TWO NOVEL MCDM APPROACHES "PODER" AND "V-PARS": EVALUATING MICROMOBILITY MODES IN PARIS AND ISTANBUL

(İKİ YENİ ÇÖKV YAKLAŞIMI "PODER" VE "V-PARS": PARİS VE İSTANBUL'DA MİKROMOBİLİTE MODLARININ DEĞERLENDİRİLMESİ)

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LIST OF SYMBOLS

Abbreviations

A.K.A. : Also Known As

AHP : Analytic Hierarchy Process

AI : Artificial Intelligence

ANP : Analytic Network Process

APPRESAL : Approach for Preference, Performance and Ranking Evaluation with SAtisfaction Level

ARAS : Additive Ratio ASsessment

ARPU : Average Revenue Per User

BWM : Best-Worst Method

CAGR : Compound Annual Growth Rate

COCOSO : COmbined COmpromise SOlution

CODAS : COmbinative Distance-based ASsessment

COMET : Characteristic Objects Method

CRITIC : CRiteria Importance Through Inter-criteria Correlation

CUTA : Canadian Urban Transit Association

CÖKV : Çok Ölçütlü Karar Verme

DEMATEL : Decision Making Trial and Evaluation Laboratory

DEVADA : Multi-Distance based Evaluation for Aggregated Dynamic Decision Analysis

E.G. : Exempli Gratia

EAMR : Evaluation by an Area-based Method of Ranking

EDAS : Evaluation Based on Distance from Average Solution

EFEE : Extracted Framework Element Effect

ELECTRE : ÉLimination Et Choix Traduisant la REalité

ERVD : Election based on Relative Value Distances

Et Al. : Et Alii

EU : European Union

FMCDM : Fuzzy Multi-Criteria Decision Making

FN : Fuzzy Number

FUCOM : FUll COnsistency Method

FWA : Fuzzy Weighted Averaging

GA : Genetic Algorithm

GHG : Greenhouse Gas

GPS : Global Positioning System

GRA : Grey Relational Analysis

I.E. : Id Est

IoT : Internet of Things

KPI : Key Performance Indicator

LCA : Life Cycle Assessment

LOPCOW : LOgarithmic Percentage Change-driven Objective Weighting

LP : Linear Programming

MABAC : Multi-Attributive Border Approximation area Comparison

MACHBETH : Measuring Attractiveness by a Categorical Based Evaluation TecHnique

MAIRCA : Multi Atributive Ideal-Real Comparative Analysis

MARCOS : Measurement of alternatives and ranking according to COmpromise Solution

MAUT : Multiple Attribute Utility Theory

MAVT : Multi-Attribute Value Theory

MAV : Micro Air Vehicle

MCDA : Multi-Criteria Decision Analysis

MCDM : Multi-Criteria Decision Making

MELCHIOR : Méthode d'ELimination et de CHoix Includent les relations d'ORdre

MEREC : MEthod based on the Removal Effects of Criteria

ML : Machine Learning

MOORA : Multi-Objective Optimization by Ratio Analysis

MULTIMOORA : Multi-Objective Optimization on the basis of a Ratio Analysis plus the full MULTIplicative form

N/A : Not Available

NACTO : National Association of City Transportation Officials

NN : Neural Network

OCRA : Operational Competitiveness RAting

ORESTE : Organization, Rangement Et Synthese De Donnes Relationnelles

PIPRECIA : PIvot Pairwise RElative Criteria Importance Assessment

PIV : Proximity Indexed Value

PLEV : Personal Light Electric Vehicle

PODER : POndération sur la Distance par ExtRaction

PROBID : Preference Ranking on the Basis of Ideal-Average Distance

PROMETHEE : Preference Ranking Organization METHod for Enrichment Evaluation

QUALIFLEX : QUALItative FLEXible

RAFSI : Ranking of Alternatives through Functional mapping of criterion subintervals into a Single Interval

SAW : Simple Additive Weighting

SERA : Selected Element Reduction Approach

SMART : Simple Multi-Attribute Rating Technique

SMCA : Spatial Multi-Criteria Analysis

SPOTIS : Stable Preference Ordering Towards Ideal Solution

SUMP : Sustainable Urban Mobility Plans

SWARA : Stepwise Weight Assessment Ratio Analysis

TODIM : TOmada de Decisão Interativa e Multicritério

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

TRUST : mulTi-noRmalization mUlti-distance aSsessmenT

UAM : Urban Air Mobility

V-PARS : Vector-Based Preference Ranking System

VIKOR : Vlseölçütijumska Optimizacija I KOmpromisno Resenje

VMT : Vehicle Miles Traveled

WASPAS : Weighted Aggregated Sum Product Assessment

WA : Weighted Averaging

WEDBA : Weighted Euclidean Distance Based Approach

WENSLO : Weights by ENvelope and SLOpe

Wi-Fi : Wireless Fidelity

Nomenclature

$(a_{ij_{obj}})_{aggr}$: aggregated objective evaluation of alternative i according to criterion j

$(a_{ij_{sub}})_{aggr}$: aggregated subjective evaluation of alternative i according to criterion j

$(a_{ij})_{aggr}$: aggregated evaluation of alternative i according to criterion j

$(w_j)_{EC}$: weight of criterion j under extraction of criterion EC

$\approx$: approximation operator

λ_{obj} : weight of objective data

λ_{sub} : weight of subjective data

$\mu_{\tilde{A}}(x)$: membership function of fuzzy number $\tilde{A}$

$\overrightarrow{OE_i}$: origin based total preference Euclidean vector of alternative i

$\overrightarrow{P_{T_i}R_{T_i}}$: total preference Euclidean vector of alternative i

$\overrightarrow{P_xR_y}$: preference Euclidean vector from alternative x to alternative y

$\prec$: precedes operator

$\preceq$: precedes or is equal operator

$\sim$: similarity operator

$\succ$: succeeds operator

$\succeq$: succeeds or is equal operator

$a_{ij_{obj}}$: objective evaluation of alternative i according to criterion j

$a_{ij_{sub}}$: subjective evaluation of alternative i according to criterion j

a_{ij} : evaluation of alternative i according to criterion j

A_i : alternative i

C_j : criterion j

$d(A,B)$: distance function between point A and point B

DM_B : beginner decision maker

DM_{EC} : expert candidate decision maker

DM_{EE} : emerging expert decision maker

DM_E : expert decision maker

DM_p : decision maker p

I_{EC} : total impact of extracted criterion EC

k : total number of decision makers

m : total number of criteria

$M(\tilde{A})$: defuzzification function of fuzzy number $\tilde{A}$

$m-dimensional$: multi-dimensional

n : total number of alternatives

NIS : negative ideal solution

PIS : positive ideal solution

r_{score} : range of score function

$s(a_{ij})$: scale function of evaluation a_{ij}

$S_{i,EC}$: point of alternative i under extraction of criterion EC

$S_{i_{initial}}$: initial point of alternative i

S_i : similarity score of alternative i

w_{DM_p} : weight of decision maker p

w_{EC} : weight of criterion EC

w_j : weight of criterion j

wa_{ij} : weighted evaluation of alternative i according to criterion j

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ABSTRACT

Distance-based Multi-Criteria Decision Making (MCDM) methods offer a robust framework for evaluating and ranking alternatives under conditions of conflicting criteria. These methods, as documented in existing literature, analyze alternatives based on their distances to reference points like positive, average, or negative ideal solutions. However, a notable gap exists in the literature – the absence of a technique where the reference point is the decision itself. While distance-based methods necessitate careful selection of distance metrics and reference points, their conceptual simplicity, visual appeal, and adaptability make them valuable tools for tackling complex decision problems across various academic disciplines. These methods are limited by their focus on distance to some reference points, neglecting the potential of self referencing and vector-based approaches in MCDM. Vectors, encompassing both magnitude (distance) and direction, are suitable for similarity operations and provide a richer understanding of an alternative's positioning within the criteria space. This doctoral thesis addresses this gap by proposing two novel MCDM procedures. The first, named POndération sur la Distance par ExtRaction (PODER), is a novel distance-based methodology designed for criteria weighting. The second, named Vector-Based Preference Ranking System (V-PARS), is a novel vector-based ranking methodology. The proposed methodologies integrate the concept of criterion extraction distance on Euclidean environment and a vectorial expansion of ideas from Social Choice Theory, specifically the Borda Count, Kemeny-Young Approach and Copeland Method. Additionally, a novel decision gathering procedure for both approaches is constructed based on Nudge Theory, which posits that individuals make better decisions when subtly guided towards a preferred outcome. This research also explores the intricacies of normalization and scaling within the context of MCDM methodologies, employing both precise and imprecise data formats (e.g. crisp and fuzzy). The proposed MCDM framework leverages this principle by incorporating both objective and subjective data to evaluate the relative suitability of alternatives. The presented choice architecture serves as a suitable framework for establishing an evaluation system centered on decision positions.

The effectiveness of the proposed hybrid procedure is demonstrated by applying it to the evaluation of micromobility modes. The rising popularity of micromobility options like scooters and e-bikes has introduced new complexities in urban transportation planning. Evaluating the micromobility vehicles for specific contexts, such as city districts, requires a comprehensive and systematic approach. The proposed methodologies are applied to a case study assessing micromobility modes for Paris/France and Istanbul/Turkey, within the context of the European Union's 2050 targets. By considering the unique characteristics of each device, the methodologies identify criteria weights and preference rankings of micromobility vehicles for specific areas, contributing to informed and sustainable micromobility decisions.

Keywords: Criteria Weighting · Distance-Based MCDM · European Union 2050 · Fuzzy Set Theory · Group Decision Making · Istanbul · Micromobility · Multi-Criteria Decision Making · Nudge Theory · Objective Data · Paris · POndération sur la Distance par ExtRaction (PODER) · Preference Ranking · Scaling · Social Choice · Subjective Data · Vector-Based MCDM · Vector-Based Preference Ranking System (V-PARS)

ÖZET

Mesafeye dayalı Çok Ölçütlü Karar Verme (ÇÖKV) yöntemleri, çelişen ölçütler koşulları altında alternatifleri değerlendirmek ve sıralamak için sağlam bir çerçeve sunar. Mevcut literatürde belgelendiği gibi bu yöntemler, alternatifleri pozitif, ortalama veya negatif ideal çözümler gibi referans noktalarına olan mesafelerine göre analiz eder. Ancak literatürde önemli bir boşluk vardır - referans noktasının kararın kendisi olduğu bir tekniğin olmaması. Mesafeye dayalı yöntemler mesafe ölçütlerinin ve referans noktalarının dikkatli bir şekilde seçilmesini gerektirirken, kavramsal basitlikleri, görsel çekicilikleri ve uyarlanabilirlikleri onları çeşitli akademik disiplinlerdeki karmaşık karar problemlerini ele almak için değerli araçlar haline getirir. Bu yöntemler, bazı referans noktalarına olan mesafeye odaklanmaları ve MCDM'deki öz referanslama ve vektör tabanlı yaklaşımların potansiyelini ihmal etmeleri nedeniyle sınırlıdır. Hem büyüklüğü (mesafeyi) hem de yönü kapsayan vektörler, benzerlik işlemleri için uygundur ve bir alternatifin ölçüt uzayındaki konumu hakkında daha zengin bir anlayış sağlar. Bu doktora tezi, iki yeni MCDM prosedürü önererek bu boşluğu ele almaktadır. İlki, Çıkarma ile Mesafeye Göre Ağırlıklandırma (POndération sur la Distance par ExtRaction (PODER)) olarak adlandırılan, ölçüt ağırlıklandırma için tasarlanmış yeni bir mesafe tabanlı metodolojidir. İkincisi, Vektör Tabanlı Tercih Sıralama Sistemi (Vector-Based Preference Ranking System (V-PARS)) olarak adlandırılan, yeni bir vektör tabanlı sıralama metodolojisidir. Önerilen metodolojiler, Öklid ortamında ölçüt çıkarma mesafesi kavramını ve Sosyal Seçim Teorisi'nden, özellikle Borda Sayımı, Kemeny-Young Yaklaşımı ve Copeland Yöntemi'nden fikirlerin vektörel genişlemesini entegre eder. Ek olarak, her iki yaklaşım için yeni bir karar toplama prosedürü, bireylerin tercih edilen bir sonuca doğru gizlice yönlendirildiklerinde daha iyi kararlar aldıklarını varsayan Dürtme Teorisi temelinde oluşturulmuştur. Bu araştırma ayrıca, hem kesin hem de kesin olmayan veri formatlarını (örneğin, net ve bulanık) kullanarak MCDM metodolojileri bağlamında normalleştirme ve ölçeklemenin karmaşıklıklarını araştırır. Önerilen MCDM çerçevesi, alternatiflerin göreceli uygunluğunu değerlendirmek için hem nesnel hem de öznel verileri birleştirerek bu ilkeden yararlanır. Sunulan seçim mimarisi, karar pozisyonlarına odaklanan bir değerlendirme sistemi kur-

mak için uygun bir çerçeve görevi görmektedir.

Önerilen hibrit prosedürün etkinliği, mikromobilite modlarının değerlendirilmesine uygulanarak gösterilmiştir. Scooter ve e-bisiklet gibi mikromobilite seçeneklerinin artan popülaritesi, kentsel ulaşım planlamasında yeni karmaşıklıklar ortaya çıkarmıştır. Mikromobilite araçlarının şehir bölgeleri gibi belirli bağlamlar için uygunluğu, kapsamlı ve sistematik bir yaklaşım gerektirir. Önerilen metodolojiler, Avrupa Birliği'nin 2050 hedefleri bağlamında Paris/Fransa ve İstanbul/Türkiye için mikromobilite modlarını değerlendiren bir vaka çalışmasına uygulanmıştır. Her bir cihazın benzersiz özelliklerini göz önünde bulundurarak, metodolojiler belirli alanlar için mikromobilite araçlarının ölçüt ağırlıklarını ve tercih sıralamalarını belirleyerek, bilgilendirilmiş ve sürdürülebilir mikromobilite kararlarına katkıda bulunmaktadır.

Anahtar Kelimeler: Ölçüt Ağırlıklandırma · Mesafe-Tabanlı ÇÖKV · Avrupa Birliği 2050 · Bulanık Küme Teorisi · Grup Karar Verme · İstanbul · Mikromobilite · Çok Ölçütlü Karar Verme · Dürtme Teorisi · Nesnel Veri · Paris · Çıkarma ile Mesafeye Göre Ağırlıklandırma (PODER) · Tercih Sıralaması · Ölçekleme · Sosyal Seçim · Öznel Veri · Vektör-Tabanlı ÇÖKV · Vektör-Tabanlı Tercih Sıralama Sistemi (V-PARS)

1 INTRODUCTION

This opening chapter establishes the groundwork for the research by providing context and outlining the author's motivations. It then clearly defines the study's objectives and the contributions it aims to make to the field. Additionally, the chapter provides a roadmap for the entire thesis, outlining the structure and briefly summarizing the content of each subsequent chapter.

1.1 Context and Motivations

In today's world, decision making processes have become increasingly complex, particularly within multifaceted systems where numerous conflicting criteria must be balanced. Multi-Criteria Decision Making (MCDM) methods have emerged as essential tools in addressing these challenges. Among the various MCDM approaches, distance-based methods stand out for their robustness in evaluating and ranking alternatives by focusing on their relative distances to reference points such as positive, average, or negative ideal solutions. These methods are well-documented in the literature and have been applied across diverse academic disciplines due to their conceptual simplicity, visual appeal, and adaptability. However, a significant gap exists in the literature: the absence of techniques where the decision itself serves as the reference point. Additionally, the prevalent focus on distance often overlooks the potential of vector-based approaches in MCDM, which can provide richer insights by considering both magnitude and direction. This doctoral thesis aims to address these gaps by proposing two novel MCDM procedures: POndération sur la Distance par ExtRaction (PODER) and the Vector-Based Preference Ranking System (V-PARS).

Distance-based MCDM methods have been extensively studied and applied in various fields, including engineering, environmental science, economics, and social sciences. The core principle of these methods is to evaluate alternatives based on their distances to predefined reference points. For instance, the Technique for Order of Preference by Simi-

larity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981) evaluates alternatives by their proximity to an fictive positive ideal solution (PIS) and their distance from a fictive negative ideal solution (NIS). On the other hand, MEREC (Method Based on the Removal Effects of Criteria) (Keshavarz-Ghorabaee et al., 2021) calculates distances between overall values of alternatives before and after removing a criterion. These distances are then used to determine the criterion's weight. These methods require careful selection of distance metrics and reference points to ensure accurate evaluations. Despite these requirements, their intrinsic simplicity and visual interpretability make them appealing for a wide range of applications.

While distance-based MCDM methods are widely used, they have some limitations. One significant drawback is their exclusive focus on distance to reference points, which can be overly simplistic and may not fully capture the complexity of decision problems. For instance, while the TOPSIS method generates hypothetical ideal points and normalizes the position of the decision according to them, the MEREC approach measures distance using Manhattan geometry, despite the absence of obstacles in the multidimensional decision-making environment defined by the criteria. Additionally, these methods often neglect the potential of vector-based approaches, which consider both the magnitude (distance) and direction, offering a more nuanced understanding of an alternative's positioning within the criteria space. This limitation highlights the need for innovative approaches that can leverage the strengths of both distance and vector-based methodologies.

The primary motivation for this research is to address the identified gap in the literature—the absence of MCDM techniques where the decision itself serves as the reference point, and the utilization of vector-based approaches. By developing novel methodologies that integrate these concepts, this research aims to present a choice architecture that builds on the robustness and comprehensiveness of MCDM frameworks.

This doctoral thesis proposes two innovative MCDM procedures:

- **POndération sur la Distance par ExtRaction (PODER):** A novel distance-based methodology designed for criteria weighting. PODER leverages the concept of criterion extraction distance on Euclidean environment.

- **Vector-Based Preference Ranking System (V-PARS):** A novel vector-based approach that integrates both magnitude and direction for a richer evaluation of alternatives. V-PARS combines the principles of Social Choice Theory with vectorial similarity operations.

The decision gathering procedure for both approaches is constructed based on Nudge Theory, which posits that individuals make better decisions when subtly guided towards a preferred outcome. By integrating Nudge Theory (Thaler and Sunstein, 2008), this research aims to enhance the decision making process, ensuring more informed and rational choices. This research focuses on creating a choice architecture by anchoring decision-makers to desirable options and providing them with a clear understanding of their status. The goal is to help people make decisions that benefit both themselves and society. Another critical aspect of this research is addressing the complexities of normalization and scaling in MCDM procedures, particularly when dealing with both crisp and uncertain data (e.g., scores, fuzzy data). The proposed MCDM framework incorporates both objective and subjective data to evaluate the relative suitability of alternatives, ensuring a more comprehensive and accurate evaluation process.

The effectiveness of the proposed hybrid procedures is demonstrated through their application to the evaluation of micromobility modes. The rising popularity of micromobility options, such as scooters and e-bikes, has introduced new complexities in urban transportation planning. Selecting and evaluating suitable micromobility vehicles for specific contexts, such as city districts, requires a comprehensive and systematic approach. By applying the proposed methodologies to a case study evaluating micromobility vehicles for Paris/France, and Istanbul/Turkey, within the context of the European Union's 2050 targets (European Commission, 2018), this research aims to contribute to more informed and sustainable micromobility decisions.

1.2 Aims and Objectives

The overarching aim of this doctoral thesis is to propose a choice architecture in order to develop and validate novel Multi-Criteria Decision Making (MCDM) methodologies

that address the limitations of existing distance-based approaches by incorporating vector-based elements and leveraging principles from Social Choice Theory (Fishburn, 1973) and Nudge Theory (Thaler and Sunstein, 2008) within Euclidean environment. The traditional distance-based MCDM approaches often fall short in adequately capturing the complexities and nuances involved in decision making scenarios characterized by conflicting criteria. By integrating vector-based elements, this research introduces a multidimensional perspective that enhances the accuracy and relevance of the evaluation process. Furthermore, by drawing on Social Choice Theory, specifically mechanisms like the Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951) methods , the proposed methodologies aim to ensure that collective decision making is fair, transparent, and reflects a more democratic ranking of individual preferences. Additionally, incorporating Nudge Theory principles seeks to subtly guide decision-makers towards more informed and rational choices, thereby improving the overall quality of the decision making process. This research aspires to offer a comprehensive and robust framework for evaluating, weighting criteria and ranking alternatives, which is essential in complex decision-making environments.

The specific objectives of this thesis are systematically enumerated and described as follows:

1. **Novel criteria weighting architecture:** The design of a novel distance-based Multi-Criteria Decision Making (MCDM) methodology for criteria weighting is a central aspect of this research. This innovative approach seeks to address the limitations of traditional MCDM methods by incorporating a precise and mathematically rigorous framework. Specifically, the methodology introduces the concept of criterion extraction distance within Euclidean n-spaces. By leveraging Euclidean distance, the new model quantifies the relative importance of different criteria based on their spatial separation. This approach allows for a nuanced and accurate determination of criteria weights, as it considers the geometric relationships between criteria. The integration of criterion extraction distance into the weighting process provides a clear and objective basis for evaluating the influence of each criterion on the overall decision making process.

2. **Novel preference ranking architecture:** This thesis aims to design a novel vector-based Multi-Criteria Decision Making (MCDM) methodology that considers both magnitude and direction for preference ranking. The innovative approach involves evaluating alternatives not only based on the magnitude of criteria but also on the directionality of these criteria vectors, providing a nuanced and accurate assessment. This method recognizes that the direction of improvement is as crucial as the extent of improvement, especially when dealing with multidimensional data. To enhance the robustness and fairness of this methodology, vector-based similarity operations are integrated with principles from Social Choice Theory, specifically employing the idea of Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951) approaches. The Borda Count method ranks alternatives based on their position, ensuring a democratic aggregation of preferences. Meanwhile, the Kemeny-Young approach offers a consensus ranking by minimizing the disagreement among ranked lists, thus aligning the preference ranking with the collective judgment. Copeland integrates winner and loser counts into the system. By combining the vector-based operations with Social Choice Theory principles, the proposed methodology aims to deliver a comprehensive and equitable framework for preference ranking in MCDM problems, ensuring that decisions are both data-driven and reflective of decision maker consensus.

3. **Data scaling:** One of the critical aims of this thesis is to address the complexities associated with normalization and scaling in MCDM procedures. Normalization is the process of adjusting values measured on different scales to a common scale, without distorting differences in the ranges of values. Scaling, on the other hand, involves adjusting the range of data. These processes are fundamental in MCDM because they ensure that each criterion contributes appropriately to the decision making process, regardless of its original scale or units of measurement. However, normalization and scaling can introduce biases and inconsistencies if not handled properly, potentially compromising the accuracy and fairness of the decision making outcomes.

Furthermore, the thesis explores the implications of various normalization and scaling methods on the decision outcomes, providing a thorough analysis of their advantages and limitations. This involves a detailed examination of how different methods affect the ranking and selection of alternatives in MCDM scenarios.

4. **Gathering decisions:** The aim of this thesis is to construct decision gathering procedures based on Nobel Prize-winning Nudge Theory, with the goal of enhancing the decision making process by subtly guiding individuals towards preferred outcomes. By incorporating principles of Nudge Theory (Thaler and Sunstein, 2008), the thesis seeks to develop methodologies that influence decision makers in a way that promotes informed and rational choices. This approach involves using psychological and behavioral insights to design decision environments that *"anchor"* decision makers to specific, desirable options, thereby improving the quality of their decisions. Additionally, the research aims to provide decision makers with a given *"status"*, enabling them to make choices that are not only beneficial to them but also align with broader societal goals. By creating a choice architecture that subtly directs individuals towards optimal decisions without restricting their freedom of choice, this thesis aspires to contribute significantly to the field of decision-making, ensuring that decisions are both well-informed and aligned with rational outcomes.

5. **Micromobility mode evaluation:** A significant aim of this thesis is to apply the proposed methodologies to the evaluation of micromobility modes, providing a detailed analysis of their effectiveness and sustainability in urban environments. This involves conducting comprehensive case studies in Paris/France, and Istanbul/Turkey, aligning the research with the European Union's ambitious 2050 targets (European Commission, 2018) for sustainable urban mobility and carbon neutrality. By examining these two distinct metropolitan areas, the research evaluates the relative suitability of various micromobility vehicles, such as e-scooters and electric bikes, for specific regions. These case studies consider a range of factors, including traffic patterns, environmental impact, socio-economic context, and existing infrastructure, to determine the efficient and sustainable micromobility solutions. The findings not only validate the proposed methodologies but also offer valuable

insights for policymakers and urban planners in their efforts to integrate micromobility into broader transportation networks, ultimately contributing to sustainable and livable cities.

6. **Analyzing effectiveness of proposed approaches:** The final objective of this doctoral thesis involves a thorough comparison of the proposed methodologies with existing distance-based and preference ranking MCDM methods. This comparative analysis is essential to highlight the innovations and improvements introduced by the new methodologies. By examining how the proposed approaches perform relative to established methods, the research elucidates their advantages in terms of accuracy, efficiency, and applicability across various decision-making scenarios. Additionally, the robustness, comprehensiveness, and practical relevance of the proposed framework are rigorously assessed. This entails evaluating the framework's ability to handle diverse and complex decision-making environments, its adaptability to different criteria and contexts, and its overall effectiveness in producing reliable and actionable outcomes. Furthermore, this objective includes providing detailed recommendations for future research and practical applications. These recommendations guides subsequent studies in refining and expanding the methodologies, ensuring that they remain at the forefront of MCDM research. Practical application guidelines are also offered, aiding practitioners in implementing these advanced decision making tools in real world scenarios. By fulfilling this objective, the thesis not only demonstrates the value of the proposed methodologies but also lays the groundwork for their ongoing development and utilization in addressing complex decision-making challenges.

In summary, this doctoral thesis aims to advance the field of MCDM by developing innovative choice architecture validated through practical case studies in the context of sustainable urban mobility.

1.3 Original Contribution

This research makes several original contributions to the field of MCDM. Firstly, it introduces two novel methodologies *"PODER"* and *"V-PARS"* that address the limitations of traditional distance-based MCDM approaches. PODER leverages criterion extraction distance on Euclidean environment principles for enhanced criteria weighting. V-PARS introduces a vector-based approach that considers both magnitude and direction with the integration of Social Choice Theory, specifically the Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951) methods, offering a nuanced evaluation of alternatives.

Secondly, the incorporation of Nudge Theory into the decision gathering procedures enhances the decision-making process by provides a robust framework for aggregating individual preferences into a collective decision. Additionally, the research addresses the complexities of normalization and scaling in MCDM procedures, particularly when dealing with both crisp and uncertain data in according with the objective and subjective data types.

Finally, by applying the proposed methodologies to the evaluation of micromobility modes in Paris and Istanbul, this research demonstrates their practical relevance and potential to contribute to sustainable urban transportation planning. The findings provide valuable insights for local authorities and stakeholders, contributing to more informed and sustainable micromobility decisions.

The contributions are listed in detail below.

- ***Development of PODER methodology***

  The POndération sur la Distance par ExtRaction (PODER) methodology is designed to address the limitations of traditional distance-based MCDM methods by introducing the concept of criterion extraction distance on Euclidean environment. This approach leverages the strengths of distance-based methods to enhance criteria weighting.

  - The criterion extraction distance is calculated based on the Euclidean distance between each alternative and the criteria reference points.
  - This approach allows for a more nuanced evaluation of alternatives, considering both the relative distances and the importance of each criterion.
  - PODER addresses the limitation of traditional distance-based methods, which often rely solely on predefined reference points.

- ***Development of V-PARS methodology***

  The Vector-Based Preference Ranking System (V-PARS) methodology is designed to address the limitations of traditional distance-based MCDM methods by incorporating vector-based elements while including ideas from Social Choice Theory (Fishburn, 1973). This approach leverages the strengths of vector-based similarity operations, considering both magnitude and direction for a richer evaluation of alternatives.

  - V-PARS evaluates alternatives based on their vector representations within the criteria n-spaces, considering both the magnitude (distance) and direction.
  - This approach provides a comprehensive understanding of an alternative's positioning, capturing the nuances of its performance across multiple criteria.
  - By integrating vector similarity operations, V-PARS addresses the limitation of traditional distance-based methods, which often focus solely on distance.
  - The proposed methodology integrates the idea of Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951) methods to enhance the evaluation process.
  - This integration ensures a robust aggregation of individual preferences, providing a comprehensive evaluation of alternatives.
  - The combination of vectorial similarity operations and Social Choice Theory principles offers a unique and innovative approach to MCDM.

- ***Integration with Nudge Theory***

  Nobel Prize-winning Nudge Theory posits that individuals make better decisions when subtly guided towards a preferred outcome (Thaler and Sunstein, 2008). This research integrates Nudge Theory into the decision gathering procedure for both the PODER and V-PARS methodologies, enhancing the decision making process.

  - The decision gathering procedure is designed to incorporate subtle nudges that guide individuals towards more informed and rational choices.
  - Proposed approach supports decision making processes by *"anchoring"* and assigning *"status"* to decision makers.
  - These nudges can take various forms, including the presentation of information, the framing of choices, and the use of default options.
  - By integrating Nudge Theory, the prosposed decision gathering prosess aims to enhance the overall effectiveness of the expert driven models.

- ***Addressing complexities in normalization and scaling***

  Normalization and scaling are critical aspects of MCDM procedures in data standardization, particularly when dealing with both crisp and uncertain data. This research addresses these complexities by developing a comprehensive framework that incorporates both objective and subjective data types.

  - The research explores scaling and various normalization techniques
  - Each technique is evaluated based on its ability to accurately represent the value of decisions, including objective and subjective data.
  - Scaling is preferred based on the conclusion that the data is stable because it maintains its position in the exact range and is not relative to the case.

- ***Application to micromobility modes***

  The application of the proposed methodologies to the evaluation of micromobility modes demonstrates their practical relevance and potential to contribute to sustainable urban transportation planning. The rising popularity of micromobility options,

such as scooters and e-bikes, has introduced new complexities in urban transportation planning.

- The case studies focus on evaluating micromobility vehicles for Paris/France, and Istanbul/Turkey, within the context of the European Union's 2050 targets (European Commission, 2018).
- Each case study involves the identification of relevant criteria, the collection of data, and the application of the proposed methodologies to rank the micromobility vehicles.
- The evaluation criteria include the concept of environmental impact, cost-effectiveness, user acceptance, safety, and technical performance.

This doctoral thesis has contributed to the scholarly literature by one article indexed in the Science Citation Index, seven conference papers, two competition participations, and three laboratory research projects. For further details, please refer to the Biographical Sketch.

1.4 Thesis Organization

This thesis is carefully structured to ensure a logical flow of information and a comprehensive exploration of the research topic as depicted in Figure 1.1. Each part and chapter is crafted to build upon the preceding sections, culminating in a robust analysis and discussion of the findings. This organization not only enhances the readability of the thesis but also ensures that each aspect of the research is thoroughly addressed.

Part 1: Introduction

The first part introduces the study, providing a comprehensive overview of the research context, the author's motivation, the aims and objectives of the thesis, and the overall layout of the study. This section sets the stage for the research by clearly outlining the problem statement and the significance of the study.

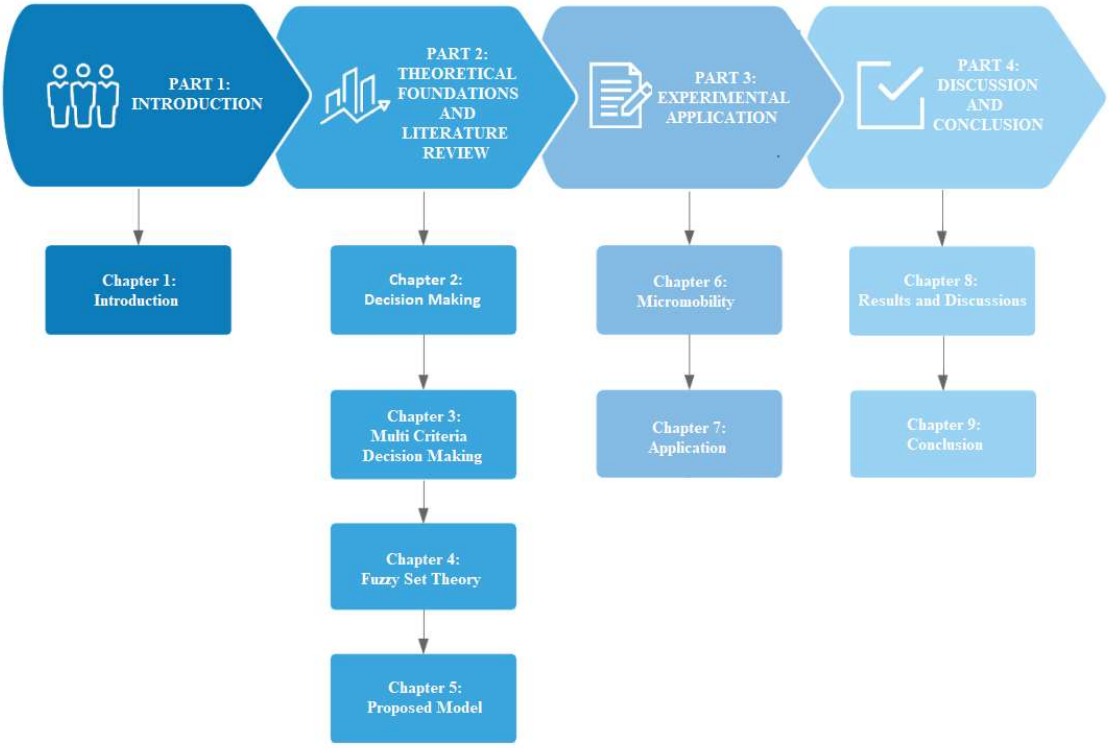


Figure 1.1: Dissertation structure.

Part 2: Theoretical Foundations and Literature Review

The second part examines the core content of the thesis. It begins with a detailed literature review, covering existing techniques and methodologies relevant to the research. Each chapter explains the theoretical underpinnings and the technical details of the methods employed. The literature review is thorough, ensuring that all relevant studies are discussed to provide a solid foundation for the research. At the conclusion of this part, two novel models are proposed, integrating the techniques introduced and building upon the insights gained from the literature.

Part 3: Experimental Application

The third part is dedicated to the experimental application of the proposed models. This section begins with an extensive research study that explores the field of application in detail. The context and specifics of the case studies are elaborated upon, providing a clear understanding of the experimental setup. The hybrid models, presented in the second

part, are then systematically applied to the case studies. This part includes a step-by-step account of the application process, ensuring transparency and reproducibility of the experiments.

Part 4: Discussion and Conclusion

The fourth and final part of the thesis focuses on the discussion of the results. This section begins by analyzing the general structure of the study, followed by a detailed comparison of the results obtained from the two MCDM models with the approximate models existing in the literature. The suitability and effectiveness of the methods are critically assessed, and the limitations of the study are thoroughly discussed. Additionally, this part provides insightful commentary on the implications of the findings and suggests directions for future research. The ideas put forward aim to guide subsequent studies in the field, contributing to the ongoing development and refinement of Multi-Criteria Decision Making (MCDM) methodologies.

The subsequent chapters of this dissertation are structured as follows:

Chapter 1 introduces the fundamental concepts of MCDM and explains the importance of robust decision making frameworks in addressing complex problems. It outlines the motivation for developing novel MCDM approaches, particularly applying in the context of urban transportation and micromobility modes. The thesis identifies the gaps in existing distance-based MCDM methods, specifically the absence of techniques where the decision itself serves as the reference point and the neglect of vector-based approaches. The problem statement sets the stage for the research objectives and contributions. This section also enumerates the primary objectives of the research, including the development of two novel MCDM methodologies—PODER and V-PARS—and their application in evaluating micromobility vehicles. The contributions of the research are detailed, highlighting the novel methodologies proposed, the integration of Social Choice Theory and Nudge Theory, scaling of objective and subjective data and the practical application to micromobility evaluation. Finally, an overview of the thesis organization by chapters is provided, giving readers a roadmap of the research content.

Chapter 2 provides a comprehensive exploration of the decision making concept, starting with an introduction to its fundamental role in human behavior. It explores how individuals process information and express their thoughts when faced with choices, examining various models and frameworks that articulate these processes. The cognitive aspects of decision making are then explored, focusing on how the mind perceives, processes, and evaluates information, while also considering the influence of heuristics, biases, and emotions on decision outcomes. The chapter introduces Nudge Theory (Thaler and Sunstein, 2008), discussing how subtle environmental changes can steer individuals toward better choices without restricting their freedom, and provides examples of its practical applications in fields such as public policy and marketing. Social Choice Theory (Fishburn, 1973) is also examined, particularly in the context of aggregating individual preferences to reach collective decisions, highlighting the challenges of group decision making processes and the potential conflicts between individual and collective rationality. Finally, the chapter reviews key studies related to decision making.

Chapter 3 offers the foundational concepts underlying decision making processes. It gives an in-depth analysis of the mathematical and geometric representations of decision elements, providing a robust framework for understanding the transformation of qualitative and quantitative information. The subsequent discussion focuses on the crucial role of standardization and scaling in ensuring comparability across diverse data types, emphasizing the multidimensional nature of decision spaces. The chapter looks into the complexities of combining multiple decisions, highlighting the challenges posed by multi-type data. It underscores the need for sophisticated methodologies to effectively handle the heterogeneity of decision analysis.

Building upon this foundation, the chapter provides a systematic overview of various MCDM techniques, elucidating their strengths and weaknesses. An in-depth exploration of distance-based MCDM methods is presented, including their strengths, limitations, and the importance of selecting appropriate distance metrics and reference points. The potential of vectors is examined, emphasizing their ability to consider both magnitude and direction, and their suitability for similarity operations. Additionally, this section explores how principles from Social Choice Theory, such as the idea of Condorcet (De Con-

dorcet, 2014), Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951) methods, can enhance MCDM methodologies. The integration of some ideas from Social Choice Theory into the discussion of multi-criteria preference ranking methods offers a nuanced perspective on collective decision making, providing a comprehensive framework for subsequent analysis. At the end of the chapter, related publications on this subject are listed.

Chapter 4 provides a foundational exploration of Fuzzy Set Theory (Zadeh, 1965), a mathematical framework specifically designed to accommodate the vagueness and uncertainty prevalent in real world systems. By introducing the concept of fuzzy sets and their properties, the chapter highlights the limitations of traditional binary logic in representing complex and ambiguous information. Through a detailed examination of various fuzzy set types and their extentions, this chapter establishes a robust understanding of fuzzy set as a valuable tool for data modeling and decision making in uncertain environments. The chapter concludes with a listing of pertinent publications related to this topic.

Chapter 5 offers an overview of two innovative MCDM methodologies: PODER and V-PARS, setting the foundation for the subsequent detailed methodological descriptions. It begins with an in-depth examination of the POndération sur la Distance par ExtRaction (PODER) methodology, addressing its theoretical foundations and rationale, mathematical formulation and criteria weighting process, and the integration of criterion extraction distance in Euclidean environment. Following this, a comprehensive description of the Vector-Based Preference Ranking System (V-PARS) methodology is presented. This includes its theoretical foundations and rationale, mathematical formulation, and vector-based similarity operations, as well as considerations of both magnitude and direction in decision making and the integration of Social Choice Theory principles. Additionally, the section explains the construction of decision gathering procedures for both methodologies, highlighting the role of Nudge Theory in improving decision quality. The discussion extends to the complexities of normalization and scaling in MCDM procedures, addressing the challenges associated with both crisp and uncertain data, including objective and subjective data types.

Chapter 6 gives a comprehensive exploration of micromobility. It commences with a historical overview, charting the evolution of these modes of transportation from their inception to the present day. A detailed taxonomy of micromobility vehicles follows, examining their design, functionalities, and usage patterns. The chapter subsequently examines the practical implications of micromobility in urban environments, assessing its contributions to traffic management, environmental quality, and social dynamics. A critical analysis of the economic and health benefits, as well as the logistical challenges associated with micromobility systems, is presented. Furthermore, the chapter identifies key limitations and obstacles to micromobility adoption, such as battery technology and infrastructure constraints. By comparing micromobility initiatives across different cities around the world, the chapter provides valuable insights into successful implementation strategies. Ultimately, with a focus on contributing to the European Union's 2050 climate neutrality goals, this chapter aims to provide a nuanced understanding of micromobility's potential to reshape urban transportation systems. The chapter concludes with a list of related publications on micromobility, specifically aligned with decision-making processes.

Chapter 7 provides an overview of the rise of micromobility modes, such as scooters and e-bikes, and the new complexities they introduce in urban transportation planning. The specific contexts of Paris/France, and Istanbul/Turkey, are described, including their unique transportation challenges and the relevance of the European Union's 2050 targets (European Commission, 2018). The selection of criteria for evaluating micromobility vehicles is detailed, encompassing economic, environmental, social, and technical factors. This section describes the application of the PODER methodology to the case studies, including data collection and preprocessing, then criteria weighting process. A similar description is provided for the application of the V-PARS methodology, covering data collection and preprocessing, vector-based evaluation and ranking process, then results.

Chapter 8 presents a summary of the key findings derived from applying the proposed methodologies to the micromobility case studies, offering a detailed analysis of the results. The results from both proposed methodologies are given, highlighting their relative strengths and weaknesses and the insights gained from their application. The implications of the findings for urban transportation planning are discussed, emphasizing how the

proposed methodologies can contribute to more informed and sustainable micromobility decisions. An evaluation of the proposed methodologies is provided, considering their theoretical robustness, practical applicability, and potential limitations with comparing existing approximate models in the literature (MEREC, SERA, TOPSIS, PROMETHEE) (Keshavarz-Ghorabaee et al., 2021; Çakır et al., 2022; Hwang and Yoon, 1981; Brans et al., 1982; Brans and Vincke, 1985). Recommendations are offered for practitioners and policymakers on how to implement the proposed MCDM methodologies in real world decision making contexts for future research.

In Chapter 9, offers a concise summary of the thesis contributions, emphasizing the development of the novel MCDM methodologies and their application to micromobility evaluation. The limitations of the research are acknowledged, and an overall assessment is provided, emphasizing areas where further exploration and development are needed. Concluding remarks that reflect on the overall significance of the research and its potential impact on the field of MCDM and urban transportation planning.

In Appendices, the following documents related to the research are provided in three languages (Turkish-English-French): the templates of "Micromobility Modes Evaluation Questionaires", the informed voluntary consent form, the post-participation information form, and the original version of approvals from the ethics committee.

This detailed thesis organization provides a clear and structured roadmap for the research, ensuring that each component is thoroughly addressed and contributes to the overall objectives and contributions of the study.

2 DECISION MAKING

Decision making is a fundamental cognitive process that involves selecting a course of action from multiple alternatives. It is pivotal in personal, professional, and societal contexts, influencing outcomes in various domains such as business, healthcare, governance, and everyday life. Expressing thought, on the other hand, is the articulation of one's cognitive processes, ideas, and decisions through language, gestures, or other forms of communication. This section explores the concept of decision making, its processes, and the methods of expressing thought in alignment with Nudge Theory (Thaler and Sunstein, 2008) and Social Choice Theory (Fishburn, 1973).

2.1 What is Decision Making and How to Express Thought?

Decision making is defined as the cognitive process of selecting a course of action from among multiple alternatives. It involves assessing options, predicting outcomes, and choosing the most suitable one based on criteria such as utility, risk, and personal values (Kahneman, 2011).

The decision making process generally involves several stages (Simon, 1979):

1. **Identification of the problem:** Recognizing the need for a decision due to a problem or opportunity.
2. **Gathering information:** Collecting relevant data and information to understand the situation better.
3. **Identifying alternatives:** Enumerating possible courses of action.
4. **Weighing evidence:** Evaluating the pros and cons of each alternative.
5. **Choosing among alternatives:** Selecting the most suitable option based on the evaluation.

6. **Taking action:** Implementing the chosen alternative.

7. **Reviewing the decision:** Assessing the outcome of the decision to learn and improve future decision making.

Various models of decision making exist, including rational, bounded rationality, intuitive, and collaborative models, each suited to different contexts and complexities (Gigerenzer, 2007).

Expressing thought is the articulation of cognitive processes, ideas, decisions, and emotions through various forms of communication. It is essential for effective interaction, collaboration, and understanding among individuals and groups.

Methods of expressing thought are:

- **Language:** The most common method, involving spoken or written words. Language allows for detailed and precise expression of thoughts and is essential for sharing complex ideas (Chomsky, 2014).

- **Non-verbal communication:** Includes gestures, facial expressions, body language, and eye contact. Non-verbal cues can enhance or contradict verbal communication and are crucial for conveying emotions and intentions (Mehrabian, 1981).

- **Visual aids:** Diagrams, charts, and images can help illustrate ideas and make complex information more understandable. Visual aids are particularly useful in presentations and educational contexts (Tufte, 1991).

- **Written communication:** Encompasses emails, reports, essays, and social media posts. Writing allows for thoughtful and structured expression of ideas, and it is often used in professional and academic settings (Crystal, 2002).

- **Digital media:** Blogs, videos, podcasts, and other digital content provide modern avenues for expressing thoughts. They enable reaching a broader audience and offer interactive engagement (Jenkins, 2011).

Effective expression of thought is essential for several reasons:

- **Clarity and precision:** Clear expression helps in avoiding misunderstandings and ensures accurate communication of ideas.
- **Collaboration and teamwork:** Effective communication is crucial for teamwork, enabling members to share their perspectives and contribute to collective decision making (Hackman, 2002).
- **Persuasion and influence:** Articulating thoughts convincingly can influence others' opinions and actions, which is vital in leadership and advocacy (Cialdini, 2009).
- **Emotional expression:** Communicating emotions helps in building empathy and understanding in personal and professional relationships (Goleman, 1996).

Decision making and expressing thought are interconnected cognitive processes that play critical roles in personal and professional contexts. Decision making involves a systematic process of evaluating options and choosing the best course of action, while expressing thought encompasses various methods of communication to articulate these decisions and underlying cognitive processes. Effective decision making and communication are essential for achieving clarity, fostering collaboration, and influencing outcomes.

2.2 Cognitive Interpretation of Decision Making

Decision making is a fundamental cognitive process that significantly influences human behavior and outcomes in various domains, including personal life, business, and public policy. The cognitive interpretation of decision making focuses on understanding the mental processes and mechanisms underlying decision choices. This literature review provides an overview of key theories and findings related to the cognitive interpretation of decision making.

The cognitive interpretation of decision making provides valuable insights into the mental processes underlying human choices. Theories such as Dual-Process Theory, Prospect

Theory, and Bounded Rationality, along with mechanisms like heuristics and emotional influences, highlight the complexity and nuances of decision making. Understanding these cognitive factors is essential for improving decision making strategies in various fields, from psychology and economics to public policy and everyday life.

- ***Dual-Process Theory:*** It posits that decision making involves two distinct cognitive systems: System 1 (intuitive) and System 2 (analytical). System 1 is fast, automatic, and often based on heuristics and biases, while System 2 is slower, deliberate, and logical (Kahneman, 2011). This theory helps explain how individuals make quick decisions under uncertainty and when they employ more rational, analytical thinking.

- ***Prospect Theory:*** Developed by Daniel Kahneman and Amos Tversky, it challenges the traditional economic view of rational decision making. It suggests that people evaluate potential losses and gains differently, leading to decisions that deviate from purely rational choices. The theory introduces concepts such as loss aversion and framing effects, which describe how the presentation of choices influences decision outcomes (Kahneman and Tversky, 1979).

- ***Bounded Rationality:*** Herbert Simon's concept of bounded rationality asserts that individuals make decisions within the constraints of limited information, cognitive limitations, and finite time. Instead of optimizing, people satisfice selecting an option that meets minimum criteria of acceptability. This model highlights the pragmatic approach humans take in real world decision making (Simon, 1957).

- ***Heuristics and Biases:*** Heuristics are mental shortcuts that simplify decision making but can lead to systematic biases. Common heuristics include availability, where individuals judge the probability of events based on how easily examples come to mind, and representativeness, where people assess the likelihood of an event based on its similarity to a prototype (Gigerenzer, 2007).

- ***Emotion and Decision Making:*** Emotions play a crucial role in decision making, influencing choices through affective forecasting and visceral factors. Studies show

that emotions can both enhance and impair decision quality, depending on the context and the type of decision being made (Lerner et al., 2015).

2.3 Nudge Theory and Decision Making

Nudge Theory, introduced by Richard Thaler (Nobel Prized - 2017) and Cass Sunstein in 2008, has reshaped the landscape of behavioral economics and public policy by illustrating how subtle changes in the environment can significantly influence decision making. Unlike traditional regulatory approaches, nudges aim to steer people towards better decisions without restricting their freedom of choice. This literature review represents the principles of Nudge Theory, its application across various domains, empirical evidence of its effectiveness, ethical considerations, and future directions.

Nudge Theory is built on the premise that small, non-coercive interventions can guide individuals toward more beneficial behaviors. A *"nudge"* is defined as any aspect of the choice architecture that predictably alters people's behavior without forbidding any options or significantly changing their economic incentives (Thaler and Sunstein, 2008). Key concepts include:

- **Choice Architecture:** The design of the environment in which decisions are made. By strategically structuring choices, decision makers can influence outcomes.
- **Libertarian Paternalism:** A philosophy advocating that it is possible to steer people's choices while preserving their freedom to choose.
- **Default Options:** Pre-set choices that take effect if the individual does nothing, leveraging inertia and status quo bias.
- **Framing Effects:** The way information is presented can significantly impact decisions.

Six principles of NUDGES are:

- i**N**centives: Offer the right incentives for good decision-making (beyond monetary), considering both individual and societal benefits.
- **U**nderstand mappings: Help people comprehend the consequences of their choices (e.g., comparison tools for mobile phone plans).
- **D**efaults: Set defaults that benefit as many people as possible, instead of a neutral *"zero"* option (e.g., predefined base contracts).
- **G**ive feedback: Provide feedback to help people improve their performance (e.g., camera click sound).
- **E**xpect error: Design systems with error tolerance (e.g., medication schedules).
- **S**tructure complex choices: Simplify complex choices through better organization (e.g., paint color groupings).

Thaler and Sunstein's seminal work, "Nudge: Improving Decisions About Health, Wealth, and Happiness", laid the foundation for understanding how these principles can be applied to various domains to improve decision-making outcomes (Thaler and Sunstein, 2008).

Some application areas of Nudge Theory are listed and explaned as follows:

- Nudge Theory has been extensively applied in public health to promote behaviors such as healthy eating, exercise, and vaccination. For instance, placing healthier foods at eye level in cafeterias or using default options for organ donation registration has been shown to improve public health outcomes. A study by Crockett et al. found that simple changes in food presentation can significantly increase the consumption of healthier options (Crockett et al., 2010).
- Financial institutions have utilized nudges to encourage better saving and investment behaviors. Automatic enrollment in retirement savings plans, with the option to opt-out, has significantly increased participation rates. Madrian and Shea

demonstrated that such default options can dramatically enhance retirement savings, highlighting the power of inertia in financial decision making (Madrian and Shea, 2001).

- Nudges have also been applied to promote environmentally friendly behaviors. Providing real time feedback on energy consumption through smart meters, for example, can reduce household energy use. Allcott and Rogers found that home energy reports, which compare a household's energy use to that of its neighbors, can lead to sustained reductions in energy consumption (Allcott and Rogers, 2014).

- In education, nudges such as reminders and goal setting prompts have been used to improve student performance and attendance. Simplifying the application process for financial aid has increased college enrollment rates among low income students. Bettinger et al. showed that personalized assistance in completing financial aid forms can significantly boost college attendance (Bettinger et al., 2009).

Numerous studies have demonstrated the effectiveness of nudges in various contexts. A meta-analysis conducted by Hummel and Maedche reviewed nudge interventions across different domains and found that they can lead to significant behavioral changes, with effect sizes comparable to more traditional policy tools (Hummel and Maedche, 2019).

However, the impact of nudges can vary depending on the context, the design of the intervention, and the target population. For instance, a study by Sunstein highlighted that while some nudges, like default options, are highly effective in increasing organ donation rates, others, such as informational nudges, may have more nuanced effects depending on the individual's baseline knowledge and attitudes (Sunstein, 2014).

In Nudge Theory, anchoring and status quo are critical concepts that influence decision making by subtly guiding individuals towards particular choices without restricting their freedom of choice. ***Anchoring*** refers to the cognitive bias where individuals rely heavily on the first piece of information (the "anchor") they receive when making decisions. In the context of Nudge Theory, anchoring can be used to influence decision making by setting a reference point that shapes subsequent judgments and choices. By presenting a

specific anchor, such as a suggested donation amount or an initial price, individuals are nudged to adjust their decisions around this anchor. For example, if a charity suggests a donation of $50, people are more likely to donate around this amount than if no suggestion were given. ***Status quo*** in Nudge Theory involves using social norms and the desire for social acceptance to influence behavior. People tend to make decisions that enhance or maintain their social status and align with the behavior of their peers or admired groups. By highlighting that a particular behavior is common or endorsed by others, individuals can be nudged to conform to these social norms. For example, informing people that a high percentage of their neighbors recycle can increase recycling rates among those who are informed.

In decision gathering procedures, anchoring and status can be effectively integrated to enhance decision quality and guide individuals towards more informed and rational choices. Establish clear and relevant anchors that align with desired outcomes. For example, when evaluating micromobility options, provide benchmarks or exemplary models to serve as anchors. Use anchors to shape initial perceptions and preferences, making it easier for individuals to evaluate options within a desirable range. Emphasize behaviors and choices that are popular or endorsed by influential groups or individuals. For example, showcase how leading cities successfully implement micromobility solutions. Design decision making contexts that highlight the positive social status associated with making certain choices, encouraging individuals to align their decisions with these social norms.

By leveraging anchoring and status within a choice architecture, decision making processes can be significantly improved. This approach can guide individuals towards better choices in various contexts, such as public policy, health, finance, and urban planning. In the case of micromobility evaluation, these principles can help shape user preferences and adoption rates by providing well-defined anchors and emphasizing the social benefits of sustainable transportation choices.

In addition to its positive aspects, Nudge Theory has faced criticism on ethical grounds. Critics argue that nudges can be manipulative, infringing on individual autonomy and freedom of choice. The debate centers on whether it is ethical to influence people's de-

cisions covertly, even if the intentions are benevolent. Hausman and Welch discuss the potential for paternalism in nudge interventions and advocate for transparency and accountability in their application (Hausman and Welch, 2010).

