H. H. Hinterhuber, “How to make product development projects more successful by integrating kano’s model of customer satisfaction into quality function deployment,” *Technovation*, vol. 18, no. 1, pp. 25–38, 1998.

[66] F. F. Reichheld and J. W. Sasser, “Zero defections: Quality comes to services.,” *Harvard business review*, vol. 68, no. 5, pp. 105–111, 1990.

[67] J. Soroor, M. J. Tarokh, F. Khoshalhan, and S. Sajjadi, “Intelligent evaluation of supplier bids using a hybrid technique in distributed supply chains,” *Journal of Manufacturing Systems*, vol. 31, no. 2, pp. 240–252, 2012.

[68] N. Agell, M. SáNchez, F. Prats, and L. Roselló, “Ranking multi-attribute alternatives on the basis of linguistic labels in group decisions,” *Information Sciences*, vol. 209, pp. 49–60, 2012.

[69] Z. Yue, "A method for group decision-making based on determining weights of decision makers using topsis," *Applied Mathematical Modelling*, vol. 35, no. 4, pp. 1926–1936, 2011.

[70] Z. Yue, "Extension of topsis to determine weight of decision maker for group decision making problems with uncertain information," *Expert Systems with Applications*, vol. 39, no. 7, pp. 6343–6350, 2012.

[71] J. R. French Jr, "A formal theory of social power.," *Psychological review*, vol. 63, no. 3, p. 181, 1956.

[72] C. Xia and Z.-p. FAN, "Study on assessment level of experts based on difference preference information," *Systems Engineering-Theory & Practice*, vol. 27, no. 2, pp. 27–35, 2007.

[73] Z. Xu, "Dependent uncertain ordered weighted aggregation operators," *Information Fusion*, vol. 9, no. 2, pp. 310–316, 2008.

[74] J.-R. Chou, "Applying fuzzy linguistic preferences to kansei evaluation," in *KEER2014. Proceedings of the 5th Kanesi Engineering and Emotion Research; International Conference; Linköping; Sweden; June 11-13*, no. 100, pp. 339–349, Linköping University Electronic Press, 2014.

[75] J. Li and J.-q. Wang, "An extended qualiflex method under probability hesitant fuzzy environment for selecting green suppliers," *International Journal of Fuzzy Systems*, vol. 19, no. 6, pp. 1866–1879, 2017.

[76] Z. Zhang and X. Chu, "Fuzzy group decision-making for multi-format and multi-granularity linguistic judgments in quality function deployment," *Expert Systems with Applications*, vol. 36, no. 5, pp. 9150–9158, 2009.

[77] L.-H. Chen and W.-C. Ko, "Fuzzy approaches to quality function deployment for new product design," *Fuzzy sets and systems*, vol. 160, no. 18, pp. 2620–2639, 2009.

[78] A. H. Lee, H.-Y. Kang, C. Y. Lin, and J.-S. Chen, "A novel fuzzy quality function deployment framework," *Quality Technology & Quantitative Management*, vol. 14, no. 1, pp. 44–73, 2017.

[79] V. Bouchereau and H. Rowlands, "Methods and techniques to help quality function deployment (qfd)," *Benchmarking: An International Journal*, vol. 7, no. 1, pp. 8–20, 2000.

[80] W.-P. Wang, "Evaluating new product development performance by fuzzy linguistic computing," *Expert Systems with Applications*, vol. 36, no. 6, pp. 9759–9766, 2009.

[81] J. Huang, X.-Y. You, H.-C. Liu, and S.-L. Si, "New approach for quality function deployment based on proportional hesitant fuzzy linguistic term sets and prospect theory," *International Journal of Production Research*, pp. 1–17, 2018.

[82] H.-B. Yan, T. Ma, and Y. Li, "A novel fuzzy linguistic model for prioritising engineering design requirements in quality function deployment under uncertainties," *International Journal of Production Research*, vol. 51, no. 21, pp. 6336–6355, 2013.

[83] Z. Iqbal, N. P. Grigg, K. Govindaraju, and N. M. Campbell-Allen, "A distance-based methodology for increased extraction of information from the roof matrices in qfd studies," *International Journal of Production Research*, vol. 54, no. 11, pp. 3277–3293, 2016.

[84] Z.-L. Wang, J.-X. You, and H.-C. Liu, "Uncertain quality function deployment using a hybrid group decision making model," *Symmetry*, vol. 8, no. 11, p. 119, 2016.

[85] T.-y. Wu, Y.-j. Li, and Y. Liu, "Study of color emotion impact on leisure food package design," in *International Conference on Human-Computer Interaction*, pp. 612–619, Springer, 2017.

[86] P. Akkawuttiwanich and P. Yenradee, "Fuzzy qfd approach for managing scor performance indicators," *Computers & Industrial Engineering*, 2018.

[87] M. Nagamachi, "Kansei engineering: a new ergonomic consumer-oriented technology for product development," *International Journal of industrial ergonomics*, vol. 15, no. 1, pp. 3–11, 1995.

[88] J. Vieira, J. M. A. Osório, S. Mouta, P. Delgado, A. Portinha, J. F. Meireles, and J. A. Santos, "Kansei engineering as a tool for the design of in-vehicle rubber keypads," *Applied ergonomics*, vol. 61, pp. 1–11, 2017.

[89] V.-N. Huynh, H. Yan, and Y. Nakamori, "A target-based decision-making approach to consumer-oriented evaluation model for japanese traditional crafts," *IEEE Transactions on Engineering Management*, vol. 57, no. 4, pp. 575–588, 2010.

[90] C. E. Osgood, G. J. Suci, and P. H. Tannenbaum, *The measurement of meaning.* University of Illinois Press, 1964.

