

**UNIVERSIDAD COMPLUTENSE DE MADRID**

**FACULTAD DE ESTUDIOS ESTADÍSTICOS**



**TESIS DOCTORAL**

Aplicación del operador OWA en las técnicas de machine learning y modelo lingüístico difuso de dos tuplas para la toma de decisiones dinámicas

Application of the OWA operator in machine learning techniques and 2-tuple linguistic model for dynamic decision-making

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

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Javier Portela García-Miguel  
Ramón Alberto Carrasco González  
Manuel Antonio Sánchez-Montañés Isla

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*To my family and to all those whom I regard as family.*

*A mi familia y a todos aquellos a quienes considero parte de ella.*



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*"If I have a thousand ideas and only one turns out to be good,*

*I am satisfied."*

*Alfred Nobel*

*"Read ten thousand books, walk ten thousand miles (读万卷书, 行万里路)"* is a famous quote by Dong Qichang, a Chinese calligrapher, poet and painter of the Ming Dynasty. This quote inspired me to decide to come to Spain to pursue my bachelor's, master's, and doctoral degrees. Our journeys towards our dreams and paths can vary in ease or difficulty, largely depending on the support from our families, as we come into this world with nothing and grow with the love and assistance of those around us. Therefore, from the depths of my heart, I would like to express my sincere gratitude to my family, especially my parents, for their unwavering support of my dreams and aspirations, their constant encouragement, and their unconditional belief in me.

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*"Si tuviera mil ideas y solo una resultase ser buena,  
estaría satisfecho."*

*Alfred Nobel*

"Leer diez mil libros, recorrer diez mil millas (读万卷书, 行万里路)" es una famosa cita de Dong Qichang, calígrafo, poeta y pintor chino de la dinastía Ming. Esta cita me inspiró a tomar la decisión de venir a España para cursar la carrera, el máster y el doctorado. Perseguir nuestros sueños o seguir nuestras propias rutas puede ser tanto fácil como difícil, a menudo dependiendo del apoyo que recibamos de nuestra familia, ya que llegamos a este mundo sin nada material y crecemos por el amor y el respaldo que nos brindan aquellos que nos rodean. Por lo tanto, desde lo más profundo de mi corazón, me gustaría expresar mi sincera gratitud a mi familia, especialmente a mis padres, por respaldar siempre mis sueños y aspiraciones de manera incondicional, por su constante aliento y por creer en mí en todo momento.

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# Abstract

Decision-making is a common process in human activities, ranging from simple daily choices like what to eat or wear to complex business or economic decisions that could affect an organization's success, financial stability, and market competitiveness. This process typically involves identifying a goal, gathering relevant information about one or more criteria, and evaluating various alternatives based on the available information to choose the best one. Decisions can be made by individuals or groups, encompassing personal choices like selecting a hotel to stay in, as well as organizational decisions such as improving hotel amenities or implementing business restructuring strategies. Most decision-making scenarios involve multi-criteria decision-making (MCDM), which determines the best alternative by considering diverse criteria in the selection process. Aggregation, a crucial step in the MCDM problem, involves merging multi-criteria evaluations of alternatives into a single value to facilitate decision-making. In many MCDM problems, the effectiveness of this fusion process depends on selecting the right aggregation operators. Decision-makers' attitudes, such as their risk tolerance and level of demand, should be considered in the aggregation process to better facilitate their decision-making.

Yager introduced the ordered weighted averaging (OWA) aggregation operator in 1988, which has served as a useful tool for decision-making processes since then. This operator can aggregate multiple criteria to form an overall decision function while also modeling decision-makers' attitudes. Specifically, the use of distinct linguistic quantifiers in the OWA aggregation operator, such as "*At least one*," "*Few*," "*Half*," "*Most*," "*All*," etc., to calculate the weights allows for the consideration and representation of the decision-maker's attitudinal character in the aggregation process. For example, an optimistic decision-maker may feel satisfied as soon as at least one of the evaluated criteria is met; the weights used to aggregate the criteria values are calculated using the linguistic quantifier "*At least one*," assigning more weight to the highest input values. Conversely, a pessimistic decision-maker may feel satisfied only when all evaluated criteria are met; the weights used to aggregate the criteria values are

calculated using the linguistic quantifier "*All*," assigning more weight to the lowest input values. The *orness* value, calculated from the weights produced by different linguistic quantifiers, forms the decision strategy space that spans from risk-prone (optimistic views or decision-making strategies) to risk-averse (pessimistic views or decision-making strategies). Higher *orness* values relate to optimistic tendencies, indicating a greater risk propensity, while lower values correspond to pessimistic inclinations, signifying risk aversion; an *orness* of 0.5 denotes a decision-maker's risk-neutral attitude.

In the literature, many researchers have applied linguistic quantifiers to model decision-makers' attitudes in the decision-making process. However, to the best of our knowledge, none of them have given practical semantics to the linguistic quantifiers to adapt their definitions to the specific context of the case study, thereby making them more intuitive and comprehensible for decision-makers. Moreover, although the OWA aggregation operator has been used in diverse decision-making contexts, its applicability in business and economics is limited. To address these research gaps, this doctoral thesis aims to improve the modeling of decision-makers' attitudes in various contexts, such as business and economic decision-making, using the OWA aggregation operator and related methods and techniques. This includes redefining the linguistic quantifiers of the OWA aggregation operator to make them more intuitive and understandable for decision-makers. Regarding the related methods and techniques, besides the OWA aggregation operator, considering that natural language is the closest expression of people's cognitive processes and communication habits in daily life when providing their feedback and opinions, the 2-tuple linguistic model, one of the most popular models for Computing with Words (CWW) processes, is used. Furthermore, the 2-tuple linguistic model is employed in this thesis as it can facilitate the conversion between numerical values and 2-tuple values without information loss while keeping the interpretability of the decision-making results. This enables the combined use of the OWA aggregation operator and the 2-tuple linguistic model to handle linguistic values while considering decision-makers' attitudes. This thesis also explores the effectiveness of other MCDM methods and analysis tools, combining them with the 2-tuple linguistic model or the OWA aggregation operator to enhance decision-making in diverse scenarios. With advanced computing technologies like machine

learning (ML) models helping to make complex decision-making more efficient and accurate, this thesis explores techniques such as clustering to further enhance decision-making processes.

The aforementioned methods and techniques have been used in one or more proposed models during this thesis to achieve the set general and specific objectives, such as creating an approach to segment hotels by emulating customers' psychological attitudes and proposing a multi-criteria decision support model to help users efficiently rank and choose restaurants based on their attitudes. The datasets collected to demonstrate the applicability of the proposed models include data from two review sites, TripAdvisor and Dianping.com, as well as data from Numbeo and other public data repositories. The results of the proposed models are visualized through developed interactive web applications, enhancing the reproducibility and transparency of findings, and thereby facilitating decision-making. During this thesis, several publications have been published and submitted, including JCR/Scopus indexed journal articles, international conference papers, and book chapters. These publications demonstrate the contributions of this thesis.

# Resumen

La toma de decisiones es un proceso común en las actividades humanas, que abarca desde elecciones diarias simples, como qué comer o vestir, hasta decisiones comerciales o económicas complejas que pueden afectar el éxito de la organización, la estabilidad financiera y la competitividad en el mercado. Este proceso suele implicar la identificación de un objetivo, la recopilación de información relevante sobre uno o varios criterios, y la evaluación de varias alternativas basada en la información disponible para elegir la mejor. Las decisiones pueden ser tomadas por individuos o grupos, y abarcan desde elecciones personales, como la selección de un hotel en el que alojarse, hasta decisiones organizativas, como la mejora de los servicios del hotel o la aplicación de estrategias de reestructuración empresarial. La mayoría de los escenarios de toma de decisiones implican la toma de decisiones multicriterio (MCDM, abreviatura en inglés), que determina la mejor alternativa considerando diversos criterios en el proceso de selección. La agregación, un paso crucial en el problema de MCDM, consiste en fusionar las evaluaciones multicriterio de las alternativas en un único valor para facilitar la toma de decisiones. En muchos problemas de MCDM, la eficacia de este proceso de fusión depende de la selección adecuada de los operadores de agregación. Las actitudes de los decisores, como su tolerancia al riesgo y su nivel de exigencia, deben tenerse en cuenta en el proceso de agregación para facilitar mejor la toma de decisiones.

En 1988, Yager introdujo el operador de agregación OWA (*Ordered Weighted Averaging*, en inglés, o "media ponderada ordenada" en español), y desde entonces ha sido una herramienta útil para los procesos de toma de decisiones. Este operador permite agregar múltiples criterios para formar una función de decisión global, a la vez que modela las actitudes de los decisores. En concreto, el uso de distintos cuantificadores lingüísticos en el operador de agregación OWA, como "*Al menos uno*", "*Pocos*", "*La mitad*", "*La mayoría*", "*Todos*", etc., para calcular las ponderaciones, permite tener en cuenta y representar el carácter actitudinal del decisor en el proceso de agregación. Por ejemplo, un decisor optimista puede sentirse satisfecho cuando se cumple al menos uno de los criterios evaluados. Las ponderaciones utilizadas para agregar los

valores de los criterios se calculan usando el cuantificador lingüístico "*Al menos uno*", asignando más peso a los valores más altos. Por el contrario, un decisor pesimista puede sentirse satisfecho solo cuando se cumplen todos los criterios evaluados. Las ponderaciones utilizadas para agregar los valores de los criterios se calculan usando el cuantificador lingüístico "*Todos*", asignando más peso a los valores más bajos. El valor de *orness*, calculado a partir de las ponderaciones generadas por distintos cuantificadores lingüísticos, define el espacio de estrategias de decisión que va desde la propensión al riesgo (opiniones o estrategias de decisión optimistas) hasta la aversión al riesgo (opiniones o estrategias de decisión pesimistas). Los valores más altos de *orness* indican tendencias optimistas y una mayor propensión al riesgo, mientras que los valores más bajos reflejan inclinaciones pesimistas y aversión al riesgo. Un valor de *orness* de 0,5 denota una actitud neutral hacia el riesgo del decisor.

En la literatura, muchos investigadores han empleado cuantificadores lingüísticos para modelar las actitudes de los decisores en el proceso de toma de decisiones. Sin embargo, según nuestro conocimiento, ninguno de ellos ha proporcionado una semántica práctica a los cuantificadores lingüísticos para adaptar sus definiciones al contexto específico del caso de estudio, haciéndolos así más intuitivos y comprensibles para los decisores. Además, aunque el operador de agregación OWA se ha utilizado en diversos contextos de toma de decisiones, su aplicabilidad en los negocios y la economía es limitada. Para abordar estas lagunas en la investigación, esta tesis doctoral pretende mejorar el modelado de las actitudes de los decisores en diversos contextos, como la toma de decisiones empresariales y económicas, usando el operador de agregación OWA y métodos y técnicas relacionados. Esto incluye la redefinición de los cuantificadores lingüísticos del operador de agregación OWA para hacerlos más intuitivos y comprensibles para los decisores. En cuanto a los métodos y técnicas relacionados, además del operador de agregación OWA, considerando que el lenguaje natural es la expresión más cercana de los procesos cognitivos y hábitos de comunicación de las personas en la vida cotidiana proporcionan sus comentarios y opiniones, se utiliza el modelo lingüístico de 2-tuplas, uno de los modelos más populares para los procesos de CWW (*Computing with Words*, en inglés, o "Computación con Palabras" en español). Además, en esta tesis se emplea el modelo lingüístico de 2-tuplas debido a su capacidad para facilitar la conversión entre valores numéricos y 2-tuplas

sin pérdida de información, al mismo tiempo que mantiene la interpretabilidad de los resultados de la toma de decisiones. Esto permite el uso combinado del operador de agregación OWA y el modelo lingüístico de 2-tuplas para manejar valores lingüísticos, teniendo en cuenta las actitudes de los decisores. Esta tesis también explora la eficacia de otros métodos MCDM y herramientas de análisis, combinándolos con el modelo lingüístico de 2-tuplas o el operador de agregación OWA para mejorar la toma de decisiones en diversos escenarios. Con técnicas de computación avanzada, como los modelos de aprendizaje automático (Machine Learning en inglés), que ayudan a que la toma de decisiones complejas sea más eficiente y precisa, esta tesis explora técnicas como el agrupamiento (clustering, en inglés) para mejorar aún más los procesos de toma de decisiones.

Los métodos y técnicas mencionados se han usado en uno o más modelos propuestos durante esta tesis para alcanzar los objetivos generales y específicos establecidos, como crear un enfoque para segmentar hoteles emulando las actitudes psicológicas de los clientes y proponer un modelo de apoyo a la toma de decisiones multicriterio para ayudar a los usuarios a clasificar y elegir restaurantes de manera eficiente en función de sus actitudes. Los conjuntos de datos coleccionados para demostrar la aplicabilidad de los modelos propuestos incluyen datos de dos sitios de reseñas, TripAdvisor y Dianping.com, así como datos de Numbeo y otros repositorios de datos públicos. Los resultados de los modelos propuestos se visualizan mediante aplicaciones web interactivas desarrolladas, lo que mejora la reproducibilidad y la transparencia de los resultados y, por lo tanto, facilita la toma de decisiones. A lo largo de esta tesis, se han publicado y sometido varias publicaciones, las cuales incluyen artículos en revistas indexadas en JCR/Scopus, artículos en congresos internacionales y capítulos de libros. Estas publicaciones demuestran las contribuciones de esta tesis.

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# List of Acronyms

**2LOWA:** 2-tuple Linguistic Ordered Weighted Averaging

**2LGOWAD:** 2-tuple Linguistic Generalized Ordered Weighted Averaging Distance

**2LIGOWAD:** 2-tuple Linguistic Induced Generalized Ordered Weighted Averaging Distance

**AEC:** AHP-Entropy-CRITIC

**AHP:** Analytic Hierarchy Process

**AI:** Artificial Intelligence

**AM:** Arithmetic Mean

**ANP:** Analytical Network Process

**BWM:** Best-Worst Method

**CHI:** Calinski-Harabasz Index

**CI:** Consistency Index

**CLI:** Climate Index

**COLI:** Cost of Living Index

**COWA:** Centered Ordered Weighted Averaging

**CR:** Consistency Ratio

**CRITIC:** CRiteria Importance Through Intercriteria Correlation

**CWW:** Computing with Words

**DBI:** Davies-Bouldin Index

**DBSCAN:** Density-Based Spatial Clustering of Applications with Noise

**DOWA:** Descending Ordered Weighted Averaging

**ELECTRE:** ELimination and Choice Translating REality (English)/ ÉLimination Et Choix Traduisant la RÉalité (French)

**eWOM:** Electronic Word of Mouth

**FCM:** Fuzzy C-Means

**GMM:** Gaussian Mixture Model

**GDP:** Gross Domestic Product

**GIS:** Geographic Information System

**GOWA:** Generalized Ordered Weighted Averaging

**HCI:** Health Care Index

**HPTIR:** House Price to Income Ratio

**IW:** Importance Weights

**IOWA:** Induced Ordered Weighted Averaging

**IGOWA:** Induced Generalized Ordered Weighted Averaging

**LRFMP:** Length, Recency, Frequency, Monetary, and Periodicity

**MCDA:** Multiple Criteria Decision Analysis

**MCDM:** Multi-Criteria Decision-Making

**ML:** Machine Learning

**OWA:** Ordered Weighted Averaging

**PCA:** Principal Component Analysis

**PCs:** Principal Components

**PI:** Pollution Index

**PPI:** Purchasing Power Index

**PROMETHEE:** Preference Ranking Organization Method for Enrichment Evaluations

**QOLI:** Quality of Life Index

**Quasi-OWA:** Quasi-arithmetic Ordered Weighted Averaging

**RFM:** Recency, Frequency, and Monetary

**RFMB:** Recency, Frequency, Monetary, and Bonding

**RFMC:** Recency, Frequency, Monetary, and Clumpiness

**RFM-D:** Recency, Frequency, Monetary, and Diversity

**RFHPS:** Recency, Frequency, Helpfulness, Promoter score, and Stability

**RFMTC:** Recency, Frequency, Monetary, Time since first purchase and Churn probability

**RI:** Random Index

**RDM:** Regular Decreasing Monotone

**RIM:** Regular Increasing Monotone

**RUM:** Regular UniModal

**SAW:** Simple Additive Weighting

**SC:** Silhouette Coefficient

**SMART:** Simple Multi-Attribute Rating Technique

**SI:** Safety Index

**SVD:** Singular Value Decomposition

**TCTI:** Traffic Commute Time Index

**TOPSIS:** Technique for Order of Preference by Similarity to Ideal Solution

**TW-K-Means:** Two-level variable weighting clustering algorithm

**WA:** Weighted Average

**WKM:** Weighted K-Means

**WPM:** Weighted Product Model



# **Part I**

# **PhD Thesis**



# Chapter 1

## Introduction

This chapter introduces the background and motivation of this doctoral thesis, outlines its objectives, and presents its structure.

### 1.1. Background and Motivation

Decision-making, a multidisciplinary research area encompassing fields such as Computer Science, Business Economics, Psychology, Engineering, Mathematics, Behavioral Sciences, Operations Research, Management Science, and others, has garnered significant interest in research circles. It is an essential aspect of people's lives, involving choosing between various options or potential solutions to address a wide range of problems, from simple daily choices like what to eat and wear to major life decisions. The decision-making process normally involves identifying a goal, gathering pertinent information about one or more criteria, and evaluating various alternatives to choose the best one. For instance, when selecting a hotel, considerations typically include criteria such as price, location, and service. This process may involve an individual (referred to as individual decision-making) or a group (referred to as group decision-making), depending on the number of decision-makers. If depending on the number of criteria, decision-making problems can be classified into single-criterion or multi-criteria decision-making (MCDM), with the majority of scenarios involving MCDM [1].

In many real-life decision situations, people express their opinions using natural language rather than numerical ratings. For example, they might praise a restaurant's food as "delicious" instead of giving it an 8 out of 10, or evaluate a region's living conditions as "very good" rather than directly using numeric values. Natural language is the closest expression to people's cognitive processes and communication habits in daily life, and importantly, natural language and fuzzy linguistic terms offer a more direct way to represent imprecise or uncertain information [2]. Many review

sites incorporate linguistic terms in their user comments and feedback, as shown in Figure 1 with some examples.



**Figure 1.** Example of user feedback on some review sites, adapted from [3, 4].

Linguistic decision-making refers to the process through which people choose the most suitable alternative by considering the linguistic information. The computational foundation for handling decision-making with linguistic information is based on using Computing with Words (CWW) processes. Among the numerous linguistic computational models developed to facilitate linguistic decision-making, the 2-tuple linguistic model [5] stands out for its computational simplicity, its ability to capture linguistic information continuously within its domain to prevent information loss, and its capacity to maintain the interpretability of the results [6]. Moreover, the 2-tuple linguistic model has defined functions to facilitate the conversion between numerical values and 2-tuple values without losing information, which enables easy extension of numerical aggregation operators to handle linguistic values [5].

Aggregation operators are information fusion techniques and are mathematical functions used in decision-making and data analysis to convert a set of values or inputs into a single datum. The arithmetic mean (AM) and the weighted average (WA) are the most well-known aggregation operators. Aggregation operators play a vital role in decision-making processes. The fusion of multi-criteria evaluations of alternatives in many MCDM problems depends on these operators.

When aggregating information, the "attitudes" (e.g., risk tolerance, level of demand, etc.) of decision-makers cannot be overlooked. Decision-makers, whether they are making personal life decisions or are responsible for decisions in various contexts such as business, economics, politics, etc., can influence the outcomes of their decisions through their attitudes. Below are some examples of different scenarios:

- With the development of the Internet, Electronic Word of Mouth (eWOM) has become an important information source for customers and companies to make decisions. Online reviews, a representative form of eWOM, provide valuable information for assessing the quality of services, making purchasing choices, and improving business strategies.
  - a. From the business perspective, effectively managing eWOM has become crucial for the hospitality industry. It is essential for maintaining a hotel's reputation, retaining existing customers, and attracting potential ones. Online reviews allow hotels to monitor customer feedback and understand their experiences. The investment costs in customer management vary depending on the size of the hotel. Small hotels may be unable to allocate many resources to managing online reviews, so their corresponding customer management departments may consider it sufficient as long as half of customer reviews are favorable (i.e., medium level of demand). However, chain hotels or luxury establishments can invest more in managing customer feedback to reduce the risk of losing customers due to unaddressed dissatisfaction or negative feedback promptly. The responsible departments may consider it sufficient only when the majority or all customer reviews are favorable (i.e., high level of demand).
  - b. From the customers' perspective, when they choose a hotel for their vacation, they often rely on eWOM platforms like Booking and TripAdvisor to learn about others' experiences. These review sites offer evaluations of various hotel aspects, such as service, location, price, and rooms, among others, for customers to consider. For customers who just need a hotel that meets basic needs to stay for one or two nights, even if other aspects of the hotel are not ideal, they may still feel satisfied if at least one or a few aspects meet their requirements. However, customers seeking a luxury hotel to stay in are more demanding, expecting every aspect of the hotel to meet their needs. They will not be satisfied unless

everything about the hotel is favorable. In this case, the overall value of each hotel should be determined by considering the high demands of these customers. Moreover, they may have specific needs in some respects, such as being more demanding about hotel dining options, hotel decoration, and security systems.

- When an investor is seeking a country to open a new branch of their company, they should consider many criteria, including geographical location, market demand, degree of economic freedom, political stability, labor costs, among others. If an investor is willing to take on higher risks for greater rewards, they may believe that meeting at least one of these criteria is favorable enough to open a new branch (i.e., an excessively optimistic view). The overall value of each alternative should be determined by considering the investor's risk-prone attitude. However, if an investor has a risk-averse attitude, believing that only when meeting most or all of the criteria is favorable suffices for opening a new branch. In this case, the overall value of each alternative should be determined by considering the investor's risk-averse attitude to facilitate the decision-making process.

As observed, it is necessary to apply an appropriate aggregation operator that considers the attitudes of the decision-makers in the decision-making process. Introduced by Yager in 1988 [7], the ordered weighted averaging (OWA) aggregation operator is a useful tool for decision-making processes, enabling different decision outcomes based on the decision-maker's attitudes. This operator finds applications such as decision-making problems under uncertainty and linguistic decision-making problems [8]. The OWA aggregation operator offers a parameterized family of aggregation functions, encompassing numerous well-known operators (e.g., the maximum, the minimum, the average, etc). This has garnered the interest of many researchers, resulting in a considerable number of published articles that explore its properties and applications [9].

In the OWA aggregation operator, weights are typically determined by linguistic quantifiers (also known as quantifier-guided OWA [10]), such as "*At least one*," "*Few*," "*Half*," "*Most*," "*All*," etc. These weights are assigned to the values of a set based on their ranking order rather than being directly assigned to specific criteria [9]. This characteristic allows the consideration and representation of the attitudinal character of the decision-maker in the aggregation process, ranging

from risk-prone (i.e., optimistic views or decision-making strategies) to risk-averse (i.e., pessimistic views or decision-making strategies) [7]. The *orness* value indicates the level of risk-taking or optimism of decision-makers in the OWA aggregation operator [7]. Higher values of *orness* suggest that the decision-maker tends to be more risk-prone, whereas lower values indicate a tendency toward risk aversion; when *orness* is equal to 0.5, a decision-maker is indifferent toward risk or risk-neutral.

Many aggregation operators, such as the induced ordered weighted averaging (IOWA) [11], quasi-arithmetic ordered weighted averaging (Quasi-OWA) [12], generalized ordered weighted averaging (GOWA) [13], centered ordered weighted averaging (COWA) [14], and induced generalized ordered weighted averaging (IGOWA) [15], have been developed by extending the OWA aggregation operator. Moreover, as the 2-tuple linguistic model can be combined with various numerical aggregation operators to handle linguistic values, several extensions of the OWA aggregation operator have been developed based on this model. These include the 2-tuple linguistic ordered weighted averaging (2LOWA) aggregation operator [5], the 2-tuple linguistic generalized ordered weighted averaging distance (2LGOWAD) aggregation operator [16], and the 2-tuple linguistic induced generalized ordered weighted averaging distance (2LIGOWAD) aggregation operator [17], among others. The OWA aggregation operator and its extensions have been widely adopted to handle MCDM problems and have found applications across many research domains, including neural networks [18, 19], geographic information system (GIS)-based multicriteria decision-making [20-28], data mining [29], business management [30-32], human resource management [33], environmental impact assessment [26, 34], risk and investment management [35, 36], and tourism management [37, 38], to name but a few.

Regarding the application of linguistic quantifiers to emulate decision-makers' attitudes, Malczewski and Rinner [22] conducted an exploratory analysis of decision strategies using linguistic quantifiers of the OWA aggregation operator within GIS-based decision support systems to evaluate the residential quality of neighborhoods in London, Ontario. Boroushaki and Malczewski [24] integrated the Analytical Hierarchy Process (AHP) method with the linguistic quantifiers of the OWA aggregation operator within GIS-based decision support systems to

generate a wide range of decision strategies and scenarios for decision-makers. Nadi and Delavar [25] proposed an MCDM model that integrates a pairwise comparison method with a quantifier-guided OWA aggregation operator, offering users various decision strategies for personalized route planning. Kazemi-Beydokhti et al. [26] introduced a hybrid MCDM approach that combines the Analytical Network Process (ANP) method with the linguistic quantifiers of the OWA aggregation operator to obtain a wide range of decision strategies and scenarios, from pessimistic (risk-averse) to optimistic (risk-taking), and uses GIS to help decision-makers identify suitable areas to establish air quality monitoring stations. Elyasi et al. [27] used seven linguistic quantifiers of the OWA aggregation operator, including "*At least one*," "*Few*," "*Some*," "*Half*," "*Many*," "*Most*," and "*All*," to help geologists quickly and easily define their desired exploration strategy (from extremely optimistic to extremely pessimistic) for mineral potential mapping. Other studies applying the linguistic quantifiers of the OWA aggregation operator to account for decision-makers' attitudes in the decision-making process can be found in [32, 36, 39-43].

Although the literature contains many related studies, to the best of our knowledge, none of them have given practical semantics to the linguistic quantifiers to adapt their definitions to the specific context of the case study, thereby making them more intuitive and comprehensible for decision-makers. Moreover, although the OWA aggregation operator has been used in diverse decision-making contexts, its applicability in business and economics is limited. To address these research gaps, this doctoral thesis investigates the application of the OWA aggregation operator in conjunction with the 2-tuple linguistic model across various problems, such as hotels, restaurants, economic indicators, etc., while also adapting the definition of linguistic quantifiers to suit each specific case. This can provide decision-makers with more efficient, flexible, and easy-to-understand results, contributing to these approaches working better in solving real-world decision-making problems. This thesis also studies other MCDM methods and other analysis tools to recognize their effectiveness, combining them with the 2-tuple linguistic model or the OWA aggregation operator to improve decision-making across various scenarios. Moreover, with advanced computing technologies like machine learning (ML) models helping to make complex decision-making more efficient and accurate, this thesis explores techniques such as clustering to further enhance decision-making processes.

## **1.2. Objectives**

This doctoral thesis establishes the following general and specific objectives based on the previously mentioned research relevance and needs.

### **1.2.1. General Objective**

The general objective of this thesis is to improve the modeling of decision-makers' attitudes in various contexts, such as business and economic decision-making, by using the OWA aggregation operator, the 2-tuple linguistic model, and other related techniques. This includes redefining the linguistic quantifiers of the OWA aggregation operator, often used in conjunction with it, to make them more intuitive and understandable for decision-makers.

### **1.2.2. Specific Objectives**

To achieve the general objective, the following specific objectives are established:

- 1) Review existing studies that have used OWA aggregation operators to represent decision-makers' attitudes in various decision-making contexts.
- 2) Segment hotels by emulating customers' psychological attitudes, from less demanding to most demanding, on various aspects, providing valuable and easy-to-understand insights for companies and customers in decision-making.
- 3) Propose a multi-criteria decision support model to help users efficiently and accurately rank and choose the restaurants based on their attitudes toward various aspects.
- 4) Construct various scenarios of economic indicators (e.g., quality of life index, index of economic freedom, etc.) considering the attitudes of relevant decision-makers.
- 5) Combine various MCDM approaches to create hybrid MCDM methods to tackle issues such as customer profiling and hotel segmentation, offering clear and understandable information for decision-making across various business aspects.

- 6) Apply the proposed models to real cases by collecting data from diverse fields, including hotels, restaurants, economic indicators, etc., to assess their applicability.
- 7) Employ advanced visualization techniques to enhance the decision-making process by creating interactive web applications, showcasing the reproducibility of proposed models, and aiding decision-makers in making appropriate choices based on their psychological attitudes.

### 1.3. Thesis Structure

This doctoral thesis is composed of two parts: the primary thesis and a collection of published and submitted papers.

The first part of this thesis is organized into four chapters:

- The current chapter introduces the background and motivation behind this doctoral thesis, followed by the general and specific objectives established throughout its completion. The structure of this thesis is also outlined.
- Chapter 2 presents the fundamental concepts employed in this thesis to develop different approaches for solving decision-making problems. Section 2.1 introduces the CWW scheme and highlights the 2-tuple linguistic model, which enables the aggregation of information without loss and maintains the interpretability of the results. Section 2.2 presents the OWA aggregation operator and its extension, the 2LOWA aggregation operator, capable of handling linguistic values while retaining the benefits of the OWA aggregation operator. Section 2.3 provides a brief overview of different MCDM methods, detailing those specifically used and developed in this thesis. Section 2.4 starts with a short introduction to ML concepts and models, with subsequent subsections elaborating on the specific ML models employed in this thesis. During this thesis, certain practical problems necessitate applying other methods to ensure the feasibility of the proposed models; therefore, Section 2.5 introduces the Recency, Frequency, and Monetary (RFM) model and its extensions developed in this thesis.
- Chapter 3 consists of eight sections, each demonstrating the application of various MCDM-based proposed models developed in this thesis to address problems such as restaurant ranking and selection, hotel segmentation, economic indicator calculation, and more. Each section provides a summary of the main results, contributions, and conclusions of each published article, ranging from JCR/Scopus indexed journal articles to book chapters and international conference papers. Figure 2 summarizes the common structure followed in this thesis for developing methodologies: starting with determining the problem to solve, which leads to the question of what information needs to be gathered and where to gather it (data layer), followed by considering what methods and techniques should be used to analyze

the collected data (methods and techniques layer), and ending with considering what insights can be obtained from the analysis to inform the final decision or solution (results visualization layer).

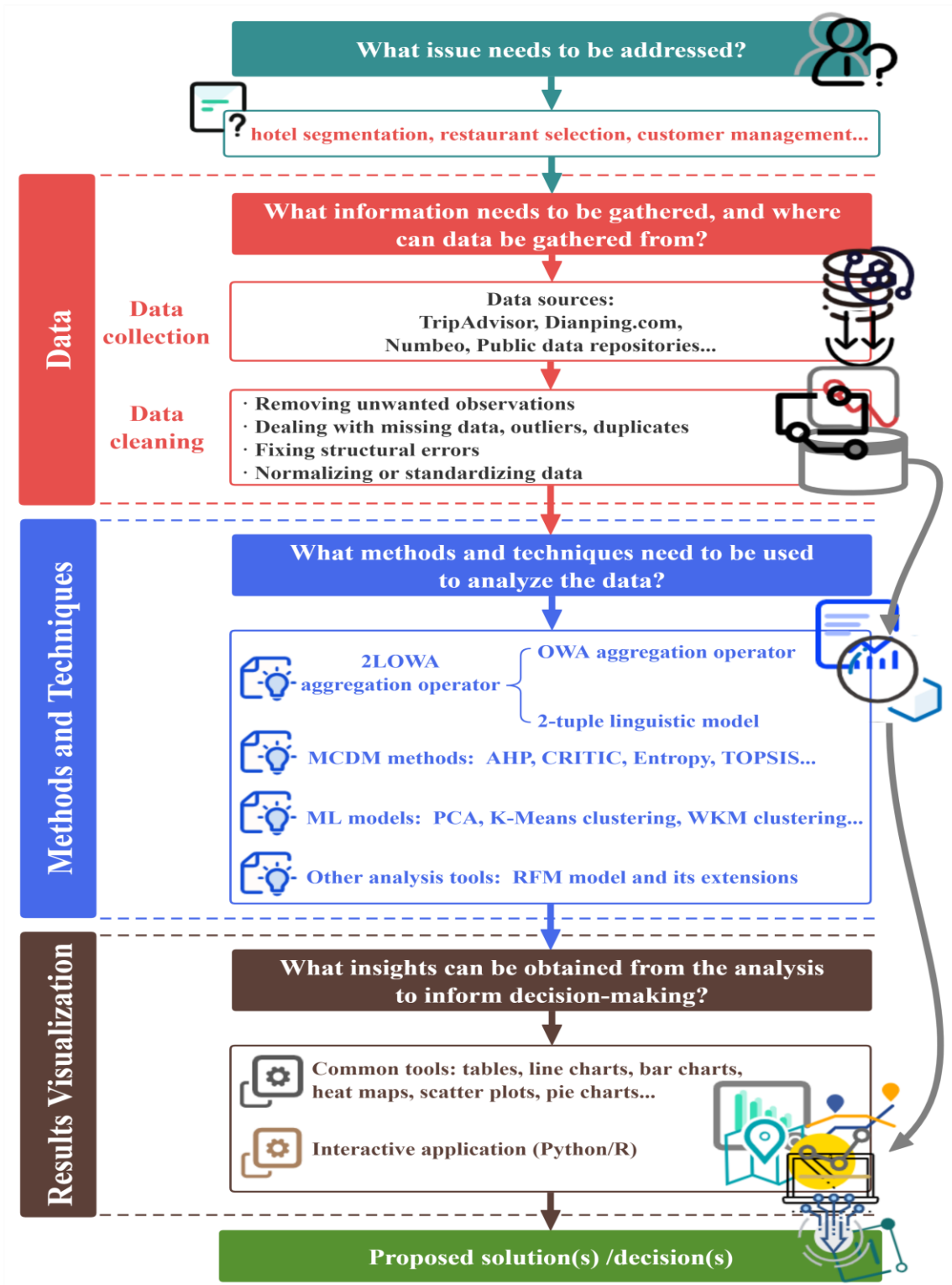


Figure 2. Methodological framework employed in this doctoral thesis.

- Chapter 4 summarizes the main conclusions and significant achievements of the thesis, while also proposing directions for future research based on the work conducted.

The second part of this doctoral thesis presents the published and submitted papers derived from it, as this thesis is completed following the modality of *Thesis by compendium of publications*.

*I have been authorized by the co-authors of the publications to compile the ideas, tables, and figures contained therein for use in this thesis.*



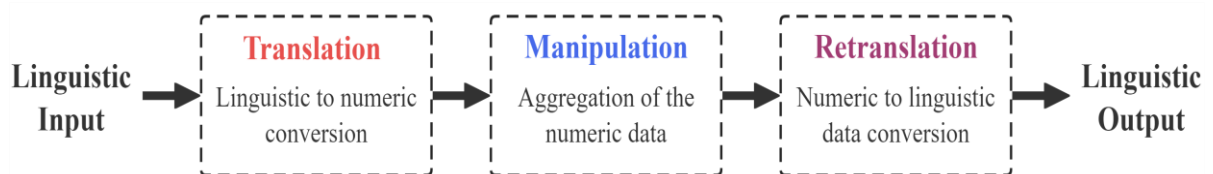
# Chapter 2

## Preliminaries

This chapter presents the main concepts used in this doctoral thesis, including the 2-tuple linguistic model, the OWA aggregation operator, different MCDM methods, ML models, and other pertinent model frameworks relevant to the research interest.

### 2.1. The 2-Tuple Linguistic Model

Decision-making is a daily activity in people's lives, involving the selection of the "best" alternative(s) from a range of options. In linguistic decision-making problems, adopting linguistic information to assess alternatives necessitates using processes of CWW. Proposed by Zadeh in 1996, CWW is a methodology that emulates human cognitive processes, enabling reasoning, computation, and decision-making using linguistic information similar to the natural language used by humans [44, 45]. It aims to bridge the gap between human-like reasoning, which often relies on linguistic descriptions, and computational processes, which traditionally deal with precise numerical data. Figure 3 shows the computational scheme of CWW, where both input and output information are linguistically expressed, making it easy-to-understand for humans.



**Figure 3.** CWW scheme, adapted from [46, 47].

CWW follows the concepts of linguistic variables and fuzzy sets [48]. A linguistic variable is a variable whose values are words or sentences in a natural language [49]. A linguistic variable serves as a translator, assigning a fuzzy set to linguistic terms and facilitating interaction between linguistic representations and numerical ones [50]. In the fuzzy linguistic approach, linguistic terms are

employed to reflect the approximate values of a linguistic variable, as they are very similar to human thinking [49]. For instance, in comparison to "The hotel location scores 1," the statement "The hotel location is poor" is less precise. The word "poor" serves as a linguistic term for the variable "hotel location", which is less precise compared to the numerical value "1," but it enables people to naturally express and handle uncertain information (i.e., the rating that a customer wants to give to the hotel location may not necessarily be precisely a 1; it could be 0.8, 0.9, or even 1.2). The linguistic term "poor" includes a broader range of possible scores than just a 1.

Although fuzzy linguistic approaches have been effectively applied in many areas, they often restrict the elicitation of linguistic information to single terms, leading to a problem of information loss. Herrera and Martínez introduced the 2-tuple linguistic model to tackle information loss in the linguistic information fusion of linguistic information [5]. This model expresses information through linguistic values consisting of a linguistic term and a symbolic translation represented by a numeric value assessed in  $[-0.5, 0.5)$ . Linguistic information is managed as a continuous domain in the 2-tuple linguistic model, preserving the CWW scheme shown in Figure 3, and yielding more accurate results. The 2-tuple linguistic model is acknowledged as the most popular and beneficial model for CWW, owing to its heightened accuracy in linguistic computations while maintaining result interpretability [51, 52]. This model has been extensively used for handling linguistic information in decision-making issues and serves as a foundation for various models in decision analysis [6, 51]. Various extensions of the 2-tuple linguistic model facilitate CWW processes in complex decision frameworks [53]. The 2-tuple model, along with its extensions, finds extensive applications across diverse fields, including the finance industry [54, 55], healthcare industry [56-58], hospitality industry [59-62], among others.

The 2-tuple linguistic model represents the linguistic information using a pair of values known as a 2-tuple value  $(s_i, \alpha)$ , where  $s_i \in S$  is a linguistic term, and  $\alpha \in [-0.5, 0.5)$  is a numerical value that represents the symbolic translation. The definition is as follows.

**Definition 1.** [5] The symbolic translation of a linguistic term  $s_i \in S = \{s_0, \dots, s_g\}$  is a numerical value assessed in  $[-0.5, 0.5)$  that supports the "difference of information" between an amount of information  $[0, g]$  and the closest value in  $\{0, \dots, g\}$  that indicates the index of the closest

linguistic term in  $S$  ( $s_i$ ), being  $[0, g]$  the interval of granularity of  $S$ .

The 2-tuple linguistic model defines a set of transformation functions between linguistic terms and 2-tuple values, as well as between 2-tuple values and numerical values.

**Definition 2.** [5] Let  $S = \{s_0, \dots, s_g\}$  be a set of linguistic terms and  $\beta \in [0, g]$  a value supporting the result of a symbolic aggregation operation, where  $g + 1$  is the cardinality of  $S$ . The function  $\Delta: [0, g] \rightarrow \langle S \rangle = Sx[-0.5, 0.5)$  is used to convert  $\beta$  into the 2-tuple value  $(s_i, \alpha)$ , as shown in Equation (1):

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases} \quad (1)$$

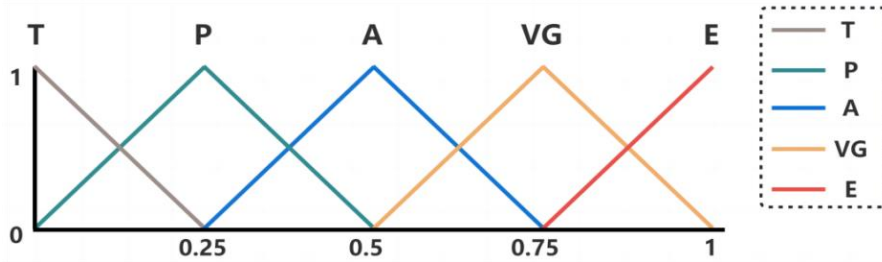
where  $\text{round}(\cdot)$  is the rounding operation;  $s_i$  has the closest index label to  $\beta$ ; and  $\alpha$  is the numerical value of the symbolic translation.

This model can perform transformations between 2-tuple values and numerical values. The function  $\Delta$  is bijective; its inverse function  $\Delta^{-1}: \langle S \rangle = Sx[-0.5, 0.5) \rightarrow [0, g]$  converts the 2-tuple value into its equivalent numerical value as follows:

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \quad (2)$$

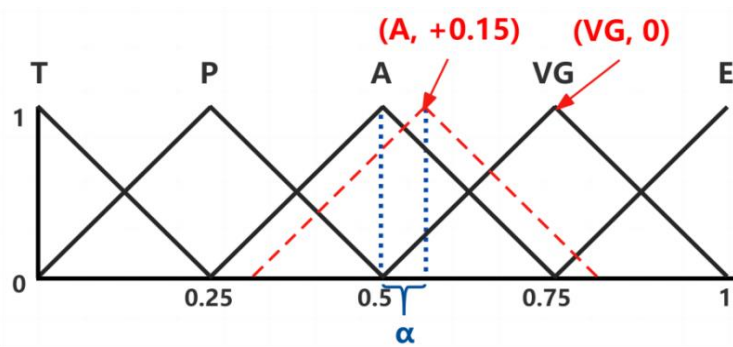
**Remark 1.** The conversion of a linguistic term into a 2-tuple value consists of adding a value 0 as symbolic translation, denoted as  $s_i \in S \Rightarrow (s_i, 0)$ .

**Example 1.** The linguistic terms used by TripAdvisor to evaluate hotel criteria are *Terrible* =  $T$ , *Poor* =  $P$ , *Average* =  $A$ , *Very Good* =  $VG$ , *Excellent* =  $E$ . Therefore,  $S = \{s_0 = T, s_1 = P, s_2 = A, s_3 = VG, s_4 = E\}$  is a set of five linguistic terms used by TripAdvisor, whose cardinality is  $g + 1 = 5$ . Figure 4 shows the distribution of the set of linguistic terms covered in the set  $S$ .



**Figure 4.** The linguistic term set  $S$  used on TripAdvisor.

Let  $\beta = 2.15$  be a value representing the result of a symbolic aggregation operation on the set of linguistic terms  $S = \{s_0 = T, s_1 = P, s_2 = A, s_3 = VG, s_4 = E\}$ . Then, its 2-tuple value is  $\Delta(2.15) = (s_{\text{round}(2.15)}, 2.15 - \text{round}(2.15)) = (s_2, +0.15) = (A, +0.15)$ . The inverse transformation is  $\Delta^{-1}(s_2, +0.15) = 2 + 0.15 = 2.15$ . In the case that  $\beta$  equals 3, its 2-tuple value is  $\Delta(3) = (s_3, 0) = (VG, 0) = VG$ , which means that the difference between  $\beta$  and this linguistic term is zero ( $\alpha = 0$ ). The two examples ( $\beta = 2.15$  and  $\beta = 3$ ) are shown in Figure 5.



**Figure 5.** Representation of examples of the 2-tuple values.

Herrera and Martínez also introduced a method to compare two 2-tuple values and the negation operator of a 2-tuple value, with the following definitions.

**Definition 3.** The comparison of linguistic information represented by 2-tuple values is performed according to an ordinary lexicographic order [5]. Let  $(s_I, \alpha_1)$  and  $(s_L, \alpha_2)$  be two 2-tuple values, the operator is generated to compare their linguistic 2-tuple values as the following:

- If  $I < L$ ,  $(s_I, \alpha_1)$  is smaller than  $(s_L, \alpha_2)$ .
- If  $I = L$ , when:
  - a.  $\alpha_1 = \alpha_2$ ,  $(s_I, \alpha_1)$  and  $(s_L, \alpha_2)$  represent the same information.
  - b.  $\alpha_1 < \alpha_2$ ,  $(s_I, \alpha_1)$  is smaller than  $(s_L, \alpha_2)$ .
  - c.  $\alpha_1 > \alpha_2$ ,  $(s_I, \alpha_1)$  is larger than  $(s_L, \alpha_2)$ .
- If  $I > L$ ,  $(s_I, \alpha_1)$  is larger than  $(s_L, \alpha_2)$ .

**Definition 4.** The negation operator of a 2-tuple value is defined as follows:

$$\text{neg}((s_i, \alpha)) = \Delta(g - \Delta^{-1}(s_i, \alpha)) = \Delta(g - \beta) \quad (3)$$

where  $g + 1$  is the cardinality of  $S$ ,  $S = \{s_0, \dots, s_g\}$ .

The 2-tuple linguistic model specifies the functions  $\Delta$  and  $\Delta^{-1}$ , which convert numerical values

into 2-tuple values and vice versa. This makes it possible to extend any numerical aggregation operator to handle 2-tuple values. Three classic aggregation operators used in the 2-tuple linguistic model are the AM operator, the WA operator, and the OWA aggregation operator [5]. Definitions 5 and 6 explain how to aggregate a set of 2-tuple values using the AM operator and WA operator, respectively. The computation associated with the OWA aggregation operator is introduced in Section 2.2.

**Definition 5.** Let  $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \dots, (r_t, \alpha_t)\}$  be a set of 2-tuple values, the 2-tuple arithmetic mean  $\bar{x}^{AM}$  is calculated as follows:

$$\bar{x}^{AM} = \Delta \left( \frac{1}{t} \sum_{i=1}^t \Delta^{-1}(r_i, \alpha_i) \right) = \Delta \left( \frac{1}{t} \sum_{i=1}^t \beta_i \right) \quad (4)$$

**Definition 6.** Let  $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \dots, (r_t, \alpha_t)\}$  be a set of 2-tuple values and  $W = \{w_1, w_2, \dots, w_t\}$  be their associated weights, the 2-tuple weighted average  $\bar{x}^{WA}$  is calculated as follows:

$$\bar{x}^{WA} = \Delta \left( \frac{\sum_{i=1}^t \Delta^{-1}(r_i, \alpha_i) \cdot w_i}{\sum_{i=1}^t w_i} \right) = \Delta \left( \frac{\sum_{i=1}^t \beta_i \cdot w_i}{\sum_{i=1}^t w_i} \right) \quad (5)$$

**Remark 2.** If all the weights are equal, the weighted average is equivalent to the arithmetic mean.

**Example 2.** Let  $x = \{(A, 0), (VG, 0), (A, 0), (E, 0)\}$  be a set of 2-tuple values representing the ratings of a hotel's location, service, cleanliness, and rooms. The 2-tuple arithmetic mean for this hotel is calculated as:  $\Delta \left( \frac{1}{4} \cdot (\Delta^{-1}(A, 0) + \Delta^{-1}(VG, 0) + \Delta^{-1}(A, 0) + \Delta^{-1}(E, 0)) \right) = \Delta \left( \frac{1}{4} \cdot (2 + 3 + 2 + 4) \right) = \Delta(2.75) = (s_{round(2.75)}, 2.75 - round(2.75)) = (s_3, -0.25) = (VG, -0.25)$ . If the negation operator is applied to this 2-tuple value, it is computed as  $neg((s_3, -0.25)) = \Delta(4 - \Delta^{-1}(s_3, -0.25)) = \Delta(4 - (3 - 0.25)) = \Delta(1.25) = (s_1, +0.25) = (P, +0.25)$ .

Suppose  $W = \{0.3, 0.2, 0.1, 0.4\}$  represents the weights associated with the hotel's location, service, cleanliness, and rooms. The 2-tuple weighted average for this hotel is calculated as:  $\Delta(\Delta^{-1}(A, 0) \cdot 0.3 + \Delta^{-1}(VG, 0) \cdot 0.2 + \Delta^{-1}(A, 0) \cdot 0.1 + \Delta^{-1}(E, 0) \cdot 0.4) = \Delta(2 \cdot 0.3 + 3 \cdot 0.2 + 2 \cdot 0.1 + 4 \cdot 0.4) = \Delta(3) = (s_{round(3)}, 3 - round(3)) = (s_3, 0) = (VG, 0) = VG$ .

## 2.2. Ordered Weighted Averaging (OWA) Aggregation Operator

The aggregation process plays a crucial role in various applications involving information processing, such as decision-making, information retrieval, and pattern recognition [63]. Introduced by Yager [7], the OWA aggregation operator addresses the problem of aggregating multicriteria to form an overall decision function [64]. The OWA aggregation operator is defined as follows:

**Definition 7.** [7] An OWA aggregation operator of dimension  $n$  is a mapping of  $OWA: R^n \rightarrow R$ , with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{j=1}^n w_j = 1$  and  $w_j \in [0, 1]$ , then:

$$OWA(a_1, a_2, \dots, a_n) = \sum_{j=1}^n w_j b_j \quad (6)$$

where  $a_1, a_2, \dots, a_n$  are the input values;  $b_j$  is the  $j$ th largest element of the input values; and  $w_j$  represents the ordered weights.

**Remark 3.** In MCDM, weights are typically assigned to each criterion to quantify their relative importance or influence on the decision-making process. Although the OWA aggregation operator also incorporates weights in its calculation, these weights are associated with the criterion values rather than directly with the criteria themselves. Unlike importance weights, ordered weights are assigned to the criterion value at the  $j$ th position in decreasing order, regardless of which criterion map the value belongs to [9, 65, 66]. Therefore, the OWA aggregation operator is also called the descending OWA (DOWA) aggregation operator.

Regarding the determination of the ordered weights, they are often calculated based on linguistic quantifiers (e.g., *At least one*, *Few*, *Half*, *Most*, *All*, etc.), as these quantifiers can translate natural language statements into mathematical expressions [22, 44, 67]. By using distinct linguistic quantifiers, the OWA aggregation operator can generate a wide range of decision strategies, reflecting the attitudinal character of decision-makers in information aggregation [7, 24, 26, 41, 68-71]. The OWA aggregation operator is suitable for modeling decision-makers' attitudes [43]. Two main categories of linguistic quantifiers exist, absolute and relative quantifiers [10, 67]. Absolute quantifiers represent imprecise natural quantities and are modeled as fuzzy subsets of the naturals [72]. Examples of absolute quantifiers include "about 10" or "more than 100". Relative quantifiers,

on the other hand, represent imprecise percentages and are modeled as fuzzy subsets of the rational interval  $[0, 1]$  [72]. Examples of relative quantifiers include "*Some*", "*Half*", "*Most*", and "*Almost all*" [24]. The relative quantifiers were further categorized by Yager [10, 73] into three classes: Regular Increasing Monotone (RIM) quantifiers, Regular Decreasing Monotone (RDM) quantifiers, and Regular UniModal (RUM) quantifiers.

Given that both RDM and RUM quantifiers can be generated from RIM quantifiers [74], this thesis primarily centers on the study of RIM quantifiers. Numerous approaches in the literature have described the process of computing weights using RIM quantifiers. Definitions 8 and 9 illustrate the method employed in this thesis to determine the ordered weights, as proposed by Yager [10]. Further methods for calculating weights based on RIM quantifiers can be found in [74-77].

**Definition 8.** [10] RIM quantifiers are used to generate a parameterized subset in the unit interval as follows:

$$Q(p) = p^\lambda, \lambda > 0 \quad (7)$$

where  $Q$  is a linguistic quantifier, expressed as a fuzzy subset over the unit interval  $[0, 1]$ ; for each  $p$  in the unit interval, the grade of membership  $Q(p)$  indicates the compatibility of  $p$  with the concept denoted by  $Q$ . Table 1 presents the parameter  $\lambda$  proposed by Boroushaki and Malczewski [23, 24] for each linguistic quantifier. Furthermore, the attitude and risk level of decision-makers represented by each quantifier are included in Table 1.

**Table 1.** Properties of linguistic quantifiers, adapted from [23, 24].

Linguistic quantifier	$\lambda$	Attitude	Risk
<i>At least one</i>	0.0001 ( $\lambda \rightarrow 0$ )	Extremely optimistic	High risk-taking
<i>Few</i>	0.1	Moderately optimistic	Moderate risk-taking
<i>Some</i>	0.5	Slightly optimistic	Low risk-taking
<i>Half</i>	1	Neutral	Neutral
<i>Many</i>	2	Slightly pessimistic	Low risk-averse
<i>Most</i>	10	Moderately pessimistic	Moderate risk-averse
<i>All</i>	1000 ( $\lambda \rightarrow \infty$ )	Extremely pessimistic	High risk-averse

**Definition 9.** [10] The ordered weights  $w_j$  ( $w_j \in [0, 1]$ ) are calculated as follows:

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right) = \left(\frac{j}{n}\right)^\lambda - \left(\frac{j-1}{n}\right)^\lambda, \lambda > 0, j = 1, \dots, n \quad (8)$$

where  $\lambda$  is the value associated with each linguistic quantifier  $Q$ . The larger  $\lambda$  is, the less optimistic the decision-makers' attitude is.  $\lambda = 1$  represents a neutral attitude (neither optimistic nor pessimistic).

Two dimensions, namely *orness* and *tradeoff*, are linked with the ordered weights, forming the decision strategy space in the OWA aggregation operator [22, 23, 78]. The equations used to calculate *orness* [7] and *tradeoff* [78] are as follows:

$$orness = \frac{1}{n-1} \sum_{j=1}^n (n-j) \cdot w_j \quad (9)$$

$$tradeoff = 1 - \sqrt{\frac{n \sum_{j=1}^n \left(w_j - \frac{1}{n}\right)^2}{n-1}} \quad (10)$$

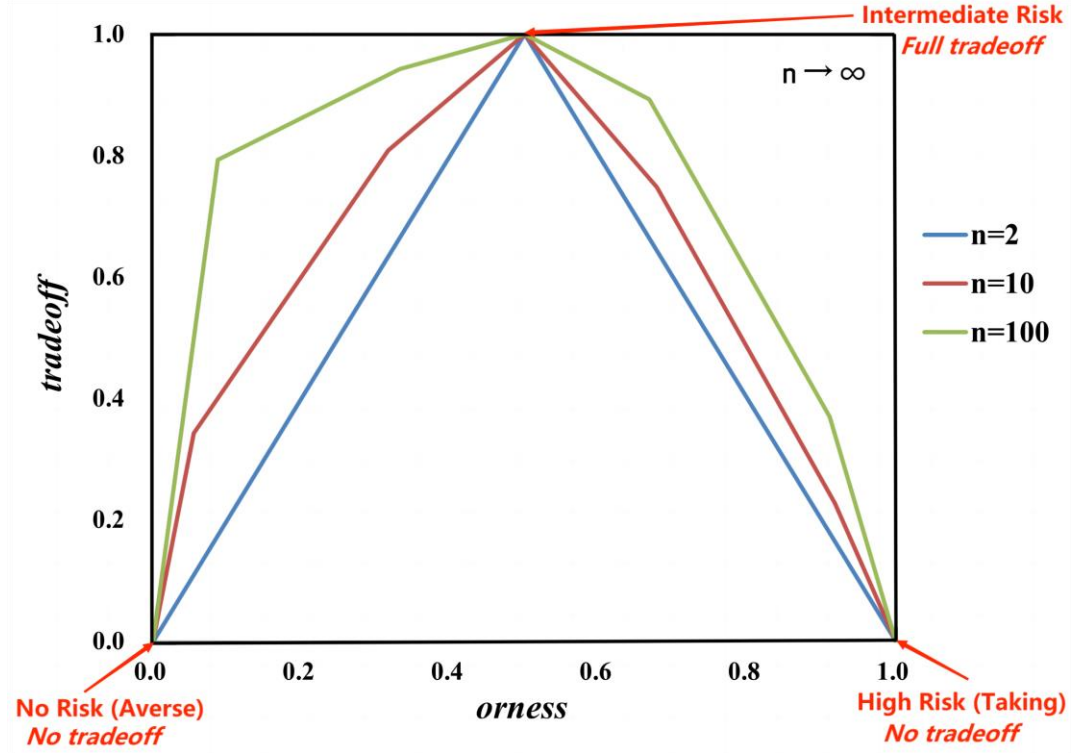
where  $0 \leq orness \leq 1$  and  $0 \leq tradeoff \leq 1$ .

The *orness* measures a decision-maker's level of optimism, reflecting their attitude towards risk. Risk-averse decision-makers are more pessimistic, assigning greater weight to negative results. The *orness* value associated with this pessimism is less than 0.5, with an *orness* of 0 indicating the allocation of total weight to the minimal value, signifying minimal risk. Conversely, risk-taking decision-makers are more optimistic, assigning higher weight to positive results. The *orness* value associated with this optimism is between 0.5 and 1, with an *orness* of 1 indicating the allocation of total weight to the maximum value, signifying maximum risk. A neutral stance towards risk is attributed to a decision-maker when the *orness* equals 0.5.

The *tradeoff* measures the allowable degree of compensation among criteria values. It increases with a more even distribution of weights; a *tradeoff* value of 1 indicates that all criteria values hold equal weight, while a value of 0 signifies an uneven distribution of weights among them (i.e., no compensation between bad and good values) [20, 65]. A high *tradeoff* value implies that low values on one criterion map can be compensated by high values on other criteria [79].

The aforementioned illustrates that the OWA aggregation operator can not only model

decision-makers' attitudes but also facilitate the adjustment of the degree of compensation between criteria according to decision-makers' attitudes. Figure 6 shows the decision strategy space in the OWA aggregation operator. For  $n = 2$ , the decision space has a triangular form. As the number of criteria increases from  $n = 2$  to a very large value ( $n \rightarrow \infty$ ), the shape of the decision strategy space gradually changes to a rectangular form [22, 23].



**Figure 6.** Decision-strategy space defined by *orness* and *tradeoff*, adapted from [23].

The 2LOWA aggregation operator is an extension of the OWA aggregation operator that can deal with 2-tuple values [5]. The definition is as follows:

**Definition 10.** A 2LOWA aggregation operator of dimension  $n$  is a mapping of 2LOWA:  $R^n \rightarrow R$  with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{j=1}^n w_j = 1$  and  $w_j \in [0, 1]$ , then:

$$2LOWA((s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_n, \alpha_n)) = \Delta \left( \sum_{j=1}^n w_j b_j \right) \quad (11)$$

where  $\{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_n, \alpha_n)\}$  is the set of 2-tuple values;  $w_j$  represents the ordered weights;  $b_j = \Delta^{-1}(s_j, \alpha_j)$ ,  $\Delta^{-1}$  has been defined in Equation (2).

**Example 3.** Following the set  $x$  presented in Example 2, apply the function  $\Delta^{-1}$  to convert the 2-tuple values into their numerical values, then sort these numerical values in descending order as  $\{4, 3, 2, 2\}$ . Using Equation (8), the ordered weights for quantifier *At least one* ( $\lambda = 0.0001$ , and  $n = 4$ ) are  $\{0.9999, 0.0001, 0, 0\}$ . Based on Equation (11), the 2-tuple value of this hotel when using the quantifier *At least one* can be calculated as:  $\Delta(4 \cdot 0.9999 + 3 \cdot 0.0001 + 0) = \Delta(3.9999) = (E, -0.0001)$ .