Another ethical concern is the lack of informed consent in many nudge interventions. People are often unaware that their choices are being influenced, which raises questions about the legitimacy of such interventions. To address this, Thaler and Sunstein argue for the importance of maintaining open and honest communication about the presence of nudges and their intended outcomes (Thaler and Sunstein, 2008).

They are also concerns about the equitable application of nudges. Some interventions may disproportionately benefit or disadvantage certain groups, leading to unintended social consequences. Reisch and Sunstein emphasize the need for careful consideration of the distributional effects of nudge policies to ensure they promote fairness and equity (Reisch and Sunstein, 2016).

One of the criticisms of Nudge Theory pertains to the sustainability of its effects. Some studies suggest that the impact of nudges may diminish over time as individuals become accustomed to the interventions or as the novelty wears off. This raises questions about the long-term effectiveness of nudge-based policies. Sunstein explores the concept of *"nudge fatigue"* and suggests that continuous innovation in choice architecture is necessary to maintain the effectiveness of nudges (Sunstein, 2014).

To enhance the sustainability of nudges, researchers have suggested combining them with other behavioral interventions, such as financial incentives or educational programs. Gneezy et al. found that hybrid approaches that integrate multiple strategies can address complex behavioral challenges more comprehensively and sustain behavior change over the long term (Gneezy and List, 2006).

In future, the integration of Nudge Theory with digital technologies presents new opportunities for personalized and scalable interventions. Digital platforms can use data analytics and machine learning to design tailored nudges that adapt to individual preferences and behaviors. Benartzi et al. discuss the potential of *"digital nudging"* to enhance decision

making in various domains, from health care to consumer finance (Benartzi et al., 2017). Future research should explore the applicability of Nudge Theory across different cultural contexts. Cultural norms and values can influence how nudges are perceived and their effectiveness, necessitating culturally sensitive designs. Reisch and Sunstein highlight the importance of considering cultural diversity in the implementation of nudge interventions to ensure they resonate with target populations (Reisch and Sunstein, 2016). Combining nudges with other policy tools, such as financial incentives or regulatory measures, may enhance their effectiveness. Hybrid approaches that integrate multiple strategies can address complex behavioral challenges more comprehensively. Gneezy et al. suggest that such combined interventions can create more robust and enduring behavior change (Gneezy and List, 2006).

In summary, Nudge Theory offers a powerful framework for influencing decision making in a non-intrusive manner. Its applications in public health, finance, environmental conservation, and education demonstrate its versatility and potential for positive impact. However, ethical considerations and questions about sustainability highlight the need for careful design and evaluation of nudge interventions. Future research should focus on leveraging digital technologies, exploring cross-cultural applications, and integrating nudges with other policy tools to maximize their effectiveness and address complex behavioral issues.

2.4 Social Choice Theory and Decision Making

Social Choice Theory is a theoretical framework for analyzing collective decision making processes. It explores how individual preferences can be aggregated to reach collective decisions and the implications of various decision making rules and mechanisms. Since its inception, Social Choice Theory has profoundly influenced economics, political science, and philosophy. This literature review examines the foundational principles, key contributions, and contemporary research in Social Choice Theory, focusing on its implications for decision making.

One of the cornerstone results in Social Choice Theory is Arrow's Impossibility Theorem, formulated by Kenneth Arrow (Nobel Prized - 1972) in 1951. The theorem states that no social welfare function can simultaneously satisfy a set of seemingly reasonable conditions (unrestricted domain, non-dictatorship, Pareto efficiency, and independence of irrelevant alternatives) when there are three or more options. This result highlights the fundamental difficulties in designing a fair and consistent collective decision making process (Arrow, 1951).

Pareto Efficiency, named after Vilfredo Pareto, is a condition where no individual can be made better off without making someone else worse off. In the context of social choice, a decision is Pareto efficient if it aligns with the preferences of all individuals in a way that no alternative can improve someone's situation without harming another's (Pareto, 1906).

Voting systems and mechanisms have been proposed to aggregate individual preferences, including ***Majority Rule***, ***Borda Count***, and ***Condorcet*** methods. Each system has its strengths and weaknesses, and their effectiveness varies depending on the context. For example, majority rule is straightforward but can lead to cyclic preferences ***(Condorcet Paradox)***, while the Borda Count provides a more nuanced ranking of options but can be susceptible to strategic manipulation (Black, 1958).

Gibbard-Satterthwaite Theorem, established independently by Allan Gibbard and Mark Satterthwaite in the 1970s, states that every non-dictatorial voting system with at least three choices is susceptible to strategic voting. This result implies that participants may have incentives to misrepresent their true preferences to influence the outcome (Gibbard, 1973; Satterthwaite, 1975).

Amartya Sen's ***Liberal Paradox*** illustrates a conflict between individual rights and collective rationality. The paradox shows that it is impossible to design a social choice rule that guarantees both individual liberty and Pareto efficiency. This result has profound implications for understanding the trade-offs between personal freedom and social welfare (Sen, 1970).

Public Choice Theory, developed by scholars such as James Buchanan and Gordon Tullock, applies the principles of economics to political decision making. It examines how self-interested behavior of voters, politicians, and bureaucrats can influence collective outcomes. Public Choice Theory provides insights into the design of political institutions and the behavior of government actors (Buchanan and Tullock, 1965).

Contemporary research of social choice in decision making can be considered as follows:

- **Behavioral Social Choice:** Recent research in behavioral social choice explores how psychological factors, such as cognitive biases and heuristics, influence collective decision making. Behavioral social choice integrates insights from behavioral economics and psychology to understand deviations from rational choice models. For instance, studies have shown that framing effects and anchoring can significantly impact voting behavior and preference aggregation (List et al., 2013).
- **Computational Social Choice:** The advent of computational methods has opened new avenues for analyzing and designing social choice mechanisms. Computational social choice explores algorithmic approaches to preference aggregation, voting system design, and strategic behavior. Techniques such as machine learning and optimization are used to develop more efficient and fair decision making processes (Brandt et al., 2016).
- **Deliberative Democracy:** Deliberative democracy emphasizes the role of discussion and reasoning in collective decision making. It posits that through open dialogue and deliberation, individuals can reach more informed and considered decisions. Research in this area examines how deliberative processes can enhance the legitimacy and quality of collective choices (Gutmann and Thompson, 2004).
- **Fair Division and Resource Allocation:** Fair division and resource allocation problems are central to Social Choice Theory. These problems involve distributing resources or goods among individuals in a way that satisfies fairness criteria. Recent research has focused on developing algorithms and mechanisms to achieve equitable outcomes in various contexts, from dividing inheritance to allocating public resources (Moulin, 2004).

Social Choice Theory provides valuable insights for designing and implementing policies that reflect collective preferences. By understanding the limitations and trade-offs of different decision making mechanisms, policymakers can create more effective and equitable policies. For example, insights from Social Choice Theory have been applied to electoral reforms, public good provision, and welfare distribution (Maskin and Sen, 2014). In the corporate world, Social Choice Theory informs governance structures and decision making processes within organizations. Voting systems and preference aggregation methods are used to make collective decisions on issues such as board elections, strategic planning, and resource allocation. Understanding the dynamics of collective decision making can help organizations design transparent and effective governance systems (Hart, 2017).

Social Choice Theory raises important ethical and normative questions about the principles of fairness, justice, and democracy. It prompts reflection on how collective decisions should be made and the values that should guide these processes. Philosophical debates in Social Choice Theory contribute to broader discussions on the legitimacy and moral foundations of collective decision making (Pettit, 2012).

Advances in technology, particularly in artificial intelligence and data analytics, have the potential to transform collective decision making processes. Computational Social Choice offers new tools for designing and implementing decision making mechanisms that can handle large scale and complex preferences. However, these technological advancements also raise ethical and practical challenges related to privacy, transparency, and accountability (Conitzer et al., 2017).

In closing, Social Choice Theory provides a comprehensive framework for understanding and analyzing collective decision making processes. From foundational principles like Arrow's Impossibility Theorem to contemporary research in behavioral and Computational Social Choice, the field offers valuable insights for various domains, including policy design, corporate governance, and ethical considerations. As collective decision making becomes increasingly complex in a globalized and technologically advanced world, Social Choice Theory will continue to play a crucial role in shaping fair and effective decision making mechanisms.

2.5 Related Studies in the Literature

To enhance the comprehensiveness of this study, relevant literature pertaining to decision-making is catalogued in Table 2.1, Table 2.2 and Table 2.3.

Table 2.1: Related studies on decision-making aligned with cognitive interpretation.

Author	**Year**	**Title**	**Type**
Simon	(1955)	"A Behavioral Model of Rational Choice"	Article
Newell and Simon	(1972)	"Human Problem Solving"	Book
Fischhoff and Beyth	(1975)	"I Knew It Would Happen: Remembered Probabilities of Once-Future Things"	Article
Beach and Mitchell	(1978)	"A Contingency Model for the Selection of Decision Strategies"	Article
Kahneman and Tversky	(1979)	"Prospect Theory: An Analysis of Decision Under Risk"	Article
Johnson-Laird	(1983)	"Mental Models: Towards a Cognitive Science of Language, Inference, and Consciousness"	Book
Johnson and Tversky	(1983)	"Affect, Generalization, and the Perception of Risk"	Article
Thaler	(1985)	"Mental Accounting and Consumer Choice"	Article
Farrell and Holmes	(1991)	"The Social and Cognitive Structure of Legal Decision-Making"	Article
Shafir et al.	(1993)	"Reason-Based Choice"	Article
Payne et al.	(1993)	"The Adaptive Decision Maker"	Book
Larrick	(1993)	"Motivational Factors in Decision Theories: The Role of Self-Protection"	Article
Stanovich and West	(2000)	"Individual Differences in Reasoning: Implications for the Rationality Debate?"	Article
Hastie	(2001)	"Problems for Judgment and Decision Making"	Article

Author	Year	Title	Type
Evans	(2003)	"In Two Minds: Dual-Process Accounts of Reasoning"	Article
Slovic et al.	(2004)	"Risk as Analysis and Risk as Feelings: Some Thoughts About Affect, Reason, Risk, and Rationality"	Article
Frederick	(2005)	"Cognitive Reflection and Decision Making"	Article
Thagard	(2005)	"Mind: Introduction to Cognitive Science"	Book
Bazerman and Moore	(2008)	"Judgment in Managerial Decision Making"	Book
Gigerenzer and Gaissmaier	(2011)	"Heuristic Decision Making"	Article
Grolemund and Wickham	(2014)	"A Cognitive Interpretation of Data Analysis"	Article
Gigerenzer and Gaissmaier	(2011)	"Heuristic Decision Making"	Article

Table 2.2: Related studies on decision-making aligned with Nudge Theory.

Author	Year	Title	Type
Kosters and Van der Heijden	(2015)	"From mechanism to virtue: Evaluating Nudge theory"	Article
Arno and Thomas	(2016)	"The efficacy of nudge theory strategies in influencing adult dietary behaviour: a systematic review and meta-analysis"	Article
Abdukadirov	(2016)	"Nudge theory in action: Behavioral design in policy and markets"	Book
Pedwell	(2017)	"Habit and the politics of social change: A comparison of nudge theory and pragmatist philosophy"	Article
Cai	(2020)	"Nudging the financial market? A review of the nudge theory"	Article

Table 2.3: Related studies on decision-making aligned with Social Choice Theory.

Author	**Year**	**Title**	**Type**
Arrow	(1951)	"Social Choice and Individual Values"	Book
May	(1952)	"A Set of Independent Necessary and Sufficient Conditions for Simple Majority Decision"	Book
Black	(1958)	"The Theory of Committees and Elections"	Book
Sen	(1970)	"Collective Choice and Social Welfare"	Book
Pattanaik	(1971)	"Voting and Collective Choice: Some Analytical Issues"	Book
Fishburn	(1973)	"The Theory of Social Choice"	Book
Plott	(1976)	"Axiomatic Social Choice Theory: An Overview and Interpretation"	Article
Sen	(1977)	"Social Choice Theory: A Re-examination"	Article
Young and Levenglick	(1978)	"A Consistent Extension of Condorcet's Election Principle "	Article
Suzumura	(1983)	"Rational Choice, Collective Decisions, and Social Welfare"	Book
Arrow and Raynaud	(1986)	"Social Choice and Multicriterion Decision-Making"	Book
Moulin	(1988)	"Axioms of Cooperative Decision Making"	Book
Young	(1995)	" Equity: In Theory and Practice"	Book
Barberà et al.	(2004)	"Handbook of Utility Theory"	Book
Gaertner	(2009)	"A Primer in Social Choice Theory: Revised Edition"	Book
Kelly	(2013)	"Social Choice Theory: An Introduction"	Book
List	(2013)	"Social Choice Theory"	Chapter
Maskin and Sen	(2014)	"The Arrow Impossibility Theorem"	Book

3 MULTI-CRITERIA DECISION MAKING

Multi-Criteria Decision Making (MCDM) offers a systematic framework for selecting or ranking competing alternatives when multiple, often conflicting, criteria are involved. This doctoral reseach deals with MCDM in depth to propose two novel MCDM models. The chapter explores the complex process of transforming numerical and verbal expressions into actionable decisions, focusing on the mathematical and geometric dimensions that shape decision making frameworks. It considers an examination of the importance of standardization and scaling, particularly in the context of data types. The discussion extends to various multi-criteria decision making methods, highlighting the similarities and differences in approaches. The potential of vectors is highlighted for considering magnitude, direction, and suitability for similarity operations. Additionally, the principles of Social Choice Theory and Preference Modeling are explored in relation to decision making, with attention given to how preferences and distance-based metrics influence outcomes. The chapter concludes with a comprehensive overview of related works on the tools and theories that guide complex decision processes.

3.1 Transformation of Decisions to Verbal and Numerical Expressions

In theoretical framework, ***Decision Theory*** provides the foundational principles for transforming decisions into both verbal and numerical expressions. It involves understanding the process of making choices under uncertainty, evaluating alternatives, and selecting the optimal course of action based on criteria such as utility, risk, and preferences (Kahneman and Tversky, 1979). Decision theory emphasizes the importance of clearly articulating decisions to ensure they are understood and actionable. On the other hand, ***cognitive psychology*** examines how individuals process information and make decisions. It provides insights into how decisions can be effectively communicated through both verbal and numerical expressions. ***Cognitive Load Theory***, for example, suggests that numerical data can simplify complex decisions by reducing cognitive demands, while verbal explanations can enhance understanding by providing context (Sweller, 1988).

For the methods of transformation the decisions, ***verbal expressions*** involve articulating decisions through spoken or written language. This method allows for detailed explanations, justifications, and contextual information, making it suitable for conveying complex decisions. Techniques such as structured interviews, decision reports, and explanatory statements are commonly used to transform decisions into verbal expressions (Bryman, 2016). ***Numerical expressions*** involve quantifying decisions using metrics, scores, or indicators. This method facilitates comparison, analysis, and visualization of decisions. Techniques such as scoring models, decision matrices, and Multi-Criteria Decision Analysis (MCDA) are employed to transform decisions into numerical expressions. Numerical expressions are particularly useful in fields such as economics, finance, and operations research, where quantitative analysis is essential (Saaty, 2008).

Certain applications serve to illuminate the transformative effects of decision expressions into concrete scenarios. For example, in business and management, decisions are often expressed numerically through key performance indicators (KPIs), financial metrics, and balanced scorecards. These numerical expressions enable managers to track performance, make data driven decisions, and communicate outcomes effectively. Verbal expressions, such as strategic plans and executive summaries, complement these numerical data by providing context and rationale (Kaplan and Norton, 2005). In healthcare, clinical decisions are transformed into numerical expressions through diagnostic scores, risk assessments, and treatment efficacy measures. These numerical data are crucial for evidence based practice and patient care. Verbal expressions, such as patient consultations and medical reports, provide the necessary context and explanation for these numerical assessments (Gawande, 2010). Public policy decisions are often expressed numerically through statistical data, cost-benefit analyses, and impact assessments. These numerical expressions help policymakers evaluate the potential outcomes and trade-offs of different options. Verbal expressions, such as policy briefs and legislative texts, articulate the decisions' goals, implications, and implementation strategies (Dunn, 2015).

3.2 Mathematical and Geometric Dimensions of Decision Expression

The expression of decisions using mathematical and geometric dimensions is a critical aspect of decision-making processes, particularly in fields such as operations research, economics, and engineering.

Mathematical Decision Theory provides the framework for quantifying and modeling decisions. It involves using mathematical models to represent decision problems, optimize outcomes, and evaluate alternatives. Key concepts include Utility Theory, Probability Theory, and optimization (Keeney, 1993). Mathematical expressions of decisions enable precise and objective analysis, facilitating rational decision making. They involve using equations, inequalities, and functions to represent decision problems. Techniques such as Linear Programming (LP), Game Theory, and Multi-Criteria Decision Analysis (MCDA) are employed to model and solve decision problems. These methods provide a structured and analytical approach to decision-making, enabling the comparison and evaluation of different alternatives (Saaty, 2008).

Geometric representation is an extension of mathematical Decision Theory, where decisions are expressed visually using geometric shapes and constructs. This approach leverages spatial relationships to illustrate decision problems and solutions. Concepts such as vector spaces, convex sets, and polyhedra are commonly used to represent decisions geometrically (Boyd and Vandenberghe, 2004). Geometric expressions use visual representations to convey decision problems and solutions. Techniques such as geometric programming, decision trees, and diagrams are employed to illustrate the relationships between variables and outcomes. Geometric representations facilitate intuitive understanding and communication of complex decision problems (Dantzig, 2016).

Although both representation methods possess significant utility, their combined application yields a more robust and comprehensible representation.

- In operations research, mathematical and geometric expressions of decisions are used to optimize resource allocation, scheduling, and logistics. Techniques such as LP and network flow models are employed to represent and solve complex decision

problems. Geometric representations, such as decision trees and flowcharts, are used to visualize decision processes (Hillier and Lieberman, 2015).

- In economics, mathematical models are used to represent and analyze decision problems related to production, consumption, and market behavior. Concepts such as utility functions, cost functions, and equilibrium models are employed to express decisions mathematically. Geometric representations, such as supply and demand curves and indifference curves, are used to illustrate economic relationships and trade-offs (Varian, 1987).

- In engineering, mathematical and geometric expressions are used to design and optimize systems and processes. Techniques such as optimization algorithms, Control Theory, and simulation models are employed to represent and solve decision problems. Geometric representations, such as block diagrams and flowcharts, are used to visualize system behavior and decision processes (Deb, 2011).

3.3 Types of Decision Data and Combination in Decision Making

The quality of decisions is heavily influenced by the types of data utilized. Decision data can generally be categorized into verbal and numerical types, which correspond to subjective (qualitative) and objective (quantitative) data, respectively. Understanding these data types and effectively combining them is crucial for developing comprehensive decision-making frameworks.

- **Objective data:** Objective data refers to quantifiable and measurable information that is independent of personal feelings or opinions. This data type is often derived from empirical observations and can be verified through repeatable experiments or calculations. Examples include statistical data, financial reports, and scientific measurements. Objective data is highly valued in decision making due to its reliability and verifiability. It provides a factual basis upon which decisions can be made, minimizing biases and errors (Citroen, 2011). However, relying solely on objective data may overlook qualitative factors that are critical in complex scenarios.

- **Subjective data:** Subjective data is based on personal opinions, interpretations, and experiences. It encompasses qualitative information that may vary from person to person, such as expert judgments, customer feedback, and personal preferences. Despite its variability, subjective data is essential in decision making because it captures human insights and emotions that are not easily quantifiable. In areas such as marketing and customer relations, subjective data provides a nuanced understanding of consumer behavior and preferences. However, the challenge lies in ensuring that subjective data is collected and interpreted consistently to avoid biases (Carlson et al., 2009).

- **Hybrid data:** Hybrid data combines elements of both objective and subjective data, providing a comprehensive view that leverages the strengths of both types. This approach acknowledges the complexity of real world decision making contexts, where both quantitative and qualitative factors must be considered. The integration of hybrid data allows for balanced decision making, accommodating both factual accuracy and human insight. It is particularly useful in MCDA, where diverse data types must be synthesized to evaluate alternatives (Merigo et al., 2016). Hybrid data supports adaptive decision making processes that can respond to dynamic environments.

Combining data types in decision making involves integrating numerical and verbal data to create a comprehensive and balanced analytical framework. This integration is crucial for addressing the multifaceted nature of real world decision making scenarios, where both quantitative and qualitative insights are vital. One key strategy for combining these data types is data integration, which utilizes techniques such as data fusion and natural language processing (NLP) to merge verbal and numerical information into a unified analytical model. Hierarchical modeling further aids this process by structuring complex relationships between different data elements, allowing decision makers to capture dependencies and interactions across data types. Additionally, MCDA offers a structured approach to evaluate and prioritize alternatives using both numerical scores and qualitative assessments, ensuring a balanced consideration of all relevant factors. The application of fuzzy idea also enhances the combination of data types by modeling the inherent

uncertainty in verbal data and integrating it with precise numerical data, which leads to nuanced decision making processes (Paramanik et al., 2022; Marković et al., 2020). By employing these strategies, decision makers can effectively synthesize diverse data types, resulting in more robust, adaptable, and informed decision making frameworks.

3.4 Standardization of Decision Data

Data standardization constitutes a fundamental component of data preprocessing, ensuring uniformity and comparability across heterogeneous datasets. In the context of MCDA, machine learning (ML), and various statistical analyses, data standardization transforms different scales, units, and ranges of data points into a common framework. This process enables effective comparisons by eliminating discrepancies arising from the diverse nature of the original data sources. Therefore, normalization and scaling are critical steps in data analysis. These techniques address issues related to multidimensionality and the varying importance of different data types, ensuring that data is appropriately standardized for MCDA. While often used interchangeably, these methods serve distinct purposes.

3.4.1 Data Normalization

Data normalization involves transforming data to have *a mean of zero* and *a standard deviation of one*. This process ensures that each feature contributes equally to the analysis, *regardless of its original scale* (Jain et al., 2000). Normalization is particularly important in algorithms that rely on distance metrics, such as k-nearest neighbors and support vector machines. Common techniques include z-score and min-max normalization. Z-score normalization adjusts data based on the mean and standard deviation, while min-max normalization transforms data to a fixed range, typically between 0 and 1 (Han and Baldwin, 2011). These methods help *mitigate the effects of outliers* and improve the performance of models. Table 3.1 presents several formulations of normalization techniques.

3.4.2 Data Scalization

Data scaling involves adjusting the range of data values to ensure that different features are on a comparable scale. This process is crucial when dealing with *multidimensional data*,

where features may have vastly *different ranges*. Scaling prevents features with larger ranges from disproportionately influencing the analysis (Bishop and Nasrabadi, 2006).

Scaling techniques include standard scaling, robust scaling, and MaxAbs scaling. Standard scaling adjusts data based on the mean and standard deviation, while robust scaling uses the median and interquartile range, making it less sensitive to outliers (Aggarwal, 2015). MaxAbs scales each feature by its maximum absolute value, preserving sparsity in the data. Table 3.1 presents several formulations of scalization techniques.

Table 3.1: Various data normalization and scaling techniques.

Technique	**Type**	**Formula**
Min-Max	Normalization / Scalization	$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$
Z-Score	Normalization	$Z = \frac{X - \mu}{\sigma}$
Unit Vector	Normalization	$X' = \frac{X}{\|X\|}$
Linear	Normalization	$X' = a + \left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) \cdot (b - a)$
Robust	Scalization	$X' = \frac{X - \text{median}}{\text{IQR}}$
MaxAbs	Scalization	$X' = \frac{X}{\|X_{\max}\|}$
Mean	Normalization / Scalization	$X' = \frac{X - \mu}{X_{\max} - X_{\min}}$
Log Transformation	Scalization	$X' = \log(X + c)$

3.4.3 Normalization versus Scalization in Decision Making

The choice between normalization and scaling depends on the specific characteristics of the data and the intended analysis. Normalization is often preferred when the distribution of data is critical for the model or analysis, as many statistical and machine learning techniques assume normally distributed data. Scaling, on the other hand, is suitable when the primary goal is to bring features to a comparable scale without altering their distributional properties.

Note that handling multidimensional data requires careful consideration of the relationships between features. Normalization and scalization are essential for ensuring that all dimensions are treated equitably, allowing for meaningful comparisons and analyses. High-dimensional data often suffers from the *"curse of dimensionality"*, where the distance between data points becomes less informative. Normalization and scaling help

mitigate this issue, improving the performance of distance-based algorithms (Bishop and Nasrabadi, 2006). They are particularly important when dealing with heterogeneous data types, such as numerical, categorical, and ordinal data (Han and Baldwin, 2011).

In the context of decision making, normalization is defined as a transformation process aimed at converting input data into numerical values that are comparable by employing a common scale. Upon the collection of input data, it is imperative to undertake preprocessing measures to ensure the comparability of criteria, thereby enhancing the utility of the data for decision modeling. Furthermore, normalization techniques in MCDM typically facilitate the mapping of attributes (criteria) with diverse measurement units to a unified range within the interval [0, 1] (Vafaei et al., 2016). However, in a multidimensional environment, it is not possible to accurately express where the data corresponds within the width of each criterion. Each criterion possesses the characteristic of independence and initially takes on values in unrelated intervals. In application phase, normalization techniques utilize the obtained data to generate ranges, whereas scaling techniques function by preserving the specific ranges of independent criteria. Therefore, although normalization is more prevalent in MCDM, it is evident that scaling also holds its significance. More specifically, while min-max scalization and min-max normalization often refer to the same mathematical process, Table 3.2 highlights their contextual differences and emphasis in usage.

For an illustrative example refer to Figure 3.1, when collecting data on air temperature, it is conceivable that the measurable values could range from [-30, 50]. In this context, a measurement of 24 degrees holds significance within this definition range *(**black** line)*. Nonetheless, when evaluating matrices with min-max normalization, the highest and lowest values are correlated with other measurement values without regard to this range *(blue line)*. Consequently, if the obtained results are 22, 25, 23, 26, and 30, positioning 24 based on these values leads to a loss of its original place within the actual range. Since the min-max scaling takes the definition range in the calculation, the position is preserved *(green line)*. In Figure 3.1, the difference is clearly illustrated in a one-dimensional context. Due to its inherent nature, the normalization process attempts to conform to a specific distribution while failing to accurately pull values into the [0, 1] range. The values cor-

Table 3.2: Comparison of min-max scalization and normalization.

Feature	**Min-Max Scaling**	**Min-Max Normalization**
Definition	Rescales feature values to a specific range.	Transforms data to fit within a defined range.
Formula	$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$	$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$
Purpose	Ensures all features contribute equally by transforming to a common scale.	Maintains relationships between distributions of data points while making them comparable.
Context of Use	Often used in machine learning preprocessing to prepare data for algorithms.	Can imply a broader context of adjusting data distributions for comparison.
Emphasis	Focuses on the adjustment of feature values.	Highlights the statistical transformation of data distributions.
Range of $X_{\min}$ and $X_{\max}$	$X_{\min}$ and $X_{\max}$ are determined from the original data's minimum and maximum values.	$X_{\min}$ and $X_{\max}$ are similarly defined from the obtained data.
Output Range	Typically [0, 1].	Typically [0, 1].

responding to [0, 1] are, in fact, derived from the measurement results. In reality, the [0, 1] interval should represent the feasible range. Therefore, employing scaling rather than normalization allows for the preservation of the data's positional context throughout the evaluation process. Otherwise, the data conforms to a distribution based on the existing values, leading to positioning that relies solely on those measurements.

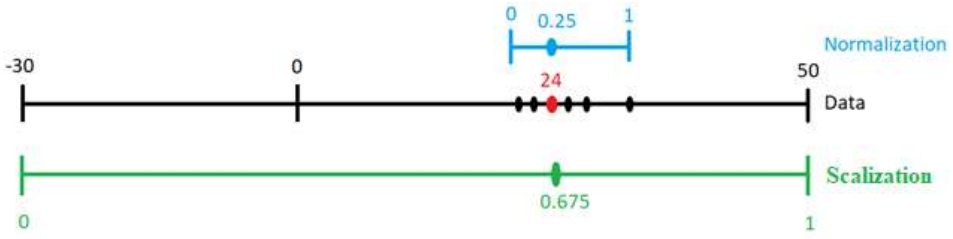


Figure 3.1: Sample for data standardization.

It is important to note that normalization and scaling can yield the same result. In fact, scaling implicitly acknowledges a process akin to normalization based on the actual range of values. In MCDM techniques, upper and lower bounds are derived from the measured data, focusing solely on the dataset itself. When considered as a fixed reference range, the

scaling performed becomes a derivative process of normalization. When each measurement is positioned relative to others within the dataset, it becomes subject to manipulation. By employing scaling that preserves the true positions of the data, volatility in the measurements can be prevented. Furthermore, no single measurement is defined in relation to another; a lower or higher evaluation of one measurement should not affect another measurement, allowing each to stand independently. Therefore, in decision making models, scaling is effective for achieving an unbiased assessment, ensuring that the data do not influence one another.

3.5 Decision Analysis

Decision analysis, as defined by B. Roy, is the process of providing answers to questions posed by participants in a decision making process through the use of a model. This decision process encompasses various strategies of intervention, including aid, communication, and justification. There are numerous approaches to providing decision support, which complicates the comparison of different methods. Consequently, defining what constitutes a "good" decision analysis model becomes challenging, as different models may yield divergent recommendations. It is important to note that definitive answers, such as an "optimal solution" or a "good decision," are often elusive within this framework. Furthermore, the models employed in decision analysis may be either formalized or informal, impacting their applicability and effectiveness in various contexts (Roy, 1972).

Decision making is a critical process across various fields, often involving multiple stakeholders with differing perspectives, objectives, and conflicting criteria for evaluating available alternatives. Multi-Criteria Decision Analysis (MCDA) (*a.k.a. Multi-Criteria Decision Making (MCDM)*) has emerged as a widely recognized research methodology designed to assist individuals and organizations in navigating complex decisions. The primary goal of MCDA is to identify the course of action that best aligns with specific objectives while considering the often conflicting views of stakeholders in a structured and transparent manner. Generally, MCDA is characterized as a decision support tool rather than a decision making process, as the ultimate choice remains with the decision

maker (DM). This methodology holds particular importance in decisions that significantly impact overall well-being.

MCDA can be categorized in various ways, one of which is based on the type of problem. Three main types of problems can be identified as follows:

- **Choice Problem:** This refers to situations where the objective is to determine the best option from a specific set of alternatives.
- **Ranking Problem:** This involves ranking alternatives according to certain criteria and prioritizing the best options.
- **Sorting Problem:** This encompasses scenarios where alternatives need to be categorized into specific groups based on defined criteria.

These problem types shape the application and objectives of MCDA methods. Additionally, methods can be established using two primary approaches. The first is ***Multi-Attribute Utility Theory (MAUT)***, a quantitative approach characterized by the principle of *"aggregate then compare"*. The second approach is ***Outranking***, which is a qualitative method that follows the principle of *"compare then aggregate"*.

3.5.1 Classification of MCDM Methodologies

Multi-Criteria Decision Making (MCDM) refers to a decision-making procedure that incorporates multiple criteria or factors in the evaluation and selection of alternatives. MCDM methods are vital as they allow decision makers to consider a broad spectrum of factors relevant to the decision at hand, which is particularly crucial in scenarios involving numerous alternatives or decisions with significant consequences (Dong et al., 2010). These methods assist decision makers in several ways: they facilitate the identification and prioritization of various criteria pertinent to the decision; enable the assessment of trade-offs between different criteria, allowing for a nuanced understanding of the implications of each choice; provide a framework for evaluating different alternatives based on the identified criteria; and support the selection of the alternative that best aligns with the decision maker's objectives while considering the relative importance of various criteria.

MCDM methods contribute to more informed, rational, and systematic decision making, particularly in complex situations where multiple factors must be considered. The properties of the criteria, alternatives, or solution set within the decision making structure serve as the basis for categorizing MCDM approaches (Arslan, 2018). Figure 3.2 presents a contemporary categorization of MCDM methods. This categorization is redesigned by the author of this thesis. It is important to acknowledge that various classifications are also possible.

As shown in Figure 3.2, a wide array of MCDM techniques is present in the literature, which can be broadly classified into Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM). Due to the extensive nature of these techniques, it is not feasible to elucidate all of their characteristics. Consequently, this thesis concentrates specifically on distance-based MADM and preference ranking MADM models, proceeding with these branches in the subsequent sections.

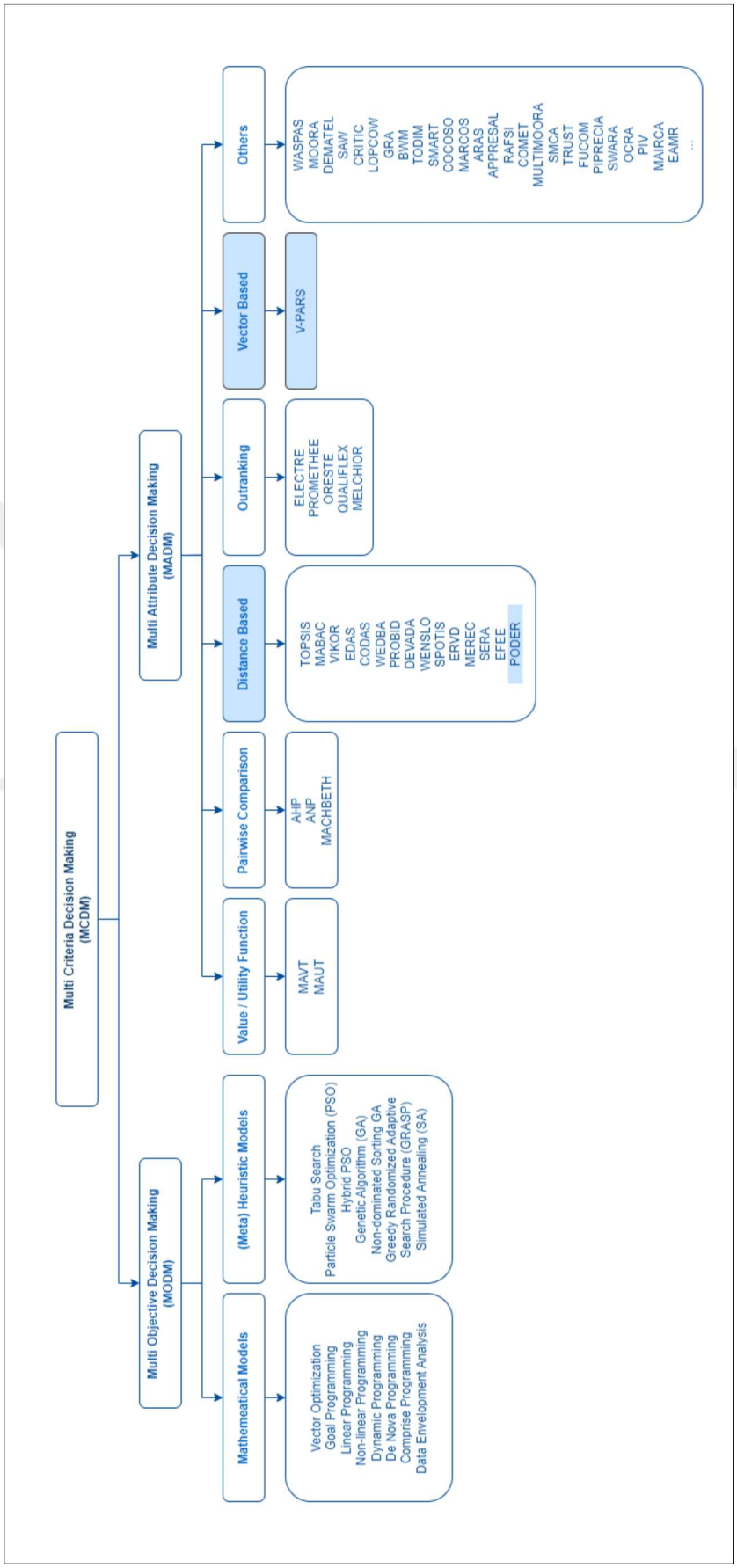


Figure 3.2: Up-to-date categorization of MCDM methodologies (Çakır and Tolga, 2024b).

3.5.2 Distance-Based MADM

Distance-based MADM methods present a unique approach for decision making processes. These methods evaluate the distance or similarity between alternatives within a multidimensional framework defined by the criteria, enabling decision makers (DMs) to rank alternatives based on their relative proximity to ideal or reference points. As part of the decision making process, DMs can specify reference points, ideal solutions, or preference structures within this multidimensional context, expressing preferences in terms of desired outcomes, acceptable ranges, or trade-offs for each criterion. Several methodologies fall under the category of distance-based MADM, each tailored to specific decision scenarios, including TOPSIS (Tzeng and Huang, 2011), MABAC (Pamučar and Ćirović, 2015), VIKOR (Opricovic, 1998), EDAS (Keshavarz Ghorabaee et al., 2015), CODAS (Keshavarz Ghorabaee et al., 2016), WEDBA (Rao and Singh, 2011) and PROBID (Wang et al., 2021).

There are some key aspects of these methodologies:

- ***Distance Measures:*** Euclidean distance, Manhattan distance, and Chebyshev distance are common measures used in MCDM to assess the difference between alternatives and ideal solutions. These distances represent the "closeness" of an alternative to either a positive ideal solution (maximizing all criteria) or a negative ideal solution (minimizing all criteria).

- ***Ideal Solutions:*** Defining ideal solutions is crucial for distance-based methods. These solutions act as reference points against which alternatives are compared. They can be constructed based on either expert judgment or through specific mathematical procedures.

3.5.2.1 Distance Metrics

A *distance metric* (or simply metric) is a function that quantifies the distance between elements in a set, allowing us to understand the structure of that set. Formally, a metric $d : X \times X \to \mathbb{R}$ must satisfy the following properties for all $x, y, z \in X$ (Munkres, 2000):

1. Non-negativity: $d(x,y) \geq 0$ and $d(x,y) = 0$ if and only if $x = y$.

2. Symmetry: $d(x,y) = d(y,x)$.

3. Triangle Inequality: $d(x,z) \leq d(x,y) + d(y,z)$.

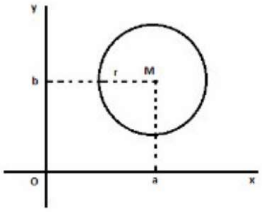
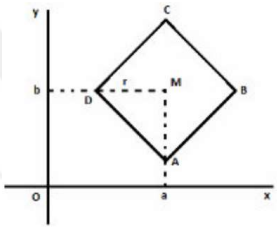
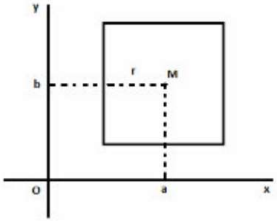
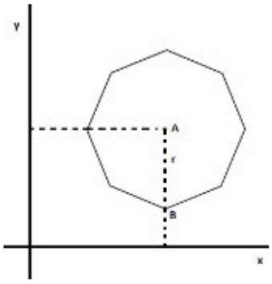
The significance of the distance metric employed is paramount, as it pertains directly to the geometric context within which the procedure is executed. Each distance metric serves to define the shortest distance between two points within specific geometries. For instance, utilizing Euclidean distance in a context governed by Manhattan geometry is inappropriate. Therefore, when developing or analyzing a model, it is essential to recognize that these distance functions indicate the geometric framework being utilized. Table 3.3 represents some distance metrics.

Table 3.3: Various distance metrics.

Distance Metric	**Description**	**Formula**
Euclidean Metric	Measures the straight-line distance between two points in a multidimensional space.	$d_{\text{euclidean}}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
Manhattan Metric (Taxicab Metric)	Calculates the distance-based on a grid-like path, summing the absolute differences of their coordinates.	$d_{\text{manhattan}}(x,y) = \sum_{i=1}^{n} \lvert x_i - y_i \rvert$
Chebyshev Metric (Maximum Metric or L∞*Metric*)	Measures the maximum distance along any coordinate dimension.	$d_{\text{chebyshev}}(x,y) = \max_i(\lvert x_i - y_i \rvert)$
Minkowski Metric	Generalizes both Euclidean and Manhattan distances, adjustable based on parameter p.	$d_{\text{minkowski}}(x,y) = (\sum_{i=1}^{n} \lvert x_i - y_i \rvert^p)^{1/p}$
Cosine Similarity	Measures the cosine of the angle between two vectors, indicating their directional similarity.	$\cos(\theta) = \frac{A \cdot B}{\lVert A \rVert \lVert B \rVert}$
Cosine Distance	Represents the dissimilarity based on the cosine similarity metric.	$d_{\text{cosine}}(A,B) = 1 - S_C(A,B)$
Chinese Checker Distance	Measures the distance on checker-like movement.	$d_{CC}(A,B) = \max\{\lvert x_1 - x_2 \rvert, \lvert y_1 - y_2 \rvert\} + (\sqrt{2} - 1) \cdot \min\{\lvert x_1 - x_2 \rvert, \lvert y_1 - y_2 \rvert\}$

To visually demonstrate the differences in distance metrics (Çolakoğlu, 2024), illustrations of circles across various geometries are presented in Table 3.4 based on the definition of a circle as "a circle as the set of points in a plane equidistant from a given point, which is the center of the circle" (Spivak, 2018).

Table 3.4: Several circle definitions in different geometries.

Geometry Name	**Circle formula with center $C(a,b)$ and radius r**	**Circle Drawing**
Euclidean Geometry	$(x-a)^2+(y-b)^2=r^2$	
Taxicab Geometry	$\|x-a\|+\|y-b\|=r$	
Chebyshev Geometry	$\max\{\|x-a\|,\|y-b\|\}=r$	
Chinese Checker Geometry	$\max\{\|x_1-x_2\|,\|y_1-y_2\|\}+(\sqrt{2}-1)\cdot \min\{\|x_1-x_2\|,\|y_1-y_2\|\}=r$	

Despite its advantages, distance-based MCDM is not free from challenges. Issues such as sensitivity to the choice of metrics, the curse of dimensionality, and the potential for subjective biases in distance metrics remain significant concerns. However, advancements in data analytics, machine learning, and the integration of hybrid decision making

approaches are aiding in the mitigation of these challenges, thereby enhancing the applicability of distance-based MCDM in contemporary decision making contexts. Table 3.5 presents a comparative overview of the distance-based MADM methods identified in the literature, along with the respective distance metrics utilized by each method.

Table 3.5: Distance metrics in various MCDM methodologies.

Method	**Distance Metric**	**Reference**
TOPSIS	Euclidean distance	(Tzeng and Huang, 2011)
MABAC	Manhattan distance	(Pamučar and Ćirović, 2015)
VIKOR	Minkowski distance and Manhattan distance	(Opricovic, 1998)
EDAS	Manhattan distance	(Keshavarz Ghorabaee et al., 2015)
CODAS	Euclidean distance and Taxicab distance	(Keshavarz Ghorabaee et al., 2016)
WEDBA	Euclidean distance	(Rao and Singh, 2011)
PROBID	Euclidean distance	(Wang et al., 2021)
DEVADA	Euclidean distance and cosine similarity	(Alkan and Kahraman, 2022)
WENSLO	Euclidean distance	(Pamučar et al., 2024)
COBRA	Euclidean distance and Taxicab distance	(Krstić et al., 2022)
MEREC	Manhattan distance	(Keshavarz-Ghorabaee et al., 2021)
SERA	Manhattan distance	(Çakır et al., 2022)
SPOTIS	Euclidean distance	(Dezert et al., 2020)
ERVD	Minkowski distance	(Shyur et al., 2015)

Some of these distance-based MADM methods are utilized for criterion weighting (score based), while others are employed for preference ranking. Each method has its own specific circumstances and procedural differences.

3.5.2.2 Determination of References

The determination of reference points is a critical component in distance-based MCDM methods. This process involves establishing ideal and anti-ideal benchmarks that serve as standards for evaluating the performance of alternatives across multiple criteria. By calculating the distance of each alternative from these reference points, decision makers can objectively assess how closely each option aligns with the optimal or suboptimal outcomes. The accuracy and relevance of the chosen references are paramount, as they significantly impact the ranking and prioritization of alternatives.

Properly defined reference points facilitate consistent and meaningful comparisons, thereby ensuring that the evaluation process accurately reflects decision criteria and preferences. In determining references for distance-based MADM methods, various approaches involves the use of various approaches, such as virtual references, average values, and the identification of minimum and maximum extremes, among others. The selection of a particular approach is contingent upon the specific method applied and the nature of the data under consideration. These methodologies may vary based on the attributes of the dataset, ensuring that the reference points accurately reflect the evaluation criteria and enable consistent comparisons across alternatives.

Furthermore, vector optimization can aid in determining references in MCDM. Methods utilizing reference vectors are particularly effective in multi-objective optimization. While multi-objective decision-making (MODM), one of the two subfields of MCDM, includes vector-based methods (Das and Dennis, 1998; Liu et al., 2013; Deb and Jain, 2013), the other branch, multi-attribute decision-making (MADM), traditionally does not encompass vector-based methods that measure similarity relative to references or perform preference outranking.

3.5.2.3 Vector Spaces

A vector space is a collection of objects called vectors, which can be added together and multiplied by numbers, known as scalars (Halmos, 1995). These vectors can represent quantities that have both magnitude and direction, such as forces or velocities. The op-

erations of vector addition and scalar multiplication must satisfy certain rules, known as axioms. These axioms include properties like closure, which means that adding two vectors together will result in another vector in the same space (Axler, 2015). Additionally, vector addition is both associative and commutative, meaning that the order of addition does not matter.

In a vector space, there is also a special vector called the zero vector, which acts as an identity element for addition. Every vector in the space has an additive inverse, ensuring that for any vector, there exists another vector that will sum to the zero vector (Lang, 2005). Scalar multiplication must also behave in a predictable way, adhering to distributive and associative properties.

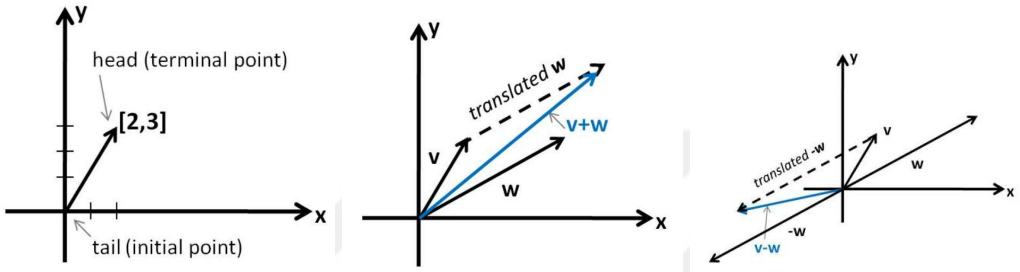
Vector spaces can be finite-dimensional, such as $\mathbb{R}^n$, where vectors are represented as ordered pairs or tuples. They can also be infinite-dimensional, like function spaces (Rudin, 1964). The concept of a vector space is fundamental in linear algebra and serves as the foundation for various mathematical and scientific applications. By studying vector spaces, we can better understand linear combinations, bases, and dimensions, which are essential for solving problems in diverse fields (Strang, 2022).

Euclidean space is a fundamental concept in both geometry and analysis, typically denoted as $\mathbb{R}^n$. It is characterized by the properties of lines, angles, and distances, providing a geometric foundation for higher-dimensional analysis.

An Euclidean n-space is the set of all n-tuples of real numbers, represented as: $\mathbb{R}^n = \{(x_1, x_2, \ldots, x_n) \mid x_i \in \mathbb{R}\}$. This space has several important features, as follows, and are illustrated with examples in Figure 3.3:

- **Vectors:** Elements of $\mathbb{R}^n$ are called vectors. Vectors are geometric entities represented as directed line segments, characterized by both a magnitude and a direction. The magnitude is indicated by the length of the vector, while the direction is represented by the orientation of the arrow at the vector's terminal point.

- **Addition and Scalar Multiplication:** Vectors in $\mathbb{R}^n$ can be added and scaled:
  - Addition: If $\overrightarrow{u} =< \overrightarrow{u_1, u_2, \ldots, u_n} >$ and $\overrightarrow{v} =< \overrightarrow{v_1, v_2, \ldots, v_n} >$, $\overrightarrow{u} + \overrightarrow{v} =< \overrightarrow{u_1 + v_1, u_2 + v_2, \ldots, u_n + v_n} >$.
  - Scalar Multiplication: For a scalar $\alpha, \overrightarrow{\alpha u} =< \overrightarrow{\alpha u_1, \alpha u_2, \ldots, \alpha u_n} >$.
- **Norm:** The norm of a vector $\overrightarrow{v}$ is given by: $\|\overrightarrow{v}\| = \sqrt{v_1^2 + v_2^2 + \ldots + v_n^2}$.



(a) A sample vector. (b) Vector addition. (c) Vector subtraction.

Figure 3.3: Sample geometric drawings for features of vectors.

Properties of vectors in Euclidean Space are as follows:

1. Zero Vector: The zero vector $< \overrightarrow{\mathbf{0}} >=< \overrightarrow{0, 0, \ldots, 0} >$ serves as the additive identity.
2. Inner (Dot) Product: The inner product of two vectors $\overrightarrow{u}$ and $\overrightarrow{v}$ in $\mathbb{R}^n$ is defined as: $\langle \overrightarrow{u}, \overrightarrow{v} \rangle = \sum_{i=1}^{n} u_i v_i$. This product relates to the angle θ between two vectors: $\langle \overrightarrow{u}, \overrightarrow{v} \rangle = \|\overrightarrow{u}\| \|\overrightarrow{v}\| \cos(\theta)$.
3. Orthogonality: Two vectors $\overrightarrow{u}$ and $\overrightarrow{v}$ are orthogonal if their inner product is zero: $\langle \overrightarrow{u}, \overrightarrow{v} \rangle = 0$.

A ***Hilbert space*** is an extension of Euclidean space that incorporates infinite dimensions while maintaining the structure of an inner product space. It is defined as a complete inner product space, meaning every Cauchy sequence of vectors converges to a limit within the space (Dunford and Schwartz, 1988).

In a Hilbert space H, the ***inner product*** is a function $\langle \cdot, \cdot \rangle : H \times H \to \mathbb{F}$ (where $\mathbb{F}$ is either $\mathbb{R}$ or $\mathbb{C}$) satisfying:

1. Conjugate symmetry: $\langle \overrightarrow{x}, \overrightarrow{y} \rangle = \overline{\langle \overrightarrow{y}, \overrightarrow{x} \rangle}$.
2. Linearity in the first argument: $\langle \overrightarrow{\alpha x} + \overrightarrow{y}, \overrightarrow{z} \rangle = \alpha \langle \overrightarrow{x}, \overrightarrow{z} \rangle + \langle \overrightarrow{y}, \overrightarrow{z} \rangle$.
3. Positive definiteness: $\langle \overrightarrow{x}, \overrightarrow{x} \rangle \geq 0 \quad \text{and} \quad \langle \overrightarrow{x}, \overrightarrow{x} \rangle = 0 \iff \overrightarrow{x} = \overrightarrow{0}$.

Note that in the context of Hilbert spaces, the dot product generalizes to the concept of an inner product. A Hilbert space is a complete inner product space, where the inner product defines the notion of angle and distance between elements (which can be vectors or functions, depending on the space). The dot product is a fundamental operation in Euclidean vector spaces that combines two vectors to yield a scalar.

A ***Banach space*** is defined as a complete normed vector space, which means it is equipped with a norm that allows for the measurement of vector lengths and satisfies the properties of a metric space (Banach, 1932).

Properties of Banach Spaces are as follows:

1. Completeness: For every Cauchy sequence $\{x_n\}$, there exists an $\overrightarrow{x}$ in the space such that $x_n \to \overrightarrow{x}$.
2. Norm Properties: The norm satisfies:
   - Non-negativity: $\|\overrightarrow{x}\| \geq 0$ and $\|\overrightarrow{x}\| = 0$ iff $\overrightarrow{x} = \overrightarrow{0}$.
   - Homogeneity: $\|\overrightarrow{\alpha x}\| = |\alpha| \|\overrightarrow{x}\|$.
   - Triangle Inequality: $\|\overrightarrow{x} + \overrightarrow{y}\| \leq \|\overrightarrow{x}\| + \|\overrightarrow{y}\|$.

The exploration of Hilbert spaces, Banach spaces, distance metrics, and Euclidean spaces reveals a rich interplay of concepts fundamental to modern mathematics. From the geometric intuition provided by Euclidean spaces to the abstract completeness of Hilbert and Banach spaces, these structures underpin much of functional analysis and its applications. Understanding the role of inner products in defining geometry within Hilbert spaces further enhances our comprehension of vector spaces in both finite and infinite dimensions.

Figure 3.4 provides an overview of the relationships between abstract spaces. The arrows represent the "is a kind of" relationship. A normed vector space is inherently a metric space, as the norm induces a metric that measures the distance between vectors. However, without an explicitly defined topology, a vector space does not automatically satisfy the conditions necessary to be considered a topological space, as it lacks the notions of proximity, continuity, or distance.

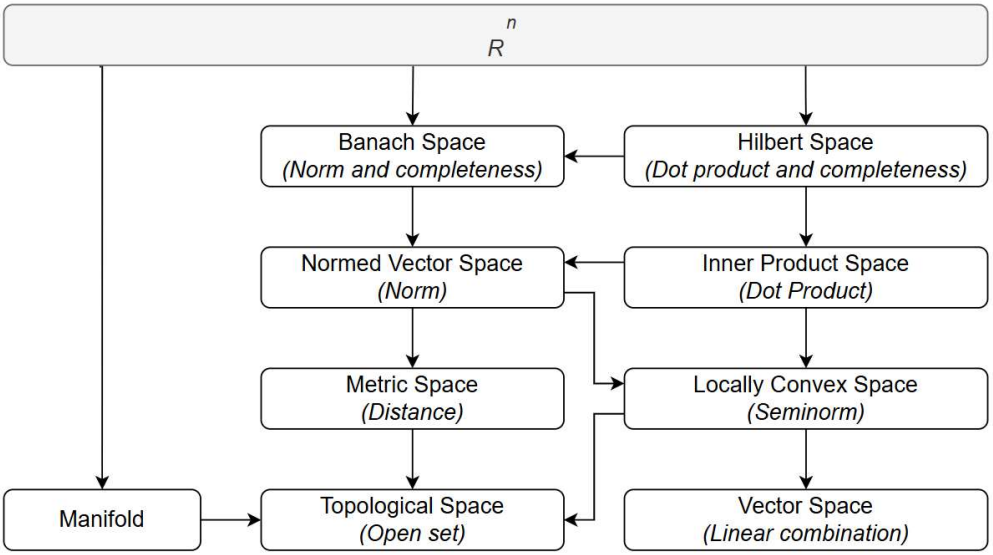


Figure 3.4: Overview of types of abstract spaces.