[91] R. M. Rodriguez, L. Martinez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making," *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 1, pp. 109–119, 2012.

[92] M. Xia and Z. Xu, "Hesitant fuzzy information aggregation in decision making," *International journal of approximate reasoning*, vol. 52, no. 3, pp. 395–407, 2011.

[93] L. Martínez, "Sensory evaluation based on linguistic decision analysis," *International Journal of Approximate Reasoning*, vol. 44, no. 2, pp. 148–164, 2007.

[94] C.-C. Li, R. M. Rodríguez, F. Herrera, L. Martinez, and Y. Dong, "A consistency-driven approach to set personalized numerical scales for hesitant fuzzy linguistic preference relations," in *Fuzzy Systems (FUZZ-IEEE), 2017 IEEE International Conference on*, pp. 1–5, IEEE, 2017.

[95] S.-P. Wan, "2-tuple linguistic hybrid arithmetic aggregation operators and application to multi-attribute group decision making," *Knowledge-Based Systems*, vol. 45, pp. 31–40, 2013.

[96] C.-T. Chen and W.-S. Tai, "Measuring the intellectual capital performance based on 2-tuple fuzzy linguistic information," in *The 10th Annual Meeting of APDSI, Asia Pacific Region of Decision Sciences Institute*, vol. 20, 2005.

[97] S.-Y. Wang, "Applying 2-tuple multigranularity linguistic variables to determine the supply performance in dynamic environment based on product-oriented strategy," *IEEE Transactions on Fuzzy Systems*, vol. 16, no. 1, pp. 29–39, 2008.

[98] E. Szmidt and J. Kacprzyk, "Distances between intuitionistic fuzzy sets," *Fuzzy sets and systems*, vol. 114, no. 3, pp. 505–518, 2000.

[99] Z. Xu, "An approach based on similarity measure to multiple attribute decision making with trapezoid fuzzy linguistic variables," in *International Conference on Fuzzy Systems and Knowledge Discovery*, pp. 110–117, Springer, 2005.

[100] E. Szmidt and J. Kacprzyk, "A similarity measure for intuitionistic fuzzy sets and its application in supporting medical diagnostic reasoning," in *International Conference on Artificial Intelligence and Soft Computing*, pp. 388–393, Springer, 2004.

[101] E. N. Weiss and V. R. Rao, "Ahp design issues for large-scale systems," *Decision Sciences*, vol. 18, no. 1, pp. 43–61, 1987.

[102] H.-C. Liu, J.-X. You, and X.-Y. You, "Evaluating the risk of healthcare failure modes using interval 2-tuple hybrid weighted distance measure," *Computers & Industrial Engineering*, vol. 78, pp. 249–258, 2014.

[103] R. Ramanathan and L. Ganesh, "Group preference aggregation methods employed in ahp: An evaluation and an intrinsic process for deriving members' weightages," *European Journal of Operational Research*, vol. 79, no. 2, pp. 249–265, 1994.

[104] M. Nagamachi, "Kansei engineering as a powerful consumer-oriented technology for product development," *Applied ergonomics*, vol. 33, no. 3, pp. 289–294, 2002.

[105] T. Childs, A. De Pennington, J. Rait, T. Robins, K. Jones, C. Workman, S. Warren, and J. Colwill, "Affective design (kansei engineering) in japan," *Faraday Packaging Partnership, Univ. Leeds, Leeds*, 2001.

[106] S. Chanyachatchawan, H.-B. Yan, S. Sriboonchitta, and V.-N. Huynh, "A linguistic representation based approach to modelling kansei data and its application to consumer-oriented evaluation of traditional products," *Knowledge-Based Systems*, vol. 138, pp. 124–133, 2017.

[107] C. E. Osgood, G. J. Suci, and P. H. Tannenbaum, "The measurement of meaning. 1957," *Urbana: University of Illinois Press*, 1978.

Publications

International journals

[1] Sirin Suprasongsin, Pisal Yenradee, Van-Nam Huynh and Chayakrit Charoensiriwath, Suitable Aggregation Models Based on Risk Preferences for Supplier Selection and Order Allocation Problem, *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Fuji Technology: Referred, 22(1), pp. 5-16, 2018.

[2] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, A 3-dimension fuzzy linguistic evaluation model, *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Fuji Technology: Accepted, 22(5), 9 pages, 2018.

[3] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, A weight-consistent model for fuzzy supplier selection and order allocation problem, *Annals of Operation Research*, Springer: Under review, 20 pages.

International conferences

[4] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, An Alternative Fuzzy Linguistic Approach for Determining Criteria Weights and Segmenting Consumers for New Product Development: A Case Study. *In: Proceedings of the 18th International Symposium on Knowledge and Systems Sciences (KSS)*, Springer: Refereed, pp. 23-37, 17th-19th November 2017, Bangkok, Thailand.

[5] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, Optimization of supplier selection and order allocation under fuzzy demand in fuzzy lead time. *In: Proceedings of the 17th International Symposium on Knowledge and Systems Sciences (KSS)*, Springer: Refereed, pp. 182-195, 4th-6th November 2016, Kobe, Japan.

[6] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, Suitable aggregation operator for a realistic supplier selection model based on risk preference of decision maker. *In: Proceedings of the 13th Modeling Decisions for Artificial Intelligence (MDAI)*, Springer: Refereed, pp. 68-81, 19th-21st September 2016, Sant Julia de Loria, Andorra.

[7] Sirin Suprasongsin, Van-Nam Huynh, and Pisal Yenradee, A weight-consistent additive model for fuzzy supplier selection and order allocation problem, *In: Proceedings of the 1st International Workshop on Optimization in Modern Computing Systems (OptiMoCS)*, Springer: Submitted, 15 pages, 12th September 2018, Como, Italy.