Similarly, the 2-tuple value of this hotel using other linguistic quantifiers is calculated as follows:

- Based on the quantifier *Few*,  $\Delta(4 \cdot 0.8706 + 3 \cdot 0.0625 + 2 \cdot 0.0385 + 2 \cdot 0.0284) = \Delta(3.8037) = (E, -0.1963)$ .
- Based on the quantifier *Some*,  $\Delta(4 \cdot 0.5 + 3 \cdot 0.2071 + 2 \cdot 0.1589 + 2 \cdot 0.134) = \Delta(3.2071) = (VG, +0.2071)$ .
- Based on the quantifier *Half*,  $\Delta(4 \cdot 0.25 + 3 \cdot 0.25 + 2 \cdot 0.25 + 2 \cdot 0.25) = \Delta(2.75) = (VG, -0.25)$ .
- Based on the quantifier *Many*,  $\Delta(4 \cdot 0.0625 + 3 \cdot 0.1875 + 2 \cdot 0.3125 + 2 \cdot 0.4375) = \Delta(2.3125) = (A, +0.3125)$ .
- Based on the quantifier *Most*,  $\Delta(4 \cdot 0 + 3 \cdot 0.001 + 2 \cdot 0.0553 + 2 \cdot 0.9437) = \Delta(2.001) = (A, +0.001)$ .
- Based on the quantifier *All*,  $\Delta(4 \cdot 0 + 3 \cdot 0 + 2 \cdot 0 + 2 \cdot 1) = \Delta(2) = (A, 0) = A$ .

The 2-tuple value calculated by quantifier *Half* coincides with that calculated by the arithmetic mean in Example 2, which is  $(VG, -0.25)$ . This suggests that when decision-makers exhibit an intermediate level of risk (neither optimistic nor pessimistic), using the quantifier *Half* to aggregate the evaluations of various hotel criteria is tantamount to employing the arithmetic mean.

## 2.3. Multi-Criteria Decision-Making (MCDM) Methods

MCDM, also known as multiple criteria decision analysis (MCDA), is one of the main types of decision-making problems and involves the consideration of multiple criteria to determine the best alternative. MCDM is a core aspect of decision theory and a crucial branch of Operations Research, offering systematic tools and techniques for evaluating and selecting alternatives [80-82].

The MCDM framework consists of four elements [83]: alternatives (choices or options), criteria (attributes or decision factors), weights for criteria, and performance ratings of alternatives concerning the criteria. An MCDM problem typically involves a finite set of  $m$  alternatives, denoted as  $A = \{A_q | q = 1, 2, \dots, m\}$ , which are evaluated based on  $n$  criteria represented as  $C = \{C_j | j = 1, 2, \dots, n\}$ . Each criterion is assigned a weight (denoted as  $W = \{w_j | j = 1, 2, \dots, n\}$ , and  $\sum_{j=1}^n w_j = 1$ ) to reflect its relative importance. The scores for the alternatives under different criteria are denoted as  $X = \{x_{qj} | q = 1, 2, \dots, m; j = 1, 2, \dots, n\}$ . Figure 7 illustrates the steps commonly involved in the MCDM process.

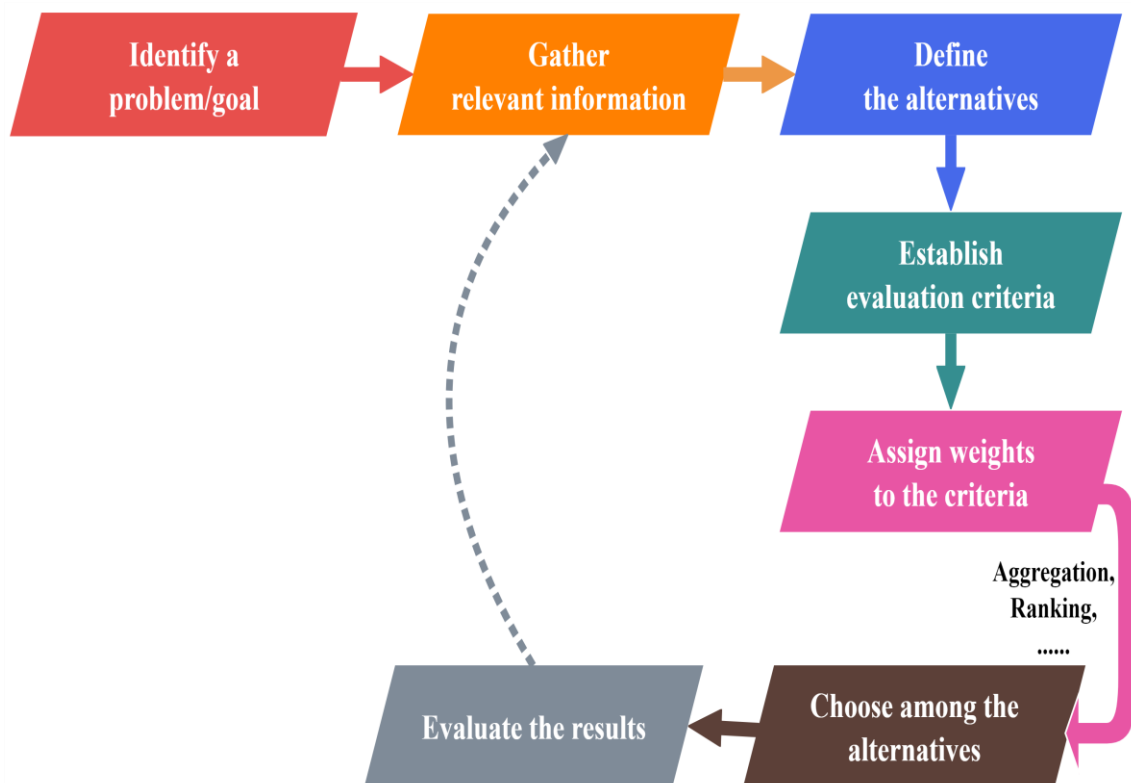


Figure 7. MCDM process, adapted from [84, 85].

MCDM methods find applications in addressing problems encountered in daily life. A variety of MCDM methods exist in the literature, each with its characteristics, and they can be classified based on different features [86]. For instance, MCDM methods can be categorized based on whether they are compensatory or non-compensatory. In compensatory methods, poor performance in some criteria can be compensated by high performance in the other criteria and may not be reflected in the aggregated performance of an option [87-89]. The compensatory aggregation-based MCDM methods include approaches such as the AHP [90, 91], ANP [92, 93], Best-Worst Method (BWM) [94], Simple Additive Weighting (SAW) [95, 96], Simple Multi-Attribute Rating Technique (SMART) [97], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [98], Weighted Product Model (WPM) [99, 100], among others. In non-compensatory aggregation-based MCDM methods, such as ELimination and Choice Translating REality (ELECTRE) [101] and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) [102, 103], poor performance in some criteria cannot be compensated by high performance in others and will be reflected in the aggregated performance of an option.

Determining criteria weights is a critical stage in MCDM process [83, 104, 105]. In this context, MCDM methods have also been categorized in the literature into subjective, objective, and mixed subjective-objective methods [88, 106-109]. Subjective methods determine criteria weights through the knowledge or opinions of decision-makers (e.g., the advice of experts, business criteria of managers, etc.), while objective methods use mathematical techniques and statistical analysis to assess data within the decision matrix for weight determination. Mixed subjective-objective methods, also known as hybrid MCDM methods, combine decision-makers' expertise and preferences with objective data analysis to mitigate potential bias from a single method and enhance the accuracy of decision outcomes. This thesis has explored one widely recognized subjective MCDM method, the AHP method, along with two prominent objective MCDM methods: the CRITIC method and the Entropy method. Some hybrid MCDM methods have also been discussed.

Moreover, the TOPSIS method has been explored in this thesis for its capability to account for both subjective and objective criteria [110]. In the literature, the weighting methods employed to determine weights for the TOPSIS method include the Entropy method [111, 112], the CRITIC

method [113, 114], and the AHP method [115-117]. Therefore, sometimes the TOPSIS method is considered a hybrid MCDM when combined with other MCDM methods to determine the criteria weights.

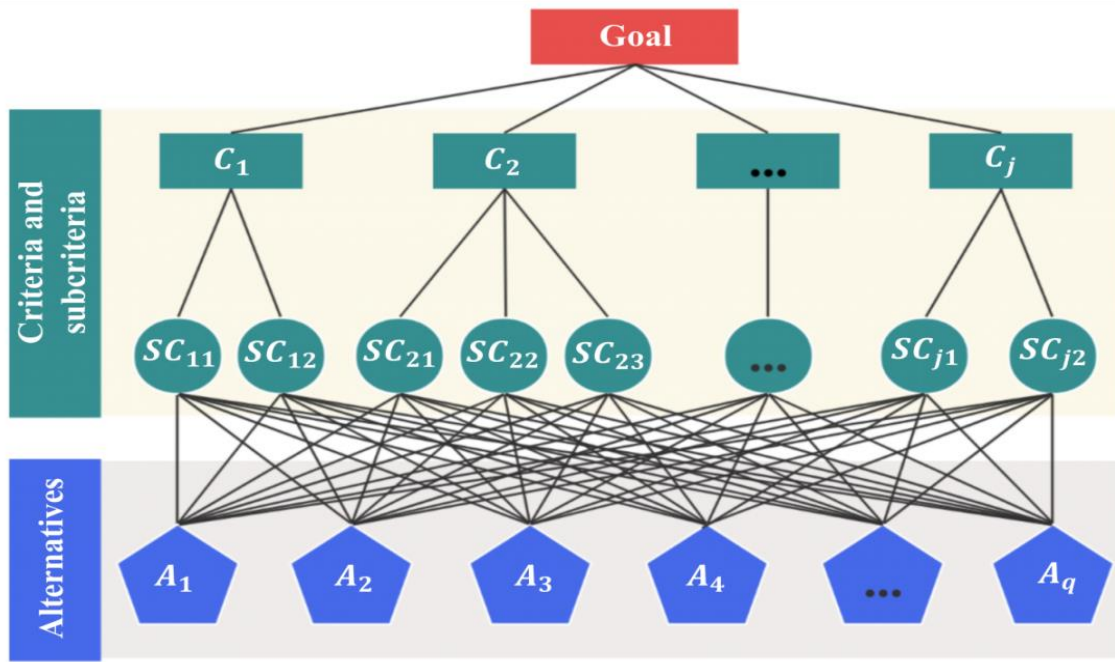
### 2.3.1. Analytical Hierarchy Process (AHP) Method

The AHP method, introduced by Saaty [90, 91], is among the most popular subjective methods and is also categorized as a pairwise comparison-based MCDM method. This method uses hierarchical structures and pairwise comparisons to address complex multi-criteria problems. The pairwise comparisons are made by experts or decision-makers to determine priorities among criteria and alternatives. Table 2 shows Saaty's 9-point scale, commonly used for pairwise comparisons in the AHP method.

**Table 2.** Saaty's 9-point scale [90].

Intensity of importance	Definition	Explanation
1	Equal importance	Judgment favors both criteria equally.
3	Moderate importance	Judgment slightly favors one criterion.
5	Strong importance	Judgment strongly favors one criterion.
7	Very strong importance	One criterion is favored strongly over another.
9	Extreme importance	There is evidence affirming that one criterion is favored over another.
2, 4, 6, 8	Immediate values between above scale values	Absolute judgment cannot be given, and a compromise is needed.
Reciprocals of the above nonzero numbers	Reciprocals for inverse comparison	If criterion $v$ is assigned one of the above nonzero numbers when compared to criterion $j$ , then criterion $j$ has the reciprocal value when compared to $v$ .

The AHP hierarchy starts by identifying a goal (the top level), followed by criteria and subcriteria (if applicable), and concludes with the alternatives (the lowest level). Figure 8 shows this hierarchy. The weights for each criterion and sub-criterion are calculated using the pairwise comparison matrix, allowing decision-makers to systematically evaluate different criteria and subcriteria. This is effective in transforming subjective judgments into weights [118].



**Figure 8.** AHP hierarchy.

The calculation process of the AHP method is detailed below:

- ① Create a hierarchical structure for the MCDM problem, as seen in Figure 8 (the level of subcriteria could be eliminated if it does not exist).
- ② Build a judgmental matrix using pairwise comparisons to represent experts' subjective preferences of  $n$  criteria and  $m$  alternatives. The pairwise comparison matrix can be represented as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \quad (12)$$

where  $p_{jv}$  represents the importance of  $j$ th criterion over  $v$ th criterion evaluated by the experts,  $j = 1, 2, \dots, n$ , and  $v = 1, 2, \dots, n$ ,  $n$  is the number of criteria; a criterion has equal relevance when compared to itself, therefore the diagonal values in this matrix are always one (i.e.,  $p_{jj} = 1$ ); the lower half of this matrix is the inverse of the higher half (i.e.,  $p_{vj} = \frac{1}{p_{jv}}$ , with  $p_{jv} > 0$ ). Therefore, the number of comparisons is determined as  $\frac{n(n-1)}{2}$ .

- ③ Calculate the AHP weight for each criterion using Equation (13):

$$w_j^{AHP} = \frac{(\prod_{v=1}^n p_{jv})^{\frac{1}{n}}}{\sum_{j=1}^n (\prod_{v=1}^n p_{jv})^{\frac{1}{n}}} \quad (13)$$

where  $j = 1, 2, \dots, n$ , and  $v = 1, 2, \dots, n$ .

- ④ Verify the consistency of the pairwise comparisons by calculating the Consistency Ratio (CR), as the judgments provided are subjective and could be inconsistent. The CR is calculated by dividing the Consistency Index (CI) by the Random Index (RI), where  $CI = \frac{\lambda_{max} - n}{n-1}$  with  $\lambda_{max}$  being the maximum eigenvalue of the pairwise comparison matrix and  $n$  being the number of criteria; RI is the consistency of a randomly generated pairwise comparison matrix. If the CR is 0.1 or less, it indicates that the pairwise comparisons are consistent, allowing the calculated weights to be used in the computation of the overall ratings for each alternative. If the CR exceeds 0.1, it shows that the pairwise comparisons are inconsistent in judgment, necessitating repeating the second and the third steps for one or more of the inconsistent pairwise comparisons until the  $CR \leq 0.1$ .

As shown in Figure 7, after acquiring the criteria weights, aggregating scores for alternatives across different criteria is necessary to compute overall ratings for each alternative. This allows the ranking of alternatives and aids in selecting the "best" alternative. The overall rating for each alternative is calculated using Equation (14):

$$Y_q = \sum_{j=1}^n (w_j^{AHP} \cdot x_{qj}) \quad (14)$$

where  $q = 1, 2, \dots, m$ ,  $m$  is the number of alternatives;  $x_{qj}$  represents the score of the  $q$ th alternative under the  $j$ th criterion,  $j = 1, 2, \dots, n$ . Note that  $x_{qj}$  should be normalized if the criteria are measured on different scales.

## 2.3.2. CRiteria Importance Through Intercriteria Correlation (CRITIC)

### Method

The CRITIC method, introduced by Diakoulaki et al. [119], calculates criterion weights without human intervention. It is a technique used to determine objective weights, which considers the contrast intensity and the conflict of the structure of the decision-making problem [119]. The contrast intensity is calculated using the standard deviations of each criterion or subcriterion (if applicable), and the conflict degree is measured through correlation analysis.

The calculation process of the CRITIC method is detailed below:

- ① Build the decision matrix with  $n$  as the number of criteria and  $m$  as the number of samples or alternatives under consideration. The decision matrix can be represented as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (15)$$

- ② Normalize the values in the decision matrix, as criteria measured at different scales do not equally contribute to the analysis, leading to inaccuracies in weight calculations. Note that normalization only scales the values and does not change the shape or pattern of the data distribution, nor does it necessarily center the data around zero or standardize it to have a standard deviation of one. The normalized decision matrix can be represented as follows:

$$X^* = \begin{bmatrix} x_{11}^* & x_{12}^* & \cdots & x_{1n}^* \\ x_{21}^* & x_{22}^* & \cdots & x_{2n}^* \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^* & x_{m2}^* & \cdots & x_{mn}^* \end{bmatrix} \quad (16)$$

where  $x_{qj}^*$  is the normalized value of the  $q$ th sample/alternative under the  $j$ th criterion,  $x_{qj}^* \in [0,1]$ ,  $q = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ ;  $x_{qj}^* = \frac{x_{qj} - \min(x_j)}{\max(x_j) - \min(x_j)}$  if the  $j$ th criterion is a positive indicator (i.e., a larger value is better);  $x_{qj}^* = \frac{\max(x_j) - x_{qj}}{\max(x_j) - \min(x_j)}$  if the  $j$ th criterion is a negative indicator (i.e., a smaller value is better);  $x_{qj}$  is the original value;  $\min(x_j)$  is the minimum value in the  $j$ th criterion;  $\max(x_j)$  is the maximum value in the  $j$ th criterion.

③ Based on the normalized decision matrix, determine the standard deviation of each criterion and the correlation matrix (i.e.,  $n \times n$  matrix) between the criteria. The calculation method for correlation can be chosen based on the specific case, commonly using either Pearson correlation or Spearman rank correlation, with the inclusion of distance correlation as another viable option [108, 118, 120, 121].

④ Compute the quantity of information contained in the  $j$ th criterion using Equation (17):

$$C_j = S_j \cdot R_j \quad (17)$$

where  $S_j$  is the standard deviation of the  $j$ th criterion;  $R_j$  is the conflict degree of the  $j$ th criterion. The conflict degree is calculated as  $R_j = \sum_{v=1}^n (1 - r_{jv})$  [119], and in some cases, it is also expressed as  $R_j = \sum_{v=1}^n (1 - |r_{jv}|)$  [108], the coefficient  $r_{jv}$  denotes the correlation between the  $j$ th criterion and the  $v$ th criterion.

⑤ Calculate the CRITIC weight for each criterion using Equation (18):

$$w_j^{CRITIC} = \frac{C_j}{\sum_{j=1}^n C_j} \quad (18)$$

where  $C_j$  represents the quantity of information contained in the  $j$ th criterion. The larger  $C_j$  is, the more weight is assigned to the  $j$ th criterion.

The computation of the overall rating for each alternative follows Equation (14), with the adjustment of changing the weight  $w_j^{AHP}$  to  $w_j^{CRITIC}$ . It is important to note that  $x_{qj}$  should be normalized when criteria are measured on different scales, denoted as  $x_{qj}^*$  in this case.

### 2.3.3. Entropy Method

The Entropy method, also known as the Entropy weighting method, introduced by Shannon [122], is a technique used in decision-making to determine criteria weights based on uncertain information using probability theory. This method provides a way to objectively assign weights based on the information content of different criteria or subcriteria (if applicable). The Entropy method is a widely used information-weighting method, as it mitigates the influence of human subjective judgment by excluding consideration of the decision-maker's preferences [123, 124].

In the Entropy method, weights are assigned to each criterion based on its degree of

diversification: the higher the degree of diversification, indicating more extractable information, the greater the weight assigned to the criterion, and vice versa. The calculation process of the Entropy method is detailed below:

- ① Build the decision matrix with  $n$  as the number of criteria and  $m$  as the number of samples or alternatives under consideration. The decision matrix is represented in the same way as Equation (15).
- ② Normalize the values in the decision matrix, as criteria measured at different scales do not equally contribute to the analysis, leading to inaccuracies in weight calculations. The normalized decision matrix is represented in the same way as Equation (16), and the normalization method remains consistent (i.e.,  $x_{qj}^* = \frac{x_{qj} - \min(x_{.j})}{\max(x_{.j}) - \min(x_{.j})}$  if the  $j$ th criterion is a positive indicator;  $x_{qj}^* = \frac{\max(x_{.j}) - x_{qj}}{\max(x_{.j}) - \min(x_{.j})}$  if the  $j$ th criterion is a negative indicator).

- ③ Compute the probability value of the  $q$ th sample under the  $j$ th criterion as follows:

$$p_{qj} = \frac{x_{qj}^*}{\sum_{q=1}^m x_{qj}^*} \quad (19)$$

where  $x_{qj}^*$  is the normalized value of the  $q$ th sample/alternative under the  $j$ th criterion,  $x_{qj}^* \in [0,1]$ ,  $q = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ .

- ④ Compute the Entropy value and the degree of diversification for each criterion. The Entropy value  $E_j$  for the  $j$ th criterion is calculated using Equation (20):

$$E_j = -K \sum_{q=1}^m p_{qj} \ln p_{qj} \quad (20)$$

where  $K = \frac{1}{\ln m}$  is a constant that ensures  $E_j \in [0,1]$ ; The higher the value of  $E_j$ , the lower the information contained in the  $j$ th criterion, resulting in a smaller relative weight, and vice versa.

The degree of diversification  $D_j$  for the  $j$ th criterion is calculated using Equation (21):

$$D_j = 1 - E_j \quad (21)$$

- ⑤ Calculate the Entropy weight for each criterion using Equation (22):

$$w_j^{Entropy} = \frac{D_j}{\sum_{j=1}^n D_j} \quad (22)$$

where  $D_j$  is the complementary of Entropy value. The larger  $D_j$  is, the more weight assigned to the  $j$ th criterion.

The computation of the overall rating for each alternative follows Equation (14), with the adjustment of changing the weight  $w_j^{AHP}$  to  $w_j^{Entropy}$ . It is important to note that  $x_{qj}$  should be normalized when criteria are measured on different scales, denoted as  $x_{qj}^*$  in this case.

### 2.3.4. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Method

The TOPSIS method, introduced by Hwang and Yoon [98], is a distance-based MCDM method that determines the "best" alternative by calculating the distances from the positive and negative ideal solutions. The "best" alternative is the one with the shortest distance from the positive ideal solution and the greatest distance from the negative ideal one [98]. The TOPSIS method has a relatively easy calculation process and is well-suited for cases with numerous criteria/subcriteria (if applicable) and alternatives [125].

The calculation process of the TOPSIS method is detailed below:

- ① Build the decision matrix with  $n$  as the number of criteria and  $m$  as the number of samples or alternatives under consideration. The decision matrix is represented in the same way as Equation (15).
- ② Normalize the values in the decision matrix, as criteria measured at different scales do not equally contribute to the analysis, leading to inaccuracies in weight calculations. The normalized decision matrix is represented in the same way as Equation (16), but the normalization method differs. The normalized value of the  $q$ th sample/alternative under the  $j$ th criterion is calculated as  $x_{qj}^* = \frac{x_{qj}}{\sqrt{\sum_{q=1}^m x_{qj}^2}}$ ,  $q = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ .

- ③ Construct the weighted normalized decision matrix, represented as follows:

$$X^w = \begin{bmatrix} x_{11}^w & x_{12}^w & \cdots & x_{1n}^w \\ x_{21}^w & x_{22}^w & \cdots & x_{2n}^w \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^w & x_{m2}^w & \cdots & x_{mn}^w \end{bmatrix} \quad (23)$$

where  $x_{qj}^w$  is the weighted normalized value for the  $j$ th criterion of the  $q$ th alternative,  $x_{qj}^w = w_j \cdot x_{qj}^*$ ,  $q = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ ;  $w_j$  represents the weight of the  $j$ th criterion. The weights of criteria can be assigned directly by decision-makers or determined using methods like AHP, CRITIC, or Entropy.

- ④ Determine the positive ideal and negative ideal solutions. The positive ideal solution is calculated as  $A^+ = \{(max_q x_{qj}^w | j \in J^+), (min_q x_{qj}^w | j \in J^-) | q = 1, 2, \dots, m\} = \{x_1^+, x_2^+, \dots, x_n^+\}$ , where  $J^+$  is associated with beneficial criteria ( $j = 1, 2, \dots, n$ ),  $J^-$  is associated with non-beneficial criteria ( $j = 1, 2, \dots, n$ ). The negative ideal solution is calculated as  $A^- = \{(min_q x_{qj}^w | j \in J^+), (max_q x_{qj}^w | j \in J^-) | q = 1, 2, \dots, m\} = \{x_1^-, x_2^-, \dots, x_n^-\}$ .

- ⑤ Calculate the distances between the  $q$ th alternative and the positive ideal and negative ideal solutions. The distance of the  $q$ th alternative from the positive ideal solution is calculated as  $D_q^+ = \sqrt{\sum_{j=1}^n (x_{qj}^w - x_j^+)^2}$ . The distance of the  $q$ th alternative from the negative ideal solution is calculated as  $D_q^- = \sqrt{\sum_{j=1}^n (x_{qj}^w - x_j^-)^2}$ .

- ⑥ Compute the relative closeness of each alternative to the ideal solution using Equation (24):

$$C_q = \frac{D_q^-}{D_q^+ + D_q^-} \quad (24)$$

where  $0 \leq C_q \leq 1$  and  $q = 1, 2, \dots, m$ .  $C_q = 1$  if and only the alternative solution has the best solution (i.e.,  $D_q^+ = 0, D_q^- = 1$ );  $C_q = 0$  if and only the alternative solution has the worst solution (i.e.,  $D_q^+ = 1, D_q^- = 0$ ).

- ⑦ Rank the alternatives based on the  $C_q$  value. The higher the value of  $C_q$ , the better the rank. The "best" alternative is the one with the largest value of  $C_q$ .

### 2.3.5. Hybrid MCDM Methods

As mentioned, objective methods are based on the statistical evaluation of data provided in a decision matrix, while subjective weighting methods depend on expert opinions. At times, the weights derived from objective methods may conflict with the subjective preferences of decision-makers, as these methods do not consider the expertise and experience of decision-makers. The main concern regarding subjective methods is the potential uncertainty in expert judgment [126]. Errors in determining weights may arise when decision-makers lack experience or information, potentially leading to incorrect decisions. That is, neither of these approaches is flawless [106]. Each of these methods possesses its advantages and disadvantages [126]. In such cases, it is necessary to consider the combination of objective and subjective methods to generate integrated weights for criteria.

In the literature, scholars have developed various combinations of objective and subjective methods. Wu et al. [127] combined the weights calculated by the BWM and CRITIC methods to determine the criteria weights for selecting a site for a photovoltaic hydrogen production project. Youssef [128] incorporated the TOPSIS and BWM methods to rank Cloud Service Providers based on evaluation criteria that characterize their services. The TOPSIS method has also been combined by some authors with the Entropy method [111, 112], the CRITIC method [113, 114], and the AHP method [115-117]. In some studies, the combination of the AHP and Entropy methods has been used [129, 130].

Furthermore, researchers have explored some combinations among the objective methods, like the integration of the Entropy and CRITIC methods [129, 132]. The combinations within subjective methods have also been developed, exemplified by the integration of the AHP and SMART methods [133, 134]. In summary, the combination of various MCDM methods has seen a consistent increase in the literature, resulting in the creation of numerous hybrid MCDM methods. The following sections present the hybrid MCDM methods that have been used and developed within this thesis.

### 2.3.5.1. The Hybrid CRITIC-AHP Method

The objective weights derived from the CRITIC method take into account the quantity of information contained in each criterion. The CRITIC method does not consider expert opinions in weight determination. This can be both advantageous and disadvantageous. It is advantageous when decision-makers' opinions are biased or difficult to reach an agreement, and it speeds up the process of weight determination. However, it can also be a disadvantage in situations where human judgment or contextual knowledge is crucial for decision-making. The weights assigned by the CRITIC method might be inconsistent with decision-makers' opinions or real-world circumstances. This could lead to inaccuracies and concerns when assessing the importance of each criterion in practical applications.

Therefore, to guarantee that weights are determined with high reliability, the hybrid CRITIC-AHP method has been developed, which combines the objectivity of the CRITIC method with the subjectivity of the AHP method [135]. Inspired by the combinative weighting method proposed by Jahan et al. [106], the hybrid CRITIC-AHP method calculates the weight for each criterion as follows:

$$w_j^{CRITIC-AHP} = \frac{(w_j^{CRITIC} \cdot w_j^{AHP})^{\frac{1}{2}}}{\sum_{j=1}^n (w_j^{CRITIC} \cdot w_j^{AHP})^{\frac{1}{2}}} \quad (25)$$

where  $w_j^{CRITIC}$  represents the weight generated by the CRITIC method (see Equation (18)), and  $w_j^{AHP}$  represents the weight obtained by the AHP method (see Equation (13)),  $j = 1, 2, \dots, n$ .

### 2.3.5.2. The Hybrid CRITIC-Entropy Method

When comparing the CRITIC method with other MCDM methods that generate the objective weights for criteria, such as the Entropy method, it is important to consider the limitations and characteristics of each method. The CRITIC method uses standard deviation to gauge the contrast intensity of each criterion and incorporates the correlation coefficient to measure conflicting relationships between criteria. However, if the standard deviation values are very close, it becomes challenging to distinguish the importance of the criteria. On the other hand, the Entropy method captures the amount of information provided by a criterion through a measure of uncertainty.

However, it ignores the horizontal influence between criteria, such as specific interdependencies or conflicting relationships between criteria.

Therefore, to ensure that the weights acquired accurately reflect the data structure and the interdependency between criteria, combining the weights from the Entropy method with those computed by the CRITIC method is necessary [136]. Inspired by the combinative weighting method proposed by Jahan et al. [106], the hybrid CRITIC-Entropy method calculates the weight for each criterion as follows:

$$w_j^{CRITIC-Entropy} = \frac{\left(w_j^{CRITIC} \cdot w_j^{Entropy}\right)^{\frac{1}{2}}}{\sum_{j=1}^n \left(w_j^{CRITIC} \cdot w_j^{Entropy}\right)^{\frac{1}{2}}} \quad (26)$$

where  $w_j^{CRITIC}$  represents the weight generated by the CRITIC method (see Equation (18)), and  $w_j^{Entropy}$  represents the weight obtained by the Entropy method (see Equation (22)),  $j = 1, 2, \dots, n$ .

### 2.3.5.3. The Hybrid AHP-Entropy-CRITIC (AEC) Method

The hybrid CRITIC-Entropy method generates criteria weights that consider the data structure and relationships between them. This leads to a more rational assignment of objective weights and helps reduce uneven weight distribution among criteria [136]. However, in the real world, it is also crucial to consider the opinions of decision-makers, as they can ensure the meaningfulness of weight assignments from a practical standpoint. Therefore, combining the hybrid CRITIC-Entropy method with a method that considers subjective judgments is necessary. As the AHP method is renowned for its ability to incorporate subjective judgments into decision-making processes effectively, it has been included in the hybrid framework.

Incorporating the AHP method into the hybrid CRITIC-Entropy method blends the benefits of objective and subjective weighting approaches. Inspired by the combinative weighting method proposed by Jahan et al. [106], the hybrid AEC method calculates the weight for each criterion as follows:

$$w_j^{AEC} = \frac{\left(w_j^{AHP} \cdot w_j^{Entropy} \cdot w_j^{CRITIC}\right)^{\frac{1}{3}}}{\sum_{j=1}^n \left(w_j^{AHP} \cdot w_j^{Entropy} \cdot w_j^{CRITIC}\right)^{\frac{1}{3}}} \quad (27)$$

where  $w_j^{AHP}$  represents the weight obtained by the AHP method (see Equation (13)),  $w_j^{Entropy}$  represents the weight obtained by the Entropy method (see Equation (22)), and  $w_j^{CRITIC}$  represents the weight generated by the CRITIC method (see Equation (18)),  $j = 1, 2, \dots, n$ .

## 2.4. Machine Learning (ML) Models

The concept of ML can be traced back to the checkers program developed by Samuel [137]. It is a subfield of Artificial Intelligence (AI) that enables machines to "learn" from example data or past experience, allowing them to identify patterns and make predictions with minimal human intervention [138]. ML stands as one of the rapidly advancing technologies, having emerged as a crucial interdisciplinary tool and advanced several fields [139]. ML models are increasingly being used in decision-making problems. In MCDM, ML models demonstrate great applicability, aiding in tasks like dimensionality reduction for criteria extraction, determination of decision parameters, network-based modeling for clarifying criteria interaction, and integration of information for MCDM-integrated solutions [140].

Numerous types of ML models exist, each with its strengths and weaknesses and suitable for different kinds of tasks and data. ML is broadly categorized into four main types: supervised, unsupervised, semi-supervised, and reinforcement learning. Supervised learning entails training a model with labeled data, whereas unsupervised learning involves analyzing unlabeled data to discover patterns within the data. Semi-supervised learning combines supervised and unsupervised learning by using both labeled and unlabeled data to train models. Reinforcement learning adopts a trial-and-error approach, wherein a computer agent learns to operate optimally within a dynamic environment by maximizing rewards and minimizing penalties.

This thesis mainly employs unsupervised learning models, including PCA to reduce the dimensionality of datasets, K-Means clustering to identify groups of similar objects within datasets, among others. The following sections present the corresponding concepts.

### 2.4.1. Principal Component Analysis (PCA)

Invented by Pearson [141] and developed by Hotelling [142], PCA is an unsupervised learning model frequently employed to reduce the dimensionality of datasets while preserving as much information as possible. This is achieved by transforming the original variables into a set of new, uncorrelated variables known as principal components (PCs).

Below is a detailed explanation of the calculation process for PCA:

- ① Standardize the data. Assuming that the dataset has  $n$  initial variables and  $m$  samples, the standardized data matrix can be represented as follows:

$$X^z = \begin{bmatrix} x_{11}^z & x_{12}^z & \cdots & x_{1n}^z \\ x_{21}^z & x_{22}^z & \cdots & x_{2n}^z \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^z & x_{m2}^z & \cdots & x_{mn}^z \end{bmatrix} \quad (28)$$

where  $x_{qj}^z$  is the standardized value of the  $q$ th sample under the  $j$ th variable,  $x_{qj}^z = \frac{x_{qj} - \bar{x}_j}{S_j}$ ,  $x_{qj}$  is the original value of the  $q$ th sample under the  $j$ th variable,  $\bar{x}_j$  is the mean of all samples for the  $j$ th variable,  $S_j$  is the standard deviation of all samples for the  $j$ th variable,  $q = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ .

- ② Calculate the eigenvectors and eigenvalues of the covariance (or correlation) matrix. Based on the standardized dataset, the covariance (or correlation) matrix (i.e.,  $n \times n$  matrix) is computed and created. While the eigendecomposition of the covariance or correlation matrix may be more intuitive, Singular Value Decomposition (SVD) can also be used to improve computational efficiency.
- ③ Sort the eigenvectors (i.e., PCs) based on their corresponding eigenvalues in descending order, ensuring that the first principal component accounts for the largest possible variance (i.e., it accounts for as much of the variability in the data as possible). Each later component in turn has the highest variance possible under the constraint of being uncorrelated with preceding components. For example, the second component is entirely uncorrelated with the first component, and accounts for the maximum variance possible that is not accounted for in the first. The third accounts for the maximum variance possible that the first two components not accounted for, and so on.
- ④ Determine the number of PCs to retain (with the rest discarded). This is typically based on the cumulative proportion of total variance explained by those components. Although a higher proportion (around 90%) is often preferred, in some cases, depending on the complexity of the analysis, a proportion of approximately 75-80% may suffice. The proportion of total variance explained by each component is calculated by dividing its eigenvalue by the sum of all eigenvalues. If it is decided to keep  $k$  ( $k \leq n$ ) PCs, then the cumulative proportion of

total variance explained by them is obtained by summing the proportions of total variance explained by each of these  $k$  components.

- ⑤ Form a matrix of eigenvectors (i.e., PCs) that have been chosen to be retained, denoted as follows:

$$V = [\text{eigenvector}_1 \quad \text{eigenvector}_2 \quad \cdots \quad \text{eigenvector}_k]$$

$$= \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1k} \\ e_{21} & e_{22} & \cdots & e_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nk} \end{bmatrix} \quad (29)$$

- ⑥ Generate the transformed data as  $X_{transformed} = X^Z V$ , where  $X^Z$  is the standardized data matrix (an  $m \times n$  matrix),  $V$  is the matrix of eigenvectors (an  $n \times k$  matrix),  $X_{transformed}$  is the resulting transformed data matrix (an  $m \times k$  matrix).

## 2.4.2. K-Means Clustering

Clustering is an unsupervised learning technique that groups a set of objects so that those in the same group (i.e., cluster) are more similar to each other than to those in other groups (i.e., other clusters). It is widely applied across various tasks such as market segmentation, image segmentation, customer segmentation, statistical data analysis, and social network analysis, among others. The main types of clustering include partitioning clustering (also known as centroid-based clustering), hierarchical clustering (also called connectivity-based clustering), density-based clustering, distribution-based clustering, and fuzzy clustering. Some well-known clustering algorithms include K-Means clustering [143], an example of centroid-based clustering; Agglomerative clustering [144, 145], an instance of hierarchical clustering; Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [146], an example of density-based clustering; Gaussian Mixture Model (GMM) [147-149], an instance of distribution-based clustering; and Fuzzy C-Means (FCM) [150, 151], an example of fuzzy clustering.

Among clustering algorithms, K-Means clustering stands out as one of the most popular due to its simplicity, ease of implementation, and scalability on large datasets [152, 153]. Introduced by MacQueen [143], K-Means clustering is used for partitioning data into  $K$  clusters based on the distance to the cluster center or centroid. The steps for K-Means clustering are as follows:

- ① Determine the number of clusters, denoted as  $K$ .
- ② Randomly selecting  $K$  initial centroids.
- ③ Measure the distance between each point and the centroid. Several methods exist for measuring distance, including Euclidean, Manhattan, Minkowski, and Hamming distance metrics. Euclidean Distance is commonly used, and it is calculated as follows:

$$d_{Euclidean}(x, c) = \sqrt{\sum_{j=1}^n (x_{qj} - c_{kj})^2} \quad (30)$$

where  $c_{kj}$  represents the value of the  $j$ th criterion of the  $k$ th cluster centroid,  $k = 1, 2, \dots, K$ ,  $j = 1, 2, \dots, n$ ;  $x_{qj}$  represents the score of the  $q$ th alternative under the  $j$ th criterion,  $q = 1, 2, \dots, m$ . Standardizing  $x_{qj}$  before clustering is a common and recommended practice, as it can lead to obtaining better quality, efficient, and accurate cluster results [154].

- ④ Assign each data point to the closest cluster.
- ⑤ Recalculate the centroids by taking the mean of all data points assigned to each cluster.
- ⑥ Repeat the third to fifth steps until convergence (no further changes) or termination (maximum number of iterations) is reached.

As observed, in K-Means clustering, the first step is determining the number of clusters, typically requiring the use of evaluation metrics to assess the clustering results and decide the "optimal" number of clusters. Different evaluation metrics for clustering may produce different "optimal" cluster numbers. Common approaches to determine this "optimal" number include the Elbow Method [155], the Calinski-Harabasz Index (CHI) [156], the Davies-Bouldin Index (DBI) [157], and the Silhouette Coefficient (SC) [158]. Other evaluation metrics, such as the Dunn Index [150, 159], Rand Index [160], and Reliability Index [161], among others, have also been recommended for use. The choice of evaluation metrics depends on the specific characteristics of the clustering problem and the analysis goals. Sometimes expert knowledge is also necessary to balance the number of clusters with practical needs. Using multiple evaluation metrics is useful for comprehensively assessing the performance of clustering technique results and determining the

"optimal" number of clusters. For instance, when employing metrics such as DBI, SC, CHI, and the Reliability Index simultaneously to assess clustering results across varying cluster numbers, the "optimal" number of clusters is the one that has a DBI closer to zero, an SC closer to one, and higher scores in CHI and the Reliability Index.

### 2.4.3. Weighted K-Means (WKM) Clustering

Despite its simplicity, computational efficiency, ease of implementation, and scalability on large datasets, K-Means clustering assigns all features equal weight, rendering it susceptible to noise and potentially compromising the accuracy of its clustering results. WKM clustering is an extension of K-Means clustering by considering that different features have different weights so that the effect of the noise dimension can be ignored as much as possible when evaluating the distance between samples [162]. It can be applied to improve the clustering scalability and clustering results [162, 163].

Huang et al. [162] proposed a WKM clustering by incorporating an additional step into the iterative K-Means clustering process to automatically calculate variable weights, thus enhancing clustering results. Other versions of WKM clustering have been introduced by other researchers, such as Entropy WKM clustering [164, 165], two-level variable weighting clustering algorithm (TW-K-Means) [166], among others. The following shows the main difference between K-Means clustering and WKM clustering when measuring the distance between each point and the centroid, using Euclidean Distance as an example.

$$d_{Euclidean}^w(x, c) = \sqrt{\sum_{j=1}^n w_j (x_{qj} - c_{kj})^2} \quad (31)$$

where  $w_j$  represents the weight of the  $j$ th criterion,  $j = 1, 2, \dots, n$ .

## 2.5. Customer Profiling Using Recency, Frequency, and Monetary (RFM) Model

The RFM model, developed by Hughes [167, 168], is named after its three dimensions: Recency, Frequency, and Monetary. This model assigns scores to each customer based on their performance on Recency, Frequency, and Monetary. These scores facilitate customer profiling, enabling decision-makers to efficiently identify valuable customers and develop effective marketing strategies. Several researchers have combined RFM indicators with clustering models to analyze customer behavior, as the RFM model proves to be a valuable approach for enhancing customer segmentation [169]. The RFM model and its extensions have been widely applied across various fields [170]. For instance, it has been successfully used in banking [171-173], retail [174-178], and tourism [61, 179-181], among other industries.

This section focuses on introducing the RFM framework, discussing both its advantages and disadvantages. Additionally, it presents some extensions of the RFM model developed within this thesis.

### 2.5.1. RFM Model

Introduced by Hughes [167, 168], the RFM model is a behavior-based model used to analyze and understand the behavior of a customer. This model is a well-known and widely used approach for measuring the strength of customer relationships, as it can effectively identify valuable customers [182]. The three indicators of the RFM model are explained as follows:

- **Recency (R)** represents the time interval between the last purchase and the analysis time (e.g., how recently a customer made a purchase, measured in days or months).
- **Frequency (F)** denotes the number of purchases made during the analysis period (e.g., how often the customer made purchases in the last three months).
- **Monetary (M)** indicates the total amount spent by a customer during the analysis period (e.g., how much the customer spent in the last three months).

The RFM model typically assigns scores to each customer using the quintiles system (also known as the customer quintile method), resulting in a maximum of 125 different scores (5x5x5).

It starts by sorting customers based on Recency in ascending order, with lower numbers of days corresponding to higher Recency scores. Customers are then divided into quintiles (five equal groups), with the top 20% receiving a Recency score of 5, the next 20% receiving a score of 4, and so on. After that, customers are sorted based on Frequency in descending order, where higher numbers of purchases correspond to higher Frequency scores. The top 20% are coded as 5, the next 20% receive a score of 4, and so on. The same process is repeated for Monetary, where higher monetary values result in higher Monetary scores. Customers who achieve high scores in all three indicators may be identified as loyal customers [183].

In the RFM model, all scores assigned to customers are finally aggregated into a single score, providing a comprehensive profile of each customer. According to Hughes [167], when generating a single score based on the three RFM indicators, each indicator holds equal weight. However, in some cases, businesses or decision-makers may adjust the weight of each RFM indicator considering their specific industry context and customer behavior patterns. Equation (32) calculates the composite RFM score for each customer, taking into account how weights could be assigned to each RFM indicator.

$$Y_q^{RFM} = w_R \cdot R + w_F \cdot F + w_M \cdot M \quad (32)$$

where  $q = 1, 2, \dots, m$ ,  $m$  represents the number of alternatives (in this section, referring to the number of customers, as it pertains to selecting the "best" or "more valuable" customers).

### 2.5.2. Extensions of the RFM Model

The RFM model is simple and easy to implement for identifying valuable customers. It uses only three indicators to summarize customer behaviors, making it cost-effective and easy for managers and decision-makers to understand [175]. While the RFM model serves as a crucial tool for firms to develop marketing strategies, it also presents several disadvantages [168, 170, 184-186]:

- (1) The simplicity of the RFM model, while beneficial for its ease of implementation and customer segmentation, may overlook other crucial customer attributes, resulting in an incomplete understanding of customer behavior.
- (2) The RFM model is not considered a precise quantitative prediction model, as the importance of each RFM indicator varies across industries (i.e., customer behaviors differ), making it

challenging to generalize their significance without considering the specific context and characteristics of each industry.

- (3) The RFM model focuses mainly on identifying valuable customers but overlooks those who make only one purchase or small orders. It provides limited meaningful scoring for Recency, Frequency, and Monetary when most customers of the firm make infrequent purchases, spend minimally, or have not made recent purchases.
- (4) The RFM model assumes that customer behavior remains consistent over time. In dynamic markets, this assumption may not hold true, possibly resulting in inaccuracies in customer segmentation and targeting.

In the literature, many researchers have developed extensions of the RFM model to address the aforementioned shortcomings. For example, Yeh et al. [186] developed the RFMTC model, expanding the RFM model with two parameters, time since first purchase and churn probability, and employing Bernoulli sequence in probability theory. Zhang et al. [187] introduced the RFMC model, incorporating clumpiness (C) as an additional metric to the RFM model to offer a more comprehensive understanding of customer behavior and value. Peker et al. [175] introduced a new RFM model called Length, Recency, Frequency, Monetary, and Periodicity (LRFMP) for classifying customers in the grocery retail industry. Smaili & Hachimi [178] improved the RFM model by incorporating diversity (D) as a fourth parameter, representing the variety of products purchased by each customer during the study period, and applied the RFM-D model in a retail market to identify customer behavior patterns. Some authors [61, 188] have incorporated the 2-tuple linguistic model into the RFM framework to tackle the problem of imprecise RFM results. This integration enhances result interpretability and facilitates value computation without losing information, thereby improving the precision of the RFM model.

Incorporating additional indicators or variables into the RFM model to improve its applicability in specific industries, and employing the 2-tuple linguistic model within RFM to enhance accuracy, are suitable approaches for extending the RFM model. The upcoming sections introduce the extensions of the RFM model developed within this thesis, following these philosophies.

### 2.5.2.1. The 2T-RFMB Model

The 2T-RFMB model comprises the 2-tuple linguistic model to enhance result accuracy and interpretability, along with an enhanced RFM framework that considers customer behavior data characteristics in a hotel management system [136]. This model expands the RFM model by modifying the definition of the Monetary indicator and introducing a new indicator, Bonding. Below are the concepts of the four indicators of the 2T-RFMB model [136]:

- **Recency (R)** represents the number of days between the customer's last check-in date and the analysis date.
- **Frequency (F)** represents the number of times the customer stays at the hotel during the analysis period.
- **Monetary (M)** represents the net revenue that the hotel earns from the customer during the analysis period, calculated as the difference between the total amount the customer spent at the hotel and the potential loss from empty rooms if the customer cancels their reservation or does not show up.
- **Bonding (B)** indicates the number of days the customer has established a relationship with the hotel during the analysis period, reflecting the degree of customer bonding with the hotel. A stronger bond increases the likelihood of the customer staying at the hotel again.

Expressing the value of these four indicators in 2-tuple values enables a more accurate assessment of customer behavior, avoiding information loss. The definition is as follows.

**Definition 11.** Let  $U_{qj} = \{U_{q1}, U_{q2}, U_{q3}, U_{q4}\}$  be a set containing the values of the four RFMB indicators for the  $q$ th customer, with  $U_{q1}$  representing the value of Recency,  $U_{q2}$  representing the value of Frequency,  $U_{q3}$  representing the value of Monetary, and  $U_{q4}$  representing the value of Bonding. For each element in  $U_{qj}$ , its 2-tuple value can be calculated using Equation (33):

$$U_{qj}^{2T-RFMB} = \Delta(U_{qj}) = \begin{cases} \Delta(\min\_max(U_{qj})), & \text{if } j \neq 1 \\ \text{neg}(\Delta(\min\_max(U_{qj}))), & \text{if } j = 1 \end{cases} \quad (33)$$

where  $q = 1, 2, \dots, m$ ,  $m$  represents the number of alternatives (in this section, referring to the number of customers);  $j = 1, 2, \dots, n$ ,  $n$  represents the number of criteria (in this section, referring to the number of indicators,  $n = 4$ );  $\min\_max(\cdot)$  represents the Min-Max normalization

method used to scale data into the range  $[0,1]$ ;  $\Delta(\cdot)$  and  $neg(\cdot)$  have been defined in Equations (1) and (3), respectively.

The 2T-RFMB overall value of the  $q$ th customer is calculated using Equation (34):

$$Y_q^{2T-RFMB} = \Delta \left( \sum_{j=1}^n w_j \cdot \Delta^{-1}(U_{qj}^{2T-RFMB}) \right) \quad (34)$$

where  $w_j$  represents the weight of each indicator;  $j = 1, 2, \dots, n$  (in this section,  $n = 4$ ).

### 2.5.2.2. The 2T-RFHPS Model

Similar to the 2T-RFMB model, the 2T-RFHPS model incorporates the 2-tuple linguistic model to improve result accuracy and interpretability. The 2T-RFHPS model is used to analyze the behavior of online reviewers based on online customer reviews. Taking into account the characteristics of online reviews, this model substitutes the Monetary indicator with Helpfulness and adds two new indicators (Promoter score and Stability) based on the RFM model [189]. Below are the concepts of the five indicators of the 2T-RFHPS model [189]:

- **Recency (R)** represents the number of days between the date of the most recent review left by the customer and the date of data extraction.
- **Frequency (F)** represents the number of reviews that the customer left during the analysis period.
- **Helpfulness (H)** represents the total number of "likes" received by the customer's review(s) during the analysis period, indicating how helpful their reviews are to other customers.
- **Promoter Score (P)** is the average of the overall ratings provided by the customer for various hotels on the selected review site (e.g., TripAdvisor, Booking, etc.) during the analysis period.
- **Stability (S)** is the standard deviation of the overall ratings provided by the customer for various hotels on the selected review site (e.g., TripAdvisor, Booking, etc.) during the analysis period.

Expressing the value of these five indicators in 2-tuple values allows for a more accurate assessment of customer behavior, preventing information loss, as defined below.

**Definition 12.** Let  $U_{qj} = \{U_{q1}, U_{q2}, U_{q3}, U_{q4}, U_{q5}\}$  be a set containing the values of the five

RFHPS indicators for the  $q$ th customer, with  $U_{q1}$  representing the value of Recency,  $U_{q2}$  representing the value of Frequency,  $U_{q3}$  representing the value of Helpfulness,  $U_{q4}$  representing the value of Promoter Score, and  $U_{q5}$  representing the value of Stability. For each element in  $U_{qj}$ , its 2-tuple value can be calculated using Equation (35):

$$U_{qj}^{2T-RFHPS} = \Delta(U_{qj}) = \begin{cases} \Delta(\text{percent\_rank}(U_{qj})), & \text{if } j \neq 1 \text{ and } j \neq 5 \\ \text{neg}(\Delta(\text{percent\_rank}(U_{qj}))), & \text{if } j = 1 \text{ or } j = 5 \end{cases} \quad (35)$$

where  $\text{percent\_rank}(\cdot) = \frac{\text{rank}_{qj}(\cdot)-1}{m-1}$  is a function used to scale data into the range  $[0,1]$ ,  $\text{rank}_{qj}(\cdot)$  represents the ranking of the  $q$ th customer in ascending order for each indicator;  $q = 1, 2, \dots, m$ ,  $m$  represents the number of alternatives (in this section, referring to the number of customers);  $j = 1, 2, \dots, n$ ,  $n$  represents the number of criteria (in this section, referring to the number of indicators,  $n = 5$ );  $\Delta(\cdot)$  and  $\text{neg}(\cdot)$  have been defined in Equations (1) and (3), respectively. The negative operator is applied to the Recency and Stability indicators because smaller values indicate better recency, while greater standard deviation values signify less stability.

The 2T-RFHPS overall value of the  $q$ th customer is calculated using Equation (36):

$$Y_q^{2T-RFHPS} = \Delta\left(\sum_{j=1}^n w_j \cdot \Delta^{-1}(U_{qj}^{2T-RFHPS})\right) \quad (36)$$

where  $w_j$  represents the weight of each indicator;  $j = 1, 2, \dots, n$  (in this section,  $n = 5$ ).



# Chapter 3

## MCDM-Based Proposed Models

This chapter presents an overview of the models proposed during the development of this doctoral thesis; each of them represents a contribution. They are designed to facilitate decision-making on topics such as restaurant selection, hotel and customer segmentation, and economic indicator calculation, among others.

### 3.1. A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com

#### 3.1.1. Introduction

The Internet breaks down information barriers, providing people with access to a wealth of information before making decisions. The eWOM, exemplified by online reviews, plays a crucial role in this process. For instance, people choose to dine at a restaurant based on its favorable reviews (i.e., positive eWOM) which describe past customers' experiences of how delicious the food is and how good the atmosphere is. However, browsing through numerous opinions can also extend the decision-making process because of the necessity to sift through and analyze a large volume of information. Choosing the "optimal" restaurant from a collection of alternatives based on online reviews provided by customers across different criteria (e.g., food, service, environment) is an MCDM problem, often requiring the integration of information across multiple criteria.

In the literature, researchers have used various MCDM methods to address restaurant selection and ranking issues using online reviews, and some have also incorporated text mining techniques, deep learning models, recommender systems, and sensitivity analysis to assist customers in making restaurant choices based on online reviews [3]. However, to the best of our knowledge, previous

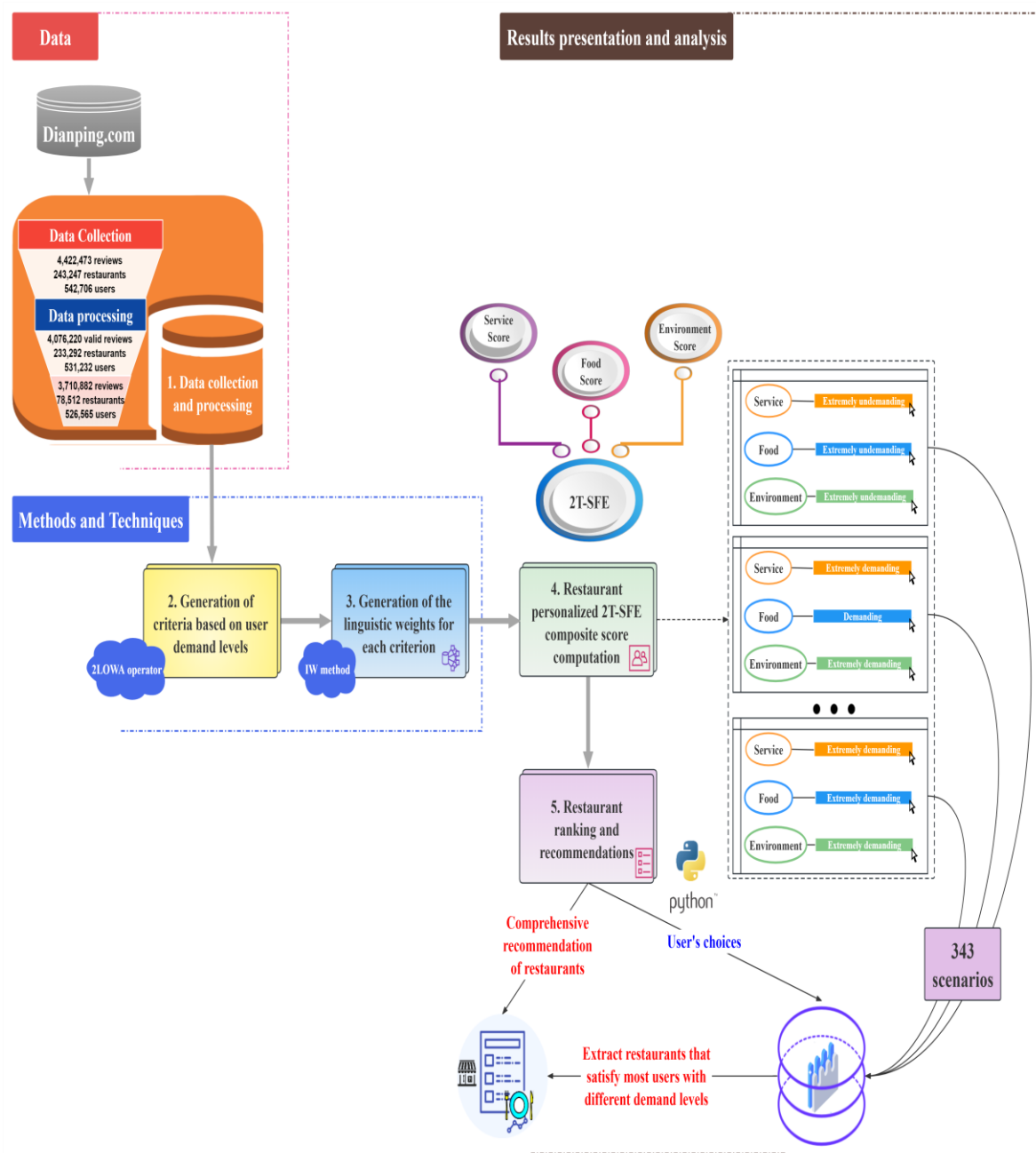
studies on restaurant selection and ranking have overlooked the diverse preferences of users regarding different aspects of a restaurant in the decision-making process. For instance, a user who is more demanding of the restaurant's environment but is lenient about the service would pay more attention to negative reviews concerning the environment rather than those criticizing the service. In such cases, relying solely on averages to calculate the overall restaurant score would fail to fully meet the user's needs. Furthermore, prior research has yet to explore the use of the OWA aggregation operator for restaurant selection and ranking based on online reviews.

Therefore, the objective of this work is to develop a multi-criteria decision support model enabling users to efficiently and accurately rank and choose restaurants according to their demand level for various restaurant aspects. The 2LOWA aggregation operator is applied for the first time to aggregate user ratings, producing linguistic ratings that reflect the diverse levels of user demand for restaurant service, food, and environment. The Importance Weights (IW) method is introduced in this work to calculate linguistic weights related to the level of user demand for the different restaurant criteria, thereby enabling the calculation of more accurate composite scores for each restaurant. The applicability of the proposed model is demonstrated using a dataset comprising over 3.7 million reviews sourced from Dianping.com. The selection of eWOM data from Dianping.com is driven by the observation that only a limited number of papers have explored eWOM data sources from China for research on restaurant selection and ranking. The results of the proposed model are showcased through an interactive application developed using the Python programming language. This application allows users to specify their demand levels for various restaurant criteria and generate a personalized ranking to facilitate a more efficient restaurant selection process. Frequency and trend analyses are also applied to analyze how restaurant rankings evolve with varying user demand levels.

### **3.1.2. Proposed Model and Its Application for Restaurant Ranking and Selection**

The model presented in this work is designed upon a tripartite structure: data, methods and techniques, and results presentation and analysis. Figure 9 shows the specific steps within each

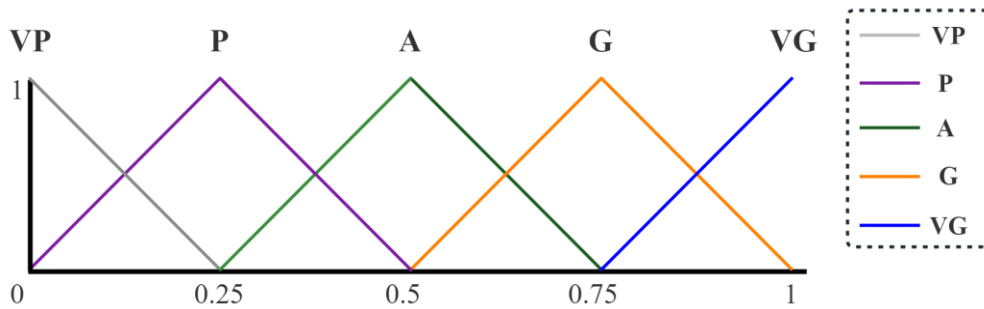
layer.



**Figure 9.** Proposed model for restaurant ranking and selection, adapted from [3].

The data layer collected and processed online reviews from Dianping.com, a popular Chinese life service review site where users can exchange information, post reviews, and discover suitable hotels, restaurants, or other entertainment options. This work used the dataset published by Zhang [190], which includes over 4.4 million reviews about restaurants on Dianping.com between April 7, 2003, and February 8, 2012. On Dianping.com, users rate restaurants on three criteria (Service, Food, and

Environment) using a 1 to 5-star scale. Reviews also contain the date, user ID, and restaurant ID. The five-star rating system is accompanied by linguistic terms ranging from "Very Poor (VP)" to "Very Good (VG)", wherein 1 star corresponds to "Very Poor (VP)", 2 stars to "Poor (P)", 3 stars to "Average (A)", 4 stars to "Good (G)", and 5 stars to "Very Good (VG)". Figure 10 shows the linguistic term set used on Dianping.com.