3.5.3 Preference Ranking and MADM

3.5.3.1 Preference Modeling

Preference modeling serves as a foundational element in outranking decision making processes across various domains, providing a structured framework for capturing and quantifying individual or collective preferences. This concept acknowledges that decision making inherently involves trade-offs among alternatives, each defined by distinct attributes or criteria. Preference modeling is rooted in Decision Theory and Social Choice Theory. Notably, Von Neumann and Morgenstern's Utility Theory, introduced in 1944, established the groundwork for understanding how individuals make choices based on their preferences, defining utility as a measure of satisfaction (Von Neumann and Morgenstern, 1947). Arrow's Impossibility Theorem, presented in 1951, further highlighted

the complexities of aggregating individual preferences into a coherent societal choice, thereby enriching the theoretical framework of preference modeling (Arrow, 1951).

Understanding preferences necessitates an exploration of cognitive aspects and behavioral patterns. Tversky and Kahneman's Prospect Theory, developed in 1979, revolutionized preference modeling by recognizing the influence of psychological factors and the impact of framing on decision making (Kahneman and Tversky, 1979). Additionally, Simon's concept of Bounded Rationality, introduced in 1955, underscores the limitations individuals face in processing information, which in turn affects how preferences are formed (Simon, 1955).

The Borda Count, formulated by Jean-Charles de Borda in the 18th century, represents a novel approach by assigning points to candidates based on their ranking in each voter's preference list. This method seeks to capture nuanced voter preferences by considering complete rankings rather than binary choices. However, concerns regarding its susceptibility to strategic manipulation and the potential distortion of true preferences have been raised (Borda, 1781). Conversely, the Condorcet method emphasizes pairwise comparisons among candidates, aiming to identify a candidate who would win in head-to-head matchups against every other candidate. While conceptually appealing, the Condorcet method encounters challenges, such as the potential for circular majorities, complicating the determination of a clear Condorcet winner. Nevertheless, it offers valuable insights into the relative preferences of candidates (De Condorcet, 2014).

Preference ranking is central to both the Borda and Condorcet voting theories. The Borda Count utilizes a complete ranking of candidates, assigning points based on ordinal positions, while Condorcet's method relies on pairwise comparisons to establish a comprehensive ranking that reflects the electorate's collective will. Both Borda and Condorcet developed their theories to address the limitations of earlier voting systems, with Borda striving to transcend binary choices and Condorcet seeking a method that consistently mirrors the collective will of the electorate.

Social Choice Theory extends the study of decision making to collective contexts, investigating how individual preferences aggregate into group decisions and societal outcomes.

Key questions within this theory pertain to fairness, efficiency, and representation in decision processes, addressing challenges such as Arrow's Impossibility Theorem and the paradoxes of voting. Arrow's theorem, proposed by Nobel laureate Kenneth Arrow in 1951, illustrates the inherent challenges in aggregating individual preferences into a collective decision, demonstrating that no voting system can simultaneously satisfy a set of desirable criteria, such as universality, transitivity, unanimity, independence of irrelevant alternatives, and non-dictatorship (Arrow, 1951). This theorem emphasizes the complexities of reconciling individual preferences with collective decision making, highlighting the limitations of democratic processes and voting systems.

Furthermore, the Kemeny-Young method offers an alternative approach to preference aggregation, focusing on identifying a consensus ranking that minimizes total discordance among individual preferences. By employing pairwise comparisons and iteratively refining rankings, the Kemeny-Young method aims to establish a compromise ranking that reflects the collective preferences of the group. This method provides insights into reconciling conflicting viewpoints and facilitating consensus building in decision making processes (Young, 1988a).

The integration of preference modeling, decision-making, and Social Choice Theory provides a comprehensive framework to analyze individual and collective choices, unraveling the complexities of human decision behavior and its societal ramifications. Understanding the interplay between preferences, decision processes, and social dynamics is essential for policymakers, social scientists, and practitioners to navigate complex decision landscapes, foster consensus, and promote societal well-being in an increasingly interconnected world.

3.5.3.2 Preference Aggregation

Preference aggregation constitutes a fundamental principle in the domain of political economy. It elucidates the processes through which individual preferences and opinions are synthesized to formulate collective decisions, which are ultimately reflected in policy enactments (Sen, 2014). This aggregation is significantly influenced by the structural characteristics of political institutions within a given nation or community, exemplified

by the prevalent mechanism of political elections (Arrow, 1951).

Engaging in preference aggregation necessitates consideration of several critical components:

- *Set of alternatives:* In the context of general elections, this encompasses the political parties vying for electoral support.
- *Individuals with preferences:* This involves the rankings assigned by individuals to the available alternatives, such as their evaluations of political parties.
- *Aggregation rule:* This rule facilitates the combination of individual preferences into a singular outcome that represents the collective choice, such as majority rule.

Social Welfare Functions

The aforementioned aggregation rule bears resemblance to a Social Welfare Function, which systematically correlates individual preference orderings with a corresponding social ordering of alternatives (Moulin, 1988). Essentially, this process articulates the collective aspirations of the group. Common examples of social welfare functions include:

- Utilitarian Function: This approach considers the aggregate of individual utilities, expressed mathematically as $W = u(x) + u(y)$ for two individuals x and y, where W signifies the social welfare function (Harsanyi, 1986).
- Rawlsian Function: This perspective emphasizes the welfare of the least advantaged members of society, represented as $W = \min[u(x), u(y)]$ for the same two individuals (Rawls, 1971).

Various schools of political thought underpin distinct social welfare functions. For instance, the democratic system—widely recognized as the predominant mode of governance—draws upon an interpretation of Jean-Jacques Rousseau's concept of the general will, as articulated in *The Social Contract* (Rousseau and Dreyfus-Brisac, 1896). In this

framework, the outcome of the democratic process is conceived as a "public and solemn declaration of the general will on an object of common interest."

In democratic systems, voting rules are fundamental mechanisms to reach a collective decision among a group of individuals. Social Choice Theory examines these rules, exploring how they can best reflect the preferences of the electorate while considering issues of fairness, manipulation, and efficiency. The fundamentals of several prominent voting methods are explained as follow:

Plurality Voting

In Plurality voting, each voter selects a single candidate. The candidate with the most votes wins, making this a "first-past-the-post" system. In cases of a tie, a pre-established rule, such as a tie-breaking authority (e.g., "the Queen" in specific cases) or random selection, determines the winner (Niou, 2001).

Example 3.1: *(from the lecture notes provided by LAMSADE)* Consider three candidates: a, b, and c, with 21 voters distributed as follows:

- 10 voters: $a \succ b \succ c$
- 6 voters: $b \succ c \succ a$
- 5 voters: $c \succ b \succ a$

In this scenario, the Plurality voting results are:

$$a : 10 \text{ votes}, \quad b : 6 \text{ votes}, \quad c : 5 \text{ votes}$$

Thus, a is elected. However, an absolute majority (11 out of 21) prefer either b or c over a, highlighting a significant drawback of Plurality voting: it can elect a candidate not preferred by the majority.

Plurality voting is simple and easy to implement but can lead to outcomes that violate majority preferences, especially when more than two candidates are involved. It assumes

that voters vote sincerely, although strategic voting can significantly impact the outcome (Miller, 2014).

Plurality with Runoff

In Plurality with Runoff, voting occurs in two rounds:

1. In the first round, if a candidate receives more than 50% of the votes, s/he is elected.
2. If no candidate achieves an absolute majority, a runoff occurs between the top two candidates, and the winner is chosen by Plurality voting (Niou, 2001).

Using the Example 3.1 with 21 voters:

- First-round results: $a = 10$, $b = 6$, $c = 5$

Since no candidate has over 50%, a second round occurs between a and b.

In the runoff, the 5 voters who preferred c are more likely to support b over a, leading to:

$$a = 10, \quad b = 11$$

Thus, b is elected in the second round, aligning with the preferences of a larger majority.

Plurality with runoff can improve majority representation compared to simple Plurality voting. However, it remains susceptible to strategic manipulation, where voters may alter their first-round choices to influence the runoff participants (Merrill III, 1999).

Condorcet Voting Rule

Condorcet voting involves pairwise comparisons between each candidate. A candidate who wins all pairwise comparisons against other candidates is termed a "Condorcet Winner". The Condorcet criterion advocates that this candidate, if one exists, should be elected (De Condorcet, 2014; Gibbard, 1973).

Using the Example 3.1 with 21 voters:

- Pairwise comparisons reveal that b is preferred over both a (11/21) and c (16/21).

Here, b emerges as the Condorcet Winner, even though a might have won by Plurality. However, Condorcet's rule can sometimes fail to elect a winner if no candidate beats all others in pairwise comparisons, a situation known as the **Condorcet Paradox**. The Condorcet method, while theoretically appealing, can sometimes produce cyclical preferences (Condorcet Paradox), making it challenging to select a winner without additional rules (Tideman, 1995; Gehrlein, 2006).

Borda Count

The Borda Count is a ranked voting system in which each voter ranks the candidates in order of preference. Higher-ranked candidates receive fewer points, with the top-ranked candidate typically receiving the fewest (e.g., 1 point for the best option). The candidates are then ordered based on their total scores, and the candidate with the lowest score is elected (Borda, 1781). (The reverse is also true. That is, if the best option is calculated to get the highest score, the candidate with the highest score wins the election.)

Consider four candidates a, b, c, and d with three voters:

- 2 voters rank: $b \succ a \succ c \succ d$
- 1 voter ranks: $a \succ c \succ d \succ b$

After assigning and summing points from 1 to 4, the counts are a=5, b=6, c=8, d=11. Candidate a receives the lowest Borda score and is elected, though candidate b may still be preferred in pairwise comparisons (Condorcet Winner).

Borda Count is efficient and often leads to satisfactory outcomes but can occasionally overlook the majority's top preferences. It is separable, monotonic, and incentivizes voter participation but may conflict with Condorcet's principle (Merrill III, 1999).

The Kemeny–Young Method

The Kemeny–Young method is an electoral system that uses ranked ballots and pairwise comparisons to determine the most popular choice in an election. It is a Condorcet method, meaning if a Condorcet Winner exists (a candidate who would win all pairwise comparisons), that candidate will always be ranked as the most popular choice in the Kemeny–Young ranking.

The method works by evaluating all possible rankings of candidates, calculating a "distance" score for each ranking. The distance is defined by how many pairwise comparisons in the ranking differ from the actual preferences in the ballots. The ranking with the least total distance score is selected as the winning sequence, with the first choice in this ranking being the most popular choice.

The Kemeny–Young method is sometimes referred to by other names, including the Kemeny rule, VoteFair popularity ranking, maximum likelihood method, and median relation (Kemeny, 1959; Young, 1988a).

In the following, Example 3.2 illustrates the preference aggregation based on the Kemeny–Young method:

Example 3.2: Consider an election to decide between four candidates a, b, c, and d, with the following distribution of voters' preferences:

- 42% of voters prefer: $a > b > c > d$
- 26% of voters prefer: $b > c > d > a$
- 15% of voters prefer: $c > d > b > a$
- 17% of voters prefer: $d > c > b > a$

The pairwise rankings for the Kemeny–Young method are as follows:

- $b > c$: 32% disagree

- $b > d$: 32% disagree
- $b > a$: 42% disagree
- $c > d$: 17% disagree
- $c > a$: 42% disagree
- $d > a$: 42% disagree

The total distance score for this ranking is the sum of these disagreements:

$$32 + 32 + 42 + 17 + 42 + 42 = 207$$

Since this is the Condorcet ranking, and switching any pair would overturn the majority in that pairing, the Kemeny–Young method identifies this ranking as the one with the lowest distance score. Thus, the winning ranking is:

$$b > c > d > a$$

Therefore, the winning candidate is b.

The Kemeny–Young method provides a robust method for aggregating preferences, especially when there is no clear Condorcet winner. It takes into account all possible rankings and minimizes the total number of disagreements with voters' preferences. However, it can be computationally expensive as the number of candidates increases, as the method requires comparing all possible rankings and calculating the associated distances. Despite this, it is an attractive method for scenarios where fairness and minimal disagreement are critical (Young, 1988a).

Copeland Method

The Copeland method is a voting system based on pairwise comparisons of candidates. For each pair of candidates, a comparison is made to see which candidate is preferred by a majority of voters. A candidate earns one point for every one-to-one victory and loses

one point for every loss. Ties in pairwise comparisons earn both candidates 0.5 points. The candidate with the highest total score is declared the winner (Copeland, 1951).

The Copeland method satisfies the Condorcet criterion: if a Condorcet Winner exists (a candidate who beats every other candidate in pairwise comparisons), that candidate will also win under the Copeland method. However, when no Condorcet Winner exists, the method identifies a winner based on the highest net score, reflecting broader support across all comparisons.

Using the Example 3.1 with 21 voters, the pairwise comparisons are:

- a vs. b: a wins (10/21), b loses (11/21)
- a vs. c: a wins (10/21), c loses (11/21)
- b vs. c: b wins (16/21), c loses (5/21)

Assigning points:

- a: $+1$ (win vs. b) $+1$ (win vs. c) = 2
- b: -1 (loss vs. a) $+1$ (win vs. c) = 0
- c: -1 (loss vs. a) -1 (loss vs. b) = -2

Thus, a is the winner with a total Copeland score of 2, despite b being the Condorcet Winner in pairwise comparisons.

The Copeland method is straightforward and effectively identifies the Condorcet Winner if one exists. It reflects the overall competitiveness of candidates in all pairwise comparisons, rather than just focusing on total or majority votes. However, it can sometimes lead to ties or rankings that do not reflect voter preferences accurately when there are many close comparisons. The method is less susceptible to strategic voting but does not fully resolve situations involving cycles or ties (as seen in the Condorcet Paradox) (Moulin, 1986).

Desirable Properties of a Democratic Voting Method

When designing a democratic voting system, it is aimed for a method that embodies fairness, consistency, and effectiveness in representing the preferences of voters. A truly democratic system should ideally meet several desirable principles that ensure that the method respects the will of the voters and produces outcomes that are representative, efficient, and resistant to manipulation (Arrow, 1951; Tideman, 1995; Gehrlein, 2006).

A key expectation from a democratic voting system is that it should always yield a result similar to the Borda Count method. The Borda Count works by ranking candidates based on the aggregated preferences of all voters, ensuring that the candidate who best reflects the collective will is chosen (Borda, 1781; Nurmi, 1999). Similarly, a fair method should always elect the Condorcet winner — the candidate who would win in every possible pairwise competition against other candidates. This ensures that the most preferred candidate, based on majority support, emerges as the winner (De Condorcet, 2014).

Moreover, the voting method should be consistent with respect to withdrawals. If a candidate withdraws from the race, the outcome should not drastically change unless the withdrawal significantly alters the preferences of the voters (Gehrlein, 2006). This consistency ensures that the voting system remains stable and predictable in the face of candidate withdrawals or other changes. Additionally, monotonicity is a crucial property — a voting system should ensure that if a candidate gains more support from voters, their ranking should either improve or remain unchanged. In other words, if a voter moves a candidate up in their preference list, that candidate's chances of winning should not be harmed (Gibbard, 1973).

Another important feature is that the method must be separable. This means the system should be capable of dealing with complex scenarios where voters have different, often divided, preferences across multiple dimensions or issues (Gehrlein, 2006). Furthermore, the voting system should incentivize voter participation by encouraging honest voting. Voters should have a clear reason to vote truthfully, without fear that their votes will be manipulated or exploited (Faliszewski et al., 2017). Finally, the method should be designed in such a way that it is resistant to manipulation. Voters should not be able to

strategically misrepresent their preferences in order to influence the outcome in their favor (Gibbard, 1973; Satterthwaite, 1975).

While these principles form the ideal for any democratic voting system, Arrow's Theorem reveals a fundamental problem: it is impossible to design a voting system that satisfies all these principles simultaneously (Arrow, 1951).

Arrow's Impossibility Theorem

Arrow's Theorem, developed by Kenneth Arrow in 1951, demonstrates that no voting method can simultaneously satisfy all of the five principles that define a fair and democratic system (Arrow, 1951). According to Arrow, if there are three or more candidates in an election, it is impossible to create a voting method that fully satisfies the following criteria:

- $n \geq 3$ candidates (If there are fewer than three candidates, the plurality method can be used, and the problem does not arise).
- $m \geq 2$ and finite voters.
- Voters rank candidates in an ordered list, denoted by $\succsim_i$ for each voter i, where the order reflects their preferences.
- The collective preference, representing the result of the voting process, is denoted by $\succsim$.

Arrow sought to determine whether it was possible to find a voting system that could satisfy a limited set of principles that are widely considered desirable (Arrow, 1951; Gehrlein, 2006). These principles form the foundation of what is needed for a fair and representative electoral system. Arrow identified five key principles that any democratic voting system should ideally meet:

1. *Universality:* The method should be able to handle any configuration of preferences, meaning that it must be able to work with any set of rankings submitted by

voters. This implies that there should be no restrictions on how voters can express their preferences.

2. *Transitivity:* The result of the voting method should be a clear, ordered ranking of candidates. The final outcome should be logically consistent, ensuring that the preferences of the collective group make sense in a transitive manner.

3. *Unanimity:* If every voter prefers one candidate over another, the method must respect this unanimous preference. This principle ensures that if all voters agree on one candidate being preferable to another, the system must reflect that agreement in the final ranking. ($\forall x, y\ [x \succsim_i y \quad \forall i = 1, \ldots, m] \Rightarrow x \succsim y$)

4. *Absence of dictatorship:* The method should not allow for any one voter, or a small group of voters, to unilaterally control the outcome of the election. This principle ensures that no individual or group can dictate the outcome regardless of the preferences of others. ($\exists_{i_0}, \forall x, y\ [x \succsim_{i_0} y \Rightarrow x \succsim y]$)

5. *Independence of irrelevant alternatives:* The comparison between two candidates should depend only on how they are ranked relative to each other by the voters. The introduction of an irrelevant candidate should not change the relative ranking of the remaining candidates. ($\forall x, y, [\forall i = 1, \ldots, m, \quad x \succsim_i y \iff x \succsim'_i y] \Rightarrow [x \succsim y \iff x \succsim' y]$)

Arrow's Theorem proves that no voting system can simultaneously satisfy all of these five principles when there are three or more candidates. This result means that, by definition, all voting methods will violate at least one of the principles, making it impossible to design a "perfect" democratic voting system. To illustrate this, consider two popular voting methods:

- The Borda Count satisfies universality, transitivity, and unanimity, meaning it can handle any set of preferences, produce a consistent ranking, and reflect unanimous preferences. However, it violates the principle of independence of irrelevant alternatives. This means that the introduction of a candidate who is irrelevant to voters' preferences can alter the rankings of other candidates (Borda, 1781).

- The Condorcet method satisfies universality, independence, and unanimity. It always elects the candidate who would win in every pairwise comparison. However, it cannot guarantee transitivity. This means that in certain situations, the collective preferences may produce intransitive cycles, where no candidate is the overall winner (De Condorcet, 2014).

Therefore, Arrow's Theorem establishes that any voting system will have inherent trade-offs and will necessarily violate at least one of the desirable principles of fairness and consistency. While voting methods like Borda and Condorcet provide certain benefits, they also come with limitations that cannot be overcome without violating other principles (Arrow, 1951; Gehrlein, 2006).

Please note the following explanation for the vector-based preference ranking model proposed in this thesis.

After considering existing preference methods for voting, imagine a system that calculates preferences using a real distance measure (continuous) instead of a discrete ordinal scoring system (a kind of Borda Count). In this system, preferences would be expressed through vectors, which would represent both agreement and disagreement. These vectors would reflect the degree of preference by measuring the exact distance between the different choices (a kind of Kemeny-Young). This approach would allow preferences to be calculated with precise measurements, considering the exact values of the winner or loser in the decision making process (a kind of Copeland). The characteristics of the proposed method are comprehensively analyzed in Section 8.4.1.

It is important to not that the proposed method does not specifically address Arrow's Theorem or refer to its fundamental development. However, the concepts introduced here lay the groundwork for the advancement of distance-based MCDM techniques. Based on some features of preference aggregation techniques in Voting Theory, a new branch for the exploration of vector-based MADM is emerged by this doctoral thesis.

3.5.3.3 Outranking MADM

Outranking methods are pivotal in the field of Multi-Attribute Decision Making (MADM) subset. In addition to some distance-based MADM techniques such as TOPSIS, VIKOR, WEDBA etc. outranking methods are fully designed to evaluate and rank multiple alternatives based on several criteria, enabling decision makers to establish a preference order. The core idea behind outranking is to compare alternatives pairwise and determine the extent to which one alternative is preferred over another, taking into account the decision maker's preferences and the relative importance of criteria (Roy, 1991).

Outranking methods differ from other MADM techniques by allowing for partial comparability of alternatives. This means that instead of forcing a strict ranking among alternatives, outranking methods can acknowledge situations where one alternative is better than another according to some criteria but worse according to others. This flexibility is crucial in complex decision making scenarios where trade-offs are necessary, and crisp rankings may not be possible or desirable (Figueira et al., 2005).

The PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) method is a prominent outranking technique that computes both positive and negative outranking flows for each alternative. These flows illustrate the degree to which one alternative outperforms another across all criteria. By analyzing these flows, PROMETHEE establishes a comprehensive partial and complete ranking of the alternatives, enabling decision makers to not only identify the best overall option but also understand the comparative strengths and weaknesses of each alternative in specific aspects. This method is particularly useful in applications where a detailed comparison of alternatives is required across multiple dimensions (Brans et al., 1986).

ELECTRE (ÉLimination Et Choix Traduisant la REalité), in contrast, assesses how effectively one alternative surpasses another by evaluating concordance and discordance sets. This approach considers both the strengths and weaknesses across different criteria, providing a nuanced view of the alternatives. Furthermore, ELECTRE is particularly adaptable, as it can incorporate weights or veto thresholds, accommodating scenarios where certain criteria may carry more weight than others in the decision making process

(Benayoun et al., 1966).

The QUALIFLEX (QUALItative FLEXible) method is a ranking approach created by Paelinck during the 1970s. This method enhances Jacquet-Lagreze's permutation technique and provides significant flexibility by handling both quantitative and qualitative data at the same time (Paelinck, 1978; Zhang and Xu, 2015). It involves evaluating all potential permutations of alternatives, conducting pairwise comparisons for each criterion. For every permutation, the method calculates indices of conformity and non-conformity between alternative pairs. The permutation that achieves the highest conformity index is deemed the optimal one, assisting in identifying the best alternative through its ranking. This capability to encompass diverse data types makes QUALIFLEX particularly adept for complex decision making situations where data is a blend of quantitative and qualitative elements.

The ORESTE (Organisation, Rangement Et Synthèse De Données Relationnelles) method was initially introduced by M. Roubens in 1979 as a solution to eliminate the necessity for assigning weights to criteria in decision making. By 1980, Roubens had formalized the method's algorithm, and in 1982, he applied it to address the challenge of selecting a computer system (Pastijn and Leysen, 1989). ORESTE functions as a ranking approach that relies on evaluating pairs of alternatives. It accounts for incomparability and can produce either a partial or complete ranking of options. This capability makes it particularly effective for handling conflicting decisions, especially when precise numerical data and criteria weights are unavailable (Chatterjee and Chakraborty, 2014). The method's focus on the order of alternatives and criteria makes it particularly suitable for problems involving qualitative data, although it can also accommodate quantitative or mixed data. One of the key advantages of ORESTE is its ability to streamline the decision making process by negating the need for decision makers to specify criteria weights.

The MELCHIOR method, proposed by Leclercq, extends the notion of dominance by incorporating order relations on pseudo-criteria (Leclercq, 1984). It focuses on enhancing the decision making process by considering the hierarchical structure of criteria, thereby providing a refined analysis of alternatives. The application of the MELCHIOR method

occurred in a context in which the decision makers claimed great difficulty in eliciting the weights of the criteria, which justifies the option for a multicriteria method that does not present interactions and that allows the analysis of alternatives without assigning weights to the criteria. MELCHIOR provides the evaluation of alternatives without the need to elicit the weights of the criteria, besides not considering interaction between them. For the establishment of preference relationships, the MELCHIOR method establishes three fundamental situations of comparison between alternatives: weak preference, strict preference, and veto. This makes MELCHIOR particularly valuable in situations where criteria weights are difficult to determine or when a non-weighted analysis is preferred (Maêda et al., 2021).

3.6 Related Studies in the Literature

To enhance the comprehensiveness of this study, relevant literature pertaining to MCDM including vector spaces is catalogued in Table 3.6.

Table 3.6: Related studies on MCDM.

Author	**Year**	**Title**	**Type**
Wilson	(1932)	"A relation between metric and euclidean spaces"	Article
Gross	(1967)	"Abstract wiener spaces"	Paper
Saaty	(1980)	"The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation"	Book
Hwang and Yoon	(1981)	"Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey"	Book
Brans and Vincke	(1986)	"How to Select and How to Rank Projects: The PROMETHEE Method"	Article
Nashed	(1987)	"Inner, Outer, and Generalized Inverses in Banach and Hilbert spaces"	Article
Nevill and Holder	(1995)	"Scaling, Normalizing, and per Ratio Standards: An Allometric Modeling Approach"	Article
Roy	(1996)	"Multicriteria Methodology for Decision Aiding"	Book

Author	Year	Title	Type
Stearns	(2002)	"Constitutional Process: A Social Choice Analysis of Supreme Court Decision Making"	Book
Karsak	(2002)	"Distance-based Fuzzy MCDM Approach for Evaluating Flexible Manufacturing System Alternatives"	Article
Mavrotas and Diakoulaki	(2005)	"Multi-criteria branch and bound: A Vector Maximization Algorithm for Mixed 0-1 Multiple Objective Linear Programming"	Article
Páez et al.	(2008)	"A Discrete-Choice Approach to Modeling Social Influence on Individual Decision Making"	Article
Zavadskas and Turskis	(2011)	"Multiple Criteria Decision Making (MCDM) Methods in Economics: An Overview"	Article
Gal et al.	(2013)	"Multicriteria Decision Making: Advances in MCDM Models, Algorithms, Theory, and Applications"	Book
Asemi et al.	(2014)	"Fuzzy Multi Criteria Decision Making Applications: A Review Study"	Paper
Chatterjee and Chakraborty	(2014)	"Flexible Manufacturing System Selection Using Preference Ranking Methods: A Comparative Study"	Article
Blanchard et al.	(2015)	"Inner Product Spaces and Hilbert spaces"	Article
Ho and Ma	(2018)	"The State-of-the-Art Integrations and Applications of the Analytic Hierarchy Process"	Article
Walach et al.	(2018)	"Data Normalization and Scaling: Consequences for the Analysis in Omics Sciences"	Paper
Nermend	(2023)	"Multi-Criteria and Multi-Dimensional Analysis in Decisions: Decision Making with Preference Vector Methods (PVM) and Vector Measure Construction Methods (VMCM)"	Book
Akram et al.	(2024)	"A new ELECTRE-based decision-making framework with spherical fuzzy information for the implementation of autonomous vehicles project in Istanbul"	Article
Otay et al.	(2024)	"Evaluation of sustainable energy systems in smart cities using a Multi-Expert Pythagorean fuzzy BWM & TOPSIS methodology"	Article

4 FUZZY SET THEORY

Fuzzy Set Theory, introduced by Lotfi A. Zadeh in 1965 (Zadeh, 1965), represents a significant departure from classical set theory, offering a framework for dealing with uncertainty and imprecision. Unlike classical sets, where elements either belong or do not belong to a set, fuzzy sets allow for partial membership, quantified by a membership function ranging between 0 and 1. This literature review explores the historical development, foundational principles, and applications of Fuzzy Set Theory.

4.1 Historical Development

The inception of Fuzzy Set Theory can be traced back to Lotfi A. Zadeh's seminal paper, "Fuzzy Sets" published in 1965. Zadeh, a professor at the University of California, Berkeley, introduced the concept to address the limitations of traditional binary logic in handling real-world complexities and uncertainties (Zadeh, 1965). He proposed that instead of a strict binary classification, elements could have degrees of membership in a set, represented by a membership function. Initially, Fuzzy Set Theory faced skepticism and criticism from the academic community, primarily due to its departure from conventional mathematical rigor. Critics argued that the theory lacked precision and clarity. However, as researchers began to explore its potential applications in various fields, the theory gained acceptance and credibility (Klir and Yuan, 1995).

During the 1970s and 1980s, Fuzzy Set Theory experienced significant development and formalization. Scholars like Zadeh, Mamdani, and Sugeno further refined the theory and introduced key concepts such as fuzzy logic, fuzzy relations, and fuzzy control systems. Mamdani's work on fuzzy control systems, particularly his application to industrial processes, demonstrated the practical utility of Fuzzy Set Theory (Mamdani, 1974). Sugeno contributed to this advancement by developing the Sugeno fuzzy control model, which provided a structured approach to fuzzy inference systems and control strategies, thus expanding the application of fuzzy logic in complex decision making scenarios (Sugeno,

1985a).

From the 1990s onwards, Fuzzy Set Theory has been expanded with various extensions, including intuitionistic fuzzy set (Atanassov, 1986), neutrosophic fuzzy set (Smarandache, 1998), hesitant fuzzy set (Torra, 2010), Pythagorean fuzzy set (Yager, 2013), q-rung orthopair fuzzy set (Yager, 2017), spherical fuzzy set (Kutlu Gündoğdu and Kahraman, 2019), fermatean fuzzy set (Senapati and Yager, 2020), circular intuitionistic fuzzy set (Atanassov, 2020), decomposed fuzzy set (Çebi et al., 2022) and their variations so on.

Furthermore, Fuzzy Set Theory has been integrated with other mathematical and computational theories, such as Neural Networks (NN), Genetic Algorithms (GA), and Multi-Criteria Decision Making (MCDM). These hybrid approaches have expanded the applicability of Fuzzy Set Theory, enabling it to address more complex and dynamic problems (Pedrycz and Gomide, 1998). Fuzzy applications can generally be categorized into three main types:

- ***Control systems:*** One of the earliest and most notable applications of Fuzzy Set Theory is in control systems. Mamdani's fuzzy control system for an industrial process control demonstrated the practical utility of fuzzy logic in managing uncertain and imprecise information (Mamdani, 1974). Fuzzy control systems have since been applied in various domains, including automotive, robotics, and home appliances.

- ***Decision making:*** Fuzzy Set Theory has been extensively used in decision making processes, particularly in situations involving uncertainty and subjective judgments. Applications include risk assessment, resource allocation, and strategic planning. Fuzzy Multi-Criteria Decision Making (FMCDM) methods combine fuzzy idea with traditional MCDM techniques to evaluate and rank alternatives based on multiple criteria (Zimmermann, 2011).

- ***Artificial intelligence and machine learning:*** The integration of Fuzzy Set Theory with Artificial Intelligence (AI) and Machine Learning (ML) has led to the develop-

ment of fuzzy neural networks and fuzzy inference systems. These hybrid models leverage the strengths of both fuzzy logic and neural networks to handle uncertain and imprecise data, enhancing the performance of AI and ML systems (Pedrycz and Gomide, 1998).

4.2 Role of Fuzziness in Expressing Uncertainty

Expressing uncertain decision is a fundamental challenge in many fields, and traditional mathematical models often fall short in capturing the nuances of real world uncertainty. Fuzzy Set Theory (Zadeh, 1965), with its flexible and robust framework, offers a powerful solution for managing and reasoning with uncertain data. Its applications in control systems, decision making, and integration with other computational techniques underscore its significance in addressing the complexities of modern data driven environments. As research and development in this field continue, Fuzzy Set Theory is poised to play an increasingly vital role in handling uncertainty and enhancing decision making processes.

4.2.1 Expressing Uncertain Decision

Uncertainty in decision arises from various sources, including measurement errors, incomplete information, and variability in the phenomena being studied. It manifests in different forms, such as vagueness, ambiguity, and imprecision. Traditional binary logic and crisp sets, which require clear boundaries and precise values, often fail to capture the nuances of uncertain data (Klir and Yuan, 1995).

Classical Probability Theory has been the conventional approach for handling uncertainty. While it is effective for stochastic uncertainty, it falls short when dealing with linguistic and subjective uncertainties that cannot be easily quantified. For instance, terms like "high temperature" or "moderate risk" are vague and cannot be precisely defined using traditional mathematical models (Dubois and Prade, 1988). This limitation necessitates alternative approaches that can accommodate the fuzziness of real world data.

Fuzzy Set Theory extends classical set theory by allowing partial membership. Instead of elements either belonging or not belonging to a set, fuzzy sets assign a membership value

between 0 and 1 to each element, representing the degree of membership. This flexibility enables the modeling of vague and ambiguous concepts more effectively (Zadeh, 1965).

The core of Fuzzy Set Theory is the membership function, which defines the degree to which an element belongs to a fuzzy set. Membership functions can take various shapes, such as triangular, trapezoidal, and Gaussian, allowing for the precise modeling of different types of uncertainty. This adaptability makes fuzzy sets particularly useful in applications where boundaries are not well-defined (Zimmermann, 2011).

4.2.2 Importance of Fuzzy Set Theory in Decision Making

Fuzzy Set Theory is particularly effective in dealing with linguistic variables, which are qualitative descriptions of data. Terms like "hot," "cold," "high," or "low" can be modeled using fuzzy sets, allowing for more intuitive and human-like reasoning. This capability is crucial in fields such as artificial intelligence, where understanding and processing natural language is essential (Zadeh, 1965).

One of the earliest and most successful applications of Fuzzy Set Theory is in control systems. Fuzzy controllers have been widely used in industrial processes, automotive systems, and consumer electronics, where they provide robust performance in the presence of uncertainty. The ability to model imprecise inputs and generate appropriate control actions has made fuzzy controllers a popular choice in various domains (Pedrycz and Gomide, 1998).

Fuzzy Set Theory has been extensively applied in decision making processes, particularly in scenarios involving multiple criteria and subjective judgments. Fuzzy Multi-Criteria Decision Making (FMCDM) methods combine fuzzy idea with traditional decision making techniques to evaluate and rank alternatives based on defined criteria. This approach allows for comprehensive and realistic assessments, improving the quality of decisions (Bellman and Zadeh, 1970). The integration of Fuzzy Set Theory with other computational techniques, such as neural networks, genetic algorithms, and machine learning, has led to the development of hybrid models that leverage the strengths of each approach. These models are capable of handling complex and dynamic systems, providing accurate

and reliable solutions in various applications (Pedrycz and Gomide, 1998).

4.2.3 Adaptability of Fuzzy Set to Data Types

Fuzzy Set Theory has been widely embraced for its ability to handle uncertainty and imprecision in various types of data. Unlike classical set theory, which requires precise membership criteria, Fuzzy Set Theory allows partial membership, making it highly adaptable to different data types (Zadeh, 1965). This adaptability is particularly relevant in the context of complex, real world problems where data may be incomplete, noisy, or ambiguous. From numerical and categorical data to temporal, spatial, and linguistic data, fuzzy sets offer a robust framework for managing the complexities of modern data, whether qualitative or quantitative.

- ***Quantitative Data:*** In addition to the crisp set (refer to data types in Chapter 3), fuzzy sets are well-suited for handling quantitative data with imprecision. For example, in control systems, fuzzy sets can model sensor readings that are subject to noise and uncertainty. The use of appropriate membership functions allows for smooth and robust control actions (Mamdani and Assilian, 1975).

  Numerical data, which includes both discrete and continuous values, is perhaps the most straightforward to handle using fuzzy sets. In classical sets, a numerical value either belongs to a set or does not. Fuzzy sets, however, allow for degrees of membership, which can be particularly useful in scenarios where boundaries are not well-defined. Fuzzy sets provide a nuanced approach to classification, enabling more accurate modeling and decision-making in fields like meteorology, engineering, and finance.

  Temporal data involves time-related information, which can be inherently fuzzy due to the continuous nature of time and the imprecision in time-related measurements. Fuzzy sets can model temporal data effectively by allowing for flexible definitions of time intervals. This adaptability is essential in project management, scheduling, and other time-sensitive applications.

  Spatial data involves information about the physical location and arrangement of objects. Fuzzy sets can handle spatial imprecision by allowing for partial mem-

bership in spatial regions. This flexibility is particularly valuable in geographic information systems (GIS), urban planning, and environmental science.

- ***Qualitative Data:*** Fuzzy sets excel in modeling qualitative data, such as linguistic variables and subjective judgments. In natural language processing, fuzzy sets can capture the nuances of human language, enabling more intuitive human-computer interactions. The ability to represent vague terms like "high," "medium," and "low" enhances the interpretability of qualitative data (Zadeh, 1965).

  Categorical data, which consists of distinct categories, can also be effectively managed using fuzzy sets. Traditional methods may struggle with categories that are not mutually exclusive, but fuzzy sets allow for partial membership in multiple categories. This approach is particularly useful in survey analysis, market research, and other areas where human perception and judgment play a significant role.

  Linguistic data involves natural language, which is inherently imprecise and subjective. Fuzzy sets can model linguistic variables by allowing for degrees of membership, making them ideal for natural language processing and artificial intelligence applications. This adaptability enhances the ability to model human reasoning and perception in intelligent systems.

- ***Hybrid Data:*** In many real world applications, data is often a mix of quantitative/objective and qualitative/subjective information. Advanced fuzzy sets, for example fuzzy rough sets and neutrosophic sets, provide the flexibility to handle hybrid data effectively. These sets can integrate different types of data, enabling comprehensive analysis and decision making (Dubois and Prade, 1990).

  Additionally, the adaptability of these fuzzy frameworks allows them to be tailored to specific application domains, whether in finance for risk assessment, marketing for consumer behavior analysis, or environmental science for ecological modeling. As data continues to evolve and grow in complexity, the ability to manage hybrid datasets will be crucial for advancing research and practical applications across various disciplines.

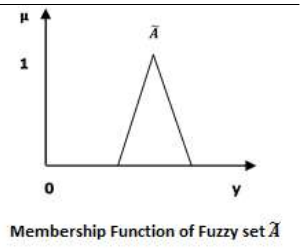
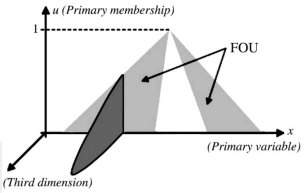
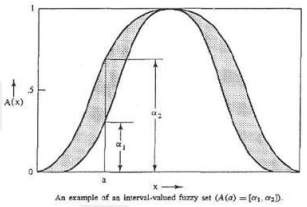
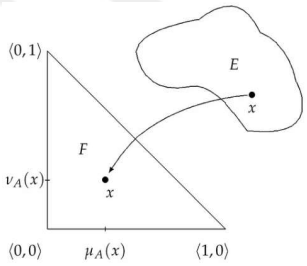
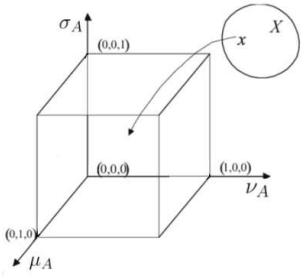
4.3 Fuzzy Sets and Extensions

Classical set theory operates on the principle that an element either belongs to a set or it does not (Zimmermann, 2011). This binary approach, rooted in classical logic, hinges on a fundamental yes-no dichotomy. However, many evaluations fall between these extremes and cannot be effectively captured by this rigid framework. The "0-1" precision of classical sets is insufficient for addressing the complexities of real life problems. Human perception and reasoning often require a more nuanced approach, as it is inherently difficult to express the uncertainty inherent in human judgments. For instance, one might inquire about an individual's age and call them as 'young'. However, this raises the question: *"is an individual who is five years older also considered 'young'? Thus, how can the relative youthfulness of these individuals be articulated?"* (Alpaydin, 2021). To address these limitations, (Zadeh, 1965) introduced Fuzzy Set Theory, which allows for the mathematical analysis of situations involving imprecision and vagueness. In Fuzzy Set Theory, the membership of elements in a set is determined by degrees, allowing a set to include elements with varying membership values. While this approach significantly improves the representation of uncertainty, some argue that it remains inadequate (Peng and Selvachandran, 2019).

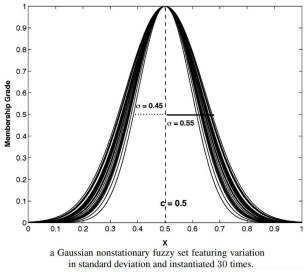
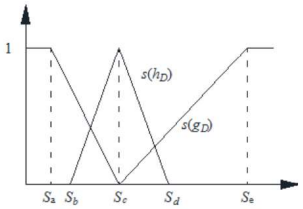
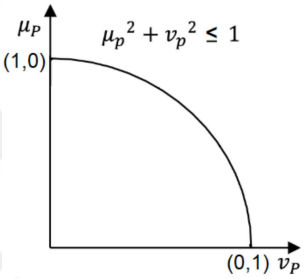
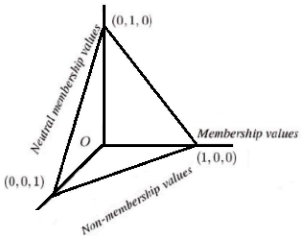
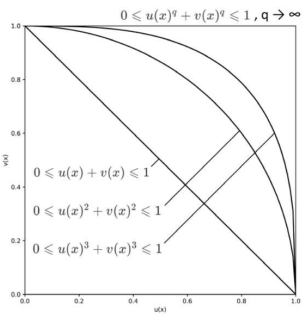
4.3.1 Main Fuzzy Sets

Over time, fuzzy sets have been expanded with various extensions. The main extensions are chronologically listed with visuals in Table 4.1 adapted from (Çakır and Taş, 2023; Donyatalab et al., 2020). There are also many side sets derived from these core sets.

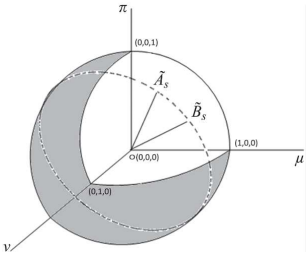
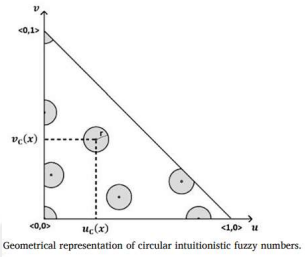
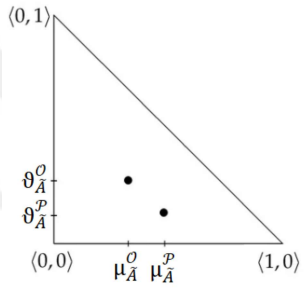
Table 4.1: Chronological extensions of main fuzzy sets.

Fuzzy Set	**Author-Year**	**Main Characteristics**	**Illustrative Example**
Ordinary fuzzy set	(Zadeh, 1965)	Elements belong to a fuzzy set with membership degrees ranging from 0 to 1.	
Type-2 fuzzy set	(Zadeh, 1975)	The membership degrees are expressed as fuzzy numbers.	
Interval-valued fuzzy set	(Zadeh, 1975)	Membership degree places inside an interval.	
Intuitionistic fuzzy set	(Atanassov, 1986)	The degree of membership and degree of non-membership are defined whose sum is ≤ 1.	
Fuzzy multi-set	(Yager, 1986)	An element of a set can form more than once with different or the same membership degrees.	The drawing of the set is not introduced to the literature.
Neutrosophic fuzzy set	(Smarandache, 1998)	Contains truth, indeterminacy, and falsity membership functions.	

Continued on next page

Fuzzy Set	Author-Year	Main Characteristics	Illustrative Example
Nonstationary fuzzy set	(Garibaldi and Ozen, 2007)	A type-1 fuzzy set that varies over time.	 a Gaussian nonstationary fuzzy set featuring variation in standard deviation and instantiated 30 times.
Hesitant fuzzy set	(Torra, 2010)	Simulates uncertainty caused by hesitation in assigning membership degrees.	 Dual hesitant triangular fuzzy number.
Pythagorean fuzzy set	(Yager, 2013)	The sum of the squares of the degrees of membership and non-membership is $\leq$ 1.	
Picture fuzzy set	(Cuòng, 2015)	Includes degrees of positive, neutral, and negative memberships.	
q-rung orthopair fuzzy set	(Yager, 2017)	The sum of the qth powers of the membership and non-membership degrees $\leq$ 1.	

Continued on next page

Fuzzy Set	Author-Year	Main Characteristics	Illustrative Example
Spherical fuzzy set	(Kutlu Gündoğdu and Kahraman, 2019)	The sum of membership, non-membership, and hesitancy degrees is ≤ 1.	
Circular intuitionistic fuzzy set	(Atanassov, 2020)	Contains a circle with a radius r that centers the membership and non-membership degrees.	 Geometrical representation of circular intuitionistic fuzzy numbers.
Decomposed fuzzy set	(Çebi et al., 2022)	Both the sum of optimistic membership and non-membership degrees and the sum of pessimistic membership and non-membership degrees are ≤ 1.	

4.3.2 Ordinary Fuzzy Set

Traditional set theory operates under binary logic, where an element either belongs to a set or does not. However, many real world scenarios are characterized by vagueness and uncertainty, necessitating a flexible approach. This is where fuzzy sets come into play. Introduced by Lotfi Zadeh in 1965, fuzzy sets allow for partial membership, providing a mathematical framework to model and reason about imprecision (Zadeh, 1965).

An ordinary fuzzy set is defined in a universe of discourse by a membership function that maps each element to a degree of membership ranging from 0 to 1. This degree signifies the extent to which an element is considered part of the fuzzy set. Among the various types of fuzzy sets, triangular fuzzy numbers are particularly prevalent in applications due to

their simplicity and intuitive representation. A triangular fuzzy number $\tilde{A}$ is characterized by a membership function defined over a continuous range of values. Specifically, it is represented by a triplet (l, m, u), where:

- l: the lower limit,
- m: the modal value (the peak of the triangle),
- u: the upper limit.

The membership function $\mu_{\tilde{A}}(x)$ for a triangular fuzzy number is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & \text{if } x < l \\ \frac{x-l}{m-l} & \text{if } l \leq x \leq m \\ \frac{u-x}{u-m} & \text{if } m < x \leq u \\ 0 & \text{if } x > u \end{cases} \tag{4.3.1}$$

This function assigns varying degrees of membership to elements based on their proximity to the modal value m. As such, values closer to m are deemed more likely to be members of the fuzzy set, while those further away receive progressively lower membership degrees. The illustration of a triangular fuzzy number is given in Figure 4.1.

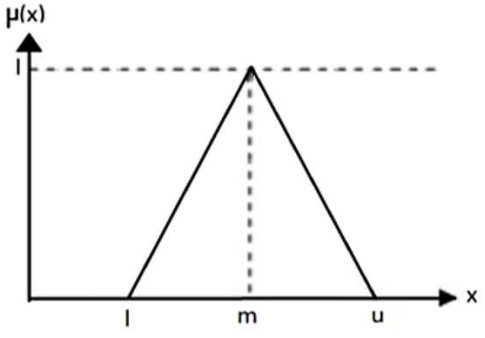


Figure 4.1: Triangular fuzzy number (l, m, u).

Similar to classical set operations, fuzzy sets support various operations, albeit tailored to accommodate the degrees of membership:

- **Union (OR)**: The union of two fuzzy sets $\tilde{A}$ and $\tilde{B}$ is defined by the maximum of their membership functions:

$$\mu_{\tilde{C}}(x) = \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x) = \max(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)) \tag{4.3.2}$$

- **Intersection (AND)**: The intersection of two fuzzy sets $\tilde{A}$ and $\tilde{B}$ is characterized by the minimum of their membership functions:

$$\mu_{\tilde{D}}(x) = \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x) = \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)) \tag{4.3.3}$$

- **Complement (NOT)**: The complement of a fuzzy set $\tilde{A}$ is defined as:

$$\mu_{\tilde{A}^c}(x) = 1 - \mu_{\tilde{A}}(x) \tag{4.3.4}$$

- **Difference**: The difference between two fuzzy sets $\tilde{A}$ and $\tilde{B}$ can be represented as:

$$\mu_{\tilde{E}}(x) = \mu_{\tilde{A}}(x) \cap (1 - \mu_{\tilde{B}}(x)) = \min(\mu_{\tilde{A}}(x), 1 - \mu_{\tilde{B}}(x)) \tag{4.3.5}$$

- **Inclusion**: A fuzzy set $\tilde{A}$ is said to be included in a fuzzy set $\tilde{B}$ if and only if:

$$\mu_{\tilde{A}(x)} \leq \mu_{\tilde{B}(x)} \tag{4.3.6}$$

4.3.3 Some Operations

Given two triangular fuzzy numbers $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$, the pseudo-arithmetic operations are defined as follows (Kaufmann and Gupta, 1985; Chen and Hwang, 1992):

- **Addition:**

$$\tilde{C} = \tilde{A} + \tilde{B} = \tilde{A} \oplus \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{4.3.7}$$

- **Subtraction:**

$$\tilde{C} = \tilde{A} - \tilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{4.3.8}$$

- **Multiplication:**

$$\tilde{C} = \tilde{A} \times \tilde{B} = \tilde{A} \odot \tilde{B}$$

$$= (\min(l_1 \cdot l_2, l_1 \cdot u_2, u_1 \cdot l_2, u_1 \cdot u_2), m_1 \cdot m_2, \max(l_1 \cdot l_2, l_1 \cdot u_2, u_1 \cdot l_2, u_1 \cdot u_2)) \tag{4.3.9}$$

- **Division:**

$$\tilde{C} = \tilde{A} \div \tilde{B} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2} \right) \tag{4.3.10}$$

  where $l_2 \neq 0$, $m_2 \neq 0$ and $u_2 \neq 0$.

The Fuzzy Weighted Averaging Operator

A vector $w = (w_1, \ldots, w_n)$ is referred to as a weighting vector if each w_i belongs to the interval [0, 1] for all $i \in [n] = \{1, \ldots, n\}$, and the sum of the weights satisfies $\sum_{i=1}^{n} w_i = 1$. Without loss of generality, we denote a fuzzy number as $\tilde{x} = (\tilde{x}_1, \ldots, \tilde{x}_n) \in \tilde{P}(\mathbb{R}^+)^n$, where each triangular fuzzy number $\tilde{x}_i = (l_i, m_i, u_i)$.

(Dong and Wong, 1987) were the pioneers in investigating the Weighted Averaging (WA) operator in situations where information cannot be precisely quantified, necessitating the use of fuzzy numbers (FNs).

Definition: The fuzzy weighted averaging operator, denoted as **FWA**, is a mapping defined as FWA : $\tilde{P}(\mathbb{R}^+)^n \to \tilde{P}(\mathbb{R}^+)$ with an associated weighting vector $(w_1, \ldots, w_n)$ such that:

$$\text{FWA}(\tilde{x}_1, \ldots, \tilde{x}_n) = \oplus_{i \in [n]} (w_i \odot \tilde{x}_i) = (\textstyle\sum_{i=1}^{n} w_i \cdot l_i, \sum_{i=1}^{n} w_i \cdot m_i, \sum_{i=1}^{n} w_i \cdot u_i)$$

$$= (WA(l_1, \ldots, l_n), WA(m_1, \ldots, m_n), WA(u_1, \ldots, u_n)) \tag{4.3.11}$$

where the pseudo-arithmetic operations $\oplus$ and $\odot$ are defined as in Equation 4.3.7 and Equation 4.3.9 (Simo and Gwét, 2018).

4.3.4 Defuzzification

Fuzzy sets are valuable for representing uncertainty, but Multi-Criteria Decision Making (MCDM) models typically require precise numerical values for their operations. To

address this challenge, defuzzification techniques convert fuzzy numbers into a single representative real number. This section discusses three widely used defuzzification methods specifically designed for triangular fuzzy numbers.

- ***Centroid Method:*** The centroid method determines a fuzzy number's defuzzified value by finding the center of gravity of its associated membership function. This method balances the area beneath the curve of the membership function, yielding a crisp value that reflects the "center of mass" of the fuzzy set. The formula for the centroid method is given by:

$$M(\tilde{A}) = \frac{\sum_{i=1}^{n} x_i \cdot \mu_{\tilde{A}}(x_i)}{\sum_{i=1}^{n} \mu_{\tilde{A}}(x_i)} \tag{4.3.12}$$

  where x_i represents the elements in the universe of discourse, and $\mu_{\tilde{A}}(x_i)$ denotes the membership function of the fuzzy number (Yager, 1996).

- ***Maxima Method:*** Triangular fuzzy numbers are characterized by a distinct peak in their membership function, which signifies the modal value within the fuzzy set. The maxima-based defuzzification method takes advantage of this feature to extract a single crisp value as follows:

$$M(\tilde{A}) = m \tag{4.3.13}$$

  where m represents the modal value of the triangular fuzzy number $\tilde{A} = (l, m, u)$ (Yager, 1996).

- ***Mean Method:*** The mean method utilizes a ranking function $g : F(\mathbb{R}) \to \mathbb{R}$, which maps each fuzzy number onto the real line, thus establishing a natural order. According to (Asady and Zendehnam, 2007), this defuzzification method minimizes the distance between two fuzzy numbers. For a triangular fuzzy number $\tilde{A} = (l, m, u)$, the formula for distance minimization is expressed as:

$$M(\tilde{A}) = \frac{l + 2m + u}{4} \tag{4.3.14}$$

  Note that the first of maxima, last of maxima, mean, and centroid methods yield identical results for symmetric triangular fuzzy numbers.

4.3.5 Ranking Rules by Defuzzification Functions

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy numbers, and let $M(\tilde{x})$ represent the defuzzification function. The ranking rules based on defuzzification are defined as follows (Saeidifar, 2011):

$$M(\tilde{A}) > M(\tilde{B}) \iff M(\tilde{A}) \succ M(\tilde{B}) \tag{4.3.15}$$

$$M(\tilde{A}) < M(\tilde{B}) \iff M(\tilde{A}) \prec M(\tilde{B}) \tag{4.3.16}$$

$$M(\tilde{A}) = M(\tilde{B}) \iff M(\tilde{A}) \approx M(\tilde{B}) \tag{4.3.17}$$

$$M(\tilde{A} \oplus \tilde{B}) = M(\tilde{A}) + M(\tilde{B}) \tag{4.3.18}$$

The order relations $\succeq$ and $\preceq$ are formulated as:

$$\tilde{A} \succeq \tilde{B} \iff \tilde{A} \succ \tilde{B} \text{ or } \tilde{A} \sim \tilde{B} \tag{4.3.19}$$

$$\tilde{A} \preceq \tilde{B} \iff \tilde{A} \prec \tilde{B} \text{ or } \tilde{A} \sim \tilde{B} \tag{4.3.20}$$

4.4 Related Studies in the Literature

To enhance the comprehensiveness of this study, relevant literature pertaining to Fuzzy Set Theory is catalogued in Table 4.2.