**Figure 10.** Linguistic term set on Dianping.com [3].

Data processing excluded user reviews with incomplete dimensional ratings, as these were deemed potential spam or intentionally negative on Dianping.com. Additionally, only restaurants with at least ten reviews were included, as this is the minimum requirement for Dianping.com to start calculating the restaurant's overall rating. Following data processing, over 3.7 million user reviews about 78,512 restaurants were retained for further analysis. Table 3 shows all the reviews received by the restaurant with ID 32519.

The methods and techniques layer was made up of two steps: generating new criteria that reflect the varying levels of user demand for the three aspects of the restaurant using diverse linguistic quantifiers within the 2LOWA aggregation operator (see Equation (11)); employing the IW method to generate diverse scenarios of linguistic weights related to the level of user demand determined in the previous step. The concepts of linguistic quantifiers and the 2LOWA aggregation operator can be found in Section 2.2 (refer to Table 1 and Definition 10). Table 4 presents the user demand levels represented by each linguistic quantifier. Table 5 presents 21 new criteria generated to reflect the different levels of user demand for service, food, and environment at the restaurant with ID 32519, along with 3 additional criteria for comparing those generated by different linguistic quantifiers with those produced by the arithmetic mean.

**Table 3.** Reviews received by a restaurant, adapted from [3].

User ID	Review date	Service	Food	Environment
37602	2006-10-11	A	A	A
83244	2008-02-05	A	G	VG
77755	2008-07-02	G	A	A
115294	2008-09-19	VG	G	G
77764	2008-09-19	A	P	P
222219	2008-12-12	A	A	A
37615	2009-05-11	G	A	G
37630	2009-05-26	A	P	A
200053	2009-12-03	G	G	G
222220	2010-04-01	A	A	A
83986	2010-05-03	VG	A	VG
222221	2010-07-07	A	P	A
1891	2011-01-13	A	A	A
77779	2011-03-14	VG	A	A
222222	2012-01-30	G	A	G

**Table 4.** Description of user demand levels and degree of importance, adapted from [3].

Linguistic quantifier	User demand levels	Degree of importance
<i>At least one</i>	<b>Extremely undemanding:</b> users are satisfied with a restaurant when it has at least one positive review, even if the remaining reviews are negative, since they are extremely undemanding of this restaurant criterion.	<b>Lowest importance (LWST):</b> the criterion being evaluated is not at all important to the user when calculating the overall score.
<i>Few</i>	<b>Very undemanding:</b> users are satisfied with a restaurant when it has a few (more than one but not many) positive reviews, even if the remaining reviews are negative, since they are very undemanding of this restaurant criterion.	<b>Very low importance (VL):</b> the criterion being evaluated is not very important to the user when calculating the overall score.
<i>Some</i>	<b>Undemanding:</b> users are satisfied with a restaurant when it has some positive reviews, since they are undemanding of this restaurant criterion.	<b>Low importance (L):</b> the criterion being evaluated is relatively unimportant to the user when calculating the overall score.
<i>Half</i>	<b>Neutral:</b> users are satisfied with a restaurant when it has reviews that are, on average, positive, since they are neither too demanding nor undemanding of this restaurant criterion.	<b>Moderate importance (M):</b> the criterion being evaluated is of some importance to the user when calculating the overall score.

Linguistic quantifier	User demand levels	Degree of importance
<i>Many</i>	<b>Demanding:</b> users are satisfied with a restaurant when it has many positive reviews, since they are demanding of this restaurant criterion.	<b>High importance (H):</b> the criterion being evaluated is relatively important to the user when calculating the overall score.
<i>Most</i>	<b>Very demanding:</b> users are satisfied with a restaurant when it has mostly positive reviews, with very few unfavorable ones, since they are very demanding of this restaurant criterion.	<b>Very high importance (VH):</b> the criterion being evaluated is very important to the user when calculating the overall score.
<i>All</i>	<b>Extremely demanding:</b> users are satisfied with a restaurant when it has no negative reviews, since they are very demanding of this restaurant criterion and are more concerned with the most unfavorable reviews.	<b>Highest Importance (HIST):</b> the criterion being evaluated is the most important to the user when calculating the overall score.

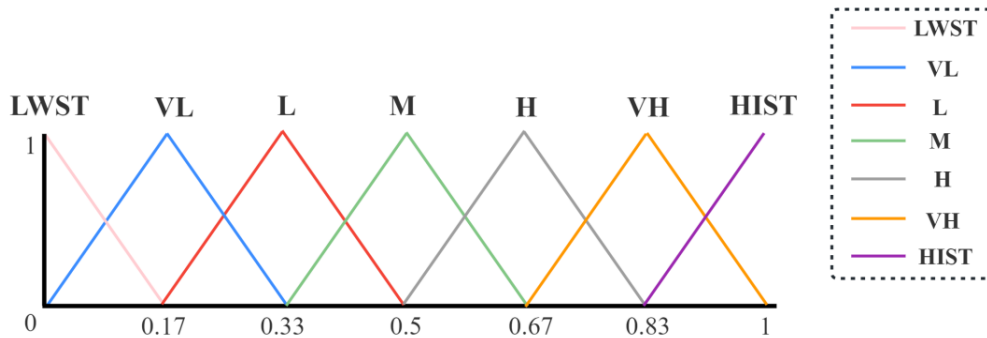
**Table 5.** New criteria generated for a restaurant, adapted from [3].

Linguistic quantifier	Service	Food	Environment
<i>At least one</i>	(VG, -0.0010)	(G, -0.0008)	(VG, -0.0010)
<i>Few</i>	(VG, -0.2218)	(G, -0.1705)	(VG, -0.2767)
<i>Some</i>	(G, +0.1307)	(A, +0.3420)	(G, -0.0360)
<i>Half</i>	(G, -0.3315)	(A, +0.0015)	(A, +0.4684)
<i>Many</i>	(A, +0.2573)	(A, -0.3204)	(A, +0.0484)
<i>Most</i>	(A, +0.0005)	(P, +0.1074)	(A, -0.4983)
<i>All</i>	A	P	P
Arithmetic mean	(G, -0.3332)	A	(A, +0.4668)

Moreover, given that a user who demands more from a restaurant's service tends to place greater importance on the level of service provided, Table 4 also includes the corresponding degree of importance aligned with varying levels of user demand. Figure 11 shows the linguistic terms set for expressing different degrees of importance, crucial for computing linguistic weights and the overall score of each restaurant based on users' specific demands. For instance, for a user who is extremely undemanding of restaurant service, but demanding of the food and environment, the 2T-SFE composite score for restaurant ID 32519 is calculated as:

$$\Delta \left( \frac{\Delta^{-1}(\text{VG}, -0.0010) \cdot \Delta^{-1}(\text{LWST}, 0) + \Delta^{-1}(\text{A}, -0.3204) \cdot \Delta^{-1}(\text{H}, 0) + \Delta^{-1}(\text{A}, +0.0484) \cdot \Delta^{-1}(\text{H}, 0)}{\Delta^{-1}(\text{LWST}, 0) + \Delta^{-1}(\text{H}, 0) + \Delta^{-1}(\text{H}, 0)} \right) =$$

$\Delta\left(\frac{3.999\cdot 0+1.6796\cdot 4+2.0484\cdot 4}{0+4+4}\right) = \Delta(1.864) = (A, -0.136)$ . The composite score of this restaurant implies that it falls slightly below the average level among the 78,512 restaurants, making it a less desirable option for this user's dining choice.



**Figure 11.** Linguistic term set of the degree of importance [3].

The results presentation and analysis layer involved visualizing the personalized 2T-SFE composite score computed for each restaurant, along with their ranking, and analyzing the results. This work developed an interactive application created using the Python programming language to present the results. This application offers more than 340 scenarios that emulate user demand levels when selecting restaurants, allowing users to effortlessly browse a list of restaurants and choose one that meets their needs. It has been found that when users have a medium level of demand for restaurant service, food, and environment (i.e., all linguistic ratings are aggregated using the linguistic quantifier *Half*), the composite scores and rankings computed for restaurants are nearly identical to those computed using the arithmetic mean, with only a slight decimal difference in their values. However, there are differences in restaurant ranking when comparing other scenarios. Therefore, frequency analysis and trend analysis have been conducted to study how restaurant rankings evolve with varying user demand levels.

A total of 92 restaurants rank in the top 10 across 342 scenarios, among which restaurants with ID 55765, 224393, 169535, and 111613 regularly appear with a frequency exceeding 70%, and detailed results are available in [3]. Given their frequent presence in the top 10, these four restaurants can meet the needs of most users regardless of their levels of demand for restaurant service, food, and environment. Furthermore, based on the Cox-Stuart test [191] to assess trends

(increasing, decreasing, or stable) in restaurant rankings that vary with user demand levels, the changes in ranking among these 92 restaurants can be categorized into: 1) restaurants with stable rankings despite fluctuations in user demand levels for restaurant service, food, and environment—for instance, restaurant with ID 55765 consistently remains within the top 10; 2) restaurants whose ranking increases as users are more demanding of restaurant service, food, and environment (e.g., restaurant with ID 23295); 3) restaurants whose ranking falls as users are more demanding of restaurant service, food, and environment (e.g., restaurant with ID 162567). All of these enable review sites to establish a more reasonable, personalized, and comprehensive ranking of restaurants for their users.

### **3.1.3. Conclusions**

This work introduced a new decision support model for restaurant selection, employing the 2LOWA aggregation operator, the IW method, and a visualization application developed using Python. The applicability of the proposed model has been demonstrated using over 3.7 million user reviews from 78,512 restaurants on Dianping.com. The principal contributions of the proposed model are outlined below:

- New criteria reflecting various levels of user demand for restaurant service, food, and environment are generated using linguistic quantifiers.
- Linguistic quantifiers, representing different levels of user demand, are linked to the degree of importance in calculating the weights of the corresponding criteria.
- The implementation of acquiring more accurate linguistic weights to compute more linguistically understandable composite scores for each restaurant leads to more precise rankings for users.
- The facilitation of generating personalized rankings through an interactive application, based on users' actual needs rather than simply average ratings, aids users in quickly finding a suitable restaurant.
- Generation of a list of restaurants that can satisfy the demands of most users with different levels of demand on review sites is based on the frequency of the restaurant's appearance in the top 10 across various scenarios and its corresponding ranking, aiming to increase

customer satisfaction and foster trust in the decision-making process.

However, some limitations of this work were identified and need to be addressed in future research. For example, while this work considered the three most commonly accepted criteria affecting restaurant ranking—food, service quality, and restaurant environment—real-world restaurant selection entails considering additional criteria like price and location. Future research could incorporate these factors into the composite score and ranking, using data from review sites like TripAdvisor, OpenTable, or Yelp. Furthermore, when calculating the composite score for each restaurant, the time frame for collecting online reviews could be restricted to, for example, the most recent year or six months. This would enhance the timeliness of restaurant reviews, offering users more realistic restaurant rankings and recommendations. The proposed model could also be adapted to other domains such as hotels, products, and movies to test its versatility and applicability.

## **3.2. Clustering Using Ordered Weighted Averaging Operator and 2-Tuple Linguistic Model for Hotel Segmentation: The Case of TripAdvisor**

### **3.2.1. Introduction**

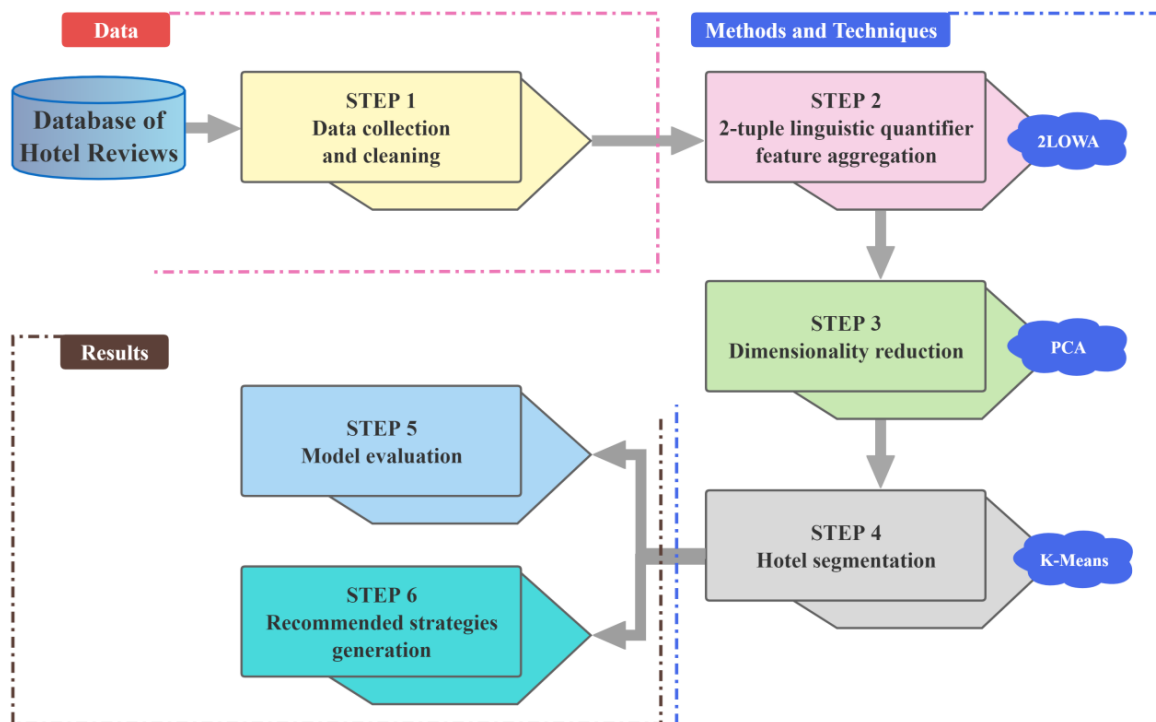
The rapid advancement of technology and the widespread use of the Internet have transformed virtual communities into a critical element for companies striving for continuous enhancement. In the tourism sector, particularly in the hotel industry, many tourists now search for accommodations on platforms like TripAdvisor, Booking, or Expedia. These platforms rank hotels based on user-generated reviews and ratings. Analyzing these reviews and ratings is crucial for enhancing a hotel's online reputation. Consequently, numerous studies focusing on online comments have been conducted, aiming for hotel segmentation and improvement. Although previous studies have used various approaches to segment hotels based on online reviews or ratings, to the best of our knowledge, none have taken into account customer preferences for looking at reviews or ratings. Ninety-six percent of customers look for negative reviews at least occasionally, and over half of them specifically search for one-star reviews [192]. Depending on customer preferences, some may prioritize positive reviews (representing less demanding customers) while others prefer negative ones (representing more demanding customers) [4].

Therefore, this work aims to segment hotels considering customer preferences (from the less demanding to the most demanding) on various hotel aspects (Service, Check-In, Business Service, Location, Value, Cleanliness, Rooms, and Sleep Quality). The proposed model uses the OWA aggregation operator, as each linguistic quantifier of this operator can be assigned a unique value to represent the decision-maker's attitude during information aggregation. Unlike other studies that only employed one or some of the linguistic quantifiers in their analysis, this work applies all linguistic quantifiers and redefined them to better suit the hotel segmentation case study, thereby generating distinct ratings that emulate attitudes ranging from less demanding to the most demanding customers. The proposed model also incorporates the 2-tuple linguistic model to enhance linguistic interpretability and minimize the risk of information loss.

Considering that directly using customer reviews aggregated by the 2LOWA aggregation operator (i.e., various "quality of reviews"), along with metrics "quantity of reviews" and "review recency," for the clustering process may contain redundant information in the analysis, PCA is employed to reduce the dimensionality of the data before applying clustering techniques. Finally, the proposed model uses K-Means clustering to segment hotels. The applicability of the proposed model is evaluated using a real dataset comprising over 50 million customer online reviews of hotels from TripAdvisor. The results demonstrate that the proposed model can produce denser and more separated clusters than the model without linguistic quantifiers.

### 3.2.2. Proposed Model and Its Application for Hotel Segmentation

The model presented in this work is constructed upon three layers: data, methods and techniques, and results. Figure 12 shows the specific steps within each layer.



**Figure 12.** Proposed model for hotel segmentation, adapted from [4].

The first step of the proposed model was to collect data and then clean it in preparation for further analysis. The dataset published by Antognini and Faltings [193], comprising over fifty million hotel reviews from 21,891,294 users who commented on TripAdvisor between February 1, 2001, and

May 14, 2019, was used. Each review contains the user ID, comment date, the corresponding ID of the hotel evaluated by the user, and ratings for eight aspects of the hotel. As mentioned in Section 2.1 (refer to Example 1), on TripAdvisor, online ratings express customers' opinions about hotels using linguistic terms, forming the linguistic term set  $S = \{ s_0 = \textit{Terrible} = T, s_1 = \textit{Poor} = P, s_2 = \textit{Average} = A, s_3 = \textit{Very Good} = VG, s_4 = \textit{Excellent} = E \}$  (see also Figure 4). Data processing was done taking into account that on TripAdvisor, only the overall rating is mandatory, while sub-aspect ratings are optional. However, in this case, missing data could not be replaced with 0, as it leads to errors in linguistic computation. Moreover, in this dataset, only 0.26% of the hotels received fewer than 5 reviews, with a median of 41. Therefore, to ensure a representative sample, only hotels with one hundred or more reviews were included in the analysis, resulting in a dataset of 178,761 hotels.

The second, third, and fourth steps constituted the methods and techniques layer. These steps employed the 2LOWA aggregation operator, PCA, and K-Means clustering, concepts introduced in Sections 2.2, 2.4.1, and 2.4.2, respectively. Based on the conducted case study and to make the linguistic quantifiers easy to understand, those listed in Table 1 have been redefined and interpreted as follows [4]:

- **At least one of the less demanding** (AtLone\_LD) is an optimistic quantifier representing the opinions of at least one of the less demanding customers, whose final value is very high.
- **Few of the less demanding** (Few\_LD) is an optimistic quantifier representing the opinions of a few less demanding customers, whose final value is high.
- **Some of the less demanding** (Some\_LD) is an optimistic quantifier representing the opinions of some less demanding customers, whose final value is relatively high.
- **Average demanding** (Average\_D) is a moderate quantifier representing customers' neutral or more realistic opinions, with all components of the weight vector generated by this quantifier being approximately equal, akin to an arithmetic mean.
- **Some of the most demanding** (Some\_MD) is a pessimistic quantifier representing the opinions of some most demanding customers, whose final value is relatively low.
- **Few of the most demanding** (Few\_MD) is a pessimistic quantifier representing the opinions of a few most demanding customers, whose final value is low.
- **At least one of the most demanding** (AtLone\_MD) is a pessimistic quantifier representing the opinions of at least one of the most demanding customers, whose final value is very low.

Table 6 shows the 2-tuple values for the recency (RecentDays) and the number of reviews

(numReview) of the Holiday Inn Express Dunfermlin Hotel, along with the values of the 56 new linguistic variables generated by the 2LOWA aggregation operator regarding hotel aspect ratings. A new dataset consisting of 58 variables has been obtained, including the newly generated linguistic variables along with the RecentDays and numReview variables. Due to close correlations among many variables in this dataset, performing PCA can reduce its dimensionality. Sixteen PCs have been selected for retention, explaining 83.64% of the total variance. Based on the 16 PCs obtained, K-Means clustering was applied to segment hotels. Using the Elbow Method, it was determined that the optimal number of clusters is eight. Therefore, eight groups of hotels were established. The original variables have been recreated using these 16 PCs to facilitate the description of the various hotel groups. Detailed results of each cluster can be found in [4].

The final two steps made up the results layer, involving model evaluation and the generation of recommended strategies. The model evaluation was conducted using four metrics: SC, DBI, CHI, and the Reliability Index. These metrics were employed to compare the clustering results of the proposed model with those of a K-Means clustering that did not include variables generated by various linguistic quantifiers. The proposed model yielded better clustering results, exhibiting an SC closer to one, a DBI closer to zero, and higher scores in both CHI and the Reliability Index.

**Table 6.** 2-tuple values for a hotel, adapted from [4].

<b>Variables</b>	<b>2-tuple value</b>	<b>Variables</b>	<b>2-tuple value</b>
RecentDays	(A, -0.033)	numReview	(VG, +0.017)
Service_AtLone_LD	E	Location_AtLone_LD	E
Service_Few_LD	(E, -0.038)	Location_Few_LD	(E, -0.048)
Service_Some_LD	(VG, 0.097)	Location_Some_LD	(VG, 0.066)
Service_Average_D	(VG, 0.005)	Location_Average_D	(VG, -0.026)
Service_Some_MD	(VG, -0.101)	Location_Some_MD	(VG, -0.107)
Service_Few_MD	(A, 0.009)	Location_Few_MD	(A, 0.061)
Service_AtLone_MD	T	Location_AtLone_MD	(T, 0.001)
Cleanliness_AtLone_LD	(VG, 0.073)	Sleep_Quality_AtLone_LD	E
Cleanliness_Few_LD	(VG, 0.065)	Sleep_Quality_Few_LD	(E, -0.049)
Cleanliness_Some_LD	VG	Sleep_Quality_Some_LD	(VG, 0.083)
Cleanliness_Average_D	(VG, -0.011)	Sleep_Quality_Average_D	(VG, 0.013)
Cleanliness_Some_MD	(VG, -0.124)	Sleep_Quality_Some_MD	(VG, -0.037)
Cleanliness_Few_MD	(P, 0.096)	Sleep_Quality_Few_MD	(A, 0.047)

<b>Variables</b>	<b>2-tuple value</b>	<b>Variables</b>	<b>2-tuple value</b>
Cleanliness_AtLone_MD	T	Sleep_Quality_AtLone_MD	P
Value_AtLone_LD	E	CheckIn_AtLone_LD	E
Value_Few_LD	(E, -0.074)	CheckIn_Few_LD	(E, -0.083)
Value_Some_LD	(VG, 0.048)	CheckIn_Some_LD	(VG, -0.052)
Value_Average_D	(VG, -0.016)	CheckIn_Average_D	(A, 0.055)
Value_Some_MD	(VG, -0.084)	CheckIn_Some_MD	(A, -0.085)
Value_Few_MD	(A, -0.038)	CheckIn_Few_MD	(T, 0.108)
Value_AtLone_MD	(T, 0.002)	CheckIn_AtLone_MD	T
Rooms_AtLone_LD	E	Business_Service_AtLone_LD	E
Rooms_Few_LD	(E, -0.063)	Business_Service_Few_LD	(E, -0.102)
Rooms_Some_LD	(VG, 0.055)	Business_Service_Some_LD	(A, 0.112)
Rooms_Average_D	(VG, -0.008)	Business_Service_Average_D	(A, -0.083)
Rooms_Some_MD	(VG, -0.082)	Business_Service_Some_MD	(P, -0.014)
Rooms_Few_MD	(A, 0.074)	Business_Service_Few_MD	(T, 0.009)
Rooms_AtLone_MD	(T, 0.002)	Business_Service_AtLone_MD	T

Table 7 provides the definition of each cluster in the proposed model, along with the number of hotels in each cluster and their descriptions, while Table 8 presents the corresponding information for each cluster obtained using the compared model. Comparing Tables 7 and 8, it can be observed that the cluster features in both models are quite similar. However, the proposed model is mathematically more accurate and reliable, and it can also provide additional explanations based on varying degrees of customer demands for the eight hotel aspects, demonstrating its ability to interpret the clustering results.

The recommended strategies were generated based on the descriptions of each cluster within the proposed model. For example, for hotels belonging to cluster 1, the most important strategy would be to increase the number of reviews (e.g., by encouraging customers to leave reviews on TripAdvisor), thereby enhancing recency. Moreover, while changing the hotel's location would be impossible, offering a free hotel-airport or hotel-train pick-up or drop-off service would be preferable. To attract customers with high demands for cleanliness and rooms, improving cleanliness, redecorating rooms, and updating room photos on the website would be necessary. More strategies generated for the other clusters can be found in [4].

**Table 7.** Hotel segmentation description of the proposed model [4].

<b>Cluster</b>	<b>Definition</b>	<b>Number of hotels</b>	<b>Description</b>
1	Hotel with a low number of recent reviews and problems about its cleanliness, room and location.	18,806	<p>This type of hotel tends to have very few recent reviews. For those customers who often give impartial reviews (average demanding customers), this type of hotel has lower cleanliness than the average level of the hotels on TripAdvisor. Their location and rooms are all worse for the most demanding customers (whether for some, few, or at least one of them). Overall, these hotels are worse for their bad location, even for some less demanding customers.</p> <p>Although its recency is at the average level, this type of hotel receives a large number of comments. Their service, cleanliness, and rooms are all very good, because they are better than the rest of the clusters even for the most demanding customers (whether for some, few, or at least one of them). Its location is better for average demanding customers, although for the most demanding customers it is not as good as clusters 3 and 5.</p>
2	Hotel with a high number of reviews, very good service, cleanliness, rooms and location.	33,996	<p>This type of hotel is well-known for its excellent location, as practically all customers of various degrees of demand believe it is superior to the other hotels, whether for less, average, or most demanding customers. In addition, its service, the value offered, and reception level are better for the most demanding customers (whether for some, few, or at least one of them). However, for at least one and a few most demanding customers, the quality of sleep and the room are worse in this type of hotel. Moreover, its cleanliness is worse for the average demanding, a few less demanding and the most demanding customers.</p>
3	Very famous hotel with many recent reviews, excellent location, very good service, reception and value, although its rooms and sleep quality are poor.	15,335	

Cluster	Definition	Number of hotels	Description
4	Recently opened hotel with high recency, very good cleanliness and rooms, but low number of comments and poor reception.	43,420	Although this type of hotel has recent reviews, as those hotels have just opened in the last few weeks, few customers have rated it. It is characterized by its particularly good cleanliness and rooms, because they are better even for the most demanding customers (whether for some, few, or at least one of them). However, the reception level in this type of hotel is worse for at least one of the most demanding customers. Its location is worse for some less demanding customers.
5	Famous hotel with a high number of recent reviews, as well as a very good location, rooms and cleanliness, but poor sleep quality.	19,979	This type of hotel has many recent reviews on TripAdvisor. Its very good rooms distinguish it, because practically all customers of various degrees of demand think it is superior to the other hotels (except those in clusters 2,4,7), whether for less, average, or most demanding customers. In addition, its location and level of cleanliness are better for the most demanding customers (whether for some, few, or at least one of them). However, due to its convenient location (city center, for example), this type of hotel always has more noise, so the quality of sleep is worse for some of the less demanding customers, at least one and a few most demanding customers. Moreover, its reception level and value offered are worse for at least one of the most demanding customers. For the average demanding customers, the value offered by this type of hotel is worse.
6	Old and unpopular hotel with poor cleanliness and location.	12,105	This type of hotel has almost no recent reviews, so the reference value of its reviews is diminishing. Its cleanliness is worse for the average demanding customers and a few less demanding ones. Its location is worse than the rest of the hotels (except those in cluster 1, as they are nearly as bad as this cluster) for almost all customers of various degrees of demand, whether for less, average, or most demanding customers.

Cluster	Definition	Number of hotels	Description
7	Newly opened hotel with high recency, very good business service, rooms and cleanliness.	25,060	This type of hotel was opened in the last few months, so it has many recent reviews. Its cleanliness, rooms, and business service are better for the most demanding customers (whether for some, few, or at least one of them). Furthermore, for some less demanding customers, the level of business service and rooms in this type of hotel are also excellent. However, its location is worse for some less demanding customers.
8	Formerly famous hotel but has lost its appeal because of its poor cleanliness and rooms.	10,060	This type of hotel has few recent comments, even though its number of customers is well above average level. It used to be called "Influencer," but now no one shows any interest in it, since: <ul style="list-style-type: none"> <li>- For a few less demanding customers and average ones, its cleanliness is worse than the rest of the hotels.</li> <li>- For some less demanding customers, its service and location are worse than the rest of the hotels.</li> <li>- For a few most demanding customers, its cleanliness and rooms are worse than the rest of the hotels.</li> <li>- For at least one of the most demanding customers, its rooms are worse than the rest of the hotels.</li> </ul>

**Table 8.** Hotel segmentation description of the compared model [4].

Cluster	Definition	Number of hotels	Description
1	Bad-Hotel in location, cleanliness and rooms, with a low number of recent reviews.	18,232	This type of hotel tends to have very few recent reviews. It is distinguished by poor cleanliness, rooms, and location. *
2	Hotel with a high number of reviews, very good service, cleanliness, rooms and location.	33,341	This type of hotel has a high number of comments. Their level of service, cleanliness, and rooms are all very good. Although their location is not as competitive as that of clusters 3 and 5, it is still superior to the rest of the hotels. *
3	Incredibly famous hotel with many recent reviews, excellent location, very good service, reception and value.	15,308	This type of hotel is well-known for its excellent location. Their service, the value offered, and the level of reception are very good. *
4	Recently opened hotel with high recency, very good cleanliness and rooms, but low number of comments and poor reception.	44,040	This type of hotel has recent reviews because they are those hotels that opened in the last few weeks. Their cleanliness and rooms are all very good, despite their poor reception. *
5	Famous hotel with a high number of recent reviews, as well as a very good location, rooms, and cleanliness.	19,609	This type of hotel is popular since the rooms and cleanliness are likelier than those in cluster 3, even though the location is slightly inferior. *
6	Old and unpopular hotel with poor cleanliness and location.	12,414	This type of hotel has almost no recent reviews, so the reference value of its reviews is diminishing. Their cleanliness and location are both inferior to those of the other hotels, although their reception is very good. *
7	Newly opened hotel with high recency, very good business service, reception,	25,455	This type of hotel was opened in the last few months, so it has many recent reviews. Their level of reception, cleanliness, and rooms are all particularly good. Those hotels have a competitive

Cluster	Definition	Number of hotels	Description
	cleanliness, rooms and location.		advantage that other hotels do not have, and their business service is superior to the rest of the hotels. *
8	Formerly famous hotel but has lost its appeal because of its poor cleanliness and rooms.	10,362	Despite having a high number of reviews, this type of hotel has few recent comments. It used to be called "Influencer," but now no one shows any interest in it because of its poor cleanliness and rooms. *

\* Other aspects of this type of hotel are at the medium level.

### 3.2.3. Conclusions

This work presented a new model to achieve hotel segmentation that considers different degree of customer demands (from the less demanding to the most demanding). The proposed model employed the 2LOWA aggregation operator, PCA, and K-Means clustering. The effectiveness of this model has been demonstrated using over 50 million reviews from TripAdvisor. This work has made significant contributions at both the theoretical and practical levels. From a theoretical standpoint, the linguistic quantifiers of the OWA aggregation operator have been redefined to make them more understandable. These redefined linguistic quantifiers can be applied to modeling the entire range of attitudes towards various hotel aspects, from less demanding to more demanding, thereby generating distinct ratings for hotel aspects. The proposed model has achieved more precise hotel segmentation, as evidenced by lower values of the DBI, SC closer to one, and higher scores in both the CHI and the Reliability Index. Moreover, it has enhanced the interpretability of hotel segmentation results.

From a practical perspective, the proposed model can provide more valuable information for both companies and customers in decision-making. For hotels, even if they receive identical reviews across different aspects (e.g., all hotel aspects labeled "Excellent" in customer reviews), the proposed model can still segment hotels by employing linguistic quantifiers to produce diverse 2-tuple values for various hotel aspects based on the degree of customer demands, thereby increasing the interpretability of the clustering results. This allows hotels to identify areas for improvement and implement necessary strategies to enhance their digital reputation on platforms

like TripAdvisor. Moreover, the proposed model introduces a new online hotel ranking method for customers, enabling them to create personalized rankings based on their degree of demand for various hotel aspects (better location, cleaner rooms, etc.), rather than relying only on average ratings. This allows for the quick selection of suitable hotels based on how customers view reviews. Some customers may prioritize negative reviews first, while others may do the opposite.

To further improve the proposed model, limitations identified in this work should be addressed in future research. For example, it only compared the hotel segmentation results of the proposed model with those of a model that applies K-Means clustering without considering the variables generated by various linguistic quantifiers. It would be necessary to compare its results with more clustering techniques in future work. Moreover, the model proposed in this work could be expanded by applying other supervised or unsupervised models, as well as incorporating recommender systems. Using other e-commerce datasets, like Amazon or AliExpress, could further validate its application across different industries.

### **3.3. Multiple Scenarios of Quality of Life Index Using Fuzzy Linguistic Quantifiers: The Case of 85 Countries in Numbeo**

#### **3.3.1. Introduction**

When evaluating a country's development level, in addition to comparing the gross domestic product (GDP) between nations, it is important to consider the quality of life to gain a comprehensive view of well-being. The measurement and study of quality of life are becoming increasingly important in social development, as it considers various aspects like healthcare, housing costs, education, and employment opportunities [194]. The quality of life index (QOLI) is a composite indicator used for measuring the quality of life in different nations. However, the QOLI is an outcome that reflects a complex balance of multiple factors, sometimes requiring adjustments to the weights of different dimensions to accommodate the circumstances in different countries. Not all countries have the same problems in improving their quality of life. For instance, the distribution of weights for different indicators should vary between emerging and developed countries.

Therefore, the objective of this work is to construct various scenarios of the QOLI, using linguistic quantifiers of the OWA aggregation operator, and the 2-tuple linguistic model. The different linguistic quantifiers of the OWA aggregation operator can reflect decision-makers' attitudes, enabling flexible weight adjustments in the aggregation process. Despite generating ordered weights distinct from importance weights, in some cases, these weights generated by the OWA aggregation operator can be combined with the different importance weights associated with the criteria in the actual aggregation [66]. The 2-tuple linguistic model aggregates information without loss and enhances the interpretability and intuitiveness of outcomes. The data used to verify the applicability of the proposed model comes from Numbeo, one of the largest databases of quality of life information. Uncertainty and sensitivity analyses are conducted to assess the robustness of the generated QOLIs. The results indicate that the proposed model can produce various QOLIs scenarios, including one consistent with expert-weighted models, while also enhancing the QOLI's linguistic interpretability.

### 3.3.2. Proposed Model and Its Application in Quality of Life Index Calculation

The model proposed in this work is structured into three layers: data, methods and techniques, and results analysis and comparison. Figure 13 shows the specific steps within each layer.

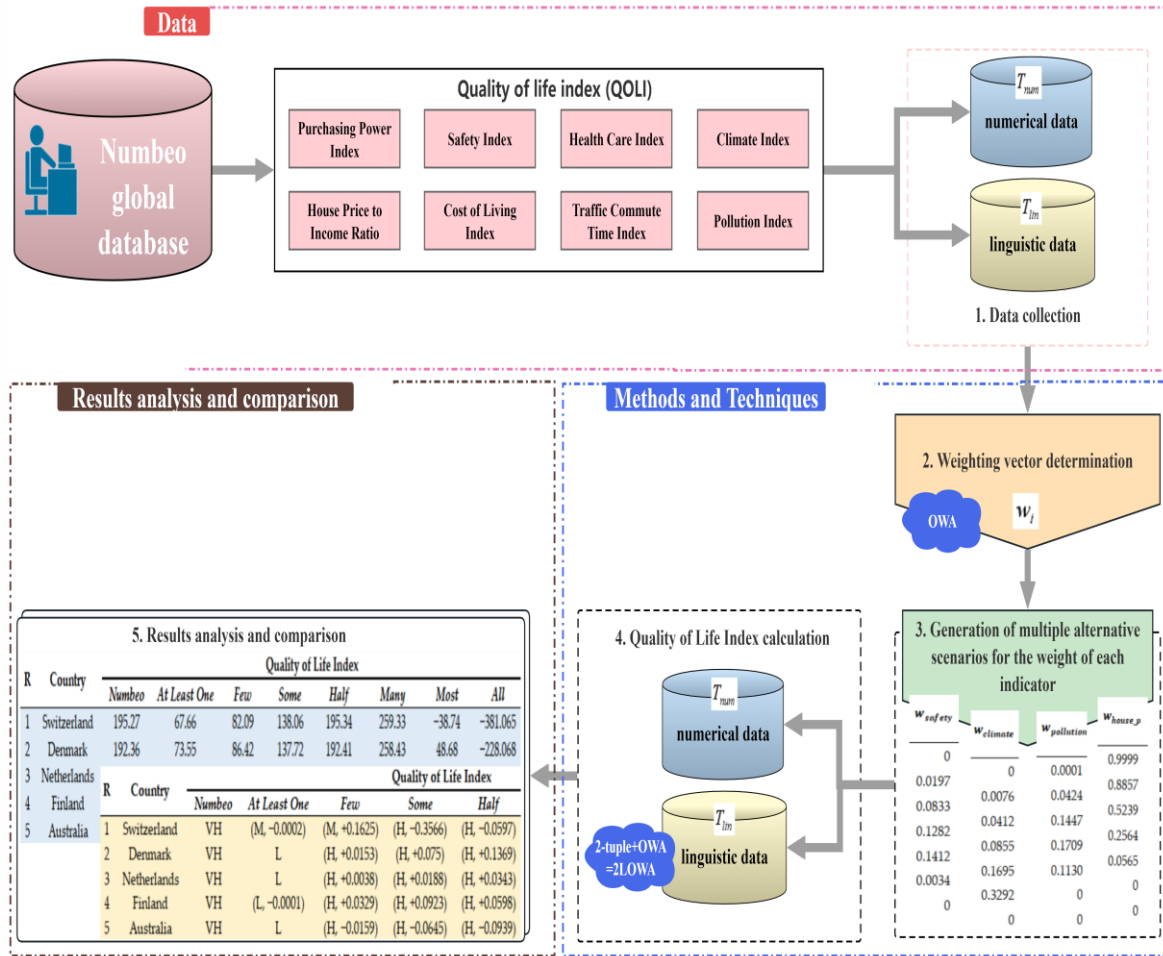


Figure 13. Proposed model for calculating the QOLI, adapted from [194].

The first step of the proposed model involved collecting quality of life data from Numbeo for 85 countries [195]. Numbeo database contains up-to-date global living condition data provided by millions of people worldwide, covering various aspects such as pollution levels, healthcare systems, safety, and property prices. Numbeo incorporates eight sub-indicators in calculating the QOLI (refer to Figure 13): purchasing power index (PPI), safety index (SI), health care index (HCI), climate index (CLI), house price to income ratio (HPTIR), cost of living index (COLI),

traffic commute time index (TCTI), and pollution index (PI). Among them, higher values for the PPI, SI, HCI, and CLI indicate a better quality of life. Conversely, lower values are preferable for the remaining sub-indicators. Numbeo uses both numerical values and linguistic terms to express the degree of these eight sub-indicators and the QOLI in various countries. Figure 14 shows an example. Consequently, two datasets were obtained in this step: one for numerical calculations ( $T_{num}$ ) and the other for linguistic terms ( $T_{lin}$ ). The linguistic terms used on Numbeo include Very Low (VL), Low (L), Moderate (M), High (H), and Very High (VH), forming the linguistic term set  $S = \{s_0 = VL, s_1 = L, s_2 = M, s_3 = H, s_4 = VH\}$ , as illustrated in Figure 15.

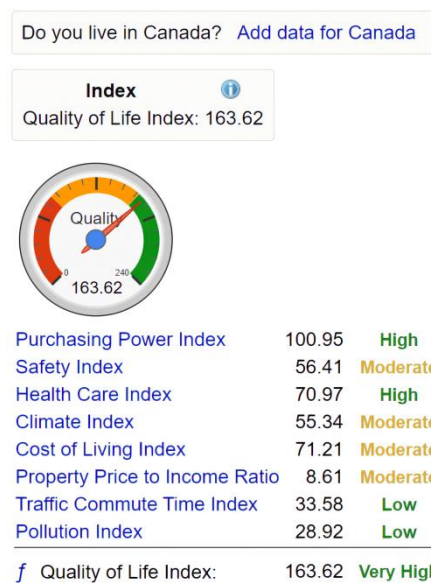


Figure 14. Quality of Life Data in Canada [194].

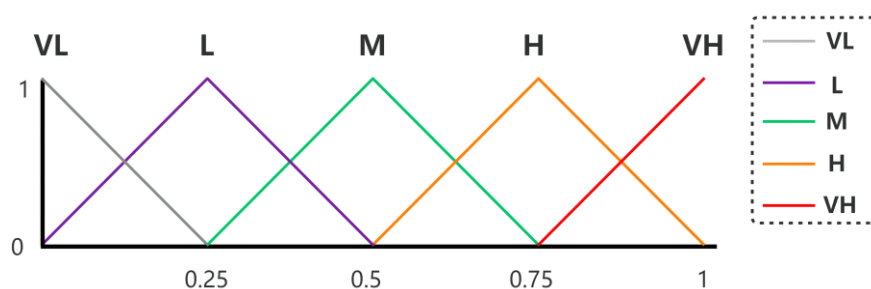


Figure 15. Linguistic term set  $S$  used by Numbeo [194].

After data collection, the subsequent three steps involved employing distinct methods and techniques to establish the weighting vector for each linguistic quantifier using Equation (8),

generate multiple alternative scenarios for the weight of each indicator, and in the fourth step, calculate various QOLIs based on the alternative scenarios for the weights obtained previously. The concepts employed in this work within the methods and techniques layer can be found in Sections 2.1 and 2.2.

The weights assigned to each sub-indicator by Numbeo's experts in calculating the QOLI are as follows: HPTIR (25.64%), PI (17.09%), SI (12.82%), TCTI (12.82%), PPI (10.26%), HCI (10.26%), CLI (8.55%), and COLI (2.56%). Table 9 shows the results of multiplying the weights assigned to each sub-indicator by the weighting vector for each quantifier. Table 10 shows the results of employing various linguistic quantifiers to calculate the QOLI for the top 10 countries, while Table 11 presents the corresponding results for the worst 10 countries.

**Table 9.** Recalculated weights (%) for each sub-indicator, adapted from [194].

	<i>At least one</i>	<i>Few</i>	<i>Some</i>	<i>Half</i>	<i>Many</i>	<i>Most</i>	<i>All</i>
HPTIR	99.99	88.57	52.39	25.64	5.65	-	-
PI	0.01	4.24	14.47	17.09	11.30	-	-
SI	-	1.97	8.33	12.82	14.12	0.34	-
TCTI	-	1.97	8.33	12.82	14.12	0.34	-
PPI	-	1.15	5.62	10.26	15.82	4.49	-
HCI	-	1.15	5.62	10.26	15.82	4.49	-
CLI	-	0.76	4.12	8.55	16.95	32.92	-
COLI	-	0.19	1.12	2.56	6.22	57.42	100

The final step involved analyzing and comparing the results. As shown in Tables 10 and 11, using the linguistic quantifier *Half* for numerical calculations of the QOLI results in the same value as Numbeo, with only a minor difference in decimals. However, in other cases, there are indeed changes, with even the rankings based on the 2-tuple values generated with the quantifier *Half* showing slight differences. For example, although ranked sixth from the bottom (number 80) according to Numbeo, Peru holds the lowest position when linguistic quantifiers *Few*, *Some*, and *Half* are employed to calculate its 2-tuple value of QOLI. Refer to [194] for the re-ranking results of countries based on various QOLI scenarios, the average rank difference between Numbeo's QOLI and those produced by diverse linguistic quantifiers, alongside other uncertainty and sensitivity analyses conducted.

**Table 10.** Numbeo top 10 countries in terms of QOLI [194].

R	Country	Quality of Life Index							
		<i>Numbeo</i>	<i>At Least One</i>	<i>Few</i>	<i>Some</i>	<i>Half</i>	<i>Many</i>	<i>Most</i>	<i>All</i>
1	Switzerland	195.27	67.66	82.09	138.06	195.34	259.33	-38.74	-381.065
2	Denmark	192.36	73.55	86.42	137.72	192.41	258.43	48.68	-228.068
3	Netherlands	185.38	72.11	83.95	132.31	185.44	252.14	71.64	-195.074
4	Finland	184.96	68.99	82.63	134.12	185.00	240.60	38.69	-185.48
5	Australia	183.81	71.91	83.20	130.33	183.87	254.85	77.19	-203.225
6	Iceland	182.26	75.19	87.54	134.84	182.30	233.81	1.78	-269.954
7	Germany	180.27	65.17	76.93	125.68	180.32	251.08	90.29	-155.762
8	Austria	179.16	58.07	71.66	124.53	179.21	243.47	67.57	-177.06
9	New Zealand	176.81	68.95	79.94	125.51	176.86	244.79	85.09	-190.628
10	Norway	176.39	68.64	80.74	127.87	176.44	231.53	-9.25	-293.51
1	Switzerland	VH	(M, -0.0002)	(M, +0.1625)	(H, -0.3566)	(H, -0.0597)	(H, +0.0281)	(L, +0.3223)	VH
2	Denmark	VH	L	(H, +0.0153)	(H, +0.075)	(H, +0.1369)	(H, +0.2033)	(M, +0.2257)	H
3	Netherlands	VH	L	(H, +0.0038)	(H, +0.0188)	(H, +0.0343)	(H, +0.0451)	(M, +0.1808)	H
4	Finland	VH	(L, -0.0001)	(H, +0.0329)	(H, +0.0923)	(H, +0.0598)	(H, -0.1187)	(M, +0.0966)	M
5	Australia	VH	L	(H, -0.0159)	(H, -0.0645)	(H, -0.0939)	(H, -0.0961)	(M, +0.1774)	H
6	Iceland	VH	(L, -0.0001)	(H, +0.0449)	(H, +0.1382)	(H, +0.1197)	(H, -0.0906)	(L, +0.2359)	VH
7	Germany	VH	(M, -0.0001)	(M, +0.12)	(H, -0.4939)	(H, -0.1965)	(H, +0.0508)	(H, -0.245)	M
8	Austria	VH	(M, -0.0001)	(M, +0.1206)	(M, +0.492)	(H, -0.2564)	(H, -0.1357)	(M, +0.3843)	M
9	New Zealand	VH	(M, -0.0001)	(M, +0.0869)	(M, +0.3554)	(H, -0.4529)	(H, -0.3108)	(M, +0.1325)	H
10	Norway	VH	(M, -0.0002)	(M, +0.1592)	(H, -0.3857)	(H, -0.1367)	(H, -0.1471)	(L, +0.2359)	VH

The results of the 2-tuple value are marked with an orange background.

**Table 11.** Numbeo worst 10 countries in terms of QOLI [194].

R	Country	Quality of Life Index							
		Numbeo	At Least One	Few	Some	Half	Many	Most	All
76	Indonesia	90.36	14.49	19.40	47.99	90.39	158.17	122.05	-39.82
77	Vietnam	89.95	19.87	22.57	46.85	89.99	163.68	123.32	-46.17
78	Egypt	89.87	53.02	50.55	58.36	89.90	159.22	164.06	-15.13
79	Philippines	83.74	-15.61	-7.62	31.80	83.77	160.90	121.78	-44.53
80	Peru	80.42	24.12	24.33	41.10	80.47	159.20	167.14	-26.87
81	Venezuela	77.43	44.01	41.70	48.56	77.47	143.22	140.90	-68.48
82	Sri Lanka	67.88	-79.29	-62.99	0.82	67.91	152.14	121.84	-22.03
83	Bangladesh	67.59	47.17	42.58	42.89	67.62	129.66	128.91	-29.21
84	Iran	64.89	-28.72	-21.35	15.57	64.92	139.29	112.96	-45.82
85	Nigeria	52.44	37.14	31.93	29.96	52.47	111.76	119.50	-18.91
76	Indonesia	VL	(VH, -0.0001)	(VL, +0.1664)	(L, -0.2684)	(L, +0.2222)	(M, -0.2315)	(H, +0.4293)	VL
77	Vietnam	VL	VH	(VL, +0.1519)	(L, -0.3027)	(L, +0.2051)	(M, -0.2203)	(H, +0.3912)	VL
78	Egypt	VL	(M, +0.0001)	(M, -0.1085)	(M, -0.3803)	(M, -0.453)	(M, -0.2202)	(VH, -0.2864)	VL
79	Philippines	VL	(VH, -0.0001)	(VL, +0.1664)	(L, -0.2684)	(L, +0.2222)	(M, -0.2315)	(H, +0.4293)	VL
80	Peru	VL	VH	(VL, +0.1004)	(VL, +0.4886)	(L, -0.094)	(M, -0.4744)	(VH, -0.2898)	VL
81	Venezuela	VL	(VH, -0.0001)	(VL, +0.1491)	(L, -0.3508)	(L, +0.0769)	(M, -0.4406)	(H, +0.0945)	L
82	Sri Lanka	VL	(VH, -0.0001)	(VL, +0.1391)	(L, -0.3929)	(L, +0.0085)	(L, +0.4578)	(H, +0.0967)	VL
83	Bangladesh	VL	(H, +0.0001)	(L, -0.0412)	(L, -0.112)	(L, -0.0513)	(L, +0.2714)	(H, +0.3776)	VL
84	Iran	VL	(VH, -0.0001)	(VL, +0.1549)	(L, -0.3246)	(L, +0.1196)	(M, -0.3897)	(H, +0.3844)	VL
85	Nigeria	VL	(H, +0.0001)	(L, -0.0412)	(L, -0.112)	(L, -0.0513)	(L, +0.2714)	(H, +0.3776)	VL

The results of the 2-tuple value are marked with an orange background.

Moreover, to explore the relationship between economic development and quality of life across different countries, the QOLI of the top 15 countries in the 2021 GDP ranking [196] were analyzed (refer to Table 12). It can be observed that not all countries with high GDP exhibit high QOLI. Only Australia and Germany have QOLIs ranking in the top 10 of Numbeo's rankings, while Brazil, China, and Russia rank below 60. Despite having a higher GDP, emerging countries such as India, Brazil,



R	Country	$R_{GDP}$	Numbeo	Quality of Life Index						All
				At Least One	Few	Some	Half	Many	Most	
26	France	7	H	M	(M, +0.0363)	(M, +0.1836)	(M, +0.3506)	(H, -0.4068)	(M, +0.1774)	H
36	Italy	8	M	M	(M, +0.0464)	(M, +0.2219)	(M, +0.4018)	(H, -0.3616)	(H, -0.2933)	M
23	Canada	9	VH	L	(H, -0.0292)	(H, -0.1357)	(H, -0.2393)	(H, -0.3729)	(M, +0.0932)	M
45	South Korea	10	M	(VH, -0.0001)	(VL, +0.2346)	(L, +0.0332)	(M, -0.2904)	(M, +0.3389)	(M, -0.1518)	H
69	Russia	11	L	H	(L, +0.0527)	(L, +0.2414)	(L, +0.4187)	(M, -0.3615)	(H, +0.0586)	VL
64	Brazil	12	L	(VH, -0.0002)	(VL, +0.1852)	(L, -0.222)	(L, +0.2478)	(M, -0.2484)	(VH, -0.2898)	VL
5	Australia	13	VH	L	(H, -0.0159)	(H, -0.0645)	(H, -0.0939)	(H, -0.0961)	(M, +0.1774)	H
18	Spain	14	VH	(M, -0.0001)	(M, +0.1104)	(M, +0.4611)	(H, -0.2735)	(H, -0.0452)	(H, +0.2843)	L
46	Mexico	15	M	M	(M, +0.0075)	(M, +0.0486)	(M, +0.1196)	(M, +0.3052)	(VH, -0.2381)	VL

The results of the 2-tuple value are marked with an orange background.

Another noteworthy aspect is that, compared with the simple linguistic terms used by Numbeo, 2-tuple values can effectively reflect information without losing it and facilitate comparisons of linguistic information across different countries. For instance, as demonstrated in Table 12, Numbeo categorizes Italy and Mexico as countries with a medium quality of life (i.e., solely with a linguistic term "M"), making it difficult to determine which country possesses a higher QOLI only by comparing their linguistic terms. However, when applying the quantifiers *Few*, *Some*, *Half*, and *Many* to compute their QOLIs expressed in 2-tuple values, it becomes evident that Italy has a higher QOLI than Mexico.

### 3.3.3. Conclusions

This work presented a new approach to calculating the QOLI, employing multiple linguistic quantifiers of the OWA aggregation operator to construct the QOLI across diverse scenarios, and ultimately interpreting the QOLI with its 2-tuple value. The applicability of the proposed model has

been demonstrated using the Numbeo database, which includes the quality of life information for different countries. The main advantages of the proposed model are outlined below:

- **Flexible weight adjustment:** Incorporating weights generated by linguistic quantifiers allows for not only the best-balanced scenario suggested by Numbeo's experts but also numerous scenarios with different indicator weights.
- **Flexible value conversion:** Computing the QOLI in both numerical values and 2-tuple values enables conducting various analyses in combination with other methods, accommodating diverse needs and perspectives to make necessary comparisons.
- **Reduction of information loss in the aggregation process:** By measuring the difference between the linguistic term and the value of a symbolic aggregation operation, a more accurate distinction of the quality of life among countries labeled with the same linguistic term by Numbeo becomes possible, preserving data integrity.
- **Diverse QOLI scenarios for decision-making:** Generating diverse QOLI scenarios with linguistic interpretability helps policymakers assess quality of life levels and tailor improvement policies to their country's conditions.

While this work presented a valuable approach, some limitations were identified that should be addressed in future research. For example, although the proposed model can generate diverse QOLIs for clearer representation of quality of life across countries, it is impossible to compare the ranking of various countries with their QOLI produced by different linguistic quantifiers. Future work could explore using unsupervised techniques like clustering to classify countries based on their QOLIs generated by different quantifiers. Furthermore, future work could expand by incorporating additional sub-indicators to build the QOLI. The proposed model could also be enhanced by integrating the aggregation operator with various weight assignment methods.

## **3.4. Ranking Luxury Hotels in Lisbon Using the 2T-AEC-TOPSIS Model**

### **3.4.1. Introduction**

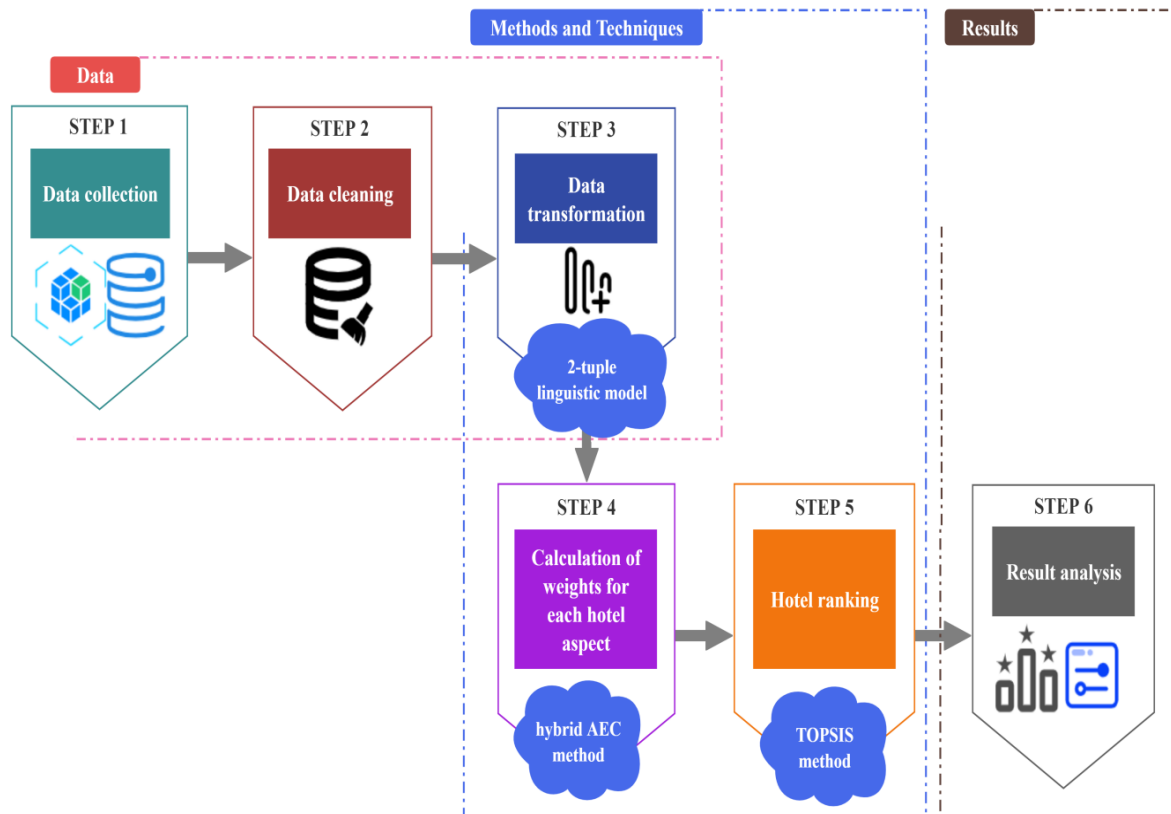
Our daily lives are inundated with rankings, and with the development of the Internet, online reviews have become increasingly influential in this process. These rankings, found on many review sites, evaluate various aspects of hotels, restaurants, and more. For example, the ranking system that TripAdvisor uses to evaluate hotels takes into account multiple criteria such as rooms, service, location, and cleanliness. Hotel rankings play a crucial role in helping customers select suitable accommodations efficiently and enable hotel managers to improve their services by comparing their performance with that of their competitors. However, most ranking models use equal weighting for various hotel aspect performances, although MCDM methods are frequently employed for ranking purposes. From a business perspective, improving weight determination to reflect better the varying importance of multiple aspects in hotel rankings and enhancing ranking results interpretation is necessary.

Therefore, this work aims to propose a novel model for hotel ranking by integrating multiple methods. Specifically, it uses the hybrid AEC method, the 2-tuple linguistic model, and the TOPSIS method. The model combines weights generated by the AHP, Entropy, and CRITIC methods, creating integrated weights that blend the benefits of both objective and subjective weighting approaches. These integrated weights are then used in the TOPSIS method to rank hotels, as to the best of our knowledge, no previous studies have used the hybrid AEC method for weight determination in the TOPSIS method [197]. Additionally, the 2-tuple linguistic model is applied to enhance the interpretability of ranking results and prevent information loss during linguistic fusion. The functionality of the proposed model is evaluated using a dataset of over 26,000 customer reviews gathered from TripAdvisor for luxury hotels in Lisbon, resulting in a top 10 list of luxury hotels for various scenarios.

### 3.4.2. Proposed Model and Its Application for Hotel Ranking

The proposed model is developed based on three layers: data, methods and techniques, and results.

Figure 16 shows the steps within these layers.



**Figure 16.** Steps of the model for hotel ranking.

The first step involved gathering customer reviews from TripAdvisor for 41 luxury hotels in Lisbon. This work chose TripAdvisor to gather data due to its widespread recognition and popularity among customers [198]. This data collection spanned from January 1, 2013, to December 31, 2022, resulting in a total of 44,755 reviews. However, in this dataset, not all aspects of the hotel (i.e., Service, Cleanliness, Rooms, Sleep quality, Location, Value, Business Service, and Check-In) were evaluated by every customer. Among these, Business Service and Check-In were not evaluated by any customers in this dataset. Of the reviews, 37.85% were evaluated based on three aspects, and 21.94% covered six aspects, with the proportion of other cases being negligible [197]. Therefore, data cleaning was conducted, focusing on customer reviews containing sub-ratings for either three or six aspects. Table 13 presents the number of customer

reviews and hotels in various scenarios; scenarios lacking customer reviews are excluded.

**Table 13.** Number of customer reviews and hotels in different scenarios [197].

Scenario ID	Included hotel aspects	Number of customer reviews	Number of hotels
$G_1$	Rooms, Service, Cleanliness, Sleep quality, Location, Value	9820	27
$G_2$	Service, Cleanliness, Sleep quality	1661	38
$G_3$	Service, Cleanliness, Location	1713	37
$G_4$	Service, Cleanliness, Value	1673	37
$G_5$	Service, Sleep quality, Location	1688	37
$G_6$	Service, Sleep quality, Value	1613	37
$G_7$	Service, Location, Value	1791	38
$G_8$	Rooms, Service, Cleanliness	1688	39
$G_9$	Rooms, Service, Sleep quality	1712	37
$G_{10}$	Rooms, Service, Location	1684	36
$G_{11}$	Rooms, Service, Value	1698	37
$G_{12}$	Rooms, Cleanliness, Sleep quality	20	2

Due to the very low number of customer reviews for scenario  $G_{12}$ , which was inadequate for thorough analysis and decision-making, this scenario was removed. Moreover, to ensure hotel rankings can be compared across the remaining 11 scenarios, only those hotels present in all 11 scenarios were considered in this work. In the end, only 25 hotels met this requirement, with a total of 26,037 reviews. The number of reviews for these hotels across various scenarios can be found in [197].

The methods used in steps three to five included the 2-tuple linguistic model, the hybrid AEC method, and the TOPSIS method. These concepts have been introduced in Sections 2.1, 2.3.5.3, and 2.3.4, respectively. The third step employed Equation (4) to aggregate the diverse customer reviews of the hotel's aspects into 2-tuple values. As mentioned in Section 2.1, the linguistic term set  $S$  used on TripAdvisor to evaluate hotel aspects consists of five terms: Terrible ( $T$ ), Poor ( $P$ ), Average ( $A$ ), Very Good ( $VG$ ), and Excellent ( $E$ ), giving  $S = \{s_0, \dots, s_g\}$  with  $g=4$ :  $s_0 = T$ ,  $s_1 = P$ ,  $s_2 = A$ ,  $s_3 = VG$ ,  $s_4 = E$ , as shown in Figure 4. Table 14 shows the results obtained for each hotel based on six aspects used for evaluation.

The fourth step in the proposed model used the hybrid AEC method to calculate weights for

each aspect of the hotel. Table 15 shows the weights for six aspects, computed separately by the AHP method, Entropy method, and CRITIC method. These weights were aggregated to calculate the integrated AEC weights using Equation (27). The integrated weights from these three methods, as shown in Table 15, indicate that the hybrid AEC method has achieved a relatively balanced and realistic distribution of weights across various hotel aspects.

**Table 14.** Performance matrix for 25 hotels (six aspects) [197].

Hotel ID	Rooms	Service	Cleanliness	Sleep quality	Location	Value
$H_1$	(VG, +0.3735)	(E, -0.3132)	(E, -0.2993)	(E, -0.3875)	(E, -0.1044)	(VG, +0.3248)
$H_2$	(E, -0.2042)	(E, -0.2667)	(E, -0.25)	(E, -0.2458)	(E, -0.4042)	(VG, +0.3125)
$H_3$	(VG, +0.2338)	(VG, +0.3632)	(VG, +0.4577)	(VG, +0.2687)	(VG, +0.4726)	(VG, +0.0995)
$H_4$	(VG, +0.4273)	(E, -0.2238)	(E, -0.2151)	(E, -0.3924)	(E, -0.093)	(VG, +0.2936)
$H_5$	(VG, +0.475)	(E, -0.4417)	(E, -0.3562)	(E, -0.3895)	(VG, +0.0185)	(VG, +0.3645)
$H_6$	(VG, +0.4434)	(VG, +0.4857)	(E, -0.4072)	(E, -0.454)	(VG, +0.1041)	(VG, +0.2127)
$H_7$	(E, -0.1681)	(E, -0.2941)	(E, -0.1471)	(E, -0.2437)	(VG, +0.0462)	(E, -0.5)
$H_8$	(E, -0.3964)	(E, -0.2364)	(E, -0.1764)	(E, -0.2509)	(VG, +0.4291)	(VG, +0.2145)
$H_9$	(E, -0.3742)	(E, -0.1733)	(E, -0.1887)	(E, -0.3144)	(E, -0.0445)	(E, -0.3727)
$H_{10}$	(E, -0.25)	(E, -0.5)	(E, -0.3333)	(E, -0.3333)	(VG, +0.3333)	(VG, +0.4167)
$H_{11}$	(E, -0.237)	(E, -0.1926)	(E, -0.1481)	(E, -0.1556)	(VG, +0.4148)	(VG, +0.363)
$H_{12}$	(E, -0.28)	(E, -0.216)	(E, -0.136)	(E, -0.192)	(E, -0.144)	(E, -0.416)
$H_{13}$	(E, -0.5)	E	E	E	(E, -0.5)	E
$H_{14}$	(E, -0.1916)	(E, -0.1018)	(E, -0.0838)	(E, -0.3593)	(VG, +0.2335)	(VG, +0.3713)
$H_{15}$	(E, -0.0581)	(E, -0.0349)	(E, -0.0581)	(E, -0.1279)	(E, -0.2674)	(E, -0.314)
$H_{16}$	(VG, +0.4675)	(E, -0.3496)	(E, -0.2937)	(E, -0.4461)	(VG, +0.1738)	(VG, +0.2866)
$H_{17}$	(E, -0.4874)	(E, -0.2773)	(E, -0.3361)	(E, -0.3193)	(E, -0.1849)	(E, -0.4286)
$H_{18}$	(E, -0.3784)	(E, -0.1892)	(E, -0.1243)	(E, -0.3784)	(E, -0.0649)	(VG, +0.3405)
$H_{19}$	(E, -0.1429)	(E, -0.0895)	(E, -0.0629)	(E, -0.1314)	(E, -0.1048)	(E, -0.3219)
$H_{20}$	(E, -0.4769)	(VG, +0.2154)	(E, -0.3692)	(E, -0.4092)	(VG, +0.0462)	(VG, -0.1015)
$H_{21}$	(VG, +0.2905)	(E, -0.4038)	(E, -0.3752)	(E, -0.4457)	(E, -0.2029)	(VG, +0.1876)
$H_{22}$	(E, -0.1667)	(E, -0.2157)	(E, -0.1176)	(E, -0.2745)	(E, -0.1373)	(E, -0.4951)
$H_{23}$	(VG, +0.4638)	(E, -0.2862)	(E, -0.2368)	(VG, +0.4803)	(E, -0.2303)	(VG, +0.3191)
$H_{24}$	(E, -0.1957)	(E, -0.1739)	(E, -0.1739)	(E, -0.1304)	(E, -0.2391)	(E, -0.3261)
$H_{25}$	(VG, +0.4286)	(E, -0.1429)	E	(E, -0.1429)	(E, -0.1429)	VG

The fifth step used the weights generated by the hybrid AEC method in the TOPSIS method to construct the weighted normalized decision matrix and calculate relative closeness values for ranking the hotels. Table 16 lists the top 10 luxury hotels for various scenarios in Table 13. The final step analyzed the obtained results. As shown in Table 16, luxury hotel customers, or potential guests,

can receive recommendations for the top 10 luxury hotels in Lisbon based on the hotels' performance in either six or three different aspects. For instance, when considering all six aspects (i.e.,  $G_1$ ) in hotel rankings, hotel  $H_{19}$  ranked first. Combined with Table 14,  $H_{19}$  garnered almost excellent evaluations in Rooms, Service, Cleanliness, Sleep quality, Location, and Value. Although hotel  $H_{13}$  boasted complete excellence in Service, Cleanliness, Sleep quality, and Value, its evaluation in Rooms and Location fell below those of  $H_{19}$ , leading to its lower ranking. Similarly, the ranking results and the 2-tuple values of hotel aspects also enable hotel managers to evaluate their performance compared to competitors and identify the aspects they should enhance to improve their ranking. For example, when comparing hotel  $H_{19}$  to the tenth-ranked hotel  $H_4$ ,  $H_{19}$  excelled in all six aspects, while the Value and Rooms of  $H_4$  were rated as "Very Good," falling clearly below "Excellent."

**Table 15.** Weight assignment for six hotel aspects [197].

<b>Hotel aspect</b>	<b>Weights derived from the Entropy method (%)</b>	<b>Weights derived from the CRITIC method (%)</b>	<b>Weights derived from the AHP method (%)</b>	<b>Integrated AEC weights (%)</b>
Rooms	17.01	13.44	9.7	14.88
Service	9.95	11.31	16.9	14.13
Cleanliness	8.01	6.01	30.9	13.02
Sleep quality	9.88	8.25	25.8	14.61
Location	37	38.08	12.7	29.84
Value	18.15	22.91	4	13.52

**Table 16.** Top 10 luxury hotels under 11 scenarios [197].

<b>Scenario ID</b>	<b>Hotel rankings</b>
$G_1$	$H_{19} > H_{15} > H_{24} > H_{12} > H_9 > H_{22} > H_{13} > H_{18} > H_{17} > H_4$
$G_2$	$H_{15} > H_{25} > H_{14} > H_{22} > H_{12} > H_8 > H_{11} > H_9 > H_{10} > H_{19}$
$G_3$	$H_{22} > H_4 > H_9 > H_{25} > H_{12} > H_1 > H_{19} > H_{15} > H_{23} > H_{18}$
$G_4$	$H_{22} > H_{10} > H_9 > H_{15} > H_{25} > H_{24} > H_{19} > H_{14} > H_1 > H_{11}$
$G_5$	$H_{25} > H_4 > H_{18} > H_9 > H_1 > H_{19} > H_{22} > H_{15} > H_{21} > H_{17}$
$G_6$	$H_{25} > H_{15} > H_{22} > H_{10} > H_9 > H_2 > H_{24} > H_{13} > H_{17} > H_{14}$
$G_7$	$H_{22} > H_9 > H_{24} > H_{15} > H_{19} > H_1 > H_{18} > H_{23} > H_{25} > H_{12}$
$G_8$	$H_{15} > H_{22} > H_4 > H_{12} > H_{14} > H_{24} > H_{17} > H_9 > H_2 > H_{25}$
$G_9$	$H_{12} > H_{22} > H_{14} > H_{15} > H_{24} > H_2 > H_9 > H_{19} > H_{25} > H_{13}$
$G_{10}$	$H_{22} > H_{25} > H_9 > H_{15} > H_{19} > H_{24} > H_{18} > H_2 > H_1 > H_4$
$G_{11}$	$H_{15} > H_{22} > H_{11} > H_{12} > H_9 > H_4 > H_7 > H_{14} > H_{24} > H_{18}$

### 3.4.3. Conclusions

This work presented a novel model for hotel ranking using the hybrid AEC method, the 2-tuple linguistic model, and the TOPSIS method. The proposed model incorporated the 2-tuple linguistic model to aggregate linguistic ratings for each hotel aspect, thereby avoiding the issue of information loss in linguistic information fusion. Moreover, it combined the advantages of objective and subjective weighting methods in the weight processing of the TOPSIS method using the hybrid AEC method. The proposed model was evaluated using a dataset of over 26,000 customer reviews from TripAdvisor for luxury hotels in Lisbon, demonstrating its functionality. The results demonstrated the model's effectiveness in generating a balanced and realistic weight distribution by considering each criterion's internal data structure, their interrelationships, and expert opinions, into the decision-making process. The model's practical implications include assisting hotel managers in identifying specific aspects to enhance to improve their ranking, and enabling customers to make informed accommodation decisions with more understandable hotel rankings.

However, this work still had certain limitations that future research should address. For instance, although this work enhanced the weight assignment in the TOPSIS method, future studies should explore using other distance metrics, such as Manhattan Distance and Hamming Distance, to determine if they yield better ranking results compared to the Euclidean distance used in this work. Future work could also incorporate time series analysis to provide a dynamic ranking that changes over different periods. Finally, the dataset collected in this paper was limited to data from luxury hotels in Lisbon. Future work should encompass data from diverse hotel categories to achieve a more comprehensive ranking of the hotel industry in Lisbon.

## **3.5. Hotel Customer Segmentation Using the Integrated Entropy-CRITIC Method and the 2T-RFMB Model**

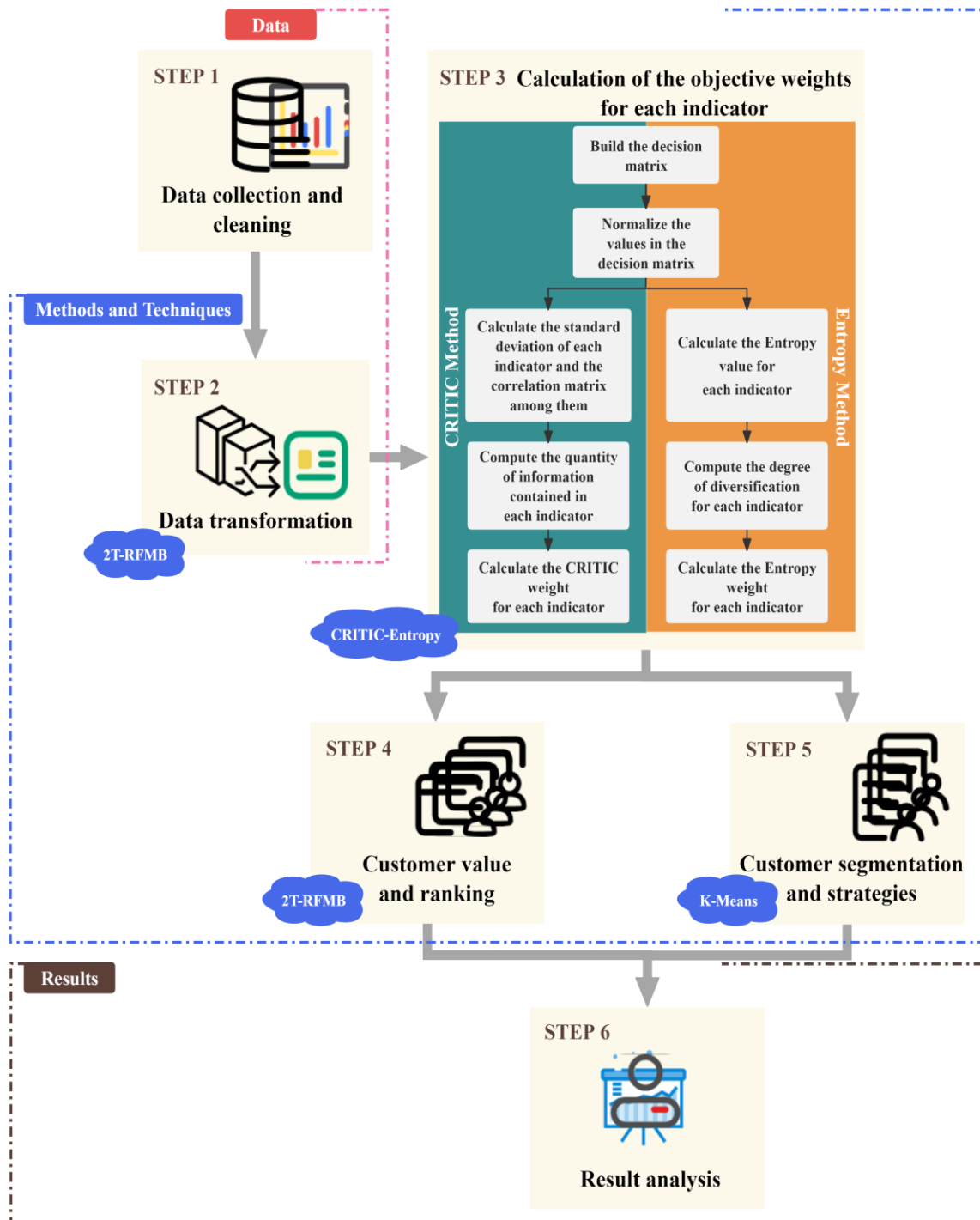
### **3.5.1. Introduction**

Customers are vital to any business, playing a pivotal role in its success and growth. Customer segmentation is a strategic process that assists business decision-makers in identifying the value of customers, targeting valuable customers, and developing suitable marketing strategies to attract or retain them. The RFM model is the most widely applied in customer behavior analysis [199-201]. It evaluates Recency, Frequency, and Monetary value to estimate customer value, thus categorizing customers into segments. However, as mentioned in Section 2.5.2, not all industries can fully adhere to the RFM principle since customer behaviors vary across different sectors, necessitating the modification of certain indicators from the original RFM model to suit each specific case.

Therefore, this work aims to develop a novel customer analysis model based on the original RFM model, considering the specific characteristics of the hotel industry. The proposed model improves the RFM framework with four indicators crucial for segmenting hotel customers: Recency, Frequency, Monetary value, and Bonding. In the Monetary Value indicator, consideration is given to the potential loss to the hotel if a customer cancels their reservation. A new indicator, Bonding, representing the degree of customer loyalty to the hotel, is also introduced. Further details on these four indicators can be consulted in Section 2.5.2.1. Moreover, to provide hotel managers with easily understandable customer segmentation results, the proposed model also incorporates the 2-tuple linguistic model, resulting in the 2T-RFMB model. The hybrid CRITIC-Entropy method, which combines two objective weights, is employed to establish an appropriate weight distribution, thereby computing the overall 2T-RFMB value for each customer. Finally, K-Means clustering is applied to generate diverse customer groups for the selected dataset.

### **3.5.2. Proposed Model and Its Application for Customer Segmentation**

The proposed model is developed based on three layers: data, methods and techniques, and results. Figure 17 shows the steps of the proposed model among these layers.



**Figure 17.** Steps for developing the proposed customer segmentation model.

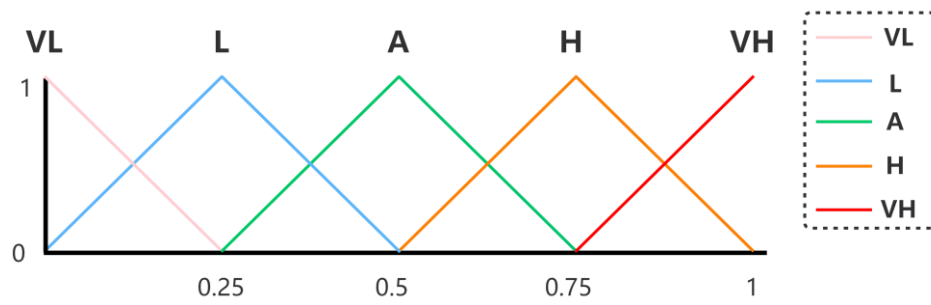
The proposed model was applied to a dataset containing the behavioral data of 83,590 customers at a hotel in Lisbon from 2015 to 2018 [202]. The initial step involved collecting data and subsequently cleaning it in preparation for further analysis. On the one hand, considering the characteristics of the proposed model, only some variables (i.e., CustomerID, LodgingRevenue,

OtherRevenue, BookingsCheckedIn, BookingsCanceled, BookingsNoShowed, DaysSinceFirstStay, and DaysSinceLastStay) were retained from the original dataset of 31 variables. The description of these variables can be consulted in [136]. On the other hand, some of the 83,590 customers have only registered on the hotel website but never stayed. Consequently, only the 63,670 customers who did stay at the hotel were used for further analysis. Table 17 shows some customer data from the dataset after data cleaning.

**Table 17.** Customer data example, adapted from [136].

<b>CustomerID</b>	<b>9865</b>	<b>54772</b>	<b>11426</b>	<b>54505</b>	<b>61562</b>
LodgingRevenue	134.1	413	468.9	385	142.5
OtherRevenue	27.5	49	224	70.8	10
BookingsCheckedIn	1	5	1	2	1
BookingsCanceled	0	1	0	0	0
BookingsNoShowed	0	0	0	0	0
DaysSinceFirstStay	905	242	883	245	187
DaysSinceLastStay	905	118	883	177	187

The methods and techniques employed in steps two to five involved the 2T-RFMB model, the hybrid CRITIC-Entropy method, and K-Means clustering. These concepts have been introduced in Sections 2.5.2.1, 2.3.5.2, and 2.4.2, respectively. The 2T-RFMB model represents a combination of the 2-tuple linguistic model and the RFMB model, adjusting the RFM framework to suit the characteristics of the hotel industry while enhancing result interpretability and mitigating potential information loss in calculations. The second step of the proposed model employed the 2T-RFMB model to transform customer data into RFMB data (i.e., Recency, Frequency, Monetary value, and Bonding) and express these data with 2-tuple values. The linguistic term set  $S$  employed in this work has five terms: Very Low ( $VL$ ), Low ( $L$ ), Average ( $A$ ), High ( $H$ ), and Very High ( $VH$ ), giving  $S = \{s_0, \dots, s_g\}$  with  $g=4$ :  $s_0 = VL$ ,  $s_1 = L$ ,  $s_2 = A$ ,  $s_3 = H$ ,  $s_4 = VH$ , as shown in Figure 18. Table 18 displays some customer RFMB data represented in 2-tuple values.



**Figure 18.** Linguistic term set  $S$  for hotel customer segmentation [136].

**Table 18.** Customer RFMB data example, adapted from [136].

CustomerID	Recency	Frequency	Monetary	Bonding
9865	(L, -0.2788)	VL	(L, -0.4468)	VL
54772	(VH, -0.4276)	(VL, +0.246)	(A, -0.0456)	(VL, +0.4732)
11426	(L, -0.1992)	VL	(H, +0.31)	VL
54505	(H, +0.3588)	(VL, +0.0616)	(A, +0.4888)	(VL, +0.2596)
61562	(H, +0.3224)	VL	(L, -0.492)	VL

The third step of the proposed model used the hybrid CRITIC-Entropy method to calculate objective weights for the four indicators: Recency, Frequency, Monetary value, and Bonding. Given that each indicator's value is represented in a 2-tuple value, before engaging in numerical computation, it is necessary to use the function  $\Delta^{-1}$  (see Equation (2)) to transform the 2-tuple value into its numerical value. Table 19 shows the CRITIC weights, Entropy weights, and the integrated CRITIC-Entropy weights generated for each indicator.

**Table 19.** Weights for each RFMB indicator [136].

Indicator	CRITIC weights (%)	Entropy weights (%)	Integrated CRITIC-Entropy weights (%)
Recency	45.4	1.62	20.28
Frequency	1.32	45.64	18.36
Monetary	48.18	2.02	23.33
Bonding	5.1	50.72	38.03

The fourth step of the proposed model employed Equation (34) to calculate each customer's 2T-RFMB overall value and rank them. Refer to [136] for computed results for more customers and their related rankings. Below is an example demonstrating the computation of the 2T-RFMB overall value for customer 54505:  $\Delta(\Delta^{-1}(H, +0.3588) \cdot 20.28\% + \Delta^{-1}(VL, +0.0616) \cdot$

$$18.36\% + \Delta^{-1}(A, +0.4888) \cdot 23.33\% + \Delta^{-1}(VL, +0.2596) \cdot 38.03\% = \Delta(3.3588 \cdot 20.28\% + 0.0616 \cdot 18.36\% + 2.4888 \cdot 23.33\% + 0.2596 \cdot 38.03\%) = \Delta(1.3718) = (L, +0.3718).$$

The fifth step of the proposed model used K-means clustering to generate various customer groups. The Elbow Method suggested that the optimal number of clusters was ten. Table 20 shows the 2-tuple values for the cluster centroids of these ten customer groups. The characteristic descriptions of each cluster can be found in [136]. The final step analyzed the results obtained by the proposed model. As shown in Table 20, all ten customer groups exhibit very low frequency and bonding, indicating minimal interaction by the hotel with its customers and a lack of long-term relationship management. An action this hotel should take for all clusters is to establish long-term relationships, encouraging customers to stay at the hotel. When facing resource constraints or the need for cost control, this hotel should focus on delivering personalized service and deep communication to clusters with higher customer monetary value and recency, as these clusters have been found to be more valuable in this work than those in other clusters.

**Table 20.** Customer cluster results, adapted from [136].

Cluster ID	Number of customers	Recency	Frequency	Monetary	Bonding
1	6112	(L, -0.1638)	(VL, +0.0016)	(H, +0.2378)	(VL, +0.0025)
2	4951	(H, +0.3257)	(VL, +0.003)	(VL, +0.4916)	(VL, +0.0219)
3	7330	(L, -0.277)	(VL, +0.0005)	(L, -0.4096)	(VL, +0.0018)
4	5990	(H, +0.3226)	(VL, +0.0025)	(H, -0.4313)	(VL, +0.0115)
5	6846	(A, +0.0995)	(VL, +0.0032)	(H, +0.388)	(VL, +0.0117)
6	5382	(H, +0.3057)	(VL, +0.0018)	(A, -0.4269)	(VL, +0.0131)
7	7480	(A, -0.0138)	(VL, +0.0008)	(L, -0.2442)	(VL, +0.007)
8	7160	(A, +0.0093)	(VL, +0.0009)	(A, +0.1321)	(VL, +0.0043)
9	6539	(L, -0.2237)	(VL, +0.0007)	(A, -0.1794)	(VL, +0.0014)
10	5880	(H, +0.3805)	(VL, +0.0133)	(VH, -0.4546)	(VL, +0.0474)
AoD*	63670	(A, +0.0912)	(VL, +0.003)	(A, -0.0012)	(VL, +0.012)

\* AoD shows the average of the 63,670 customers.

### 3.5.3. Conclusions

This work developed a novel method for customer segmentation, employing the 2T-RFMB model,

the hybrid CRITIC-Entropy method, and K-Means clustering. The proposed model was successfully applied to a dataset containing behavioral data from 83,590 customers at a hotel in Lisbon, demonstrating its applicability. The results demonstrated the following advantages of the proposed model:

- Consideration of the relationship between different indicators and the level of data diversification contained in each indicator in determining the weights for the indicators.
- Provide hotel managers with linguistically easy-to-understand clustering results and customer values, enabling them to develop more efficient resource distribution strategies.

However, this work also had some limitations that should be addressed in future work. For example, this work only employed objective weighting approaches to calculate the weight of each indicator in the 2T-RFMB model, without considering decision-makers opinions. Future work could combine the hybrid CRITIC-Entropy method with other methods to incorporate subjective weights given by decision-makers. Other clustering techniques, such as hierarchical clustering, WKM clustering, and others, could be applied to the same dataset to compare their clustering results with those obtained in the current work.

## **3.6. A Model Integrating the 2-Tuple Linguistic Model and the CRITIC-AHP Method for Hotel Classification**

### **3.6.1. Introduction**

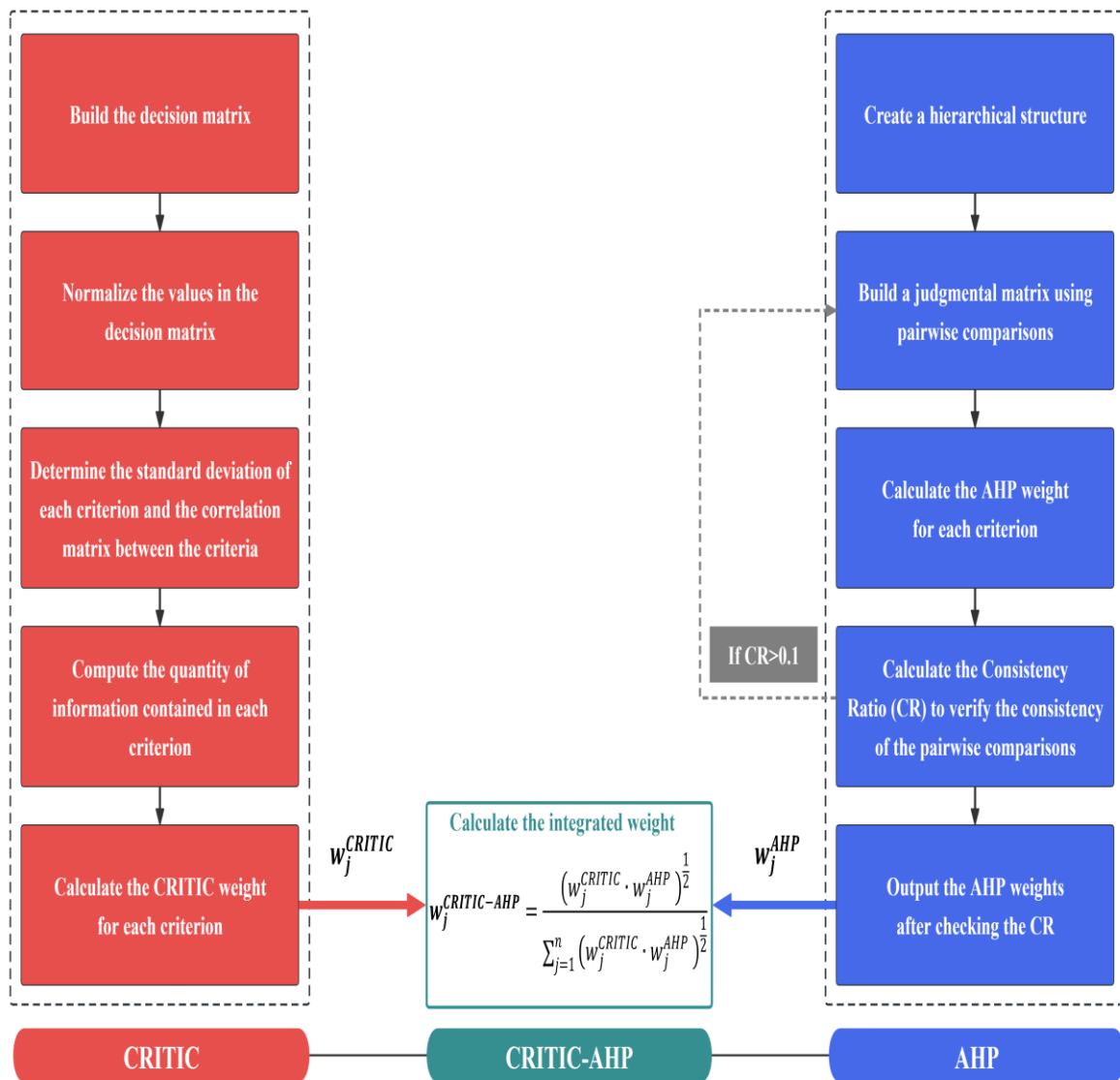
Hotel classification is crucial in the hospitality industry. It helps customers choose establishments that match their preferences and allows hotel managers to understand customer needs better, leading to improvements in various aspects of the hotel through relevant strategies. While K-Means clustering is commonly used in the literature for hotel classification, it overlooks the relevance of each feature attribute in the dataset [203]. Therefore, as one of the results of this thesis, a model that employs WKM clustering to address this issue was presented at the 11th International Conference on Data Science, Technology, and Applications [204] (refer also to Section 3.7). The weights were generated considering the varying quantities of information included in each criterion or aspect. Following the conference presentation, further research revealed that incorporating a combinative weighting method can lead to more accurate weight assignments for each criterion in MCDM issues [126]. Specifically, the model developed in the previous work relied solely on objective weights for each hotel aspect but ignored the opinions of experts. This could raise concerns about the assignment of weights conflicting with decision-makers' opinions.

This work aims to extend the model presented in the previous work by incorporating expert opinions to improve its practical usefulness. The model proposed in this work continues to use the 2-tuple linguistic model to tackle the issue of information loss in linguistic information fusion, but it incorporates combinative weights in WKM clustering. It integrates objective weights calculated using the CRITIC method with subjective weights determined by the AHP method. By employing weights that combine the objective information of each aspect with expert judgments on their importance, this new approach can achieve a more effective and accurate hotel classification.

### **3.6.2. Proposed Model and Its Application for Classifying Hotels**

The structure of the proposed model consists of three layers: data, methods and techniques, and results. In this work, a dataset from TripAdvisor hotels was chosen to apply the proposed model

for classifying hotels. The methods and techniques employed in the model proposed in this work are based on four concepts: the 2-tuple linguistic model, the AHP method, the CRITIC method, and WKM clustering. These concepts have been introduced in Sections 2.1, 2.3.1, 2.3.2, and 2.4.3, respectively. The AHP and CRITIC methods were combined to mitigate their disadvantages, addressing the concern about the potential uncertainty in expert judgment associated with the AHP method, and alleviating worries about the inconsistency of objective weights generated by the CRITIC method with practical applications. Figure 19 shows the process to generate the weights using the AHP and CRITIC methods, respectively, as well as the equation to calculate the integrated weight for each criterion (refer also to Section 2.3.5.1)

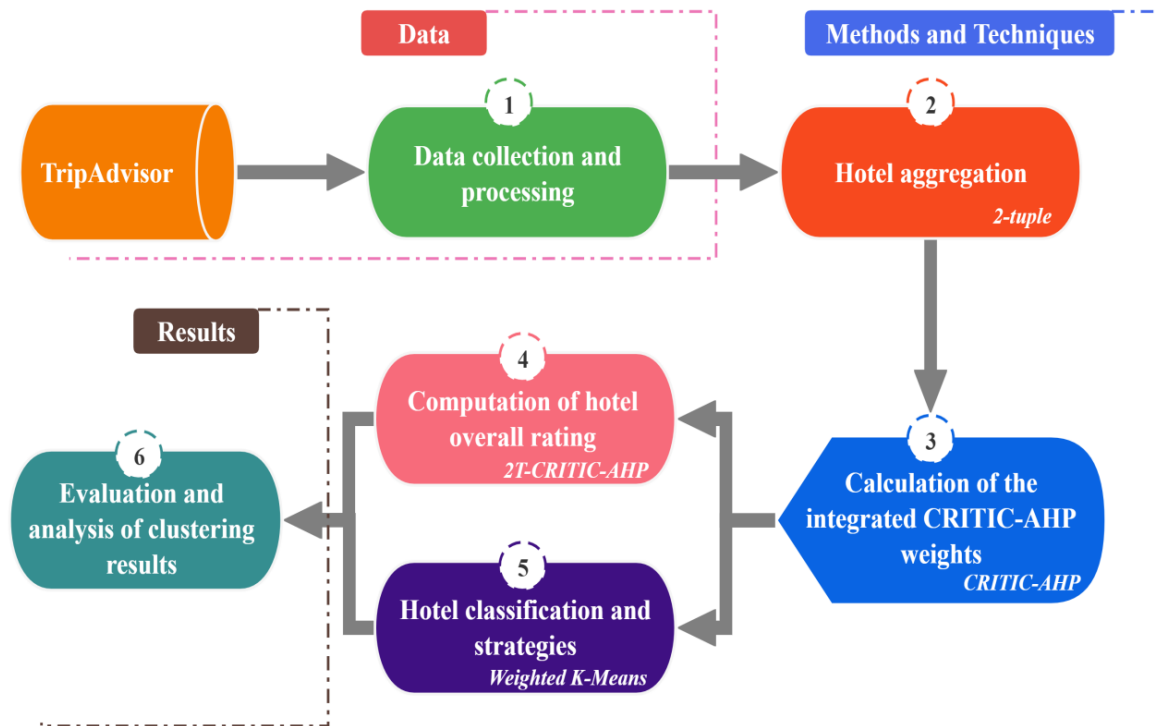


**Figure 19.** The weight generation process of the hybrid CRITIC-AHP method.

The application of the 2-tuple linguistic model was to address the issue of information loss in linguistic information fusion and enhance the interpretability of the results. The WKM clustering was employed to partition the data into distinct clusters while considering the weight associated with each criterion. Below are the steps of the proposed model as applied for classifying hotels (also refer to Figure 20):

- **Step 1. Data collection and processing:**

In this step, data provided by [193], comprising over fifty million hotel reviews from 21.89 million users who commented on TripAdvisor between February 1, 2001, and May 14, 2019, was used. The textual reviews were removed. Only hotels that received scores in all six aspects (i.e., Service, Cleanliness, Value, Rooms, Location, and Sleep Quality) were considered for this research, resulting in a dataset of 228,339 hotels.



**Figure 20.** Proposed model for hotel classification, adapted from [135].

- **Step 2. Hotel aggregation:**

This step employed Equation (4) to aggregate the diverse user evaluations of the hotel's six aspects into 2-tuple values. As mentioned in Section 2.1, the ratings for the hotel aspects are

expressed using linguistic terms. The linguistic term set used by TripAdvisor is  $S = \{ s_0 = \text{Terrible} = T, s_1 = \text{Poor} = P, s_2 = \text{Average} = A, s_3 = \text{Very Good} = VG, s_4 = \text{Excellent} = E \}$ , as shown in Figure 4. Refer to [135] for examples illustrating the aggregation of hotel aspect ratings represented in 2-tuple values.

● **Step 3. Calculation of the integrated CRITIC-AHP weights:**

This step used Equation (25) to compute the integrated CRITIC-AHP weights for the six aspects of the hotel. Since each aspect's rating is expressed in a 2-tuple value, before proceeding with the numerical computation, it is necessary to employ the function  $\Delta^{-1}$  (see Equation (2)) to transform the 2-tuple value into its numerical value. Table 21 displays the CRITIC weights, AHP weights, and the integrated CRITIC-AHP weights generated for each hotel aspect.

**Table 21.** Weights for each hotel aspect [135].

Hotel Aspect	CRITIC weights (%)	AHP weights (%)	Integrated CRITIC-AHP weights (%)
Service	10.97	8.09	10.08
Cleanliness	27.16	16.60	22.73
Value	14.08	3.72	7.75
Rooms	15.06	16.61	16.93
Location	14.67	43.32	26.98
Sleep quality	18.06	11.66	15.53

● **Step 4. Computation of hotel overall rating:**

This step involved multiplying the scores of the hotel's six aspects by their corresponding weights to calculate the overall score for each hotel. The overall rating, which aggregates six hotel aspects, enables both customers and hotel managers to grasp the general situation of the hotels. Refer to [135] for computed results for more hotels. Below is an example illustrating how to compute the overall rating for hotel 152011:  $\Delta(\Delta^{-1}(E, -0.4444) \cdot 10.08\% + \Delta^{-1}(A, +0.49) \cdot 22.73\% + \Delta^{-1}(E, -0.25) \cdot 7.75\% + \Delta^{-1}(VG, +0.4286) \cdot 16.93\% + \Delta^{-1}(E, -0.1) \cdot 26.98\% + \Delta^{-1}(A, -0.14) \cdot 15.53\%) = \Delta(3.5556 \cdot 10.08\% + 2.49 \cdot 22.73\% + 3.75 \cdot 7.75\% + 3.4286 \cdot 16.93\% + 3.9 \cdot 26.98\% + 1.86 \cdot 15.53\%) = \Delta(3.1365) = (VG, +0.1365)$ .

- **Step 5. Hotel classification and strategies:**

In this step, homogeneous groups of hotels were formed using WKM clustering. Equation (31) was used to categorize hotels based on their weighted Euclidean distance. The Elbow Method determined that the optimal number of clusters is 8, resulting in eight distinct hotel groups. Table 22 presents the results of the hotel clusters, depicted in 2-tuple values, alongside the number of hotels included in each cluster. The characteristic descriptions of each cluster can be found in [135].

The classification results for hotels enable hotel managers to identify weaknesses and take appropriate actions to address them. For instance, both clusters 1 and 5 exhibit similar levels of service, cleanliness, rooms, and location. In this case, hotels in Cluster 5 seeking to attract more customers should enhance either their value or the quality of sleep in the hotel. On the other hand, for customers, understanding the characteristics of the clusters allows them to quickly choose a hotel that better suits their needs. For example, for a customer seeking a hotel with an excellent location or service, the hotels in Cluster 3 might be the most suitable choice.

- **Step 6. Evaluation and analysis of clustering results:**

In this step, the clustering results of the proposed model were evaluated using three metrics: CHI, SC, and Reliability index. Additionally, an analysis was conducted to compare the results of the proposed model with those of the model presented in the previous work. Table 23 compares the clustering results. Despite both models generating eight clusters, the proposed model in this work outperforms the previous one, as evidenced by its closer SC value to 1, higher CHI value, and greater RI value. The proposed model in this work is better at separating clusters and improving the accuracy of clustering results.

**Table 22.** Hotel cluster results [135].

Cluster ID	Number of hotels	Service	Cleanliness	Value	Rooms	Location	Sleep quality
1	31,358	(VG, -0.237)	(VG, +0.025)	(A, +0.21)	(VG, +0.0783)	(VG, -0.063)	(A, +0.093)
2	30,062	(A, +0.023)	(P, +0.138)	(A, -0.122)	(P, +0.22)	(P, +0.21)	(A, +0.021)
3	29,055	(E, -0.31)	(A, +0.25)	(VG, +0.36)	(A, -0.25)	(E, -0.12)	(A, -0.15)
4	25,580	(A, +0.027)	(VG, +0.072)	(A, +0.178)	(VG, +0.091)	(A, +0.263)	(A, +0.05)
5	29,320	(VG, -0.149)	(VG, +0.073)	(A, +0.15)	(VG, +0.01)	(VG, +0.056)	(A, +0.047)
6	30,586	(A, +0.031)	(P, -0.228)	(A, +0.195)	(A, +0.271)	(P, -0.137)	(A, +0.053)
7	25,798	(A, +0.028)	(P, -0.137)	(A, +0.168)	(P, -0.063)	(A, +0.251)	(A, +0.062)
8	26,580	(A, +0.01)	(VG, -0.037)	(VG, -0.012)	(A, +0.082)	(A, +0.102)	(A, +0.052)
All_Data *	228,339	(A, +0.021)	(A, +0.159)	(A, +0.18)	(A, +0.289)	(A, +0.265)	(A, +0.035)

\* The average level of these 228,339 hotels is shown by All\_Data.

**Table 23.** Comparison of models, adapted from [135].

	CHI	SC	Reliability index
Proposed model in this work	57,116.5	0.932	18.95
Model presented in the previous work	56,685.3	0.903	17.13

### 3.6.3. Conclusions

This work combined the CRITIC method with the AHP method to ensure reliable weight determination and enhance its practical significance in the application. This extended the model presented in the previous work [204], and segmented hotels using the 2T-CRITIC-AHP model and WKM clustering. The primary difference between the extended model and the previous one lies in the application of integrated weights during the WKM clustering process. Unlike the previous model, which only relied on weights calculated by the CRITIC method, the extended model has incorporated integrated CRITIC-AHP weights that consider both expert opinions and the objective

quantity of information provided for each criterion in the weight assignment. The proposed model was evaluated using a dataset comprising over fifty million hotel reviews from TripAdvisor, the same dataset used to evaluate the model developed in the previous work. The results demonstrated that the extended model could segment hotels more accurately than the model presented in the previous work, while still keeping its clustering results linguistically interpretable. Interpretable clustering results enable hotel managers to identify their shortcomings and competitors' characteristics, enabling the development of targeted strategies to improve weaknesses and gain a competitive advantage in attracting customers from other clusters. In addition, these results can help customers quickly choose a hotel more suited to their needs.

While the extended model has addressed some limitations of the model presented in the previous work, further improvements are still necessary. For example, the equation for integrating objective and subjective weights might need refinement to accurately capture the importance of each aspect. Some experiments could be performed to check if clustering results improve when objective weights represent a significant portion of the integrated weights, or vice versa. Another possible future work could be the application of the extended model to diverse datasets from other sectors, with a subsequent comparison of its performance against other classification methods to validate its effectiveness and applicability across different industries.

## **3.7. A Model Based on 2-Tuple Linguistic Model and CRITIC Method for Hotel Classification**

### **3.7.1. Introduction**

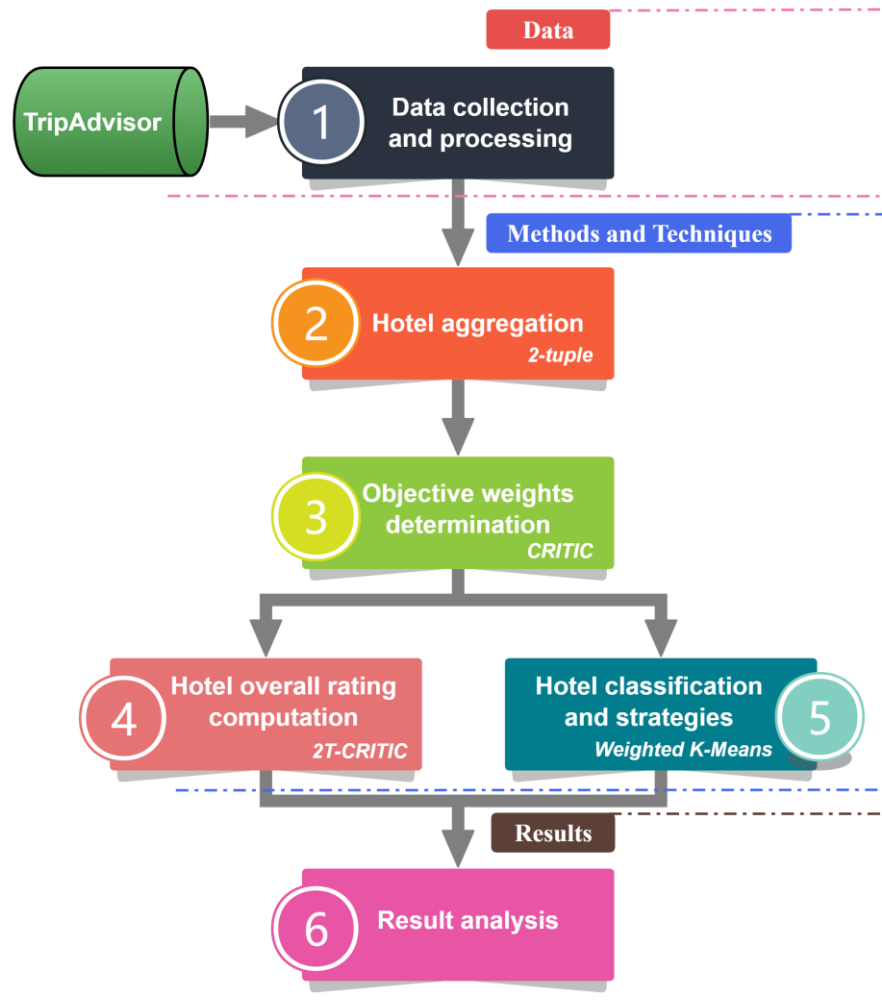
Hotels can be classified based on different characteristics using various models, such as K-means clustering, hierarchical clustering, decision trees, and factor analysis, among others. The present work serves as the foundation for the model presented in Section 3.6. The demonstration of the feasibility of the model proposed in this work during the 11th International Conference on Data Science, Technology, and Applications has enabled the expansion of related research in subsequent endeavors to optimize its practical applicability. This work classifies hotels using WKM clustering in conjunction with the 2-tuple model and the CRITIC method. Unlike standard K-Means clustering, the proposed model can assign different weights to variables in the clustering process, considering that the quantity of information contained in each variable varies.

### **3.7.2. Proposed Model and Its Application to Hotel Classification**

The methods and techniques employed in the model proposed in this work are based on three concepts: the 2-tuple linguistic model, the CRITIC method, and WKM clustering. These concepts have been introduced in Sections 2.1, 2.3.2, and 2.4.3, respectively. The 2-tuple linguistic model was employed to address the issue of information loss in linguistic information fusion. The CRITIC method was used in the proposed model as it can generate objective weights for distinct hotel aspects without requiring expert evaluations, thus expediting the weight determination process. The WKM clustering was applied to enhance clustering scalability and results by considering weights associated with each criterion during the computation of cluster centroids. To evaluate its functionality, the proposed model was applied to a dataset containing over fifty million TripAdvisor hotel reviews. The steps of the proposed model are shown in Figure 21.

When comparing Figure 21 with Figure 20, it can be observed that the first two steps remain the same, and the main difference between the present model and its extended version outlined in Section 3.6 lies in the third step. The current model only used weights calculated by the CRITIC

method, while the extended model used the integrated CRITIC-AHP weights. Table 24 shows the weights calculated using Equation (18), along with their respective standard deviations and the amount of information contained.



**Figure 21.** The process steps of the proposed model, adapted from [204].

**Table 24.** Weights for each hotel aspect, adapted from [204].

Aspect	Standard Deviation	Quantity of information	CRITIC weights (%)
Service	0.479	0.0326	10.97
Cleanliness	0.486	0.0807	27.16
Value	0.492	0.0418	14.08
Rooms	0.497	0.0447	15.06
Location	0.495	0.0436	14.67
Sleep quality	0.511	0.0537	18.06

The weights obtained were used in the following two steps: in the fourth step to calculate the overall rating of the hotel and in the fifth step for WKM clustering to classify the hotels. The results of the fourth and fifth steps can be found in [204]. The final step was the analysis of the results. This analysis showed that the proposed model in this work can improve clustering results by considering objective weights for each criterion, and it can make clustering results more linguistically interpretable. These results of classification aid hotel managers in developing appropriate strategies for gaining a new competitive advantage or improving those aspects that they need to make a change. Furthermore, these results can help customers choose a hotel that is more appropriate for their needs.

### **3.7.3. Conclusions**

The 2-tuple linguistic model, the CRITIC method, and WKM clustering were employed in this work for the classification of hotels. The proposed model was successfully applied to analyze data from over fifty million TripAdvisor hotel reviews, showcasing its functionality. The results demonstrated that this model allows for weighting the aspects of the hotel, considering the varying quantities of information included in each of them, thus enhancing clustering results. The clustering results, represented with 2-tuple values, can also increase their linguistic interpretability. All of these results not only assist hotel managers in understanding the aspects that require improvement and in designing corresponding strategies to enhance them but also aid customers in selecting accommodations that align with their needs. In conclusion, this work has laid the groundwork for broader research applications. Future studies could investigate the use of methods enabling the calculation of subjective weights of criteria to enhance this approach. Additionally, variables such as duration of stay, hotel price, reservation number, cancel number, etc., could be incorporated into hotel classification to attain a comprehensive understanding of hotels.



# Chapter 4

## Conclusions and Future Work

This chapter presents the primary conclusions and contributions of this thesis and proposes directions for future research based on the works conducted herein.

### 4.1. Conclusions

Decision-making is a common process in human activities, spanning from simple daily choices to complex business and economic decisions. This process is often influenced by the attitudes of the decision-makers. This thesis mainly aimed to improve the modeling of decision-makers' attitudes in various decision-making contexts by using the OWA aggregation operator, the 2-tuple linguistic model, and other related techniques, including redefining the linguistic quantifiers of the OWA aggregation operator to make them more intuitive and understandable for decision-makers. The publications of this thesis presented in Chapter 3, such as restaurant selection [3], hotel segmentation [4], and the calculation of the quality of life index [194], demonstrate the achievement of this objective. Likewise, all the specific objectives set forth have been met by one or several of these publications.

All the works conducted during this thesis align with the three layers of the architecture defined in Figure 2. Various datasets have been gathered to apply the proposed models and evaluate their applicability in different cases. These include eWOM data from two review sites, TripAdvisor and Dianping.com, as well as data from Numbeo and other public data repositories. When it comes to the methods and techniques applied, besides the OWA aggregation operator and the 2-tuple linguistic model, other MCDM methods, ML models, and analysis tools have been considered to enhance decision-making processes. For instance, certain hybrid MCDM methods and analysis tools have been used alongside the 2-tuple linguistic model to improve their strengths and mitigate potential limitations. By integrating ML models with either the 2LOWA aggregation operator or

hybrid MCDM methods, it becomes possible to furnish user-friendly insights for decision-making. This enables businesses to allocate customer relationship management resources effectively and efficiently, tailoring them to customer characteristics. When visualizing the results of the proposed models, beyond employing common tools like tables and line charts, interactive web applications have been implemented, enhancing the reproducibility and transparency of its findings, and thereby facilitating decision-making.

Based on all the above, it can be concluded that this thesis has fulfilled all of its stated objectives. The practical case and main contributions of each publication are summarized below in chronological order:

- (1) **Shu et al. (2022)** [194] presented an approach to computing the quality of life index. From a theoretical perspective, the incorporation of weights generated by linguistic quantifiers of the OWA aggregation operator contributes not only to the exploration of the best-balanced scenario suggested by Numbeo's experts but also to the examination of numerous scenarios with different indicator weights. By employing the 2-tuple linguistic model to aggregate linguistic information, it becomes possible to achieve a more precise differentiation of the quality of life among countries that share the same linguistic label while preserving the integrity of the data. From a practical standpoint, generating various quality of life index scenarios with linguistic interpretability provides decision-makers with valuable tools to adapt to changing attitudes under varying country conditions in assessing quality of life levels, thereby making appropriate improvement policies.
- (2) **Shu et al. (2022)** [204] presented a hotel classification approach that permits considering the differing quantity of information each variable holds and assigning varying weights to variables to enhance the clustering results. The clustering results, represented with 2-tuple values, can also improve their linguistic interpretability. From a practical perspective, these findings provide tangible benefits for hotel managers and customers. Hotel managers can understand the areas needing improvement and devise strategies to enhance them. Additionally, customers can quickly select accommodations that meet their needs.
- (3) **Shu et al. (2023)** [4] presented an approach to segment hotels. From a theoretical standpoint,

the linguistic quantifiers of the OWA aggregation operator are redefined to make them semantically more understandable. This contributes to modeling the entire range of customer attitudes towards various hotel aspects, from less demanding to more demanding, and generating distinct ratings for each hotel aspect. It can achieve more precise hotel segmentation, as evidenced by lower values of the DBI, SC closer to one, and higher scores in both the CHI and the Reliability Index. Moreover, it enhances the interpretability of hotel segmentation results. From a practical perspective, more valuable information can be provided for companies and customers in decision-making. For hotels, even if they receive identical reviews across different aspects (e.g., all hotel aspects labeled "Excellent" in customer reviews), the proposed model can still segment hotels by employing linguistic quantifiers to produce diverse 2-tuple values for various hotel aspects based on the degree of customer demands, thereby increasing the interpretability of the clustering results. This allows hotels to identify areas for improvement and implement necessary strategies to enhance their digital reputation on platforms like TripAdvisor. Moreover, the proposed model introduces a new online hotel ranking method for customers, enabling them to create personalized rankings based on their degree of demand for various hotel aspects (better location, cleaner rooms, etc.), rather than relying only on average ratings. This allows for the quick selection of suitable hotels based on how customers view reviews.

- (4) **Shu et al. (2023)** [136] presented an approach for customer segmentation. Theoretical improvements have been made to the RFM framework by four indicators (Recency, Frequency, Monetary value, and Bonding) for segmenting hotel customers based on their behavior data. The determination of weights for each indicator in this approach can consider the relationship between different indicators and the level of data diversification within each, using the 2-tuple linguistic model alongside, resulting in computing the overall 2T-RFMB value for each customer. From a practical perspective, it offers hotel managers linguistically easy-to-understand clustering results and customer values. This enables them to develop more efficient resource distribution strategies.
- (5) **Shu et al. (2023)** [135] presented an approach for classifying hotels, extending the model

presented in [204] by integrating objective weights calculated using the CRITIC method with subjective weights determined by the AHP method. This contributes to a more effective and accurate hotel classification by considering both the objective information of each aspect and expert judgments on their importance. On the practical side, the extended model demonstrates improved accuracy in hotel segmentation compared to its predecessor while maintaining linguistically interpretable clustering results. These results allow hotel managers to identify their weaknesses and competitors' characteristics, enabling them to develop targeted strategies to improve weaknesses and gain a competitive advantage. These results can also assist customers in quickly selecting a hotel that best suits their needs.

- (6) **Shu et al. (2024)** [3] presented an approach for ranking and selecting restaurants. From a theoretical point of view, the linguistic quantifiers of the OWA aggregation operator are redefined and used to generate new criteria reflecting the different levels of user demand for restaurant service, food, and environment. Furthermore, linguistic quantifiers representing different levels of user demand are associated with the degree of importance in calculating the weights of the corresponding criteria. This enables the acquisition of more accurate linguistic weights to compute the composite score for each restaurant, resulting in more precise restaurant rankings for users. From a practical point of view, more linguistically understandable composite scores of restaurants are generated, considering the levels of user demand for restaurant service, food, and environment. Restaurant rankings, generated based on users' actual needs rather than simply average ratings, are presented through an interactive application, helping users quickly find a suitable restaurant. In addition, based on the frequency of the restaurant's appearance in the top 10 across various scenarios and its corresponding ranking, review sites can generate a list of restaurants that can satisfy the demands of most users with different demand levels of demand. This can increase customer satisfaction and foster trust in the decision-making process.
- (7) **Shu and Carrasco (2024)** [197] presented an approach for ranking hotels, integrating the hybrid AEC, 2-tuple linguistic, and TOPSIS methods. This contributes to achieving a relatively balanced and realistic weight distribution in the weight assignment within the TOPSIS method,

due to its consideration of each criterion's internal data structure, their interrelationships, and expert opinions, in the decision-making process. From a practical point of view, it can generate a list of the top 10 luxury hotels in Lisbon for various scenarios (i.e., considering six aspects or three aspects in the ranking) and uses the 2-tuple values of different hotel aspects to explain the ranking results. This assists hotel managers in comparing their hotels to competitors and identifying the specific aspects they should enhance to improve their ranking. Additionally, it helps customers find suitable luxury hotels more efficiently with more understandable hotel rankings.

## 4.2. Future Works

While the contributions of the works conducted during this thesis have been acknowledged through the published papers, improvements can still be made in future works. One of the future works would be improving the calculation of ordered weights generated by linguistic quantifiers, considering the data structure of numerical and linguistic inputs in addition to decision-makers' attitudes. Future work should also address the limitations identified in the published papers during the research period to enhance the functionality of the proposed models. For instance, although the 2-tuple linguistic model excels in CWW for its accuracy and interpretability in handling linguistic terms, it remains constrained by the use of individual linguistic terms. Future work could extend the 2-tuple linguistic model by incorporating context-aware adjustments to process more complex linguistic information extracted from the text and improve the fusion of numerical and linguistic data.

Moreover, although the models proposed in this doctoral thesis have demonstrated their applicability in addressing decision-making problems such as hotel segmentation, restaurant selection, and customer management, further investigation should be conducted to explore their effectiveness in other real-world scenarios. These include collecting data from other industries, geographical regions, and diverse demographic groups to ensure broader applicability and robustness. Finally, the accepted papers currently pending publication, as well as others submitted to JCR/Scopus journals, are waiting for publication in the future to demonstrate the continued research efforts beyond the completion of this thesis.

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**Part II**  
**Published and Submitted**  
**Papers**



This part presents the papers published and submitted during the research period, forming the core of this doctoral thesis. This thesis has produced the following JCR/Scopus indexed journal articles, international conference papers, and book chapters:

- (1) A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com. *Information Processing & Management*, 61(3), 103650. (Published)
- (2) A linguistic-based approach to identifying and monitoring online customer dissatisfaction: a case study on TripAdvisor. *Information Sciences*. (Submitted: INS-D-24-4042)
- (3) Incorporating investor risk attitudes into a personalized index of economic freedom: An approach using the OWA aggregation operator, 2-tuple linguistic model, FCM clustering, and interactive visualization techniques. *Financial Innovation*. (Submitted: FINI-D-23-00889R1)
- (4) Clustering using ordered weighted averaging operator and 2-tuple linguistic model for hotel segmentation: The case of TripAdvisor. *Expert Systems with Applications*, 213, 118922. (Published)
- (5) Multiple Scenarios of Quality of Life Index Using Fuzzy Linguistic Quantifiers: The Case of 85 Countries in Numbeo. *Mathematics*, 10(12), 2091. (Published)
- (6) Ranking Luxury Hotels in Lisbon Using the 2T-AEC-TOPSIS Model. In J. L. Reis, J. Zelený, B. Gavurová, & J. P. M. dos Santos (Eds.), *Marketing and Smart Technologies. Smart Innovation, Systems and Technologies*, 386, 669–686. Springer Nature. (Published)
- (7) A Model Integrating the 2-Tuple Linguistic Model and the CRITIC-AHP Method for Hotel Classification. *SN Computer Science*, 5, 1–11. (Published)
- (8) Hotel Customer Segmentation Using the Integrated Entropy-CRITIC Method and the 2T-RFMB Model. In J. L. Reis, M. K. Peter, J. A. Varela González, & Z. Bogdanović (Eds.), *Marketing and Smart Technologies. Smart Innovation, Systems and Technologies*, 337, 55–72. Springer Nature. (Published)
- (9) Navigating the Landscape of Artificial Intelligence: Computing with Words in Marketing.