Table 4.2: Related studies on Fuzzy Set Theory.

Author	**Year**	**Title**	**Type**
Zadeh	(1965)	"Fuzzy Sets"	Article
Bellman and Zadeh	(1970)	"Decision-making in a fuzzy environment"	Article
Zadeh	(1973)	"Outline of a new approach to the analysis of complex systems and decision processes"	Article
Mamdani and Assilian	(1975)	"An experiment in linguistic synthesis with a fuzzy logic controller"	Article
Zadeh	(1978)	"Fuzzy Sets as a Basis for a Theory of Possibility"	Article
Dubois and Prade	(1980)	"Fuzzy Sets and Systems: Theory and Applications"	Book
Bezdek	(1981)	"Pattern Recognition with Fuzzy Objective Function Algorithms"	Book
Takagi and Sugeno	(1985)	"Fuzzy identification of systems and its applications to modeling and control"	Article
Kaufmann and Gupta	(1985)	"Introduction to Fuzzy Arithmetic"	Book
Sugeno	(1985b)	"An introductory survey of fuzzy control"	Article
Ruspini	(1986)	"A new approach to clustering"	Article
Baldwin	(1990)	"A new approach to approximate reasoning using a fuzzy logic"	Article
Lee	(1990)	"Fuzzy logic in control systems: Fuzzy logic controller"	Article
Dubois and Prade	(1990)	"Rough fuzzy sets and fuzzy rough sets"	Article
Kosko	(1992)	"Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence"	Book
Kandel	(1992)	"Fuzzy Mathematical Techniques with Applications"	Book

Author	Year	Title	Type
Tanaka and Sugeno	(1993)	"Stability analysis and design of fuzzy control systems"	Article
Giles	(1994)	"A computer-oriented concept of fuzzy subsethood"	Article
Yager and Filev	(1994)	"Essentials of Fuzzy Modeling and Control"	Book
Klir and Yuan	(1995)	"Fuzzy Sets and Fuzzy Logic: Theory and Applications"	Book
Mizumoto and Tanaka	(1996)	"Some properties of fuzzy sets of type-2"	Article
Wang	(1997)	"A Course in Fuzzy Systems and Control"	Book
Pedrycz	(1998)	"Fuzzy Control and Fuzzy Systems"	Book
Yen and Langari	(1999)	"Fuzzy Logic: Intelligence, Control, and Information"	Book
Novák et al.	(1999)	"Mathematical Principles of Fuzzy Logic"	Book
Mendel	(2001)	"Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions"	Book
Kahraman et al.	(2003)	"Multi-criteria supplier selection using fuzzy AHP"	Article
Ross	(2004)	"Fuzzy Logic with Engineering Applications"	Book
Zimmermann	(2011)	"Fuzzy Set Theory—and Its Applications"	Book
Kaya et al.	(2019)	"A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making"	Article
Jeon et al.	(2023)	"An innovative probabilistic hesitant fuzzy set MCDM perspective for selecting flexible packaging bags after the prohibition on single-use plastics"	Article
Çakır and Taş	(2023)	"Circular intuitionistic fuzzy decision making and its application"	Article
Bouraima et al.	(2023)	"An integrated fuzzy MCDM model for prioritizing strategies for successful implementation and operation of the bus rapid transit system"	Article
Alkan and Kahraman	(2024)	"CODAS extension using novel decomposed Pythagorean fuzzy sets: Strategy selection for IOT based sustainable supply chain system"	Article

Author	Year	Title	Type
Aydoğan et al.	(2024)	"A Decision-Making Approach Incorporating TODIM Method and Sine Entropy in q-Rung Picture Fuzzy Set Setting"	Article
Kahraman	(2024)	"Proportional picture fuzzy sets and their AHP extension: Application to waste disposal site selection"	Article

5 PROPOSED MODELS

In this chapter, two novel Multi-Criteria Decision Making (MCDM) models are introduced: POndération sur la Distance par ExtRaction (PODER) for criteria weighting and the Vector-Based Preference Ranking System (V-PARS) for preference ranking. These models are the culmination of extensive analysis and synthesis of the existing literature, as reviewed in the previous chapters. The PODER model offers a sophisticated approach to criteria weighting by leveraging distance-based extraction techniques, providing a nuanced and accurate method for prioritizing different factors in decision making processes. Meanwhile, V-PARS introduces an innovative vector-based methodology for ranking preferences, which enhances the ability to differentiate and evaluate alternatives effectively.

Both models aim to address the limitations and challenges identified in traditional MCDM methods, offering improved precision and adaptability in handling complex decision-making scenarios. The development of these models is informed by a thorough understanding of current trends and gaps in the field, ensuring that they are both theoretically robust and practically applicable. Detailed descriptions, including the theoretical foundations, methodological steps, and potential applications of each model, are provided in the relevant subsections, offering a comprehensive guide to their implementation and use in various decision making contexts.

5.1 POndération sur la Distance par ExtRaction (PODER)

5.1.1 Description of the Core Idea of PODER

This section introduces the novel POndération sur la Distance par ExtRaction (PODER) as a novel methodology for weighting criteria in MCDM problems based on the ideas of MEREC (Keshavarz-Ghorabaee et al., 2021) and SERA (Çakır et al., 2022). PODER offers a unique distance-based approach to assigning criteria weights that functions within Euclidean n-spaces and accommodates different levels of decision makers. It leverages

the concept of the "extraction effect" to assess the relative importance of each criterion. By systematically extracting individual criteria and observing the subsequent distance change in the overall evaluation, PODER reveals their significance within the decision making process.

PODER reveals the scores of not-presence of criteria in the evaluation system takes into account positions of objective and subjective evaluation data sets. It is presented in a hybrid structure that includes both expert driven and data driven MCDM structure. In the expert driven phase, objective and subjective evaluations are collected based on Nudge Theory and aggregated. In the data driven phase, in the light of the distance-based MCDM methods in the literature, it produces the criteria weights using Euclidean distance by extracting one element from the system which means reduce one dimension in each iteration in m-dimensional environment (i.e. m-criteria).

The expert driven phase *(Phase 1)* of PODER is aimed at proposing a hierarchical decision maker structure based on Nudge Theory, to evaluate both objective/quantitative (e.g. crisp, certain etc.) and subjective/qualitative (e.g. score, fuzzy etc.) data and to produce an aggregated decision. As noted in Chapter 4, fuzzy expressions can be applied to both objective and subjective data; however, they are generally preferred for articulating linguistic and ambiguous concepts. According to Nudge Theory, decision makers can be categorized among themselves based on their experience and knowledge. Individuals' inclination towards the status quo and their sense of being valued will nudge them to be selective and cautious during the decision making process. If this perspective is integrated into the method, the weighting metric based on Nudge Theory is proposed to determine the hierarchy between DMs as in Table 5.1.

Additionally, leveraging the anchoring bias, a concept within Nudge Theory that highlights the influence of initial information on subsequent judgments, an objective evaluation serves as a reference point for the decision-maker's subjective assessment. When combining scaled objective and subjective data, PODER assumes that objective data and subjective data have their own weights. Generally, they are weighted equally, and the two types of evaluation contribute equally to the model. Different weighting systems can be

used in subcategories. The person applying the method can suggest his/her own metric according to the case. Since this thesis introduces the model, the equally weighted version is selected.

Table 5.1: Nudge Theory based hierarchical decision maker system and group weights.

Weight	**Hierarchy**	**Code**	**Description**
0.40	Expert	DM_E	An experienced person who encounters the case frequently and can easily understand it. $DM_E = \{DM_{E_1}, DM_{E_2}, ..., DM_{E_{ep}}\}$ $W_{DM_E} = \{W_{DM_{E_1}}, W_{DM_{E_2}}, ..., W_{DM_{E_{ep}}}\}$ where $W_{DM_{E_p}} \geq 0, W_{DM_{E_p}} = \frac{0.4}{ep}$ and $\sum W_{DM_{E_p}} = 0.4$
0.30	Expert Candidate	DM_{EC}	An experienced person who rarely encounters a case and can understand it easily. $DM_{EC} = \{DM_{EC_1}, DM_{EC_2}, ..., DM_{EC_{ecp}}\}$ $W_{DM_{EC}} = \{W_{DM_{EC_1}}, W_{DM_{EC_2}}, ..., W_{DM_{EC_{ecp}}}\}$ where $W_{DM_{EC_p}} \geq 0, W_{DM_{EC_p}} = \frac{0.3}{ecp}$ and $\sum W_{DM_{EC_p}} = 0.3$
0.20	Emerging Expert	DM_{EE}	An experienced person who often encounters a case and can hardly understand it. $DM_{EE} = \{DM_{EE_1}, DM_{EE_2}, ..., DM_{E_{eep}}\}$ $W_{DM_{EE}} = \{W_{DM_{EE_1}}, W_{DM_{EE_2}}, ..., W_{DM_{EE_{eep}}}\}$ where $W_{DM_{EE_p}} \geq 0, W_{DM_{EE_p}} = \frac{0.2}{eep}$ and $\sum W_{DM_{EE_p}} = 0.2$
0.10	Beginner	DM_B	An experienced person who has rarely encountered a case and can hardly understand it. $DM_B = \{DM_{B_1}, DM_{B_2}, ..., DM_{B_{bp}}\}$ $W_{DM_B} = \{W_{DM_{B_1}}, W_{DM_{B_2}}, ..., W_{DM_{B_{bp}}}\}$ where $W_{DM_{B_p}} \geq 0, W_{DM_{B_p}} = \frac{0.1}{bp}$ and $\sum W_{DM_{B_p}} = 0.1$

In the data driven phase *(Phase 2)* of PODER, an overall evaluation is performed. Afterwards, all criteria are iteratively extracted from the evaluation system and the difference of this new exclusion point with the overall evaluation point of the alternatives is checked. Euclidean distance is used as the distance metric, because the evaluation results represent

a point in an multidimensional (*m*-criteria) environment. Measurement by extracting criterion from the system actually results in an evaluation in *m-1* dimensions. To measure the distance between decision points across different dimensions (*m* and *m-1*), it is essential to align them to the same dimension. Consequently, the missing dimension in the *m-1* representation is assigned a value of 0. It is important to note that the criteria weights differ between the evaluation in the *m* dimension and the *m-1* dimension. Therefore, the impact of the extracted criterion is not directly equal to evaluation value. The sum of these distances over the alternative evaluation shows how much impact the criteria add to the system. Therefore, weights of criteria arise.

5.1.2 Procedure of PODER

The approach of *POndération sur la Distance par ExtRaction (PODER)* can be outlined in the following steps:

PODER Phase 1: Expert Driven Model

Problem Definition

Step 1.1: Define the case. Identify the sets of alternatives $A_i = \{A_1, A_2, ..., A_n\}$ and criteria $C_j = \{C_1, C_2, ..., C_m\}$.

Step 1.2: Select the decision makers $DM_p = \{DM_1, DM_2, ..., DM_k\}$ and categorize them as $\{DM_E, DM_{EC}, DM_{EE}, DM_B\}$ according to the Table 5.1. $W_{DM} = \{W_{DM_E} = 0.4, W_{DM_{EC}} = 0.3, W_{DM_{EE}} = 0.2, W_{DM_B} = 0.1\}$ is the weight set of categorized DMs and each DM has equal weight in its category.

Note that group weights are assigned as fixed values. However, these weights may be adjusted as needed, provided that the decreasing order is maintained.

Step 1.3: Determine the linguistic expressions and corresponding values to be used in the subjective evaluation.

Data Collection

Step 1.4: Based on the criteria, collect decision matrices from the DMs. Convert all of

them to benefit type. The conversion varies according to the type of data set used.

Note that the nature of objective matrices can vary depending on the specific case. In scenarios where all decision makers share a common perspective or a particular rapport, a single objective matrix may suffice. However, when individual decision makers conduct independent measurements, separate matrices may be necessary to capture their unique viewpoints.

Aggregation

Step 1.5: Aggregate decisions of k number of DMs as $(DM_{obj})_{aggr}$ and $(DM_{sub})_{aggr}$ respectively using

- the weighted average operation for objective data.

$$(a_{ij_{obj}})_{aggr} = \sum_{p=1}^{k} w_{DM_p} \cdot (a_{ij_{obj}})_{DM_p} \quad \forall i, j \tag{5.1.1}$$

- a weighted aggregation operator for subjective data.

  $(a_{ij_{sub}})_{aggr}$:the operator varies according to the type of set used (ie. score, fuzzy etc.)

Note that alternative aggregation operators such as averaging, conjunctive, disjunctive, or mixed methods may be preferred. However, in the context of MADM, averaging functions are generally recommended for DM aggregation (Beliakov et al., 2007).

Scalization

Step 1.6: Compute the scaled decision values for aggregated DM matrices as $s((DM_{obj})_{aggr})$ and $s((DM_{sub})_{aggr})$.

To scale objective decision:

Step 1.6.1: Determine the range limits as $r_j = [r_{j\min}, r_{j\max}]$ for each criterion j according to its definition unit.

Step 1.6.2: Obtain the scaled value of each a_{ij} in the range of [0, 1] as following formula:

$$s((a_{ij_{obj}})_{aggr}) = \frac{(a_{ij_{obj}})_{aggr} - r_{j\min}}{r_{j\max} - r_{j\min}} \quad \forall i,j \tag{5.1.2}$$

To scale subjective decision:

Step 1.6.3: Calculate the score (accuracy or defuzzification) values of each subjective decision by using score function according to the set (e.g. score, fuzzy etc.).

Step 1.6.4: If the definition range of the function $r_{score} = [r_{score\min}, r_{score\max}]$ is not [0, 1], scale the value as follows.

$$s((a_{ij_{sub}})_{aggr}) = \frac{score_fonk((a_{ij_{sub}})_{aggr}) - r_{score\min}}{r_{score\max} - r_{score\min}} \quad \forall i,j \tag{5.1.3}$$

Combination

Step 1.7: The final combination of scaled aggregated decisions DM_{aggr} proposed by this research is:

$$(a_{ij})_{aggr} = \frac{\lambda_{obj} \cdot s((a_{ij_{obj}})_{aggr}) + \lambda_{sub} \cdot s((a_{ij_{sub}})_{aggr})}{\lambda_{obj} + \lambda_{sub}} \quad \forall i,j \tag{5.1.4}$$

In this context, lambdas represent the weights assigned to objective and subjective data evaluated. These values are determined by the individual applying the method to their specific problem. Depending on the application area, the researcher may select these values using the appropriate methodology.

As previously mentioned, lambda values can be adjusted based on the specific case; however, in the absence of a particular reason, it is generally advisable to set these values at 0.5. In scenarios where the evaluation consists solely of objective or subjective data (i.e., in an environment where only one type of data is present for a criterion), the lambda value for the absent evaluations can be set to 0, while the lambda value for the existing evaluations can be set to 1.

PODER Phase 2: Data Driven Model

Initial Point

Step 2.1: Calculate weighted aggregated decision matrix $w(DM_{aggr})$.

$$wa_{ij_{aggr}} = w_j \cdot (a_{ij})_{aggr} \quad \forall i, j \tag{5.1.5}$$

where $w_j \geq 0$, $w_j = 1/m$ and $\sum w_j = 1$.

Step 2.2: Create the initial point $S_{iinitial}$ for each alternative using weighted aggregated decision values $wa_{ij_{aggr}}$ as the value represented in each dimension (criterion).

$$S_{iinitial} = (wa_{i1_{aggr}}, wa_{i2_{aggr}}, ..., wa_{im_{aggr}}) \quad \forall i \tag{5.1.6}$$

Extracted Point

Step 2.3: Calculate the extracted element weighted aggregated decision matrix $w_{EC}(DM_{aggr})$ for each extracted criterion $(EC \in C_j)$.

$$w_{EC}a_{ij_{aggr}} = (w_j)_{EC} \cdot (a_{ij})_{aggr} \quad \forall i, j, EC \tag{5.1.7}$$

where $(w_j)_{EC} \geq 0$, $(w_j)_{EC} = 1/(m-1)$ and $\sum (w_j)_{EC} = 1$.

Step 2.4: Create the extracted element point $S_{i,EC}$ for each alternative using extracted element weighted aggregated decision values $w_{EC}a_{ij_{aggr}}$ as the value represented in each dimension (criterion).

$$S_{i,EC} = (w_{EC}a_{i1_{aggr}}, w_{EC}a_{i2_{aggr}}, ..., w_{EC}a_{im_{aggr}}) \quad \forall i, EC \tag{5.1.8}$$

where $a_{iEC_{aggr}} = 0$.

Impact Assessment

Step 2.5: Quantify the total impact I_{EC} of each *"extracted criterion (EC)"* on the n number of initial scores $(S_{iinitial})$ by Euclidean distance.

$$I_{EC} = \sqrt{\sum_{i=1}^{n} (S_{iinitial} - S_{i,EC})^2} \quad \forall EC \tag{5.1.9}$$

Weight Assignment

Step 2.6:Normalize the impact values to obtain final weights for each criterion.

$$w_{EC} = \frac{I_{EC}}{\sum_{EC=1}^{m} I_{EC}} \quad \forall EC \tag{5.1.10}$$

It is important to note that the specific aggregation operator, scale formula and normalization methods used in PODER depend on the type of data employed. This flexibility allows PODER to adapt to various data characteristics and model requirements.

Figure 5.1 depicts an example for extracted elements of PODER. The figure shows the initial score $(S_{iinitial})$ and extraction score $(S_{i,EC})$ results for each alternative. The sum of the distances in the same color (the distance lines of the missing criterion are in the same color) is used to calculate the weight of the criterion extracted from the system (refer to Step 2.5). POndération sur la Distance par ExtRaction (PODER) procedure is briefly given as a flowchart in Figure 5.2. The detailed background, limitations and future ideas of the PODER are discussed in Section 8.4.1.

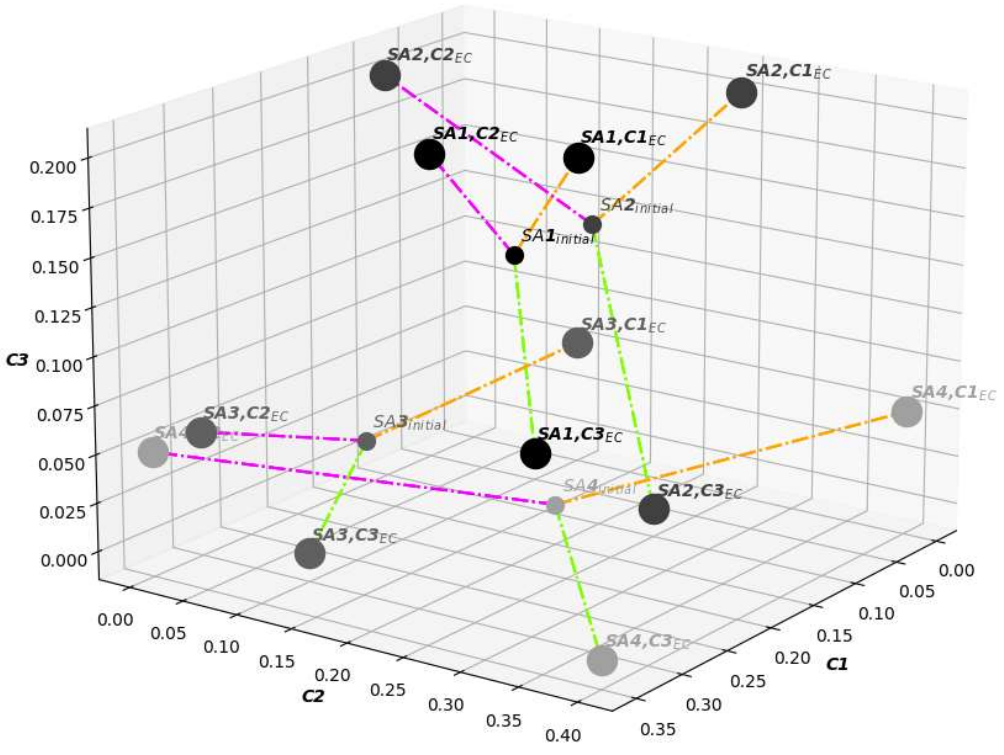


Figure 5.1: Sample geometric drawing of PODER for 4 alternatives and 3 criteria (3-dimensional environment).

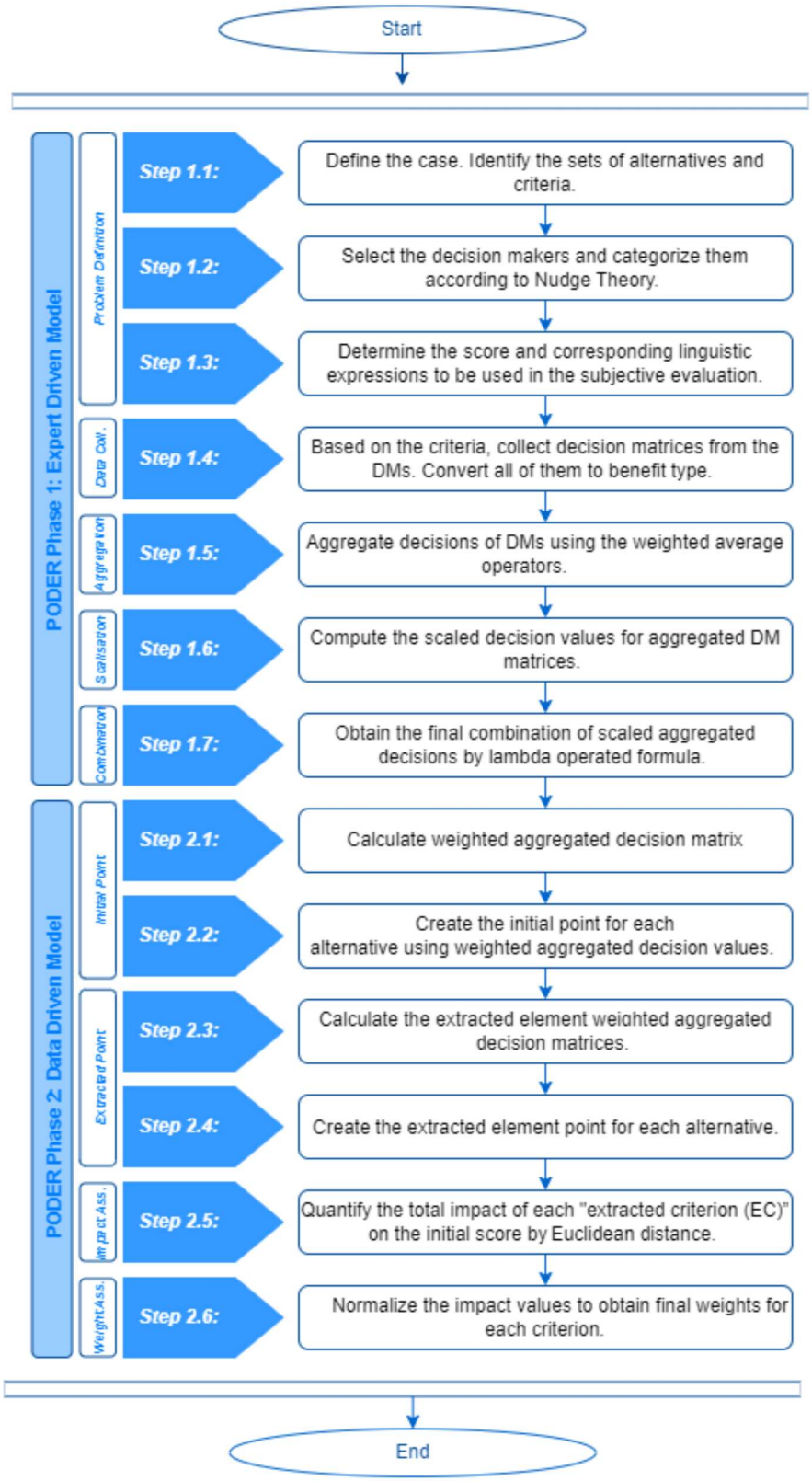


Figure 5.2: Flowchart of POndération sur la Distance par ExtRaction (PODER) procedure.

5.2 Vector-Based Preference Ranking System (V-PARS)

5.2.1 Description of the Core Idea of V-PARS

Vector-Based Preference Ranking System (V-PARS) considers preferences of alternatives based on criteria and creates vectors takes into account positions of objective and subjective evaluation data sets in the preferences. It is presented in a hybrid structure that includes both expert driven and data driven MCDM structure. In the expert driven phase, objective and subjective evaluations are collected based on Nudge Theory and aggregated. In the data driven phase, in the light of the preference ranking and distance-based MCDM methods in the literature, it ranks the alternatives with the effect of the criterion weight by creating vectors from the positions of the preference data relative to each other in m-dimensional environment (i.e. m-criteria).

The expert driven phase *(Phase 1)* of V-PARS is aimed at proposing a hierarchical decision maker structure based on Nudge Theory, to evaluate both objective/quantitative and subjective/qualitative data and to produce an aggregated decision. As noted in Chapter 4, fuzzy expressions can be applied to both objective and subjective data; however, they are generally preferred for articulating linguistic and ambiguous concepts. According to Nudge Theory, decision makers can be categorized among themselves based on their experience and knowledge. Individuals' inclination towards the status quo and their sense of being valued will nudge them to be more selective and cautious during the decision-making process. If this perspective is integrated into the method, the weighting metric based on Nudge Theory is proposed to determine the hierarchy between DMs as in Table 5.2. Additionally, leveraging the anchoring bias, a concept within Nudge Theory that highlights the influence of initial information on subsequent judgments, an objective evaluation serves as a reference point for the decision maker's subjective assessment. In general, within applications, objective data consists of precise and definitive numbers such as crisp or certain, while subjective data encompasses imprecise expressions, such as scores or fuzzy values. Notably, all data types can be employed in both directions; for instance, a fuzzy range may also be applied as objective data. It is crucial to emphasize that objective data is derived from measurements, whereas subjective data is informed by

opinions. When combining scaled objective and subjective data, V-PARS assumes that objective data and subjective data have their own weights. Generally, they are weighted equally, and the two types of evaluation contribute equally to the model. Different weighting systems can be used in subcategories. The person applying the method can suggest his/her own metric according to the case. Since this study introduces the model, the equally weighted version was selected.

Table 5.2: Nudge Theory based hierarchical decision maker system and group weights.

Weight	**Hierarchy**	**Code**	**Description**
0.40	Expert	DM_E	An experienced person who encounters the case frequently and can easily understand it. $DM_E = \{DM_{E_1}, DM_{E_2}, ..., DM_{E_{ep}}\}$ $W_{DM_E} = \{W_{DM_{E_1}}, W_{DM_{E_2}}, ..., W_{DM_{E_{ep}}}\}$ where $W_{DM_{E_p}} \geq 0, W_{DM_{E_p}} = \frac{0.4}{ep}$ and $\sum W_{DM_{E_p}} = 0.4$
0.30	Expert Candidate	DM_{EC}	An experienced person who rarely encounters a case and can understand it easily. $DM_{EC} = \{DM_{EC_1}, DM_{EC_2}, ..., DM_{EC_{ecp}}\}$ $W_{DM_{EC}} = \{W_{DM_{EC_1}}, W_{DM_{EC_2}}, ..., W_{DM_{EC_{ecp}}}\}$ where $W_{DM_{EC_p}} \geq 0, W_{DM_{EC_p}} = \frac{0.3}{ecp}$ and $\sum W_{DM_{EC_p}} = 0.3$
0.20	Emerging Expert	DM_{EE}	An experienced person who often encounters a case and can hardly understand it. $DM_{EE} = \{DM_{EE_1}, DM_{EE_2}, ..., DM_{E_{eep}}\}$ $W_{DM_{EE}} = \{W_{DM_{EE_1}}, W_{DM_{EE_2}}, ..., W_{DM_{EEeep}}\}$ where $W_{DM_{EE_p}} \geq 0, W_{DM_{EE_p}} = \frac{0.2}{eep}$ and $\sum W_{DM_{EE_p}} = 0.2$
0.10	Beginner	DM_B	An experienced person who has rarely encountered a case and can hardly understand it. $DM_B = \{DM_{B_1}, DM_{B_2}, ..., DM_{B_{bp}}\}$ $W_{DM_B} = \{W_{DM_{B_1}}, W_{DM_{B_2}}, ..., W_{DM_{B_{bp}}}\}$ where $W_{DM_{B_p}} \geq 0, W_{DM_{B_p}} = \frac{0.1}{bp}$ and $\sum W_{DM_{B_p}} = 0.1$

In the data driven phase *(Phase 2)* of V-PARS, the overall preference ranking is revealed by similarity of the total preference Euclidean vector formed in multidimensional environment (m-criteria) according to other alternatives, to the positive ideal vector. It is proposed in the lights of the Condorcet (De Condorcet, 2014), Borda Count (Borda, 1781), Kemeny-Young (Young, 1988a) and Copeland (Copeland, 1951)) idea in Social Choice Theory for enlarging distance-based MCDM procedures. These methods are not used directly but are adapted to the steps of the novel methodology V-PARS according to the data used in MCDM *(refer to Section 8.4.1, for detailed discussion)*.

5.2.2 Procedure of V-PARS

In line with the given perspectives in previous section, the steps of *Vector-Based Preference Ranking System (V-PARS)* evolved as follows:

V-PARS Phase 1: Expert Driven Model

Problem Definition

Step 1.1: Define the case. Identify the sets of alternatives $A_i = \{A_1, A_2, ..., A_n\}$ and criteria $C_j = \{C_1, C_2, ..., C_m\}$.

Step 1.2: Select the decision makers $DM_p = \{DM_1, DM_2, ..., DM_k\}$ and categorize them as $\{DM_E, DM_{EC}, DM_{EE}, DM_B\}$ according to the Table 5.2. $W_{DM} = \{W_{DM_E} = 0.4, W_{DM_{EC}} = 0.3, W_{DM_{EE}} = 0.2, W_{DM_B} = 0.1\}$ is the weight set of categorized DMs and each DM has equal weight in its category.

Note that group weights are assigned as fixed values. However, these weights may be adjusted as needed, provided that the decreasing order is maintained.

Step 1.3: Determine the linguistic expressions and corresponding values to be used in the subjective evaluation.

Data Collection

Step 1.4: Based on the criteria, collect decision matrices from the DMs. Convert all of them to benefit type. The conversion varies according to the type of data set used.

Note that the nature of objective matrices can vary depending on the specific case. In scenarios where all decision makers share a common perspective or a particular rapport, a single objective matrix may suffice. However, when individual decision makers conduct independent measurements, separate matrices may be necessary to capture their unique viewpoints.

Aggregation

Step 1.5: Aggregate decisions of k number of DMs as $(DM_{obj})_{aggr}$ and $(DM_{sub})_{aggr}$ respectively using

- the weighted average operation for objective data.

$$(a_{ij_{obj}})_{aggr} = \sum_{p=1}^{k} w_{DM_p} \cdot (a_{ij_{obj}})_{DM_p} \quad \forall i, j \tag{5.2.1}$$

- a weighted aggregation operator for subjective data.

  $(a_{ij_{sub}})_{aggr}$:the operator varies according to the type of set used (e.g. score, fuzzy etc.)

Note that alternative aggregation operators such as averaging, conjunctive, disjunctive, or mixed methods may be preferred. However, in the context of MADM, averaging functions are generally recommended for DM aggregation (Beliakov et al., 2007).

Scalization

Step 1.6: Compute the scaled decision values for aggregated DM matrices as $s((DM_{obj})_{aggr})$ and $s((DM_{sub})_{aggr})$.

To scale objective decision:

Step 1.6.1: Determine the range limits as $r_j = [r_{j\min}, r_{j\max}]$ for each criterion j according to its definition unit.

Step 1.6.2: Obtain the scaled value of each a_{ij} in the range of [0, 1] as following formula:

$$s((a_{ij_{obj}})_{aggr}) = \frac{(a_{ij_{obj}})_{aggr} - r_{j\min}}{r_{j\max} - r_{j\min}} \quad \forall i, j \tag{5.2.2}$$

To scale subjective decision:

Step 1.6.3: Calculate the score (accuracy or defuzzification) values of each subjective decision by using score function according to the set (score, fuzzy etc.).

Step 1.6.4: If the definition range of the function $r_{score} = [r_{score\min}, r_{score\max}]$ is not [0, 1], scale the value as follows.

$$s((a_{ij_{sub}})_{aggr}) = \frac{score_fonk((a_{ij_{sub}})_{aggr}) - r_{score\min}}{r_{score\max} - r_{score\min}} \quad \forall i,j \tag{5.2.3}$$

Combination

Step 1.7: The final combination of scaled aggregated decisions DM_{aggr} proposed by this research is:

$$(a_{ij})_{aggr} = \frac{\lambda_{obj} \cdot s((a_{ij_{obj}})_{aggr}) + \lambda_{sub} \cdot s((a_{ij_{sub}})_{aggr})}{\lambda_{obj} + \lambda_{sub}} \quad \forall i,j \tag{5.2.4}$$

In this context, lambdas represent the weights assigned to objective and subjective data evaluated. These values are determined by the individual applying the method to their specific problem. Depending on the application area, the researcher may select these values using the appropriate methodology.

As previously mentioned, lambda values can be adjusted based on the specific case; however, in the absence of a particular reason, it is generally advisable to set these values at 0.5. In scenarios where the evaluation consists solely of objective or subjective data (i.e., in an environment where only one type of data is present for a criterion), the lambda value for the absent evaluations can be set to 0, while the lambda value for the existing evaluations can be set to 1.

V-PARS Phase 2: Data Driven Model

Creation of Preference Euclidean Vector

Step 2.1: Calculate weighted aggregated decision matrix $w(DM_{aggr})$.

$$wa_{ij_{aggr}} = w_j \cdot (a_{ij})_{aggr} \quad \forall i,j \tag{5.2.5}$$

where $w_j \geq 0$ and $\sum w_j = 1$.

Step 2.2: Create the preference Euclidean vector $\overrightarrow{P_x R_y}$ from alternative x to alternative y according to all criteria for all pair of alternatives.

$$\overrightarrow{P_x R_y} = < \overrightarrow{P_x; R_y} > \quad \forall x, y \tag{5.2.6}$$

where point $P_x = (wa_{x1_{aggr}}, wa_{x2_{aggr}}, ..., wa_{xm_{aggr}})$, point $R_y = (wa_{y1_{aggr}}, wa_{y2_{aggr}}, ..., wa_{ym_{aggr}})$, $x, y \in A_i$ and $x \neq y$.

Step 2.3: Sum the preference Euclidean vectors that point alternative *i (which is the target point)* to obtain the total preference Euclidean vector $\overrightarrow{P_{T_i} R_{T_i}}$ for all alternatives.

$$\overrightarrow{P_{T_i} R_{T_i}} = \sum_{x=1}^{n} \overrightarrow{P_x R_i} \quad \forall i \tag{5.2.7}$$

Step 2.4: Calculate the origin based total preference Euclidean vector $\overrightarrow{OE_i}$ of alternative i for all alternatives to take them to the same reference point for comparison.

$$\overrightarrow{OE_i} = < \overrightarrow{0_1, 0_2, ..., 0_m; R_{T_i} - P_{T_i}} > \quad \forall i \tag{5.2.8}$$

Similarity to Ideal Vector

Step 2.5: Calculate the similarity S_i of origin based total preference Euclidean vector $\overrightarrow{OE_i}$ to the positive ideal Euclidean vector $< \overrightarrow{0_1, 0_2, ..., 0_m; 1_1, 1_2, ..., 1_m} >$ (in short $< \overrightarrow{1_1, 1_2, ..., 1_m} >$) by dot product for all alternatives.

$$S_i = \overrightarrow{OE_i} \cdot < \overrightarrow{0_1, 0_2, ..., 0_m; 1_1, 1_2, ..., 1_m} > \quad \forall i \tag{5.2.9}$$

where $S_i \in [-m, m]$.

Preference Ranking

Step 2.6:Rank alternatives by their similarity score. The most preferred alternative has highest score.

Note that the value of S_i has no meaning about weighting. It is a score value used only for preference ranking alternatives to represent their preferences in the system. Therefore, its use in criteria weighting is not recommended.

Figure 5.3 depicts an example for vector steps of V-PARS. Vector-Based Preference Ranking Approach (V-PARS) procedure is briefly given as a flowchart in Figure 5.4. The detailed background, limitations and future ideas of the V-PARS are discussed in Section 8.4.1.

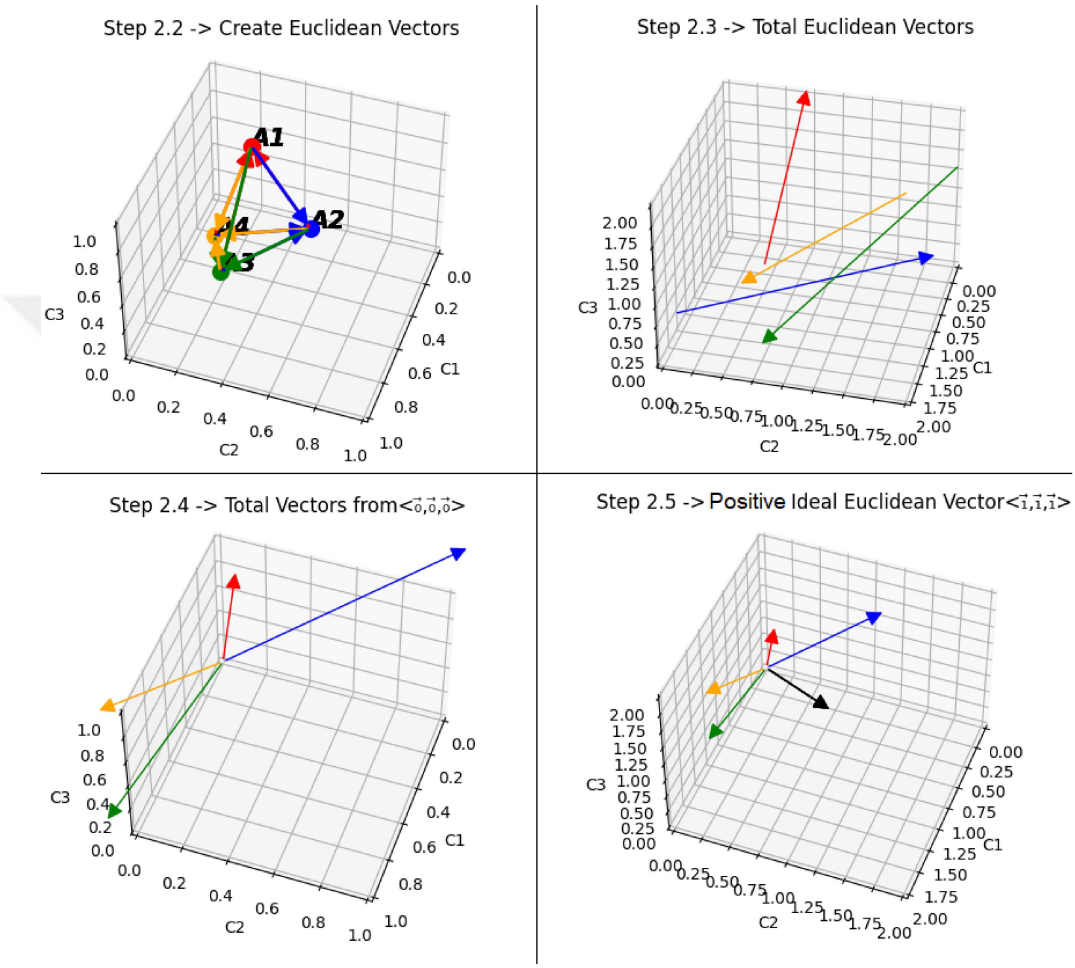


Figure 5.3: Sample geometric drawing of V-PARS for 4 alternatives and 3 criteria (3-dimensional environment).

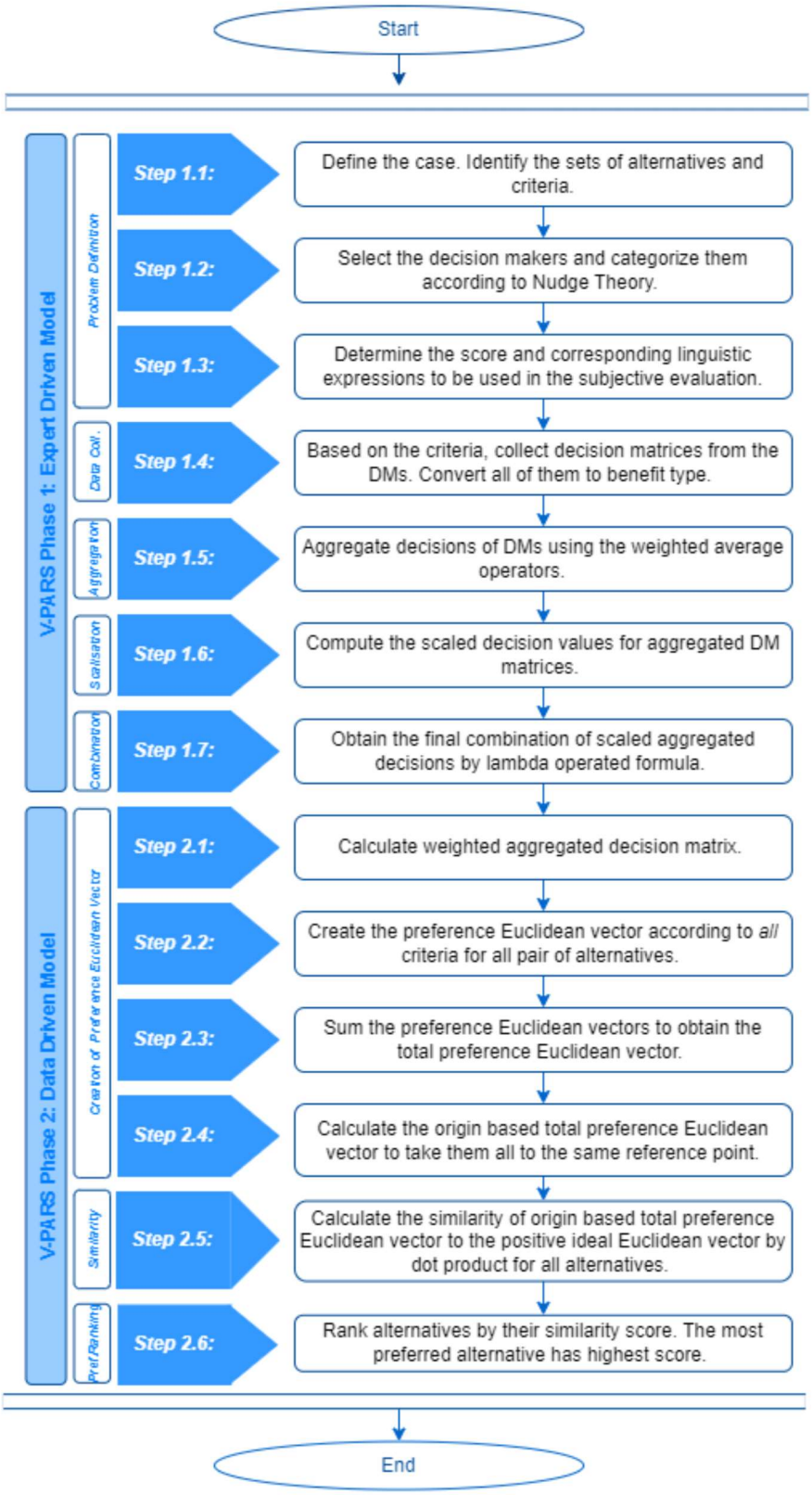


Figure 5.4: Flowchart of Vector-Based Preference Ranking System (V-PARS) procedure.

6 MICROMOBILITY

Micromobility encompasses a variety of small, human powered or electrically assisted vehicles designed for short distance travel. From traditional bicycles to innovative personal transporters, these vehicles offer efficient,environmentally friendly, and convenient transportation options for urban dwellers. Their growing popularity is driven by factors such as portability, affordability, and the desire for sustainable mobility solutions. As cities worldwide integrate micromobility into their transportation systems, it is essential to address challenges related to safety, infrastructure, and public acceptance to maximize its benefits.

This chapter presents a comprehensive overview of micromobility, examining its history, various types, and current practices globally highlighting their unique characteristics and challenges. By understanding the global landscape and local contexts, this chapter contributes to the broader discussion of micromobility's role in shaping urban transportation systems. It also provides in-depth analyses of micromobility in Paris and Istanbul.

6.1 History of Micromobility

Micromobility has become an essential aspect of urban transportation, providing sustainable, efficient, and cost-effective solutions for short distance travel. The history of micromobility is marked by significant milestones, from the invention of bicycles to the modern proliferation of electric scooters and bike-sharing systems. This literature review traces the historical evolution of micromobility worldwide, highlighting key developments, technological advancements, and policy shifts that have shaped its current landscape.

Early Beginnings: The Advent of Bicycles

The history of micromobility can be traced back to the early 19th century with the invention of the bicycle. In 1817, Karl von Drais, a German inventor, introduced the "Laufmaschine" or "running machine," which is considered the precursor to the modern bicycle

(Herlihy, 2004). This two wheeled, human powered vehicle gained popularity across Europe, leading to further innovations, such as the addition of pedals and the development of the "penny-farthing" in the 1870s.

The late 19th century witnessed the "Bicycle Boom," particularly in Europe and North America, where bicycles became a popular mode of personal transportation (Ritchie, 1975). The introduction of the "safety bicycle" with equal sized wheels and a chain drive in the 1880s revolutionized cycling, making it accessible and practical for everyday use. This period also saw the establishment of cycling clubs and the first competitive cycling events, further promoting the adoption of bicycles.

Early 20th Century: Motorized Micromobility

The early 20th century marked the advent of motorized micromobility with the introduction of motor scooters and mopeds. The invention of the motorized bicycle, or "moped," allowed for greater speed and ease of travel. In 1946, Piaggio introduced the Vespa, an iconic motor scooter that became synonymous with personal mobility in post-war Europe (Rapini, 2019). The Vespa's compact design, affordability, and fuel efficiency made it a popular choice for urban commuters.

During this period, other motorized micromobility options, such as the Lambretta scooter and various small motorcycles, also gained traction. These vehicles provided an alternative to cars, particularly in densely populated urban areas where traffic congestion and parking were significant concerns.

Mid to Late 20th Century: The Rise of Bike-Sharing Programs

The mid to late 20th century saw the emergence of bike-sharing programs, which aimed to provide affordable and convenient access to bicycles for short distance travel. The first notable bike-sharing program was Amsterdam's "White Bikes" initiative in 1965. This program, initiated by the Provo counterculture movement, involved placing white painted bicycles around the city for public use. Although the program was short lived due to issues such as theft and vandalism, it laid the groundwork for future bike-sharing schemes (Shaheen et al., 2010).

In 1995, Copenhagen launched the "Bycyklen" or "City Bike" program, which became one of the world's first large scale, successful bike-sharing systems. The program featured specially designed bikes that could be rented from and returned to designated stations around the city (DeMaio, 2009). The success of Copenhagen's bike-sharing program inspired similar initiatives in other cities, including Paris, Lyon, and Barcelona.

Early 21st Century: Technological Advancements and Dockless Systems

The early 21st century witnessed significant technological advancements that transformed micromobility. The introduction of Global Positioning System (GPS) technology, mobile applications, and improved bike designs enabled the development of more sophisticated and user friendly bike-sharing systems. In 2007, Paris launched the "Vélib'" program, which quickly became one of the largest and successful bike-sharing schemes in the world (DeMaio, 2009).

The late 2010s marked the proliferation of dockless bike-sharing systems, which allowed users to locate, unlock, and rent bikes using smartphone apps. Companies such as Ofo and Mobike, originating in China, expanded rapidly to cities around the world, offering a flexible and convenient alternative to traditional dock based systems (Zhang and Mi, 2018). E-bikes began to gain popularity during this period, offering a pedal assist option that made cycling more accessible to a broader range of users. The integration of electric motors into bikes provided an efficient and eco-friendly mode of transport for urban commuters (Cherry et al., 2009).

The concept of Mobility-as-a-Service (MaaS) emerged, emphasizing the integration of micromobility with public transport systems. MaaS platforms aimed to provide seamless connectivity between different modes of transport, enhancing the overall efficiency and convenience of urban mobility networks. Cities began developing multimodal transport hubs and integrating micromobility options into public transit routes (Jittrapirom et al., 2017).

The environmental benefits of micromobility became a focal point, with studies highlighting the potential for significant reductions in greenhouse gas (GHG) emissions and

air pollution. Life cycle assessments (LCAs) provided insights into the sustainability of different micromobility options, emphasizing the importance of durable designs and efficient recycling processes (Hollingsworth et al., 2019).

Modern Era: E-Scooters and Shared Micromobility

The modern era of micromobility is characterized by the rise of electric scooters (e-scooters) and the expansion of shared micromobility services. In 2017, companies like Bird and Lime introduced dockless e-scooters in the United States, quickly expanding to Europe and other regions (Freemark et al., 2019). E-scooters offered a convenient, eco-friendly alternative for short trips, particularly in urban areas with heavy traffic congestion.

The rapid proliferation of e-scooters led to significant growth in the shared micromobility market. According to the National Association of City Transportation Officials (NACTO), the number of shared micromobility trips in the United States increased from 35 million in 2017 to 136 million in 2019 (National Association of City Transportation Officials (NACTO), 2019).

As micromobility options expanded, cities and governments worldwide began to develop policies and regulations to manage their growth and ensure safety. In 2018, the European Commission published guidelines for the safe integration of micromobility into urban transportation systems, emphasizing the need for dedicated infrastructure, such as bike lanes and e-scooter parking zones (European Commission, 2018). To support improvements in city planning, the European Commission introduced the concept of sustainable urban mobility and published guidelines for developing and implementing Sustainable Urban Mobility Plans (SUMP, 2019).

In the United States, cities like San Francisco and Washington, D.C., implemented permit systems for e-scooter operators, requiring companies to adhere to safety standards and data sharing agreements. These regulatory frameworks aimed to balance the benefits of micromobility with concerns about safety, sidewalk clutter, and equitable access (McKenzie, 2019).

The adoption of micromobility has had a profound impact on urban transportation systems. Studies have shown that micromobility can reduce traffic congestion, lower greenhouse gas emissions, and improve public health by encouraging active transportation (Fishman, 2016). For instance, replacing short car trips with bike or e-scooter trips can significantly decrease urban CO_2 emissions.

Micromobility has also contributed to the concept of the "15-minute city," where essential services and amenities are accessible within a 15-minute walk or bike ride. Cities like Paris and Barcelona have embraced this concept, redesigning urban spaces to prioritize pedestrians and micromobility users over cars (Moreno et al., 2021).

The COVID-19 pandemic had a profound impact on urban transportation, accelerating the adoption of micromobility solutions. The pandemic led to a significant shift in commuting patterns, with many people avoiding public transport due to health concerns. Micromobility options, such as e-scooters and bike-sharing, provided a safe and socially distanced alternative for short trips. Cities experienced a surge in demand for these services during the pandemic (Linares-Rendón and Garrido-Cumbrera, 2021). In response to the increased demand for micromobility, many cities implemented supportive policies and infrastructure. Temporary bike lanes, reduced speed limits, and expanded pedestrian zones were introduced to accommodate the growing number of micromobility users. These measures not only supported pandemic-era mobility but also laid the groundwork for long-term sustainable transport solutions. The pandemic highlighted the resilience and adaptability of micromobility systems. Companies adapted their operations to meet changing demand patterns, implementing enhanced cleaning protocols and promoting contactless rentals. The ability of micromobility solutions to quickly respond to the evolving needs of urban commuters underscored their value as a flexible and resilient mode of transport (Black, 1958).

6.2 Types and Features of Micromobility Vehicles

Micromobility refers to a range of small, lightweight vehicles operating at speeds typically below 25 kilometers per hour (15 mph), designed for short distance travel. These

vehicles, which include bicycles, e-scooters, skateboards, and other personal transport devices, play a crucial role in urban transportation systems by providing efficient, sustainable, and cost-effective solutions for city dwellers. This literature review explores the various types of micromobility vehicles commonly encountered in daily life, their features, and their contributions to modern urban mobility.

- **Bicycles:** Bicycles are one of the oldest and most widely used forms of micromobility. They come in various forms, including traditional pedal powered bicycles and electric assisted bicycles (e-bikes). Pedal powered bicycles are human powered and are favored for their simplicity and environmental benefits (Ritchie, 1975). E-bikes, which feature electric motors to assist with pedaling, have gained popularity due to their ability to cover longer distances with less physical effort, making them suitable for a broader range of users (Cherry and Cervero, 2007). While bikes are typically designed for one or two riders, cargo bikes are specifically built to handle heavy loads, making them an ideal solution for transporting goods and bulky items. A visual example is provided in Figure 6.1.



Figure 6.1: Various bicycle visuals.

- **Electric Scooters (E-Scooters, fr. Trottinettes):** E-scooters have become a prominent mode of micromobility in recent years. These battery powered vehicles are typically dockless, allowing users to rent and return them at various locations using smartphone apps of sharing mobility systems. E-scooters are known for their convenience, ease of use, and ability to navigate through congested urban areas

(Gössling, 2020). They are often used for short trips, last-mile connectivity, and recreational purposes. A visual example is provided in Figure 6.2.



Figure 6.2: Various e-scooter visuals.

- **Skateboards and E-Skateboards:** Traditional skateboards and electric skateboards (e-skateboards) are popular among younger demographics and urban commuters. E-skateboards, equipped with electric motors, offer greater speed and range compared to their non-motorized counterparts. They provide a fun, agile way to navigate city streets and are often used for short distance travel (Freemark et al., 2019). A visual example is provided in Figure 6.3.



Figure 6.3: Various skateboard visuals.

- **Mopeds and Motor Scooters:** Mopeds and motor scooters are small, motorized vehicles commonly used in densely populated urban areas. They offer a balance between speed and maneuverability, making them suitable for both short and moderate-

distance commutes. These vehicles are often used in cities with high traffic congestion, providing an efficient alternative to cars (Rapini, 2019). A visual example is provided in Figure 6.4.



Figure 6.4: Various moped visuals.

- **Segways:** Segways are self-balancing, electric vehicles designed for short distance travel in pedestrian areas. They are commonly used by security personnel, tourists, and urban commuters. Segways offer a unique riding experience and are known for their stability and ease of use (Shaheen et al., 2010). A visual example is provided in Figure 6.5.



Figure 6.5: Various segway visuals.

- **Hoverboards:** Hoverboards are self-balancing, two wheeled personal transport devices powered by electric motors. They are popular among younger users for recreational purposes and short distance travel. Hoverboards are compact and portable, making them easy to carry and store (Freemark et al., 2019). A visual example is provided in Figure 6.6.



Figure 6.6: Various hoverboard visuals.

- **Drones:** Drones are an integral part of the micromobility concept, specifically under urban air mobility (UAM), where autonomous aerial vehicles, such as cargo and taxi drones, provide innovative solutions for urban transportation. These electric powered drones aim to reduce traffic congestion and emissions by offering short distance air travel alternatives within densely populated cities. As a subset of micromobility, UAM promotes more sustainable and efficient transport solutions, contributing to greener urban environments. Cities like Dubai and Los Angeles have initiated pilot programs exploring the feasibility of UAM in real world settings (Cohen et al., 2021; Thipphavong et al., 2018). A visual example is provided in Figure 6.7.



Figure 6.7: Various drone visuals.

Additionally, kick scooters, unicycles, electric unicycles, tricycles, quadracycles, handcycles, hobcarts, mobility scooters, roller skates, onewheels, wheelchairs, strollers, golf

carts, microcars (depending on size), and velomobiles are all considered types of micromobility vehicles (Dündar, 2023). Various visual examples are provided in Figure 6.8. As a key observation, some studies classify walking as a form of micromobility but it is not common (Comi et al., 2022).



Figure 6.8: Some other micromobility visuals.

The common features of micromobility vehicles can be categorized as follows:

1. **Portability and convenience:** One of the key features of micromobility vehicles is their portability. Most micromobility vehicles are lightweight and compact, making them easy to carry, store, and maneuver in urban environments. This portability enhances their convenience, allowing users to combine micromobility with other modes of transportation, such as public transit (Gössling, 2020).

2. **Environmental benefits:** Micromobility vehicles are environmentally friendly, producing little to no emissions. Traditional bicycles and e-bikes contribute to reduced air pollution and carbon emissions compared to motor vehicles. E-scooters and e-skateboards also offer lower environmental impacts, particularly when charged using renewable energy sources (Fishman, 2016).

3. **Cost effectiveness:** Micromobility vehicles are generally more affordable than cars and other motorized transportation options. The lower purchase and maintenance costs, combined with the availability of shared micromobility services, make them accessible to a wide range of users. Shared micromobility systems, in particular, provide a cost-effective alternative for short distance travel without the need for vehicle ownership (Shaheen et al., 2022).

4. **Ease of use:** The design of micromobility vehicles prioritizes user-friendliness. Most vehicles feature intuitive controls and require minimal training to operate. E-scooters and e-bikes, for instance, often include features such as throttle controls, regenerative braking, and adjustable speed settings to enhance the riding experience (McKenzie, 2019).

5. **Integration with technology:** Modern micromobility vehicles are equipped with advanced technologies, including GPS, Bluetooth, and mobile app integration. These technologies enable features such as real-time tracking, remote locking and unlocking, and route optimization. Shared micromobility systems leverage these technologies to offer seamless rental experiences, allowing users to locate, rent, and return vehicles using smartphone apps (Zhang and Mi, 2018).

6. **Safety features:** Safety is a critical consideration in the design of micromobility vehicles. Many vehicles come with safety features such as lights, reflectors, and bells to enhance visibility and communication with other road users. E-scooters and e-bikes often include braking systems, suspension, and robust tires to ensure stability and control (Fishman, 2016).

7. **Flexibility and accessibility:** Micromobility vehicles offer flexible transportation options that can be tailored to individual needs. Shared micromobility systems provide on-demand access to vehicles, allowing users to choose the most convenient mode of transport for their journey. The accessibility of micromobility vehicles, particularly e-bikes and e-scooters, makes them suitable for a wide range of users, including those with limited physical mobility (Shaheen et al., 2022).

6.3 Micromobility in Practice

This part explores the practical applications of micromobility, focusing on how these vehicles integrate with existing transportation networks and their impact on urban mobility. It also examines the challenges and opportunities micromobility presents for city planners, policymakers, and users. Through real world implementations, this section highlights the increasing role of micromobility in shaping urban transportation.

6.3.1 Traffic Flow

Micromobility, encompassing vehicles like electric scooters and bikes, has the potential to significantly influence urban traffic patterns. By offering a convenient and efficient mode of transportation for short distances, it can reduce car usage, leading to decreased congestion and improved air quality. However, the actual impact is complex and depends on various factors, including urban density, infrastructure, and regulatory frameworks. Challenges such as sidewalk obstructions, safety concerns, and potential mode shift from walking need to be addressed.

Several studies have examined the impact of micromobility on traffic congestion. For instance, a study by (Shaheen et al., 2020) in San Francisco found that the introduction of e-scooters led to a measurable reduction in vehicle miles traveled (VMT), suggesting a shift from car trips to micromobility options. Similarly, (Hollingsworth et al., 2019) reported that cities like Austin and Portland observed smoother traffic flow and reduced congestion following the deployment of shared e-scooter programs. A study conducted in Seattle estimated that up to 18% of short car trips could be replaced by micromobility modes, significantly easing traffic flows in urban areas (Fan and Harper, 2022). Additionally, research from Portland demonstrated that e-scooters can move more people safely and efficiently, reducing traffic congestion as the city grows (Portland Bureau of Transportation, 2018).

Research by (Fishman, 2016) suggests that a significant portion of micromobility users are substituting car trips with e-scooter or bike trips, thereby reducing overall traffic volume. Another study by (McQueen et al., 2021b) found that micromobility users in Euro-

pean cities were primarily young adults who previously relied on public transportation or private cars, indicating a potential for mode shift.

The safety of micromobility users is a critical concern. Studies by (Yang and Ma, 2020) and (Sanders et al., 2022) have highlighted the need for improved infrastructure, such as dedicated bike lanes and better lighting, to ensure the safety of e-scooter and bike users. These studies emphasize that while micromobility can reduce traffic congestion, it also introduces new safety challenges that need to be addressed. Despite its benefits, micromobility poses safety challenges and regulatory hurdles. The increase in e-scooter usage has led to a rise in traffic accidents and injuries. A study in Lithuania noted the confusion and traffic conflicts caused by e-scooters, emphasizing the need for clear legislation and traffic rules (Jasiūnienė and Tumavičė, 2022). Another research highlighted the health impacts of e-scooters, suggesting that while they offer mobility benefits, they also pose significant safety risks (Felipe-Falgas et al., 2022). The methodologies employed in studying the traffic impact of micromobility vary widely. Common approaches include surveys, travel diaries, GPS tracking, and traffic simulation models. For example, simulation models, as utilized by (Faghih-Imani et al., 2017), provide insights into the potential long term impacts of micromobility on urban traffic.

6.3.2 Environmental Impact

The environmental benefits of micromobility largely stem from its potential to replace short car trips, thereby reducing greenhouse gas emissions. Studies have shown that shared micromobility systems can significantly lower transportation related emissions. For instance, a study assessed the environmental impacts of shared e-scooters and found that they can reduce the carbon footprint of urban transportation when replacing car trips (Peng et al., 2022). However, the net environmental impact of micromobility depends on several factors, including the materials used in vehicle production, the energy sources for charging, and the operational models of shared micromobility services.

Despite these benefits, some studies have highlighted potential drawbacks. For example, shared micromobility vehicles can sometimes increase the carbon footprint if they replace more environmentally friendly modes of transport, such as walking or public tran-

sit. Additionally, the production, maintenance, and disposal of micromobility vehicles can contribute to environmental degradation if not managed sustainably (International Transport Forum, 2020).

Carbon Neutral Zone

The concept of carbon neutral zones involves creating urban areas where net carbon emissions are zero. Micromobility plays a crucial role in these zones by providing an eco-friendly alternative to cars. Cities like Berlin have integrated micromobility into their urban planning to achieve low carbon and livable environments (Aartsma, 2020). By promoting the use of e-scooters and e-bikes, these cities aim to reduce traffic congestion and lower emissions, contributing to their carbon neutrality goals.

Moreover, research has demonstrated that cities adopting shared micromobility services have observed reductions in overall transportation emissions. For example, a study found that shared micromobility vehicles reduced net carbon emissions across their life cycles in five out of six cities analyzed (Badalian, 2023). This indicates that with proper implementation and integration, micromobility can be a vital component of carbon neutral zones.

The impact of micromobility on urban air quality is another critical aspect. (Felipe-Falgas et al., 2022) found that while shared micromobility modes decrease greenhouse gas emissions, they can increase particulate matter emissions due to the electricity generation mix and battery production processes. This underscores the need for clean energy sources to power micromobility solutions. Micromobility can complement public transportation systems, further enhancing its environmental benefits. (Calan et al., 2024) systematically reviewed the life cycle greenhouse gas emissions of shared electric micromobility and emphasized the importance of integrating micromobility with public transportation to maximize emission reductions.

European Union's Target for 2050

The European Commission has set ambitious climate goals, aiming to achieve climate neutrality by 2050. This includes a 90% reduction in transport related emissions (Eu-

ropean Commission, 2024). Micromobility is a key element in this strategy, offering a sustainable alternative to conventional vehicles and supporting the transition to greener urban mobility aligns with several of the Green Deal's core objectives.

- The European Commission has set a target of reducing greenhouse gas (GHG) emissions by at least 55% by 2030, relative to 1990 levels, and achieving climate neutrality by 2050 (European Commission, 2019). Micromobility can significantly contribute to this goal by replacing short car trips with zero emission alternatives. The Commission's sustainability rapport highlights micromobility as a critical component in reducing transport emissions and promoting clean, efficient urban mobility (European Commission, 2020b).

- By 2030, the European Commission aims to have at least 100 climate neutral cities (*including Paris and Istanbul*) in Europe (European Commission, 2020a). Micromobility is expected to play a pivotal role in achieving this goal by providing accessible, affordable, and sustainable transportation options. Investments in infrastructure, such as dedicated bike lanes and charging stations for e-scooters, are essential to support this transition.

- The rapid expansion of micromobility has outpaced the development of regulatory frameworks in many European cities. The European Commission's guidelines on micromobility (ITDP Europe, 2019) stress the importance of harmonizing regulations across member states to ensure safety, accessibility, and environmental sustainability. Standardizing rules on speed limits, vehicle specifications, and usage zones is essential for fostering widespread adoption.

- While micromobility devices produce zero tailpipe emissions, their manufacturing and disposal can have environmental impacts. The production of batteries for e-scooters and e-bikes, in particular, raises concerns about resource extraction and waste. The European Commission's Battery Directive (Heineke et al., 2021) aims to address these issues by promoting sustainable battery production and recycling practices.

- Ensuring that micromobility solutions are accessible to all segments of the population is critical for achieving the European Commission's environmental and social goals. The Commission's Inclusive Mobility Strategy (European Cyclists' Federation, 2020) highlights the need to address barriers to access, such as affordability and availability in underserved areas. Promoting equity in micromobility can enhance its environmental benefits by encouraging widespread adoption.

Policies promoting micromobility, such as subsidies for e-scooters and e-bikes, are expected to contribute significantly to meeting these targets. For instance, the European Union's "Fit for 55" package includes measures to promote the adoption of low emission vehicles and enhance urban mobility infrastructure (Campisi et al., 2021). By encouraging the use of micromobility, the EU aims to reduce dependency on fossil fuels and lower GHG.

Furthermore, the integration of micromobility with public transportation systems can amplify its environmental benefits. A study on urban mobility solutions highlighted that shared micromobility services, when combined with public transit, can significantly reduce emissions and improve the overall efficiency of urban transportation networks (Pagoni and Papatheodorou, 2024).

Life Cycle Assessment of Micromobility

Life Cycle Assessment (LCA) is a methodology used to evaluate the environmental impacts of a product throughout its life cycle, from production to disposal. Numerous studies have applied LCA to micromobility to assess its overall sustainability and identify opportunities for improvement.

A study conducted an LCA on shared e-scooters and found that their environmental performance varies significantly depending on factors such as the materials used, the vehicle lifespan, and the energy sources for charging (Calão et al., 2022). The study emphasized that maximizing the lifespan of e-scooters and using renewable energy for charging can substantially reduce their environmental impact.

(De Bortoli, 2021) compared the environmental performance of shared micromobility services to personal alternatives using integrated modal LCA. The study found that shared micromobility services, such as e-scooters and e-bikes, offer potential environmental benefits, including reduced CO_2 emissions and lower energy consumption compared to private car usage.

Another research focused on the environmental performance of shared micromobility services compared to private alternatives. The study used an integrated modal LCA to assess the impacts of various micromobility services in Paris and found that shared e-scooters and e-bikes have a lower environmental impact than private cars when used to replace short trips (De Bortoli, 2021).

Moreover, a systematic review of LCA studies on shared electric micromobility services highlighted the importance of considering the entire life cycle of these vehicles, including production, operation, and end-of-life disposal. The review found that while shared micromobility services can reduce greenhouse gas emissions, their environmental benefits are maximized when they are efficiently managed and integrated with other sustainable transportation options (Calan et al., 2024).

The production and disposal of batteries are significant factors in the environmental impact of micromobility. (Felipe-Falgas et al., 2022) assessed the environmental performance of shared micromobility modes in Barcelona using an LCA approach. Their findings indicate that battery production and disposal contribute substantially to the overall environmental impact, underscoring the need for sustainable battery technologies.

Comprehensive LCA studies that consider all stages of the vehicle's life cycle are essential to accurately assess the environmental impact of micromobility. (Marques and Coelho, 2022) emphasized the need for holistic LCA studies that encompass production, operation, maintenance, and disposal. Policy and regulatory frameworks play a crucial role in promoting the adoption of micromobility and ensuring its sustainability. (Calan et al., 2024) stressed the importance of supportive policies to facilitate the integration of micromobility with other sustainable transportation modes and clean energy sources.

6.3.3 Sociocultural Impact

Micromobility has the potential to democratize urban mobility by providing affordable and accessible transportation options. Studies show that micromobility can enhance social equity by offering mobility solutions to underserved communities, including low-income neighborhoods and areas with limited public transportation (Group, 2022). By bridging gaps in existing transit networks, micromobility fosters greater social inclusion and connectivity.

Moreover, shared micromobility services, such as dockless e-scooters, have changed the way people navigate cities. These services encourage spontaneous and flexible travel, allowing users to explore urban spaces more freely. This shift in travel behavior promotes a culture of exploration and spontaneity, altering traditional patterns of commuting and leisure activities (Reck et al., 2022).

The widespread adoption of micromobility has also influenced social interactions in urban environments. Shared micromobility systems create opportunities for social engagement by bringing people into closer contact with one another. For instance, docking stations and designated parking areas for e-scooters and e-bikes often become informal gathering spots, fostering social interactions among users (McQueen et al., 2021a).

Additionally, the visibility of micromobility users on streets and bike lanes can enhance the sense of community and shared space. As more people adopt micromobility, cities may experience a cultural shift towards valuing and prioritizing non-motorized transportation. This shift can lead to increased social cohesion and a stronger sense of community among residents (Fitt and Curl, 2020).

Micromobility is influencing cultural practices related to urban living and mobility. For example, the rise of e-scooters and e-bikes has led to the emergence of new cultural norms and etiquettes, such as sharing road space with other users, following safety protocols, and respecting pedestrian areas. These changes in behavior reflect a broader cultural adaptation to new forms of mobility and the integration of micromobility into daily life (Aguilera-García et al., 2021).

Furthermore, micromobility is contributing to the reimagining of urban spaces. Cities are increasingly investing in infrastructure to accommodate micromobility, such as dedicated bike lanes, e-scooter parking zones, and traffic calming measures. These changes not only improve safety and convenience for micromobility users but also enhance the overall urban environment, making cities more livable and pedestrian friendly (Comi and Polimeni, 2024).

Despite the positive sociocultural impacts, micromobility also presents challenges that need to be addressed. Issues such as pedestrian safety, regulatory compliance, and the environmental impact of discarded vehicles can hinder the successful integration of micromobility into urban culture. Policymakers and urban planners must consider these challenges and develop strategies to mitigate negative impacts while maximizing the benefits of micromobility (International Transport Forum (ITF), 2021).

6.3.4 Health Impact

Micromobility can significantly contribute to increased physical activity, which is crucial for preventing various health conditions such as obesity, cardiovascular diseases, and diabetes. Cycling, for example, is a form of moderate intensity physical activity that is associated with numerous health benefits. Studies have shown that individuals who use bicycles or e-bikes for commuting or recreational purposes tend to have higher levels of physical fitness compared to those who rely on motorized transport (Oja et al., 2011).

Additionally, micromobility can help integrate physical activity into daily routines, making it easier for people to meet the recommended levels of physical activity. For instance, a study in Barcelona found that the use of e-bikes significantly increased physical activity levels among users, contributing to better overall health outcomes (López-Dóriga et al., 2022).

Despite the directly health benefits, micromobility also presents safety challenges. The rise in the usage of e-scooters and e-bikes has been associated with an increase in traffic accidents and injuries. A study conducted in the United States found that e-scooter related injuries have risen sharply, with head injuries and fractures being the most common types

of injuries (Trivedi et al., 2019). The lack of protective infrastructure, such as dedicated bike lanes, further exacerbates these safety risks. Moreover, the safety of micromobility users is influenced by their behavior and adherence to traffic regulations. Research indicates that many e-scooter users do not consistently follow traffic rules, such as wearing helmets or using designated lanes, increasing the risk of accidents (Trivedi et al., 2019).

Micromobility can positively impact mental health and overall well-being. The act of cycling or riding an e-scooter can reduce stress levels, improve mood, and enhance mental clarity. The outdoor physical activity associated with micromobility can also reduce symptoms of depression and anxiety (Bratman et al., 2021). Additionally, micromobility options can provide a sense of autonomy and freedom, contributing to improved mental well-being.

Furthermore, the convenience and accessibility of micromobility can lessen our dependence on cars, leading to less time spent in traffic and decreased commuting related stress. This can have a positive effect on individuals' mental health, as shorter and more enjoyable commutes are linked to higher levels of life satisfaction (Mokhtarian and Pendyala, 2018).

By minimizing reliance on motorized transport, micromobility can also contribute to improved air quality and lower levels of noise pollution in urban areas. Cleaner air and reduced noise levels can have significant health benefits, including lower rates of respiratory and cardiovascular diseases. A study in Texas found that the uptake of micromobility could lead to a substantial reduction in air pollutants, contributing to better public health (Xu et al., 2022).

6.3.5 Economic Impact

The economic impact of micromobility extends beyond immediate cost savings and convenience, with significant implications for the broader economic system through the lens of the circular economy.

Micromobility offers substantial cost savings for users compared to traditional motorized transportation. For instance, the cost of using shared e-scooters or bikes is generally lower

than owning and maintaining a car. According to a study by the International Transport Forum, the average cost per mile for micromobility is significantly less than for car travel, making it an attractive option for short trips (International Transport Forum, 2021). Cities also benefit economically from micromobility by reducing the need for expensive infrastructure projects such as road expansions and parking facilities. A report from Deloitte highlights that by promoting micromobility, cities can decrease congestion, leading to lower maintenance costs for urban infrastructure (Deloitte, 2020).

The micromobility industry has spurred job creation and economic growth, particularly in urban areas. The deployment, maintenance, and management of shared micromobility fleets create new employment opportunities. A study by McKinsey and Company estimated that the micromobility market could generate up to $200 billion annually by 2030, driven by increased adoption and the resulting demand for related services (Heineke et al., 2021). Moreover, the growth of micromobility services has led to the emergence of new business models and startups, fostering innovation and entrepreneurship. This economic activity contributes to local economies, creating a ripple effect of economic benefits.

Circular Economy

The circular economy emphasizes the sustainable use of resources, minimizing waste, and maximizing the life cycle of products. Micromobility aligns well with these principles, promoting sustainability and economic efficiency.

Micromobility vehicles, particularly shared fleets, are designed to be durable and easily maintainable. Companies like Lime and Bird have developed maintenance programs to extend the lifespan of their vehicles, reducing the need for frequent replacements. This approach not only minimizes waste but also maximizes the utilization of resources, aligning with circular economy principles (Lime, 2021).

Furthermore, the adoption of electric micromobility vehicles contributes to reducing the consumption of fossil fuels, decreasing the environmental footprint of urban transportation. By shifting from single-occupancy vehicles to shared micromobility, cities can significantly reduce greenhouse gas emissions and other pollutants.

The circular economy involves recycling and repurposing materials to create new products. Micromobility companies are increasingly focusing on the recyclability of their vehicles. For example, the materials used in e-scooters and e-bikes, such as aluminum and lithium-ion batteries, can be recycled and repurposed for new vehicles or other applications. This not only reduces waste but also lowers production costs, contributing to economic sustainability (Bird, 2023).

Moreover, the implementation of take-back schemes, where companies collect and recycle old or damaged vehicles, further supports the circular economy. These initiatives ensure that materials are reused, reducing the demand for new raw materials and minimizing environmental impact.

6.3.6 Logistic

Micromobility offers several advantages for urban logistics, primarily by addressing the challenges of last-mile delivery. The rise of e-commerce has increased the demand for efficient and sustainable last-mile solutions. Micromobility vehicles, being small and agile, can navigate congested urban areas more effectively than traditional delivery trucks, reducing delivery times and congestion (Castiglione et al., 2022). Additionally, these vehicles produce lower emissions, contributing to greener city logistics (Rześny-Cieplińska and Tomaszewski, 2023).

The integration of micromobility into urban freight systems is gaining traction. In many cities, logistics companies are adopting micromobility solutions to complement their existing fleet for last-mile deliveries. For instance, some logistics firms are using e-cargo bikes for parcel deliveries, which not only reduce carbon footprints but also enhance delivery efficiency in densely populated areas. Moreover, the use of shared micromobility systems can further optimize urban logistics by reducing the need for dedicated delivery vehicles (Oeschger et al., 2023).

Despite its benefits, micromobility in logistics faces several challenges. One significant issue is the limited cargo capacity of micromobility vehicles, which restricts their use to small and lightweight deliveries. Additionally, the lack of standardized infrastructure and

regulations for micromobility can hinder its widespread adoption. Safety concerns, particularly related to the interaction between micromobility vehicles and other road users, also need to be addressed (The Possible, 2022).

Innovation in micromobility is driving new trends in urban logistics. The development of specialized cargo bikes and electric vehicles designed for urban deliveries is expanding the potential applications of micromobility in logistics. Moreover, the use of advanced technologies such as GPS and IoT for route optimization and fleet management is enhancing the efficiency of micromobility solutions (WSP Australia, 2022). Another emerging trend is the collaboration between micromobility providers and logistics companies to create integrated delivery networks (Ernst & Young, 2024). Micromobility systems also serve as valuable assets in natural disaster management and humanitarian aid logistics with significant potential for practical implementation in complex and resource-constrained environments (Fitch-Polse et al., 2024).

6.3.7 Shared Transportation

Shared micromobility, encompassing vehicles such as e-scooters, e-bikes, mopeds and shared bicycles, has rapidly integrated into urban transportation systems. It has been identified as a promising solution to enhance urban transportation sustainability. Studies have shown that these modes can significantly reduce greenhouse gas emissions by substituting car trips with micromobility options (Şengül and Mostofi, 2021). For example, research in various cities demonstrated that shared micromobility programs have the potential to decrease urban transportation emissions by shifting travel behavior away from personal car use (Sun and Ertz, 2022).

Additionally, shared micromobility contributes to reduced congestion and improved air quality in urban environments. The increased adoption of e-scooters and e-bikes helps in mitigating traffic jams and lowering noise pollution, thus making cities more livable (Krauss et al., 2022).

Understanding user preferences is crucial for the successful implementation of shared micromobility systems. Research indicates that users prefer shared micromobility for

its convenience, cost effectiveness, and environmental benefits. For instance, a study examining user preferences in urban areas found that shared e-bikes and e-scooters are favored for their flexibility and ease of use (Jaber et al., 2023).

Moreover, shared micromobility appeals to a broad demographic, including both daily commuters and occasional users. The availability of these services in densely populated urban areas enhances accessibility and mobility for residents, contributing to a more inclusive transportation system (McKinsey and Company, 2023).

6.3.8 Weaknesses of Electric and Micromobility Tools

While micro vehicles offer numerous advantages in terms of urban mobility and environmental sustainability, they also exhibit several logical weaknesses and limitations that hinder their widespread adoption. These include design and structural limitations, power and energy constraints, technological and functional challenges, and practical and operational issues. Addressing these weaknesses through innovative design, advanced materials, and improved technologies will be crucial for realizing the full potential of micro vehicles in urban transportation systems.

One of the primary weaknesses of micro vehicles lies in their design and structural limitations. Due to their small size, micro vehicles often suffer from stability issues, which can affect their performance and safety. For instance, micro air vehicles (MAVs) face significant challenges in terms of aerodynamic stability and control, making them difficult to operate reliably in various environmental conditions (Petricca et al., 2011). Additionally, the compact design of micro vehicles limits the integration of advanced safety features, which are crucial for ensuring the safety of both the vehicle and its occupants.

Micro vehicles also face significant power and energy constraints. The small size of these vehicles restricts the capacity of batteries that can be used, leading to limited operational range and endurance. This is particularly evident in electric micro vehicles, where the battery life is a critical factor influencing the practicality and usability of the vehicle (Skouras et al., 2019). Furthermore, the energy efficiency of micro vehicles is often compromised by the need for lightweight materials and compact designs, which can reduce the overall

performance and reliability of the vehicle.

The technological and functional challenges associated with micro vehicles are another significant area of concern. For instance, the integration of advanced navigation and control systems in micro vehicles is often limited by their small size and power constraints. This can lead to issues with precision and accuracy in navigation, especially in complex urban environments (Coppola et al., 2020).

Additionally, the limited computational power available in micro vehicles restricts the implementation of sophisticated algorithms and artificial intelligence (AI), which are essential for autonomous operation and decision making. Micro vehicles also exhibit several practical and operational issues that limit their effectiveness in real world applications. The limited payload capacity of micro vehicles restricts their ability to carry essential equipment and supplies, which can be a significant drawback in applications such as surveillance and delivery services (Davis et al., 1996). Moreover, the compact design of micro vehicles often leads to comfort and usability issues for the users, making them less appealing for long distance or regular use.

6.3.9 Micromobility versus Microcars in Urban Transportation

While microcars can be categorized as micromobility vehicles, they typically exceed speed limits for micromobility modes and have a larger capacity, allowing them to transport objects in addition to passengers. Consequently, microcars are not restricted to micromobility specific infrastructure and instead share the road with other traditional vehicles. Given these distinctions, a comparison with other micromobility modes remains relevant.

Both micromobility vehicles and micro cars offer distinct advantages and face unique challenges in urban transportation. Micromobility vehicles excel in terms of environmental benefits, space efficiency, accessibility, and cost effectiveness, making them suitable for short trips and complementing public transit systems. Micro cars, on the other hand, provide greater comfort, safety, and utility for longer trips or when carrying more cargo.

Micromobility vehicles have a significant positive impact on urban sustainability. They are generally electric powered, producing zero emissions during operation, which helps

reduce urban air pollution. Studies have shown that the adoption of micromobility solutions can lead to a reduction in greenhouse gas emissions, contributing to a more sustainable urban environment (Sun and Ertz, 2022). In contrast, micro cars, although smaller and more efficient than traditional cars, still contribute to emissions. However, the development of electric micro cars has mitigated this impact to some extent (Karaca et al., 2018).

One of the primary advantages of micromobility vehicles is their minimal space requirement. They are compact and can be easily maneuvered through congested urban areas, reducing the need for extensive parking infrastructure. This is particularly beneficial in densely populated cities where space is at a premium (Şengül and Mostofi, 2021). Micro cars, while smaller than conventional cars, still require more space for parking and maneuvering compared to micromobility vehicles. Consequently, they may not offer the same level of efficiency in space utilization (Masry et al., 2022). Also, micro cars offer more comfort and protection from weather conditions, making them suitable for slightly longer trips or when carrying more cargo. However, they may not offer the same level of convenience in terms of accessibility and ease of use as micromobility vehicles (Leone et al., 2021).

Safety is a critical concern for both micromobility vehicles and micro cars. Micromobility vehicles, such as e-scooters, have been associated with higher accident rates due to their smaller size, lower visibility, and lack of protective features (Dozza et al., 2022). Micro cars, while offering more protection to occupants, also face safety challenges, particularly in collisions with larger vehicles. Studies have shown that micro cars have a higher crash involvement rate, although advancements in safety features are addressing these concerns (Mu and Yamamoto, 2019).

Micromobility vehicles are generally more affordable than micro cars, both in terms of purchase price and operational costs. Additionally, the lower maintenance costs and the absence of fuel expenses contribute to their economic appeal (Boglietti et al., 2021). Micro cars, while more expensive, offer higher comfort and utility, which can justify the higher cost for some users. However, the economic impact of widespread adoption of mi-

cro cars is still under study, particularly in terms of infrastructure and maintenance costs (Brunner et al., 2018).

6.4 Micromobility Usage Worldwide

Micromobility - *including e-scooters, bikes, e-bikes and e-mopeds* - has become a significant element of urban transportation globally. The adoption, regulatory frameworks, and impacts of micromobility vary widely across countries, influenced by cultural, economic, and infrastructural factors. This comparative literature review examines micromobility usage in various countries, highlighting patterns, challenges, and opportunities in North America, Europe, Asia, Latin America, and Africa.

6.4.1 North America

- ***United States:*** The United States has seen a rapid adoption of micromobility, particularly in urban centers. Companies like Bird, Lime, and Spin have pioneered the e-scooter market. A study by (Shaheen and Cohen, 2019b) highlights that e-scooters have become a popular mode of transport for short trips, especially in cities with high traffic congestion. As of 2019, over 136 million trips were made on shared micromobility devices in the U.S.. A 2020 report by the National Association of City Transportation Officials (NACTO) indicates that e-scooter ridership grew by 45% from 2018 to 2019, with over 88 million trips taken on e-scooters. The regulatory landscape in the U.S. is fragmented, with cities and states implementing their own rules. Common regulations include speed limits, designated parking zones, and safety requirements. For example, Los Angeles has implemented a 15 mph speed limit for e-scooters and requires operators to provide data on usage and compliance. However, the rapid proliferation of micromobility has led to challenges such as sidewalk clutter and safety concerns (Parkes et al., 2013; Marsden et al., 2011). Micromobility has positively impacted urban mobility by reducing car trips, alleviating traffic congestion, and lowering greenhouse gas emissions. Studies show that micromobility options are particularly effective for last-mile connectivity, complementing public transport systems (Smith and Schwieterman, 2018). A study

by Populus found that 70% of e-scooter trips in the U.S. replaced car trips, highlighting the potential for micromobility to reduce traffic congestion and emissions (Clewlow, 2019).

- ***Canada:*** Micromobility adoption in Canada has been slower compared to the U.S., but it is gaining momentum. Cities like Toronto and Montreal have introduced bike-sharing programs and are beginning to embrace e-scooters. The cold climate and seasonal variations impact the usage patterns, limiting micromobility to warmer months (Hess, 2012). In 2019, Montreal's BIXI bike-sharing program recorded over 5 million trips, demonstrating significant usage during the warmer months. Canadian cities have implemented regulations to manage micromobility, focusing on safety and integration with existing transport systems. Regulations often include helmet requirements, speed limits, and designated parking areas (Anciaes and Jones, 2020). For instance, Toronto requires e-scooter operators to have insurance and limits e-scooter speeds to 20 km/h. Micromobility has the potential to address urban transport challenges in Canada by providing flexible and sustainable transport options. The integration of micromobility with public transit is crucial for maximizing its benefits. In 2022, shared micromobility trips increased significantly, with over 130 million trips taken across the US and Canada, marking a 40% increase since 2018 (National Association of City Transportation Officials (NACTO), 2022).

6.4.2 Europe

- ***Austria:*** Austria has embraced micromobility with enthusiasm, particularly in cities like Vienna. The city's bike-sharing program "Citybike Wien" recorded over 1.3 million trips in 2019. The introduction of e-scooters by companies like Lime and Bird has diversified transportation options (Grosse-Ophoff et al., 2017). Austria has established regulations to manage micromobility, including speed limits, designated parking zones, and safety requirements. The government has also invested in infrastructure to support micromobility, such as dedicated bike lanes (Bundesministerium für Nachhaltigkeit und Tourismus, 2018). Vienna has implemented a speed limit of 25 km/h for e-scooters and requires operators to provide data on usage

and compliance. Micromobility has significantly enhanced urban mobility in Austria, contributing to reduced traffic congestion, improved air quality, and increased physical activity. The integration of micromobility with public transport systems has been a key factor in its success (Grosse-Ophoff et al., 2017). The e-scooter sharing market in Austria is projected to reach a revenue of approximately $14.71 million by 2024, with an expected annual growth rate of 3.19% (Statista Research Department, 2024b).

- ***Belgium:*** Belgium has seen a growing interest in micromobility, particularly in cities like Brussels and Antwerp. Bike-sharing programs and the introduction of e-scooters have been positively received by urban commuters. In 2019, Brussels' bike-sharing program, Villo!, recorded over 2 million trips (Fishman, 2016). Belgian cities have implemented regulations to manage micromobility, focusing on safety and integration with public transport. Regulations include speed limits, designated parking areas, and safety requirements such as helmet use (Jennings, 2020). Brussels has implemented a speed limit of 25 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has the potential to address urban transport challenges in Belgium by providing flexible and sustainable transport options. The micromobility market in Belgium, especially the e-scooter sharing segment, is expected to generate a revenue of approximately US$17,190,000 in 2024, with a projected annual growth rate of 1.88% (Statista Research Department, 2024c).

- ***Denmark:*** Denmark is known for its cycling culture, and cities like Copenhagen have been pioneers in promoting micromobility. The city's extensive bike-sharing program, Bycyklen, recorded over 1.5 million trips in 2019. The introduction of e-scooters has further expanded transportation options (Fishman, 2016). Denmark has established comprehensive regulations to manage micromobility, including speed limits, designated parking zones, and safety requirements. The government has also invested in infrastructure to support micromobility, such as dedicated bike lanes (Jennings, 2020). Copenhagen has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Mi-

cromobility has significantly enhanced urban mobility in Denmark, contributing to reduced traffic congestion, improved air quality, and increased physical activity. The Shared Mobility market in Denmark is projected to grow by 2.06% from 2024 to 2029, reaching a market volume of approximately US$5,223 million by 2029. Specifically, the e-scooter sharing market is expected to grow by 3.87% during the same period, with a projected market volume of about US$17,630k by 2029 (Statista Research Department, 2024d).

- ***Germany:*** Germany has warmly adopted micromobility solutions, particularly in cities like Berlin and Munich. Bike-sharing programs have been popular for years, and the introduction of e-scooters has further diversified transportation options. Companies like Tier and Voi operate extensively across German cities (Grosse-Ophoff et al., 2017). In 2019, over 38 million e-scooter trips were recorded in Germany, demonstrating significant adoption. Germany has established stringent regulations to manage micromobility. These include requirements for vehicle safety, designated parking areas, and integration with public transport. The German government has also supported the adoption of micromobility through initiatives like the National Cycling Plan (Bundesministerium für Digitales und Verkehr, 2024). Berlin has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has played a significant role in enhancing urban mobility in Germany. The environmental benefits, such as reduced emissions and improved air quality, have been substantial. The integration of micromobility with public transport has also improved the efficiency and convenience of urban mobility networks (Grosse-Ophoff et al., 2017). Germany is the largest market for e-scooters in Europe, with over 1.36 million units sold in 2020. The demand for e-scooters continues to grow, with around 80 million e-scooter journeys recorded in 2023, up from 75.1 million in 2022 (Clean Energy Wire, 2023).

- ***France:*** France has been a leader in micromobility adoption, with Paris being a prime example. The city's Vélib' bike-sharing program, launched in 2007, recorded over 20 million trips in 2019. The introduction of e-scooters by companies like

Lime and Bolt has further expanded micromobility options (Fishman, 2016). France has implemented comprehensive regulations to manage micromobility. These include speed limits, designated parking zones, and safety requirements such as mandatory insurance for e-scooter operators. The government has also invested in infrastructure to support micromobility, such as dedicated bike lanes (Gössling, 2020). Paris has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has significantly enhanced urban mobility in France, contributing to reduced traffic congestion, improved air quality, and increased physical activity. The integration of micromobility and public transit has been instrumental in its widespread adoption (EU Urban Mobility Observatory, 2022). A report by Paris City Hall indicates that e-scooters are increasingly replacing car use in Paris, with nearly 20% of e-scooter trips substituting for car journeys (Lime, 2023). For detailed information on Paris, please refer to Section 6.4.6.

- ***Italy:*** Italy has seen a growing interest in micromobility, particularly in cities like Rome and Milan. Bike-sharing programs and the introduction of e-scooters have been positively received by urban commuters. Milan's bike-sharing program, BikeMi, recorded over 3 million trips in 2019 (Fishman, 2016). Italian cities have implemented regulations to manage micromobility, focusing on safety and integration with public transport. Regulations include speed limits, designated parking areas, and safety requirements such as helmet use (Gössling, 2020). Rome has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has the potential to address urban transport challenges in Italy by providing flexible and sustainable transport options. In early 2024, Italy recorded 65,000 e-moped rides, 60,000 e-scooter trips, and 42,000 e-bike rides, with Milan leading the statistics with 105,000 rides (Whannell, 2024).

- ***Norway:*** Norway has embraced micromobility, particularly in cities like Oslo. Bike-sharing programs and the introduction of e-scooters have diversified transportation options. In 2019, Oslo's bike-sharing program recorded over 2 million

trips. The country's commitment to sustainability has driven the adoption of micromobility (Fishman, 2016). Norway has established comprehensive regulations to manage micromobility, including speed limits, designated parking zones, and safety requirements. The government has also invested in infrastructure to support micromobility, such as dedicated bike lanes (Gössling, 2020). Oslo has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has significantly enhanced urban mobility in Norway, contributing to reduced traffic congestion, improved air quality, and increased physical activity. The successful adoption of micromobility has largely depended on its integration with public transport systems (EU Urban Mobility Observatory, 2022). A survey indicated that 47% of respondents over the age of 20 in Norway had used an e-scooter more than 50 times in 2021, showing significant engagement with micromobility options (Statista Research Department, 2023).

- ***Spain:*** Spain has seen a growing interest in micromobility, particularly in cities like Madrid and Barcelona. Bike-sharing programs and the introduction of e-scooters have been positively received by urban commuters. In 2019, Madrid's bike-sharing program, BiciMAD, recorded over 3 million trips (Fishman, 2016). Spanish cities have implemented regulations to manage micromobility, focusing on safety and integration with public transport. Regulations include speed limits, designated parking areas, and safety requirements such as helmet use (Gössling, 2020). Barcelona has implemented a speed limit of 20 km/h for e-scooters and requires operators to provide data on usage and compliance. Micromobility has the potential to address urban transport challenges in Spain by providing flexible and sustainable transport options. The use of micromobility vehicles in Barcelona is expected to increase by 31% by 2024, as the city implements various measures to promote sustainable transport options (Catalonia, 2024).

- ***Switzerland:*** Switzerland has embraced micromobility, particularly in cities like Zurich and Geneva. Zurich's bike-sharing program, Züri rollt, recorded over 1 million trips in 2019. The introduction of e-scooters by companies like Lime and Bird has diversified transportation options, with over 2 million e-scooter trips recorded

in 2019 (Lime, 2019). Switzerland has established comprehensive regulations to manage micromobility, including speed limits of 20 km/h for e-scooters, designated parking zones, and safety requirements. The government has also invested in infrastructure to support micromobility, such as dedicated bike lanes (Swiss Federal Roads Office, 2019). Micromobility has significantly enhanced urban mobility in Switzerland, contributing to reduced traffic congestion, improved air quality, and increased physical activity. A study by the Swiss Federal Institute of Technology found that 35% of micromobility trips replaced car trips, highlighting the potential for micromobility to reduce traffic congestion and emissions (Reck et al., 2022).

- ***Turkey:*** Turkey, particularly its major cities like Istanbul and Ankara, has seen a growing interest in micromobility. The introduction of bike-sharing programs and e-scooters has been positively received. In Istanbul, the İSBİKE bike-sharing program (initiated by Yapıdrom Teknoloji A.Ş. in 2012) recorded over 500,000 trips in 2019. Additionally, e-scooter companies like Martı (a member of New Urban Mobility Alliance) have gained popularity, with over 1 million users and 5 million trips recorded in 2020 (Martı, 2020). Turkish cities have begun to implement regulations to manage micromobility, focusing on safety and integration with public transport. Regulations include speed limits of 20 km/h for e-scooters, designated parking areas, and safety requirements. The government is also investing in infrastructure to support micromobility, such as dedicated bike lanes (Istanbul Metropolitan Municipality, 2020). Micromobility has the potential to address urban transport challenges in Turkey by providing flexible and sustainable transport options. A study by the Istanbul Metropolitan Municipality found that 25% of micromobility trips replaced car trips, highlighting the potential for micromobility to reduce traffic congestion and emissions (Istanbul Metropolitan Municipality, 2020). For detailed information on Istanbul, please refer to Section 6.4.6.

- ***Netherlands:*** The Netherlands is renowned for its cycling culture, with cities like Amsterdam and Utrecht leading the way in promoting micromobility. Amsterdam's bike-sharing program, OV-fiets, recorded over 4 million trips in 2019. The introduction of e-scooters has further diversified transportation options, with companies like

Felyx expanding their operations (Department, 2019). The Netherlands has established comprehensive regulations to manage micromobility, including speed limits of 25 km/h for e-scooters, designated parking zones, and safety requirements. The government has also invested heavily in cycling infrastructure, such as dedicated bike lanes and secure parking facilities (Wauters, 2021). Micromobility has significantly enhanced urban mobility in the Netherlands, contributing to reduced traffic congestion, improved air quality, and increased physical activity. A study by the Dutch Cycling Embassy found that 50% of micromobility trips replaced car trips, highlighting the potential for micromobility to reduce traffic congestion and emissions (Government of the Netherlands, 2020).

6.4.3 Asia

- ***China:*** China has been at the forefront of the micromobility revolution, particularly with dockless bike-sharing systems. Companies like Ofo and Mobike pioneered the dockless model, allowing users to locate and unlock bikes using mobile apps. In 2019, Mobike recorded over 200 million trips across Chinese cities. The introduction of e-scooters has further expanded micromobility options, with over 50 million e-scooter trips recorded in 2019 (EBMA Brussels, 2019). The regulatory environment in China has evolved to address challenges such as bike clutter, vandalism, and safety. Cities like Shanghai and Beijing have implemented regulations governing the operation and maintenance of micromobility services. These regulations include requirements for fleet management, designated parking zones, and safety standards (Sudmant et al., 2020). Micromobility has had a profound impact on urban mobility in China, providing an efficient solution for last-mile connectivity and reducing reliance on cars. A study by Tsinghua University found that 40% of micromobility trips replaced car trips, highlighting the potential for micromobility to reduce traffic congestion and emissions (Sudmant et al., 2020).

- ***Japan:*** Japan has shown a cautious but growing interest in micromobility. Bike-sharing programs have been introduced in cities like Tokyo and Osaka, with Tokyo's Docomo Bike Share recording over 3 million trips in 2019. There is increasing in-

terest in e-scooters, with companies like Luup expanding their operations (Cycle, 2019; Luup, 2023). Japan has implemented regulations to manage micromobility, focusing on safety and integration with public transport. Regulations include speed limits of 20 km/h for e-scooters, designated parking zones, and safety requirements such as helmet use. The government is also exploring ways to promote micromobility as part of its broader transport policy (Kubota, 2021). Micromobility has the potential to enhance urban mobility in Japan by providing flexible and sustainable transport options.The micromobility charging infrastructure market in Japan is predicted to grow at a compound annual growth rate (CAGR) of 27.3% from 2024 to 2030, reflecting the significant investment in supporting infrastructure for micromobility (Grand View Research, 2024b).

6.4.4 Latin America

- ***Mexico:*** Mexico City has been a leader in micromobility adoption in Latin America. The city's bike-sharing program, Ecobici, recorded over 10 million trips in 2019. The introduction of e-scooters by companies like Grin and Lime has further expanded micromobility options, with over 3 million e-scooter trips recorded in 2019 (Gobierno De la Ciudad de México, 2019; Cronkite News, 2019). Mexico City has implemented regulations to manage micromobility, focusing on safety and integration with existing transport systems. Regulations include speed limits of 20 km/h for e-scooters, designated parking areas, and safety requirements such as helmet use. The city government has also invested in infrastructure to support micromobility (ITF-OECD, 2020). Micromobility has significantly enhanced urban mobility in Mexico City, contributing to reduced traffic congestion, improved air quality, and increased physical activity. The Shared Mobility market in Mexico is projected to reach a revenue of US$23,820 million by 2024 and is expected to grow at a compound annual growth rate (CAGR) of 1.99% from 2024 to 2029, resulting in a market volume of US$26,280 million by 2029 (Statista Research Department, 2024e).

- ***Brazil:*** Brazil has seen growing interest in micromobility, particularly in cities like São Paulo and Rio de Janeiro. Bike-sharing programs have been introduced, with São Paulo's Bike Sampa recording over 1 million trips in 2019. The introduction of e-scooters by companies like Yellow and Lime has further expanded micromobility options, with over 2 million e-scooter trips recorded in 2019 (Pacheco and Batista, 2019; Marasciulo, 2024). The regulatory environment for micromobility in Brazil is still developing. Cities have implemented pilot programs to test micromobility solutions, focusing on safety, infrastructure, and integration with public transport. Comprehensive regulations are needed to address these challenges (Rosa et al., 2023). Micromobility has the potential to significantly improve urban mobility in Brazil by providing flexible and affordable transport options. The micromobility charging infrastructure market in Brazil is projected to grow at a compound annual growth rate (CAGR) of 21.9% from 2024 to 2030, indicating a strong investment in supporting infrastructure (Grand View Research, 2024a).

6.4.5 Africa

- ***South Africa:*** Micromobility adoption in South Africa is relatively limited compared to other regions. However, there is growing interest in bike-sharing and e-scooter programs as solutions to urban transport issues. In Cape Town, the Upcycle bike-sharing program recorded over 100,000 trips in 2019. E-scooter companies like Lime are beginning to explore the market (Lime, 2019). The regulatory environment for micromobility in South Africa is still developing. Few cities have established comprehensive regulations, but pilot programs and partnerships with private companies are being used to test the feasibility and impact of micromobility solutions (De Villiers and Sinclair, 2023). Micromobility has the potential to address significant urban transport challenges in South Africa, such as traffic congestion and limited access to public transport. The average revenue per user (ARPU) for e-scooter sharing in South Africa in 2024 is projected to be US$9.11. This reflects the growth potential in the pricing and consumer base for micromobility services (Statista Research Department, 2024a).

- ***Kenya:*** Kenya is beginning to explore the potential of micromobility to address urban transport challenges. In Nairobi, the Kbike bike-sharing program recorded over 50,000 trips in 2019. There is growing interest in e-scooters, with companies like Bolt expanding their operations (Bolt, 2023). The regulatory environment for micromobility in Kenya is still developing. Few cities have established comprehensive regulations, but pilot programs and partnerships with private companies are being used to test the feasibility and impact of micromobility solutions (International Climate Initiative, 2024). Micromobility has the potential to address significant urban transport challenges in Kenya, such as traffic congestion and limited access to public transport. The Kenyan government aims to support the acquisition of 200,000 e-motorcycles by the end of 2024, highlighting a significant push towards electrification in the micromobility sector (Capital FM, 2024).

In the light of given table for e-scooter legal regulations presented in the book of (Dündar, 2023), Table 6.1 summarizes the legal micromobility rules in various countries worldwide. It is important to note that the information may vary based on different micromobility vehicles, age, local practices and regulations, and it is subject to updates over time. Figure 6.9 presents a visual representation of the distribution of micromobile usage across countries worldwide.



Figure 6.9: Use of micromobility modes worldwide (NUMO, 2023).

Table 6.1: Overview of legal micromobility rules in various countries worldwide.

Country	Reference	Legal Regulation	Regulation Year	Mandatory Insurance	Driver's License	Age Limit	Mandatory Helmet	Alcohol Limit	On Vehicle Roads	On Pedestrian Roads	In Public Transport	Parking Rules
United States	(National Association of City Transportation Officials (NACTO), 2018)	Yes	State-based	Variable	State-based	16+	Variable	State-based	Yes	N/A	Variable	Variable
Canada	(Apollo Scooters, 2024)	Yes	2022	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
Austria	(Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie, 2024)	Yes	2019	No	No	12+	Yes	0.5	Yes	No	Yes	Permitted Zone
Belgium	(Brussels Times, 2022)	Yes	2022	Yes	No	16+	Yes	0.5	Yes	No	Yes	Permitted Zone
Denmark	(State of Green, 2021)	Yes	2019	No	No	15+	Yes	0.0	Yes	No	Yes	Permitted Zone
Germany	(Micromobility for Europe, 2024)	Yes	2019	Yes	No	14+	Recommended	0.0	Yes	No	Yes	Permitted Zone
France	(Pinheiro, 2023)	Yes	2023	No	Yes	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
Italy	(Mondaq, 2023)	Yes	2021	No	No	14+	Yes	0.0	Yes	No	Yes	Permitted Zone
Norway	(Ydersbond et al., 2023)	Yes	2022	No	No	12+	Yes	0.0	Yes	No	Yes	Permitted Zone
Spain	(Sur In English, 2023)	Yes	2024	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
Switzerland	(T-Wheels, 2022)	Yes	2012	No	No	14+	Recommended	0.0	Yes	No	Yes	Permitted Zone
Turkey	(Ersin and Hotan, 2020)	Yes	2021	No	No	18+	Recommended	0.0	Yes	No	Yes	Permitted Zone
Netherlands	(DutchX, 2024)	Yes	2022	Yes	Yes	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
China	(Musa, 2024)	Yes	2019	No	No	16+	Recommended	0.0	Yes	N/A	Yes	Permitted Zone
Japan	(Japan Times, 2023)	Yes	2023	No	No	16+	Recommended	0.0	Yes	No	Yes	Permitted Zone
Mexico	(Licea Viñas, 2021)	Yes	2022	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
Brazil	(São Paulo Decree, 2019)	Yes	2019	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
South Africa	(Department of Transport, South Africa, 2020)	Yes	2024	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone
Kenya	(Transport Kenya, 2021)	Yes	N/A	No	No	16+	Yes	0.0	Yes	No	Yes	Permitted Zone

6.4.6 Micromobility in Paris and Istanbul

Paris City

Micromobility has played a pivotal role in transforming urban transportation in Paris. From its early beginnings with bike-sharing programs to the widespread adoption of electric scooters, Paris has embraced micromobility as a sustainable and efficient mode of transport. With comprehensive legal regulations, significant contributions to urban mobility, carbon neutral zone initiatives, extensive municipal works, and ambitious future plans, Paris continues to lead the way in promoting micromobility and creating a greener, more sustainable city.

The history of micromobility in Paris dates back to the early 2000s with the introduction of bike-sharing programs like Vélib'. Launched in 2007, Vélib' became one of the largest bike-sharing systems in the world, setting the stage for the development of other micromobility solutions. The success of Vélib' led to the introduction of electric scooters and other shared mobility options in the late 2010s. By 2018, several companies, including Lime and Bird, had launched their electric scooter services in Paris, marking a significant shift towards sustainable urban transportation (Vélib', 2021).

Paris has implemented comprehensive legal regulations to manage the use of micromobility vehicles. Electric scooters (*fr. trottinette électrique*) are classified as Personal Light Electric Vehicles (PLEVs) and are subject to specific rules. They are limited to a maximum speed of 25 km/h and the bicycles must be used on bike lanes or roads where the speed limit is below 50 km/h (Wysling and Purves, 2022). Riding on sidewalks is prohibited, and helmets are recommended but not mandatory for adults. Additionally, operators of shared micromobility services must obtain permits and adhere to strict guidelines regarding fleet size, parking, and maintenance (City of Paris, 2019).

As of 2023, the ban on shared micromobility in Paris City (*fr. les arrondissements*) serves as a critical case study in the regulation and management of emerging transportation technologies. While shared electric scooters offer numerous benefits, their integration into urban environments must be carefully managed to ensure safety and public order. Paris's

experience suggests that without effective regulation and enforcement, the negative impacts of shared micromobility can outweigh its benefits, leading to drastic measures such as outright bans (Relman, 2023).

The primary reasons for the ban on shared electric scooters in Paris revolve around safety concerns, public nuisance, and regulatory challenges. A significant increase in accidents involving electric scooters, including fatal incidents, raised alarm among city officials and the public. Reports indicate that pedestrian safety was frequently compromised due to reckless scooter riding and indiscriminate parking on sidewalks, which obstructed pathways and created hazards (Paris Mobility Report, 2023).

Moreover, the regulatory framework struggled to keep pace with the rapid deployment of shared scooters. Despite efforts to impose speed limits, designate parking zones, and require insurance, enforcement proved challenging. The lack of compliance from both users and operators led to widespread disregard for the rules, exacerbating public frustration and ultimately prompting the ban (Paris Municipal Regulations, 2023).

Micromobility has significantly contributed to urban mobility in Paris by providing an alternative to traditional modes of transportation. It has helped reduce traffic congestion, improve air quality, and provide convenient, last-mile connectivity. The integration of micromobility with public transportation systems has further enhanced its utility, making it easier for residents and tourists to navigate the city. Studies have shown that micromobility trips in Paris often replace short car trips, thereby reducing the overall carbon footprint (Paris Mobility Report, 2020).

The municipal government of Paris has invested heavily in infrastructure to support micromobility. This includes the construction of dedicated bike lanes, parking zones for electric scooters, and the expansion of bike-sharing stations. The city's commitment to creating a micromobility friendly environment is evident in its continuous efforts to improve safety and accessibility. The introduction of smart traffic management systems and the use of geofencing technology are also part of the city's initiatives to ensure the smooth operation of micromobility services (Paris Infrastructure Development Plan, 2021).