*FLINS-ISKE 2024 Conference*. (Accepted and in the process of publication)

- (10) Scenarios of Material Deprivation in Poor Households Using the OWA Aggregation Operator and the Linguistic Model. *XXXVII International Conference on Applied Economics-ASEPELT 2024*. (Accepted and in the process of publication)
- (11) Strategic Management of Hotel Customers based on their Online Reviews: The Case of Luxury Hotels in Spain. *2023 AMA Summer Academic Conference*, 778–780. (Published)
- (12) A Model based on 2-tuple Linguistic Model and CRITIC Method for Hotel Classification. *Proceedings of the 11th International Conference on Data Science, Technology and Applications (DATA)*, 127–134. (Published)

Some of the earlier mentioned publications are published papers, while others are not. Consequently, the published papers are presented first, aligned with the order of the overviews in Chapter 3. Following this, the accepted and pending publications, as well as submitted papers, are presented through abstracts. Each publication is presented along with its current status (e.g., published, submitted, etc.) and quality indices within the research field.

# 1. A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com









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## A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com

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## A Multi-Criteria Decision Support Model for Restaurant Selection Based on Users' Demand Level: The Case of Dianping.com

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### ABSTRACT

The Internet, by offering a variety of information sources such as online reviews, aids people in selecting restaurants. However, it also prolongs their decision-making process due to the need to integrate information across multiple criteria. Existing decision support models for choosing satisfactory restaurants overlook users' varying demand levels for each aspect of the restaurant, making the process less efficient. This paper aims to develop a multi-criteria decision support model for users to efficiently and accurately rank and select restaurants based on their demand level for various restaurant aspects. The 2-tuple linguistic ordered weighted averaging (2LOWA) aggregation operator is applied for the first time to aggregate user ratings, generating linguistic ratings that mirror the diverse levels of user demand for restaurant service, food, and environment. The importance weights (IW) method is introduced to calculate linguistic weights, thereby obtaining customized 2T-SFE composite scores under various user demand scenarios. The proposed model's applicability is demonstrated using a dataset comprising over 3.7 million reviews sourced from Dianping.com. The results show multiple personalized restaurant rankings with more linguistically understandable composite scores, enabling users to efficiently choose a suitable restaurant based on their preferences and requirements. Moreover, a list of restaurants satisfying most users with different demand levels can be generated by assessing their frequency of appearance in the top 10 restaurants across over 340 scenarios established by the proposed model. This contributes to offering more reliable and comprehensive restaurant recommendations and rankings, ultimately increasing customer satisfaction in the selection process.

### 1. Introduction

The development of the Internet has empowered individuals to access a wealth of information before making decisions. The swift evolution of social media has significantly changed the way information is acquired and disseminated, with electronic word of mouth (eWOM) playing a crucial role. Henning-Thurau et al. (2004) defined eWOM as "any positive or negative statement made by potential, actual, or former customers about a product or company that is made available to a multitude of people and institutions via the

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Internet." The eWOM plays a crucial role in furnishing necessary information to potential customers (Jeong & Jang, 2011). The eWOM assists customers in evaluating options and eliminates ambiguity in the decision-making process, thereby reducing both cost and time (Lee, 2014). Online reviews, typically composed of a star rating and a textual comment, serve as representative forms of eWOM and are widely recognized as reliable sources of information (Yang et al., 2015). Review sites such as TripAdvisor, Yelp, and Google Reviews are commonly used by both tourists and locals to discover suitable restaurants, hotels, or entertainment venues. These platforms provide opinions from previous customers, facilitating decision-making and minimizing the risk of a negative experience.

When selecting a restaurant, most customers typically read online reviews of the restaurant before making their choice (Carter, 2022). Online reviews serve as reference points for many people when deciding which restaurant to choose (Tuş & Adalı, 2022). According to TripAdvisor’s review research, 70% of restaurant customers consider online reviews crucial in their decision-making process (DiegoCoquillat.com, 2022). For instance, favorable reviews (i.e., positive eWOM) increase the restaurant’s clientele by informing customers that the restaurant’s cuisine is delicious, and the environment is excellent. Online reviews are crucial for customers without knowledge about restaurants when selecting a suitable restaurant (Shambour et al., 2023). They show evaluations of several criteria of the restaurants, which influence customers’ choices (Rahman et al., 2022). Food, service quality, and environment are the three most commonly agreed-upon criteria that affect restaurant survival and ranking (Parsa et al., 2005; Ryu & Jang, 2007; DiPietro et al., 2011; Jeong & Jang, 2011; Ryu et al., 2012; Jurafsky et al., 2014). Bertan’s research indicates that five criteria influence restaurant rankings: food and beverage, ingredients, personnel, environment, and service (Bertan, 2020). Hartanto and Utama (2020) used seven parameters to create restaurant recommendations: customer interest, budget, distance between the customer and the restaurant, taste rating, cleanliness rating, facilities rating, and halal or non-halal status.

Selecting the "optimal" restaurant from a collection of alternatives based on online reviews given by customers regarding various criteria (e.g., food, service, environment) is a Multi-Criteria Decision-Making (MCDM) problem (Ayşegül & Esra Aytac, 2022). MCDM methods are characterized by taking into account multiple criteria, which are typically at odds with one another, as well as the preferences of the involved decision-makers (Roy, 1996). These methods fall within a category of approaches used in decision support models (Vatankhah et al., 2023). MCDM methods usually aggregate the scores of multiple factors (e.g., food, service quality,

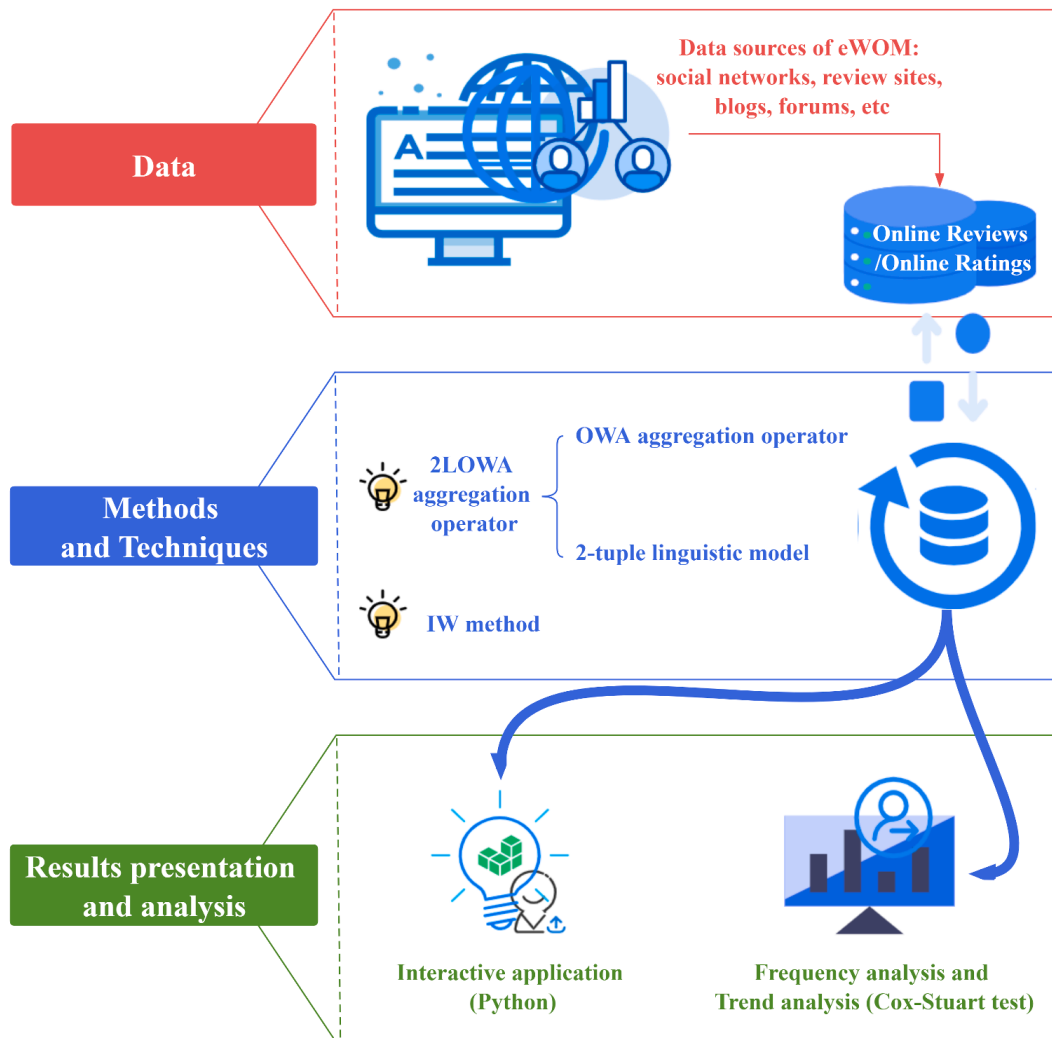


Fig. 1. Architecture for achieving the stated objective.

environment, price, etc.) into overall scores of diverse restaurants to facilitate their ranking. For instance, [Osvaldo and Pangemanan \(2016\)](#) applied the analytic hierarchy process (AHP) method to assist the customer in selecting restaurants. [Zhang et al. \(2017\)](#) developed a decision-support approach to help travelers use social information on TripAdvisor.com to select restaurants. In the literature, many MCDM techniques have been used for restaurant selection and ranking ([Yildiz & Yildiz, 2015](#); [Osvaldo & Pangemanan, 2016](#); [Fang & Partovi, 2021](#); [Bu & Zhang, 2021](#); [Ayşegül & Esra Aytac, 2022](#); [Dyondra et al., 2023](#)).

However, although existing models have contributed to the ranking and selection of restaurants based on online reviews, previous studies have overlooked the fact that users have diverse preferences for reading reviews due to their varying demands on different aspects of a restaurant. For example, a user who is more demanding of the restaurant's environment but tolerant of the service would read and focus more on negative reviews related to the restaurant's environment than those critiquing its service. In this scenario, relying solely on the average to calculate the overall restaurant score would not fully meet the user's needs.

Moreover, while certain review sites allow users to rank restaurants based on their preferences for specific criteria, such as environmental online ratings or food quality, they do not provide a direct way for users to obtain comprehensive restaurant rankings that align with their individualized preferences across various criteria at the same time. This makes it difficult to promptly recommend suitable restaurants to users, aiding them in decision-making when they have simultaneous demands for service, environment, or other aspects of the restaurant.

Therefore, the objective of this paper is to develop a multi-criteria decision support model to help users efficiently and accurately rank and select the restaurants based on their level of demand for various restaurant aspects. To achieve this, various sub-objectives are also set (see [Section 2.2](#)). [Fig. 1](#) illustrates the use of distinct methods and techniques in this paper to achieve the stated objective.

Selecting an appropriate eWOM data source is important for assessing the feasibility of the proposed model. This paper leverages Dianping.com to gather user reviews on restaurants, assessing the practical application of the proposed model in restaurant ranking and selection. In terms of the methods and techniques employed to analyze and process collected user reviews into useful eWOM outcomes for the decision-making process, the proposed model employs the following ones:

- **2-tuple Linguistic Ordered Weighted Averaging (2LOWA) aggregation operator:** It is an extension of the Ordered Weighted Averaging (OWA) aggregation operator, incorporating the 2-tuple linguistic model. The 2-tuple linguistic model is applied in the OWA aggregation operator for three reasons: (i) it allows aggregating information without loss; (ii) it makes the aggregation results easier to understand; (iii) it can perform transformations between 2-tuple values and numerical values, so that weight calculation and composite score computation will not be a problem. Various linguistic quantifiers from the 2LOWA aggregation operator, designed to represent different user demand levels, are applied to aggregate user ratings for each restaurant criterion. This process generates new criteria that reflect different levels of user demand concerning restaurant service, food, and environment.
- **Importance Weights (IW) method:** This method is introduced in this paper to calculate the linguistic weights of three restaurant criteria. It can generate importance weights related to the level of user demand for the different restaurant criteria, thereby enabling the calculation of the composite score for each restaurant using more accurate linguistic weights. This method allows review platforms to provide users with a list of top-ranked personalized restaurants, making it easier for users to select restaurants.

To sum up, the proposed model introduces a novel approach to restaurant ranking and selection, using the 2LOWA aggregation operator and the IW method. This offers practical utility by enabling users to quickly find a suitable restaurant, as restaurant rankings are determined based on individual needs rather than solely on average ratings. The results of this approach, as depicted in [Fig. 1](#), are presented through an interactive application created using the Python programming language. Through this application, users can specify their level of demand for various restaurant criteria, generating a personalized restaurant ranking to facilitate a more efficient restaurant selection process. Frequency analysis and trend analysis are also employed to study how restaurant rankings evolve with varying user demand levels. These analyses enable review sites to recommend restaurants that can meet the demands of the majority of users with different levels of demand based on the frequency of the restaurant appearing in the top 10 in a variety of scenarios.

The remainder of this paper is structured as follows. [Section 2](#) provides an overview of models developed in recent years for restaurant selection and ranking based on online reviews, and indicates the research objectives of this paper. [Section 3](#) introduces several fundamental concepts on which the proposed model is based. [Section 4](#) demonstrates the application of the proposed model on a dataset comprising over 3.7 million reviews from Dianping.com. [Section 5](#) analyzes the ranking and selection of restaurants under multiple scenarios. [Section 6](#) discusses the advantages and disadvantages of the proposed model. [Section 7](#) presents the conclusions of this work and explores possible future research directions.

## 2. Literature review and research objectives

[Section 2.1](#) provides a literature review on decision support models for restaurant selection and ranking based on online reviews, with a primary focus on MCDM methods. The review spans from 2018 to the present, conducting a comparative analysis of existing methods to identify any gaps in the literature. [Section 2.2](#) outlines the research objectives of this paper.

### 2.1. Restaurant selection and ranking based on online review

Decision support models help people make correct and on-target decisions ([Minartiningtyas & Prawira, 2019](#)). MCDM methods belong to decision support models ([Vatankhah et al., 2023](#)). A systematic search is conducted on the Web of Science, Scopus, and Google Scholar databases to explore studies related to restaurant selection and ranking based on online reviews, covering the period

from 2018 to the present. This search encompasses articles published in the last five years, including 2018, as the papers from 2023 do not cover the entire year.

The following terms were used in the literature search query: "decision support models", "restaurant selection", "restaurant ranking", "Multi-Criteria Decision-Making", "online reviews", "online ratings", as well as their respective synonyms and abbreviations (e.g., "MCDM" for "Multi-Criteria Decision-Making"). The literature review process conducted in this study to identify pertinent and valid papers for the research is shown in Fig. 2. Table 1 presents works related to restaurant selection and ranking based on online reviews, outlining the eWOM data sources, methods and techniques employed in each study.

As can be seen in Table 1, many researchers have used MCDM methods like AHP, CRITIC, ELECTRE, and WP to address restaurant selection and/or ranking issues based on online reviews. Furthermore, some researchers have incorporated text mining techniques, deep learning models, recommender systems, and sensitivity analysis to assist customers in choosing restaurants based on online reviews.

However, to the best of our knowledge, existing research on restaurant selection and ranking lacks consideration of users' demand levels in the decision-making process. Specifically, previous research has not yet explored the application of the OWA aggregation operator to restaurant selection and ranking based on online reviews. This operator can aggregate evaluations of multiple criteria, taking into account the decision-maker's attitude. Moreover, the most commonly used eWOM data source in previous studies is TripAdvisor. Only a few papers have explored eWOM data sources from China, such as Dianping.com, Meituan, Ele.me, etc., to conduct research on restaurant selection and ranking.

To fill these voids, this paper proposes a novel approach that combines the 2LOWA aggregation operator (an extension of the OWA aggregation operator) with a new method to calculate linguistic weights introduced here, the IW method. This approach can produce customized 2T-SFE composite scores, catering to different user demand scenarios. Each of these scores fluctuates based on the level of user demand, enabling the creation of more personalized restaurant rankings to help users quickly choose suitable restaurants. These results are presented through an interactive application developed in Python, allowing users to specify their demand levels for various restaurant criteria and generate a personalized ranking.

## 2.2. Research objectives

Section 2.1 points out a literature gap concerning the consideration of users' demand levels in restaurant selection and ranking based on online reviews. Existing models have neglected the varied demand levels of each user for different aspects of restaurants. Therefore, the main objective of this paper is to develop a multi-criteria decision support model to help users efficiently and accurately rank and select the restaurants based on their level of demand for various restaurant aspects.

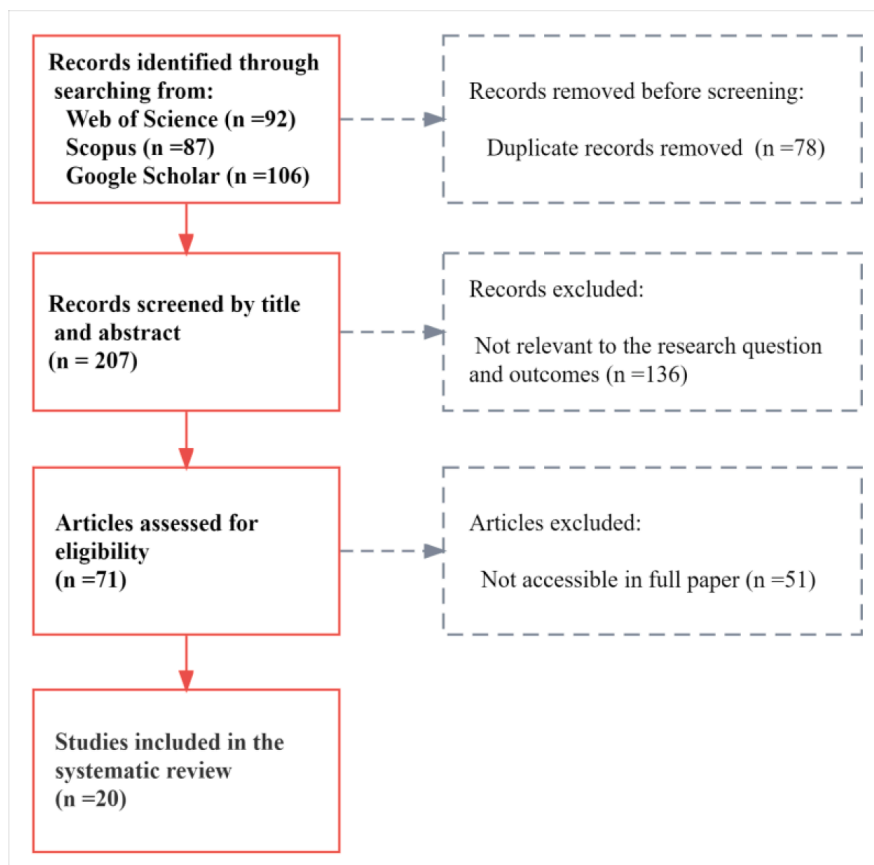


Fig. 2. Literature review flow diagram.

**Table 1**  
Studies related to restaurant selection and ranking based on online reviews.

Author(s) (year)	eWOM data source(s)	Methods and techniques
Asadabadi et al. (2018)	Google Maps	Fuzzy Concept of Stratification (Fuzzy CST), Bi-Objective CST (BOCST)
Agüero-Torales et al. (2019)	TripAdvisor	Opinion mining, Valence Aware Dictionary for sEntiment Reasoning (VADER)
Minartiningtyas and Prawira (2019)	Google Maps	Weighted Product (WP), Geographic Information System (GIS)
Wardhani and Lutfina (2020)	Mobile Phone data	WP
Zhang et al. (2020b)	Yelp, Dianping.com	Deep Neural Network (DNN), Matrix Factorization (MF), Multi-View Visual Bayesian Personalized Ranking from implicit feedback method (MVBPR)
Asani et al. (2021)	TripAdvisor	Sentiment analysis, Agglomerative Hierarchical Clustering
Bu and Zhang (2021)	OpenRice	AHP
Fang and Partovi (2021)	TripAdvisor	AHP, Latent Dirichlet Allocation (LDA)
Liang et al. (2021)	Meituan, Ele.me	Content analysis, AHP, Probabilistic Linguistic Term Set (PLTS), Fuzzy Comprehensive Evaluation (FCE)
Jabreel et al. (2021)	TripAdvisor	ELECTRE-III, Support Vector Machine (SVM), Aspect-Based Sentiment Analysis (ABSA)
Zuheros et al. (2021)	TripAdvisor	Sentiment Analysis based Multi-person Multi-criteria Decision Making (SA-MpMcDM), ABSA, Convolutional Neural Networks (CNN), Long-Short-Term Memories (LSTM) networks, Multi-Task Learning (MTL)
Aysegül and Esra Aytac (2022)	TripAdvisor	Interval-Valued Intuitionistic Fuzzy-Criteria Importance Through Intercriteria (IVIF-CRITIC), Combined Compromise Solution (CoCoSo)
Lee et al. (2022)	Yelp	User-Based Collaborative Filtering (UBCF) with filtering recommendation candidate
Angamuthu and Trojovský (2023)	TripAdvisor	Sentiment Analysis in Recommender Systems with Multi-person, Multi-criteria Decision Making (SAR-MCMD), Residual Attention CNN (RACNN), Bi-LSTM networks
Darko and Liang (2023)	TripAdvisor	Term Frequency-Inverse Document Frequency (TF-IDF), K-means, Probabilistic Linguistic Linear Programming Technique for Multidimensional Analysis of Preference (PL-LINMAP), Probabilistic Linguistic Measurement Alternatives and Ranking according to the COMpromise Solution (PL-MARCOS)
Dyondra et al. (2023)	TripAdvisor	AHP
Krishankumar et al. (2023)	TripAdvisor, Goibibo, Trivago	Probabilistic linguistic comprehensive (PLC), CRiteria Importance Through Intercriteria Correlation (CRITIC), Discriminative Weighted Muirhead Mean (DWMM) operator, Dempster-Shafer theory based Bayesian approximation (DSBA)
Novas et al. (2023a)	TripAdvisor	LDA, ELECTRE, Preference Ranking Organization Method for Enrichment Evaluation (Promethee)
Novas et al. (2023b)	TripAdvisor	Benchmark ranking model, Fuzzy logic, LDA
Tayal et al. (2023)	TripAdvisor	ABSA, Plithogenic sets-based MCDM

The following sub-objectives contribute to the achievement of the main objective:

- 1) To generate more personalized composite scores of restaurants.
- 2) To improve linguistic understanding of restaurant rankings.
- 3) To explore how restaurant rankings change based on user demand levels.
- 4) To offer users more reliable and comprehensive restaurant choices.
- 5) To examine the applicability of the proposed model by using a large database of online reviews.

### 3. Theoretical framework

This section introduces the fundamental concepts on which the proposed model is based. [Section 3.1](#) presents the use of linguistic variables in online review platforms to express customer satisfaction regarding restaurants, with a specific focus on Dianping.com. [Section 3.2](#) introduces the 2-tuple linguistic model that can solve the information loss problem of the fuzzy linguistic approach in linguistic term fusion. [Section 3.3](#) introduces the OWA aggregation operator and its extension using the 2-tuple linguistic model (i.e., 2LOWA aggregation operator), as they can express the attitudinal character of the decision-maker in information aggregation. The linguistic quantifiers of the 2LOWA aggregation operator are used to aggregate users' evaluations of each restaurant criterion according to the user demand levels for various restaurant-related criteria. [Section 3.4](#) presents the IW method that proposes in this paper to obtain the linguistic weight corresponding to the user demand level to compute the composite score for each restaurant.

#### 3.1. Linguistic variables used on Dianping.com

Dianping.com, founded in April 2003, is one of the first Chinese life service review sites. It mainly provides recommendations to users on a variety of topics including restaurants, hotels, movie tickets, home improvement, beauty salons, sporting events, etc. It is widely regarded as a popular travel and dining platform in China. This platform makes it easy for users to exchange information, post reviews, and discover suitable hotels and restaurants. Users can access three different types of restaurant ratings on Dianping.com: ratings based on service, food, and environment. In addition, Dianping.com determines the restaurant's overall star rating based on these three criteria. It employs a five-star rating system that uses linguistic terms to express users' reviews of restaurants on these three criteria ([dianping.com, 2022](#)). [Fig. 3](#) shows an example.

As shown in [Fig. 3](#), user reviews on each restaurant criterion on Dianping.com can be considered as a linguistic variable. A linguistic variable is a variable whose values are words or sentences in a natural language ([Zadeh, 1975](#)). Linguistic terms are used in the fuzzy

linguistic approach to reflect the approximate values of a linguistic variable since they are very similar to human thinking (Zadeh, 1975). Although the use of linguistic terms is less specific than the use of numerical values, it is much more in line with the way people express their thoughts. For example, in comparison to "The restaurant environment has a rating of 3," the statement "The restaurant environment is good" is less precise. The word "good" is a linguistic term for the variable "restaurant environment", which is less precise than the numerical value "3". However, the term "good" allows people to naturally express and deal with uncertain information (the user may not want to rate the restaurant environment with a 3, but with a 3.1, a 3.2, or a 2.9). In other words, the linguistic term "good" contains many more possible scores than just a 3. Therefore, using linguistic variables allows for achieving better modeling of the information concerned than using traditional numerical variables (Cid-López et al., 2015; Malik & Hussain, 2018; Hassan et al., 2022; Li et al., 2022).

In fact, except for Dianping.com, many restaurant review sites like TripAdvisor, OpenTable, Yelp, etc., employ the five-star rating system with linguistic terms to evaluate restaurants based on various criteria. This system ensures that users are not overwhelmed by too many or too few alternatives when rating, allowing them to express their opinions correctly. It is generally used with linguistic terms such as *Very Good*, *Good*, *Average*, *Poor*, *Very Poor*, etc. The arithmetic mean is typically used by review sites to aggregate ratings for various restaurant criteria to obtain an overall score, with restaurants ranked from highest to lowest.

Furthermore, the reviews on Dianping.com are reliable, as they are rigorously monitored by its algorithm. User reviews with missing partial dimensional ratings are considered spam reviews or intentionally bad reviews on Dianping.com (dianping.com, 2022). All reviews go through a rigorous filtering process before being published. For instance, a review written by a newly registered user will not be published, which prevents advertising or unfair competition among peers. Those users who have repeatedly written unreasonable or irresponsible reviews will be suspended. In addition, Dianping.com will not begin computing the restaurant's overall star rating until the restaurant receives ten or more reviews (Operation Research Institute, 2021).

Dianping.com applies its stringent guidelines to rank the restaurants, which gives it a unique competitiveness that its rivals cannot easily match. However, the method Dianping.com uses to aggregate user ratings of restaurants' various criteria could be improved. This paper advocates using the 2LOWA aggregation operator to aggregate user ratings rather than the arithmetic mean, so that new criteria that consider the different levels of user demand for restaurant service, food, and environment can be created. More information on the 2LOWA aggregation operator can be found in Section 3.3.

### 3.2. The 2-tuple Linguistic model

Many aspects of real life can be evaluated quantitatively, as well as qualitatively. As linguistic terms are very close to human thinking, several review sites, such as TripAdvisor, Trip.com Group, Dianping.com, etc., employ them to express user satisfaction with various aspects of hotels, restaurants, or attractions.

However, the fuzzy linguistic approach has a problem of information loss due to its information representation model and the computation methods used in the linguistic term fusion processing (Herrera & Martínez, 2000). To address this problem, Herrera and Martínez developed the 2-tuple linguistic model, which expresses information by means of linguistic values composed of a linguistic term and its symbolic translation represented by a numeric value assessed in  $[-0.5, 0.5]$  (Herrera & Martínez, 2000). This model manages linguistic information as a continuous rather than a discrete range, which provides more accurate results. The 2-tuple linguistic model excels over the other symbolic fuzzy-based models regarding precision and interpretability (Rodríguez et al., 2016). This model has been used to solve several kinds of linguistic decision-making issues in the actual world (Martinez et al., 2015). For instance, several authors have used it to model online customer reviews, obtaining more comprehensible results than those obtained using only numerical scales (Mi et al., 2014; Montes et al., 2015; Liu & Chen, 2018; Sohaib et al., 2019; Zhang et al., 2020a; Marín Díaz et al., 2021; Bueno et al., 2021).

The 2-tuple linguistic model represents linguistic information by a 2-tuple value  $(s_i, \alpha)$ , where  $s_i \in S$  is a linguistic term, and  $\alpha \in [-0.5, 0.5]$  is a numerical value that represents the distance to the central value of  $s_i$ . The definition is as follows.

**Definition 1.** Let  $S = \{s_0, \dots, s_g\}$  be a set of linguistic terms, and  $\beta \in [0, g]$  be a value that represents the result of a symbolic aggregation operation, where  $g + 1$  is the cardinality of  $S$ . The function  $\Delta : [0, g] \rightarrow \langle S \rangle = S \times [-0.5, 0.5]$  is used to convert  $\beta$  into the 2-tuple value  $(s_i, \alpha)$  as shown in Formula (1):

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} i = \text{round}(\beta) \\ \alpha = \beta - i, \alpha \in [-0.5, 0.5] \end{cases} \tag{1}$$

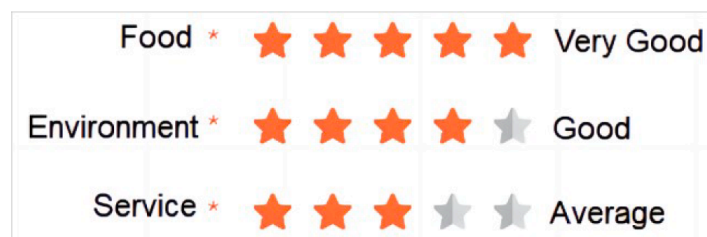


Fig. 3. Example of a user review in the Dianping.com database.

where  $round(\cdot)$  is the rounding operation;  $s_i$  is the index label closest to  $\beta$ ; and  $\alpha$  is a numerical value of the symbolic translation.

This model can perform transformations between 2-tuple values and numerical values. The function  $\Delta$  is bijective, its inverse function  $\Delta^{-1} : \langle S \rangle = Sx[-0.5, 0.5] \rightarrow [0, g]$  converts the 2-tuple value into its equivalent numerical value as  $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$ .

**Example 1.** The linguistic terms used by Dianping.com to evaluate restaurant criteria are *Very Poor* = VP, *Poor* = P, *Average* = A, *Good* = G, *Very Good* = VG. Therefore,  $S = \{s_0 = VP, s_1 = P, s_2 = A, s_3 = G, s_4 = VG\}$  is a set of five linguistic terms used by Dianping.com, whose cardinality is  $g + 1 = 5$  and whose definition is shown in Fig. 4.

Let  $\beta = 2.3$  be a value representing the result of a symbolic aggregation operation on the set of linguistic terms  $S = \{s_0 = VP, s_1 = P, s_2 = A, s_3 = G, s_4 = VG\}$ . Then, its 2-tuple value is  $\Delta(2.3) = (s_{round(2.3)}, 2.3 - round(2.3)) = (s_2, + 0.3) = (A, + 0.3)$ . The inverse transformation is  $\Delta^{-1}(s_2, + 0.3) = 2 + 0.3 = 2.3$ .

In the case that  $\beta$  equals 3, its 2-tuple value is  $\Delta(3) = (s_3, 0) = (G, 0)$ , which means that the difference between  $\beta$  and this linguistic term is zero ( $\alpha = 0$ ). Adding a zero as a symbolic translation,  $s_i \in S \rightarrow (s_i, 0)$ , is identical to the label without symbolic translation (eg.,  $(G, 0) = G$ ). The two examples ( $\beta = 2.3$  and  $\beta = 3$ ) are shown in Fig. 5.

In addition, Herrera and Martínez introduced a way to perform a comparison between two 2-tuple linguistic values and the negation operator of a 2-tuple value, whose definitions are as follows.

**Definition 2.** The comparison of linguistic information represented by 2-tuple values is performed according to an ordinary lexicographic order (Herrera & Martínez, 2000). Let  $(s_M, \alpha_1)$  and  $(s_L, \alpha_2)$  be two 2-tuple values, the operator is generated to compare their linguistic 2-tuple values as the following:

- If  $M < L$ ,  $(s_M, \alpha_1)$  is smaller than  $(s_L, \alpha_2)$ .
- If  $M = L$ , when:
  - $\alpha_1 = \alpha_2$ ,  $(s_M, \alpha_1)$  and  $(s_L, \alpha_2)$  represent the same information.
  - $\alpha_1 < \alpha_2$ ,  $(s_M, \alpha_1)$  is smaller than  $(s_L, \alpha_2)$ .
  - $\alpha_1 > \alpha_2$ ,  $(s_M, \alpha_1)$  is larger than  $(s_L, \alpha_2)$ .
- If  $M > L$ ,  $(s_M, \alpha_1)$  is larger than  $(s_L, \alpha_2)$ .

**Definition 3.** The negation operator of a 2-tuple value is defined as Formula (2):

$$neg((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha))) = \Delta(g - \beta) \tag{2}$$

where  $g+1$  is the cardinality of  $S$ ,  $S = \{s_0, \dots, s_g\}$ .

Since the 2-tuple linguistic model specifies the functions  $\Delta$  and  $\Delta^{-1}$  that convert numerical values into 2-tuple values and vice versa, any numerical aggregation operator can be easily adapted to cope with 2-tuple values. The arithmetic mean, the Weighted Average (WA) operator, and the OWA aggregation operator are three classical aggregation operators applied in the 2-tuple linguistic model (Herrera & Martínez, 2000). In this paper, the arithmetic mean and the OWA aggregation operator are applied to aggregate 2-tuple values. Definition 4 shows how to use the arithmetic mean to aggregate a set of 2-tuple values. The OWA aggregation operator is introduced in Section 3.3.

**Definition 4.** Let  $X_k = \{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_n, \alpha_n)\}$  be a set of 2-tuple values of the  $k$ th criterion, whose arithmetic mean is calculated using Formula (3):

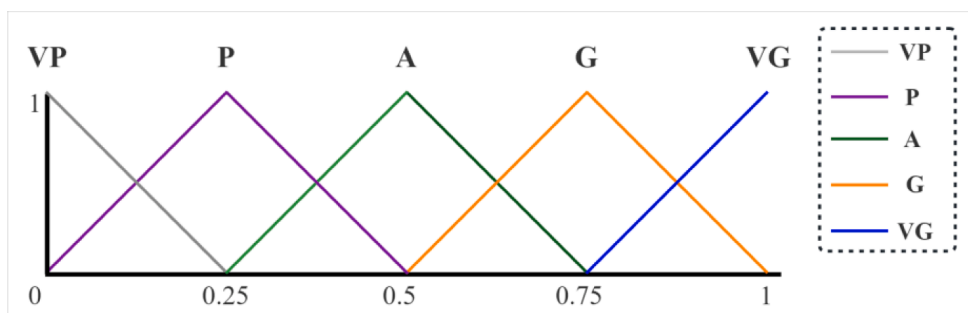


Fig. 4. Definition of the linguistic term set  $S$  at Dianping.com.

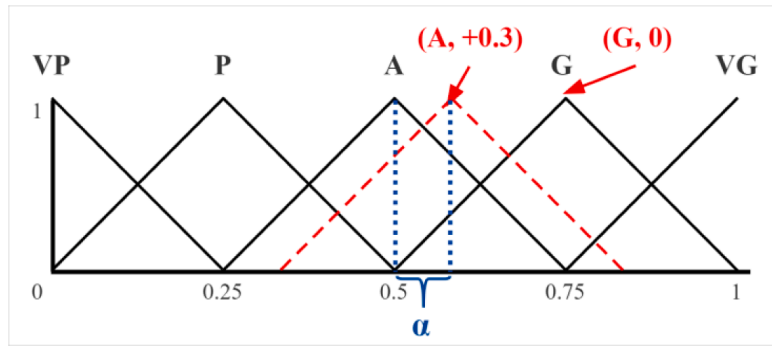


Fig. 5. Representation of examples of the 2-tuple values.

$$\bar{X}_k = \Delta \left( \frac{1}{n} \sum_{i=1}^n \Delta^{-1}(s_i, \alpha_i) \right) = \Delta \left( \frac{1}{n} \sum_{i=1}^n \beta_i \right) \tag{3}$$

where  $n$  is the number of users who have rated each restaurant criterion,  $i = 1, \dots, n$ .

**Example 2.** Let  $X_{service} = \{(A, 0), (G, 0), (G, 0), (A, 0), (A, 0), (G, 0), (A, 0), (G, 0), (A, 0), (VG, 0)\}$  be a set of 2-tuple values representing the ratings of ten users who evaluated the restaurant’s service. With the function  $\Delta^{-1}$ , this set can be converted into a set that includes their corresponding numeric values as  $\Delta^{-1}(X_{service}) = \{2, 3, 3, 2, 2, 3, 2, 3, 2, 4\}$ , whose arithmetic mean is 2.6. The 2-tuple value of its arithmetic mean is  $\Delta(2.6) = (s_{round(2.6)}, 2.6 - round(2.6)) = (s_3, -0.4) = (G, -0.4)$ . If the negation operator is applied to this 2-tuple value, it is computed as  $neg((s_3, -0.4)) = \Delta(4 - (\Delta^{-1}(s_3, -0.4))) = \Delta(4 - (3 - 0.4)) = \Delta(1.4) = (s_1, +0.4) = (P, +0.4)$ .

### 3.3. The Ordered Weighted Averaging (OWA) aggregation operator

The OWA aggregation operator was introduced by Yager (1988) as an information aggregation tool to address MCDM problems, which has been applied in many fields (Cho, 1995; Rinner & Malczewski, 2002; Torra, 2004; Li & Fei, 2019; Bueno et al., 2019; Wen et al., 2021; Shu, 2022). This aggregation operator is appropriate for modeling user attitudes (Serrano-Guerrero et al., 2022). In the OWA aggregation operator, the values of the variables are usually sorted in descending order beforehand (also called descending OWA (DOWA) aggregation operator). Another crucial issue is to determine the associated weights for each ordered value.

In the literature, several ways to determine the weights have been developed. Linguistic quantifiers (*At least one, Few, Half, Most, All*, etc.) can convey in a natural language different levels of user demand using formal mathematical formulas (Zadeh, 1996). By changing the linguistic quantifiers, the OWA aggregation operator can generate a wide range of decision strategies to express the decision-makers’ attitudinal character in information aggregation (Yager, 1988; Peláez & Doña, 2003; Boroushaki & Malczewski, 2008; Ahn, 2010; Merigó et al., 2017; Kazemi-Beydokhti et al., 2019; Hao & Chiclana, 2020; Lakicevic & Srdjevic, 2022). Therefore, they have been employed in this paper to determine the weights associated with each ordered value.

Definitions 5 and 6 show the method applied to determine the weights. Other methods for calculating OWA weights are available in Xu (2005).

**Table 2**  
Linguistic quantifiers and their corresponding  $\lambda$  parameters.

User demand levels	Linguistic quantifiers $Q_q$	$\lambda$
<b>Extremely undemanding:</b> users are satisfied with a restaurant when it has at least one positive review, even if the remaining reviews are negative, since they are extremely undemanding of this restaurant criterion.	$Q_1 = At\ least\ one$	0.0001
<b>Very undemanding:</b> users are satisfied with a restaurant when it has a few (more than one but not many) positive reviews, even if the remaining reviews are negative, since they are very undemanding of this restaurant criterion.	$Q_2 = Few$	0.1
<b>Undemanding:</b> users are satisfied with a restaurant when it has some positive reviews, since they are undemanding of this restaurant criterion.	$Q_3 = Some$	0.5
<b>Neutral:</b> users are satisfied with a restaurant when it has reviews that are, on average, positive, since they are neither too demanding nor undemanding of this restaurant criterion.	$Q_4 = Half$	1
<b>Demanding:</b> users are satisfied with a restaurant when it has many positive reviews, since they are demanding of this restaurant criterion.	$Q_5 = Many$	2
<b>Very demanding:</b> users are satisfied with a restaurant when it has mostly positive reviews, with very few unfavorable ones, since they are very demanding of this restaurant criterion.	$Q_6 = Most$	10
<b>Extremely demanding:</b> users are satisfied with a restaurant when it has no negative reviews, since they are very demanding of this restaurant criterion and are more concerned with the most unfavorable reviews.	$Q_7 = All$	1000

**Definition 5.** Regular increasing monotone (RIM) quantifiers can be applied to generate a parameterized subset in the unit interval (Yager, 1996), as shown in Formula (4):

$$Q_q(p) = p^\lambda, \lambda > 0 \tag{4}$$

where  $Q_q$  is a linguistic quantifier, represented as a fuzzy subset over the unit interval  $[0, 1]$ ; for each  $p$  in the unit interval, the grade of membership  $Q_q(p)$  indicates the compatibility of  $p$  with the concept denoted by  $Q_q$ .

Table 2 shows the levels of user demand defined in this paper, which represent the different preferences of users when viewing restaurant reviews. This is similar to the concept of degree of optimism based on the use of the OWA aggregation operator introduced by Filev and Yager (1995). For instance, when a user is more demanding of the service of a restaurant, they tend to focus more on negative reviews about it and has a less optimistic view of its service. In this case, more weights should be assigned to negative evaluations when aggregating various customer reviews for each restaurant criterion. This aggregation process taking into account the user demand levels can be achieved by using the ordered weights generated by the respective linguistic quantifier to aggregate the evaluations for each restaurant criterion. The corresponding linguistic quantifier for each user demand level, along with the parameters  $\lambda$  proposed by Boroushaki and Malczewski (2008) for each linguistic quantifier, are also shown in Table 2.

**Definition 6.** The ordered weights  $w_i$  ( $w_i \in [0, 1]$ ) are calculated with Formula (5):

$$w_i = Q_q\left(\frac{i}{n}\right) - Q_q\left(\frac{i-1}{n}\right) = \left(\frac{i}{n}\right)^\lambda - \left(\frac{i-1}{n}\right)^\lambda, \lambda > 0 \tag{5}$$

where  $n$  is the number of users who have rated each restaurant criterion,  $i = 1, \dots, n$ ; and  $\lambda$  is the value associated with each linguistic quantifier  $Q_q$ . The higher  $\lambda$  is, the more demanding the user is.  $\lambda=1$  indicates a medium level of demand (neither too demanding nor too undemanding).

The OWA aggregation operator is defined (Yager, 1988) as follows:

**Definition 7.** An OWA aggregation operator of dimension  $n$  is a mapping of  $OWA : R^n \rightarrow R$ , with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{i=1}^n w_i = 1$  and  $w_i \in [0, 1]$ . The OWA for each linguistic quantifier is computed using Formula (6):

$$OWA_{Q_q}(a_1, a_2, \dots, a_n) = \sum_{i=1}^n w_i b_i \tag{6}$$

where  $a_1, a_2, \dots, a_n$  are the input values (i.e., user ratings);  $b_i$  is the  $i$ th largest element of the input values;  $Q_q$  is the linguistic quantifier; and  $w_i$  represents the ordered weights.

The 2LOWA aggregation operator is an extension of the OWA aggregation operator that can deal with 2-tuple values. The definition is as follows:

**Definition 8.** Let  $X_k = \{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_n, \alpha_n)\}$  be a set of 2-tuple values of the  $k$ th criterion. A 2LOWA aggregation operator of dimension  $n$  is a mapping of 2LOWA:  $R^n \rightarrow R$  with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{i=1}^n w_i = 1$  and  $w_i \in [0, 1]$ . The 2LOWA for each linguistic quantifier is computed using Formula (7):

$$2LOWA_{Q_q}((s_1, \alpha_1), \dots, (s_n, \alpha_n)) = \Delta \left( \sum_{i=1}^n w_i b_i \right) \tag{7}$$

where  $w_i$  represents the ordered weights;  $b_i = \Delta^{-1}(s_i, \alpha_i)$ .

**Example 3.** Take the set of  $\Delta^{-1}(X_{service})$  from Example 2 and sort the values of it in descending order as  $\{4, 3, 3, 3, 3, 2, 2, 2, 2, 2\}$ . Using Formula (5), the weights for quantifier  $Q_1$  ( $\lambda = 0.0001$ , and  $n = 10$ ) are  $\{0.9998, 0.0001, 0, 0, 0, 0, 0, 0, 0, 0\}$ . Based on Formula (7), the 2-tuple value of this restaurant's service when using the quantifier  $Q_1$  can be calculated as:  $2LOWA_{Q_1}(X_{service}) = \Delta(4 * 0.9998 + 3 * 0.0001 + 0) = \Delta(3.9995) = (VG, - 0.0005)$ .

**Table 3**  
Description of the degree of importance.

User demand levels	Degree of importance
Extremely undemanding	<b>Lowest importance:</b> the criterion being evaluated is not at all important to the user when calculating the overall score.
Very undemanding	<b>Very low importance:</b> the criterion being evaluated is not very important to the user when calculating the overall score.
Undemanding	<b>Low importance:</b> the criterion being evaluated is relatively unimportant to the user when calculating the overall score.
Neutral	<b>Moderate importance:</b> the criterion being evaluated is of some importance to the user when calculating the overall score.
Demanding	<b>High importance:</b> the criterion being evaluated is relatively important to the user when calculating the overall score.
Very demanding	<b>Very high importance:</b> the criterion being evaluated is very important to the user when calculating the overall score.
Extremely demanding	<b>Highest importance:</b> the criterion being evaluated is the most important to the user when calculating the overall score.

Similarly, the 2-tuple value of this restaurant’s service using the rest of the linguistic quantifiers are:  $2LOWA_{Q_2}(X_{service}) = (VG, - 0.2725)$ ,  $2LOWA_{Q_3}(X_{service}) = (G, + 0.0235)$ ,  $2LOWA_{Q_4}(X_{service}) = (G, - 0.4)$ ,  $2LOWA_{Q_5}(X_{service}) = (A, + 0.26)$ ,  $2LOWA_{Q_6}(X_{service}) = (A, + 0.001)$ , and  $2LOWA_{Q_7}(X_{service}) = (A, 0)$ , respectively. The 2-tuple value calculated by quantifier  $Q_4$  coincides with that calculated by the arithmetic mean in [Example 2](#), which is  $(G, - 0.4)$ . This indicates that when users have average demand for the restaurant’s service, using the quantifier  $Q_4$  to aggregate the ratings of different users is equivalent to using the arithmetic mean.

### 3.4. The Importance Weights (IW) method

In [Section 3.3](#), it was explained that different levels of user demand could be expressed by means of linguistic quantifiers. In reality, if a user is more demanding of the restaurant’s service, it also means that the level of the restaurant’s service is more important to this user. Therefore, in order to achieve more accurate customized weights to compute the restaurant’s overall score, this paper proposes to identify the degree of importance of various restaurant criteria according to the level of user demand. [Table 3](#) shows the degree of importance corresponding to the level of user demand and its description.

According to [Table 3](#), the set of linguistic terms used to express the degree of importance can be defined as  $DI = \{di_0 = Lowest = LWST, di_1 = Very Low = VL, di_2 = Low = L, di_3 = Moderate = M, di_4 = High = H, di_5 = Very High = VH, di_6 = Highest = HIST\}$ , whose cardinality is  $g + 1 = 7$ . [Fig. 6](#) shows the set of linguistic terms with seven labels to indicate the degree of importance.

The IW method is defined as follows:

**Definition 9.** The weight of the  $k$ th criterion is calculated using Formula (8):

$$w_k = \frac{\Delta^{-1}(di_k, \alpha_k)}{\sum_{k=1}^m \Delta^{-1}(di_k, \alpha_k)} \tag{8}$$

where  $(di_k, \alpha_k)$  is a 2-tuple value representing the degree of importance corresponding to the  $k$ th criterion’s user demand level. If the user is extremely demanding of the restaurant’s service,  $(di_{Service}, \alpha_{Service}) = (HIST, 0)$ .

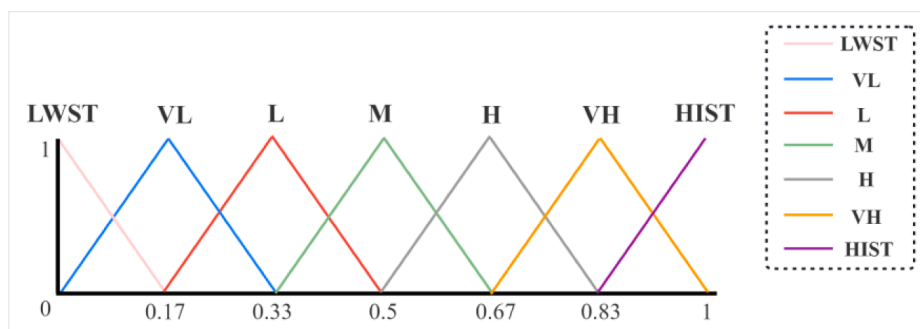
**Definition 10.** Let  $V = \{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_m, \alpha_m)\}$  be a set of ratings expressed in 2-tuple values for  $m$  criteria, and  $LI = \{(di_1, \alpha_1), \dots, (di_m, \alpha_m)\}$  be a vector of 2-tuple values corresponding to the degree of importance associated with each value in  $V$ . The overall score for each restaurant is determined by Formula (9):

$$Score = \Delta \left( \frac{\sum_{k=1}^m \Delta^{-1}(s_k, \alpha_k) \cdot w_k}{\sum_{k=1}^m \Delta^{-1}(di_k, \alpha_k)} \right) = \Delta \left( \frac{\sum_{k=1}^m \Delta^{-1}(s_k, \alpha_k) \cdot \Delta^{-1}(di_k, \alpha_k)}{\sum_{k=1}^m \Delta^{-1}(di_k, \alpha_k)} \right) \tag{9}$$

where  $(s_k, \alpha_k)$  represents the rating of the  $k$ th criterion obtained by Formula (7),  $k=1,2,\dots,m$ . If  $(di_1, \alpha_1) = (di_2, \alpha_2) = \dots = (di_k, \alpha_k)$ , these  $m$  criteria have the same importance.

**Example 4.** Suppose that user A is extremely demanding of the restaurant’s service, food, and environment, so the vector of 2-tuple values corresponding to the degree of importance associated with these three restaurant criteria is  $LI_A = \{(HIST, 0), (HIST, 0), (HIST, 0)\}$ . The ratings of service, food, and environment of the three restaurants calculated by Formula (7) using the quantifier  $Q_7$  are shown in [Table 4](#).

The overall score for restaurant 1 is calculated as follows:



**Fig. 6.** Definition of linguistic term set  $DI$ .

**Table 4**  
Restaurant ratings expressed in 2-tuple values (User A).

Restaurant	Service	Food	Environment
1	(P, +0.12)	(G, +0.20)	(A, +0.05)
2	(A, +0.10)	(P, +0.20)	(G, -0.08)
3	(A, -0.10)	(G, +0.06)	(A, -0.15)

**Table 5**  
Restaurant ratings expressed in 2-tuple values (User B).

Restaurant	Service	Food	Environment
1	(A, +0.11)	(G, +0.20)	(G, +0.10)
2	(G, +0.08)	(P, +0.20)	(VG, -0.12)
3	(G, -0.20)	(G, +0.06)	(G, -0.21)

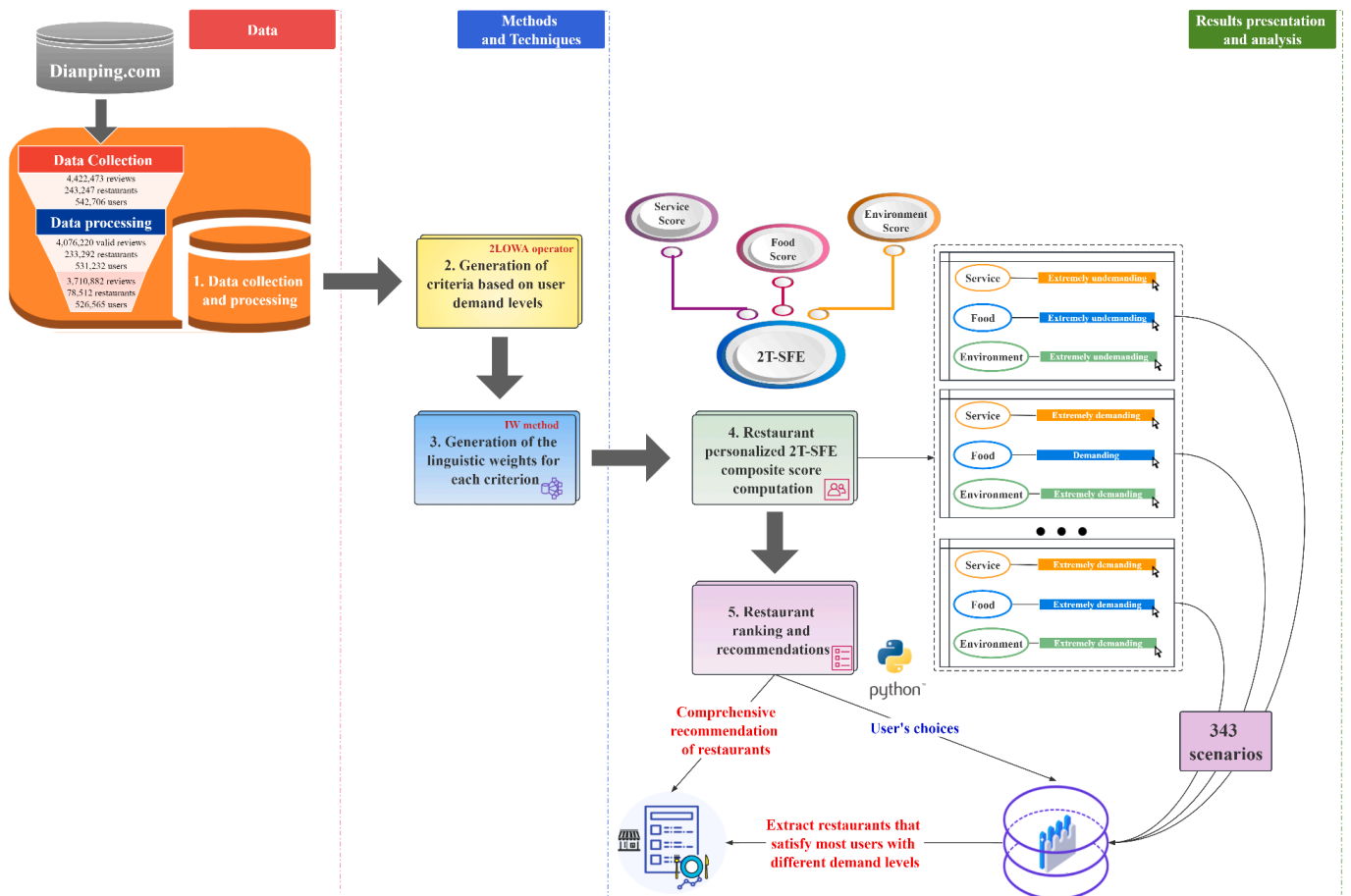
$$Score_1 = \Delta \left( \frac{\Delta^{-1}(P, +0.12) \cdot \Delta^{-1}(HIST, 0) + \Delta^{-1}(G, +0.2) \cdot \Delta^{-1}(HIST, 0) + \Delta^{-1}(A, +0.05) \cdot \Delta^{-1}(HIST, 0)}{\Delta^{-1}(HIST, 0) + \Delta^{-1}(HIST, 0) + \Delta^{-1}(HIST, 0)} \right)$$

$$= \Delta \left( \frac{1.12 \cdot 6 + 3.2 \cdot 6 + 2.05 \cdot 6}{6 + 6 + 6} \right) = \Delta(2.123) = (A, +0.123)$$

Similarly, the overall scores for restaurants 2 and 3 are  $Score_2 = (A, + 0.073)$ , and  $Score_3 = (A, + 0.27)$ . Since  $Score_3 > Score_1 > Score_2$ , user A will choose Restaurant 3.

If user B is extremely demanding of the restaurant’s food, but is undemanding of the restaurant’s service and environment, the vector of 2-tuple values corresponding to the degree of importance associated with these three restaurant criteria is  $LI_B = \{(L, 0), (HIST, 0), (L, 0)\}$ . The ratings of service, food, and environment of the three restaurants are shown in Table 5.

The difference between Table 4 and Table 5 is that the ratings of restaurant service and environment are different, as the level of



**Fig. 7.** Proposed model for restaurant ranking and selection.

user demand for these two criteria has changed from “extremely demanding” to “undemanding”. For user B, the overall scores for these three restaurants are  $Score_1 = (G, - 0.038)$ ,  $Score_2 = (A, + 0.112)$ , and  $Score_3 = (G, - 0.046)$ , respectively. Since  $Score_1 > Score_3 > Score_2$ , user B will choose Restaurant 1.

#### 4. Proposed model

The proposed model is composed of five steps: section 4.1 shows the process of collecting and cleaning the dataset; section 4.2 shows the process of extracting useful information from the dataset, and aggregating it into new criteria reflecting different levels of user demand of restaurant service, food, and environment; section 4.3 presents how to generate diverse scenarios of the linguistic weights for each new criterion; section 4.4 calculates the customized composite score of the restaurant based on user demand levels of restaurant service, food, and environment; section 4.5 shows the results of restaurant ranking and recommendations. Fig. 7 shows each step in the proposed model, corresponding to the structure introduced in Fig. 1.

##### 4.1. Data collection and processing

This step obtains online reviews of Chinese restaurants from Dianping.com. Like many other review sites, Dianping.com uses a five-star rating system and linguistic terms to express users’ reviews of various restaurant aspects (see Fig. 3). As shown in Fig. 3, the rating scale employed by Dianping.com is as follows: "1 star=Very Poor, 2 stars=Poor, 3 stars=Average, 4 stars=Good, and 5 stars=Very Good".

This paper uses the dataset published by Zhang (2013), a collection of user reviews about restaurants collected from Dianping.com between April 7, 2003, and February 8, 2012. This dataset comprises more than 4.4 million reviews from 542,706 users on 243,247 restaurants. Each review contains ratings the user gives (ranging from 1 to 5 stars) for three criteria (Service, Food, and Environment) to evaluate the restaurants. It also includes the review date, user ID, and restaurant ID.

When performing data processing, considering user reviews with missing partial dimensional ratings would be considered spam or intentionally bad reviews on Dianping.com (see Section 3.1), only those restaurants that have received valid reviews with all three criteria (Service, Food, and Environment) are included in this study. It results in a new dataset of 233,292 restaurants with 4,076,220 reviews from 531,232 users. However, only 78,512 of the 233,292 restaurants in the new dataset received no less than ten reviews, which is the minimum requirement for Dianping.com to start calculating the restaurant’s overall rating. Therefore, this paper only analyses these 78,512 restaurants that appeared in the list of user-recommended restaurants and were given overall scores by the algorithm.

Let  $T = \{t_1, \dots, t_{\#T}\}$  be the set of restaurants, and  $C = \{Service, Food, Environment\}$  be the set of restaurant criteria evaluated by users  $U = \{u_1, \dots, u_{\#U}\}$  on Dianping.com. The number of user reviews received by each restaurant is different, so the set of users associated with each restaurant can be expressed as  $U^1 = \{u_1^1, \dots, u_{\#U^1}^1\}$ ,  $U^2 = \{u_1^2, \dots, u_{\#U^2}^2\}, \dots, U^{\#T} = \{u_1^{\#T}, \dots, u_{\#U^{\#T}}^{\#T}\}$ , with  $U^1, U^2, \dots, U^{\#T} \subseteq U$ .