Paris has been proactive in its commitment to become a zero net carbon neutral zone. The year 2050 has been set as the target date for this milestone and it is expected that the temperature increase in Paris will not surpass 2°C. According to the 2017 Paris Climate and Energy Plan (Marie de Paris, 2022), the city needs to achieve a 74% reduction in greenhouse gas emissions and to produce 50% less waste compared to 2013 levels. The Plan's strategies revolve around five main aspects, namely energy, transport, adaptation, circular economy, and the fight against air pollution. In terms of transport, there are three main measures proposed in the Plan. The above measures are also in parallel with the mobility measures for achieving a healthy city and avoiding "car dependent societies" as mentioned in the Environmental Action Plan in the Micromobility Policy Atlas (Shared-Use Mobility Center, 2019), such as the expansion of the cycle network and the application of traffic reduction policies.

Since September 2018, Paris is a member of the C40 cities (C40 Cities, 2018) leadership group, which connects Paris with other cities around the world that are working towards the same climate change goals. Paris aims to become a zero net carbon city of this initiative. As part of the first city goal of the Breath Life campaign (BreatheLife2030, 2024)(by WHO and the Climate and Clean Air Coalition) to honor this landmark achievement, Paris had joined an international coalition of cities in 2016 that are pledging to take effective actions to improve the quality of life and the air that their citizens breathe (Sustainable Development Goals, 2016) for the implementation of the Paris Agreement. The city aims to phase out diesel powered vehicles by 2024 and petrol powered vehicles by 2030, in a bid to significantly cut down urban mobility emissions and align with the Paris Agreement's goals of limiting global temperature rise (United Nations Framework Convention on Climate Change, 2023). This means that the combustion engine vehicles on the road in Paris will have to be phased out and the land that is currently used as car parks will be freed up for other purposes like developing green public areas in the future.

Looking ahead, Paris aims to further integrate micromobility into its urban transport system. Future plans include expanding the network of bike lanes, increasing the availability of shared micromobility vehicles, and promoting the use of electric bikes and scooters. The city also plans to implement more stringent regulations to ensure the safety and sus-

tainability of micromobility services. By 2025, Paris hopes to significantly reduce car usage in the city center, making micromobility the preferred mode of transportation for short trips (Paris 2025 Mobility Vision, 2022). Various visual examples from Paris are provided in Figure 6.10.



Figure 6.10: Micromobility visual examples from Paris.

Istanbul

Micromobility has played a transformative role in Istanbul's urban transportation landscape. From its early beginnings with bike-sharing programs to the rapid adoption of electric scooters, Istanbul has embraced micromobility as a sustainable and efficient mode of transport. With comprehensive legal regulations, significant contributions to urban mobility, carbon neutral zone initiatives, extensive municipal works, and ambitious future plans, Istanbul continues to promote micromobility and work towards a greener, more sustainable city.

The concept of micromobility in Istanbul began with the introduction of bike-sharing programs in the early 2010s. The city's first bike-sharing system, İSBİKE, was launched in

2012 and has since grown significantly. The rise of electric scooters followed in the late 2010s, with companies like Martı and BinBin entering the market. By 2020, the popularity of electric scooters had surged, driven by the need for convenient and sustainable urban transportation options (Istanbul Transportation Report, 2021).

In Turkey, the first use of e-scooter was in 2019 and the first fatal rideshare e-scooter accident occurred on February 26, 2020. Following this, on April 14, 2021, the e-scooter regulation was published in Official Gazette of the Republic of Turkey (Ulaştırma ve Altyapı, Çevre ve Şehircilik ile İçişleri Bakanlıkları, 2021; Çakır, 2020; Haber Merkezi, 2020). With electric scooters becoming an increasingly popular mode of transport in most countries, many e-scooter related injuries are also recorded, often affecting the head, face, and extremities (Puzio et al., 2020; Kim et al., 2022).

Istanbul has developed specific regulations to manage the growing use of micromobility vehicles. Electric scooters are classified under Personal Light Electric Vehicles (PLEVs) and are subject to rules that include a speed limit of 20 km/h (12.5 km/h in some districts). These vehicles are allowed on bike lanes and roads but are prohibited from sidewalks. Helmets are recommended but not mandatory. In addition, operators of shared micromobility services must obtain licenses and follow guidelines regarding fleet management, parking, and maintenance (Istanbul Municipality, 2020).

The Ministry of Transport and Infrastructure and the Turkish Intelligent Transportation Systems Association closely examine the regulations, activities, and research related to micromobility issues in Turkey. Several ministries in Turkey have implemented programs to promote bicycle usage, including the Ministry of Health's "Physical Activity Promotion Project" and "Turkey Healthy Nutrition and Active Life Program" from 2015-2018. In 2018, the Ministry of Environment and Urbanization and İLBANK A.Ş. announced financial support for municipalities to enhance bicycle infrastructure as part of the "President's 100-Day Action Program," emphasizing the role of ecofriendly transportation options like electric bicycles and scooters in improving urban quality of life (Önder and Akdemir, 2022).

Micromobility has made substantial contributions to urban mobility in Istanbul. It provides a solution to the city's notorious traffic congestion and offers an efficient mode of transport for short distances. Micromobility options like electric scooters and bikes have become popular for last-mile connectivity, bridging the gap between public transportation hubs and final destinations. This has not only alleviated traffic but also improved the overall transportation network's efficiency (Istanbul Mobility Study, 2020).

Istanbul's efforts to combat climate change include the promotion of micromobility as part of its carbon neutral zone initiatives. The city aims to reduce greenhouse gas emissions by encouraging the use of electric scooters and bikes. Specific areas have been designated as low emission zones, where high emission vehicles are restricted. These initiatives are part of Istanbul's broader strategy to achieve carbon neutrality by 2050 (Istanbul Climate Action Plan, 2019).

The Istanbul municipality has invested significantly in infrastructure to support micromobility. This includes the construction of dedicated bike lanes and parking zones for electric scooters. The municipal government has also expanded the İSBİKE network, adding more stations and bikes to meet the growing demand. Efforts to improve safety include the implementation of smart traffic management systems and the use of geofencing technology to regulate scooter usage in specific areas (Istanbul Infrastructure Development Plan, 2021). Additionally, the EuroVelo initiative, particularly the EuroVelo 8 - Mediterranean Route, extends into Turkey and enhances cycling infrastructure, promoting long distance cycling and improving urban mobility options within Istanbul (EuroVelo, 2024). This cycling route not only supports local tourism but also aligns with sustainable urban transport goals by integrating cycling into the broader transport network.

Looking forward, Istanbul has ambitious plans to further integrate micromobility into its urban transport system. Future initiatives include expanding the network of bike lanes and increasing the availability of shared micromobility vehicles. The city plans to implement stricter regulations to enhance safety and sustainability. Additionally, Istanbul aims to reduce car usage in the city center significantly by 2030, positioning micromobility as a primary transportation mode for short trips (Istanbul 2030 Mobility Vision, 2022).

Various visual examples from Istanbul is provided in Figure 6.11.



Figure 6.11: Micromobility visual examples from Istanbul.

6.5 Future Trends and Innovations on Micromobility

The future of micromobility is characterized by rapid advancements in technology, integration with public transportation, sustainability efforts, and innovative business models. Electrification, autonomous technology, data driven solutions, and regulatory frameworks are all contributing to the evolution of micromobility. As cities continue to embrace these innovations, micromobility is set to play an increasingly vital role in creating sustainable, efficient, and accessible urban transportation systems.

One of the most significant trends in micromobility is the ongoing advancement in electrification and battery technology. Innovations in battery design are leading to longer lasting, faster charging, and more efficient power sources. For instance, solid-state batteries are expected to replace traditional lithium-ion batteries, offering higher energy density and improved safety (Olabi et al., 2023). These advancements will enhance the performance of electric scooters and bikes, making them more reliable and appealing for daily use.

The integration of micromobility with public transportation systems is another emerging trend. Cities are increasingly recognizing the potential of micromobility to complement existing transit networks. This integration involves creating seamless connections between micromobility hubs and public transportation nodes, such as bus stops and train stations. Smart infrastructure, including dedicated lanes and parking zones, is being developed to facilitate this integration (Shaheen and Cohen, 2019a). Such efforts aim to create a cohesive and efficient urban mobility ecosystem.

Autonomous technology is gradually making its way into the micromobility sector. Autonomous scooters and bikes equipped with sensors and AI-driven navigation systems are being tested in various cities. These vehicles can navigate complex urban environments, avoid obstacles, and even return to docking stations autonomously (Arthur D. Little, 2024). The development of autonomous micromobility holds the promise of enhanced safety, reduced operational costs, and increased accessibility.

Data analytics and artificial intelligence are playing a crucial role in optimizing micromobility services. Operators are leveraging data to understand usage patterns, predict demand, and optimize fleet management. AI-driven algorithms can dynamically adjust the distribution of vehicles based on real-time demand, ensuring availability where it is needed most (Gössling, 2020). Additionally, data driven insights are helping cities design better infrastructure and regulations to support micromobility.

Sustainability remains a core focus of micromobility innovations. Future trends include the adoption of green energy sources, such as solar and wind power, to charge micromobility vehicles. Shared micromobility services are exploring ways to reduce their carbon footprint by utilizing renewable energy and promoting recycling programs for batteries and components (Olabi et al., 2023). These efforts align with global initiatives to combat climate change and promote ecofriendly transportation alternatives.

As micromobility continues to evolve, regulatory frameworks are also adapting to ensure safety and compliance. Future regulations are expected to focus on standardizing vehicle design, implementing stricter safety measures, and enhancing user education. Innovations in safety technology, such as improved braking systems, enhanced visibility features, and

collision avoidance systems, are being integrated into micromobility vehicles to reduce accidents and improve rider safety (Shaheen and Cohen, 2019a).

The future of micromobility is also being shaped by innovative business models. Shared micromobility services are expanding, offering flexible and affordable transportation options. Subscription models, where users pay a monthly fee for unlimited access to vehicles, are gaining popularity. These models provide convenience and predictability for users while ensuring a steady revenue stream for operators (Gössling, 2020).

6.6 Micromobility in Multi-Criteria Decision Making

Multi-Criteria Decision Making (MCDM) methodologies are crucial for evaluating and optimizing micromobility solutions in urban environments. As cities pursue sustainable and efficient transportation alternatives, micromobility has emerged as a viable option for short distance travel, often complementing existing public transit systems. MCDM techniques enable decision makers to assess various micromobility modes, including bike-sharing programs, electric scooters, and e-bikes, based on multiple criteria such as accessibility, environmental impact, safety, cost effectiveness, and user preferences. By integrating these diverse criteria, MCDM provides a structured framework for comparing and prioritizing micromobility options, ultimately facilitating the selection and implementation of strategies that align with the needs of urban residents while promoting sustainable urban mobility.

Moreover, MCDM enhances stakeholder engagement and promotes transparent decision-making processes, allowing for the inclusion of varied perspectives in micromobility planning and policy development. As cities face complex transportation challenges—such as mode selection, infrastructure planning, regulatory framework development, integration with existing public transportation, understanding user behavior and preferences, ensuring safety, and managing associated risks—the application of MCDM methodologies provides valuable insights and guidance for the effective deployment and management of micromobility initiatives, thereby contributing to more resilient, equitable, and livable urban environments.

Given its current relevance and rapid growth as a research topic, numerous studies in the literature have applied MCDM methods to micromobility. A summary of recent studies directly related to this doctoral research is presented in Table 6.2. The reviewed articles highlight the diverse applications and innovations in this domain, offering important insights for future research and implementation.

Table 6.2: Various micromobility studies employing MCDM methods in the literature.

Author	**Year**	**Approach**	**Title**
Wankmüller et al.	(2020)	BWM	"Selecting E-Mobility Transport Solutions for Mountain Rescue Operations"
Torkayesh and Deveci	(2021)	TRUST	"A MulTi-NoRmalization MUlti-Distance ASsessmenT (TRUST) Approach for Locating a Battery Swapping Station for Electric Scooters"
Fazio et al.	(2021)	SMCA	"Planning Suitable Transport Networks for E-Scooters to Foster Micromobility Spreading"
Kalakoni et al.	(2022)	AHP	"A novel methodology for micromobility system assessment using multi-criteria analysis" It is applied on Paris City.
Deveci et al.	(2022b)	WASPAS	"Fuzzy Einstein WASPAS approach for the economic and societal dynamics of the climate change mitigation strategies in urban mobility planning."
Ayyildiz	(2022)	SWARA, CODAS	"A novel pythagorean fuzzy multi-criteria decision-making methodology for e-scooter charging station location-selection"
Altintasi and Yalcinkaya	(2022)	AHP	"Siting charging stations and identifying safe and convenient routes for environmentally sustainable e-scooter systems"
Aydin et al.	(2022)	AHP, WASPAS	"Planning Location of Mobility Hub for Sustainable Urban Mobility"
Ziemba and Gago	(2022)	PROMETHEE, PROSA, GAIA	"Compromise multi-criteria selection of E-scooters for the vehicle sharing system in Poland"

Author	Year	Approach	Title
Kubik	(2022)	ELECTRE III	"Selection of an electric scooter for shared mobility services using multicriteria decision support methods"
Deveci et al.	(2022a)	WASPAS	"Safe E-scooter operation alternative prioritization using a q-rung orthopair Fuzzy Einstein based WASPAS approach"
Ecer et al.	(2023)	DELPHI, LOPCOW, COCOSO	"Sustainability performance analysis of micromobility solutions in urban transportation with a novel IVFNN-Delphi-LOPCOW-CoCoSo framework"
Çakır	(2023)	SERA	"Neutrosophic Fuzzy Selected Element Reduction Approach (NF-SERA): Assessment of E-Scooter Parking Area"
Garipagaoglu et al.	(2023)	AHP	"E-bike sharing system location analysis on city level with AHP method: The case of Istanbul"
Garipagaoglu and Celikoglu	(2023)	AHP	"Prioritization of smart bicycle cage locations at district level using AHP method: Case of Istanbul"
Ayyildiz and Erdogan	(2023)	SWOT, AHP	"SWOT Analysis Integrated Interval Type-2 Triangular Fuzzy AHP: Application on e-Scooter Adaptation in Turkiye"
Deveci et al.	(2023)	RAFSI	"Sustainable E-scooter parking operation in urban areas using fuzzy Dombi based RAFSI model"
Simic et al.	(2022)	MEREC, MARCOS	"Mitigating Climate Change Effects of Urban Transportation Using a Type-2 Neutrosophic MEREC-MARCOS Model"
Zagorskas and Turskis	(2024)	ARAS-G	"Enhancing Sustainable Mobility: Evaluating New Bicycle and Pedestrian Links to Car-Oriented Industrial Parks with ARAS-G MCDM Approach"
Çakır	(2024a)	EFEE	"Criteria Weighting of Micromobility Modes via Extracted Framework Element Effect (EFEE) Methodology"

Author	Year	Approach	Title
Çakır and Tolga	(2024a)	EFEE	"New Multi Criteria Decision Making Methodology EFEE under Uncertainty on Paris City Micromobility"
Çakır and Tolga	(2024b)	V-PARS	"Vector-Based Preference Aided Ranking System (V-PARS): Application on Micromobility Modes in Paris"

The future of MCDM in micromobility involves integrating advanced technologies such as artificial intelligence and big data analytics to enhance decision making accuracy and efficiency. MCDM can be applied to various aspects of micromobility, enhancing decision-making processes and optimizing outcomes.

MCDM can be used to develop algorithms for optimizing micromobility routes based on multiple criteria, such as travel time, safety, and environmental impact. Real-time data from IoT devices can be integrated into these algorithms to provide dynamic route recommendations (Shafique et al., 2020). MCDM can inform the planning and development of micromobility infrastructure, such as bike lanes and e-scooter parking areas. Decision makers can evaluate various design options based on criteria such as cost, user convenience, and environmental benefits (Cinelli et al., 2014). MCDM can be applied to the management of micromobility fleets, optimizing maintenance schedules, and resource allocation. Criteria such as vehicle durability, maintenance costs, and user satisfaction can be considered to ensure efficient and sustainable fleet operations (Saaty, 2008). Policymakers can use MCDM to evaluate and develop policies that promote the adoption of micromobility solutions. Criteria such as environmental impact, public health benefits, and economic feasibility can be assessed to create balanced and effective policies (Hwang and Yoon, 1981).

While MCDM offers significant benefits for micromobility, several challenges must be addressed to fully realize its potential. Integrating diverse data sources, such as IoT devices, user feedback, and environmental sensors, into MCDM models can be complex. Developing standardized data formats and robust integration frameworks will be crucial

for effective decision making (Shafique et al., 2020). The dynamic nature of urban mobility requires MCDM models that can operate in real-time. Advances in computational power and algorithm optimization will be needed to support real-time decision making in micromobility (Cinelli et al., 2014). Engaging users in the decision making process is essential for the success of micromobility solutions. MCDM models must incorporate user preferences and feedback to ensure that the solutions developed are aligned with user needs and expectations (Saaty, 2008).

In summary, the future of MCDM in micromobility is promising, with numerous opportunities for enhancing urban transport systems. By integrating advanced MCDM methodologies with real-time data and user-centric approaches, decision makers can develop optimized and sustainable micromobility solutions. Addressing challenges related to data integration, dynamic decision making, and user engagement will be crucial for realizing the full potential of MCDM in this rapidly evolving field. Additionally, there is a growing emphasis on sustainability and resilience, prompting the development of frameworks that prioritize environmental and social criteria.

6.7 Related Studies in the Literature

To enhance the comprehensiveness of this study, relevant literature pertaining to micromobility is catalogued in Table 6.3.

Table 6.3: Related studies on micromobility.

Author	Year	Title	Type
Cervero et al.	(2017)	"Beyond mobility: Planning cities for people and places"	Book
Press	(2018)	"Faster, Smarter, Greener: The Future of the Car and Urban Mobility"	Book
DuPuis et al.	(2019)	"Micromobility in Cities: A History and Policy Overview"	Article

Author	Year	Title	Type
Oeschger et al.	(2020)	"Micromobility and Public Transport İntegration: The Current State of Knowledge"	Article
Santacreu et al.	(2020)	"Safe Micromobility"	Article
Yang et al.	(2020)	"Safety of Micro-mobility: Analysis of E-Scooter Crashes by Mining News reports"	Article
Fearnley	(2020)	"Micromobility–Regulatory Challenges and Opportunities"	Article
O'hern and Estgfaeller	(2020)	"A Scientometric Review of Powered Micromobility"	Article
Abduljabbar et al.	(2021)	"The Role of Micro-mobility in Shaping Sustainable Cities: A Systematic Literature Review"	Article
Meng and Brown	(2021)	"Docked vs. Dockless Equity: Comparing Three Micromobility Service Geographies"	Article
Bozzi and Aguilera	(2021)	"Shared E-Scooters: A Review of Uses, Health and Environmental Impacts, and Policy Implications of a New Micro-Mobility Service"	Article
Shaheen et al.	(2022)	"Shared Micromobility Policy, Practices, and Emerging Futures"	Book
Kalakoni et al.	(2022)	"A Novel Methodology for Micromobility System Assessment Using Multi-Criteria Analysis"	Article
Marques and Coelho	(2022)	"A Literature Review of Emerging Research Needs for Micromobility—Integration Through A Life Cycle Thinking Approach"	Article
Stefancová et al.	(2022)	"Research on the Impact of COVID-19 on Micromobility Using Statistical Methods"	Article
Bretones and Marquet	(2022)	"Sociopsychological Factors Associated with the Adoption and Usage of Electric Micromobility. A literature review"	Article
Dozza et al.	(2022)	"A Data-driven Framework for the Safe Integration of Micro-Mobility into the Transport System: Comparing Bicycles and e-Scooters in Field Trials"	Article
Berger	(2023)	"The Future of Urban Mobility"	Book

Author	Year	Title	Type
Aba and Esztergár-Kiss	(2024)	"Electric Micromobility from A Policy-Making Perspective Through European Use Cases"	Article
Sarker et al.	(2024)	"Exploring Micromobility Choice Behavior across Different Mode Users Using Machine Learning Methods"	Article
SAE International	(2024)	"The New Mobility Handbook"	Book
Amirgholy and Yang	(2024)	"Decision Making and Policy Analysis in Transportation Planning"	Book
Lane	(2024)	"Micro-Mobility Revolution"	Book
Guan et al.	(2024)	"Shared Micro-mobility and Transport Equity: A Case Study of three European Countries"	Article
Çakır and Tolga	(2024b)	"Vector-Based Preference Aided Ranking System (V-PARS): Application on Micromobility Modes in Paris"	Article
Çakır et al.	(2024)	"Milk-run optimization under time windows for collection and replacement of low-charge e-scooters"	Paper

7 APPLICATION

This chapter presents a hybrid methodological approach to evaluate micromobility mode alternatives within the urban contexts of Paris/France and Istanbul/Turkey. By integrating the novel proposed POndération sur la Distance par ExtRaction (PODER) and Vector-Based Preference Ranking System (V-PARS) MCDM models, a comprehensive framework is established to support informed decision making.

The application procedure commences with the identification of relevant micromobility modes for both cities. Subsequently, a robust set of evaluation criteria is established based on social, environmental, and user related factors, aligning with the EU's 2050 sustainability goals. A participatory approach involving expert stakeholders is employed to identify these criteria, ensuring their relevance to the specific urban contexts. In the hybrid approach, the PODER is applied to determine the importance of each criterion, providing a decision centered foundation for the subsequent evaluation. The V-PARS is performed to rank the micromobility alternatives based on the weighted criteria, enabling a comparative assessment of their performance.

Through this integrated approach, the chapter seeks to contribute to the advancement of micromobility research by providing a structured and replicable MCDM methodology for evaluating alternative modes in complex urban environments both Paris and Istanbul.

Briefly, the structure and procedural steps of the application are given in Figure 7.1.

7.1 Case Description

The discussion of micromobility in Paris is closely tied to the city's evolving transportation landscape, significantly influenced by the introduction of new mobility options and the impact of the Covid-19 pandemic on travel habits. This exploration focuses on the legal and regulatory changes that have accompanied these shifts, particularly the "Loi d'orientation des mobilités" of 2019, which gave cities the authority to regulate trans-

portation. This law, along with the decree on personal transport, set clear rules for the use of micromobility vehicles.

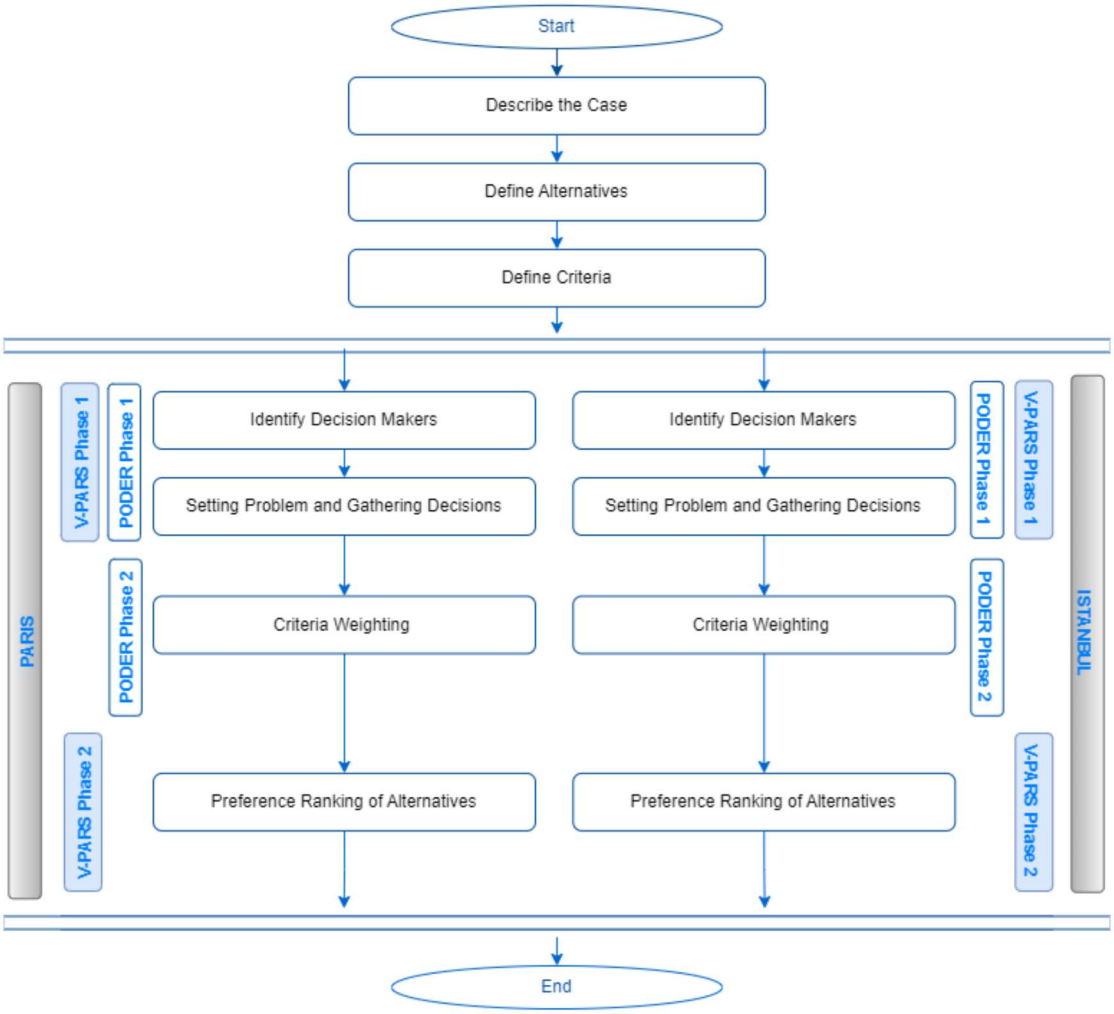


Figure 7.1: Flowchart of hybrid procedure of PODER and V-PARS for micromobility mode evaluation of Paris and Istanbul.

Paris implemented a regulatory framework in 2020 to manage the use of e-scooters, limiting the number of operating companies to three and enforcing strict rules on where these vehicles can be parked. The city also introduced "coronapistes," temporary bike lanes created during the pandemic, which led to a surge in the use of bicycles and scooters. In this context, researchers are examining the various micromobility devices in use, aiming to understand their broader impact, including benefits like reduced car use and challenges such as safety and accident rates.

Meanwhile, Istanbul, as a large and congested city, faces significant transportation challenges that have sparked interest in micromobility as a potential solution. The introduction of e-scooters and shared bicycles has been seen as a way to alleviate traffic and reduce pollution. However, the rapid influx of these vehicles initially led to problems like overcrowded sidewalks, safety issues, and conflicts with existing transport modes due to the lack of a comprehensive regulatory framework.

In response, Istanbul has begun developing a more organized approach to micromobility, including designated parking areas for e-scooters, safety regulations, and efforts to incorporate micromobility into a broader sustainable urban mobility strategy. The Covid-19 pandemic also accelerated the adoption of micromobility in the city as people looked for alternatives to crowded public transit. Current research in Istanbul is focused on evaluating the success of these measures, exploring how micromobility can be better integrated into the city's transportation system, and assessing its impact on traffic, pollution, and safety.

Both Paris and Istanbul serve as important examples for understanding the complexities of integrating micromobility into urban environments. In Paris, shared micromobility is restricted within the city center, with the exception of the local bike-sharing program, Vélib'. In contrast, Istanbul allows not only the local bike-sharing service, İSBİKE, but also numerous other micromobility companies to operate within the city. This difference in policy makes Paris and Istanbul interesting cases for comparison. To enable a meaningful analysis, this study includes the corresponding types and features of micromobility options available in both cities.

7.1.1 Definition of Alternatives

In the case study, the evaluation of four micromobility modes for comparison between Paris and Istanbul is centered on the top commonly used private vehicles. This focus ensures a consistent and relevant analysis across both cities, allowing for a meaningful comparison. The study specifically examined private bike (*fr. "vélo privé"*), private e-bike (*fr. "vélo électrique privé"*), private e-moped (*fr. "cyclomoteur électrique privé "*), and private e-scooter (*fr. "trottinette électrique privée"*) as these modes represent the most

prevalent and widely utilized forms of micromobility in both urban environments.

By concentrating on these prevalent modes, the study seeks to provide a clear and comparable understanding of how private micromobility is integrated into the transportation networks of both Paris and Istanbul. This approach not only highlights the similarities and differences in the use of these vehicles but also takes into account the unique urban dynamics, infrastructural contexts, and regulatory frameworks of each city. Such an analysis offers valuable insights into how these micromobility options contribute to and are shaped by the distinct characteristics of each urban environment. To visually support the discussion, some illustrative examples of these micromobility modes are provided in Figure 7.2.

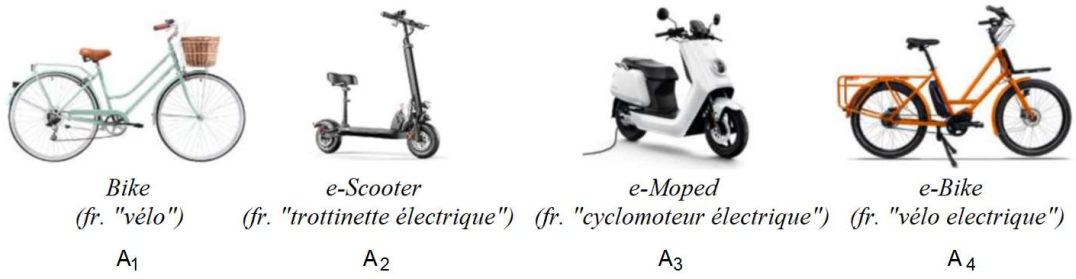


Figure 7.2: Alternative micromobility modes for Istanbul and Paris City.

7.1.2 Definition of Criteria

To thoroughly assess the urban usage preferences for micromobility vehicles in Paris and Istanbul, fourteen criteria have been established. These criteria are selected based on a comprehensive review of existing literature, consultations with experts, and alignment with the EU 2050 climate targets. Each criterion addresses different aspects of micromobility, such as user convenience, safety, environmental impact, and contribution to sustainability goals, ensuring a holistic evaluation of how these vehicles are integrated into the urban transportation systems of both cities.

The criteria are carefully chosen to capture a wide range of factors that influence micromobility usage, with particular attention given to aligning with the EU 2050 targets for reducing carbon emissions and promoting sustainable urban mobility. For instance,

some criteria focus on the practicality and accessibility of the vehicles, while others consider their potential to reduce greenhouse gas emissions, enhance air quality, and support overall environmental goals. These criteria and their respective ranges have been systematically incorporated into the evaluation framework to provide a detailed understanding of user preferences and operational dynamics in both cities.

- **Average lifespan (C_1):** This criterion evaluates the overall durability and longevity of micromobility vehicles. In the context of sustainability, a longer lifespan reduces the need for frequent replacements, lowering resource consumption and waste. A longer life cycle aligns with EU goals to minimize environmental impact through efficient use of resources and reducing the carbon footprint associated with production and disposal.

- **Charging time (C_2):** Charging time is critical for the usability of electric micromobility vehicles. Shorter charging times enhance vehicle availability and encourage more frequent use. Efficient energy use during charging also aligns with the EU's carbon neutral goals by promoting energy efficiency, especially if renewable energy sources are used for recharging.

- **Maximum driving range in one charge (C_3):** A higher driving range supports longer trips and wider adoption of electric micromobility options, reducing reliance on fossil-fuel-based transportation. This aligns with the EU's sustainability targets by encouraging the use of low carbon transport solutions for extended urban mobility, ultimately contributing to reduced greenhouse gas emissions.

- **Speed limit (C_4):** Ensuring a balanced speed limit promotes safety and aligns with urban mobility regulations. Sustainable micromobility solutions must prioritize user safety without compromising the efficiency of transport. Setting appropriate speed limits also ensures that micromobility options are accessible for a wide range of users while supporting the reduction of traffic congestion and pollution in cities.

- **Usage rate at least once a week (C_5):** This criterion measures how frequently micromobility vehicles are used. A high usage rate is crucial for integrating these

vehicles into everyday urban life, which supports the EU's vision of promoting sustainable and low carbon mobility as a norm by 2050. More frequent usage reflects societal shifts towards more sustainable and environmentally friendly transport habits.

- **Accident rate (C_6):** Safety is a key factor in urban transportation. By assessing the accident rate, cities can address concerns about the adoption of micromobility. Reducing accident rates ensures public confidence, further supporting the shift to low emission transportation modes. Safety improvements contribute to the EU's broader goals for sustainable, safe urban environments.

- **Intermodality rate (C_7):** Intermodality refers to the ability of micromobility vehicles to be integrated with other forms of public transportation. High intermodality supports seamless transitions between transport modes, reducing car dependency. This contributes to the EU's goal of creating a sustainable, low emission urban mobility system by 2050, where different transportation modes work together to minimize carbon emissions.

- **Security (C_8):** Security addresses both personal safety and protection against theft or damage to micromobility vehicles. Ensuring secure transportation solutions is vital for encouraging usage and investment in such systems. Secure micromobility solutions also contribute to creating livable, sustainable cities by fostering public trust and acceptance of these modes.

- **Saving time (C_9):** Time savings contribute to the overall appeal and practicality of micromobility solutions, particularly in comparison to more polluting modes of transport like cars. If users can save time using eco-friendly vehicles, they are more likely to switch, thereby reducing traffic congestion and pollution. This criterion supports the EU's goals of enhancing the efficiency of urban transport systems.

- **Comfort (C_{10}):** Comfort is crucial for the widespread adoption of micromobility. Comfortable, user-friendly vehicles encourage sustainable travel habits and reduce reliance on cars. Ensuring a high standard of comfort aligns with the EU's vision for inclusive and equitable mobility systems that are accessible to all urban citizens.

- **Health benefit (C_{11}):** Micromobility promotes active transport modes, such as electric scooters and bikes, which contribute to physical health through increased activity. Health benefits from using these vehicles align with the EU's broader goals of creating healthier, more sustainable urban living environments, with reduced pollution and enhanced quality of life.

- **Environmental noise (C_{12}):** Electric micromobility vehicles tend to generate less noise than traditional motor vehicles, contributing to quieter urban environments. Reducing environmental noise supports the EU's sustainability objectives, particularly in enhancing the livability of cities and improving the well-being of residents by mitigating noise pollution.

- **Eco-design (C_{13}):** Eco-design involves creating vehicles with environmentally friendly materials and processes that minimize resource use and waste. Vehicles designed with sustainability in mind have a lower environmental impact over their life cycle. This criterion supports the EU's emphasis on sustainable production and consumption patterns, contributing to carbon neutrality and resource efficiency.

- **Low carbon emission (Sustainability) (C_{14}):** One of the most critical criteria, this evaluates the extent to which micromobility vehicles contribute to reducing carbon emissions. Aligning directly with the EU's 2050 climate targets, this criterion promotes the shift towards carbon neutral urban transport, aiming to lower greenhouse gas emissions and combat climate change.

Information about each criterion and its range is presented in Table 7.1, which serves as a comprehensive reference for the evaluation process. This table includes specific metrics and benchmarks for each criterion, offering a clear and organized view of the factors being analyzed. By using these criteria, the study aims to provide valuable insights into the effectiveness and appeal of micromobility vehicles in Paris and Istanbul, contributing to a better understanding of their roles in the transportation ecosystems of these cities and their alignment with the EU's long-term sustainability objectives. The identified criteria are independent and do not influence one another. Each criterion is evaluated separately,

without reliance on the others. Note that the objective data with their range limits are gathering from the sources (Agence de la Mobilité, Paris, 2022; Turkish Government, 2024; Önder and Akdemir, 2022; Karahan et al., 2023; Okudan and Dündar, 2023; Turkish Statistical Institute, 2023; Lang et al., 2022) and the range limits of subjective data from Table 7.1 are the values obtained by defuzzifying them using the mean defuzzification function given in Equation 4.3.14.

7.1.3 Profiles of Decision Makers

To ensure a thorough and nuanced preference assessment of micromobility vehicles in Paris and Istanbul, five decision makers (DMs) have been selected for this study, each chosen for their expertise and direct experience with mobility tools. These individuals include professionals who are experts in the mobility industry, as well as those who either work directly with or have substantial daily experience using various micromobility options. Their diverse perspectives and deep understanding of the field provide a well-rounded basis for evaluating the different modes of micromobility.

The selected decision makers bring valuable insights into the practical and theoretical aspects of micromobility, making them well-suited to assess the preferences and effectiveness of these vehicles in each city. Their profiles, which include details about their professional backgrounds and areas of expertise, are presented in Table 7.2. This table highlights their roles and qualifications, offering a comprehensive view of the individuals contributing to the assessment.

Following the selection process, the profiles of these decision makers are categorized into appropriate groups as outlined in Table 5.1. This categorization helps in understanding their specific contributions to the decision making process and clarifies how their individual insights influence the evaluation of micromobility vehicles. By integrating their perspectives into the decision making system, the study aims to capture a wide range of expert opinions and experiences, thereby enhancing the reliability and depth of the preference assessment. In order to reach the details of the process regarding the decision maker and the collection of opinions; the survey template, informed voluntary consent form, post-participation information form, and approvals from the ethics committee prepared

Table 7.1: Information of evaluation criteria.

Code	**Name**	**Benefit / Cost**	**Objective Indicator**	**Range Limits (Obj.)**	**Subjective Indicator (Linguistic)**	**Range Limits (Subj.)**
C_1	Average lifespan	B	Year	[0, 50]	Low/Middle/High	[3, 7]
C_2	Charging time	C	Hour	[0, 10]	Low/Middle/High	[0.149, 0.467]
C_3	Maximum driving range in one charge	B	Km	[0, 200]	Low/Middle/High	[3, 7]
C_4	Speed limit	B	Km/h	[0, 30]	Low/Middle/High	[3, 7]
C_5	Usage rate at least once a week	B	Rate	[0, 1]	Low/Middle/High	[3, 7]
C_6	Accident rate	C	Rate	[0, 1]	Low/Middle/High	[0.149, 0.467]
C_7	Intermodality rate	B	Rate	[0, 1]	Low/Middle/High	[3, 7]
C_8	Security	B	-	-	Low/Middle/High	[3, 7]
C_9	Saving time	B	-	-	Low/Middle/High	[3, 7]
C_{10}	Comfort	B	-	-	Low/Middle/High	[3, 7]
C_{11}	Health benefit	B	-	-	Low/Middle/High	[3, 7]
C_{12}	Environmental noise	C	-	-	Low/Middle/High	[0.149, 0.467]
C_{13}	Eco-design	B	-	-	Low/Middle/High	[3, 7]
C_{14}	Low carbon emission (Sustainability)	B	-	-	Low/Middle/High	[3, 7]

for the research are available in the Appendices.

Table 7.2: Information about decision makers.

	Decision Maker	**Age**	**Sex**	**Education Level**	**Profession**	**Experience on Micromobility Devices (year)**	**Category by Nudge Hierarchy**
Paris	DM_1	38	M	Bachelor	Customer Success Manager	10	Expert
	DM_2	54	F	Ph.D.	CEO	12	Expert
	DM_3	29	M	Master	Warranty Manager	8	Expert Candidate
	DM_4	34	M	Master	After Sales Manager	5	Emerging Expert
	DM_5	27	F	Bachelor	Technician	3	Beginner
Istanbul	DM_1	42	M	Ph.D.	Insurance Professional	9	Expert
	DM_2	45	F	Ph.D.	Marketing and Communica-tions	13	Expert
	DM_3	51	F	Master	Micromobility Service Provider	11	Expert Candidate
	DM_4	32	F	Master	Transportation Engineer	7	Emerging Expert
	DM_5	29	M	Bachelor	Data Analyst	4	Beginner

7.2 Micromobility Mode Evaluation for Paris City

By adhering to the procedure specified in Chapter 5, the evaluation of micromobility in Paris follows each step of the proposed methodology in detail. This approach ensures that every phase of the assessment is conducted in line with the outlined guidelines, guaran-

teeing a thorough and accurate analysis of the micromobility initiatives.

7.2.1 Setting Problem and Gathering Decisions (Phase 1)

The prosedure of initial phase (Phase 1: Expert Driven Model) for both PODER and V-PARS methodologies is identical. Note that the criteria weights differ in Phase 2 (PODER initially assumes the weights to be equal, V-PARS uses the determined weights). Therefore, the current phase (Phase 1) can be executed uniformly for both models.

PODER and V-PARS Phase 1: Expert Driven Model

This phase requires expert input and follows a structured process. It involves defining the sets based on information from Section 7.1, collecting data from decision-makers, aggregating matrices, and ultimately creating a single, comprehensive decision matrix.

Problem Definition

Step 1.1: According to the Section 7.1, the sets of numerical case are established as follows:

The sets of alternatives $A_i = \{A_1 : Private\ Bike, A_2 : Private\ e-Scooter, A_3 : Private\ e-Moped, A_4 : Private\ e-Bike\}$ and the set of criteria is $C_j = \{C_1, C_2, ..., C_{14}\}$ is determined in Table 7.1.

Step 1.2: According to given Table 7.2 the set of decision makers are established as follows:

The set of decision makers is $DM_p = \{DM_1, DM_2, DM_3, DM_4, DM_5\}$ and the decision makers are categorized as $\{DM_E, DM_{EC}, DM_{EE}, DM_B\}$ according to their profiles in Table 5.1. $W_{DM} = \{W_{DM_E} = 0.4, W_{DM_{EC}} = 0.3, W_{DM_{EE}} = 0.2, W_{DM_B} = 0.1\}$ and Nudge Theory based hierarchy given in the Table 7.2.

DM_1 and DM_2 are *"Expert"s*, DM_3 is *"Expert Candidate"*, DM_4 is *"Emerging Expert"* , DM_5 is *"Beginner"*. The set of categorized decision makers are as follows:

- $DM_E = \{DM_1, DM_2\}$ with $W_{DM_E} = \{W_{DM_1} = 0.2, W_{DM_{E2}} = 0.2\}$

Table 7.3: Linguistic expressions and their ordinary fuzzy correspondings.

Linguistic Expression	**Ordinary Fuzzy Corresponding**	**Inverse of Ordinary Fuzzy Corresponding for Benefit-Cost Conversion**
Low	(1,3,5)	(1/5,1/3,1/1)
Medium	(3,5,7)	(1/7,1/5,1/3)
Height	(5,7,9)	(1/9,1/7,1/5)

- $DM_{EC} = \{DM_3\}$ with $W_{DM_{EC}} = \{W_{DM_3} = 0.3\}$
- $DM_{EE} = \{DM_4\}$ with $W_{DM_{EE}} = \{W_{DM_4} = 0.2\}$
- $DM_B = \{DM_5\}$ with $W_{DM_B} = \{W_{DM_5} = 0.1\}$

Step 1.3: The ordinary fuzzy numbers and their corresponding linguistic expressions to be used in the subjective evaluation are set in Table 7.3 and illustrated in Figure 7.3. The inverses of ordinary fuzzy numbers have also been included for benefit-cost conversions.

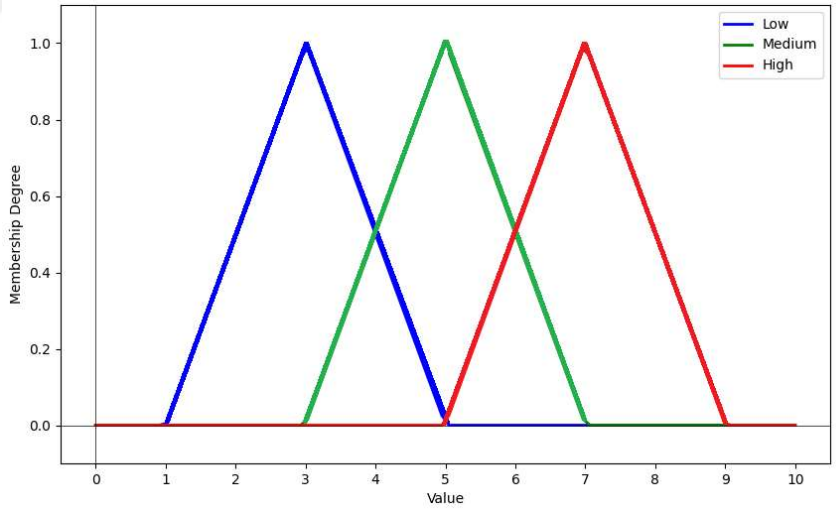


Figure 7.3: Triangular fuzzy numbers for linguistic expressions.

The fuzzy weighted average operator *(FWA)* by (Dong and Wong, 1987) (given in Equation 4.3.11) is re-defined for the aggregation of subjective data consisting of ordinary triangular fuzzy numbers as in Equation 7.2.1 to be used in Step 1.6.

$$(\tilde{a}_{ij_{sub}})_{aggr} = \oplus_{p=1}^{k}(w_{DM_p} \odot (\tilde{a}_{ij_{sub}})_{DM_p}) \quad \forall i,j \tag{7.2.1}$$

Data Collection

Step 1.4: Five DMs are asked about their evaluation on alternatives based on the determined criteria. All decisions are converted to *benefit type* by subtracting the objective data from their maximum values, and the subjective "low to high" score data was also converted according to Table 7.3.

Note that since the objective values are based on the Paris City rapport (Agence de la Mobilité, Paris, 2022), the objective decision matrix are identical for each DM in this application. In instances where each decision maker conducts his/her own assessment, separate matrices may be required. The objective and subjective evaluation of DMs are given as follows:

$$\mathrm{DM}_{1_{obj}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 30 & 10 & 150 & 20 & 0.57 & 0.85 & 0.12 & - & - & - & - & - & - & - \\ 3 & 5 & 50 & 25 & 0.61 & 0.74 & 0.13 & - & - & - & - & - & - & - \\ 7 & 2 & 65 & 30 & 0.73 & 0.85 & 0.08 & - & - & - & - & - & - & - \\ 10 & 6 & 100 & 25 & 0.87 & 0.49 & 0.14 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

where $DM_{1_{obj}}, DM_{2_{obj}}, DM_{3_{obj}}, DM_{4_{obj}}, DM_{5_{obj}}$ are identical.

$$\mathrm{DM}_{1_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) & (3,5,7) & (0.20,0.33,1.00) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.20,0.33,1.00) & (3,5,7) & (3,5,7) & (3,5,7) & (0.20,0.33,1.00) & (1,3,5) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (0.11,0.14,0.20) & (3,5,7) & (3,5,7) \\ (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (5,7,9) & (5,7,9) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (5,7,9) & (5,7,9) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (1,3,5) \\ (5,7,9) & (0.14,0.20,0.33) & (5,7,9) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (1,3,5) & (5,7,9) & (3,5,7) & (3,5,7) & (3,5,7) & (0.14,0.20,0.33) & (5,7,9) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{2_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) & (1,3,5) & (0.20,0.33,1.00) & (3,5,7) & (3,5,7) & (1,3,5) & (3,5,7) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (3,5,7) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (1,3,5) & (5,7,9) & (3,5,7) & (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \\ (3,5,7) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) & (5,7,9) & (0.20,0.33,1.00) & (1,3,5) & (5,7,9) & (5,7,9) & (5,7,9) & (3,5,7) & (0.11,0.14,0.20) & (3,5,7) & (1,3,5) \\ (5,7,9) & (0.20,0.33,1.00) & (3,5,7) & (3,5,7) & (5,7,9) & (0.11,0.14,0.20) & (3,5,7) & (3,5,7) & (3,5,7) & (3,5,7) & (3,5,7) & (0.11,0.14,0.20) & (5,7,9) & (3,5,7) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{3_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) & (1,3,5) & (0.20,0.33,1.00) & (3,5,7) & (3,5,7) & (3,5,7) & (1,3,5) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (1,3,5) & (3,5,7) & (1,3,5) & (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \\ (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (5,7,9) & (3,5,7) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (5,7,9) & (5,7,9) & (1,3,5) & (0.11,0.14,0.20) & (3,5,7) & (3,5,7) \\ (5,7,9) & (0.14,0.20,0.33) & (5,7,9) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (5,7,9) & (3,5,7) & (3,5,7) & (0.14,0.20,0.33) & (5,7,9) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{4_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.2,0.33,1) & (5,7,9) & (5,7,9) & (3,5,7) & (0.2,0.33,1) & (1,3,5) & (3,5,7) & (1,3,5) & (3,5,7) & (5,7,9) & (0.2,0.33,1) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.2,0.33,1) & (1,3,5) & (5,7,9) & (3,5,7) & (0.14,0.2,0.33) & (1,3,5) & (1,3,5) & (3,5,7) & (1,3,5) & (3,5,7) & (0.14,0.2,0.33) & (5,7,9) & (5,7,9) \\ (3,5,7) & (0.11,0.14,0.2) & (1,3,5) & (5,7,9) & (5,7,9) & (0.14,0.2,0.33) & (1,3,5) & (5,7,9) & (3,5,7) & (5,7,9) & (3,5,7) & (0.14,0.2,0.33) & (1,3,5) & (3,5,7) \\ (5,7,9) & (0.14,0.2,0.33) & (3,5,7) & (5,7,9) & (5,7,9) & (0.14,0.2,0.33) & (1,3,5) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (0.14,0.2,0.33) & (5,7,9) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM5}_{sub} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.2,0.33,1) & (5,7,9) & (5,7,9) & (3,5,7) & (0.2,0.33,1) & (1,3,5) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (0.2,0.33,1) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.2,0.33,1) & (3,5,7) & (3,5,7) & (3,5,7) & (0.14,0.2,0.33) & (1,3,5) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (0.11,0.14,0.2) & (3,5,7) & (3,5,7) \\ (1,3,5) & (0.14,0.2,0.33) & (3,5,7) & (3,5,7) & (3,5,7) & (0.2,0.33,1) & (1,3,5) & (3,5,7) & (5,7,9) & (3,5,7) & (3,5,7) & (0.11,0.14,0.2) & (1,3,5) & (1,3,5) \\ (5,7,9) & (0.14,0.2,0.33) & (5,7,9) & (3,5,7) & (5,7,9) & (0.11,0.14,0.2) & (3,5,7) & (3,5,7) & (5,7,9) & (3,5,7) & (5,7,9) & (0.14,0.2,0.33) & (5,7,9) & (3,5,7) \end{bmatrix} \end{array}$$

Aggregation

Step 1.5: Aggregate decisions of five *DM*s as $(DM_{obj})_{aggr}$ and $(DM_{sub})_{aggr}$ calculated respectively using Equation 5.1.1 and Equation 7.2.1 (for subjective data aggregation specified in Step 1.3 as Equation 7.2.1 for this case) as follows:

$$(\mathrm{DM}_{obj})_{aggr} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 30 & 10 & 150 & 20 & 0.57 & 0.85 & 0.12 & - & - & - & - & - & - & - \\ 3 & 5 & 50 & 25 & 0.61 & 0.74 & 0.13 & - & - & - & - & - & - & - \\ 7 & 2 & 65 & 30 & 0.73 & 0.85 & 0.08 & - & - & - & - & - & - & - \\ 10 & 6 & 100 & 25 & 0.87 & 0.49 & 0.14 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

$$(\mathrm{DM}_{sub})_{aggr} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{bmatrix} (3.8,5.8,7.8) & (0.2,0.333,1) & (5,7,9) & (4.2,6.2,8.2) & (2,4,6) & (0.2,0.333,1) & (2,4,6) \\ (1.4,3.4,5.4) & (0.183,0.293,0.8) & (2.2,4.2,6.2) & (3.4,5.4,7.4) & (2,4,6) & (0.154,0.227,0.467) & (1.4,3.4,5.4) \\ (2.2,4.2,6.2) & (0.130,0.177,0.28) & (1.6,3.6,5.6) & (4.4,6.4,8.4) & (4.2,6.2,8.2) & (0.189,0.307,0.867) & (1,3,5) \\ (5,7,9) & (0.154,0.227,0.467) & (4.2,6.2,8.2) & (3.4,5.4,7.4) & (5,7,9) & (0.133,0.183,0.293) & (2.2,4.2,6.2) \end{bmatrix} \end{array} \text{->}$$

$$\text{->} \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3.4, 5.4, 7.4) & (1.8, 3.8, 5.8) & (2, 4, 6) & (5, 7, 9) & (0.2, 0.333, 1) & (5, 7, 9) & (5, 7, 9) \\ (1, 3, 5) & (4, 6, 8) & (1.4, 3.4, 5.4) & (1.4, 3.4, 5.4) & (0.133, 0.183, 0.293) & (3.4, 5.4, 7.4) & (3.4, 5.4, 7.4) \\ (3.8, 5.8, 7.8) & (4.6, 6.6, 8.6) & (4.8, 6.8, 8.8) & (2, 4, 6) & (0.117, 0.154, 0.227) & (2, 4, 6) & (2, 4, 6) \\ (3.4, 5.4, 7.4) & (3.8, 5.8, 7.8) & (3, 5, 7) & (3.6, 5.6, 7.6) & (0.137, 0.189, 0.307) & (5, 7, 9) & (4.4, 6.4, 8.4) \end{bmatrix} \end{array}$$

Scalization

Step 1.6: The scaled decision values are calculated by Equation 5.1.2 and Equation 5.1.3 according to eh range limits given in Table 7.1 for each criterion.