Thus, a processed dataset  $TA = \{(t_1, \{(u_1^1, d_1^1, v_1^{Service_1}, v_1^{Food_1}, v_1^{Environment_1}), \dots, (u_{\#U^1}^1, d_{\#U^1}^1, v_{\#U^1}^{Service_1}, v_{\#U^1}^{Food_1}, v_{\#U^1}^{Environment_1})\}), \dots, (t_{\#T}, \{(u_1^{\#T}, d_1^{\#T}, v_1^{Service_{\#T}}, v_1^{Food_{\#T}}, v_1^{Environment_{\#T}}), \dots, (u_{\#U^{\#T}}^{\#T}, d_{\#U^{\#T}}^{\#T}, v_{\#U^{\#T}}^{Service_{\#T}}, v_{\#U^{\#T}}^{Food_{\#T}}, v_{\#U^{\#T}}^{Environment_{\#T}})\})\}$  is obtained, where:

- $t_f$ : is the identifying code of each restaurant, with  $t_f \in T$  and  $f = 1, \dots, \#T$ .

**Table 6**  
Reviews received by the restaurant  $t_{32519}$ .

$t_f$	$u_i^f$	$d_i^f$ (YYYY – MM – DD)	$v_i^{Service_f}$	$v_i^{Food_f}$	$v_i^{Environment_f}$
32519	37602	2006-10-11	A	A	A
32519	83244	2008-02-05	A	G	VG
32519	77755	2008-07-02	G	A	A
32519	115294	2008-09-19	VG	G	G
32519	77764	2008-09-19	A	P	P
32519	222219	2008-12-12	A	A	A
32519	37615	2009-05-11	G	A	G
32519	37630	2009-05-26	A	P	A
32519	200053	2009-12-03	G	G	G
32519	222220	2010-04-01	A	A	A
32519	83986	2010-05-03	VG	A	VG
32519	222221	2010-07-07	A	P	A
32519	1891	2011-01-13	A	A	A
32519	77779	2011-03-14	VG	A	A
32519	222222	2012-01-30	G	A	G

- $u_i^f$ : is the identifying code of each user, which is used to distinguish the user reviews received by each restaurant  $t_f$ , with  $i = 1, \dots, \#U, f = 1, \dots, \#T$ , and  $u_i^f \in U$ .
- $d_i^f$ : is the date on which the user  $u_i^f$  evaluated the restaurant  $t_f$ ,  $d_i^f \in d$ .  $d$  is the analysis period delimited by the start date  $d_s = \text{April 7, 2003}$  and the end date  $d_e = \text{February 8, 2012}$ .
- $(v_i^{Service_f}, v_i^{Food_f}, v_i^{Environment_f})$ : are the ratings of service, food, and environment for each restaurant expressed on a linguistic scale, where  $i = 1, \dots, \#U$  and  $f = 1, \dots, \#T$ . According to the rating scale on Dianping.com, the linguistic scale contains five values: “Very Poor=VP”, “Poor=P”, “Average=A”, “Good=G”, and “Very Good=VG”. These linguistic values are symmetrical, whose central value is neutral (i.e., “Average”) (Tao et al., 2014; Marín Díaz et al., 2021; Bueno et al., 2022). They are modeled by fuzzy triangular labels  $(v_{\#U}^{C\#T} \in S)$ , as shown in Fig. 4.

Table 6 shows an example of a restaurant from the dataset TA, which received more than ten reviews.

#### 4.2. Generation of criteria based on user demand levels

Dianping.com uses the ratings of service, food, and environment to update the overall star rating of the restaurant. This step generates new criteria that reflect the different levels of user demand for these three aspects of the restaurant.

The seven linguistic quantifiers of the 2LOWA aggregation operator are applied to each of the three restaurant aspects, resulting in the creation of 21 new criteria to reflect the varying levels of user demand for restaurant service, food, and environment. Utilizing the newly generated criteria, a new dataset is created as:

$$TA\_2LOWA = \left\{ \begin{array}{l} (t_1, (O_{Q_1}^{Service_1}, \dots, O_{Q_7}^{Service_1}), (O_{Q_1}^{Food_1}, \dots, O_{Q_7}^{Food_1}), (O_{Q_1}^{Environment_1}, \dots, O_{Q_7}^{Environment_1})), \\ \vdots \\ (t_{\#T}, (O_{Q_1}^{Service_{\#T}}, \dots, O_{Q_7}^{Service_{\#T}}), (O_{Q_1}^{Food_{\#T}}, \dots, O_{Q_7}^{Food_{\#T}}), (O_{Q_1}^{Environment_{\#T}}, \dots, O_{Q_7}^{Environment_{\#T}})) \end{array} \right\} \text{ where:}$$

- $t_f$ : is the identifying code of each restaurant, with  $t_f \in T$  and  $f = 1, \dots, \#T$ .
- $\{(O_{Q_1}^{Service_f}, \dots, O_{Q_7}^{Service_f}), (O_{Q_1}^{Food_f}, \dots, O_{Q_7}^{Food_f}), (O_{Q_1}^{Environment_f}, \dots, O_{Q_7}^{Environment_f})\}$ : are the linguistic ratings aggregated by the 2LOWA aggregation operator with seven linguistic quantifiers for service, food, and environment of each restaurant  $t_f$ ,  $O_{Q_q}^{Service_f} \in Sx[-0.5, 0.5]$ .  $O_{Q_q}^{Service_f} = 2LOWA_{Q_q}(v_1^{Service_f}, \dots, v_i^{Service_f})$ , with  $i = 1, \dots, \#U; f = 1, \dots, \#T; Q_q$  represents linguistic quantifiers defined in Table 2;  $2LOWA_{Q_q}(\cdot)$  has been defined in Formula (7). Both  $O_{Q_q}^{Food_f}$  and  $O_{Q_q}^{Environment_f}$  belong to  $Sx[-0.5, 0.5]$ , and the formula used to calculate their 2-tuple values is  $2LOWA_{Q_q}(\cdot)$ .

Table 7 shows the 21 new criteria generated to reflect the different levels of user demand for the service, food, and environment of restaurant  $t_{32519}$ .

To compare with this newly generated dataset TA\_2LOWA, the arithmetic mean score dataset TA\_MEAN is generated as:  $TA\_MEAN = \{(t_1, M^{Service_1}, M^{Food_1}, M^{Environment_1}), \dots, (t_{\#T}, M^{Service_{\#T}}, M^{Food_{\#T}}, M^{Environment_{\#T}})\}$ , where  $t_f$  is the same as that defined in the dataset TA\_2LOWA;  $(M^{Service_f}, M^{Food_f}, M^{Environment_f})$  are the average ratings expressed in 2-tuple values for service, food, and environment of each restaurant, with  $M^{Service_f} = \overline{X}_k(v_1^{Service_f}, \dots, v_i^{Service_f}), M^{Food_f} = \overline{X}_k(v_1^{Food_f}, \dots, v_i^{Food_f}), M^{Environment_f} = \overline{X}_k(v_1^{Environment_f}, \dots, v_i^{Environment_f}), i = 1, \dots, \#U; f = 1, \dots, \#T; \overline{X}_k(\cdot)$  has been defined in Formula (3). Table 8 shows an example of the dataset TA\_MEAN.

#### 4.3. Generation of the linguistic weights for each criterion

This step generates diverse scenarios of the weights for each criterion produced in the previous step. A total of 343 (i.e.,  $7 \times 7 \times 7$ )

**Table 7**  
21 new criteria generated for restaurant  $t_{32519}$ .

$t_f$	$O_{Q_1}^{Service_f}$	$O_{Q_2}^{Service_f}$	$O_{Q_3}^{Service_f}$	$O_{Q_4}^{Service_f}$	$O_{Q_5}^{Service_f}$	$O_{Q_6}^{Service_f}$	$O_{Q_7}^{Service_f}$
32519	(VG, -0.0010)	(VG, -0.2218)	(G, +0.1307)	(G, -0.3315)	(A, +0.2573)	(A, +0.0005)	A
$t_f$	$O_{Q_1}^{Food_f}$	$O_{Q_2}^{Food_f}$	$O_{Q_3}^{Food_f}$	$O_{Q_4}^{Food_f}$	$O_{Q_5}^{Food_f}$	$O_{Q_6}^{Food_f}$	$O_{Q_7}^{Food_f}$
32519	(G, -0.0008)	(G, -0.1705)	(A, +0.3420)	(A, +0.0015)	(A, -0.3204)	(P, +0.1074)	P
$t_f$	$O_{Q_1}^{Environment_f}$	$O_{Q_2}^{Environment_f}$	$O_{Q_3}^{Environment_f}$	$O_{Q_4}^{Environment_f}$	$O_{Q_5}^{Environment_f}$	$O_{Q_6}^{Environment_f}$	$O_{Q_7}^{Environment_f}$
32519	(VG, -0.0010)	(VG, -0.2767)	(G, -0.0360)	(A, +0.4684)	(A, +0.0484)	(A, -0.4983)	P

**Table 8**  
The data of the restaurant  $t_{32519}$  in the dataset  $TA\_MEAN$ .

$t_j$	$M^{Service_j}$	$M^{Food_j}$	$M^{Environment_j}$
32519	(G, -0.3332)	A	(A, +0.4668)

**Table 9**  
Examples of weight scenarios for the restaurants on Dianping.com.

Scenario id	Scenario description	Input variables	Service	Food	Environment
$Scenario_1$	Users are extremely demanding of restaurant service, food, and environment.	$O_{Q_7}^{Service_j}, O_{Q_7}^{Food_j}, O_{Q_7}^{Environment_j}$	33.33%	33.33%	33.33%
$Scenario_2$	Users are very demanding of restaurant service, but undemanding of the food and environment.	$O_{Q_6}^{Service_j}, O_{Q_3}^{Food_j}, O_{Q_3}^{Environment_j}$	55.56%	22.22%	22.22%
$Scenario_3$	Users are neutral about restaurant food and environment, but demanding of the service.	$O_{Q_5}^{Service_j}, O_{Q_4}^{Food_j}, O_{Q_4}^{Environment_j}$	40%	30%	30%
$Scenario_4$	Users are neutral (neither too demanding nor undemanding) about restaurant service, food, and environment.	$O_{Q_4}^{Service_j}, O_{Q_4}^{Food_j}, O_{Q_4}^{Environment_j}$	33.33%	33.33%	33.33%
$Scenario_5$	Users are very undemanding of restaurant service, food, and environment.	$O_{Q_2}^{Service_j}, O_{Q_2}^{Food_j}, O_{Q_2}^{Environment_j}$	33.33%	33.33%	33.33%
$Scenario_6$	Users are extremely demanding of restaurant environment, demanding of restaurant food, and undemanding of restaurant service.	$O_{Q_3}^{Service_j}, O_{Q_5}^{Food_j}, O_2^{Environment_j}$	16.67%	33.33%	50%
$Scenario_7$	Users are extremely undemanding of restaurant service, but demanding of the food and environment.	$O_{Q_1}^{Service_j}, O_{Q_5}^{Food_j}, O_{Q_7}^{Environment_j}$	0%	50%	50%
$Scenario_8$	Users are extremely undemanding of restaurant service, food, and environment. <sup>1</sup>	$O_{Q_1}^{Service_j}, O_{Q_1}^{Food_j}, O_{Q_5}^{Environment_j}$	0%	0%	0%
$Scenario_{Mean}$	Users have average demand of restaurant service, food, and environment.	$M^{Service_j}, M^{Food_j}, M^{Environment_j}$	33.33%	33.33%	33.33%

<sup>1</sup> If users are extremely undemanding of restaurant service, food, and environment, none of these three criteria is considered important when selecting a restaurant. In such a case, restaurants would be randomly recommended to users.

$7 = 7^3$ ) possible weight scenarios are obtained using Formula (8). Table 9 shows some of the 343 weight scenarios obtained for the dataset  $TA\_ZLOWA$ , and the scenario of the weights for the dataset  $TA\_MEAN$ .

As shown in Table 9, when users have the same level of demand for restaurant service, food, and environment—whether they are extremely demanding or undemanding—these three criteria are considered equally important in their restaurant selection and thus have the same weights.

However, even though the weight distribution in some scenarios coincides with the one derived using the arithmetic mean, it does not mean that the overall scores of the restaurants are also the same. This is because the values of the new criteria generated by various linguistic quantifiers differ from those of the  $TA\_MEAN$ . Only when the user demand for restaurant service, food, and environment is at a moderate level are the restaurant’s overall score and the weights of each restaurant criterion the same as those calculated by the

**Table 10**  
Composite score results for the restaurant  $t_{32519}$ .

	Scenario for User A			Scenario for User B		
	Data	Weight	Data x Weight	Data	Weight	Data x Weight
Service	$\Delta^{-1}((VG, - 0.0010)) = 3.999$	0%	0	$\Delta^{-1}((A)) = 2$	33.33%	0.6666
Food	$\Delta^{-1}((A, - 0.3204)) = 1.6796$	50%	0.8398	$\Delta^{-1}((P)) = 1$	33.33%	0.3333
Environment	$\Delta^{-1}((A, + 0.0484)) = 2.0484$	50%	1.0242	$\Delta^{-1}((P)) = 1$	33.33%	0.3333
Composite Score	$\Delta(1.864) = (A, - 0.136)$			$\Delta(1.3332) = (P, + 0.3332)$		

**Table 11**  
Top 10 restaurants on Dianping.com under eight diverse scenarios.

R	Scenario <sub>1</sub>		Scenario <sub>2</sub>		Scenario <sub>3</sub>		Scenario <sub>4</sub>		Scenario <sub>5</sub>		Scenario <sub>6</sub>		Scenario <sub>7</sub>		Scenario <sub>Mean</sub>	
	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score	<i>t<sub>f</sub></i>	Composite Score
1	55765	(G,+0.3332)	55765	(VG,-0.4472)	55765	(VG,-0.2052)	169535	(VG,-0.1552)	169535	(VG,-0.0168)	55765	(G,+0.4892)	169535	(VG,-0.2836)	169535	(VG,-0.1540)
2	235986*	(G,+0.3332)	169535	(VG,-0.4864)	169535	(VG,-0.2064)	55765	(VG,-0.1688)	55765	(VG,-0.0204)	111613	(G,+0.4840)	55765	(VG,-0.3092)	55765	(VG,-0.1668)
3	224393*	(G,+0.3332)	224393	(G,+0.4540)	224393	(VG,-0.2640)	224393	(VG,-0.2000)	224393	(VG,-0.0236)	224393	(G,+0.4824)	224393	(VG,-0.3200)	224393	(VG,-0.2000)
4	111613*	(G,+0.3332)	232652	(G,+0.4360)	28868	(VG,-0.2880)	28868	(VG,-0.2432)	28868	(VG,-0.0284)	27486	(G,+0.4756)	210784	(VG,-0.4016)	28868	(VG,-0.2432)
5	120560*	(G,+0.3332)	27486	(G,+0.4108)	232652	(VG,-0.3232)	232652	(VG,-0.2732)	196652	(VG,-0.0292)	118253	(G,+0.4724)	74395	(VG,-0.4120)	74395	(VG,-0.2692)
6	169535	G	111613	(G,+0.3916)	117698	(VG,-0.3368)	74395	(VG,-0.2768)	210158	(VG,-0.0304)	120560	(G,+0.4716)	118253	(VG,-0.4408)	232652	(VG,-0.2728)
7	27486*	G	210784	(G,+0.3908)	27486	(VG,-0.3516)	117698*	(VG,-0.2768)	74395	(VG,-0.0308)	57877	(G,+0.4452)	235986	(VG,-0.4492)	196652	(VG,-0.2752)
8	118253*	G	149066	(G,+0.3876)	196652	(VG,-0.3572)	210158	(VG,-0.2796)	117698	(VG,-0.0312)	235986	(G,+0.4416)	28868	(VG,-0.4588)	210158	(VG,-0.2780)
9	232652*	G	117698	(G,+0.3840)	27865	(VG,-0.3580)	196652	(VG,-0.2940)	175441	(VG,-0.0332)	232652	(G,+0.4264)	120560	(VG,-0.4688)	117698	(VG,-0.2788)
10	57877*	G	139963	(G,+0.3804)	210158	(VG,-0.3624)	27865	(VG,-0.3008)	27865	(VG,-0.0344)	29244	(G,+0.4228)	27486	(VG,-0.4756)	27865	(VG,-0.2888)

\* This restaurant is ranked the same as the previous one, as they have the same composite scores. For example, in Scenario<sub>4</sub>, as restaurants 74395 and 117698 have the same 2-tuple scores, higher than restaurant 210158, they are ranked 6th, 6th, and 8th, respectively.

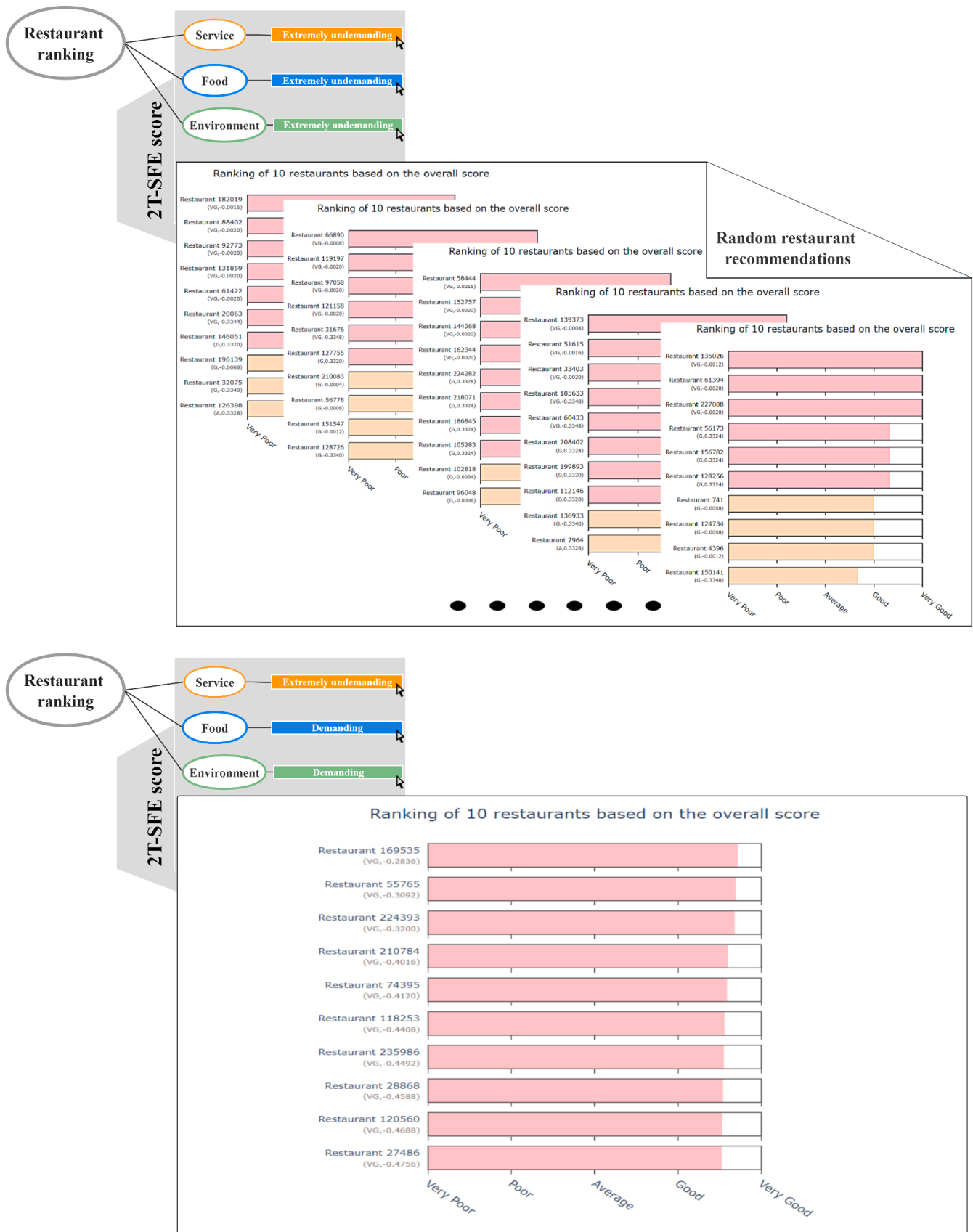


Fig. 8. Examples of the top 10 restaurants under Scenario<sub>7</sub> and Scenario<sub>8</sub>.

arithmetic mean. The new criteria generated by quantifier  $Q_4$  for restaurant service, food, and environment are essentially identical to those calculated using the arithmetic mean, with only slight decimal differences, as evident in the examples provided in Tables 7 and 8.

4.4. Restaurant personalized 2T-SFE composite score computation

Based on the 343 different weight scenarios obtained in the previous step, this step generates customized 2T-SFE composite scores for 78,512 restaurants. A total of 343 composite scoring schemes are obtained using Formula (9). For example, user A is extremely undemanding of restaurant service, but demanding of the food and environment. User B is extremely demanding of these three restaurant criteria. Table 10 shows the process and results of the composite score calculation for the restaurant  $t_{32519}$  in the two scenarios mentioned above.

As shown in Table 10, despite restaurant  $t_{32519}$  having very good service, for user A, its composite score indicates that the establishment falls slightly below the average level among the 78,512 restaurants, making it less desirable for user A to select it. Regarding user B, this restaurant will never be included in the consideration list. In fact, the process of selecting a restaurant could be further facilitated by combining it with the ranking of the restaurants, which will be discussed in the next step.

4.5. Restaurant ranking and recommendations.

In this step, the 78,512 restaurants are ranked based on the previously obtained comprehensive scores, and the results are showcased in an interactive application created using the Python programming language. This allows users to visualize the restaurant list and effortlessly select a restaurant that aligns with their needs. Additionally, the platform can make more accurate and satisfying recommendations for users.

Table 11 shows the IDs of the top 10 restaurants and their corresponding overall scores for the scenarios presented in Table 9, except for Scenario<sub>8</sub>. Scenario<sub>8</sub> is not included in Table 11 because, in this case, none of the three restaurant aspects (Service, Food, and Environment) is deemed important when selecting a restaurant. The restaurants will be randomly recommended in this situation. Fig. 8 presents screenshot examples of the top 10 restaurants according to Scenario<sub>8</sub> in the interactive application, along with the top 10 restaurants according to Scenario<sub>7</sub>. As shown in Fig. 8, in the case of Scenario<sub>8</sub>, these top 10 restaurants are not fixed but appear randomly. In contrast, in Scenario<sub>7</sub>, they are fixed and match the list of the top 10 restaurants in Table 11.

In addition, Table 12 shows the 92 restaurants that rank in the top 10, as well as their respective frequencies of appearance, except

**Table 12**  
Frequency list of the restaurant appearance in the top 10 across 342 scenarios.

$t_f$	Frequency of appearance in the top 10		$t_f$	Frequency of appearance in the top 10		$t_f$	Frequency of appearance in the top 10	
	frequency	%		frequency	%		frequency	%
55765	335	97.95	80065	17	4.97	121080		
224393	325	95.03	27865	16	4.68	195681		
169535	262	76.61	83552	15	4.39	117389		
111613	246	71.93	89383	13	3.80	62007		
27486	225	65.79	54807			116309		
120560	200	58.48	139827	12	3.51	96804		
232652	194	56.73	180524	10	2.92	68287		
235986	168	49.12	23295			215217		
118253	159	46.49	207649	9	2.63	175427		
149066	150	43.86	179699			139581		
57877			80969	8	2.34	213001		
210784	136	39.77	231714			19407		
28868	94	27.49	26758			206372		
240650	81	23.68	209761	7	2.05	2211		
32073	71	20.76	162567			223491		
117698	59	17.25	141881	6	1.75	179840	1	0.29
29244	58	16.96	209530			105940		
137778	56	16.37	181266	5	1.46	141479		
175441	47	13.74	197815	4	1.17	138070		
74395	43	12.57	18795			208508		
85881	36	10.53	18570			112002		
110358			85483			239926		
139963	33	9.65	52134			141544		
210158	30	8.77	27423			210426		
57349	28	8.19	168664	3	0.88	237073		
172635	27	7.89	155851			240107		
196652	26	7.60	83940			25213		
171960			201088			183514		
200002	23	6.73	50850			147349		
145920	22	6.43	1290	1	0.29	3756		
65112	21	6.14	70498					

for the extreme case where restaurants will be randomly recommended to users (i.e., *Scenario<sub>8</sub>*). The analytical details of [Tables 11](#) and [12](#) are described in [Section 5](#).

### 5. Analysis of results and comparison

This section analyzes the results of the restaurant rankings produced by the proposed model. As shown in [Table 11](#), when users have a medium level of demand of restaurant service, food, and environment (i.e., *Scenario<sub>4</sub>*, all linguistic ratings are aggregated using the quantifier  $Q_4$ ), most of the results for *Scenario<sub>4</sub>* and *Scenario<sub>Mean</sub>* are the same. The ranking of the top ten restaurants is almost identical, except for a slight decimal difference in their 2-tuple values.

However, there are differences in restaurant ranking when comparing other scenarios. For example, when comparing *Scenario<sub>3</sub>* and *Scenario<sub>4</sub>*, it can be observed that the ranking of the restaurant changes if the degree of user demand of restaurant service increases, even though the level of user demand of restaurant food and environment is constant. In particular, restaurant 27486 was not in the top 10 in *Scenario<sub>4</sub>*, but ranked seventh in *Scenario<sub>3</sub>*. In *Scenario<sub>4</sub>*, restaurant 74395 ranked sixth; however, it was not among the top ten in *Scenario<sub>3</sub>*.

Similarly, the rankings of the top 10 restaurants change significantly when the level of user demand changes dramatically. For instance, in *Scenario<sub>5</sub>*, none of the restaurants that appear in the top 10 are present in the top 10 of *Scenario<sub>1</sub>*, except for restaurants 55765, 224393, and 169535 (these three restaurants have a high frequency of appearance in the top 10; see [Table 12](#)). This shows that the ranking of some restaurants decreases as users become more demanding of the restaurant service, food, and environment, as they fail to meet the high level of user demand.

In addition, [Table 12](#) shows that several restaurants regularly appear in the top 10 under 342 scenarios, such as restaurants 55765, 224393, 169535, and 111613, with a frequency of over 70%. Since they frequently appear in the top 10, these four restaurants on Dianping.com can satisfy the requirements of most users with different levels of demand of service, food, and environment. However, some restaurants have less than 1% frequency of appearance in the top 10.

The Cox-Stuart test (COX & STUART, 1955) has been used in this paper to assess the trend (increasing, decreasing, or stable) of restaurant rankings that change with user demand levels, as it is particularly robust for trend analysis. Since a lower number indicates a higher ranking (e.g., 1 means it ranks first), if the Cox-Stuart result indicates a decreasing trend (e.g., from 1000 to 1), the restaurant is ranked higher as users are more demanding of restaurant criteria. [Table 13](#) shows the trend of change in the ranking of the 92

**Table 13**  
Ranking changes of 92 restaurants.

$t_f$	Cox-Stuart result	Average ranking	$t_f$	Cox-Stuart result	Average ranking	$t_f$	Cox-Stuart result	Average ranking
55765	stable <sup>1</sup>	2	80065	decreasing <sup>2</sup>	54	121080	decreasing <sup>2</sup>	64
224393	stable <sup>1</sup>	4	27865	increasing <sup>3</sup>	5572	195681	decreasing <sup>2</sup>	250
169535	stable <sup>1</sup>	7	83552	increasing <sup>3</sup>	199	117389	decreasing <sup>2</sup>	241
111613	decreasing <sup>2</sup>	24	89383	decreasing <sup>2</sup>	47	62007	decreasing <sup>2</sup>	5145
27486	decreasing <sup>2</sup>	18	54807	decreasing <sup>2</sup>	245	116309	decreasing <sup>2</sup>	80
120560	decreasing <sup>2</sup>	23	139827	decreasing <sup>2</sup>	88	96804	decreasing <sup>2</sup>	102
232652	decreasing <sup>2</sup>	11	180524	increasing <sup>3</sup>	391	68287	decreasing <sup>2</sup>	4394
235986	decreasing <sup>2</sup>	29	23295	decreasing <sup>2</sup>	313	215217	decreasing <sup>2</sup>	1466
118253	decreasing <sup>2</sup>	24	207649	decreasing <sup>2</sup>	50	175427	decreasing <sup>2</sup>	97
149066	decreasing <sup>2</sup>	22	179699	decreasing <sup>2</sup>	63	139581	decreasing <sup>2</sup>	101
57877	decreasing <sup>2</sup>	17	80969	increasing <sup>3</sup>	1581	213001	decreasing <sup>2</sup>	209
210784	stable <sup>1</sup>	20	231714	decreasing <sup>2</sup>	61	19407	decreasing <sup>2</sup>	154
28868	increasing <sup>3</sup>	2834	26758	decreasing <sup>2</sup>	47	206372	increasing <sup>3</sup>	3146
240650	decreasing <sup>2</sup>	57	209761	decreasing <sup>2</sup>	69	2211	increasing <sup>3</sup>	2498
32073	increasing <sup>3</sup>	185	162567	increasing <sup>3</sup>	801	223491	increasing <sup>3</sup>	1232
117698	increasing <sup>3</sup>	28	141881	decreasing <sup>2</sup>	56	179840	decreasing <sup>2</sup>	61
29244	decreasing <sup>2</sup>	29	209530	decreasing <sup>2</sup>	26	105940	decreasing <sup>2</sup>	303
137778	increasing <sup>3</sup>	158	181266	increasing <sup>3</sup>	195	141479	decreasing <sup>2</sup>	976
175441	increasing <sup>3</sup>	48	197815	increasing <sup>3</sup>	312	138070	decreasing <sup>2</sup>	409
74395	increasing <sup>3</sup>	5464	18795	decreasing <sup>2</sup>	655	208508	decreasing <sup>2</sup>	286
85881	increasing <sup>3</sup>	186	18570	decreasing <sup>2</sup>	97	112002	decreasing <sup>2</sup>	3431
110358	decreasing <sup>2</sup>	26	85483	decreasing <sup>2</sup>	533	239926	decreasing <sup>2</sup>	99
139963	decreasing <sup>2</sup>	40	52134	decreasing <sup>2</sup>	35	141544	decreasing <sup>2</sup>	285
210158	increasing <sup>3</sup>	39	27423	decreasing <sup>2</sup>	486	210426	decreasing <sup>2</sup>	1111
57349	decreasing <sup>2</sup>	346	168664	decreasing <sup>2</sup>	70	237073	decreasing <sup>2</sup>	598
172635	increasing <sup>3</sup>	68	155851	decreasing <sup>2</sup>	160	240107	decreasing <sup>2</sup>	201
196652	increasing <sup>3</sup>	5582	83940	decreasing <sup>2</sup>	2087	25213	decreasing <sup>2</sup>	684
171960	decreasing <sup>2</sup>	41	201088	decreasing <sup>2</sup>	597	183514	decreasing <sup>2</sup>	161
200002	decreasing <sup>2</sup>	27	50850	decreasing <sup>2</sup>	45	147349	decreasing <sup>2</sup>	269
145920	increasing <sup>3</sup>	1730	1290	decreasing <sup>2</sup>	2316	3756	increasing <sup>3</sup>	35550
65112	decreasing <sup>2</sup>	26	70498	decreasing <sup>2</sup>	633			

<sup>1</sup> Ranking is steady.

<sup>2</sup> Ranking rises as users are more demanding of restaurant service, food, and environment.

<sup>3</sup> Ranking falls as users are more demanding of restaurant service, food, and environment.

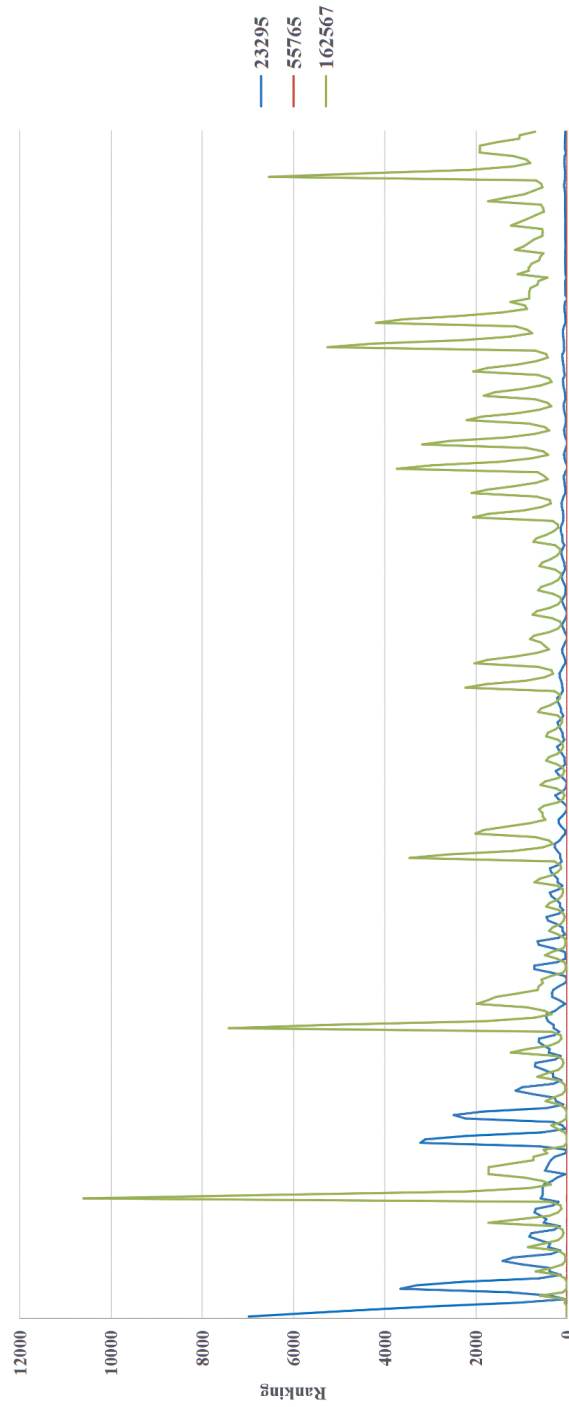


Fig. 9. Examples of changes in restaurant rankings. The closer to the X-axis, the higher the ranking. The level of user demand increases from left to right on the X-axis.

restaurants in Table 12 under 342 different scenarios (user demand for each restaurant criterion from lowest to highest). The average ranking of these 92 restaurants is also included in Table 13.

Considering Tables 12 and 13, it can be concluded that restaurants with a frequency of appearance in the top 10 for all 342 scenarios equal to or greater than 40% (even close to 40%) are those whose ranking is constant or increases as the user is more demanding of restaurant service, food, and environment. For restaurants with a frequency of appearance in the top 10 for the 342 scenarios less than 40%, some rank lower when the level of user demand is higher, and others rank higher when the level of user demand is higher.

In general, the changes in the ranking of these 92 restaurants can be divided into three different situations. Fig. 9 compares the differences between these three situations using the change in the ranking of several restaurants.

- Restaurants with stable ranking, although the levels of user demand of restaurant service, food, and environment change. For example, according to Table 13 and Fig. 9, the ranking of restaurant 55765 is stable and high, fluctuating among the top 10.
- Restaurants whose ranking increases as users are more demanding of restaurant service, food, and environment. For example, as shown in Fig. 9, restaurant 23295 ranks low when the levels of user demand of restaurant service, food, and environment are not very high. However, it achieves a higher ranking when users are more demanding. This indicates that this restaurant did not receive many extremely positive reviews, but hardly any negative ones. Thus, the ranking of this restaurant rises as users become pickier about restaurant service, food, and environment.
- Restaurants whose ranking falls as users are more demanding of restaurant service, food, and environment. For example, as shown in Fig. 9, restaurant 162567 ranks high when the levels of user demand of restaurant service, food, and environment are not very high. However, it achieves a lower ranking when users are more demanding. This means that although this restaurant received many very positive reviews, the negative ones are so bad that it drops in ranking as users become more critical and read more unfavorable reviews.

In fact, the preferences of users when reading reviews are proportional to their levels of demand of restaurant service, food, and environment. When users are not demanding, they only care about the favorable evaluations of the restaurant before going to eat there, ignoring the negative ones. In this case, the composite score calculated for the restaurant will be relatively high. In contrast, fussy users are likely to pay more attention to adverse evaluations, which reduces their perception of the restaurant's overall rating.

Combined with the composite score of each restaurant in Table 11, it can be observed that although the ranking of restaurant 55765 consistently fluctuates in the top 2, its composite score is (VG,-0.0204) when users are very undemanding of restaurant service, food, and environment (i.e., Scenario<sub>5</sub>), while its composite score is (G,+0.3332) when users are extremely demanding of these three criteria (i.e., Scenario<sub>1</sub>). Its composite score goes from slightly worse than "Very Good" to better than "Good." As a result, those restaurants

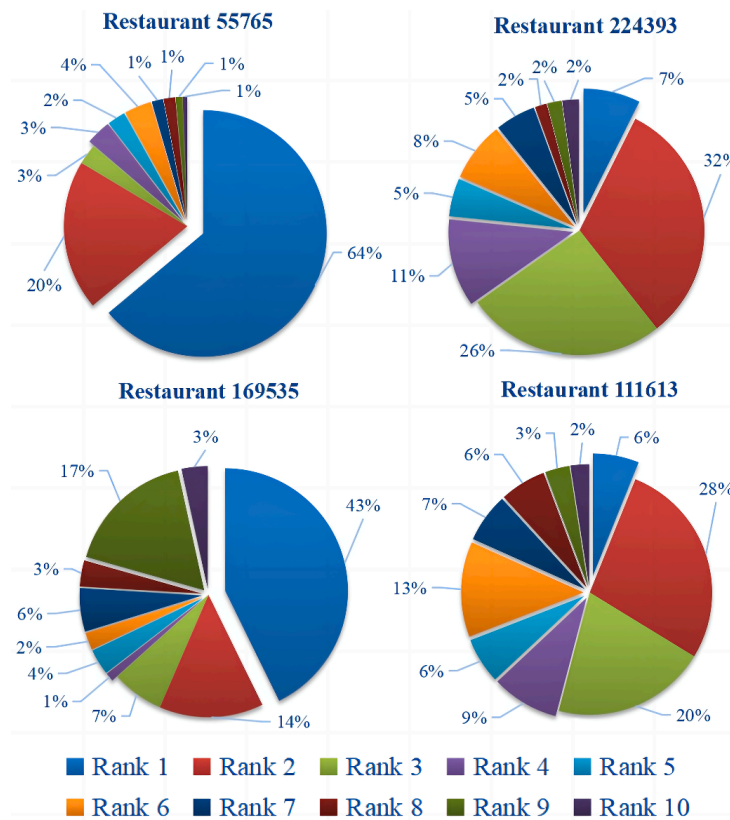


Fig. 10. Distribution of the ranking of restaurants with more than 70% frequency of appearance in the top 10 out of 342 scenarios.

whose ranking rises with increasing user demand (i.e., with more demanding users) may satisfy those who like to read negative reviews and have higher expectations for restaurant service, food, and environment. And those restaurants whose ranking goes down with increasing user demand may satisfy those who are undemanding or nearly not picky about any aspect of the restaurant.

Additionally, it can be concluded from Tables 12 and 13 that restaurants 55765, 224393, 169535, and 111613 not only appear frequently on the top 10 restaurants lists, but also maintain or improve their rankings when users are more demanding of restaurant service, food, and environment. Therefore, before users decide to make personalized restaurant rankings, these four restaurants can serve as comprehensive recommendations, as they can meet the needs of most users with different levels of demand.

However, comprehensive recommendations are also necessary to analyze how often they appear in the first place, second place, and so on. In that way, the platform can determine the ranking of each restaurant in the comprehensive recommendation. Fig. 10 shows the percentage of each ranking for the restaurants 55765, 224393, 169535, and 111613 over the total number of times they appeared in the top 10.

As shown in Fig. 10, restaurant 55765 not only appears most frequently in 342 scenarios, but also has the highest probability of being ranked first (i.e.,  $64\% \times 335 = 214$ ). Therefore, this restaurant should be ranked first among these four restaurants. Similarly, the frequency with which restaurant 224393 ranks second (i.e.,  $32\% \times 325 = 104$ ) is higher than that of the other restaurants. Therefore, it should be ranked second. By analogy, restaurants 111613 and 169535 should be ranked third and fourth, respectively.

## 6. Discussion

This paper introduces a novel decision support model that takes into account user demand levels for different restaurant aspects, the applicability of which has been demonstrated through user reviews of 78,512 restaurants on Dianping.com. This model uses various linguistic quantifiers to generate new variables that can reflect the levels of user demand for restaurant service, food, and environment. Each linguistic quantifier is mapped to a more easily understood business concept: the level of user demand. The proposed model also incorporates the degree of importance and linguistic quantifiers representing user demand levels. This allows for more accurate personalized weights to compute the restaurant's overall score. All these features improve the adaptability and comprehensibility of the proposed model in practical situations.

In addition, the proposed model can produce multiple scenarios of restaurant rankings to help users quickly select a restaurant that meets their levels of demand for the different restaurant aspects. This model not only includes the ranking generated by the arithmetic mean, but also generates more personalized rankings that consider the different user demand levels related to restaurant service, food, and environment. As shown in Section 5, when users have a medium level of demand for restaurant service, food, and environment (i.e., restaurant ratings are aggregated using the quantifier  $Q_4$ ), the proposed model produces a restaurant ranking almost identical to that obtained using the arithmetic mean, while in other cases it is different.

Compared to the conventional approach of determining restaurant ranking using the arithmetic mean, the proposed model can also investigate the changing pattern of restaurant rankings with variations in user demand levels. Restaurants whose ranking rises as users become more demanding may satisfy those who like to read bad reviews and have higher expectations for restaurant service, food, and environment. Restaurants whose ranking decreases as users become more demanding may satisfy those who are nearly not picky about any of the restaurant criteria, as they tend to select it only based on positive reviews.

Moreover, except for the extreme case of randomly generating restaurant rankings to recommend to users, a more reasonable and comprehensive ranking of restaurants can be established from the 342 personalized ranking scenarios generated by the proposed model. Specifically, those restaurants with a frequency of appearance in the top 10 or top 20 above 70% (review platforms determine the number of restaurants recommended in the top positions) can meet the requirements of most users regardless of their levels of demand for restaurant service, food, and environment.

In summary, the main theoretical and practical contributions of the proposed model can be summarized as follows:

- From a theoretical point of view, the proposed model incorporates the linguistic quantifier to generate new criteria reflecting the different levels of user demand for restaurant service, food, and environment. Furthermore, linguistic quantifiers representing different levels of user demand have been associated with the degree of importance in calculating the weights of the corresponding criteria. This enables the acquisition of more accurate linguistic weights to compute the composite score for each restaurant, resulting in more precise restaurant rankings for users.
- From a practical point of view, the proposed model generates a more linguistically understandable composite score for each restaurant, taking into account the levels of user demand for restaurant service, food, and environment. Restaurant rankings, generated based on users' actual needs rather than simply average ratings, are presented through an interactive application, helping users quickly find a suitable restaurant. In addition, based on the frequency of the restaurant's appearance in the top 10 across various scenarios and its corresponding ranking, review sites can generate a list of restaurants that can satisfy the demands of most users with different levels of demand. This can increase customer satisfaction and foster trust in the decision-making process.

## 7. Conclusions and future work

The eWOM significantly influences customers' decision-making processes. Review sites, important sources of eWOM for customers seeking information, host a plethora of online reviews and ratings covering various hotels, restaurants, and entertainment venues. To make informed decisions when choosing a restaurant, many people read online reviews, which provide them with a wealth of information and give them more autonomy in their restaurant selection process. This paper introduces a new decision support model

designed to help users quickly and accurately rank and select restaurants on Dianping.com based on their level of demand for various restaurant criteria. This approach uses the linguistic quantifiers of the 2LOWA aggregation operator to aggregate user ratings for each restaurant criterion. The IW method is proposed in this paper to obtain more accurate personalized weights based on user demand levels regarding restaurant service, food, and environment. Using more than 3.7 million restaurant reviews from Dianping.com, the feasibility and usefulness of the proposed model are demonstrated.

The personalized ranking of restaurants is displayed through an interactive application, demonstrating the effectiveness and interpretability of the proposed model in providing users with customized information. With this model, restaurants can be ranked according to different levels of user demand for restaurant service, food, and environment, rather than using the arithmetic mean that merely represents the average level of user demand. Moreover, according to the results of the Cox-Stuart test, restaurants that experience a rise in ranking with increasing user demand tend to satisfy those users who are more demanding and like to read negative reviews. Restaurants whose ranking decreases as users become more demanding may satisfy those users who are undemanding or hardly picky about any of the restaurant criteria. In this way, this model helps users more quickly choose a restaurant that aligns with their preferences.

The main contributions of the proposed model have been discussed in Section 6. However, this model also has the following limitations that need to be addressed:

- Although this paper has already taken into account the three most commonly accepted criteria that affect restaurant ranking—food, service quality, and restaurant environment—in reality, user decision-making in restaurant selection is dynamic, considering more criteria such as price, location, among others.
- The timeliness of online reviews has not been taken into account. However, older reviews, whether positive or negative, usually have less impact on the user's decision-making.
- Since the proposed model requires conversion between numbers and scales for numerical computations (e.g., IW weights of each restaurant criterion in the computation of the overall score, ranking of restaurants, etc.), only ordinal variables on linguistic scales can be applied to this model. Qualitative variables such as the type of restaurant or restaurant location cannot be directly included in this model, as they lack numerical values that can be ordered in linguistic terms.
- The proposed model cannot process textual comments that capture nuanced details and personal experiences, even though they also play a significant role in influencing the restaurant selection process.

The above limitations should be addressed in future work. First, in order to take into account other criteria such as price, location, the popularity of the restaurant, etc., in the composite score and ranking, new data could be collected from other review sites such as TripAdvisor, OpenTable, or Yelp. Secondly, when calculating the composite score for each restaurant, the time frame for collecting online reviews could be limited to, for example, the most recent year or six months. This would improve the timeliness of restaurant reviews, providing users with more realistic restaurant rankings and recommendations. Thirdly, the proposed model could be improved by integrating it with other machine learning algorithms to address issues where certain qualitative variables cannot be ordered in linguistic terms. Fourth, future work should incorporate text mining techniques with the proposed model to deal with textual comments, providing a comprehensive analysis and better assisting users in making informed decisions when choosing a restaurant. Future research could also explore the application of the proposed model in restaurant classification to determine whether it can explain segmentation results with greater linguistic interpretability. Finally, the proposed model could be adapted to other domains, such as hotels, products and movies, testing its versatility and applicability.

### Data availability

Dataset related to this article can be found at <https://www.yongfeng.me/dataset/> (Zhang, 2013).

### CRedit authorship contribution statement

**Ziwei Shu:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Ramón Alberto Carrasco:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Funding acquisition. **Manuel Sánchez-Montañés:** Data curation, Writing – review & editing, Supervision, Funding acquisition. **Javier Portela García-Miguel:** Software, Project administration, Visualization.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## 2. Clustering Using Ordered Weighted Averaging Operator and 2-Tuple Linguistic Model for Hotel Segmentation: The Case of TripAdvisor








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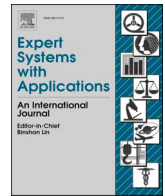
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# Clustering using ordered weighted averaging operator and 2-tuple linguistic model for hotel segmentation: The case of TripAdvisor

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## ABSTRACT

With the growth of online tourism, it is important to analyze the reviews left by numerous customers on social networks to improve the hotel's online reputation. Hotel segmentation based on online reviews has attracted an increasing interest from many academics. The problem is that many hotel segmentation models overlook the fact that some customers focus on positive reviews when choosing a hotel, while others focus on negative ones. To address this shortcoming, this paper develops a novel approach to classify hotels using the ordered weighted averaging (OWA) operator, the 2-tuple linguistic model, and K-means clustering. The proposed approach has been evaluated with a real dataset from TripAdvisor, which contains more than 50 million customer online reviews on eight aspects of the hotel. The results show that the proposed model can produce denser and more separated clusters than the model without linguistic quantifiers. From a business point of view, this model enables hotels to distinguish customers' perceptions (from the less demanding to the most demanding) about their eight aspects, allowing them to specify which of them need to be improved and develop strategies more quickly. At the same time, it introduces a new way of ranking hotels online, allowing customers to create personalized rankings of hotels based on their degree of demand for various hotel aspects (better location, cleaner rooms, etc.) rather than the average ratings, so that they can select the most suitable hotels more quickly.

## 1. Introduction

The unstoppable development of digital technologies and the Internet has made virtual communities a strategic factor for companies' continuous improvement, emphasizing the need to analyze large amounts of data to understand customers' true feelings, as well as to create strategies to adapt to their demands.

In the tourism sector, specifically the hotel industry, customer loyalty strategies involve carrying out a sequence of measures to ensure that customers are pleased and return next time to the same hotel or hotel brand. Nowadays, many tourists search for hotels and apartments on platforms such as TripAdvisor, Booking, or Expedia, where hotels are ranked based on user reviews expressed on various rating scales. Therefore, to have a prominent position on these platforms, analyzing customer demands based on their online reviews is necessary.

According to the Oxford Economics analysis, TripAdvisor is the world's largest travel website, whose global influence has increased in recent years (Oxford Economics, 2018). It is a metasearch engine where different users post textual comments and express ratings on several linguistic scales about a hotel where they have stayed or a restaurant where they have eaten. It is also possible to make reservations for hotels, restaurants, and transportation. TripAdvisor employs a bubble rating, whose popularity index is calculated based on three major parameters (TripAdvisor, 2018):

- **Quantity of reviews:** a sufficient number of comments are required to offer a statistically meaningful comparison with other similar entities. For instance, if many individuals have evaluated a hotel, future customers are more inclined to book it.

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


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# 3. Multiple Scenarios of Quality of Life Index Using Fuzzy Linguistic Quantifiers: The Case of 85 Countries in Numbeo

Open Access Editor's Choice Article

## Multiple Scenarios of Quality of Life Index Using Fuzzy Linguistic Quantifiers: The Case of 85 Countries in Numbeo

by  Ziwei Shu <sup>1,\*</sup>  ,  Ramón Alberto Carrasco <sup>2</sup>  ,  Javier Portela García-Miguel <sup>1</sup>  and  Manuel Sánchez-Montañés <sup>3</sup> 

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## Article

# Multiple Scenarios of Quality of Life Index Using Fuzzy Linguistic Quantifiers: The Case of 85 Countries in Numbeo

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**Abstract:** In economic development, in addition to comparing the gross domestic product (GDP) between nations, it is critical to assess the quality of life to gain a holistic perspective of their different aspects. However, the quality of life index (QOLI) is a subjective term that can be difficult to quantify. Although this composite index is typically calculated using universal weights proposed by experts to aggregate indicators, such as safety indexes, healthcare indexes, pollution indexes, and housing indicators, it is complicated to balance multiple dimensions whose weights are adjusted to account for different countries' circumstances. Therefore, this paper aims to construct various scenarios of the QOLI, using linguistic quantifiers of the ordered weighted averaging (OWA) operator, and the 2-tuple linguistic model. Numbeo, one of the largest quality of life information databases, was used in this paper to estimate the QOLI in 85 countries. Uncertainty and sensitivity analyses were employed to assess the robustness of the QOLI. The results of the proposed model are compared with those obtained using the Numbeo formulation. The results show that the proposed model increases the linguistic interpretability of the QOLI, and obtains different QOLIs, based on diverse country contexts.

**Keywords:** quality of life; OWA operators; 2-tuple linguistic model; linguistic quantifiers; multi-criteria decision-making

**MSC:** 90B50



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## 1. Introduction

The gross domestic product (GDP) of a country reflects economic growth, and GDP per capita has a strong relationship with the evolution of living standards over time. But GDP is not equal to well-being, as it does not include some factors that contribute to a good life. Quality of life (QOL) is a concept introduced to reflect a comprehensive view of many aspects of well-being in a country or a city. The measurement and study of QOL are increasingly significant in social development, as it encompasses many aspects, such as healthcare, housing costs, education, employment opportunities, etc.

However, QOL is a difficult concept to measure as it is multifaceted, interacts with a variety of living settings, and is influenced by people's lifestyles and preferences. In many studies [1–10], QOL is considered a subjective term to describe people's well-being in their countries. In the literature, QOL is defined in various ways [11–15].

The Quality of Life Index (QOLI), developed by the World Health Organization (WHO), and the Better Life Index (BLI), developed by the Organization for Economic Co-operation and Development (OECD), are two typical indices for measuring the quality

of life in various nations. Both are determined by considering variables such as housing indicators, environmental issues, safety indexes, and healthcare indexes, among others.

The QOLI can be considered a composite indicator, as it aggregates separate metrics to reflect the overall quality of life of a country or city. To obtain this composite indicator to compare the quality of life in different countries, many experts propose using universal weights. Nevertheless, this index is a complex balance of multiple factors, the weights of which should vary according to the circumstances of each country. For instance, the weight distribution of various indicators should be different in emerging and developed countries.

Therefore, the purpose of this paper is to construct various scenarios of QOLI using linguistic quantifiers of the ordered weighted averaging (OWA) operator, and the 2-tuple linguistic model. The advantage of employing the 2-tuple linguistic model in the proposed model is that it allows aggregating the information without information distortion and loss, as well as improving the understandability and intuitiveness of its outcomes presented in linguistic terms [16]. Numerical values need to be sorted to determine their low or high level, but linguistic terms can be comprehended directly by people without needing for further comparison. The advantage of using linguistic terms is that it directly shows whether the QOLI is very low, low, moderate, high, or very high, even when the data for the different sub-indicators are not on the same scale.

In summary, the contribution of this proposed model is to use the OWA operator and 2-tuple linguistic model to form the 2-tuple linguistic ordered weighted averaging (2LOWA) operator. The novelties of this model in the construction of the QOLI are that it can not only adjust the weights used by Numbeo's experts to obtain many QOLI scores considering country-specific situations, but it also can convert the numbers into linguistic scales that are easily understandable and interpretable by humans. The data used to verify the applicability of the proposed model came from Numbeo, one of the largest databases of quality of life information. The results show that this model enables assigning different weights to each dimension to generate more QOLI scores, and produces the same QOLI as the model using the weights proposed by experts. Moreover, it aggregates numerous indicators to a 2-tuple value, reducing information loss and improving the linguistic interpretability of the QOLI.

The rest of this paper is organized as follows. In Section 2, the essential concepts on which the proposed model is based are introduced. In Section 3, the proposed methodology to obtain more scenarios for the QOLI computation is presented. In Section 4, the results of the QOLI obtained by the proposed model for 85 countries are analyzed and compared. In Section 5, the advantages and shortcomings of the proposed model are discussed, including its validation by uncertainty and sensitivity analysis. In Section 6, the conclusions and future work are described.

## 2. Theoretical Framework

### 2.1. Composite Indicators

Composite indicators can summarize the information contained in several sub-indicators or variables, which is more accessible than attempting to discover a common trend in various sub-indicators [17]. They are generally used to identify competitiveness, innovation capacity, and sustainable development of countries or companies; some examples are the Human Development Index (HDI), the Environmental Performance Index (EPI), the Air Quality Index (AQI), the Quality of Life Index (QOLI), the Corruption Perceptions Index (CPI), and the Globalization Index (GI). For composite indicators, a framework is always necessary to determine which variables to include and their corresponding weights. When creating composite indicators, one of the crucial steps is how to weight the sub-indicators [18]. Weighting the sub-indicators leads to the last step in building composite indicators: aggregation.

There are a variety of aggregation methods for building composite indicators. For substitutable sub-indicators or variables, one of the most commonly used aggregation methods is principal component analysis (PCA) [19], as it can handle high dimensional data [20] by

summarizing them in fewer dimensions while keeping the maximum proportion of the original data variance [21].

For non-substitutable sub-indicators or variables, non-linear approaches are employed, such as non-compensatory multi-criteria analysis, or multiplicative functions (partially compensatory approach) [22]. Indeed, multi-criteria decision-making (MCDM) approaches are frequently utilized to create composite indicators, because they are ideal for converting multiple sub-indicators into a composite indicator [23]. Table 1 demonstrates several MCDM approaches to constructing composite indicators, and some examples of their application, each with distinct weight distribution.

**Table 1.** MCDM methods for the construction of composite indicators.

Method	Description	Literature	Application
Analytic hierarchy process (AHP)	A method for measuring the weights of structure components by using a paired comparison scale.	Saaty, 1987 [24]	Composite cyclical-performance index [25], environmental sustainability index [26], agricultural sustainability index [27]
Analytic network process (ANP)	An extension of the AHP that allows for interdependencies between criteria.	Saaty, 1996 [28]	Disaster resilience indicator [29], ecological water quality index [30]
Criteria importance through intercriteria correlation (CRITIC)	A method for determining objective weights for each criterion by employing correlation analysis between criteria.	Diakoulaki et al., 1995 [31]	Energy security index [32]
Data envelopment analysis (DEA)	A non-parametric method for measuring the efficiency of a group of multiple decision-making units, with multiple inputs and outputs.	Charnes et al., 1978 [33]	Spanish public university quality index [34], sustainability index [35]
Elimination et choix traduisant la réalité (ELECTRE)	A method for determining the concordance and discordance indices of a group of alternatives, and ranking them from best to worst.	Roy, 1968 [36]	Human development index [37], land-use policy efficiency index [38]
Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)	A method for producing a ranking based on choosing a preference function for each criterion in an MCDM issue.	Brans and Vincke, 1985 [39]	European countries sustainability index [40]
Simple Additive Weighting (SAW)	A method for calculating a weighted score for each alternative by multiplying each attribute's contributions by their weights.	Churchman and Ackoff, 1954 [41]	Neighborhood sustainability index [42]
Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	A compensatory aggregation method for choosing between the shortest Euclidean distance to the ideal solution, and the biggest distance to the negative ideal solution.	Hwang and Yoon, 1981 [43]	Road safety performance index [44], financial and diversity performance index [45], clean energy index [46]
Ordered weighted averaging (OWA)	A symmetric aggregation method for distributing weights based on the input value and unifies multiple inputs in one operator.	Yager, 1988 [47]	Energy supply security index [48], disaster resilience index [49]
Visekriterijumska Optimizacija I kompromisno resenje (VIKOR)	A method for calculating the compromise ranking list of a group of alternatives, based on the measure of closeness to the ideal option.	Duckstein and Opricovic, 1980 [50]	Academic performance index [51]
Benefit of the doubt (BoD)	A method derived from the DEA, which is a linear mathematical programming methodology, to assign the most favorable weight for each observation. These weights enable both data normalization and objective weighing.	Melyn and Moesen, 1991 [52]	Digital access index [53], human development index [54,55], non-parametric corporate social responsibility index [56]

MCDM approaches can be divided into compensatory and non-compensatory approaches [57,58]. Compensation refers to compensating a 'disadvantage' of some attribute with a sufficiently large 'advantage' of another, whereas it would not be possible to do so

with lesser ‘advantages’ [59,60]. The compensatory aggregation-based MCDM methods include AHP, SAW, and TOPSIS. Non-compensatory means that a decision determined by some attributes cannot be altered by others [61]. Non-compensatory approaches include preference aggregation-based methods (e.g., ELECTRE, PROMETHEE, etc.) and rules-based methods [62]. This type of aggregation method speeds up and facilitates decision-making. However, non-compensatory approaches do not consider all relevant data, and often overlook the relative importance of certain attributes [61].

In addition to recognizing the characteristics of various models to construct composite indicators, it is necessary to verify the robustness of the composite indicator. The changeability in the weights, and the imputation of missing data, contribute to the uncertainty in the calculation of composite indicators [21]. If composite indicators are poorly constructed, they may convey misleading messages.

In the literature, sensitivity analysis is often applied to investigate the robustness of the ranking of the weights of multiple criteria in the MCDM process [63–65]. Alexander’s A indicator (AAI) [66], one of the sensitivity indicators, is utilized to quantify the degree of change in the rankings of these indicators, where 0 represents no change, and 1 represents a complete reversal in ranks. The robustness of composite indicators can be assessed by uncertainty analysis and sensitivity analysis [67]. Uncertainty analysis measures the fluctuations in the result (i.e., the value of the composite indicators) derived from the uncertainty in the input factors (i.e., the construction stages of composite indicators: selection of aggregation approaches, weights of the sub-indicators, etc.) [68,69]. The sensitivity analysis determines how much of the overall output variation is attributable to such uncertainties [67].

The robustness of the composite indicator ranking can be assessed by a combination of uncertainty and sensitivity analysis [70]. The rank assigned by the composite indicator to each country is an output of the uncertainty and sensitivity analysis [70]. It can be used to determine the average change in country ranking and assess the quality of the composite indicator. Its definition is as follows:

**Definition 1.** *The average of the absolute differences in country rankings [67,70] is shown in Formula (1):*

$$\overline{R_s} = \frac{1}{M} \sum_{c=1}^M \left| \text{rank}_{ref}(CI_c) - \text{rank}_q(CI_c) \right| \quad (1)$$

where  $M$  is the number of countries;  $\text{rank}_{ref}(CI_c)$  represents the reference ranking of each country (in this paper, it is the actual rank of each country’s quality of life index on Numbeo); and  $\text{rank}_q(CI_c)$  represents the ranking assigned to each country based on the quality of life index calculated by diverse quantifiers.

## 2.2. The Quality of Life Index

The QOL is a complex term that can be defined in various ways in different disciplines, such as medicine, international development, and politics, so it does not have a commonly accepted definition. The WHO defines it as a person’s perception of his or her position in life in the context of the culture and value systems in which he or she lives, and in relation to his or her goals, expectations, standards, and concerns [71]. Therefore, the QOL combines a person’s assessment of numerous dimensions of safety, education, medical and healthcare services, and other aspects of life that cannot be easily equated with terms such as “life satisfaction”, “happiness”, or “income level”.

Many researchers and institutions, such as Eurostat, WHO, and WorldData, among others, have attempted to measure the QOL using the quality of life index (QOLI). Numbeo, one of the world’s largest databases of quality of life information, has been developing and improving its algorithm for calculating the QOLI. The factors that Numbeo takes into account in calculating the QOLI are listed below (see also Figure 1):

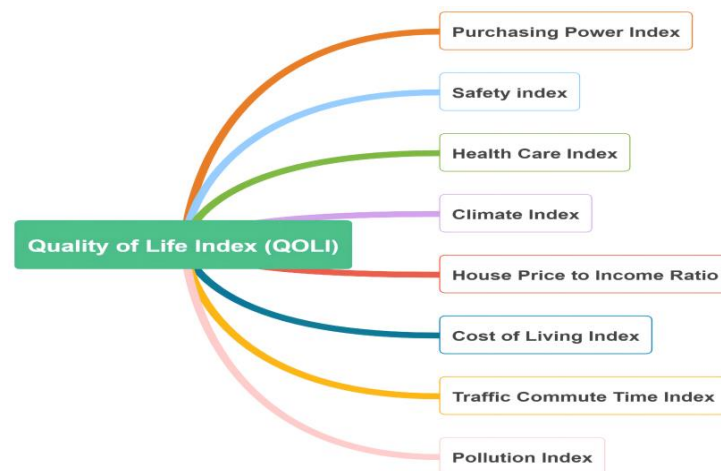


Figure 1. Graphical presentation of the quality of life index.

- Purchasing power index ( $I_{\text{purchasing\_p}}$ , including rent index): a relative purchasing power in buying goods and services in a given city or country for the average net salary;
- Safety index ( $I_{\text{safety}}$ ): an indicator taking into account concerns about robberies, vehicle theft, and other crimes, as well as the incidence of narcotics, property crime, violent crime, and corruption and bribery. This index is the opposite of the crime index;
- Health care index ( $I_{\text{health\_c}}$ ): an estimation of the overall quality of the health care system, health care professionals, equipment, staff, doctors, cost, etc.;
- Climate index ( $I_{\text{climate}}$ ): an estimation of the climate likability of a given city or a country;
- House price to income ratio ( $I_{\text{house\_p}}$ ): the basic measure for apartment purchase affordability. It is calculated as the ratio of median apartment prices to median familial disposable income, expressed as years of income;
- Cost of living index ( $I_{\text{cost\_liv}}$ , excluding rent index): a relative indicator of consumer goods prices, including groceries, restaurants, transportation, and utilities. This index does not include accommodation expenses such as mortgage or rent;
- Traffic commute time index ( $I_{\text{traffic\_t}}$ ): a composite index of time consumed in traffic due to job commute, estimation of time consumption dissatisfaction, estimation of CO<sub>2</sub> consumption in traffic, and overall inefficiencies in the traffic system;
- Pollution index ( $I_{\text{pollution}}$ ): an estimation of the overall pollution in a given city or a country, taking into account air pollution, water pollution, and other pollution types.

**Definition 2.** The current formula applied by Numbeo [72] is shown in Formula (2):

$$\begin{aligned}
 \text{QOLI} &= 100 + \frac{I_{\text{purchasing\_p}}}{2.5} + \frac{I_{\text{safety}}}{2} + \frac{I_{\text{health\_c}}}{2.5} + \frac{I_{\text{climate}}}{3} - I_{\text{house\_p}} - \frac{I_{\text{cost\_liv}}}{10} - \frac{I_{\text{traffic\_t}}}{2} - \frac{2 \cdot I_{\text{pollution}}}{3} \\
 &= 100 + 3.9 \cdot (10.26\% \cdot I_{\text{purchasing\_p}} + 12.82\% \cdot I_{\text{safety}} + 10.26\% \cdot I_{\text{health\_c}} + 8.55\% \cdot I_{\text{climate}} \\
 &\quad - 25.64\% \cdot I_{\text{house\_p}} - 2.56\% \cdot I_{\text{cost\_liv}} - 12.82\% \cdot I_{\text{traffic\_t}} - 17.09\% \cdot I_{\text{pollution}})
 \end{aligned} \tag{2}$$

Among these eight sub-indicators, the larger the value of the four sub-indicators—purchasing power index, safety index, health care index, and climate index—the better. The smaller the rest of the sub-indicators, the better.

### 2.3. The 2-Tuple Linguistic Model

The 2-tuple linguistic model introduced by Herrera and Martínez has a continuous and ordinal scale, in order to avoid information loss in the fusion of linguistic information [73], which provides linguistically accurate and more understandable results. Based on the concept of symbolic translation, this model represents the linguistic information by a 2-tuple value  $(s_i, \alpha)$ , where  $s_i \in S$  is a linguistic term, and

$\alpha \in [-0.5, 0.5)$  is a numerical value representing the distance to the central value of  $s_i$ .  $S = \{s_0 = \text{Very Low} = VL, s_1 = \text{Low} = L, s_2 = \text{Moderate} = M, s_3 = \text{High} = H, s_4 = \text{Very High} = VH\}$  is a set of five linguistic terms used in the Numbeo database, whose definition is shown in Figure 2.

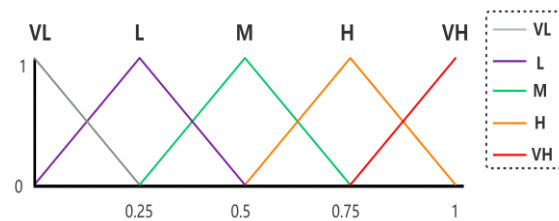


Figure 2. Linguistic term set of five labels used in the Numbeo database.

**Definition 3.** Let  $S = \{s_0, \dots, s_g\}$  be a set of linguistic terms, whose cardinality is  $g + 1$ .  $\beta \in [0, g]$  is a value that supports the outcome of a symbolic aggregation operation. The function  $\Delta : [0, g] \rightarrow S \times [-0.5, 0.5)$  is used to convert  $\beta$  to 2-tuple value  $(s_i, \alpha)$  as shown in Formula (3):

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} i = \text{round}(\beta) \\ \alpha = \beta - i, \alpha \in [-0.5, 0.5) \end{cases} \quad (3)$$

where  $\text{round}(\cdot)$  is the rounding operation;  $s_i$  is the index of the label nearest to  $\beta$ ; and  $\alpha$  is a numerical value representing the symbolic translation. Note that the function  $\Delta$  is bijective, so the function  $\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g]$  can be used to return an equivalent numerical value  $\beta$  as  $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$ .

The following is an example of a transformation from a numerical value to a 2-tuple value, as well as a retranslation from a 2-tuple value to a numerical value.

Assume that  $\beta = 1.2$  is a value representing the result of a symbolic aggregation operation on the set of linguistic terms  $S = \{s_0 = VL, s_1 = L, s_2 = M, s_3 = H, s_4 = VH\}$ , whose 2-tuple value is calculated as  $\Delta(1.2) = (s_{\text{round}(1.2)}, 1.2 - s_{\text{round}(1.2)}) = (s_1, +0.2) = (L, +0.2)$ . Its numerical transformation is performed by the function  $\Delta^{-1}$ , that is  $\Delta^{-1}(s_1, +0.2) = 1 + 0.2 = 1.2$ . If  $\beta$  is equal to 3, its 2-tuple value is  $\Delta(3) = (s_3, 0) = (H, 0)$ , which means that the difference between  $\beta$  and this linguistic term is 0 ( $\alpha = 0$ ). Note that adding the value zero as a symbolic translation,  $s_i \in S \rightarrow (s_i, 0)$ , is identical to the label without symbolic translation  $(H, 0) = H$ . Figure 3 shows the two examples mentioned above.

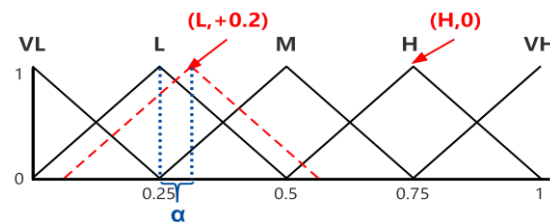


Figure 3. Representation of 2-tuple values.

The negation operator and a comparison between two linguistic 2-tuple values were also introduced in the 2-tuple linguistic model as follows:

**Definition 4.** The negation operator of a 2-tuple value is defined as Formula (4):

$$\text{neg}((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha))) = \Delta(g - \beta) \quad (4)$$

**Definition 5.** The comparison of linguistic information represented by 2-tuple values is performed according to a lexicographic order. Let  $(s_G, \alpha_1)$  and  $(s_M, \alpha_2)$  be two 2-tuple values, so that their linguistic 2-tuple values are compared as follows:

- If  $G < M$ ,  $(s_G, \alpha_1)$  is smaller than  $(s_M, \alpha_2)$ ;
- If  $G = M$ , when:
  - a.  $\alpha_1 = \alpha_2$ ,  $(s_G, \alpha_1)$  is the same as  $(s_M, \alpha_2)$ ;
  - b.  $\alpha_1 < \alpha_2$ ,  $(s_G, \alpha_1)$  is smaller than  $(s_M, \alpha_2)$ ;
  - c.  $\alpha_1 > \alpha_2$ ,  $(s_G, \alpha_1)$  is larger than  $(s_M, \alpha_2)$ ;
- If  $G > M$ ,  $(s_G, \alpha_1)$  is larger than  $(s_M, \alpha_2)$ .

2.4. The Ordered Weighted Averaging (OWA) Operator

Yager introduced the concept of the OWA operator in 1988 to solve the MCDM problems, and to generate an overall decision function [47].

**Definition 6.** An OWA operator of dimension  $n$  is a mapping of  $OWA : R^n \rightarrow R$ , with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{i=1}^n w_i = 1$  and  $w_i \in [0, 1]$ . Thus, the OWA for each linguistic quantifier is calculated using Formula (5):

$$OWA(a_1, a_2, \dots, a_n) = \sum_{i=1}^n w_i b_i \tag{5}$$

where  $a_1, a_2, \dots, a_n$  are the input values;  $b_i$  is the  $i$ th largest element of the input values; and  $w_i$  represents the ordered weights.

The ordered weights  $w_i$  ( $w_i \in [0, 1]$ ) are always calculated according to the linguistic quantifiers (*At least one, Some, Half, Most, All*, etc.) because they express different degrees of demand in natural language by using formal mathematical formulas [74]. The complementary values *orness* and *tradeoff* are computed from these quantifiers to represent the degree of optimism, or different attitudes toward risk, while making decisions.

In fact, compared with other approaches (see Table 1) used to generate composite indicators, using linguistic quantifiers, the OWA operator can aggregate the information to make a compensation levels regulation between variables [75]. The OWA operator can be used to reflect compensatory and non-compensatory preferences. This attribute is expressed by the degree of *orness* of an OWA operator [47]. As each linguistic quantifier is associated with a particular value, the OWA operator can be used to express the attitudinal character of the decision-maker in the information aggregation [76]. It means that, with the application of different linguistic quantifiers, numerous scenarios that consider different country circumstances can be obtained from the initial weights supplied by the experts. Furthermore, the OWA operator solves non-compensatory aggregation issues [61], resulting in a statistically consistent composite indicator [77].

**Definition 7.** Regular increasing monotone (RIM) quantifiers can be applied to generate a parameterized subset in the unit interval [78], as shown in Formula (6):

$$Q(p) = p^\lambda, \lambda > 0 \tag{6}$$

where  $Q$  is a linguistic quantifier, represented as a fuzzy subset over the unit interval  $[0, 1]$ ; for each  $p$  in the unit interval, the grade of membership  $Q(p)$  indicates the compatibility of  $p$  with the concept denoted by  $Q$ . Table 2 shows the parameter  $\lambda$  proposed by [79] for each linguistic quantifier.

**Table 2.** Linguistic quantifiers with their associated parameters  $\lambda$ .

Linguistic Quantifier	$\lambda$
<i>At least one</i>	0.0001
<i>Few</i>	0.1
<i>Some</i>	0.5
<i>Half</i>	1
<i>Many</i>	2
<i>Most</i>	10
<i>All</i>	1000

**Definition 8.** The ordered weights  $w_i$  ( $w_i \in [0, 1]$ ) are calculated using Formula (7):

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right) = \left(\frac{i}{n}\right)^\lambda - \left(\frac{i-1}{n}\right)^\lambda, \lambda > 0, i = 1, \dots, n \tag{7}$$

where  $n$  is the number of criteria or sub-indicators  $i = 1, \dots, n$ , and  $\lambda$  is the value related to each linguistic quantifier  $Q$ . The larger  $\lambda$  is, the less risky the decision is.  $\lambda = 1$  represents a moderate degree of risk.

**Definition 9.** Related to the ordered weights, orness and tradeoff represent different attitudes toward risk while making decisions. Orness shows the level of risk in the aggregation process, while the tradeoff is its compensation. They can be calculated as shown in Formulas (8) and (9) [47,80]:

$$orness(w) = \frac{1}{n-1} \sum_{i=1}^n (n-i) * w_i, i = 1, \dots, n \tag{8}$$

$$tradeoff(w) = 1 - \sqrt{\frac{n \sum_{i=1}^n (w_i - \frac{1}{n})^2}{n-1}} \tag{9}$$

If the quantifier *At least one* is employed to calculate the ordered weights, orness is one and tradeoff zero, representing the maximum risk. When orness and tradeoff equal zero, using the quantifier *All*, the minimum risk is attained. If the quantifier *Half* is used, orness equaling 0.5 and tradeoff equaling 1 represents the medium risk.

2.5. The 2-Tuple Linguistic Ordered Weighted Averaging (2LOWA) Operator

The 2-tuple linguistic ordered weighted averaging (2LOWA) operator is an extension of the OWA operator that uses linguistic information expressed in 2-tuple values. It is particularly effective when the decision-maker cannot analyze the information only based on numerical scales, but also requires a linguistic interpretation. The definition is as follows.

**Definition 10.** A 2LOWA operator of dimension  $n$  is a mapping of 2LOWA:  $R^n \rightarrow R$ , with an associated weighting vector  $W$  of dimension  $n$ , such that  $\sum_{i=1}^n w_i = 1$  and  $w_i \in [0, 1]$ . The function  $\Delta : [0, g] \rightarrow S$  is used to convert numerical values into 2-tuple values, as shown in Formula (10):

$$2LOWA((s_1, \alpha_1), \dots, (s_n, \alpha_n)) = \Delta\left(\sum_{i=1}^n w_i b_i\right) \tag{10}$$

where  $\{(s_1, \alpha_1), \dots, (s_n, \alpha_n)\}$  is the set of 2-tuple values;  $w_i$  represents the ordered weights; and  $b_i = \Delta^{-1}(s_i, \alpha_i)$ .

### 3. Methodology

This section demonstrates the procedure for acquiring alternative scenarios about the quality of life index, based on the 2LOWA–QOLI model. This model is shown in Figure 4, which includes the following five steps:

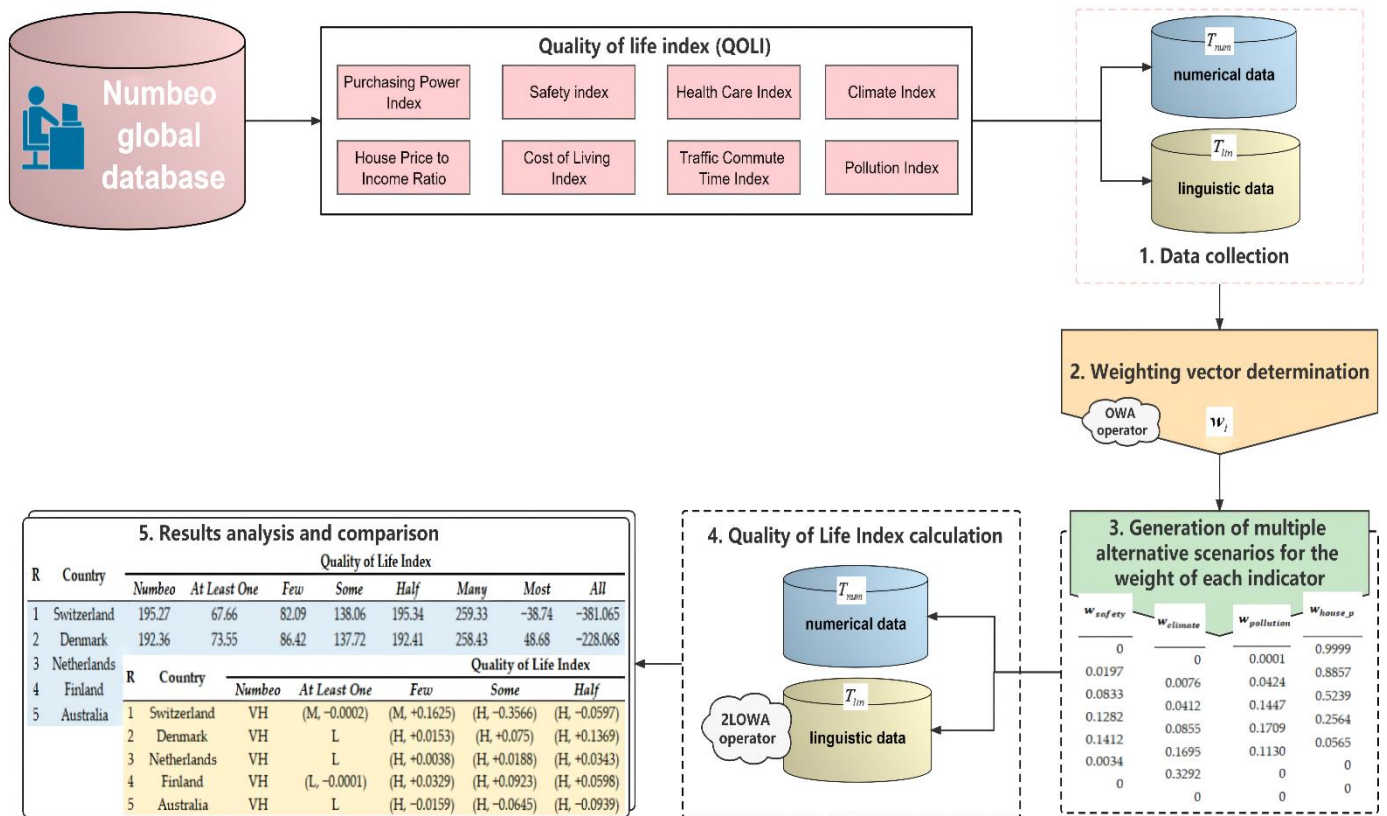


Figure 4. Steps of the 2LOWA–QOLI model.

#### Step 1. Data collection.

The purpose of this step was to obtain information about the quality of life in 85 countries from Numbeo. This database [81] contains current data on global living conditions, given by millions of people worldwide. It provides data ranging from pollution levels to information on traffic, the health system, safety, and property prices. For information about the QOLI and its sub-indicators, Numbeo uses both numbers and linguistic quantifiers to express them. Figure 5 shows an example [82].

Let  $C = \{c_1, \dots, c_{\#C}\}$  be a set of countries obtained from Numbeo database [81]. As Numbeo uses numbers and a linguistic scale to express the degree of the quality of life in different countries, two datasets were obtained in this step: one for numerical calculations ( $T_{num}$ ), and the other for linguistic terms ( $T_{lin}$ ). For each dataset, the eight sub-indicators used in Numbeo to generate the QOLI were analyzed: the purchasing power index ( $I_{purchasing\_p}$ ), the safety index ( $I_{safety}$ ), the health care index ( $I_{health\_c}$ ), the climate index ( $I_{climate}$ ), the house price to income ratio ( $I_{house\_p}$ ), the cost of living index ( $I_{cost\_liv}$ ), the traffic commute time index ( $I_{traffic\_t}$ ), and the pollution index ( $I_{pollution}$ ).

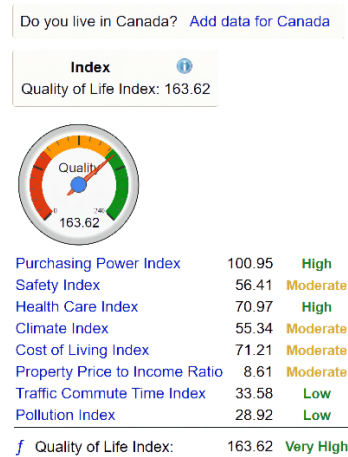


Figure 5. Example of quality of life data in Canada in the Numbeo database.

Let  $T_{num} = \left\{ \begin{matrix} (c_1, \{v_{num}(I_{purchasing\_p}^{c_1}), \dots, v_{num}(I_{pollution}^{c_1})\}) \\ \dots \\ (c_{\#T_{num}}, \{v_{num}(I_{purchasing\_p}^{c_{\#T_{num}}}), \dots, v_{num}(I_{pollution}^{c_{\#T_{num}}})\}) \end{matrix} \right\}$  be the numerical data for these eight sub-indicators from 85 different countries, and  $T_{lin} = \left\{ \begin{matrix} (c_1, \{v_{lin}(I_{purchasing\_p}^{c_1}), \dots, v_{lin}(I_{pollution}^{c_1})\}) \\ \dots \\ (c_{\#T_{lin}}, \{v_{lin}(I_{purchasing\_p}^{c_{\#T_{lin}}}), \dots, v_{lin}(I_{pollution}^{c_{\#T_{lin}}})\}) \end{matrix} \right\}$  be their linguistic data, where:

- $c_r$  is the name of each country, with  $c_r \in C$ , and  $r = 1, \dots, \#C$ ;
- $\{v_{num}(I_{purchasing\_p}^{c_r}), \dots, v_{num}(I_{pollution}^{c_r})\}$  are the numerical values of eight sub-indicators for each country;
- $\{v_{lin}(I_{purchasing\_p}^{c_r}), \dots, v_{lin}(I_{pollution}^{c_r})\}$  are the 2-tuple values of eight sub-indicators for each country, expressed on a linguistic scale. Based on Numbeo, this linguistic scale contains five values: “Very Low”, “Low”, “Moderate”, “High”, and “Very High”. These linguistic values are symmetrical, whose center value is neutral (i.e., “Moderate”) [83–85]. They can be modeled by fuzzy triangular labels, as shown in Figure 2.

**Step 2. Weighting vector determination.**

This step was to establish the weighting vector for each linguistic quantifier, whose results are shown in Table 3. These values are determined based on Formula (7).

Table 3. Weighting vector for each linguistic quantifier.

Linguistic Quantifier	Weighting Vector					
<i>At least one</i>	0.9998	0.0001	0	0	0	0
<i>Few</i>	0.8360	0.06	0.0371	0.0272	0.0217	0.0181
<i>Some</i>	0.4082	0.1691	0.1298	0.1094	0.0964	0.0871
<i>Half</i>	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
<i>Many</i>	0.0278	0.0833	0.1389	0.1944	0.2500	0.3056
<i>Most</i>	0	0	0.0010	0.0164	0.1442	0.8385
<i>All</i>	0	0	0	0	0	1

The following is an example of how to calculate the weights for the quantifier *At least one* ( $\alpha = 0.0001$ ), and  $n = 6$ , as several indicators should have the same weight, although Numbeo uses eight sub-indicators to calculate the quality of life [72,86,87]

$$w_i = Q\left(\frac{i}{6}\right) - Q\left(\frac{i-1}{6}\right) = \left(\frac{i}{6}\right)^{0.0001} - \left(\frac{i-1}{6}\right)^{0.0001}, i = 1, \dots, 6$$

$$w_i = (0.9998, 0.0001, 0, 0, 0, 0)$$

**Step 3. Generation of multiple alternative scenarios for the weight of each indicator.**

Let  $v = (0.2564, 0.1709, 0.1282, 0.1282, 0.1026, 0.1026, 0.0855, 0.0256)$  be the vector that represents the weight of each indicator given by Numbeo’s experts in the calculation of the QOLI [72], corresponding to the indicators of house price to income ratio, the pollution index, the safety index, the traffic commute time index, the purchasing power index, the health care index, the climate index, and the cost of living index, respectively.

Since the QOLI is a subjective term that is a complicated balance of numerous sub-indicators, whose weights should differ depending on the country’s circumstances, this step aimed to obtain different alternative scenarios for the weight of each sub-indicator, by using various linguistic quantifiers. Therefore, based on the approach for calculating weights introduced by [88], the vector  $v$  was recalculated by multiplying it with the weighting vector of each linguistic quantifier (see Table 3). Table 4 shows the results of these computations.

**Table 4.** Results of the recalculated weights for each indicator.

Linguistic Quantifier	$w_{house\_p}$	$w_{pollution}$	$w_{safety}$	$w_{traffic\_t}$	$w_{purchasing\_p}$	$w_{health\_c}$	$w_{climate}$	$w_{cost\_liv}$	Orness	Tradeoff
At least one	0.9999	0.0001	0	0	0	0	0	0	0.9999	0.0002
Few	0.8857	0.0424	0.0197	0.0197	0.0115	0.0115	0.0076	0.0019	0.9215	0.1960
Some	0.5239	0.1447	0.0833	0.0833	0.0562	0.0562	0.0412	0.0112	0.6844	0.7015
Half	0.2564	0.1709	0.1282	0.1282	0.1026	0.1026	0.0855	0.0256	0.5000	1
Many	0.0565	0.1130	0.1412	0.1412	0.1582	0.1582	0.1695	0.0622	0.3055	0.7454
Most	0	0	0.0034	0.0034	0.0449	0.0449	0.3292	0.5742	0.0360	0.1821
All	0	0	0	0	0	0	0	1	0	0

An example of how to obtain the weights of each sub-indicator based on the quantifier *At least one* ( $\alpha = 0.0001$ ) is shown below:

- $w_{house\_p} = (0.9998 \cdot 0.2564) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0.9999$ ;
- $w_{pollution} = (0.0001 \cdot 0.1709) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0.0001$ ;
- $w_{safety} = (0 \cdot 0.1282) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ ;
- $w_{traffic\_t} = (0 \cdot 0.1282) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ ;
- $w_{purchasing\_p} = (0 \cdot 0.1026) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ ;
- $w_{health\_c} = (0 \cdot 0.1026) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ ;
- $w_{climate} = (0 \cdot 0.0855) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ ;
- $w_{cost\_liv} = (0 \cdot 0.0256) / (0.9998 \cdot 0.2564 + 0.0001 \cdot 0.1709 + 0) = 0$ .

The weights for each sub-indicator based on other quantifiers would be calculated similarly. As shown in Table 4, the quantifier *Half* obtains the same weights as those given by the Numbeo’s experts, that is, a moderate degree of risk (*orness* = 0.5) with a maximum balance among the eight sub-indicators employed in Numbeo (*tradeoff* = 1). The quantifiers *At least one* and *All* represent two extreme cases, in which the QOLI is calculated using only one sub-indicator: the house price to income ratio (*At least one*) and the cost of living index (*All*), respectively. The higher the cost of living index or the house price to income ratio are, the lower the QOLI is.

**Step 4. Quality of Life Index calculation.**

This step aimed to calculate various QOLIs, based on the alternative scenarios for the weights obtained in the previous step.

For the numerical data ( $T_{num}$ ), the QOLI for each quantifier (*At least one, Few, Some, Half, Many, Most, All*) was calculated, based on the Formula (2). This index was constructed for the linguistic data ( $T_{lin}$ ), using the Formula (10) and the negative function  $neg(\cdot)$ , with respect to these sub-indicators: the house price to income ratio, the cost of living index, the traffic commute time index, and the pollution index, as they are better when they are lower.

Spain was taken as an example of how to calculate this index. Table 5 shows the data collected from Numbeo [81], and its translation from the 2-tuple value into the numerical value.

**Table 5.** Data about eight sub-indicators used to measure the quality of life index in Spain.

	Numbeo Database		$\Delta^{-1}(\cdot)$ and $neg(\cdot)$
	$T_{num}$	$T_{lin}$	
$I_{house\_p}^{Spain}$ *	8.78	M	$\Delta^{-1}(neg(M)) = \Delta^{-1}(\Delta(4 - 2)) = \Delta^{-1}(M) = 2$
$I_{pollution}^{Spain}$ *	39.66	L	$\Delta^{-1}(neg(L)) = \Delta^{-1}(\Delta(4 - 1)) = \Delta^{-1}(H) = 3$
$I_{safety}^{Spain}$	66.13	H	$\Delta^{-1}(H) = 3$
$I_{traffic\_t}^{Spain}$ *	29.24	L	$\Delta^{-1}(neg(L)) = \Delta^{-1}(\Delta(4 - 1)) = \Delta^{-1}(H) = 3$
$I_{purchasing\_p}^{Spain}$	70.04	M	$\Delta^{-1}(M) = 2$
$I_{health\_c}^{Spain}$	78.37	H	$\Delta^{-1}(H) = 3$
$I_{climate}^{Spain}$	93.83	VH	$\Delta^{-1}(VH) = 4$
$I_{cost\_liv}^{Spain}$ *	53.88	L	$\Delta^{-1}(neg(L)) = \Delta^{-1}(\Delta(4 - 1)) = \Delta^{-1}(H) = 3$
Quality of life index	168.48	VH	$\Delta^{-1}(VH) = 4$

\* The lower the better.

The QOLI based on the quantifiers *At least one, Half, and All* can be calculated as follows:

- For the numerical data:

$$QOLI_{At\ least\ one}^{Spain} = 100 + 3.9 \cdot (-8.78 \cdot 0.9999 - 39.66 \cdot 0.0001 + 0) = 65.75$$

$$QOLI_{Half}^{Spain} = 100 + 3.9 \cdot (-8.78 \cdot 0.2564 - 39.66 \cdot 0.1709 + 66.13 \cdot 0.1282 - 29.24 \cdot 0.1282 + 70.04 \cdot 0.1026 + 78.37 \cdot 0.1026 + 93.83 \cdot 0.0855 - 53.88 \cdot 0.0256) = 168.52$$

$$QOLI_{All}^{Spain} = 100 + 3.9 \cdot (0 - 53.88 \cdot 1) = -110.13$$

- For the linguistic data:

$$\begin{aligned} \text{QOLI}_{\text{At least one}}^{\text{Spain}} &= \text{neg}(\Delta(2 \cdot 0.9999 + 3 \cdot 0.0001 + 0)) = \text{neg}(\Delta(2.0001)) = \Delta(4 - \Delta^{-1}(\Delta(2.0001))) \\ &= \Delta(4 - 2.0001) \\ &= \Delta(1.9999) = (s_2, -0.0001) = (M, -0.0001) \end{aligned}$$

$$\begin{aligned} \text{QOLI}_{\text{Half}}^{\text{Spain}} &= \Delta(2 \cdot 0.2564 + 3 \cdot 0.1709 + 3 \cdot 0.1282 + 3 \cdot 0.1282 + 2 \cdot 0.1026 + 3 \cdot 0.1026 + 4 \cdot 0.0855 + 3 \cdot 0.0256) \\ &= \Delta(2.7265) \\ &= (s_3, -0.2735) = (H, -0.2735) \end{aligned}$$

$$\begin{aligned} \text{QOLI}_{\text{All}}^{\text{Spain}} &= \text{neg}(\Delta(0 + 3 \cdot 1)) = \text{neg}(\Delta(3)) = \Delta(4 - \Delta^{-1}(\Delta(3))) \\ &= \Delta(4 - 3) \\ &= \Delta(1) = (s_1, 0) = (L, 0) = L \end{aligned}$$

Table 6 shows the results of employing various linguistic quantifiers to calculate the QOLI for Spain.

**Table 6.** Spain’s quality of life index calculation using linguistic quantifiers.

Linguistic Quantifier	Quality of Life Index	
	$T_{num}$	$T_{lin}$
<i>At least one</i>	65.75	(M, -0.0001) <sup>2</sup>
<i>Few</i>	74.99	(M, +0.1104)
<i>Some</i>	116.92	(M, +0.4611)
<i>Half</i>	168.52 <sup>1</sup>	(H, -0.2735)
<i>Many</i>	241.42	(H, -0.0452)
<i>Most</i>	126.29	(H, +0.2843)
<i>All</i>	-110.13	L <sup>3</sup>

<sup>1</sup> The QOLI calculated by the quantifier *Half* is identical to those published by Numbeo, with a rounding error. <sup>2</sup> The QOLI calculated by the quantifier *At least one* represents the house price to income ratio, so the function *neg()* was used for its calculation. <sup>3</sup> The QOLI calculated by the quantifier *All* represents the cost of living index, so the function *neg()* was used for its calculation.

**Step 5. Results analysis and comparison.**

This step aimed to present all the results obtained. Firstly, two tables were created to compare the quality of life index estimated by the 2LOWA-QOLI model with that calculated by Numbeo, one for the top 10 countries in terms of QOLI (evaluation from position 1 to 10, see Table 7), and another for the worst 10 countries (evaluation from position 76 to 85, see Table 8). Furthermore, to investigate the relationship between economic development and quality of life in various countries, the QOLI of the top 15 countries in the 2021 GDP ranking [89] are analyzed (see Table 9). Section 4 contains the analytical details of these tables.

Table 7. Number top 10 countries in terms of quality of life index (number versus. 2-tuple value).

R	Country	Quality of Life Index									
		Numero	At Least One	Few	Some	Half	Many	Most	All		
1	Switzerland	195.27	67.66	82.09	138.06	195.34	259.33	−38.74	−381.065		
2	Denmark	192.36	73.55	86.42	137.72	192.41	258.43	48.68	−228.068		
3	Netherlands	185.38	72.11	83.95	132.31	185.44	252.14	71.64	−195.074		
4	Finland	184.96	68.99	82.63	134.12	185.00	240.60	38.69	−185.48		
5	Australia	183.81	71.91	83.20	130.33	183.87	254.85	77.19	−203.225		
6	Iceland	182.26	75.19	87.54	134.84	182.30	233.81	1.78	−269.954		
7	Germany	180.27	65.17	76.93	125.68	180.32	251.08	90.29	−155.762		
8	Austria	179.16	58.07	71.66	124.53	179.21	243.47	67.57	−177.06		
9	New Zealand	176.81	68.95	79.94	125.51	176.86	244.79	85.09	−190.628		
10	Norway	176.39	68.64	80.74	127.87	176.44	231.53	−9.25	−293.51		
1	Switzerland	VH	(M, −0.0002)	(M, +0.1625)	(H, −0.3566)	(H, −0.0597)	(H, +0.0281)	(L, +0.3223)	VH		
2	Denmark	VH	L	(H, +0.0153)	(H, +0.075)	(H, +0.1369)	(H, +0.2033)	(M, +0.2257)	H		
3	Netherlands	VH	L	(H, +0.0038)	(H, +0.0188)	(H, +0.0343)	(H, +0.0451)	(M, +0.1808)	H		
4	Finland	VH	(L, −0.0001)	(H, +0.0329)	(H, +0.0923)	(H, +0.0598)	(H, −0.1187)	(M, +0.0966)	M		
5	Australia	VH	L	(H, −0.0159)	(H, −0.0645)	(H, −0.0939)	(H, −0.0961)	(M, +0.1774)	H		
6	Iceland	VH	(L, −0.0001)	(H, +0.0449)	(H, +0.1382)	(H, +0.1197)	(H, −0.0906)	(L, +0.2359)	VH		
7	Germany	VH	(M, −0.0001)	(M, +0.12)	(H, −0.4939)	(H, −0.1965)	(H, +0.0508)	(H, −0.245)	M		
8	Austria	VH	(M, −0.0001)	(M, +0.1206)	(M, +0.492)	(H, −0.2564)	(H, −0.1357)	(M, +0.3843)	M		
9	New Zealand	VH	(M, −0.0001)	(M, +0.0869)	(M, +0.3554)	(H, −0.4529)	(H, −0.3108)	(M, +0.1325)	H		
10	Norway	VH	(M, −0.0002)	(M, +0.1592)	(H, −0.3857)	(H, −0.1367)	(H, −0.1471)	(L, +0.2359)	VH		

The results of the 2-tuple value are marked with an orange background.

Table 8. Numbeo worst 10 countries in terms of quality of life index (number versus. 2-tuple value).

R	Country	Quality of Life Index									
		Numbeo	At Least One	Few	Some	Half	Many	Most	All		
76	Indonesia	90.36	14.49	19.40	47.99	90.39	158.17	122.05	−39.82		
77	Vietnam	89.95	19.87	22.57	46.85	89.99	163.68	123.32	−46.17		
78	Egypt	89.87	53.02	50.55	58.36	89.90	159.22	164.06	−15.13		
79	Philippines	83.74	−15.61	−7.62	31.80	83.77	160.90	121.78	−44.53		
80	Peru	80.42	24.12	24.33	41.10	80.47	159.20	167.14	−26.87		
81	Venezuela	77.43	44.01	41.70	48.56	77.47	143.22	140.90	−68.48		
82	Sri Lanka	67.88	−79.29	−62.99	0.82	67.91	152.14	121.84	−22.03		
83	Bangladesh	67.59	47.17	42.58	42.89	67.62	129.66	128.91	−29.21		
84	Iran	64.89	−28.72	−21.35	15.57	64.92	139.29	112.96	−45.82		
85	Nigeria	52.44	37.14	31.93	29.96	52.47	111.76	119.50	−18.91		
76	Indonesia	VL	(VH, −0.0001)	(VL, +0.1664)	(L, −0.2684)	(L, +0.2222)	(M, −0.2315)	(H, +0.4293)	VL		
77	Vietnam	VL	VH	(VL, +0.1519)	(L, −0.3027)	(L, +0.2051)	(M, −0.2203)	(H, +0.3912)	VL		
78	Egypt	VL	(M, +0.0001)	(M, −0.1085)	(M, −0.3803)	(M, −0.453)	(M, −0.2202)	(VH, −0.2864)	VL		
79	Philippines	VL	(VH, −0.0001)	(VL, +0.1664)	(L, −0.2684)	(L, +0.2222)	(M, −0.2315)	(H, +0.4293)	VL		
80	Peru	VL	VH	(VL, +0.1004)	(VL, +0.4886)	(L, −0.094)	(M, −0.4744)	(VH, −0.2898)	VL		
81	Venezuela	VL	(VH, −0.0001)	(VL, +0.1491)	(L, −0.3508)	(L, +0.0769)	(M, −0.4406)	(H, +0.0945)	L		
82	Sri Lanka	VL	(VH, −0.0001)	(VL, +0.1391)	(L, −0.3929)	(L, +0.0085)	(L, +0.4578)	(H, +0.0967)	VL		
83	Bangladesh	VL	(H, +0.0001)	(L, −0.0412)	(L, −0.112)	(L, −0.0513)	(L, +0.2714)	(H, +0.3776)	VL		
84	Iran	VL	(VH, −0.0001)	(VL, +0.1549)	(L, −0.3246)	(L, +0.1196)	(M, −0.3897)	(H, +0.3844)	VL		
85	Nigeria	VL	(H, +0.0001)	(L, −0.0412)	(L, −0.112)	(L, −0.0513)	(L, +0.2714)	(H, +0.3776)	VL		

The results of the 2-tuple value are marked with an orange background.

**Table 9.** The quality of life index in top 15 countries in GDP (number versus. 2-tuple value).

R	Country	R <sub>GDP</sub>	Quality of Life Index							
			Numbco	At Least One	Few	Some	Half	Many	Most	All
15	United States	1	17072	84.54	91.56	125.86	170.77	235.98	72.49	-173.51
66	China	2	10507	-13.28	-3.60	43.61	105.11	194.63	129.67	-62.90
16	Japan	3	16948	57.01	67.85	114.74	169.53	242.05	66.82	-200.42
7	Germany	4	18027	65.17	76.93	125.68	180.32	251.08	90.29	-155.76
22	United Kingdom	5	16174	65.43	73.65	112.39	161.79	233.13	85.99	-171.64
59	India	6	11099	60.35	60.43	75.5838	111.02	178.76	149.23	4.72
26	France	7	15665	61.22	69.13	107.22	156.71	229.38	78.32	-189.11
36	Italy	8	14107	66.40	70.91	98.66	141.12	209.46	91.35	-159.23
23	Canada	9	16038	70.66	79.35	116.86	160.43	216.83	42.83	-173.86
45	South Korea	10	12504	-14.67	-0.66	58.35	125.09	210.35	52.22	-185.56
69	Russia	11	10328	42.11	45.26	67.44	103.32	161.58	100.99	-37.51
64	Brazil	12	10704	36.57	40.77	66.64	107.07	177.15	165.19	-29.64
5	Australia	13	18381	71.91	83.20	130.33	183.87	254.85	77.19	-203.23
18	Spain	14	16848	65.75	74.99	116.92	168.52	241.42	126.29	-110.13
46	Mexico	15	124.9	66.09	68.08	87.92	124.94	191.92	148.31	-37.87
15	United States	1	VH	(VL, +0.0001)	(VH, -0.1359)	(H, +0.4294)	(H, +0.1026)	(H, -0.1469)	(M, +0.4224)	M
66	China	2	L	VH	(VL, +0.173)	(L, -0.2015)	(L, +0.3847)	(M, +0.0339)	(H, -0.0932)	L
16	Japan	3	VH	(M, -0.0001)	(M, +0.1099)	(M, +0.4678)	(H, -0.2477)	(H, +0.0056)	(M, +0.2223)	H
7	Germany	4	VH	(M, -0.0001)	(M, +0.12)	(H, -0.4939)	(H, -0.1965)	(H, +0.0508)	(H, -0.245)	M
22	United Kingdom	5	VH	M	(M, +0.0579)	(M, +0.2781)	(H, -0.4956)	(H, -0.2034)	(H, -0.2484)	M
59	India	6	L	(M, +0.0001)	(M, -0.0507)	(M, -0.1644)	(M, -0.1624)	(M, +0.0397)	(H, +0.4742)	VL
26	France	7	H	M	(M, +0.0363)	(M, +0.1836)	(M, +0.3506)	(H, -0.4068)	(M, +0.1774)	H
36	Italy	8	M	M	(M, +0.0464)	(M, +0.2219)	(M, +0.4018)	(H, -0.3616)	(H, -0.2933)	M
23	Canada	9	VH	L	(H, -0.0292)	(H, -0.1357)	(H, -0.2393)	(H, -0.3729)	(M, +0.0932)	M
45	South Korea	10	M	(VH, -0.0001)	(VL, +0.2346)	(L, +0.0332)	(M, -0.2904)	(M, +0.3389)	(M, -0.1518)	H
69	Russia	11	L	H	(L, +0.0527)	(L, +0.2414)	(L, +0.4187)	(M, -0.3615)	(H, +0.0586)	VL
64	Brazil	12	L	(VH, -0.0002)	(VL, +0.1852)	(L, -0.222)	(L, +0.2478)	(M, -0.2484)	(VH, -0.2898)	VL
5	Australia	13	VH	L	(H, -0.0159)	(H, -0.0645)	(H, -0.0939)	(M, +0.1774)	(M, +0.1774)	H
18	Spain	14	VH	(M, -0.0001)	(M, +0.1104)	(M, +0.4611)	(H, -0.2735)	(H, -0.0452)	(H, +0.2843)	L
46	Mexico	15	M	M	(M, +0.0075)	(M, +0.0486)	(M, +0.1196)	(M, +0.3052)	(VH, -0.2381)	VL

The results of the 2-tuple value are marked with an orange background.

#### 4. Analysis of Results and Comparison

The results of the 2LOWA–QOLI model are shown in this section, along with a comparison to the QOLI generated by Numbeo. Tables 7–9 compare the QOLI of the Numbeo top 10 countries, the worst 10 countries, and the GDP top 15 countries with their QOLI estimated by various linguistic quantifiers, respectively. Tables 10–12 show the re-ranking based on the 2LOWA–QOLI model of the top 10 countries, the worst 10 countries, and the GDP top 15 countries, respectively, which provide a variety of QOLIs based on different scenarios, using the weights obtained by the OWA operator.

In the ranking of the top 10 countries on Numbeo, as shown in Table 7, the QOLI computed by the quantifier *Half* is the same as that determined by Numbeo, except for a slight decimal variation. However, when their 2-tuple values are compared, this ranking changes slightly. In the 2LOWA–QOLI model, Denmark, Iceland, Finland, and Netherlands, in that order, rank ahead of Switzerland. Only when the linguistic quantifier *Half* is used for the numerical calculations is the result the same as that of Numbeo. Otherwise, even the rankings based on the 2-tuple values generated with the quantifier *Half* are slightly different.

In the ranking of the worst 10 countries on Numbeo, as shown in Table 8, a similar conclusion is drawn as in Table 7, that is, only when the linguistic quantifier *Half* is employed for the numerical calculations is the result the same as that of Numbeo. In other cases, some slight changes are found. For example, despite being sixth from the bottom (number 80) in the Numbeo ranking, Peru ranks worst when the linguistic quantifiers *Few*, *Some*, and *Half* are used to calculate its 2-tuple value of QOLI.

**Table 10.** Re-ranked QOLI of top 10 countries (number versus. 2-tuple value).

R	Numbeo		At Least One		Few		Some		Half		Many		Most		All	
	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>	<i>T<sub>num</sub></i>	<i>T<sub>lin</sub></i>
1	CH	CH	SA	OM	US	OM	CH	OM	CH	OM	CH	DK	TR	BG	PK	NG
2	DK	DK	ZAF	US	SA	US	DK	DK	DK	DK	DK	OM	TN	BA	IN	PE
3	NL	NL	US	PR	OM	UAE	ISL	ISL	NL	ISL	AU	DE	CO	MX	CO	SL
4	FI	FI	PR	ZAF	UAE	SA	FI	US	FI	US	NL	NL	KE	EC	TN	ID
5	AU	AU	UAE	UAE	ZAF	ZAF	NL	FI	AU	FI	DE	EE	PE	TR	TR	MY
6	ISL	ISL	OM	SA	ISL	PR	AU	NL	ISL	NL	NZ	CH	AR	CO	KZ	BD
7	DE	DE	QA	ISL	DK	ISL	OM	UAE	DE	UAE	LUX	JP	BR	KE	EG	IR
8	AT	AT	ISL	FI	PR	FI	NO	CH	AT	CH	AT	ES	EG	AR	AZ	PK
9	NZ	NZ	CYP	DK	NL	DK	SE	EE	NZ	EE	JP	LUX	AZ	SRB	GE	UA
10	NO	NO	IE	NL	AU	NL	US	AU	NO	AU	ES	ISL	PK	GE	NG	VN

The results of the 2-tuple value are marked with an orange background. Country abbreviations: AR: Argentina; AT: Austria; AU: Australia; AZ: Azerbaijan; BA: Bosnia and Herzegovina; BD: Bangladesh; BG: Bulgaria; BR: Brazil; CA: Canada; CH: Switzerland; CHN: China; CL: Chile; CO: Colombia; CYP: Cyprus; DE: Germany; DK: Denmark; EC: Ecuador; EE: Estonia; EG: Egypt; ES: Spain; FI: Finland; FR: France; GE: Georgia; IE: Ireland; ID: Indonesia; IL: Israel; IN: India; IR: Iran; ISL: Iceland; IT: Italy; JP: Japan; KE: Kenya; KR: South Korea; KW: Kuwait; KZ: Kazakhstan; LUX: Luxembourg; MX: Mexico; MY: Malaysia; NG: Nigeria; NL: Netherlands; NO: Norway; NZ: New Zealand; OM: Oman; PE: Peru; PH: Philippines; PK: Pakistan; PR: Puerto Rico; QA: Qatar; RUS: Russia; SA: Saudi Arabia; SE: Sweden; SG: Singapore; SL: Sri Lanka; SRB: Serbia; TH: Thailand; TN: Tunisia; TR: Turkey; UA: Ukraine; UAE: United Arab Emirates; UK: United Kingdom; US: United States; VE: Venezuela; VN: Vietnam; and ZAF: South Africa.

Table 9 shows that not all countries with high GDP have high QOLI. Only the QOLIs of Australia and Germany rank in the top 10 of the Numbeo rankings, while Brazil, China, and Russia rank below 60. Emerging countries such as India, Brazil, China, and Russia have a higher GDP but a low QOLI. Although the 2-tuples values of the QOLI computed by various linguistic quantifiers do not produce the same sorting results as Numbeo’s ranking, when using the quantifiers *Few*, *Some*, and *Half*, in the GDP top 15 countries, Brazil, China, and Russia always have the lowest QOLI.

**Table 11.** Re-ranked QOLI of worst 10 countries (number versus. 2-tuple value).

R	Numbeo		At Least One		Few		Some		Half		Many		Most		All	
	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>
76	ID	ID	VN	KE	VN	CO	ID	BR	ID	BR	PH	ID	IL	IL	IE	IE
77	VN	VN	TH	CL	TH	KR	VN	CO	VN	ID	EG	PH	DK	QA	JP	JP
78	EG	EG	ID	TH	ID	CHN	CHN	KR	EG	PH	PE	BR	CA	FI	AU	AU
79	PH	PH	KE	CO	KE	ID	KR	ID	PH	VN	ID	RUS	KW	CA	LUZ	LUX
80	PE	PE	AR	AZ	AR	PH	BD	PH	PE	IR	SL	IR	FI	IE	SG	SG
81	VE	VE	CHN	SRB	KR	IR	PE	VN	VE	VE	KZ	VE	QA	KR	DK	IL
82	SL	SL	KR	KR	CHN	VN	PH	IR	SL	SL	VE	PE	SG	SG	IL	DK
83	BD	BD	PH	PR	PH	VE	NG	VE	BD	BD	IR	SL	ISL	CH	ISL	ISL
84	IR	IR	IR	VN	IR	SL	IR	SL	IR	NG	BD	BD	NO	ISL	NO	NO
85	NG	NG	SL	CHN	SL	PE	SL	PE	NG	PE	NG	NG	CH	NO	CH	CH

The results of the 2-tuple value are marked with an orange background. Country abbreviations: AR: Argentina; AT: Austria; AU: Australia; AZ: Azerbaijan; BA: Bosnia and Herzegovina; BD: Bangladesh; BG: Bulgaria; BR: Brazil; CA: Canada; CH: Switzerland; CHN: China; CL: Chile; CO: Colombia; CYP: Cyprus; DE: Germany; DK: Denmark; EC: Ecuador; EE: Estonia; EG: Egypt; ES: Spain; FI: Finland; FR: France; GE: Georgia; IE: Ireland; ID: Indonesia; IL: Israel; IN: India; IR: Iran; ISL: Iceland; IT: Italy; JP: Japan; KE: Kenya; KR: South Korea; KW: Kuwait; KZ: Kazakhstan; LUX: Luxembourg; MX: Mexico; MY: Malaysia; NG: Nigeria; NL: Netherlands; NO: Norway; NZ: New Zealand; OM: Oman; PE: Peru; PH: Philippines; PK: Pakistan; PR: Puerto Rico; QA: Qatar; RUS: Russia; SA: Saudi Arabia; SE: Sweden; SG: Singapore; SL: Sri Lanka; SRB: Serbia; TH: Thailand; TN: Tunisia; TR: Turkey; UA: Ukraine; UAE: United Arab Emirates; UK: United Kingdom; US: United States; VE: Venezuela; VN: Vietnam; and ZAF: South Africa.

Another point worth mentioning is that, compared with the simple linguistic terms used by Numbeo, 2-tuple values cope with unbalanced linguistic term sets, aggregate information without losing it, and allow comparing linguistic information between different 2-tuple values of the QOLI. For instance, Numbeo marks Italy and Mexico as countries with medium quality of life, making it impossible to determine which country has a higher QOLI by comparing their linguistic terms. However, when utilizing the quantifiers *Few*, *Some*, *Half*, and *Many* in the 2LOWA–QOLI model, it is observed that Italy has a higher QOLI than Mexico.

Table 10 shows that, despite being in first place in Numbeo’s ranking, the ranking of Switzerland fluctuates in the top 10 when using the linguistic quantifiers *Some*, *Half*, and *Many*. Moreover, based on Table 4, it is found that the QOLI calculated by the quantifier *All* represents the cost of living index, as the weight of this index occupies 100% when this linguistic quantifier is used. Similarly, the QOLI calculated by the quantifier *At least one* represents the house price to income ratio. When these indicators are lower, the higher the QOLI is, and the higher the ranking is. For example, Saudi Arabia ranks first when using the quantifier *At least one* in the numerical calculation of the QOLI, showing that this country has the lowest house price to income ratio among these 85 countries. In the case of the 2-tuple value of the QOLI calculated with this quantifier, Oman ranks first.

Table 11 demonstrates the re-ranking of the worst 10 countries using the 2LOWA–QOLI model. Niger, Peru, and Sri Lanka are last when using the linguistic quantifiers *Few*, *Some*, *Half*, and *Many*. Although the worst-ranked country may vary in some cases (*At least one*, *Most*, and *All*), Niger is almost always ranked last, consistent with its position in Numbeo.

**Table 12.** Re-ranked QOLI of top 15 countries in GDP (number versus. 2-tuple value).

R	Country	R <sub>GDP</sub>	At Least One		Few		Some		Half		Many		Most		All	
			T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>	T <sub>num</sub>	T <sub>lin</sub>
15	US	1	US	US	US	US	AU	US	AU	US	AU	DE	BR	MX	IN	IN
66	CHN	2	AU	AU	AU	AU	US	AU	DE	AU	DE	JP	IN	BR	BR	BR
16	JP	3	CA	CA	CA	CA	DE	CA	US	DE	JP	ES	MX	IN	RUS	RUS
7	DE	4	IT	DE	DE	DE	ES	DE	JP	CA	ES	AU	CHN	ES	MX	MX
22	UK	5	MX	ES	ES	ES	CA	JP	ES	JP	US	US	ES	RUS	CHN	CHN
59	IN	6	ES	JP	UK	JP	JP	ES	UK	ES	UK	UK	RUS	CHN	ES	ES
26	FR	7	UK	UK	IT	UK	UK	UK	CA	UK	FR	IT	IT	DE	DE	DE
36	IT	8	DE	IT	FR	IT	FR	IT	FR	IT	CA	CA	DE	UK	IT	UK
23	CA	9	FR	FR	MX	FR	IT	FR	IT	FR	KR	FR	UK	IT	UK	IT
45	KR	10	IN	MX	JP	MX	MX	MX	KR	MX	IT	KR	FR	US	US	US
69	RUS	11	JP	IN	IN	IN	IN	IN	MX	IN	CHN	MX	AU	JP	CA	CA
64	BR	12	RUS	RUS	RUS	RUS	RUS	RUS	IN	KR	MX	IN	US	AU	KR	AU
5	AU	13	BR	BR	BR	KR	BR	KR	BR	RUS	IN	CHN	JP	FR	FR	FR
18	ES	14	CHN	KR	KR	BR	KR	CHN	CHN	CHN	BR	BR	KR	CA	JP	JP
46	MX	15	KR	CHN	CHN	CHN	CHN	BR	RUS	BR	RUS	RUS	CA	KR	AU	KR

The results of the 2-tuple value are marked with an orange background. Country abbreviations: AR: Argentina; AT: Austria; AU: Australia; AZ: Azerbaijan; BA: Bosnia and Herzegovina; BD: Bangladesh; BG: Bulgaria; BR: Brazil; CA: Canada; CH: Switzerland; CHN: China; CL: Chile; CO: Colombia; CYP: Cyprus; DE: Germany; DK: Denmark; EC: Ecuador; EE: Estonia; EG: Egypt; ES: Spain; FI: Finland; FR: France; GE: Georgia; IE: Ireland; ID: Indonesia; IL: Israel; IN: India; IR: Iran; ISL: Iceland; IT: Italy; JP: Japan; KE: Kenya; KR: South Korea; KW: Kuwait; KZ: Kazakhstan; LUX: Luxembourg; MX: Mexico; MY: Malaysia; NG: Nigeria; NL: Netherlands; NO: Norway; NZ: New Zealand; OM: Oman; PE: Peru; PH: Philippines; PK: Pakistan; PR: Puerto Rico; QA: Qatar; RUS: Russia; SA: Saudi Arabia; SE: Sweden; SG: Singapore; SL: Sri Lanka; SRB: Serbia; TH: Thailand; TN: Tunisia; TR: Turkey; UA: Ukraine; UAE: United Arab Emirates; UK: United Kingdom; US: United States; VE: Venezuela; VN: Vietnam; and ZAF: South Africa.

Furthermore, combining Tables 7 and 11, Switzerland is described as a country with a high quality of life, an average level of house prices, but a remarkably high cost of living. In other words, if an expert considers the cost of living as the only indicator to measure the quality of life in a country, Switzerland is not a good place to live, as its cost of living is extremely high, with the lowest QOLI value when using the quantifier *All*.

The countries with an excessive cost of living on the re-ranked list of the worst 10 countries are all developed countries (Switzerland, Norway, Iceland, Denmark, Japan, etc.). This circumstance is very typical in developed countries, but their other social welfare is higher, so their QOLI cannot be determined based on just the cost of living index but should consider more sub-indicators to balance the situation. It could be more appropriate to use the quantifier *Half* or *Many* to calculate their QOLI.

Similarly, although the cost of living in developing countries, such as Nigeria, Peru, or Pakistan, is inexpensive (see Table 10), the medical and educational systems may lag behind other countries. Nor is it appropriate to use only the cost of living index to assess their QOLI. It could be more acceptable to use the quantifier *Some* to calculate their QOLI.

Moreover, if an expert considers the house price to income ratio as the only indicator to gauge the quality of life in a country, some countries with high GDP may also be inappropriate to live in. For example, people living in China do not have enough money to pay for high-priced housing (see Tables 11 and 12), making this country unsuitable for living. In fact, according to the International Monetary Fund (IMF), Chinese cities are the most expensive places in the world to buy property on a price to income ratio, and 7 of the 10 most expensive real estate markets are in China [90]. China is currently confronting a housing bubble problem. As a result, China is regarded as a country with rapid GDP growth, but low QOLI (see Table 9), and high property prices.