The scaled decision values are given as follows:

$$\mathrm{s}((\mathrm{DM}_{obj})_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.60 & 1.00 & 0.75 & 0.67 & 0.57 & 0.85 & 0.12 & - & - & - & - & - & - & - \\ 0.06 & 0.50 & 0.25 & 0.83 & 0.61 & 0.74 & 0.13 & - & - & - & - & - & - & - \\ 0.14 & 0.20 & 0.33 & 1.00 & 0.73 & 0.85 & 0.08 & - & - & - & - & - & - & - \\ 0.20 & 0.60 & 0.50 & 0.83 & 0.87 & 0.49 & 0.14 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

For subjective matrix, before the scalization fuzzy expressions are defuzzified by mean defuzzification function given in Equation 4.3.14 as follows:

$$\text{def_fonk}((\text{DM}_{sub})_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 5.800 & 0.467 & 7.000 & 6.200 & 4.000 & 0.467 & 4.000 & 5.400 & 3.800 & 4.000 & 7.000 & 0.467 & 7.000 & 7.000 \\ 3.400 & 0.392 & 4.200 & 5.400 & 4.000 & 0.269 & 3.400 & 3.000 & 6.000 & 3.400 & 3.400 & 0.198 & 5.400 & 5.400 \\ 4.200 & 0.191 & 3.600 & 6.400 & 6.200 & 0.417 & 3.000 & 5.800 & 6.600 & 6.800 & 4.000 & 0.163 & 4.000 & 4.000 \\ 7.000 & 0.269 & 6.200 & 5.400 & 7.000 & 0.198 & 4.200 & 5.400 & 5.800 & 5.000 & 5.600 & 0.205 & 7.000 & 6.400 \end{bmatrix} \end{array}$$

$$\text{s}(\text{def_fonk}((\text{DM}_{sub})_{aggr})) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.700 & 1.000 & 1.000 & 0.800 & 0.250 & 1.000 & 0.250 & 0.600 & 0.200 & 0.250 & 1.000 & 1.000 & 1.000 & 1.000 \\ 0.100 & 0.766 & 0.300 & 0.600 & 0.250 & 0.376 & 0.100 & 0.000 & 0.750 & 0.100 & 0.100 & 0.154 & 0.600 & 0.600 \\ 0.300 & 0.132 & 0.150 & 0.850 & 0.800 & 0.844 & 0.000 & 0.700 & 0.900 & 0.950 & 0.250 & 0.044 & 0.250 & 0.250 \\ 1.000 & 0.376 & 0.800 & 0.600 & 1.000 & 0.154 & 0.300 & 0.600 & 0.700 & 0.500 & 0.650 & 0.176 & 1.000 & 0.850 \end{bmatrix} \end{array}$$

Combination

Step 1.7: The final aggregated decision which includes objective and subjective decisions by using Equation 5.1.4 as follows:

$$\text{DM}_{aggr} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.650 & 1.000 & 0.875 & 0.733 & 0.410 & 0.925 & 0.185 & 0.600 & 0.200 & 0.250 & 1.000 & 1.000 & 1.000 & 1.000 \\ 0.080 & 0.633 & 0.275 & 0.717 & 0.430 & 0.558 & 0.115 & 0.000 & 0.750 & 0.100 & 0.100 & 0.154 & 0.600 & 0.600 \\ 0.220 & 0.166 & 0.238 & 0.925 & 0.765 & 0.847 & 0.040 & 0.700 & 0.900 & 0.950 & 0.250 & 0.044 & 0.250 & 0.250 \\ 0.600 & 0.488 & 0.650 & 0.717 & 0.935 & 0.322 & 0.220 & 0.600 & 0.700 & 0.500 & 0.650 & 0.176 & 1.000 & 0.850 \end{bmatrix} \end{array}$$

Note that, in this evaluation since the objective evaluations are based on the particular rapport, there is no both objective and subjective data for all alternative-criterion pair. In any cases, the final aggregation formula is valid. When using Equation 5.1.4, lambda value is set as 0 on the non-data side and lambda value is set as 1 on the data side. Therefore, the values are preserved in the explained way and the final aggregated matrix is obtained.

7.2.2 Criteria Weighting by PODER (Phase 2)

Utilizing a distance-based geometric methodology, this phase determines the weight of each criterion based on its influence within the aggregated decision matrix from the Phase 1. The values of each alternative across different criteria establish its position within a multidimensional space. The significance of a criterion is quantified by determining its proximity to a point representing the extraxtion of that criterion.

PODER Phase 2: Data Driven Model

Initial Point

Step 2.1: The weighted aggregated decision matrix $w(DM_{aggr})$ of alternatives are calculated by Equation 5.1.5 where $w_j = 1/14$.

$$\mathrm{w(DM}_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0464 & 0.0714 & 0.0625 & 0.0524 & 0.0293 & 0.0661 & 0.0132 & 0.0429 & 0.0143 & 0.0179 & 0.0714 & 0.0714 & 0.0714 & 0.0714 \\ 0.0057 & 0.0452 & 0.0196 & 0.0512 & 0.0307 & 0.0399 & 0.0082 & 0.0000 & 0.0536 & 0.0071 & 0.0071 & 0.0110 & 0.0429 & 0.0429 \\ 0.0157 & 0.0119 & 0.0170 & 0.0661 & 0.0546 & 0.0605 & 0.0029 & 0.0500 & 0.0643 & 0.0679 & 0.0179 & 0.0031 & 0.0179 & 0.0179 \\ 0.0429 & 0.0349 & 0.0464 & 0.0512 & 0.0668 & 0.0230 & 0.0157 & 0.0429 & 0.0500 & 0.0357 & 0.0464 & 0.0126 & 0.0714 & 0.0607 \end{bmatrix} \end{array}$$

Step 2.2: The initial points $S_{iinitial}$ of alternatives are emerged as follows:

$$S_{A_1 initial} = (0.0464, 0.0714, 0.0625, 0.0524, 0.0293, 0.0661, 0.0132, 0.0429, 0.0143, 0.0179, 0.0714, 0.0714, 0.0714, 0.0714)$$

$$S_{A_2 initial} = (0.0057, 0.0452, 0.0196, 0.0512, 0.0307, 0.0399, 0.0082, 0.0000, 0.0536, 0.0071, 0.0071, 0.0110, 0.0429, 0.0429)$$

$$S_{A_3 initial} = (0.0157, 0.0119, 0.0170, 0.0661, 0.0546, 0.0605, 0.0029, 0.0500, 0.0643, 0.0679, 0.0179, 0.0031, 0.0179, 0.0179)$$

$$S_{A_4 initial} = (0.0429, 0.0349, 0.0464, 0.0512, 0.0668, 0.0230, 0.0157, 0.0429, 0.0500, 0.0357, 0.0464, 0.0126, 0.0714, 0.0607)$$

Extracted Point

Step 2.3: The extracted element weighted aggregated decision matrix $w_{EC}(DM_{aggr})$ is obtained by Equation 5.1.7 where $EC \in C_j$ and $(w_j)_{EC} = 1/13$.

$$\mathrm{w}_{EC}(DM_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0500 & 0.0769 & 0.0673 & 0.0564 & 0.0315 & 0.0712 & 0.0142 & 0.0462 & 0.0154 & 0.0192 & 0.0769 & 0.0769 & 0.0769 & 0.0769 \\ 0.0062 & 0.0487 & 0.0212 & 0.0551 & 0.0331 & 0.0429 & 0.0088 & 0.0000 & 0.0577 & 0.0077 & 0.0077 & 0.0118 & 0.0462 & 0.0462 \\ 0.0169 & 0.0128 & 0.0183 & 0.0712 & 0.0588 & 0.0652 & 0.0031 & 0.0538 & 0.0692 & 0.0731 & 0.0192 & 0.0034 & 0.0192 & 0.0192 \\ 0.0462 & 0.0375 & 0.0500 & 0.0551 & 0.0719 & 0.0248 & 0.0169 & 0.0462 & 0.0538 & 0.0385 & 0.0500 & 0.0135 & 0.0769 & 0.0654 \end{bmatrix} \end{array}$$

Step 2.4: The extracted element points $S_{i,EC}$ of alternatives are derived using extracted element weighted aggregated decision values $w_{EC}a_{ij_{aggr}}$ as the value represented in each dimension (criteria) where $a_{iEC_{aggr}} = 0$.

$$S_{A_1,C_1} = (0.000, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$

$$S_{A_2,C_1} = (0.000, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$

$$S_{A_3,C_1} = (0.000, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$

$$S_{A_4,C_1} = (0.000, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_2} = (0.050, 0.000, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$

$$S_{A_2,C_2} = (0.006, 0.000, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_2} = (0.017, 0.000, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_2} = (0.046, 0.000, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_3} = (0.050, 0.077, 0.000, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_3} = (0.006, 0.049, 0.000, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_3} = (0.017, 0.013, 0.000, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_3} = (0.046, 0.038, 0.000, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_4} = (0.050, 0.077, 0.067, 0.000, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_4} = (0.006, 0.049, 0.021, 0.000, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_4} = (0.017, 0.013, 0.018, 0.000, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_4} = (0.046, 0.038, 0.050, 0.000, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_5} = (0.050, 0.077, 0.067, 0.056, 0.000, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_5} = (0.006, 0.049, 0.021, 0.055, 0.000, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_5} = (0.017, 0.013, 0.018, 0.071, 0.000, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_5} = (0.046, 0.038, 0.050, 0.055, 0.000, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_6} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.000, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_6} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.000, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_6} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.000, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_6} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.000, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_7} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.000, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_7} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.000, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_7} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.000, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_7} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.000, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_8} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.000, 0.015, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_8} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_8} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.000, 0.069, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_8} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.000, 0.054, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_9} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.000, 0.019, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_9} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.000, 0.008, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_9} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.000, 0.073, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_9} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.000, 0.038, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_{10}} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.000, 0.077, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_{10}} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.000, 0.008, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_{10}} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.000, 0.019, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_{10}} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.000, 0.050, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_{11}} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.000, 0.077, 0.077, 0.077)$$
$$S_{A_2,C_{11}} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.000, 0.012, 0.046, 0.046)$$
$$S_{A_3,C_{11}} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.000, 0.003, 0.019, 0.019)$$
$$S_{A_4,C_{11}} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.000, 0.014, 0.077, 0.065)$$

$$S_{A_1,C_{12}} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.000, 0.077, 0.077)$$
$$S_{A_2,C_{12}} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.000, 0.046, 0.046)$$
$$S_{A_3,C_{12}} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.000, 0.019, 0.019)$$
$$S_{A_4,C_{12}} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.000, 0.077, 0.065)$$

$$S_{A_1,C_{13}} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.000, 0.077)$$
$$S_{A_2,C_{13}} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.000, 0.046)$$
$$S_{A_3,C_{13}} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.000, 0.019)$$
$$S_{A_4,C_{13}} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.000, 0.065)$$

$$S_{A_1,C_{14}} = (0.050, 0.077, 0.067, 0.056, 0.032, 0.071, 0.014, 0.046, 0.015, 0.019, 0.077, 0.077, 0.077, 0.000)$$
$$S_{A_2,C_{14}} = (0.006, 0.049, 0.021, 0.055, 0.033, 0.043, 0.009, 0.000, 0.058, 0.008, 0.008, 0.012, 0.046, 0.000)$$
$$S_{A_3,C_{14}} = (0.017, 0.013, 0.018, 0.071, 0.059, 0.065, 0.003, 0.054, 0.069, 0.073, 0.019, 0.003, 0.019, 0.000)$$
$$S_{A_4,C_{14}} = (0.046, 0.038, 0.050, 0.055, 0.072, 0.025, 0.017, 0.046, 0.054, 0.038, 0.050, 0.014, 0.077, 0.000)$$

Impact Assessment

Step 2.5: The total impact I_{EC} of each *"extracted criterion (EC)"* on the initial score $(S_{iinitial})$ by Euclidean distance is calculated by Equation 5.1.9.

$$\begin{matrix} \mathrm{I}_{C_1} \\ \mathrm{I}_{C_2} \\ \mathrm{I}_{C_3} \\ \mathrm{I}_{C_4} \\ \mathrm{I}_{C_5} \\ \mathrm{I}_{C_6} \\ \mathrm{I}_{C_7} \\ \mathrm{I}_{C_8} \\ \mathrm{I}_{C_9} \\ \mathrm{I}_{C_{10}} \\ \mathrm{I}_{C_{11}} \\ \mathrm{I}_{C_{12}} \\ \mathrm{I}_{C_{13}} \\ \mathrm{I}_{C_{14}} \end{matrix} \begin{bmatrix} 0.124 \\ 0.173 \\ 0.155 \\ 0.265 \\ 0.189 \\ 0.197 \\ 0.066 \\ 0.151 \\ 0.192 \\ 0.142 \\ 0.154 \\ 0.118 \\ 0.211 \\ 0.200 \end{bmatrix}$$

Weight Assignment

Step 2.6: The normalized impact values which are the final weights of criteria by Equation 5.1.10 are given as follows:

$$\begin{matrix} \mathrm{w}_{C_1} \\ \mathrm{w}_{C_2} \\ \mathrm{w}_{C_3} \\ \mathrm{w}_{C_4} \\ \mathrm{w}_{C_5} \\ \mathrm{w}_{C_6} \\ \mathrm{w}_{C_7} \\ \mathrm{w}_{C_8} \\ \mathrm{w}_{C_9} \\ \mathrm{w}_{C_{10}} \\ \mathrm{w}_{C_{11}} \\ \mathrm{w}_{C_{12}} \\ \mathrm{w}_{C_{13}} \\ \mathrm{w}_{C_{14}} \end{matrix} \begin{bmatrix} 0.053 \\ 0.074 \\ 0.066 \\ 0.113 \\ 0.081 \\ 0.084 \\ 0.028 \\ 0.065 \\ 0.082 \\ 0.061 \\ 0.066 \\ 0.050 \\ 0.090 \\ 0.086 \end{bmatrix}$$

7.2.3 Alternative Ranking by V-PARS (Phase 2)

In this phase, a vector-based preference ranking is created for the alternatives based on the final aggregated matrix. In a setting with dimensions equal to the number of criteria, the criteria evaluations of each alternative form a coordinate. The preference ranking is obtained by the vectorial positions of these 14-dimensional points relative to each other.

Given the hybrid nature of the PODER and V-PARS models employed in this study, criteria weights are not established during Phase 1. Instead, the weights generated by the PODER in its Phase 2 are subsequently assigned as $W_{C_j} = \{w_{C_1} = 0.053, w_{C_2} = 0.074, w_{C_3} = 0.066, w_{C_4} = 0.113, w_{C_5} = 0.081, w_{C_6} = 0.084, w_{C_7} = 0.028, w_{C_8} = 0.065, w_{C_9} = 0.082, w_{C_{10}} = 0.061, w_{C_{11}} = 0.066, w_{C_{12}} = 0.050, w_{C_{13}} = 0.090, w_{C_{14}} = 0.086\}$

V-PARS Phase 2: Data Driven Model

Creation of Preference Euclidean Vector

Step 2.1: The weighted aggregated decision matrix is calculated by Equation 5.2.5 as follows:

$$\mathrm{w(DM}_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0346 & 0.0740 & 0.0580 & 0.0831 & 0.0332 & 0.0778 & 0.0052 & 0.0387 & 0.0165 & 0.0152 & 0.0660 & 0.0505 & 0.0901 & 0.0857 \\ 0.0043 & 0.0469 & 0.0182 & 0.0812 & 0.0348 & 0.0470 & 0.0032 & 0.0000 & 0.0617 & 0.0061 & 0.0066 & 0.0078 & 0.0541 & 0.0514 \\ 0.0117 & 0.0123 & 0.0157 & 0.1049 & 0.0619 & 0.0713 & 0.0011 & 0.0452 & 0.0741 & 0.0578 & 0.0165 & 0.0022 & 0.0225 & 0.0214 \\ 0.0319 & 0.0361 & 0.0431 & 0.0812 & 0.0756 & 0.0271 & 0.0062 & 0.0387 & 0.0576 & 0.0304 & 0.0429 & 0.0089 & 0.0901 & 0.0728 \end{bmatrix} \end{array}$$

Step 2.2: The preference Euclidean vectors $\overrightarrow{P_x R_y}$ are created by Equation5.2.6. Since there are fourteen criteria in this case, it is clear that there is a 14-dimensional environment as follows:

$$\overrightarrow{P_{A_2} R_{A_1}} = < \overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051}; \overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086} >$$

$$\overrightarrow{P_{A_3} R_{A_1}} = < \overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021}; \overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086} >$$

$$\overrightarrow{P_{A_4} R_{A_1}} = < \overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073}; \overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086} >$$

$\overrightarrow{P_{A_1}R_{A_2}} = <\overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086};$
$\overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051} >$

$\overrightarrow{P_{A_3}R_{A_2}} = <\overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021};$
$\overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051} >$

$\overrightarrow{P_{A_4}R_{A_2}} = <\overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073};$
$\overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051} >$

$\overrightarrow{P_{A_1}R_{A_3}} = <\overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086};$
$\overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021} >$

$\overrightarrow{P_{A_2}R_{A_3}} = <\overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051};$
$\overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021} >$

$\overrightarrow{P_{A_4}R_{A_3}} = <\overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073};$
$\overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021} >$

$\overrightarrow{P_{A_1}R_{A_4}} = <\overrightarrow{0.035, 0.074, 0.058, 0.083, 0.033, 0.078, 0.005, 0.039, 0.016, 0.015, 0.066, 0.050, 0.090, 0.086};$
$\overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073} >$

$\overrightarrow{P_{A_2}R_{A_4}} = <\overrightarrow{0.004, 0.047, 0.018, 0.081, 0.035, 0.047, 0.003, 0.000, 0.062, 0.006, 0.007, 0.008, 0.054, 0.051};$
$\overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073} >$

$\overrightarrow{P_{A_3}R_{A_4}} = <\overrightarrow{0.012, 0.012, 0.016, 0.105, 0.062, 0.071, 0.001, 0.045, 0.074, 0.058, 0.017, 0.002, 0.023, 0.021};$
$\overrightarrow{0.032, 0.036, 0.043, 0.081, 0.076, 0.027, 0.006, 0.039, 0.058, 0.030, 0.043, 0.009, 0.090, 0.073} >$

Step 2.3: The total preference Euclidean vectors $\overrightarrow{P_{T_i}R_{T_i}}$ are calculated by Equation 5.2.7 as follows:

$\overrightarrow{P_{T_{A_1}}R_{T_{A_1}}} = <\overrightarrow{0.048, 0.095, 0.077, 0.267, 0.172, 0.145, 0.011, 0.084, 0.193, 0.094, 0.066, 0.019, 0.167, 0.146};$
$\overrightarrow{0.104, 0.222, 0.174, 0.249, 0.099, 0.234, 0.016, 0.116, 0.049, 0.046, 0.198, 0.151, 0.270, 0.257} >$
$\overrightarrow{P_{T_{A_2}}R_{T_{A_2}}} = <\overrightarrow{0.078, 0.122, 0.117, 0.269, 0.171, 0.176, 0.013, 0.123, 0.148, 0.103, 0.125, 0.062, 0.203, 0.180};$
$\overrightarrow{0.013, 0.141, 0.055, 0.244, 0.104, 0.141, 0.010, 0.000, 0.185, 0.018, 0.020, 0.023, 0.162, 0.154} >$
$\overrightarrow{P_{T_{A_3}}R_{T_{A_3}}} = <\overrightarrow{0.071, 0.157, 0.119, 0.246, 0.144, 0.152, 0.015, 0.077, 0.136, 0.052, 0.116, 0.067, 0.234, 0.210};$
$\overrightarrow{0.035, 0.037, 0.047, 0.315, 0.186, 0.214, 0.003, 0.136, 0.222, 0.173, 0.050, 0.007, 0.068, 0.064} >$

$$\overrightarrow{P_{T_{A_4}}R_{T_{A_4}}} = < \overline{0.051, 0.133, 0.092, 0.269, 0.130, 0.196, 0.010, 0.084, 0.152, 0.079, 0.089, 0.060, 0.167, 0.158}; \overrightarrow{0.096, 0.108, 0.129, 0.244, 0.227, 0.081, 0.019, 0.116, 0.173, 0.091, 0.129, 0.027, 0.270, 0.218} >$$

Step 2.4: The origin based total preference Euclidean vectors $\overrightarrow{OE_i}$ are obtained by Equation 5.2.8 follows:

$$\overrightarrow{OE_{A_1}} = < \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000}; \overrightarrow{0.056, 0.127, 0.097, -0.018, -0.073, 0.088, 0.005, 0.032, -0.144, -0.049, 0.132, 0.133, 0.104, 0.111} >$$

$$\overrightarrow{OE_{A_2}} = < \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000}; \overrightarrow{-0.065, 0.018, -0.062, -0.026, -0.066, -0.035, -0.003, -0.123, 0.037, -0.085, -0.106, -0.038, -0.041, -0.026} >$$

$$\overrightarrow{OE_{A_3}} = < \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000}; \overrightarrow{-0.036, -0.120, -0.072, 0.069, 0.042, 0.062, -0.011, 0.058, 0.086, 0.122, -0.066, -0.060, -0.167, -0.146} >$$

$$\overrightarrow{OE_{A_4}} = < \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000}; \overrightarrow{0.045, -0.025, 0.037, -0.026, 0.097, -0.115, 0.009, 0.032, 0.021, 0.012, 0.040, -0.034, 0.104, 0.060} >$$

Similarity to the Ideal Vector

Step 2.5: The similarity of the origin based total preference Euclidean vectors $\overrightarrow{OE_i}$ are calculated by Equation 5.2.9 as follows: $S_{A_1} = 0.601, S_{A_2} = -0.620, S_{A_3} = -0.239, S_{A_4} = 0.258$.

Preference Ranking

Step 2.6: Preference ranking of the alternatives according to the similarity scores is $A_2 \prec A_3 \prec A_4 \prec A_1$.

7.3 Micromobility Mode Evaluation for Istanbul City

According to the procedure described in Chapter 5, the evaluation of micromobility in Istanbul follows each step of the proposed plan. This ensures that every part of the assessment is done as outlined, leading to a thorough and precise analysis of the city's micromobility programs.

7.3.1 Setting Problem and Gathering Decisions (Phase 1)

The procedures for the initial phase (Phase 1: Expert Driven Model) are identical for both PODER and V-PARS. Differences in criteria weighting arise in Phase 2 (PODER commences with equal weights, V-PARS commences with determined weights), yet the current Phase 1 can be processed uniformly for both methodologies.

PODER and V-PARS Phase 1: Expert Driven Model

This phase operates through a structured approach guided by expert knowledge. It begins by defining sets using information from Section 7.1, proceeds to collect data from decision makers, aggregates matrices, and concludes with the creation of a single, comprehensive decision matrix.

Problem Definition

Step 1.1: According to the Section 7.1, the sets of numerical case are established as follows:

The sets of alternatives $A_i = \{A_1 : Private\ Bike, A_2 : Private\ e-Scooter, A_3 : Private\ e-Moped, A_4 : Private\ e-Bike,\}$ and the set of criteria is $C_j = \{C_1, C_2, ..., C_{14}\}$ is determined in Table 7.1.

Step 1.2: According to given Table 7.2 the set of decision makers are established as follows:

The set of decision makers is $DM_p = \{DM_1, DM_2, DM_3, DM_4, DM_5\}$ and the decision makers are categorized as $\{DM_E, DM_{EC}, DM_{EE}, DM_B\}$ according to their profiles in Table 5.1. $W_{DM} = \{W_{DM_E} = 0.4, W_{DM_{EC}} = 0.3, W_{DM_{EE}} = 0.2, W_{DM_B} = 0.1\}$ and Nudge Theory based hierarchy given in the Table 7.2.

DM_1 and DM_2 are *"Expert"s*, DM_3 is *"Expert Candidate"*, DM_4 is *"Emerging Expert"* , DM_5 is *"Beginner"*. The set of categorized decision makers are as follows:

- $DM_E = \{DM_1, DM_2\}$ with $W_{DM_E} = \{W_{DM_1} = 0.2, W_{DM_{E2}} = 0.2\}$

Table 7.4: Linguistic expressions and their ordinary fuzzy correspondings.

Linguistic Expression	**Ordinary Fuzzy Corresponding**	**Inverse of Ordinary Fuzzy Corresponding for Benefit-Cost Conversion**
Low	(1,3,5)	(1/5,1/3,1/1)
Medium	(3,5,7)	(1/7,1/5,1/3)
Height	(5,7,9)	(1/9,1/7,1/5)

- $DM_{EC} = \{DM_3\}$ with $W_{DM_{EC}} = \{W_{DM_3} = 0.3\}$
- $DM_{EE} = \{DM_4\}$ with $W_{DM_{EE}} = \{W_{DM_4} = 0.2\}$
- $DM_B = \{DM_5\}$ with $W_{DM_B} = \{W_{DM_5} = 0.1\}$

Step 1.3: The linguistic expressions and their corresponding ordinary fuzzy numbers to be used in the subjective evaluation are set in Table 7.4 and illustrated in Figure 7.4. The inverses of ordinary fuzzy numbers have also been included for benefit-cost conversions.

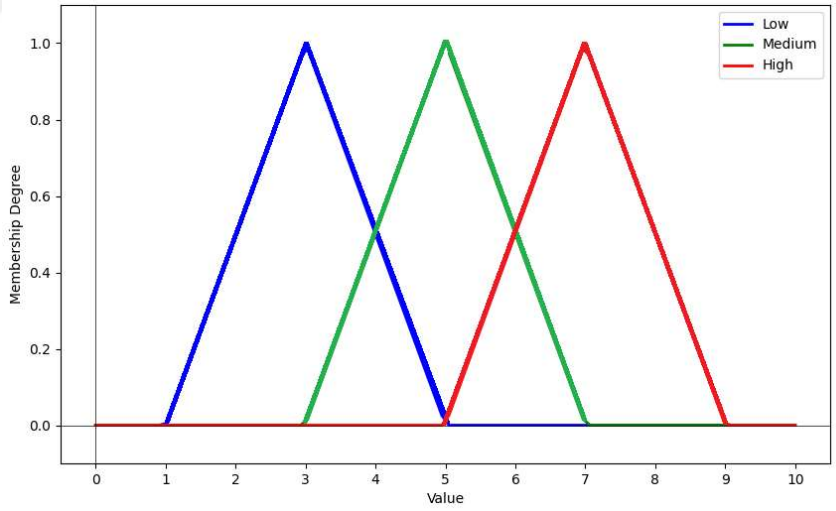


Figure 7.4: Triangular fuzzy numbers for linguistic expressions.

The fuzzy weighted average operator *(FWA)* by (Dong and Wong, 1987) (given in Equation 4.3.11) is re-defined for the aggregation of subjective data consisting of ordinary triangular fuzzy numbers as in Equation 7.3.1 to be used in Step 1.6.

$$(\tilde{a}_{ij_{sub}})_{aggr} = \oplus_{p=1}^{k}(w_{DM_p} \odot (\tilde{a}_{ij_{sub}})_{DM_p}) \quad \forall i,j \tag{7.3.1}$$

Data Collection

Step 1.4: Five DMs are asked about their evaluation on alternatives based on the determined criteria. All decisions are converted to *benefit type* by subtracting the objective data from their maximum values, and the subjective "low to high" score data was also converted according to Table 7.3.

Note that since the objective values are based on some publications (Agence de la Mobilité, Paris, 2022; Turkish Government, 2024; Önder and Akdemir, 2022; Karahan et al., 2023; Okudan and Dündar, 2023), the objective decision matrix are identical for each DM in this application. In instances where each decision maker conducts his/her own assessment, separate matrices may be required. The objective and subjective evaluation of DMs are given as follows:

$$\mathrm{DM}_{1_{obj}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 30 & 10 & 150 & 20 & 0.28 & 0.52 & 0.04 & - & - & - & - & - & - & - \\ 3 & 5 & 50 & 25 & 0.82 & 0.64 & 0.09 & - & - & - & - & - & - & - \\ 7 & 2 & 65 & 30 & 0.36 & 0.33 & 0.02 & - & - & - & - & - & - & - \\ 10 & 6 & 100 & 25 & 0.47 & 0.48 & 0.05 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

where $DM_{1_{obj}}, DM_{2_{obj}}, DM_{3_{obj}}, DM_{4_{obj}}, DM_{5_{obj}}$ are identical.

$$\mathrm{DM}_{1_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (1,3,5) & (3,5,7) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \\ (3,5,7) & (0.11,0.14,0.20) & (3,5,7) & (5,7,9) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (1,3,5) & (1,3,5) & (5,7,9) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) \\ (5,7,9) & (0.14,0.20,0.33) & (5,7,9) & (5,7,9) & (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (1,3,5) & (5,7,9) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{2_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (1,3,5) & (1,3,5) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) \\ (3,5,7) & (0.11,0.14,0.20) & (3,5,7) & (3,5,7) & (3,5,7) & (0.11,0.14,0.20) & (1,3,5) & (1,3,5) & (3,5,7) & (1,3,5) & (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \\ (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) & (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (1,3,5) & (3,5,7) & (5,7,9) & (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \\ (3,5,7) & (0.11,0.14,0.20) & (3,5,7) & (5,7,9) & (3,5,7) & (0.14,0.20,0.33) & (1,3,5) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{3_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (1,3,5) & (3,5,7) & (1,3,5) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (5,7,9) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (3,5,7) \\ (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) & (5,7,9) & (3,5,7) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (1,3,5) \\ (3,5,7) & (0.14,0.20,0.33) & (5,7,9) & (5,7,9) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (1,3,5) & (5,7,9) & (1,3,5) & (3,5,7) & (0.14,0.20,0.33) & (5,7,9) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{4_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) & (3,5,7) & (0.14,0.20,0.33) & (1,3,5) & (3,5,7) & (3,5,7) & (5,7,9) & (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (5,7,9) \\ (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (5,7,9) & (5,7,9) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (3,5,7) & (1,3,5) & (3,5,7) & (0.14,0.20,0.33) & (1,3,5) & (5,7,9) \\ (3,5,7) & (0.11,0.14,0.20) & (1,3,5) & (5,7,9) & (1,3,5) & (0.14,0.20,0.33) & (1,3,5) & (3,5,7) & (5,7,9) & (5,7,9) & (3,5,7) & (0.14,0.20,0.33) & (1,3,5) & (1,3,5) \\ (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (5,7,9) & (3,5,7) & (0.20,0.33,1.00) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (5,7,9) \end{bmatrix} \end{array}$$

$$\mathrm{DM}_{5_{sub}} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} (3,5,7) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (0.20,0.33,1.00) & (3,5,7) & (5,7,9) \\ (1,3,5) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (5,7,9) & (0.14,0.20,0.33) & (1,3,5) & (5,7,9) & (1,3,5) & (1,3,5) & (1,3,5) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) \\ (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (1,3,5) & (0.20,0.33,1.00) & (1,3,5) & (1,3,5) & (5,7,9) & (3,5,7) & (3,5,7) & (0.11,0.14,0.20) & (1,3,5) & (3,5,7) \\ (5,7,9) & (0.20,0.33,1.00) & (5,7,9) & (3,5,7) & (3,5,7) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) & (3,5,7) & (5,7,9) & (5,7,9) & (0.14,0.20,0.33) & (3,5,7) & (3,5,7) \end{bmatrix} \end{array}$$

Aggregation

Step 1.5: Aggregate decisions of five *DM*s as $(DM_{obj})_{aggr}$ and $(DM_{sub})_{aggr}$ calculated respectively using Equation 5.1.1 and Equation 7.3.1 (for subjective data aggregation specified in Step 1.3 as Equation 7.3.1 for this case) as follows:

$$(\mathrm{DM}_{obj})_{aggr} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 30 & 10 & 150 & 20 & 0.28 & 0.52 & 0.04 & - & - & - & - & - & - & - \\ 3 & 5 & 50 & 25 & 0.82 & 0.64 & 0.09 & - & - & - & - & - & - & - \\ 7 & 2 & 65 & 30 & 0.36 & 0.33 & 0.02 & - & - & - & - & - & - & - \\ 10 & 6 & 100 & 25 & 0.47 & 0.48 & 0.05 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

$$(\mathrm{DM}_{sub})_{aggr} = \begin{array}{c} \\ A_1 \\ \mathrm{A}_2 \\ \mathrm{A}_3 \\ \mathrm{A}_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{bmatrix} (3.80,5.80,7.80) & (0.20,0.33,1.00) & (5,7,9) & (4.40,6.40,8.40) & (1.40,3.40,5.40) & (0.19,0.31,0.87) & (1,3,5) \\ (1.40,3.40,5.40) & (0.13,0.18,0.28) & (2.20,4.20,6.20) & (4,6,8) & (4.60,6.60,8.60) & (0.15,0.22,0.44) & (2,4,6) \\ (2,4,6) & (0.12,0.17,0.25) & (2.20,4.20,6.20) & (3.80,5.80,7.80) & (1,3,5) & (0.12,0.16,0.24) & (1,3,5) \\ (4,6,8) & (0.14,0.20,0.37) & (4.20,6.20,8.20) & (4.80,6.80,8.80) & (2,4,6) & (0.16,0.24,0.53) & (2,4,6) \end{bmatrix} \end{array} \text{->}$$

$$\text{->=} \begin{array}{c} \\ \mathrm{A}_1 \\ \mathrm{A}_2 \\ \mathrm{A}_3 \\ \mathrm{A}_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} \mathrm{C}_8 & \mathrm{C}_9 & \mathrm{C}_{10} & \mathrm{C}_{11} & \mathrm{C}_{12} & \mathrm{C}_{13} & \mathrm{C}_{14} \end{array} \\ \begin{bmatrix} (2.40,\ 4.40,\ 6.40) & (2.20,\ 4.20,\ 6.20) & (2.40,\ 4.40,\ 6.40) & (5,\ 7,\ 9) & (0.20,\ 0.33,\ 1.00) & (4.80,\ 6.80,\ 8.80) & (4.60,\ 6.60,\ 8.60) \\ (1.40,\ 3.40,\ 5.40) & (4.20,\ 6.20,\ 8.20) & (1,\ 3,\ 5) & (1.80,\ 3.80,\ 5.80) & (0.14,\ 0.19,\ 0.32) & (1.80,\ 3.80,\ 5.80) & (3.40,\ 5.40,\ 7.40) \\ (2,\ 4,\ 6) & (4.60,\ 6.60,\ 8.60) & (4.20,\ 6.20,\ 8.20) & (2,\ 4,\ 6) & (0.12,\ 0.17,\ 0.25) & (1.40,\ 3.40,\ 5.40) & (1.60,\ 3.60,\ 5.60) \\ (2,\ 4,\ 6) & (4,\ 6,\ 8) & (2.80,\ 4.80,\ 6.80) & (3.80,\ 5.80,\ 7.80) & (0.14,\ 0.20,\ 0.33) & (3.60,\ 5.60,\ 7.60) & (4.40,\ 6.40,\ 8.40) \end{bmatrix} \end{array}$$

Scalization

Step 1.6: The scaled decision values are calculated by Equation 5.1.2 and Equation 5.1.3 according to eh range limits given in Table 7.1 for each criterion.

The scaled decision values are given as follows:

$$\mathrm{s}((\mathrm{DM}_{obj})_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.60 & 1.00 & 0.75 & 0.67 & 0.28 & 0.52 & 0.04 & - & - & - & - & - & - & - \\ 0.06 & 0.50 & 0.25 & 0.83 & 0.82 & 0.64 & 0.09 & - & - & - & - & - & - & - \\ 0.14 & 0.20 & 0.33 & 1.00 & 0.36 & 0.33 & 0.02 & - & - & - & - & - & - & - \\ 0.20 & 0.60 & 0.50 & 0.83 & 0.47 & 0.48 & 0.05 & - & - & - & - & - & - & - \end{bmatrix} \end{array}$$

For subjective matrix, before the scalization fuzzy expressions are defuzzified by mean defuzzification function given in Equation 4.3.14 as follows:

$$\text{def_fonk}((\text{DM}_{sub})_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 5.800 & 0.467 & 7.000 & 6.400 & 3.400 & 0.417 & 3.000 & 4.400 & 4.200 & 4.400 & 7.000 & 0.467 & 6.800 & 6.600 \\ 3.400 & 0.191 & 4.200 & 6.000 & 6.600 & 0.255 & 4.000 & 3.400 & 6.200 & 3.000 & 3.800 & 0.212 & 3.800 & 5.400 \\ 4.000 & 0.177 & 4.200 & 5.800 & 3.000 & 0.170 & 3.000 & 4.000 & 6.600 & 6.200 & 4.000 & 0.177 & 3.400 & 3.600 \\ 6.000 & 0.230 & 6.200 & 6.800 & 4.000 & 0.293 & 4.000 & 4.000 & 6.000 & 4.800 & 5.800 & 0.219 & 5.600 & 6.400 \end{bmatrix} \end{array}$$

$$\text{s}(\text{def_fonk}((\text{DM}_{sub})_{aggr})) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.700 & 1.000 & 1.000 & 0.850 & 0.100 & 0.844 & 0.000 & 0.350 & 0.300 & 0.350 & 1.000 & 1.000 & 0.950 & 0.900 \\ 0.100 & 0.132 & 0.300 & 0.750 & 0.900 & 0.332 & 0.250 & 0.100 & 0.800 & 0.000 & 0.200 & 0.198 & 0.200 & 0.600 \\ 0.250 & 0.088 & 0.300 & 0.700 & 0.000 & 0.066 & 0.000 & 0.250 & 0.900 & 0.800 & 0.250 & 0.088 & 0.100 & 0.150 \\ 0.750 & 0.254 & 0.800 & 0.950 & 0.250 & 0.454 & 0.250 & 0.250 & 0.750 & 0.450 & 0.700 & 0.220 & 0.650 & 0.850 \end{bmatrix} \end{array}$$

Combination

Step 1.7: The final aggregated decision which includes objective and subjective decisions by using Equation 5.1.4 as follows:

$$\text{DM}_{aggr} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.650 & 1.000 & 0.875 & 0.758 & 0.190 & 0.682 & 0.020 & 0.350 & 0.300 & 0.350 & 1.000 & 1.000 & 0.950 & 0.900 \\ 0.080 & 0.316 & 0.275 & 0.792 & 0.860 & 0.486 & 0.170 & 0.100 & 0.800 & 0.000 & 0.200 & 0.198 & 0.200 & 0.600 \\ 0.195 & 0.144 & 0.313 & 0.850 & 0.180 & 0.198 & 0.010 & 0.250 & 0.900 & 0.800 & 0.250 & 0.088 & 0.100 & 0.150 \\ 0.475 & 0.427 & 0.650 & 0.892 & 0.360 & 0.467 & 0.150 & 0.250 & 0.750 & 0.450 & 0.700 & 0.220 & 0.650 & 0.850 \end{bmatrix} \end{array}$$

Note that, in this evaluation since the objective evaluations are based on the particular rapport, there is no both objective and subjective data for all alternative-criterion pair. In any cases, the final aggregation formula is valid. When using Equation 5.1.4, lambda value is set as 0 on the non-data side and lambda value is set as 1 on the data side. Therefore, the values are preserved in the explained way and the final aggregated matrix is obtained.

7.3.2 Criteria Weighting by PODER (Phase 2)

In this phase, a distance-based geometric methodology is employed to ascertain the weight of each criterion based on its influence within the aggregated decision matrix from Phase 1. Each alternative's values across various criteria are used to define its location within a multidimensional space. The importance of a criterion is quantified by evaluating its proximity to a point that represents the extraction of that criterion.

PODER Phase 2: Data Driven Model

Initial Point

Step 2.1: The weighted aggregated decision matrix $w(DM_{aggr})$ of alternatives are calculated by Equation 5.1.5 where $w_j = 1/14$.

$$\mathrm{w(DM}_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0464 & 0.0714 & 0.0625 & 0.0542 & 0.0136 & 0.0487 & 0.0014 & 0.0250 & 0.0214 & 0.0250 & 0.0714 & 0.0714 & 0.0679 & 0.0643 \\ 0.0057 & 0.0226 & 0.0196 & 0.0565 & 0.0614 & 0.0347 & 0.0121 & 0.0071 & 0.0571 & 0.0000 & 0.0143 & 0.0141 & 0.0143 & 0.0429 \\ 0.0139 & 0.0103 & 0.0223 & 0.0607 & 0.0129 & 0.0141 & 0.0007 & 0.0179 & 0.0643 & 0.0571 & 0.0179 & 0.0063 & 0.0071 & 0.0107 \\ 0.0339 & 0.0305 & 0.0464 & 0.0637 & 0.0257 & 0.0334 & 0.0107 & 0.0179 & 0.0536 & 0.0321 & 0.0500 & 0.0157 & 0.0464 & 0.0607 \end{bmatrix} \end{array}$$

Step 2.2: The initial points $S_{iinitial}$ of alternatives are emerged as follows:

$$S_{A_1 initial} = (0.046, 0.071, 0.063, 0.054, 0.014, 0.049, 0.001, 0.025, 0.021, 0.025, 0.071, 0.071, 0.068, 0.064)$$

$$S_{A_2 initial} = (0.006, 0.023, 0.020, 0.057, 0.061, 0.035, 0.012, 0.007, 0.057, 0.000, 0.014, 0.014, 0.014, 0.043)$$

$$S_{A_3 initial} = (0.014, 0.010, 0.022, 0.061, 0.013, 0.014, 0.001, 0.018, 0.064, 0.057, 0.018, 0.006, 0.007, 0.011)$$

$$S_{A_4 initial} = (0.034, 0.031, 0.046, 0.064, 0.026, 0.033, 0.011, 0.018, 0.054, 0.032, 0.050, 0.016, 0.046, 0.061)$$

Extracted Point

Step 2.3: The extracted element weighted aggregated decision matrix $w_{EC}(DM_{aggr})$ is obtained by Equation 5.1.7 where $EC \in C_j$ and $(w_j)_{EC} = 1/13$.

$$\mathrm{w}_{EC}(DM_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0500 & 0.0769 & 0.0673 & 0.0583 & 0.0146 & 0.0525 & 0.0015 & 0.0269 & 0.0231 & 0.0269 & 0.0769 & 0.0769 & 0.0731 & 0.0692 \\ 0.0062 & 0.0243 & 0.0212 & 0.0609 & 0.0662 & 0.0374 & 0.0131 & 0.0077 & 0.0615 & 0.0000 & 0.0154 & 0.0152 & 0.0154 & 0.0462 \\ 0.0150 & 0.0111 & 0.0240 & 0.0654 & 0.0138 & 0.0152 & 0.0008 & 0.0192 & 0.0692 & 0.0615 & 0.0192 & 0.0068 & 0.0077 & 0.0115 \\ 0.0365 & 0.0328 & 0.0500 & 0.0686 & 0.0277 & 0.0359 & 0.0115 & 0.0192 & 0.0577 & 0.0346 & 0.0538 & 0.0169 & 0.0500 & 0.0654 \end{bmatrix} \end{array}$$

Step 2.4: The extracted element points $S_{i,EC}$ of alternatives are derived using extracted element weighted aggregated decision values $w_{EC}a_{ij_{aggr}}$ as the value represented in each dimension (criteria) where $a_{iEC_{aggr}} = 0$.

$$S_{A_1,C_1} = (0.000, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$

$$S_{A_2,C_1} = (0.000, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$

$$S_{A_3,C_1} = (0.000, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$

$$S_{A_4,C_1} = (0.000, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_2} = (0.050, 0.000, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$

$$S_{A_2,C_2} = (0.006, 0.000, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_2} = (0.015, 0.000, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_2} = (0.037, 0.000, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_3} = (0.050, 0.077, 0.000, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_3} = (0.006, 0.024, 0.000, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_3} = (0.015, 0.011, 0.000, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_3} = (0.037, 0.033, 0.000, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_4} = (0.050, 0.077, 0.067, 0.000, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_4} = (0.006, 0.024, 0.021, 0.000, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_4} = (0.015, 0.011, 0.024, 0.000, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_4} = (0.037, 0.033, 0.050, 0.000, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_5} = (0.050, 0.077, 0.067, 0.058, 0.000, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_5} = (0.006, 0.024, 0.021, 0.061, 0.000, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_5} = (0.015, 0.011, 0.024, 0.065, 0.000, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_5} = (0.037, 0.033, 0.050, 0.069, 0.000, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_6} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.000, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_6} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.000, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_6} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.000, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_6} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.000, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_7} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.000, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_7} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.000, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_7} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.000, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_7} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.000, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_8} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.000, 0.023, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_8} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.000, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_8} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.000, 0.069, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_8} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.000, 0.058, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_9} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.000, 0.027, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_9} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.000, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_9} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.000, 0.062, 0.019, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_9} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.000, 0.035, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_{10}} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.000, 0.077, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_{10}} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_{10}} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.000, 0.020, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_{10}} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.000, 0.054, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_{11}} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.000, 0.077, 0.073, 0.069)$$
$$S_{A_2,C_{11}} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.000, 0.015, 0.015, 0.046)$$
$$S_{A_3,C_{11}} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.000, 0.007, 0.008, 0.012)$$
$$S_{A_4,C_{11}} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.000, 0.017, 0.050, 0.065)$$

$$S_{A_1,C_{12}} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.000, 0.073, 0.069)$$
$$S_{A_2,C_{12}} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.000, 0.015, 0.046)$$
$$S_{A_3,C_{12}} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.000, 0.008, 0.012)$$
$$S_{A_4,C_{12}} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.000, 0.050, 0.065)$$

$$S_{A_1,C_{13}} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.000, 0.069)$$
$$S_{A_2,C_{13}} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.000, 0.046)$$
$$S_{A_3,C_{13}} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.000, 0.012)$$
$$S_{A_4,C_{13}} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.000, 0.065)$$

$$S_{A_1,C_{14}} = (0.050, 0.077, 0.067, 0.058, 0.015, 0.052, 0.002, 0.027, 0.023, 0.027, 0.077, 0.077, 0.073, 0.000)$$
$$S_{A_2,C_{14}} = (0.006, 0.024, 0.021, 0.061, 0.066, 0.037, 0.013, 0.008, 0.062, 0.000, 0.015, 0.015, 0.015, 0.000)$$
$$S_{A_3,C_{14}} = (0.015, 0.011, 0.024, 0.065, 0.014, 0.015, 0.001, 0.019, 0.069, 0.062, 0.019, 0.007, 0.008, 0.000)$$
$$S_{A_4,C_{14}} = (0.037, 0.033, 0.050, 0.069, 0.028, 0.036, 0.012, 0.019, 0.058, 0.035, 0.054, 0.017, 0.050, 0.000)$$

Impact Assessment

Step 2.5: The total impact I_{EC} of each *"extracted criterion (EC)"* on the initial score $(S_{iinitial})$ by Euclidean distance is calculated by Equation 5.1.9.

$$\begin{matrix} \mathrm{I}_{C_1} \\ \mathrm{I}_{C_2} \\ \mathrm{I}_{C_3} \\ \mathrm{I}_{C_4} \\ \mathrm{I}_{C_5} \\ \mathrm{I}_{C_6} \\ \mathrm{I}_{C_7} \\ \mathrm{I}_{C_8} \\ \mathrm{I}_{C_9} \\ \mathrm{I}_{C_{10}} \\ \mathrm{I}_{C_{11}} \\ \mathrm{I}_{C_{12}} \\ \mathrm{I}_{C_{13}} \\ \mathrm{I}_{C_{14}} \end{matrix} \begin{bmatrix} 0.112 \\ 0.143 \\ 0.157 \\ 0.275 \\ 0.126 \\ 0.139 \\ 0.055 \\ 0.082 \\ 0.203 \\ 0.130 \\ 0.161 \\ 0.120 \\ 0.145 \\ 0.185 \end{bmatrix}$$

Weight Assignment

Step 2.6:The normalized impact values which are the final weights of criteria by Equation 5.1.10 is given as follows:

$$\begin{matrix} \mathrm{w}_{C_1} \\ \mathrm{w}_{C_2} \\ \mathrm{w}_{C_3} \\ \mathrm{w}_{C_4} \\ \mathrm{w}_{C_5} \\ \mathrm{w}_{C_6} \\ \mathrm{w}_{C_7} \\ \mathrm{w}_{C_8} \\ \mathrm{w}_{C_9} \\ \mathrm{w}_{C_{10}} \\ \mathrm{w}_{C_{11}} \\ \mathrm{w}_{C_{12}} \\ \mathrm{w}_{C_{13}} \\ \mathrm{w}_{C_{14}} \end{matrix} \begin{bmatrix} 0.055 \\ 0.070 \\ 0.077 \\ 0.135 \\ 0.062 \\ 0.068 \\ 0.027 \\ 0.040 \\ 0.100 \\ 0.064 \\ 0.079 \\ 0.059 \\ 0.072 \\ 0.091 \end{bmatrix}$$

7.3.3 Alternative Ranking by V-PARS (Phase 2)

In this phase, a preference ranking of alternatives is established based on a vector representation derived from the final aggregated matrix. Each alternative is represented as a point in a space with dimensions matching the number of criteria, with each coordinate corresponding to an evaluation of the alternative according to the criteria. The preference ranking is determined by vectorial positions of these 14-dimensional points relative to one another.

Due to the hybrid nature of the PODER and V-PARS models used in this study, criteria weights are not determined in Phase 1. Instead, these weights are computed by the PODER in its Phase 2 and are then assigned as $W_{C_j} = \{w_{C_1} = 0.055, w_{C_2} = 0.070, w_{C_3} = 0.077, w_{C_4} = 0.135, w_{C_5} = 0.062, w_{C_6} = 0.068, w_{C_7} = 0.027, w_{C_8} = 0.040, w_{C_9} = 0.100, w_{C_{10}} = 0.064, w_{C_{11}} = 0.079, w_{C_{12}} = 0.059, w_{C_{13}} = 0.072, w_{C_{14}} = 0.091\}$

V-PARS Phase 2: Data Driven Model

Creation of Preference Euclidean Vector

Step 2.1: The weighted aggregated decision matrix is calculated by Equation 5.2.5 as follows:

$$\mathrm{w(DM}_{aggr}) = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} & C_{13} & C_{14} \end{array} \\ \begin{bmatrix} 0.0358 & 0.0704 & 0.0678 & 0.1026 & 0.0118 & 0.0465 & 0.0005 & 0.0141 & 0.0300 & 0.0224 & 0.0791 & 0.0590 & 0.0679 & 0.0819 \\ 0.0044 & 0.0223 & 0.0213 & 0.1071 & 0.0532 & 0.0331 & 0.0046 & 0.0040 & 0.0799 & 0.0000 & 0.0158 & 0.0117 & 0.0143 & 0.0546 \\ 0.0107 & 0.0101 & 0.0242 & 0.1150 & 0.0111 & 0.0135 & 0.0003 & 0.0101 & 0.0899 & 0.0512 & 0.0198 & 0.0052 & 0.0072 & 0.0136 \\ 0.0261 & 0.0301 & 0.0503 & 0.1206 & 0.0223 & 0.0318 & 0.0041 & 0.0101 & 0.0749 & 0.0288 & 0.0554 & 0.0130 & 0.0465 & 0.0773 \end{bmatrix} \end{array}$$

Step 2.2: The preference Euclidean vectors $\overrightarrow{P_x R_y}$ are created by Equation5.2.6. Since there are fourteen criteria in this case, it is clear that there is a 14-dimensional environment as follows:

$$\overrightarrow{P_{A_2} R_{P_{A_1}}} = < \overrightarrow{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055}; \overrightarrow{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082} >$$

$$\overrightarrow{P_{A_3} R_{P_{A_1}}} = < \overrightarrow{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014}; \overrightarrow{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082} >$$

$$\overrightarrow{P_{A_4}R_{P_{A_1}}} =< \overline{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077}; \overrightarrow{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082} >$$

$$\overrightarrow{P_{A_1}R_{P_{A_2}}} =< \overline{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082}; \overrightarrow{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055} >$$

$$\overrightarrow{P_{A_3}R_{P_{A_2}}} =< \overline{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014}; \overrightarrow{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055} >$$

$$\overrightarrow{P_{A_4}R_{P_{A_2}}} =< \overline{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077}; \overrightarrow{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055} >$$

$$\overrightarrow{P_{A_1}R_{P_{A_3}}} =< \overline{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082}; \overrightarrow{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014} >$$

$$\overrightarrow{P_{A_2}R_{P_{A_3}}} =< \overline{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055}; \overrightarrow{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014} >$$

$$\overrightarrow{P_{A_4}R_{P_{A_3}}} =< \overline{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077}; \overrightarrow{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014} >$$

$$\overrightarrow{P_1R_{P_4}} =< \overline{0.036, 0.070, 0.068, 0.103, 0.012, 0.046, 0.001, 0.014, 0.030, 0.022, 0.079, 0.059, 0.068, 0.082}; \overrightarrow{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077} >$$

$$\overrightarrow{P_2R_{P_4}} =< \overline{0.004, 0.022, 0.021, 0.107, 0.053, 0.033, 0.005, 0.004, 0.080, 0.000, 0.016, 0.012, 0.014, 0.055}; \overrightarrow{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077} >$$

$$\overrightarrow{P_3R_{P_4}} =< \overline{0.011, 0.010, 0.024, 0.115, 0.011, 0.013, 0.000, 0.010, 0.090, 0.051, 0.020, 0.005, 0.007, 0.014}; \overrightarrow{0.026, 0.030, 0.050, 0.121, 0.022, 0.032, 0.004, 0.010, 0.075, 0.029, 0.055, 0.013, 0.046, 0.077} >$$

Step 2.3: The total preference Euclidean vectors $\overrightarrow{P_{T_i}R_{T_i}}$ are calculated by Equation 5.2.7 as follows:

$$\overrightarrow{P_{T_{A_1}}R_{T_{A_1}}} =< \overline{0.041, 0.062, 0.096, 0.343, 0.087, 0.078, 0.009, 0.024, 0.245, 0.080, 0.091, 0.030, 0.068, 0.146}; \overrightarrow{0.107, 0.211, 0.203, 0.308, 0.035, 0.139, 0.002, 0.042, 0.090, 0.067, 0.237, 0.177, 0.204, 0.246} >$$

$$\overrightarrow{P_{T_{A_2}}R_{T_{A_2}}} =< \overline{0.073, 0.111, 0.142, 0.338, 0.045, 0.092, 0.005, 0.034, 0.195, 0.102, 0.154, 0.077, 0.122, 0.173};$$

$\overrightarrow{0.013, 0.067, 0.064, 0.321, 0.160, 0.099, 0.014, 0.012, 0.240, 0.000, 0.047, 0.035, 0.043, 0.164} >$

$\overrightarrow{P_{T_{A_3}} R_{T_{A_3}}} =< \overline{0.066, 0.123, 0.139, 0.330, 0.087, 0.111, 0.009, 0.028, 0.185, 0.051, 0.150, 0.084, 0.129, 0.214};$

$\overrightarrow{0.032, 0.030, 0.073, 0.345, 0.033, 0.040, 0.001, 0.030, 0.270, 0.154, 0.059, 0.016, 0.021, 0.041} >$

$\overrightarrow{P_{T_{A_4}} R_{T_{A_4}}} =< \overline{0.051, 0.103, 0.113, 0.325, 0.076, 0.093, 0.005, 0.028, 0.200, 0.074, 0.115, 0.076, 0.089, 0.150};$

$\overrightarrow{0.078, 0.090, 0.151, 0.362, 0.067, 0.095, 0.012, 0.030, 0.225, 0.086, 0.166, 0.039, 0.139, 0.232} >$

Step 2.4: The origin based total preference Euclidean vectors $\overrightarrow{OE_i}$ are obtained by Equation 5.2.8 follows:

$\overrightarrow{OE_{A_1}} =< \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000};$

$\overrightarrow{0.066, 0.149, 0.107, -0.035, -0.051, 0.061, -0.007, 0.018, -0.155, -0.013, 0.146, 0.147, 0.136, 0.100} >$

$\overrightarrow{OE_{A_2}} =< \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000};$

$\overrightarrow{-0.059, -0.044, -0.078, -0.017, 0.114, 0.008, 0.009, -0.022, 0.045, -0.102, -0.107, -0.042, -0.079, -0.009} >$

$\overrightarrow{OE_{A_3}} =< \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000};$

$\overrightarrow{-0.034, -0.092, -0.067, 0.015, -0.054, -0.071, -0.008, 0.002, 0.085, 0.102, -0.091, -0.068, -0.107, -0.173} >$

$\overrightarrow{OE_{A_4}} =< \overline{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000};$

$\overrightarrow{0.028, -0.013, 0.038, 0.037, -0.009, 0.002, 0.007, 0.002, 0.025, 0.013, 0.051, -0.037, 0.050, 0.082} >$

Similarity to the Ideal Vector

Step 2.5: The similarity of the origin based total preference Euclidean vectors $\overrightarrow{OE_i}$ are calculated by Equation 5.2.9 as follows: $S_{A_1} = 0.670, S_{A_2} = -0.380, S_{A_3} = -0.560, S_{A_4} = 0.276$.