When using the linguistic quantifier *At least one*, as seen in Table 12, regardless of whether it is a numerical calculation or a 2-tuple value calculation of the QOLI, Russia, Brazil, China, and South Korea occupy the bottom four places. It means that house prices are significantly higher than earnings in these four countries. However, among these

four nations, South Korea is the only one with a high house price to income ratio and a prohibitive cost of living, in the sense that it is not a suitable country to live in, despite having a relatively good economic development.

## 5. Discussion

The applicability of the 2LOWA–QOLI model is demonstrated in this paper using the Numbeo database, which contains the quality of life information for 85 countries. Comparing the quality of life index published by Numbeo, the 2LOWA–QOLI model provides a variety of QOLI results, including not only the best-balanced scenario suggested by Numbeo’s experts (*Half*), but also numerous scenarios of indicator weights (*Few*, *Some*, *Many*, *Most*, etc.) to adjust the weights used by Numbeo’s experts.

The results and rankings of the QOLI calculated by the quantifier *Half* and Numbeo are identical for different countries, since they use the same weights to produce the QOLI. However, when other quantifiers are used to generate the QOLI, the QOLI ranking of countries changes slightly. This phenomenon is logical, as the weights applied to integrate the multiple sub-indicators into the QOLI change. Despite the varying weights obtained by the different quantifiers, it should be emphasized that the importance ranking of these sub-indicators is essentially the same as that proposed by Numbeo’s experts. Figure 6 presents the ranking of the weights of the sub-indicators under different linguistic quantifiers.

As shown in Figure 6, the ranking of importance of these eight sub-indicators does not change when the quantifiers *Few*, *Some*, and *Half* are used, implying that the sub-indicator house price to income ratio continues to play the most significant role in the QOLI calculation, as suggested by Numbeo’s experts. Nevertheless, this ranking of importance changes slightly when other linguistic quantifiers are used. In Section 2.1, the AAI was introduced as a tool to assess the quality of composite indicators. It can quantify the degree of change in the rankings of these indicators. The AAI of this proposed model is 0.2776, indicating that the importance of these eight sub-indicators does not vary much with different linguistic quantifiers.

Indeed, the ranking of the QOLI obtained by the quantifier *Half* is undoubtedly consistent with that of Numbeo, as it uses the same weights to calculate the QOLI as Numbeo. Consequently, when altering the weights of sub-indicators, what should be evaluated is which linguistic quantifier (excluding the quantifier *Half*) produces a QOLI that best represents the multidimensional phenomena, and does not deviate significantly from the QOLI ranking on Numbeo. Table 13 shows the average rank difference between Numbeo’s QOLI and other QOLI produced by diverse linguistic quantifiers. As seen in Table 13, except for the linguistic quantifier *Half*, the mean difference between the QOLI ranking obtained by the quantifier *Some* and the ranking on Numbeo is relatively small, regardless of whether the ranking is made based on the numerical value of the QOLI, or its 2-tuple value.

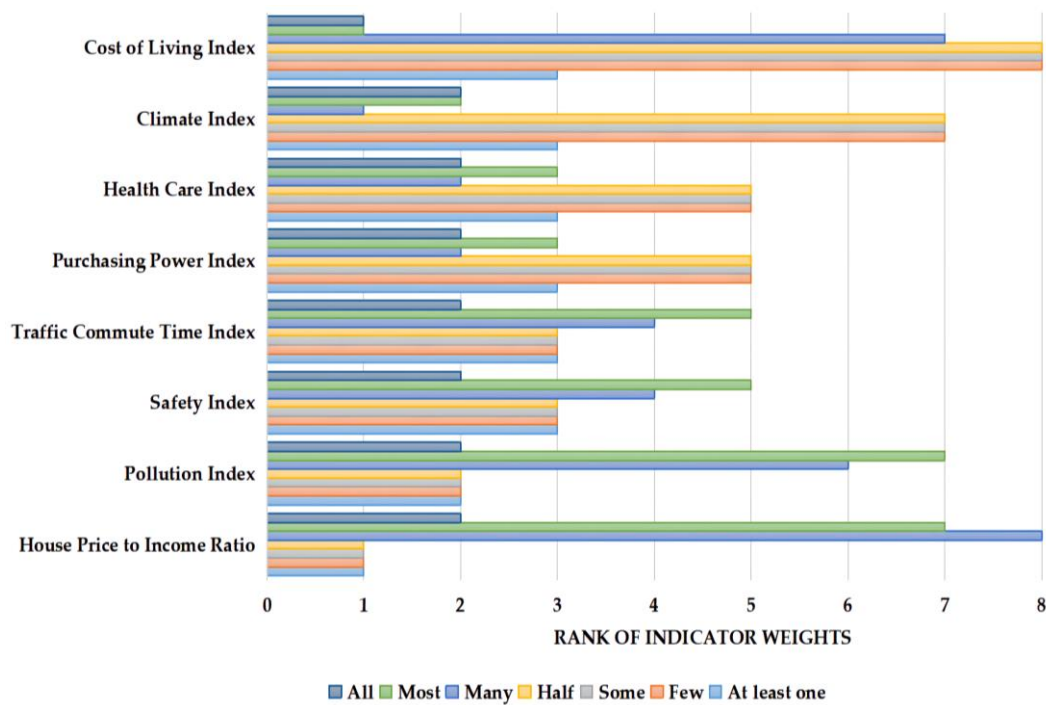


Figure 6. Ranking of the weights of the eight sub-indicators under different linguistic quantifiers.

Table 13. The average rank difference between Numbeo’s QOLI and other QOLI produced by diverse linguistic quantifiers (number versus. 2-tuple value).

		QOLI <sub>At least one</sub>	QOLI <sub>Few</sub>	QOLI <sub>Some</sub>	QOLI <sub>Half</sub>	QOLI <sub>Many</sub>	QOLI <sub>Most</sub>	QOLI <sub>All</sub>
QOLI <sub>Numbeo</sub>	$\overline{R}_S$	15.29	10.94	3.48	0	4	36.24	37.08
QOLI <sub>Numbeo</sub>	$\overline{R}_S$	14.68	11.88	5.07	0.78	6.18	38.26	43.89

The results of the 2-tuple value are marked with an orange background.

Table 14 refers to the correlation analysis between the different values of the QOLI and GDP per capita, while Table 15 shows the correlation analysis between their rankings. Pearson correlation coefficient, which ranges from  $-1$  to  $+1$  in correlation analysis, measures the direction and strength of the relationship between the two indicators.

- When comparing the QOLI value with GDP per capita, GDP per capita has a significant relationship with all the QOLIs generated by those seven linguistic quantifiers, although it is highly negatively correlated with the QOLI calculated by the quantifiers *Most* and *All*. The QOLI generated by the quantifier *Some* has a highly positive association ( $PCC > 0.7$ , whether in numerical value or 2-tuple value) with GDP per capita. It means that if a country calculates its QOLI using the quantifier *Some*, its QOLI grows in lockstep with its GDP per capita. Moreover, the correlation between them is considerably stronger than that between the quantifier *Half* and GDP per capita, while the QOLI obtained by the quantifier *Some* and the QOLI acquired by the quantifier *Half* are strongly positively correlated. Therefore, the QOLI generated by the quantifier *Some* can be considered the “best” choice to replace Numbeo’s QOLI, especially because it is more closely correlated with GDP per capita;
- When comparing the QOLI ranking with that of GDP per capita, the same conclusion is drawn as before. For example, the ranking of GDP per capita is strongly negatively related to that of the QOLI generated by quantifier *All*. Combined with Table 14, it indicates that the country with a high position in GDP per capita also has increased house prices, so its QOLI and QOLI ranking are low in this scenario. Furthermore, except for the quantifier *Half*, the quantifier *Some* obtains a QOLI ranking highly

similar to the GDP per capita ranking, and they are stronger correlated when ranked using the 2-tuple value of the QOLI.

Moreover, rather than just computing a number to rank, the 2LOWA–QOLI model enables the calculation of various quality of life indexes, taking into consideration more country-specific situations. It also aggregates numerous indicators to a 2-tuple value, which reduces the loss of information and improves the linguistic interpretability of the QOLI. Specifically, it distinguishes the quality of life of those countries labeled by Numbeo with the same linguistic label, since it measures the difference between the linguist term and the value of a symbolic aggregation operation.

In fact, not all the countries have the same problems in improving their quality of life; because of that, an index that aggregates many metrics should account for differing situations in different countries, by giving varying weights. In particular, this weighting in certain nations with unbalanced development should not be precisely the same as in developed countries. For example, many developing countries are facing a health or education crisis, which might seriously affect their economic, social, and long-term development. People living in these countries usually have a low income and low cost of living, yet they can hardly afford to buy a house. Therefore, they often feel anxious, due to the excessive cost of housing. Instead of adopting the universal weights recommended by Numbeo’s experts, it could be preferable to calculate their QOLI using the weights generated by the quantifier *Some*.

Although the 2LOWA–QOLI model can produce diverse QOLI based on the country-specific circumstances, with more understandable results to represent the quality of life in different countries, it is impossible to compare the ranking of various countries with their QOLI produced by different linguistic quantifiers. In reality, the weights of the eight sub-indicators of the QOLI fluctuate when different linguistic quantifiers are used. In other words, when comparing the QOLI of two countries, it is necessary to consider whether they are using the same criteria to assign weights. Comparing the QOLI between different countries is feasible only if they apply the same weighting criteria. For example, if both use the quantifier *Half* to compute their QOLI, Switzerland has a higher QOLI than that of Spain. However, it is not possible to compare their QOLIs if this is not the case, because the weights of sub-indicators differ, and it is difficult to conclude which nation has a higher QOLI.

Another limitation of the proposed model is that, when using linguistic quantifiers *At least one* and *All*, they are too extreme to represent the QOLI, as they assign practically all the weights to one sub-indicator (*At least one* corresponds to the house price to income ratio, and *All* corresponds to the cost of living index), without taking into consideration the importance of other sub-indicators. These two extreme cases could represent the house price to income ratio and cost of living in this country, respectively. Although these two sub-indicators account for a massive part of the measure of the quality of life in some countries, they should be considered on a case-by-case basis, rather than being assigned all the weights.

**Table 14.** Correlation analysis between the QOLI values and GDP per capita (number versus. 2-tuple value).

		GDP per Capita (\$)	QOLI <sub>Numero</sub>	QOLI <sub>At least one</sub>	QOLI <sub>Few</sub>	QOLI <sub>Some</sub>	QOLI <sub>Half</sub>	QOLI <sub>Many</sub>	QOLI <sub>Most</sub>	QOLI <sub>All</sub>
Numerical value	Pearson correlation coefficient (PCC)	1	0.696 **	0.359 **	0.460 **	0.703 **	0.696 **	0.680 **	-0.780 **	-0.813 **
	Sig. (2-tailed)		0	0	0	0	0	0	0	0
Numerical value	Pearson correlation coefficient (PCC)	0.696 **	1	0.624 **	0.752 **	0.977 **	1.000 **	0.970 **	-0.621 **	-0.735 **
	Sig. (2-tailed)	0	0	0	0	0	0	0	0	0
2-tuple value	Pearson correlation coefficient (PCC)	1	0.673 **	0.374 **	0.406 **	0.713 **	0.662 **	0.623 **	-0.802 **	-0.808 **
	Sig. (2-tailed)	0	0	0	0	0	0	0	0	0
2-tuple value	Pearson correlation coefficient (PCC)	0.673 **	1	0.587 **	0.632 **	0.934 **	0.907 **	0.794 **	-0.611 **	-0.666 **
	Sig. (2-tailed)	0	0	0	0	0	0	0	0	0

\*\* Correlation is significant at the 0.01 level (2-tailed). The results of the 2-tuple value are marked with an orange background.

**Table 15.** Correlation analysis between the QOLI ranking and the GDP per capita ranking (number versus. 2-tuple value).

		<b>GDP per Capita (\$)</b>	<b>QOLI<sub>Numbeo</sub></b>	<b>QOLI<sub>At Least One</sub></b>	<b>QOLI<sub>Few</sub></b>	<b>QOLI<sub>Some</sub></b>	<b>QOLI<sub>Half</sub></b>	<b>QOLI<sub>Many</sub></b>	<b>QOLI<sub>Most</sub></b>	<b>QOLI<sub>All</sub></b>
Numerical value	Pearson correlation coefficient (PCC)	1	0.754 **	0.508 **	0.613 **	0.747 **	0.754 **	0.732 **	-0.762 **	-0.784 **
	Sig. (2-tailed)		0	0	0	0	0	0	0	0
Numerical value	Pearson correlation coefficient (PCC)	0.754 **	1	0.690 **	0.832 **	0.978 **	1.000 **	0.974 **	-0.619 **	-0.758 **
	Sig. (2-tailed)	0	0	0	0	0	0	0	0	0
2-tuple value	Pearson correlation coefficient (PCC)	1	0.754 **	0.559 **	0.567 **	0.753 **	0.751 **	0.695 **	-0.763 **	-0.714 **
	Sig. (2-tailed)		0	0	0	0	0	0	0	0
2-tuple value	Pearson correlation coefficient (PCC)	0.754 **	1	0.778 **	0.794 **	0.939 **	0.967 **	0.841 **	-0.605 **	-0.603 **
	Sig. (2-tailed)	0	0	0	0	0	0	0	0	0

\*\* Correlation is significant at the 0.01 level (2-tailed). The results of the 2-tuple value are marked with an orange background.

Regardless of its drawbacks, the proposed model contributes an intriguing way to calculate the QOLI, that is, assigning different weights to various sub-indicators by using the multiple linguistic quantifiers of the OWA operator. This model also shows the convenience of using the 2-tuple value to reflect and interpret the quality of life index.

## 6. Conclusions and Future Work

The quality of life can be defined in many ways. There is no widely accepted definition. Given its subjectivity, this study used data from the Numbeo database to calculate the quality of life index based on information about the eight sub-indicators shared by individuals from various countries.

This paper presents a novel approach to compute the quality of life index, the 2LOWA–QOLI model. This approach uses multiple linguistic quantifiers to construct the QOLI under diverse scenarios, and finally interprets the QOLI with its 2-tuple value. Its usefulness is demonstrated using the Numbeo database. The results show that this approach can generate diverse QOLIs based on a country's circumstances by altering the weights used by Numbeo's experts, with more understandable results to represent the quality of life in different countries.

The QOLI calculated using the quantifier *Half* is the same as that determined by Numbeo, except for some slight decimal variation. However, when their 2-tuple values are compared, this ranking changes slightly. For example, Brazil, China, South Korea, and Russia are the 4 countries out of the top 15 countries in terms of GDP that rank bottom in the QOLI 2-tuple value ranking. Their ranking constantly fluctuates between the bottom four when using linguistic quantifiers *At least one*, *Few*, *Some*, and *Half*, as the house price to income ratio is very high in these countries, and is given a larger weight than other sub-indicators when using these quantifiers mentioned above.

In summary, this model generates different scenarios of the quality of life index, which could aid policymakers in recognizing their own quality of life level, and developing suitable policies to improve it, considering their country's condition. It also aggregates numerous indicators to a 2-tuple value, which decreases information loss, and improves the linguistic interpretability of the QOLI.

For future work, the proposed model could include more sub-indicators to construct the QOLI. This model could also be extended by combining the 2LOWA operator with other weight assignment methods. As this paper only analyzed the correlation between the QOLI derived from different linguistic quantifiers and the reference indicator of GDP per capita, in future work, it would be better to incorporate more economic and environmental indicators, in order to assess the validation of the proposed model's QOLI. In addition, although it is difficult to rank different countries based on their QOLI generated by different linguistic quantifiers, using unsupervised algorithms, such as clustering, to classify different countries might be a possibility to attempt. Therefore, a country segmentation, based on their QOLI obtained by different quantifiers, could be a part of future work.

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## 4. Ranking Luxury Hotels in Lisbon Using the 2T-AEC-TOPSIS Model

### Ranking Luxury Hotels in Lisbon Using the 2T-AEC-TOPSIS Model

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# Chapter 45

## Ranking Luxury Hotels in Lisbon Using the 2T-AEC-TOPSIS Model



Ziwei Shu  and Ramón Alberto Carrasco 

**Abstract** Hotel rankings help customers choose accommodations quickly and assist hotel managers in improving their performance by comparing them to competitors. However, most ranking models use equal weighting for various hotel aspect performances. From a business perspective, improving weight determination to reflect better the varying importance of multiple aspects in hotel rankings and enhancing ranking results interpretation is necessary. Therefore, this paper introduces the 2T-AEC-TOPSIS model for hotel ranking, incorporating five fundamental concepts: the 2-tuple linguistic model, Analytic Hierarchy Process (AHP) method, Entropy method, CRiteria Importance Through Intercriteria Correlation (CRITIC) method, and Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) method. The 2-tuple linguistic model aggregates linguistic ratings for each hotel aspect, avoiding information loss in linguistic fusion. The AHP, Entropy, and CRITIC methods generate weights for each hotel aspect that are combined to form integrated weights that blend the benefits of objective and subjective weighting approaches. These integrated weights are employed to execute the necessary steps in the TOPSIS method to rank hotels. The functionality of the proposed model has been evaluated with a dataset of over 26,000 customer reviews gathered from TripAdvisor for luxury hotels in Lisbon. The results show that the proposed model achieves a relatively balanced and realistic weight distribution in the weight assignment within the TOPSIS method, and produces a top 10 list of luxury hotels in Lisbon for different scenarios. It provides hotel managers and customers with more interpretable ranking results for making more informed and faster decisions.

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## 5. Hotel Customer Segmentation Using the Integrated Entropy-CRITIC Method and the 2T-RFMB Model

### Hotel Customer Segmentation Using the Integrated Entropy-CRITIC Method and the 2T-RFMB Model

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# Chapter 5

## Hotel Customer Segmentation Using the Integrated Entropy-CRITIC Method and the 2T-RFMB Model



Ziwei Shu , Ramón Alberto Carrasco González ,  
Javier Portela García-Miguel , and Manuel Sánchez-Montañés 

**Abstract** Customer segmentation helps the company better understand its target audience, which is vital to optimizing marketing strategies and maximizing the customer value for the company. This paper improves the original RFM model by including the potential loss to the hotel from a customer canceling their reservation in the indicator “Monetary” and adding a new indicator “Bonding” to indicate the degree of customer bonding with the hotel. The proposed model also includes the 2-tuple linguistic model to give hotel managers or decision-makers more easily understandable customer segmentation results. The aggregation of the four indicators (recency, frequency, monetary, and bonding) into a unique value is a Multi-Criteria Decision-Making (MCDM) problem. To generate the weights that can consider the relationship between various indicators and the level of data diversification contained in each indicator, the Entropy method and the CRiteria Importance Through Intercriteria Correlation (CRITIC) method have been integrated. Customer overall values are generated based on the 2T-RFMB model and the integrated Entropy-CRITIC method. Finally, various customer segments are obtained with K-means clustering. This proposal has been evaluated by a real dataset from a hotel in Lisbon. The results show that the proposed model can increase the linguistic interpretability of clustering results. It also demonstrates that the proposed model can provide hotel managers with more realistic customer values to assist them in allocating their Customer Relationship Management (CRM) resources efficiently.

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## 6. A Model Integrating the 2-Tuple Linguistic Model and the CRITIC-AHP Method for Hotel Classification

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### A Model Integrating the 2-Tuple Linguistic Model and the CRITIC-AHP Method for Hotel Classification

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# A Model Integrating the 2-Tuple Linguistic Model and the CRITIC-AHP Method for Hotel Classification

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## Abstract

Hotel classification is essential for hotel managers and customers. It can assist hotel managers in better understanding the needs of their customers and in improving various aspects of the hotel through relevant strategies. It also aids customers in choosing appropriate accommodations according to their preferences regarding hotel location, services, and other aspects. This paper aims to improve our previous model by incorporating expert opinions into the weight calculation, thereby increasing its practical applicability. The extended model combines the analytical hierarchy process (AHP) and the CRiteria Importance Through Intercriteria Correlation (CRITIC) methods, introducing a novel approach for calculating the weights of each aspect. The 2-tuple linguistic model is retained in the extended model to resolve the problem of information loss in linguistic information fusion. Finally, various hotel segments are obtained with the weighted *K*-means clustering. A dataset with over fifty million hotel reviews from TripAdvisor has been applied to evaluate the extended model. The results show that the extended model achieves denser and better separated hotel clusters than our previous model, while maintaining the same advantages. This model is more likely to help hotel managers create better strategies to tackle hotel weaknesses or gain competitive advantages, as it combines two types of weights that improve clustering results: the quantity of information in each hotel aspect and the expert judgment of each aspect's importance in hotel development.

**Keywords** Hotel classification · 2-Tuple linguistic model · CRiteria Importance through Intercriteria Correlation (CRITIC) method · Analytical hierarchy process (AHP) method · Weighted *K*-means clustering · Multi-criteria decision making (MCDM)

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## Introduction

Accommodation is a crucial component of the tourism industry, with online hotel booking holding a substantial market share. Websites like Booking.com and TripAdvisor attract millions of visits per month, and by 2023, 700 million people are expected to book hotel rooms online [1]. Hotel classification is a vital aspect of hotel development, holding significant importance for customers as well. It enables hotel managers to make informed decisions, addressing any possible weaknesses in different aspects of their hotel. Simultaneously, it allows customers to select suitable accommodations based on their preferences regarding hotel location, services, and other aspects.

In the last few years, various approaches have been developed to explore hotel classification [2–7]. For instance, Yadegaridehkordi et al. used segmentation and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to prioritize green hotel attributes

# 7. A Model Based on 2-Tuple Linguistic Model and CRITIC Method for Hotel Classification

## A Model based on 2-tuple Linguistic Model and CRITIC Method for Hotel Classification

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

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**Keyword(s):** Hotel Classification, Weighted K-means Clustering, 2-tuple Linguistic Model, CRITIC Method, Multi-criteria Decision Making.

**Abstract:** Hotel classification is critical for both customers and hotel managers. It can help hotel managers better understand their customers' needs and improve their various aspects by implementing relevant strategies. Moreover, it can assist customers in recognizing different hotel aspects and making a more informed decision. This paper categorizes hotels on TripAdvisor based on their six aspects. The 2-tuple linguistic model is applied to solve the problem of information loss in linguistic information fusion. The CRITIC Importance Through InterCriteria Correlation (CRITIC) approach is employed to generate objective weights to calculate the overall score of each hotel, as this method does not require any human participation in the weighting computation. Finally, various hotels segments are obtained with Weighted K-means clustering. This proposal has been evaluated by a use case with more than fifty million TripAdvisor hotel reviews. The results demonstrate that the proposed model can incr (More)

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# A Model based on 2-tuple Linguistic Model and CRITIC Method for Hotel Classification

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**Abstract:** Hotel classification is critical for both customers and hotel managers. It can help hotel managers better understand their customers' needs and improve their various aspects by implementing relevant strategies. Moreover, it can assist customers in recognizing different hotel aspects and making a more informed decision. This paper categorizes hotels on TripAdvisor based on their six aspects. The 2-tuple linguistic model is applied to solve the problem of information loss in linguistic information fusion. The CRITIC approach is employed to generate objective weights to calculate the overall score of each hotel, as this method does not require any human participation in the weighting computation. Finally, various hotels segments are obtained with Weighted K-means clustering. This proposal has been evaluated by a use case with more than fifty million TripAdvisor hotel reviews. The results demonstrate that the proposed model can increase the linguistic interpretability of clustering results and provide customers with a more understandable objective overall hotel score, which can assist them in selecting a better hotel. Moreover, these classification results aid hotel managers in designing more effective tactics for acquiring a new competitive advantage or enhancing those aspects that require improvement.


## 1 INTRODUCTION


Accommodation is one of the most important aspects of the tourism industry, in which online hotel reservations account for a significant portion of the market. TripAdvisor and Booking receive millions of visits per month, by 2023, 700 million individuals will be reserving hotel rooms online (Deane, 2022). The classification of hotels is an essential component of hotel development and is also critical for customers as it allows them to choose the appropriate accommodation based on their demands.


In recent years, different approaches to exploring hotel classification have been developing, such as

(Beracha et al., 2018), (Mody et al., 2019), (Nilashi et al., 2019), (Ali et al., 2020), (Çınar et al., 2020), and so on. Among them, Nilashi et al. presented a hybrid method for analyzing online opinions through multi-criteria decision-making and Machine Learning techniques to examine the relevance of aspects influencing visitors' decision-making in choosing hotels. Although K-means clustering has been commonly utilized in the literature (El Khediri et al., 2020; Abdullah et al., 2021; Chowdhury et al., 2021; Jahangoshai Rezaee et al., 2021; Zhao et al., 2021), few studies have taken into account that the different quantity of information contained in the variables will affect the clustering results.

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Therefore, this paper presents a segmentation of hotels on TripAdvisor through a Weighted K-means clustering based on the 2-tuple model and the CRiteria Importance Through Intercriteria Correlation (CRITIC) method. The CRITIC approach is used in this proposal as it can generate objective weights for distinct hotel aspects without the requirement of expert evaluations. And the 2-tuple linguistic model is applied to solve the problem of information loss in linguistic information fusion. In this way, this proposal allows weighting the aspects of the hotel, considering the different quantities of information included in each of them, and increasing the linguistic interpretability of clustering results.

The rest of this paper is structured as follows. Section 2 introduces the key concepts that will be utilized to build the proposed model. Section 3 demonstrates a use case with more than fifty million TripAdvisor hotel reviews to evaluate the proposed model. Section 4 presents some conclusions and future work.

## 2 THEORETICAL FRAMEWORK

In this section, the essential concepts on which this proposal is based are presented: 2-tuple linguistic model, CRITIC method, 2T-CRITIC model and Weighted K-means clustering.

### 2.1 The 2-tuple Linguistic Model

In the fuzzy linguistic approaches, linguistic terms are employed to assist computation and identify the variety of each assessment item (Herrera & Martínez, 2000; Ju et al., 2012). To solve the problem of information loss in linguistic information fusion, Herrera and Martínez introduced the 2-tuple linguistic model (Herrera & Martínez, 2000). Numerous authors have utilized it to model customer reviews with fuzzy linguistic scales, which provides more understandable results than using solely numerical scales (Liu & Chen, 2018; Carrasco et al., 2018; Sohaib et al., 2019; Díaz et al., 2021).

The 2-tuple linguistic model expresses the linguistic information through a pair of values called 2-tuple value  $(s_i, \alpha)$ , where  $s_i \in S$  is a linguistic term, and  $\alpha \in [-0.5, 0.5]$  is a numeric value that represents the distance to the central value of  $s_i$ . The definition is as follows.

**Definition 1.** Let  $S = \{s_0, \dots, s_g\}$  be a linguistic term set, and  $\beta \in [0, g]$  be a value that represents the result of an operation of symbolic aggregation. The function

$\Delta: [0, g] \rightarrow \langle S \rangle = Sx \in [-0.5, 0.5]$  is used to convert  $\beta$  to 2-tuple value  $(s_i, \alpha)$  as the Equation (1):

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} i = \text{round}(\beta) \\ \alpha = \beta - i, \alpha \in [-0.5, 0.5] \end{cases} \quad (1)$$

where  $\text{round}(\cdot)$  is the rounding operation;  $s_i$  has the nearest index label to  $\beta$ ; and  $\alpha$  is a numerical value of the symbolic translation. The function  $\Delta^{-1}: \langle S \rangle = Sx \in [-0.5, 0.5] \rightarrow [0, g]$  is the inverse function of  $\Delta$ , so that a 2-tuple value can be converted into its equivalent numerical value as  $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$ . The negation operator of a 2-tuple value is defined as  $\text{neg}((s_i, \alpha)) = \Delta(g - \Delta^{-1}(s_i, \alpha)) = \Delta(g - \beta)$ .

The comparison and aggregation operators for 2-tuple linguistic computation are described in (Herrera et al., 2004). In this paper, the arithmetic mean is used to aggregate 2-tuple values, which is defined as follows.

**Definition 2.** Let  $T_v = \{(s_1, \alpha_1), \dots, (s_n, \alpha_n)\}$  be a set of 2-tuple values of the  $v$ th criterion, whose arithmetic mean is calculated using Equation (2):

$$\bar{T}_v = \Delta\left(\frac{1}{n} \sum_{i=1}^n \Delta^{-1}(s_i, \alpha_i)\right) = \Delta\left(\frac{1}{n} \sum_{i=1}^n \beta_i\right) \quad (2)$$

### 2.2 CRiteria Importance Through Intercriteria Correlation (CRITIC) Method

Introduced by Diakoulaki et al., the CRiteria Importance Through Intercriteria Correlation (CRITIC) method is one of the weighting methods for determining objective weights for each criterion (Diakoulaki et al., 1995). This method is extremely useful when the correlation between variables is high, as it employs correlation analysis to determine the differences between various criteria. Furthermore, human intervention such as expert evaluations is not required in the weight calculation process, as CRITIC is an objective weighting approach.

The CRITIC method consists of four steps:

- 1) Calculate the standard deviation of each criterion.
- 2) Compute the linear correlation matrix to obtain the correlation coefficient between the two criteria.
- 3) Obtain the quantity of information on each criterion.
- 4) Determine the objective weights for each criterion.

The definition is as follows.

**Definition 3.** Let  $S_v$  be the standard deviation of the  $v$ th criterion out of a total of  $m$  criteria, and  $r_{vf}$  be the

correlation coefficient between  $v$ th and  $f$ th criterion. The quantity of information contained in the  $v$ th criterion is calculated using Equation (3):

$$C_v = S_v \sum_{f=1}^m (1 - |r_{vf}|) \quad (3)$$

where  $v=1,2,\dots,m$  and  $f=1,2,\dots,m$ .

**Definition 4.** The weight of the  $v$ th criterion is calculated using Equation (4):

$$w_v = \frac{C_v}{\sum_{f=1}^m C_f} \quad (4)$$

where  $C_v$  represents the quantity of information contained in the  $v$ th criterion;  $\sum_{f=1}^m C_f$  represents the quantity of information contained in these  $m$  criteria. The larger  $C_v$  is, the more weight given to the  $v$ th criterion.

### 2.3 2T-CRITIC Model

The 2T-CRITIC model consists of aggregating the scores of different criteria into an overall score. The definition is as follows.

**Definition 5.** Based on the 2-tuple value aggregated for each criterion and the weights defined in Equation (4), the overall score of these  $m$  criteria is calculated using Equation (5):

$$R_{2T-CRITIC} = \Delta \left( \sum_{v=1}^m w_v \cdot \Delta^{-1}(\bar{T}_v) \right) \quad (5)$$

### 2.4 Weighted K-means Clustering

Traditional K-means clustering is computationally efficient and works well with large datasets. However, it assigns all observations identical weight, ignoring the relevance of each feature attribute in the dataset (Yu et al., 2020).

Weighted K-means clustering is a K-means clustering extension that allows for user-defined weighting. This method takes into account the weights associated with each criterion or dimension when computing the cluster centroid. It can be applied to improve the clustering scalability (Kerdprasop et al., 2005), and clustering results (Baswade et al., 2012). The definition is as follows.

**Definition 6.** Let  $k$  be the optimal number of clusters, the weighted Euclidean distance of each object to the cluster centroid is calculated using Equation (6):

$$d(m, c) = \sqrt{\sum_{v=1}^m w_v (\Delta^{-1}(x_{mv}) - \Delta^{-1}(k_{cv}))^2} \quad (6)$$

where  $w_v$  represents the weight of the  $v$ th criterion, as defined in Equation (4).

For more details on the Weighted K-means clustering processing steps, see (Yu et al., 2020).

The following is an example of how to calculate the weighted Euclidean distance.

Let  $S = \{s_0 = T, s_1 = P, s_2 = A, s_3 = VG, s_4 = E\}$  be a linguistic term set,  $W = (0.2, 0.3, 0.5)$  be the vector to represent the weight of three criteria determined by the Equation (4), and  $X_A = \{(A, 0), (P, -0.2), (A, +0.3)\}$  be a set of 2-tuple values to represent the ratings of object A on three different criteria. Let  $k = 3$ , so that the centroid of Cluster 1 is  $C_1 = \{(A, +0.03), (P, -0.2), (A, +0.1)\}$ , the centroid of Cluster 2 is  $C_2 = \{(VG, 0), (VG, +0.1), (A, +0.1)\}$ , and the centroid of Cluster 3 is  $C_3 = \{(A, 0), (VG, -0.1), (A, +0.11)\}$ .

The weighted Euclidean distance between hotel A and the centroid of Cluster 1 is determined as:

$$\begin{aligned} d(X_A, C_1) &= \sqrt{0.2(\Delta^{-1}(A, 0) - \Delta^{-1}(A, +0.03))^2} \\ &\quad + 0.3(\Delta^{-1}(P, -0.2) - \Delta^{-1}(P, -0.2))^2 \\ &\quad + 0.5(\Delta^{-1}(A, +0.3) - \Delta^{-1}(A, +0.1))^2 \\ &= \sqrt{0.2(2 - 2.03)^2 + 0.3(0.8 - 0.8)^2 + 0.5(2.3 - 2.1)^2} \\ &= 0.1421 \end{aligned}$$

In the same way,  $d(X_A, C_2) = 1.3442$  and  $d(X_A, C_3) = 1.158$  are the weighted Euclidean distance between object A and the centroid of Cluster 2 and 3, respectively. As the distance between object A and the centroid of Cluster 1 is the smallest ( $d(X_A, C_1) < d(X_A, C_3) < d(X_A, C_2)$ ), it will be given a cluster number 1.

## 3 PROPOSED MODEL AND APPLICATION TO THE SEGMENTATION OF TRIPADVISOR HOTELS

This section explains how the proposed model was developed, as well as its application in the hotel classification. This model is divided into five steps, as shown in Figure 1.

### Step 1. Data Collection and Processing

In this step, the dataset provided by (Antognini & Faltings, 2020) has been applied in this paper. This dataset contains more than fifty million TripAdvisor hotel reviews from 21.89 million users that commented from February 1, 2001, to May 14, 2019.

This dataset contains both textual reviews and numerical ratings of hotels. However, considering the purpose of this paper is to classify hotels based on their various aspects, the textual reviews have been eliminated.

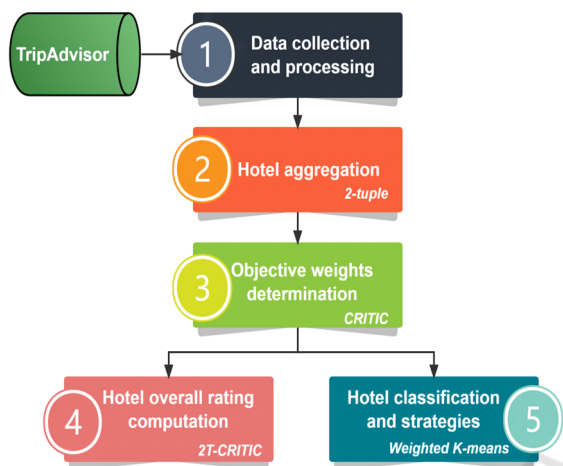


Figure 1: Steps of the proposed model.

Furthermore, as TripAdvisor's sub-ratings are optional, not all aspects (up to eight) are assessed by users. Most sub-ratings are evaluated in groups of

three or six aspects, with Check-In and Business Service being the two aspects that are rarely scored.

Therefore, in this study, only those hotels that have been scored in all six aspects are included, obtaining a dataset of 228,339 hotels with the following variables: user ID, hotel ID, Service aspect rating, Cleanliness aspect rating, Value aspect rating, Location aspect rating, Rooms aspect rating, and Sleep quality aspect rating. Table 1 shows an example of the dataset after data processing.

### Step 2. Hotel Aggregation with the 2-tuple Linguistic Model

This step is to aggregate the various user evaluations of the hotel's six aspects into 2-tuple values.

The linguistic term set  $S$  used by TripAdvisor to rate hotels has five terms: Terrible (T), Poor (P), Average (A), Very Good (VG) and Excellent (E). Thus, let  $S = \{s_0, \dots, s_g\}$  with  $g=4$ :  $s_0 = Terrible = T$ ,  $s_1 = Poor = P$ ,  $s_2 = Average = A$ ,  $s_3 = Very Good = VG$ ,  $s_4 = Excellent = E$ , as shown in Figure 2. Based on the Equation (2), the ratings of customers on hotel aspects have been aggregated into 2-tuple values. Table 2 shows an example of aggregation of hotel aspect ratings expressed in 2-tuple values.

Table 1: Example of hotel aspect ratings.

User ID	Hotel ID	Service	Cleanliness	Value	Rooms	Location	Sleep quality
204966	54046	E	E	E	E	E	E
12459774	54046	A	A	A	A	A	A
7622513	193760	E	E	E	E	E	E
3868105	152011	E	E	E	E	E	E
17640662	33026	VG	VG	VG	VG	VG	VG
8954809	177981	A	A	A	A	A	A
3583774	177981	VG	VG	VG	VG	VG	VG
288708	177981	T	T	T	T	T	T
9010318	203518	VG	VG	VG	VG	VG	VG
16145194	227714	P	P	P	P	P	A

Table 2: Example of aggregation of hotel aspect ratings expressed in 2-tuple values.

Hotel ID	Service	Cleanliness	Value	Rooms	Location	Sleep quality
54046	(A, +0.0384)	(P, -0.248)	(A, +0.2616)	(A, +0.1449)	(P, -0.243)	(A, +0.0685)
190291	(A, -0.01)	(P, +0.0659)	(A, -0.117)	(P, +0.236)	(P, +0.0588)	(A, +0.009)
193760	(VG, +0.046)	(VG, +0.0602)	(A, +0.0577)	(VG, +0.0174)	(VG, -0.0323)	(A, +0.1155)
152011	(E, -0.4444)	(A, +0.49)	(E, -0.25)	(VG, +0.4286)	(E, -0.1)	(A, -0.14)
33026	(VG, -0.141)	(VG, +0.0198)	(A, +0.0986)	(VG, +0.0375)	(VG, -0.0647)	(A, +0.0957)
177981	(A, -0.035)	(P, -0.1279)	(A, -0.3904)	(P, -0.0668)	(A, +0.0872)	(A, +0.056)
203518	(A, +0.001)	(VG, +0.0755)	(A, +0.1075)	(VG, -0.0589)	(VG, +0.109)	(A, +0.037)
227714	(VG, -0.1333)	(VG, +0.0267)	(A, +0.0806)	(VG, +0.0502)	(VG, -0.0489)	(A, +0.107)
113986	(A, -0.0302)	(VG, +0.0513)	(A, -0.0685)	(VG, +0.0921)	(A, +0.152)	(A, +0.0509)
44257	(A, +0.0135)	(VG, -0.01)	VG	(A, +0.07)	(A, +0.1)	(A, +0.0278)

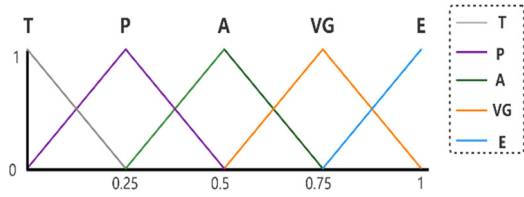


Figure 2: Definition of linguistic term set S.



Figure 3: Correlation matrix for each pair of criteria.

**Step 3. Determination of the Objective Weights for each Aspect of Hotel with the CRITIC Method**

This step is to obtain the objective weights for the hotel's six aspects using the CRITIC method.

In the previous step, the arithmetic mean has been used to aggregate the 2-tuple values of different customer ratings for distinct aspects of the hotel, resulting in the 2-tuple value for each hotel aspect. Using the function  $\Delta^{-1}$  to transform the 2-tuple value into its numerical value, so that correlation coefficients have been obtained as shown in Figure 3. These six aspects are highly correlated since their correlation coefficients are all more than 0.7. Their objective weights are derived by using Equations (3) and (4), as shown in Table 3.

Table 3: Weights for each hotel aspect.

Aspect	Standard Deviation	Quantity of information	weights
Service	0.479	0.0326	10.97%
Cleanliness	0.486	0.0807	27.16%
Value	0.492	0.0418	14.08%
Rooms	0.497	0.0447	15.06%
Location	0.495	0.0436	14.67%
Sleep quality	0.511	0.0537	18.06%

**Step 4. 2T-CRITIC Hotel Overall Rating Computation**

This step is to aggregate the scores of six aspects of the hotel into an overall score by using Equation (5). The results of the calculations for some hotels are shown in Table 5.

The example below shows how to calculate overall score for hotel 152011:

$$\begin{aligned}
 R_{2T-CRITIC} &= \Delta \left( \begin{aligned} &\Delta^{-1}(E, -0.4444) \times 10.97\% \\ &+ \Delta^{-1}(A, +0.49) \times 27.16\% \\ &+ \Delta^{-1}(E, -0.25) \times 14.08\% \\ &+ \Delta^{-1}(VG, +0.4286) \times 15.06\% \\ &+ \Delta^{-1}(E, -0.1) \times 14.67\% \\ &+ \Delta^{-1}(A, -0.14) \times 18.06\% \end{aligned} \right) \\
 &= \Delta \left( \begin{aligned} &3.5556 \times 10.97\% + 2.49 \times 27.16\% \\ &+ 3.75 \times 14.08\% + 3.4286 \times 15.06\% \\ &+ 3.9 \times 14.67\% + 1.86 \times 18.06\% \end{aligned} \right) \\
 &= \Delta(3.0187) = (VG, +0.0187)
 \end{aligned}$$

**Step 5. Hotel Classification and Strategies**

In this step, Weighted K-means clustering has been applied to create homogeneous groups of hotels. It entails utilizing Equation (6) to categorize hotels based on their weighted Euclidean distance.

As the Elbow Method reveals that  $k=8$  is the optimal number of clusters, 8 distinct groups of hotels have been obtained. Table 4 demonstrates the results of the hotel clusters expressed in the 2-tuple value and the number of hotels included in each cluster.

Ten distinct hotels are presented in Table 5, with their relation to the cluster characteristics indicated in Table 6.

Table 4: Results of clusters expressed in 2-tuple value.

Cluster ID	Number of hotels	Service	Cleanliness	Value	Rooms	Location	Sleep quality
1	31,566	(VG, -0.12)	(VG, +0.01)	(A, +0.1)	(VG, +0.04)	(VG, -0.02)	(A, +0.12)
2	29,869	(A, +0.01)	(P, +0.17)	(A, -0.12)	(P, +0.2)	(P, +0.19)	(A, +0.01)
3	28,993	(E, -0.21)	(A, +0.05)	(VG, +0.1)	(A, -0.05)	(E, -0.08)	(A, -0.13)
4	25,627	(A, -0.03)	(VG, +0.06)	(A, -0.05)	(VG, +0.08)	(A, +0.17)	(A, +0.06)
5	29,656	A	(VG, +0.08)	(A, +0.11)	(VG, -0.07)	(VG, +0.08)	(A, +0.02)
6	30,815	(A, +0.03)	(P, -0.21)	(A, +0.13)	(A, +0.15)	(P, -0.07)	(A, +0.07)
7	25,295	(A, -0.04)	(P, -0.15)	(A, -0.07)	(P, -0.06)	(A, +0.02)	(A, +0.05)
8	26,518	A	(VG, -0.05)	(VG, +0.01)	(A, +0.09)	(A, +0.11)	(A, +0.06)
All Data*	228,339	(A, +0.03)	(A, +0.13)	(A, +0.09)	(A, +0.2)	(A, +0.1)	(A, +0.02)

\*The average level of these 228,339 hotels is shown by All Data.

Table 5: 2T-CRITIC Overall Score and Cluster ID for some hotels.

Hotel ID	2T-CRITIC Overall Score	Cluster ID
54046	(A, -0.4461)	6
190291	(P, +0.2966)	2
193760	(VG, -0.2731)	1
152011	(VG, +0.0187)	3
33026	(VG, -0.3042)	1
177981	(P, +0.4971)	7
203518	(VG, -0.3959)	5
227714	(VG, -0.2977)	1
113986	(A, +0.4685)	4
44257	(A, +0.4414)	8

Therefore, based on their objective overall score aggregated by six hotel aspects, customers could

choose a hotel that is more relevant to their needs. For example, as shown in Table 5, the hotels in cluster 1 (193760, 33026, 227714) have a similar 2T-CRITIC overall score, indicating that this cluster consists of upper-midscale hotels. Combined with the information demonstrated in Table 6, it can be concluded that this group of hotels is appropriate for customers who desire particularly good cleanliness, service, rooms, and location, but cannot afford the price of a first-class hotel (cluster 3, such as hotel 152011).

Likewise, hotel managers could take suitable actions to fix their weaknesses based on the descriptions in Table 6 for each cluster. For instance, as the cleanliness, service, rooms, and location of cluster 1 are already very good, it might be beneficial to increase the value or sleep quality of this sort of hotel to gain a new competitive advantage.

Table 6: Description for each group of hotels.

Cluster ID	Cluster Name	Description
1	Hotel with a very good cleanliness, service, rooms, and location.	It consists of hotels with a very good level of cleanliness, service, and rooms. The quality of sleep in this sort of hotel is superior to that of other hotels, but it is still average level. Despite not having as good a location as clusters 3 and 5, they are still better than the rest of the hotels.
2	Hotel with poor cleanliness, location, and rooms.	It consists of hotels with much lower-than-average cleanliness, rooms, and location. Their value is a touch below average. The other two aspects are nearly identical to the average.
3	A first-class hotel with an excellent location, very good service, and value.	It consists of hotels that are well-known for their outstanding location, which sets them apart from the rest of the hotels. Their service and value are also better than the rest of the hotels, although the sleep quality in this type of hotel is lower than the average level. The other two aspects are nearly identical to the average.
4	Hotel with very good cleanliness and rooms.	It consists of hotels with higher-than-average cleanliness and rooms, although the other four aspects are nearly identical to the average.
5	Hotel with very good cleanliness, rooms, and location.	It consists of hotels with very good cleanliness, rooms, and location, although the other three aspects are almost as same as average. Despite not having as excellent a location as cluster 3, their rooms and cleanliness are superior to those of it.
6	Hotel with poor cleanliness and bad location.	It consists of hotels that are less hygienic and have a worse location than the other hotels. The other four aspects are nearly identical to the average.
7	Hotel with poor cleanliness and rooms.	It consists of hotels with a poor level of cleanliness and rooms. Their rooms are inferior to those of the other hotels. The other four aspects are nearly identical to the average.
8	Hotel with very good cleanliness and value.	It consists of hotels with higher-than-average cleanliness and value. Although the other four aspects are roughly comparable to the average, the service level of this group of hotels is the same as cluster 5, and its sleep quality is the same as cluster 4.

## 4 CONCLUSIONS AND FUTURE WORK

In this paper, a new method for segmenting hotels based on the 2T-CRITIC model and Weighted K-means clustering is presented. Unlike standard K-means clustering, this proposed model assigns different weights to variables in the clustering process as it considers the quantity of information included in variables is different. A use case with more than 50 million TripAdvisor hotel reviews has been employed to evaluate its functionality.

The results show that the proposed model can improve clustering results by considering objective weights for each criterion and make clustering results more linguistically interpretable by using the 2-tuple linguistic model. By interpreting these linguistic scores of each hotel, hotel managers can develop more effective strategies to improve their hotel ranking. In fact, these results of classification aid hotel managers in developing appropriate strategies for gaining a new competitive advantage or improving those aspects that they need to make a change, so that they can attract more customers from the other clusters. Furthermore, combined with the objective overall hotel score, these results can help customers choose a hotel that is more appropriate for their needs.

Despite all the benefits of the proposed model in this study, certain shortcomings should be pointed out. First, as this proposal uses CRITIC method to calculate the objective weight of each hotel aspect, it ignores that the customers evaluated hotels with different subjective feelings and levels of perception. For example, perhaps 3 is very high (total score of 5) for a very demanding customer, but for a less demanding customer, 3 is only a medium score. Another weakness is that this approach still relies on the traditional 2-tuple model. It cannot be applied to those variables without linguistic scales, such as sex, hair color, country, etc., which are nominal variables.

Therefore, for future work, some practical problems of the proposed model should be addressed. This model could be extended by applying some methods that allow calculating the subjective weights of variables, such as the analytic hierarchy process (AHP) method, Delphi method, Point allocation method, etc. It could also develop a model that combines subjective and objective weights into a single function. Other variables like travel country, duration of stay, hotel price, reservation number, cancel number, etc., could also be included in the hotel segmentation to get an all-round understanding of the hotel.

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## 8. Strategic Management of Hotel Customers based on their Online Reviews: The Case of Luxury Hotels in Spain

*Strategic Management of Hotel Customers Based on their Online Reviews: The Case of Luxury Hotels in Spain* 778

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## **STRATEGIC MANAGEMENT OF HOTEL CUSTOMERS BASED ON THEIR ONLINE REVIEWS: THE CASE OF LUXURY HOTELS IN SPAIN**

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**Keywords:** RFM model, 2-tuple linguistic model, customer segmentation, marketing strategies, TripAdvisor

**Description:** Based on the classic RFM model, this paper introduces a new RFHPS model, which considers the Helpfulness, the Promoter score, and the Stability of the customer as additional dimensions to enhance the interpretability of the segmentation results.

### **EXTENDED ABSTRACT**

#### **Research Question**

The use of the RFM model is very popular in marketing environments, either on its own or in combination with some other models, the main reason being its easy interpretability and the possibility of making explainable decisions. The current purchasing process relies heavily on internet content, such as hotel ratings and reviews. During the process of gathering information,

the potential customer not only looks at the ratings (e.g., hotel stars, global scores, etc.) but also obtains information through the responses that other users give to the satisfaction questionnaires and by reading their opinions expressed in natural language and by looking at the pictures uploaded to expand the information provided. This work aims to provide some guidelines for practitioners to manage their customers strategically by using clustering techniques to identify the different customer profiles based on their reviews

### **Method and Data**

Based on the widely used RFM model, a new model called RFHPS that includes five dimensions obtained from customer reviews (Recency, Frequency, Helpfulness, Promoter Score, and Stability) has been proposed. Moreover, to improve the accuracy and interpretable capacity of this new model, the 2-tuple fuzzy linguistic model has also been included. Finally, customer segmentation is done using K-means clustering.

Data was collected from TripAdvisor using web scraping for a set of Luxury hotels in Spain. The dataset gathered includes 447,180 reviews from the 422 luxury hotels in Spain. However, after cleaning the missing value and setting the study period as the last ten years, 401,007 comments left by 338,361 customers on TripAdvisor between December 19, 2012, and December 19, 2022, are employed to analyze the proposed model.

### **Summary of Findings**

This work has proved the validity of a new model which expands the scope of the RFM model, adding three new dimensions to it. The use of the 2-tuple linguistic model allows for direct interpretation of results without the need to have a reference number, using intuitive expressions instead. The proposed model achieves a more accurate hotel customer segmentation with better interpretability of results, allowing a description of the segments in a way that enables the design

of different marketing strategies for each segment. For instance, the customers with the highest value to the brand should be treated differently by providing some special treatment for permanence (discount when doing a transaction in a third-party platform, providing a scale of customer badges as proof of the value to the community, etc.). The most valuable customers are the ones who have been active in the last 5 years and who are considered helpful by their peers (community). However, it is also necessary to pay attention to those customers whose helpfulness score is relatively low because of their recent membership, but can potentially become an important group for the community.

### **Statement of Key Contributions**

An improved model of customer segmentation is proposed in this work, based on the widespread use of the RFM model, in which the Monetary value is substituted by Helpfulness and adds two new dimensions (Promoter value and Stability) related to hotel reviews. Customer segments are identified from over 400,000 customer reviews extracted from TripAdvisor, using K-means clustering and the 2-tuple linguistic model. Results show that the proposed model is effective in customer segment identification, enabling hotel practitioners to activate a differentiated marketing strategy for each segment. This model improves the accuracy and linguistic interpretation of previous existing RFM models. The applicability goes beyond the use case, being a useful model for hotel chains and online travel agencies.

### **Acknowledgements**

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# 9. Navigating the Landscape of Artificial Intelligence: Computing with Words in Marketing

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<b>Status:</b>	Accepted and in the process of publication
<b>Conference name:</b>	FLINS-ISKE 2024 Conference
<b>Conference areas:</b>	Artificial Intelligence, Computational Intelligence, Fuzzy Logic, Soft Computing, Marketing, Multicriteria Decision Making, Machine Learning
<b>Quality indicators:</b>	<b>Core Conference</b> , Proceedings indexed in Scopus

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## Abstract

Artificial Intelligence (AI) is increasingly playing a vital role and transforming our lives. Explainable AI is promoted by the concept of Computing with Words (CWW), which uses a human-like analytical framework to interpret and process information. In marketing, it is crucial to transform ambiguous information from customer feedback or expert knowledge into interpretable information for effective decision-making and the creation of marketing strategies. This paper aims to explore the application of the 2-tuple linguistic model, a widely used methodology for CWW, in the field of marketing. Through a systematic exploration of articles published from 2000 to 2003, this paper identifies areas of investigation worthy of further exploration and analysis.

**Keywords:** Computing with Words; Artificial Intelligence; 2-tuple Linguistic Model; Aggregation Operators; Marketing.

## 10. Scenarios of Material Deprivation in Poor Households Using the OWA Aggregation Operator and the Linguistic Model

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<b>Status:</b>	Accepted and in the process of publication
<b>Conference name:</b>	XXXVII International Conference on Applied Economics-ASEPELT 2024
<b>Conference areas:</b>	Quantitative methods for Economics and Business, International Economy, Data Science for the Data Economy, Environmental Economics and Natural Resources, Business Economics and Social Responsibility
<b>Quality indicators:</b>	Conference organized by the International Association of Applied Economics ASEPELT, Proceedings indexed in Scopus, with the opportunity to publish in a Special Issue indexed in JCR Q1, <b>First Prize in the "Josefa Eugenia Fernández Arufe" 2024 Award for Best Young Researcher</b>

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### Abstract

Traditionally, the concept of poverty has been defined in terms of income. In 1995, Sen proposed a broader definition, arguing that poverty also implies a deprivation of basic capabilities that limits the ability of households to lead a decent life. This new perspective has significantly influenced how poverty is understood and measured. It has been recognized by the European Union Social Protection Committee and Eurostat as a means to categorize poverty and social exclusion using indicators of household deprivation. This deprivation is gauged by the lack of a certain quantity of essential goods or services. However, the possibility of other measurements based on the level of

demand regarding the number of deprivations that themselves imply the consideration of poverty or social exclusion has not been explored. Therefore, this work aims to define various scenarios of material deprivation, considering the varying levels of demand in measuring such deprivation. To this end, the ordered weighted averaging (OWA) aggregation operator, the 2-tuple linguistic model, and hierarchical clustering are used. The proposed model is used to identify material deprivation in economically poor households, employing microdata from the 2023 Living Conditions Survey of the Spanish National Statistics Institute (INE). The results show that not all economically poor households lack access to the basic goods and services needed for a decent life. The clusters by autonomous communities and degree of urbanization summarize the material deprivations in Spanish households. The proposed model provides a more comprehensive and dynamic approach to measuring material deprivation in households, facilitating a deeper and more understandable analysis of this measurement.

**Keywords:** Poverty, Material deprivation, Ordered weighted averaging aggregation operator, Linguistic quantifiers, Decision-making.

# 11. Incorporating investor risk attitudes into a personalized index of economic freedom: An approach using the OWA aggregation operator, 2-tuple linguistic model, FCM clustering, and interactive visualization techniques

## Financial Innovation

Incorporating investor risk attitudes into a personalized index of economic freedom: An approach using the OWA aggregation operator, 2-tuple linguistic model, FCM clustering, and interactive visualization techniques

--Manuscript Draft--

Manuscript Number:	FINI-D-23-00889R1
Full Title:	Incorporating investor risk attitudes into a personalized index of economic freedom: An approach using the OWA aggregation operator, 2-tuple linguistic model, FCM clustering, and interactive visualization techniques
Article Type:	Research

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<b>Status:</b>	Submitted
<b>Journal Name:</b>	Financial Innovation
<b>Category (Ranking):</b>	Social Sciences, Mathematical Methods (1/53)
<b>Quality indicators:</b>	Impact Factor 8.4 (JCR D1), CIRC: Grupo A+, CiteScore 11.4 (Scopus), SJR Q1, SNIP 2.149

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### Abstract

It is essential to evaluate economic freedom because it correlates with economic development and prosperity. Even countries with a high GDP need economic freedom in order to foster sustainable economic growth and attract investment. The Index of Economic Freedom (IoEF), developed by the Heritage Foundation and The Wall Street Journal, assesses economic freedom using 12 criteria,

providing a crucial composite indicator for governments and investors. However, all 12 IoEF criteria are equally weighted and do not account for investors' risk attitudes when measuring economic freedom. This is an issue because cautious investors focus more on the less favorable criteria in the calculation of the IoEF, while the opposite is true for adventurous investors. This paper aims to model investor risk attitudes when measuring economic freedom, yielding distinct versions of the IoEF. This paper makes a number of novel contributions: 1) it is the first work that employs different linguistic quantifiers of the Ordered Weighted Averaging aggregation operator for modeling investor risk attitudes, creating more personalized IoEF versions by applying criterion weights matching investor attitudes; 2) it applies the 2-tuple linguistic model for a more intuitive interpretation of the newly generated IoEF while maintaining computational precision; 3) it uses Fuzzy C-Means clustering to classify countries based on the newly generated IoEF, allowing them to belong to multiple clusters and identifying those with high membership degrees in specific clusters; 4) it develops an interactive web application to visualize the results of the proposed model, demonstrating its reproducibility while enabling investors to efficiently identify desirable investment destinations based on their risk attitudes.

**Keywords:** Index of Economic Freedom, Multi-criteria decision-making, Ordered weighted averaging aggregation operator, Linguistic quantifiers, 2-Tuple linguistic model, Fuzzy c-means clustering

# 12. A linguistic-based approach to identifying and monitoring online customer dissatisfaction: a case study on TripAdvisor

## Information Sciences

A linguistic-based approach to identifying and monitoring online customer dissatisfaction: a case study on TripAdvisor

--Manuscript Draft--

Manuscript Number:	INS-D-24-4042
Article Type:	Full length article

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<b>Status:</b>	Submitted
<b>Journal Name:</b>	Information Sciences
<b>Category (Ranking):</b>	Computer Science, Information Systems (13/158)
<b>Quality indicators:</b>	Impact Factor 8.1 (JCR D1), CIRC: Grupo A+, CiteScore 14 (Scopus), SJR Q1, SNIP 2.111

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### Abstract

Recognizing customers' feelings is vital across all industries. With the rise of social media, hotel managers now need to analyze online reviews to identify aspects that satisfy or dissatisfy customers. This study aims to develop a model for identifying and monitoring online customer dissatisfaction, considering customer demand levels related to hotel star ratings. The proposed model incorporates the concept of the Ordered Weighted Averaging (OWA) aggregation operator, the 2-tuple linguistic model, and the Prophet forecasting model. One deficiency of the OWA aggregation operator is mitigated in this study, and diverse linguistic quantifiers of this improved aggregation operator are applied to model customer demand levels for different hotel star ratings during the integration of

customer opinions on various hotel aspects into a comprehensive score. The 2-tuple linguistic model is employed to enhance the intuitive interpretation of the comprehensive score, capturing customer dissatisfaction while maintaining computational precision. The Prophet model is applied to anticipate the future level of customer dissatisfaction. The proposed model's applicability is evaluated using online reviews collected from TripAdvisor about Madrid hotels. Its results are presented through an interactive visualization application, helping hotel managers comprehend and predict customer dissatisfaction, compare with competitors, and identify areas for improvement.

**Keywords:** Customer dissatisfaction, Linguistic quantifiers, Ordered weighted averaging aggregation operator, 2-tuple linguistic model, Opinion mining