Preference Ranking

Step 2.6: Preference ranking of the alternatives according to the similarity scores is $A_3 \prec A_2 \prec A_4 \prec A_1$.

A comprehensive examination of the results and comparisons is presented in Chapter 8.

8 RESULTS and DISCUSSION

This section presents the findings of the micromobility mode evaluation conducted in Paris and Istanbul using the PODER and V-PARS models which are proposed in the thesis. The results of the criteria weighting and alternative ranking processes are given, followed by a detailed analysis of the outcomes. By comparing the results obtained for both cities, the study aims to identify commonalities and differences in micromobility preferences and to draw implications for urban transportation planning and policymaking. The subsequent analysis includes sensitivity analysis to assess the robustness of the findings. The results of proposed methods are contextualized through comparison with existing methodologies, and the limitations of the study are discussed. Finally, the implications of the findings for urban transportation planning and policymaking are explored, providing directions for future research.

8.1 Results of Application

Paris and Istanbul have both actively embraced a diverse range of micromobility options, reflecting a strong commitment to sustainable and efficient urban transportation. Bikes, e-bikes, e-mopeds, and e-scooters have become integral components of daily life in both cities, contributing to reduced car dependency and urban congestion.

This study focuses on evaluating specific micromobility modes in Paris and Istanbul, aligning with the restrictions outlined in the French loi on shared mobility. Particular emphasis is placed on the experiences and opinions of decision makers. By analyzing the usage and perception of these modes, the study offers valuable insights into the ongoing discourse on sustainable urban mobility.

In Istanbul, the widespread adoption of e-scooters, shared bicycles, and other micromobility vehicles is seen as a means to alleviate traffic congestion and reduce the city's carbon footprint. This study explores how these modes are utilized across various parts of the city, considering the diverse geography, traffic patterns, and socioeconomic factors that influ-

Table 8.1: Preference ranking results of applying the PODER and V-PARS models to micromobility mode evaluations in Paris and Istanbul.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
Paris City	0.601	-0.620	-0.239	0.258
	1	4	3	2
Istanbul City	0.670	-0.380	-0.560	0.276
	1	3	4	2

ence micromobility usage. User feedback is central to this analysis, providing insights into the accessibility, convenience, and effectiveness of these transportation options in a city center that is still evolving in its approach to micromobility.

A comparative analysis is conducted on four prevalent private micromobility modes in both Paris and Istanbul, evaluated according to a framework of fourteen criteria aligned with the EU's 2050 sustainability objectives. The PODER method is employed to determine the criteria weights, reflecting their relative importance in the decision making process. Subsequently, the V-PARS model is performed to establish preference rankings for the micromobility modes in each city. The comparative results are presented in Table 8.1. This combined approach provides a comprehensive understanding of the factors influencing micromobility preferences in these urban environments.

The preference ranking results for micromobility modes in Paris and Istanbul reveal notable differences in how each city prioritizes various transportation options, based on the PODER and V-PARS models, as outlined below.

- In Paris, the preference rankings and scores for different micromobility modes highlight the prominence of the private bike, which tops the list with a score of 0.601 (rank 1). This result suggests that the Parisian population finds bikes to be a highly favorable mode of transport, likely due to their suitability for navigating urban areas and reflecting Paris's long-standing cycling infrastructure and culture. The private e-bike follows with a score of 0.258 (rank 2), indicating a strong preference while

benefiting from electric assistance.

On the other hand, the private e-scooter performs poorly in Paris, with a negative score of -0.620 (rank 4). This indicates that scooters are the least preferred option, possibly due to safety concerns, regulations, or public perception in the city's congested and narrow streets. Similarly, the private e-moped receives a modest score of -0.239 (rank 3), suggesting that while it is more favored than the e-scooter, it still does not enjoy widespread popularity, possibly due to noise or emissions concerns in a city that promotes ecofriendly modes of transport.

- When shifting the focus to Istanbul, the scores offer a notable contrast. The private bike ranks first with a score of 0.670, outperforming its score in Paris, indicating a stronger preference for traditional cycling in Istanbul, possibly due to different urban layouts or climate conditions that make biking attractive. The private e-bike, same as in Paris, ranks second in Istanbul with a score of 0.276.

  In Istanbul, the private e-scooter shows an improved performance compared to Paris, coming in third with a score of -0.620. Although still ranking below the bikes, this suggests a more positive reception to scooters in Istanbul, potentially due to their ability to navigate through the city's often heavy traffic. Finally, the private e-moped ranks lowest in Istanbul with a score of -0.560, indicating a low preference, which might be attributed to similar factors as in Paris, such as environmental concerns or operational costs. Differences may reflect different levels of adoption or acceptance of transport modes between the two cities, which may be due to infrastructure or cost factors.

The rankings reflect variations in urban infrastructure, cultural acceptance, and policy priorities aimed at advancing sustainability goals through micromobility solutions. In Paris, the clear preference for private bikes (ranked 1) and a notable inclination towards private e-bikes (ranked 2) align with the city's strong emphasis on promoting low-carbon, efficient transportation methods. Conversely, the lower acceptance of private e-scooters (ranked 4) and private e-mopeds (ranked 3) indicates a more cautious approach towards these modes. In Istanbul, there is a strong preference for private bikes (ranked 1) as well,

but the acceptance of private e-scooters (ranked 3) is comparatively higher than in Paris. The preference for private e-mopeds (ranked 4) suggests a unique stance towards micromobility options, indicating a different yet progressive strategy in aligning with the EU's 2050 sustainability benchmarks. Overall, while both cities show a commitment to integrating micromobility solutions, their specific preferences highlight diverse approaches influenced by local contexts.

Micromobility Strategies for EU 2050 Targets: Paris and Istanbul

To align with the European Union's ambitious 2050 sustainability targets, cities like Paris and Istanbul must develop and implement distinct yet complementary strategies for the integration of micromobility. These strategies must involve targeted investments in infrastructure, policy reforms, and economic measures tailored to the unique urban contexts of each city. Such approaches will enable these cities to contribute meaningfully to the EU's broader environmental and transportation goals, which include achieving carbon neutrality, improving air quality, and fostering sustainable urban mobility solutions.

In the case of Paris, the significant preference for private bikes and e-bikes points to a rising demand for personal micromobility options that support the city's overarching commitment to sustainability and low-carbon transport solutions. To effectively support this demand, Paris should prioritize the expansion and enhancement of its cycling infrastructure. This could include the development of a more extensive network of dedicated bike lanes, the provision of secure and accessible bike parking facilities, and the installation of sufficient charging stations for e-bikes to ensure their practicality for daily commuters. Furthermore, the city could explore the potential of public-private partnerships to stimulate private sector investment in both e-bike sharing schemes and models of private ownership. By offering targeted economic incentives such as subsidies, tax rebates, or reduced registration fees for e-bikes, Paris could accelerate the adoption of these environmentally friendly transport modes, particularly among lower-income demographics. Policies that promote the integration of personal micromobility with the city's existing public transport network would also be crucial. Such integration could enhance the overall efficiency and convenience of the urban mobility system, enabling users to

seamlessly switch between modes of transportation. Additionally, Paris should continue to emphasize its commitment to improving air quality by promoting low-carbon transportation options, like e-bikes, as part of a broader strategy to reduce urban pollution. This would also position the city to take advantage of EU funding opportunities for green infrastructure projects, further accelerating the transition to sustainable mobility.

For Istanbul, the relatively higher preference for private bikes and e-scooters suggests that the city has significant potential to incorporate micromobility solutions into its broader transportation strategy. However, the city's more cautious stance towards e-mopeds indicates a nuanced approach may be necessary. Istanbul should prioritize a balanced approach that not only supports the continued growth of private micromobility options but also enhances its public transport infrastructure. By investing in the expansion of shared micromobility services, such as e-scooter sharing systems, Istanbul can offer its residents more flexible and accessible alternatives to private car use. The integration of shared micromobility into the public transport system could play a pivotal role in reducing congestion and lowering emissions by providing residents with greater mobility options for short trips, while also supporting the overarching goal of reducing private car dependency. Additionally, Istanbul should focus on creating a connected network of safe bike lanes and e-scooter charging stations, which would form the foundation for a sustainable micromobility ecosystem. Such infrastructure investments would not only support the growth of personal and shared micromobility but also contribute to a reduction in car usage, which is critical for achieving the EU's 2050 climate targets. Public-private collaborations could play an important role in funding these infrastructure projects, with the aim of making micromobility both affordable and accessible to a larger segment of the population. Economic incentives, such as subsidies or tax rebates for micromobility users, would help further drive adoption, especially among low-income communities.

In both cities, substantial economic investment in green infrastructure will be critical for meeting the EU's 2050 climate goals. This includes investments in both urban design and digital infrastructure to support the widespread adoption of micromobility. For instance, the development of real-time tracking systems for shared micromobility services, as well as the integration of these services with public transport apps, will enhance the overall

efficiency and effectiveness of the urban mobility system. These innovations will ensure that users can easily access and navigate multi-modal transportation options, improving the user experience and increasing the uptake of micromobility. Additionally, the creation of seamless connections between micromobility services and other forms of sustainable transport, such as public buses and metro systems, will provide residents with an efficient, environmentally friendly, and cost-effective alternative to car travel.

Ultimately, both Paris and Istanbul must adopt a holistic and integrated approach to urban mobility, one that connects micromobility solutions with broader sustainability initiatives. This approach will not only contribute to the achievement of the EU's 2050 climate and transport goals but also improve the quality of life for urban residents. The comparative analysis given this study not only deepens our understanding of sustainable transportation but also offers practical insights for city planners and policymakers on how to enhance urban mobility in an environmentally friendly and efficient way. By developing tailored strategies that reflect the unique characteristics and challenges of each city, both Paris and Istanbul can become leaders in sustainable urban mobility, setting an example for other cities striving to meet the demands of the future.

8.2 Sensitivity Analysis

Sensitivity analysis is a critical technique used to assess how changes in input parameters affect the outputs of a decision making model. In the context of complex decision making frameworks such as PODER and V-PARS, sensitivity analysis helps assess the robustness and reliability of results. By systematically changing certain components, such as weights, parameters, and functions, sensitivity analysis allows researchers to determine which inputs exert the most significant influence on the model's results. This process not only improves the transparency of the decision making process, but also increases confidence in the robustness of the final rankings.

8.2.1 Sensitivity Analysis of PODER

This section explores the sensitivity of the PODER model to changes in lambda parameters, defuzzification techniques, and decision maker weights within the framework of micromobility evaluations for Paris and Istanbul.

Sensitivity in Lambda Parameters

The sensitivity analysis presented in Table 8.2 and Table 8.3 highlights the influence of variations in the lambda parameters (λ_{obj} and λ_{sub}) on the criteria weighting for micromobility evaluation in Paris and Istanbul.

The Table 8.2 displays the sensitivity analysis of the λ_{obj} and λ_{sub} parameters using the PODER method for micromobility evaluation in Paris. The values of λ_{obj} range from 0.0 to 1.0, with a corresponding decrease in λ_{sub} from 1.0 to 0.0.

The results show that Speed limit (C_4) consistently remains the most important criterion, ranking first across all λ_{obj} values. Similarly, Eco-design (C_{13}) ranks second throughout, while Charging time (C_2) holds the seventh position. These three criteria demonstrate stability in their ranking, suggesting they are relatively insensitive to changes in the weight distributions between subjective and objective components. On the other hand, Average lifespan (C_1) and Accident rate (C_6) exhibit the most significant variability in both their values and ranking positions. Average lifespan (C_1), Maximum driving range in one charge (C_3), Saving time (C_9) and Low carbon emission (C_{14}) decrease their rankings as λ_{obj} increases, showing sensitivity to changes in the objective component. Criteria like Security (C_8), Comfort (C_{10}) and Environmental noise (C_{12}) show minor fluctuations, maintaining middle-ranking positions. Intermodality rate (C_7) remains the least important criterion across all values, consistently ranked fourteenth. This analysis highlights the robust importance of Charging time (C_2), Speed limit (C_4), Intermodality rate (C_7) and Eco-design (C_{13}) in the micromobility context of Paris, regardless of the changes in λ parameters, while criteria like Average lifespan (C_1), Maximum driving range in one charge (C_3) and Accident rate (C_6) are sensitive to weight shifts.

Table 8.2: Sensitivity analysis results of lambda parameters used in PODER for Paris.

λ_{obj} λ_{sub}	0.0 1.0	0.1 0.9	0.2 0.8	0.3 0.7	0.4 0.6	0.5 0.5	0.6 0.4	0.7 0.3	0.8 0.2	0.9 0.1	1.0 0.0
C_1	0.068 9	0.065 10	0.062 11	0.059 12	0.056 12	0.053 12	0.050 13	0.047 13	0.044 13	0.042 13	0.039 13
C_2	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7	0.074 7
C_3	0.073 8	0.071 8	0.070 8	0.069 8	0.068 8	0.066 8	0.065 9	0.064 10	0.063 10	0.061 10	0.060 11
C_4	0.105 1	0.107 1	0.108 1	0.110 1	0.112 1	0.113 1	0.115 1	0.117 1	0.118 1	0.120 1	0.121 1
C_5	0.074 6	0.076 6	0.077 6	0.078 6	0.080 6	0.081 6	0.082 6	0.084 5	0.085 5	0.086 4	0.088 4
C_6	0.077 5	0.078 5	0.080 5	0.081 5	0.083 4	0.084 4	0.086 3	0.087 3	0.089 3	0.090 2	0.092 2
C_7	0.031 14	0.030 14	0.030 14	0.029 14	0.029 14	0.028 14	0.027 14	0.027 14	0.027 14	0.026 14	0.026 14
C_8	0.064 11	0.064 11	0.064 10	0.064 10	0.065 10	0.065 10	0.065 10	0.065 9	0.065 9	0.065 9	0.065 9
C_9	0.082 4	0.082 4	0.082 4	0.082 4	0.082 5	0.082 5	0.082 5	0.082 6	0.082 6	0.082 6	0.082 6
C_{10}	0.061 12	0.061 12	0.061 12	0.061 11	0.061 11	0.061 11	0.061 11	0.061 11	0.061 11	0.061 11	0.061 10
C_{11}	0.066 10	0.066 9	0.066 9	0.066 9	0.066 9	0.066 9	0.066 8	0.066 8	0.066 8	0.066 8	0.066 8
C_{12}	0.050 13	0.050 13	0.050 13	0.050 13	0.050 13	0.050 13	0.050 12	0.051 12	0.051 12	0.051 12	0.051 12
C_{13}	0.090 2	0.090 2	0.090 2	0.090 2	0.090 2	0.090 2	0.090 2	0.090 2	0.090 2	0.090 3	0.090 3
C_{14}	0.085 3	0.085 3	0.085 3	0.085 3	0.086 3	0.086 3	0.086 4	0.086 4	0.086 4	0.086 5	0.086 5

Table 8.3: Sensitivity analysis results of lambda parameters used in PODER for Istanbul.

λ_{obj} / λ_{sub}	0.0 / 1.0	0.1 / 0.9	0.2 / 0.8	0.3 / 0.7	0.4 / 0.6	0.5 / 0.5	0.6 / 0.4	0.7 / 0.3	0.8 / 0.2	0.9 / 0.1	1.0 / 0.0
C_1	0.0687	0.0657	0.06310	0.06010	0.05812	0.05512	0.05212	0.05012	0.04812	0.04512	0.04312
C_2	0.05811	0.06010	0.0639	0.0658	0.0687	0.0707	0.0736	0.0765	0.0785	0.0814	0.0834
C_3	0.0874	0.0854	0.0834	0.0814	0.0794	0.0775	0.0755	0.0736	0.0716	0.0699	0.0679
C_4	0.1321	0.1331	0.1341	0.1341	0.1351	0.1351	0.1361	0.1361	0.1361	0.1371	0.1371
C_5	0.05512	0.05612	0.05712	0.05812	0.06010	0.06210	0.06410	0.0669	0.0689	0.0708	0.0717
C_6	0.0648	0.0658	0.0667	0.0677	0.0678	0.0688	0.0698	0.0708	0.0718	0.0727	0.0726
C_7	0.03214	0.03114	0.03014	0.02914	0.02914	0.02814	0.02714	0.02514	0.02514	0.02414	0.02314
C_8	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013	0.04013
C_9	0.1002	0.1002	0.1002	0.1002	0.1002	0.1002	0.1002	0.1002	0.0992	0.0992	0.0992
C_{10}	0.0649	0.0649	0.0648	0.0649	0.0649	0.0649	0.0649	0.06410	0.06410	0.06410	0.06410
C_{11}	0.0795	0.0795	0.0795	0.0795	0.0795	0.0794	0.0794	0.0794	0.0794	0.0795	0.0795
C_{12}	0.05910	0.05911	0.05911	0.05911	0.05911	0.05911	0.05911	0.05911	0.05911	0.05911	0.05911
C_{13}	0.0716	0.0716	0.0716	0.0716	0.0716	0.0726	0.0717	0.0717	0.0717	0.0716	0.0718
C_{14}	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913	0.0913

The sensitivity analysis in Table 8.3 applies to the PODER method in Istanbul. In this context, Speed limit (C_4) continues to dominate, ranking first across all λ values, confirming its strong and stable significance in the evaluation of micromobility modes. Saving time (C_9) and Low carbon emission (C_{14}) rank consistently in the top three. Conversely, Charging time (C_2) and Accident rate (C_6) exhibit the most considerable shifts in ranking, with Charging time (C_2) advancing from eleventh to fouth place as the objective weight increases. Comfort (C_{10}) shows a consistent decline in ranking, reflecting its sensitivity to weight changes, particularly when the objective component dominates. The rankings for Health benefit (C_{11}), and Eco-design (C_{13}) are relatively stable, with minor variations across the spectrum of lambda (λ) values. As expected, Intermodality rate (C_7) consistently ranks at the bottom, indicating its marginal importance in both Paris and Istanbul.

Note that when lambda values are at their extremes (0 or 1), only one data type is used, effectively eliminating the other. Furthermore, in these instances, there is no objective value present between criteria C_8 and C_{14}. As a result, the lambda values consistently assume extreme positions in these criteria during the sensitivity analysis. The fluctuations in rankings between cities highlight the dataset's impact on results, indicating that there is no single pattern due to varying opinions influencing upward or downward rankings. Additionally, as noted in Chapter 5, it is advisable to incorporate both objective and subjective data equally in model proposals, as this balance is essential for robust decision making.

Overall, this sensitivity analysis for Istanbul further emphasizes the stability of top ranking criteria like Speed limit (C_4), Saving time (C_9), and Low carbon emission (C_{14}), and the sensitivity of Charging time (C_2) and Accident Rate (C_6) to parameter changes, aligning with observations made in the Paris case.

Sensitivity in Defuzzification

The findings displayed in Table 8.4 and Table 8.5 highlight the results of various defuzzification functions used in the PODER method for both Paris and Istanbul.

Table 8.4: Results of different defuzzification function used in PODER for Paris.

	Mean Function	Maxima Function	Centroid Function
C_1	0.0532 12	0.0528 13	0.0532 12
C_2	0.0740 7	0.0753 7	0.0738 7
C_3	0.0663 8	0.0658 8	0.0663 8
C_4	0.1134 1	0.1128 1	0.1135 1
C_5	0.0809 6	0.0803 6	0.0810 6
C_6	0.0841 4	0.0855 3	0.0839 4
C_7	0.0281 14	0.0280 14	0.0281 14
C_8	0.0646 10	0.0641 10	0.0646 10
C_9	0.0823 5	0.0817 5	0.0828 5
C_{10}	0.0609 11	0.0605 11	0.0609 11
C_{11}	0.0660 9	0.0656 9	0.0661 9
C_{12}	0.0505 13	0.0531 12	0.0500 13
C_{13}	0.0901 2	0.0895 2	0.0902 2
C_{14}	0.0857 3	0.0850 4	0.0858 3

Table 8.5: Results of different defuzzification function used in PODER for Istanbul.

	Mean Function	Maxima Function	Centroid Function
C_1	0.0550 12	0.0545 12	0.0551 12
C_2	0.0704 7	0.0719 6	0.0702 7
C_3	0.0774 5	0.0767 5	0.0776 5
C_4	0.1353 1	0.1340 1	0.1355 1
C_5	0.0619 10	0.0612 11	0.0620 10
C_6	0.0681 8	0.0698 8	0.0678 8
C_7	0.0270 14	0.0268 14	0.0270 14
C_8	0.0403 13	0.0400 13	0.0404 13
C_9	0.0999 2	0.0989 2	0.1001 2
C_{10}	0.0640 9	0.0634 10	0.0641 9
C_{11}	0.0791 4	0.0783 4	0.0793 4
C_{12}	0.0590 11	0.0637 9	0.0583 11
C_{13}	0.0715 6	0.0708 7	0.0716 6
C_{14}	0.0910 3	0.0901 3	0.0912 3

In these instances, it is noted that the selection of the defuzzification function had a negligible effect on the resulting weights. This can be explained by the use of an ordinary fuzzy set, which features a symmetric geometric structure in its fuzzy expressions. Such symmetry tends to restrict variability in the rankings, leading to consistent scores across various defuzzification methods. For these numerical results, the defuzzification functions presented in Section 4.3.4 exhibit certain limitations. As illustrated in Table 7.3 and Table 7.4, the fuzzy numbers employed are symmetric; consequently, the three defuzzification functions yield similar values. However, when considering their inverse versions used for cost criteria, the results diverge. The given functions produce identical defuzzification outcomes for benefit criteria, while functions yields values that are approximate but not identical for cost criteria. The variability in function outputs for cost criteria leads to adjustments in the minimum and maximum limits during the scaling operation, consequently resulting in altered scaled values. The comparisons based on the mean, maxima and centroid methods are provided in Table 8.4 and Table 8.5.

These findings imply that the characteristics of the fuzzy sets used play a significant role in influencing the sensitivity of the ranking process. Specifically, it is possible that utilizing more complex and asymmetric fuzzy sets would introduce greater variability in preference rankings. Asymmetric fuzzy sets, with their distinct characteristics, may more effectively capture the nuances and intricacies of real world decision making scenarios, potentially resulting in different ranking outcomes based on the selected defuzzification approach.

Sensitivity in Weights of Decision Makers

The sensitivity of decision makers' weights is a critical factor in multi-criteria decision making frameworks, affecting the evaluation and ranking of various criteria weights. The findings presented in Table 8.6 and Table 8.7 illustrate the influence of hierarchical versus equally weighted decision makers within the PODER framework for both Paris and Istanbul.

In the case of Paris, the criterion weights remained relatively stable. A similar trend is observed in Istanbul, where the scores for each criterion show only minor variations when decision maker weights are adjusted.

Although the immediate impact of decision maker weights on criteria weighting is not markedly evident in the analyses for Paris and Istanbul, it is clear that in more extensive and complex decision making scenarios, such variations could lead to significant shifts in rankings. This underscores the importance of decision makers conducting comprehensive evaluations of weight assignments to enhance the reliability and validity of preference rankings in multi-criteria decision making frameworks.

8.2.2 Sensitivity Analysis of V-PARS

This part investigates the sensitivity of the V-PARS model to variations in lambda parameters, defuzzification methods, and the weights of decision makers in the context of micromobility evaluation for Paris and Istanbul.

Sensitivity in Lambda Parameters

The sensitivity analysis presented in Table 8.8 and Table 8.9 illustrates the impact of varying the lambda parameters (λ_{obj} and λ_{sub}) on the preferences of different modes of transport in Paris and Istanbul.

If the tables are read from left to right, an increase in the influence of objective data can be observed. Conversely, reading from right to left highlights the impact of subjective data on the ranking. In the cases Paris and Istanbul, all alternatives maintain their positions. This situation can be elucidated by examining the magnitude of the gaps between the score values. In both scenarios, the scores for the bike and e-bike increase as the weight of the subjective data rises, whereas the scores for the e-scooter and e-moped increase with a greater emphasis on the objective data.

It is evident that the score values fluctuate depending on the lambda values; however, the proposed model ensures a robust solution, such that the differences in scores cannot be reconciled merely by altering the lambda. It is important to note, though, that this does not imply that changes will be absent in a different dataset. This phenomenon is specific to the current overlap, and it cannot be asserted that the rankings always will remain unaffected by variations in lambda.

Table 8.6: Results of hierarchical and equally weighted DMs within PODER for Paris.

	$w_{DM_1} = 0.2, w_{DM_2} = 0.2$ $w_{DM_3} = 0.3, w_{DM_4} = 0.2$ $w_{DM_5} = 0.1$	$w_{DM_1} = 0.2, w_{DM_2} = 0.2$ $w_{DM_3} = 0.2, w_{DM_4} = 0.2$ $w_{DM_5} = 0.2$
C_1	0.0532 12	0.0531 12
C_2	0.0740 7	0.0751 7
C_3	0.0663 8	0.0668 9
C_4	0.1134 1	0.1125 1
C_5	0.0809 6	0.0822 6
C_6	0.0841 4	0.0837 3
C_7	0.0281 14	0.0276 14
C_8	0.0646 10	0.0646 10
C_9	0.0823 5	0.0837 4
C_{10}	0.0609 11	0.0605 11
C_{11}	0.0660 9	0.0687 8
C_{12}	0.0505 13	0.0499 13
C_{13}	0.0901 2	0.0888 2
C_{14}	0.0857 3	0.0828 5

Table 8.7: Results of hierarchical and equally weighted DMs within PODER for Istanbul.

	$w_{DM_1} = 0.2, w_{DM_2} = 0.2$ $w_{DM_3} = 0.3, w_{DM_4} = 0.2$ $w_{DM_5} = 0.1$	$w_{DM_1} = 0.2, w_{DM_2} = 0.2$ $w_{DM_3} = 0.2, w_{DM_4} = 0.2$ $w_{DM_5} = 0.2$
C_1	0.0550 12	0.0565 12
C_2	0.0704 7	0.0717 6
C_3	0.0774 5	0.0774 5
C_4	0.1353 1	0.1330 1
C_5	0.0619 10	0.0626 10
C_6	0.0681 8	0.0671 8
C_7	0.0270 14	0.0269 14
C_8	0.0403 13	0.0417 13
C_9	0.0999 2	0.0981 2
C_{10}	0.0640 9	0.0671 9
C_{11}	0.0791 4	0.0807 4
C_{12}	0.0590 11	0.0583 11
C_{13}	0.0715 6	0.0681 7
C_{14}	0.0910 3	0.0907 3

Table 8.8: Sensitivity analysis results of lambda parameters used in V-PARS for Paris.

λ_{obj}	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
λ_{sub}	1.0	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0.0
Private Bike	0.696 1	0.678 1	0.660 1	0.641 1	0.622 1	0.601 1	0.580 1	0.558 1	0.536 1	0.513 1	0.490 1
Private e-Scooter	-0.732 4	-0.709 4	-0.687 4	-0.665 4	-0.643 4	-0.620 4	-0.598 4	-0.576 4	-0.553 4	-0.531 4	-0.509 4
Private e-Moped	-0.301 3	-0.287 3	-0.273 3	-0.261 3	-0.249 3	-0.239 3	-0.229 3	-0.220 3	-0.213 3	-0.206 3	-0.200 3
Private e-Bike	0.337 2	0.318 2	0.300 2	0.285 2	0.270 2	0.258 2	0.247 2	0.238 2	0.230 2	0.224 2	0.219 2

Table 8.9: Sensitivity analysis results of lambda parameters used in V-PARS for Istanbul.

λ_{obj}	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
λ_{sub}	1.0	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0.0
Private Bike	0.797 1	0.774 1	0.750 1	0.724 1	0.697 1	0.670 1	0.641 1	0.612 1	0.581 1	0.550 1	0.518 1
Private e-Scooter	-0.482 3	-0.463 3	-0.444 3	-0.424 3	-0.404 3	-0.384 3	-0.364 3	-0.344 3	-0.324 3	-0.305 3	-0.286 3
Private e-Moped	-0.708 4	-0.678 4	-0.648 4	-0.619 4	-0.590 4	-0.562 4	-0.533 4	-0.505 4	-0.477 4	-0.450 4	-0.422 4
Private e-Bike	0.393 2	0.367 2	0.343 2	0.319 2	0.297 2	0.276 2	0.256 2	0.238 2	0.220 2	0.204 2	0.190 2

Table 8.10: Results of different defuzzification function used in V-PARS for Paris.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
Mean Function	0.601 1	-0.620 4	-0.239 3	0.258 2
Maksima Function	0.592 1	-0.611 4	-0.247 3	0.265 2
Centroid Function	0.603 1	-0.622 4	-0.237 3	0.257 2

Table 8.11: Results of different defuzzification function used in V-PARS for Istanbul.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
Mean Function	0.670 1	-0.384 3	-0.562 4	0.276 2
Maksima Function	0.563 1	-0.370 3	-0.570 4	0.284 2
Centroid Function	0.671 1	-0.390 3	-0.560 4	0.275 2

It is important to note that when the lambda values are at their extreme limits (0 and 1), only a single data type is utilized. This essentially implies the elimination of one type of data from consideration. As emphasized in Chapter 5, when proposing a model, it is recommended that, unless in a special case, objective and subjective data be equally incorporated into the system. This balanced approach is crucial for ensuring robust decision making.

Sensitivity in Defuzzification

The results presented in Table 8.10 and Table 8.11 outline the outcomes of different defuzzification functions employed in the V-PARS method for both Paris and Istanbul.

In these cases, it is observed that the choice of defuzzification function had a minimal impact on the resulting scores. This outcome can be attributed to the utilization of a ordinary fuzzy set, characterized by a symmetric geometric structure in its fuzzy expressions. Such symmetry tends to limit the variability in the rankings, resulting in consistent scores across different defuzzification approaches. The defuzzification functions introduced in Section 4.3.4 exhibit certain constraints. As demonstrated in Table 7.3 and Table 7.4, the fuzzy numbers utilized are symmetrical, leading to comparable outcomes from the three defuzzification functions. However, when examining their inverse versions, the results diverge. The three functions produce identical defuzzification values for benefit criteria however, they do not produce the same values for cost criteria.

The implications of these findings suggest that the nature of the fuzzy sets employed is crucial in determining the sensitivity of the ranking process. Specifically, it is conceivable that the adoption of more complex and asymmetric fuzzy sets would introduce a higher degree of variability in the preference rankings. Asymmetric fuzzy sets, due to their inherent characteristics, may better capture the nuances and complexities of real world decision making scenarios, thereby leading to differing outcomes in rankings depending on the chosen defuzzification method.

Sensitivity in Weights of Decision Makers

The sensitivity of the weights of decision makers is a pivotal aspect in multi-criteria decision making frameworks, influencing how various alternatives are evaluated and ranked. The results presented in Table 8.12 and Table 8.13 reflect the impact of hierarchical and equally weighted decision-makers within the V-PARS framework for both Paris and Istanbul.

In the results for Paris, despite the application of varied weights, the preferences across the alternatives relatively stable. A similar observation can be made for the results in Istanbul, where the scores for each alternative exhibit only slight variations with adjustments in the decision maker weights.

Table 8.12: Results of hierarchical and equally weighted DMs within V-PARS for Paris.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
$w_{DM_1} = 0.2$ $w_{DM_2} = 0.2$ $w_{DM_3} = 0.3$ $w_{DM_4} = 0.2$ $w_{DM_5} = 0.1$	0.601 1	-0.620 4	-0.239 3	0.258 2
$w_{DM_1} = 0.2$ $w_{DM_2} = 0.2$ $w_{DM_3} = 0.2$ $w_{DM_4} = 0.2$ $w_{DM_5} = 0.2$	0.615 1	-0.592 4	-0.273 3	0.251 2

Table 8.13: Results of hierarchical and equally weighted DMs within V-PARS for Istanbul.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
$w_{DM_1} = 0.2$ $w_{DM_2} = 0.2$ $w_{DM_3} = 0.3$ $w_{DM_4} = 0.2$ $w_{DM_5} = 0.1$	0.670 1	-0.384 3	-0.562 4	0.276 2
$w_{DM_1} = 0.2$ $w_{DM_2} = 0.2$ $w_{DM_3} = 0.2$ $w_{DM_4} = 0.2$ $w_{DM_5} = 0.2$	0.670 1	-0.406 3	-0.516 4	0.252 2

While the immediate effects of DM weights on preference rankings are not significantly observed in the analyses for Paris and Istanbul, it is evident that in more extensive and complex decision making contexts, such variations can lead to substantial shifts in rankings. This emphasizes the necessity for decision-makers to conduct thorough examinations of weight assignments to enhance the reliability and validity of preference rankings in multi-criteria decision making frameworks.

8.3 Comparative Analysis

To rigorously assess the performance of the proposed PODER and V-PARS models, a comprehensive comparative analysis with established methods is imperative. Given the novel nature of these approaches, benchmarking their results against existing models from the literature is crucial.

PODER can be conceptualized as an extension of the MEREC (Keshavarz-Ghorabaee et al., 2021) and SERA (Çakır et al., 2022) methods, incorporating innovative elements such as Nudge Theory, scaling techniques, and the integration of objective and subjective data within a geometric framework. To underscore these advancements, the original case study is revisited using MEREC and SERA with minor adjustments, facilitating a direct comparison.

While V-PARS introduces a groundbreaking vector-based perspective to MCDM, opportunities for direct comparisons with existing methods are limited. However, due to its reliance on distance metrics and the utilization of extreme points as reference points, TOPSIS (Hwang and Yoon, 1981) emerges as the suitable benchmark. Additionally, PROMETHEE (Brans et al., 1982; Brans and Vincke, 1985), another preference ranking methodology, offers a valuable comparative perspective, particularly given its incorporation of the Kemeny-Young system and the flows. Consequently, two cases are reapplied using TOPSIS and PROMETHEE, with necessary modifications, to provide a comprehensive evaluation of V-PARS' performance.

By conducting these comparative analyses, the study aims to elucidate the unique contributions of PODER and V-PARS, identify their strengths and weaknesses, and establish their position within the broader landscape of MCDM methodologies. It is also necessary to touch upon some important points when evaluating the case results.

8.3.1 PODER versus MEREC and SERA

A comparative analysis is conducted between the PODER method and the existing methods of MEREC (Keshavarz-Ghorabaee et al., 2021) and SERA (Çakır et al., 2022) in the context of criteria weighting. The aim is to illustrate the advantages of the PODER approach, particularly in addressing the extraction effect of criteria, which can significantly impact decision making outcomes.

The PODER method which has been proposed in this doctoral thesis, taking into account the characteristic features of the existing MEREC and SERA techniques in the literature. MEREC is a distance-based criteria weighting method designed for precise (objective, crisp) data, which aims to assess the impact of absent criteria from the evaluation through the use of Manhattan distance in Taxicab geometry. Similarly, SERA (also proposed by the author of this thesis) follows a procedure akin to MEREC but is applicable exclusively to fuzzy numbers, utilizing Manhattan distance as the measure of distance. PODER presents an advanced version that addresses the shortcomings of these two methods. In MEREC and SERA, performance values are expressed in a one-dimensional environment following logarithmic and aggregation functions. In contrast, PODER consistently operates with point data in a multidimensional environment, making the use of Euclidean geometry highly applicable. Table 8.14 presents a comparative analysis of PODER, SERA, and MEREC, highlighting their core methodologies, decision making approaches, and key characteristics within the context of multi-criteria analysis.

To enable a comprehensive comparison, the proposed PODER method is evaluated alongside SERA using criteria weighting cases for Paris and Istanbul. It is important to note that a numerical application with MEREC is not conducted. MEREC operates exclusively with crisp sets, and the majority of fuzzy MEREC studies found in the literature are not directly applicable. The logarithmic score function proposed in MEREC is employed to

Table 8.14: Comparison of PODER with MEREC and SERA procedures.

Characteristic	PODER	MEREC	SERA
Determination of decision makers and weights	It is possible to have DMs from all hierarchical levels. Weights of DMs are assigned by the Nudge Theory-based weighting system.	There is no specific method. DMs are often experts, and weight assignment may vary from case to case.	There is no specific method. DMs are often experts, and weight assignment may vary from case to case.
Determination of criterion weights	Since this is a methodology for generating criteria weights, wherein all criteria are initially considered equally important.	Since this is a methodology for generating criteria weights, wherein all criteria are initially considered equally important.	Since this is a methodology for generating criteria weights, wherein all criteria are initially considered equally important.
Objective and subjective data usage	Any type of data can be included in the system during the evaluation process. A lambda parameter combines objective and subjective data.	A formulation for combining different types of data is not proposed. Applications typically include crisp, certain, objective data types.	A formulation for combining different types of data is not proposed. Applications typically include fuuzy, uncertain data type.
Cost-benefit conversion	All criteria are required to be beneficial. Conversion is provided according to data type.	It transforms all the criteria into the minimization type criteria.	All criteria are required to be beneficial.
Data normalization vs. scalization	Aggregated decision data is scaled.	Aggregated decision data is normalized by simple linear normalization.	Owing to the fuzzy nature of the expressions, normalization or scaling of the aggregated decision data is not required. For crisp data use, no specific recommendations exist.
Evaluation data	For m-criteria, the m-coordinate position of each alternative is determined in the m-dimensional environment. The entire process is in Euclidean n-spaces.	For m-criteria, the m-coordinate position of each alternative is determined in the m-dimensional environment. Performance values derived from the logarithmic function are one-dimensional.	For m-criteria, the m-coordinate position of each alternative is determined in the m-dimensional environment, utilizing the defuzzification function tailored to the set employed. Performance values derived from the aggregation function are one-dimensional.
Determination of extracted / removed / reduced criterion	Criteria are systematically extracted from the system in a sequential manner.	Criteria are systematically removed from the system in a sequential manner.	Criteria are systematically reduced from the system in a sequential manner.
Distance metric	Euclidean distance metric is performed.	Manhattan distance metric is performed.	Manhattan distance metric is performed.
Calculation of weights of criteria	The total distance is calculated, normalized and assigned as the criterion weight.	The total distance is calculated, normalized and assigned as the criterion weight.	The total distance is calculated, normalized and assigned as the criterion weight.

standardize data of varying magnitudes to the [0,1] range. However, this function is redundant when working with fuzzy sets. Given MEREC's incompatibility with fuzzy sets, SERA, which handles fuzzy data and was proposed by the author of this thesis prior to PODER, is selected for comparison. Minor adjustments are made to the application of each method to ensure consistency and comparability across the approaches as follow:

- The decision maker type, weights, and data types remain unchanged throughout the analysis.
- ***PODER:*** Scaling and normalization are applied to the data separately, followed by the standard PODER procedure for aggregated decision matrix.
- ***SERA:*** Scaling and normalization are implemented separately, followed by the standard SERA procedure for aggregated decision matrix.

To provide a comparative analysis based on the results presented in Table 8.15 and 8.16, we observe that the rankings derived for both the PODER and SERA methods exhibit notable differences.

In the case of Paris, the results of PODER from the scaled data indicate a ranking where Speed limit (C_4) emerges as the most critical criterion, followed by Eco-design (C_{13}), with the lowest ranked criterion being Intermodality rate (C_7). When normalized data is employed, some rankings shift significantly, positioning Environmental noise (C_{12}) as the least important criterion. This discrepancy illustrates how data scaling and normalization can lead to variations in the importance assigned to the criteria.

Similarly, for SERA, the scaled data also prioritizes Speed limit (C_4) as the highest-ranking criterion, consistent with PODER's findings. However, the normalized data produces same ranking, wherein Speed limit (C_4) again is regarded as the most important criterion, while Environmental noise (C_{12}) ranks lowest. Scaled data and normalized data produced consistent results among themselves, regardless of the method. The trends observed in both methodologies underline the significance of data treatment, as it can substantially influence the resulting rankings of important criteria.

Table 8.15: Comparative results of PODER for Paris.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
PODER (Scaled data) *-original-*	0.0532	0.0740	0.0663	0.1134	0.0809	0.0841	0.0281	0.0646	0.0823	0.0609	0.0660	0.0505	0.0901	0.0857
	12	7	8	1	6	4	14	10	5	11	9	13	2	3
PODER (Normalized data)	0.0517	0.0723	0.0633	0.1007	0.0742	0.0813	0.0485	0.0895	0.0859	0.0595	0.0625	0.0494	0.0836	0.0776
	12	8	9	1	7	5	13	2	3	11	9	14	4	6
SERA (Scaled data)	0.0612	0.0723	0.0686	0.1039	0.0762	0.0779	0.0462	0.0665	0.0763	0.0650	0.0680	0.0585	0.0809	0.0786
	12	7	8	1	6	4	14	10	5	11	9	13	2	3
SERA (Normalized data)	0.0604	0.0716	0.0673	0.0978	0.0732	0.0771	0.0584	0.0804	0.0770	0.0636	0.0657	0.0574	0.0765	0.0734
	12	8	9	1	7	3	13	2	4	11	10	14	5	6

Table 8.16: Comparative results of PODER for Istanbul.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
PODER (Scaled data) *-original-*	0.0550	0.0704	0.0774	0.1353	0.0619	0.0681	0.0270	0.0403	0.0999	0.0640	0.0791	0.0590	0.0715	0.0910
	12	7	5	1	10	8	14	13	2	9	4	11	6	3
PODER (Normalized data)	0.0594	0.0642	0.0643	0.1091	0.0619	0.0678	0.0491	0.0800	0.0952	0.0742	0.0651	0.0521	0.0668	0.0908
	12	10	9	1	11	6	14	4	2	5	8	13	7	3
SERA (Scaled data)	0.0620	0.0705	0.0745	0.1182	0.0653	0.0696	0.0437	0.0542	0.0856	0.0655	0.0751	0.0639	0.0708	0.0812
	12	7	5	1	10	8	14	13	2	9	4	11	6	3
SERA (Normalized data)	0.0646	0.0679	0.0679	0.1031	0.0660	0.0703	0.0565	0.0753	0.0819	0.0719	0.0665	0.0593	0.0678	0.0810
	12	8	7	1	11	6	14	4	2	5	10	13	9	3

The Table 8.16 presents the comparative results of the PODER and SERA methods applied to the important criteria for Istanbul. The first segment of the table shows the scaled data for both methods, criterion Speed limit (C_4) stands out as the most critical criterion for PODER, receiving the top ranking of 1, while Intermodality rate (C_7) is the least important, ranked 14 same as Paris.

In the normalized data section, PODER's results slightly vary, indicating shifts in the importance of specific criteria. This reflects the method's adaptability to normalization while retaining the significance of key criteria.

Similarly, the SERA method shows comparable results. Criterion Speed limit (C_4) ranks as the most important, reaffirming its significance across both methods, while Intermodality rate (C_7) is the least important, ranked 14. The normalized results indicate that SERA's rankings for the important criteria remain consistent, with minimal changes compared to PODER, illustrating that both methods identify similar key areas of focus within the evaluated criteria as group of scaled and normalized data. In all trials, the criteria C_1, C_4, C_9 and C_{14} maintained their positions.

For both cases, it is essential to recognize that, PODER and SERA generate significantly different scores as a result of their respective metrics. The ranking results for the scaled versions are nearly identical, and similarly, the ranking results for the normalized versions are also consistent. The observed disparities and similarities can be attributed to several underlying factors:

- The normalization of the data in the final step resulted in closely clustered scores across all variations of the same dataset. Given the data range of 0 to 1, the impact of distance metrics is evident; however, it did not lead to significant changes in the overall outcomes. Nevertheless, when the same dataset was subjected to different distance metrics, variations in the order of weights were observed.

- The original PODER method employed in this study utilizes scaled data. As evidenced in the comparative results, the weights derived from normalized and scaled data versions may exhibit differences. This outcome is anticipated, as the position-

ing of the data within the multidimensional coordinate plane alters, leading to new distance calculations.

- Both PODER and SERA methods are founded on the MEREC framework, which suggests that they are likely to yield similar results. Indeed, comparable outcomes were achieved for the same type of dataset. However, given the differences in distance metrics employed, variations in the assigned weights are unavoidable.

Overall, the comparison highlights the critical role that data normalization and scaling play in shaping the rankings of important criteria across different decision making methods. This finding emphasizes the need for careful consideration of data processing techniques in multi-criteria decision making frameworks.

8.3.2 V-PARS versus TOPSIS and PROMETHEE

The V-PARS method, a pioneering vector-based approach in Multi-Attribute Decision Making (MADM), is employed for the first time in this study. To validate its efficacy and compare its results with existing models, a comparative analysis with TOPSIS (Hwang and Yoon, 1981) and PROMETHEE (Brans et al., 1982; Brans and Vincke, 1985) is being conducted.

TOPSIS -a distance-based preference ranking MADM method- and PROMETHEE -a preference ranking MADM method based on flows- are chosen as the suitable comparators due to their alignment with the vector-based perspective of V-PARS. TOPSIS's reliance on extreme points and distance measurement mirrors the vector's magnitude and similarity, while PROMETHEE's partial and complete preference rankings based on flows align with the directional aspect of the vector approach. Table 8.17 outlines the similarities and differences between V-PARS, TOPSIS, and PROMETHEE I-II procedures, comparing their core methodologies, decision making approaches, and key characteristics in multi-criteria analysis.

To facilitate a comprehensive comparison, the micromobility evaluation cases for Paris and Istanbul are being re-applied using TOPSIS and PROMETHEE, with minor adjustments to ensure consistency and comparability across the methods. Considering the sim-

Table 8.17: Comparison of V-PARS with TOPSIS and PROMETHEE procedures.

Characteristic	V-PARS	TOPSIS	PROMETHEE I-II
Determination of decision makers and weights	It is possible to have DMs from all hierarchical levels in the system. Weights of DMs are assigned to decision makers using the Nudge Theory-based weighting system.	There is no specific method. DMs are often experts, and weight assignment may vary from case to case.	There is no specific method. DMs are often experts, and weight assignment may vary from case to case.
Determination of criterion weights	Criterion weights should be determined in advance.	Criterion weights should be determined in advance.	Criterion weights should be determined in advance.
Objective and subjective data usage	Any type of data can be included in the system during the evaluation process. A lambda parameter combines objective and subjective data.	A formulation for combining different types of data is not proposed. Applications typically include only one data type (crisp or fuzzy).	A formulation for combining different types of data is not proposed. Applications typically include only one data type (crisp or fuzzy).
Cost-benefit conversion	All criteria are required to be beneficial. Conversion is provided according to data type.	No need for Cost-Benefit conversion. Applicable to both cost and benefit types in the procedure.	Criteria are converted using preference functions and thresholds are applied as needed.
Data normalization vs. scalization	Aggregated decision data is scaled.	Aggregated decision data is normalized.	Normalization or scaling of the aggregated decision data is not required.
Evaluation data	For m-criteria, the m-coordinate position of each alternative is determined in the m-dimensional environment. Vectors are created and added to generate a total Euclidean vector in Euclideas n-spaces.	For m-criteria, a point with m coordinates is obtained for each alternative in an m-dimensional environment.	For m-criteria, preference values are assigned for each pair of alternatives based on predefined functions in an m-dimensional environment to create the total flows.
Determination of reference points	The positive ideal Euclidean vector $< \overrightarrow{0_1, 0_2, ..., 0_m; 1_1, 1_2, ..., 1_m} >$ is taken for reference.	For m criteria, a pair of Positive and Negative Ideal Solution points are determined, creating a virtual PIS-NIS pair in an m-dimensional environment.	Instead of using reference points, it relies on pairwise comparisons and preference functions.
Calculation of evaluation score	For each alternative, the similarity of the total preference Euclidean vector to the positive ideal Euclidean vector is calculated.	PIS and NIS points are determined as two extremes. The Euclidean distance of each alternative to the ideal points is subject to normalization.	Version I involves the calculation of positive and negative flows, while version II calculates the net flow magnitude.

ilarities and differences highlighted in Table 8.17 , a comparative analysis of several distinct outcomes is presented in Table 8.18 and Table 8.19, following these modifications:

- The decision maker type, weights, and data types remain unchanged throughout the analysis.
- ***V-PARS:*** Scaling and normalization are applied to the data separately, followed by the standard V-PARS procedure for aggregated decision matrix.
- ***TOPSIS:*** Scaling and normalization are implemented separately, followed by the standard TOPSIS procedure for aggregated decision matrix. In addition, the reference points are updated as $(0_1, 0_2, ..., 0_m)$ and $(1_1, 1_2, ..., 1_m)$, then all other steps for scaled data are applied according to the standard TOPSIS procedure.
- ***PROMETHEE II:*** Scaling and normalization are applied separately, followed by the standard PROMETHEE II procedure using the U-type (Brans and Vincke, 1985) preference function (which aligns with the Kemeny-Young approach detailed in Chapter 3) for aggregated decision matrix. *(It is noteworthy that while the procedure of PROMETHEE does not necessitate scaling or normalization, the impact of alterations to the aggregated matrix can still be observed.)*

For the case of Paris, V-PARS displays a clear preference for the private bike and private e-bike across different data forms. V-PARS ranks the bike as the best option (rank first), followed by the e-bike (rank second). Private e-Moped and Private e-Scooter, are ranked third and fourth, respectively. The e-scooter consistently ranks lowest, suggesting that, according to V-PARS, it is the least favorable alternative across all scenarios.

TOPSIS, another prominent multi-criteria decision making method, follows a similar pattern to V-PARS but exhibits slight variations when different data types are applied. Using normalized data *-original version-*, TOPSIS ranks the bike as the best option, with e-bike ranked second. In the scaled data version, however, bike takes the top spot (rank first), while e-bike moves to second place, indicating that TOPSIS places more emphasis on the scaling process. Furthermore, when the reference points are updated during the scaling

Table 8.18: Comparative results of V-PARS for Paris.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
V-PARS (Scaled data) *-original-*	0.601 1	-0.620 4	-0.239 3	0.258 2
V-PARS (Normalized data)	0.752 1	-0.885 4	-0.255 3	0.388 2
TOPSIS (Normalized data) *-original-*	0.297 2	0.163 4	0.241 3	0.299 1
TOPSIS (Scaled data)	0.322 1	0.174 4	0.215 3	0.290 2
TOPSIS (Scaled data and updated references)	0.296 1	0.199 4	0.241 3	0.263 2
PROMETHEE II (Scaled data)	0.093 1	-0.099 4	-0.013 3	0.020 2
PROMETHEE II (Normalized data)	0.078 1	-0.102 4	-0.012 3	0.036 2

process, which is most similar form to V-PARS, bike once again assumes rank first. The shifts in rankings between scaled and normalized data reveal that TOPSIS is highly responsive to data scaling and reference point adjustments, yet the general preference for other vehicles remains.

In comparison, PROMETHEE II, while agreeing with V-PARS and TOPSIS on the general ranking of alternatives, shows some distinctive traits. Under normalized data, bike is ranked highest, mirroring V-PARS and contracting TOPSIS rankings, while e-scooter ranks lowest, a position it retains across all data types and methods. This consistency suggests that all three methods view e-scooter as the least preferable alternative. In the case of normalized data, however, PROMETHEE II differs slightly by placing Private Bike at

rank first and Private e-Bike at rank second, reflecting a sensitivity to data normalization that is also present in V-PARS and TOPSIS.

Table 8.19: Comparative results of V-PARS for Istanbul.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
V-PARS (Scaled data) *-original-*	0.670 1	-0.384 3	-0.562 4	0.276 2
V-PARS (Normalized data)	0.766 1	-0.590 3	-0.670 4	0.496 2
TOPSIS (Normalized data) *-original-*	0.317 1	0.148 4	0.240 3	0.295 2
TOPSIS (Scaled data)	0.338 1	0.192 3	0.176 4	0.294 2
TOPSIS (Scaled data and updated references)	0.294 1	0.221 3	0.218 4	0.267 2
PROMETHEE II (Scaled data)	0.075 1	-0.072 3	-0.072 4	0.069 2
PROMETHEE II (Normalized data)	0.046 2	-0.102 4	-0.004 3	0.061 1

For the case of Istanbul, the V-PARS method highlights a significant preference for the bike and e-bike, demonstrating consistent performance across different data formats. In the scenario of both data, V-PARS ranks the bike as the top option (rank first), followed closely by the e-bike (rank second). Other alternatives, e-scooter and e-moped, occupy the third and fourth ranks, respectively.

TOPSIS shows a somewhat similar trend with V-PARS with scaled data. With both type of data, TOPSIS identifies the bike as the best alternative, followed by the e-bike at rank second. However, when normalized data were employed, a change occurred in the third

and fourth rankings.

Although the PROMETHEE II method does not fully overlap with the general findings of V-PARS and TOPSIS, it shows unique features in its rankings. Under scaled data conditions, the bike takes rank first, while the e-bike follows closely in rank second, mirroring the results seen in scaled TOPSIS. The e-moped, consistently ranked lowest across all datasets, further supports the consensus among the three methods regarding its lower desirability. Interestingly, in normalized data, PROMETHEE II ranks the e-bike highest, and others vary from each version.

The underlying reasons for these disparities and similarities can be attributed to the following factors:

- Final scores differed due to the definition range. As stated in the method, it is not recommended to associate these values with weighting since they are based on distance or similarity. The fact that the order is the same is sufficient to observe that both methods produce similar results.

- V-PARS proposed in this study uses scaled data and is compatible with scaled data in TOPSIS and scaled data in PROMETHEE II. However, scaled and normalization versions differ. The reason for this is that scaled data determines its position independently of the elements in the system. In the expert driven phase, all alternatives are actually calculated independently of each other. Alternatives make their effects felt on each other during vector calculation. The normalization used in MCDM methods in the literature does not allow this. Because the data used for normalization are the data existing in the system and their positions relative to each other are affected during normalization. It is noteworthy that in the PROMETHEE application, utilizing the U-type preference function with an identical raw dataset, distinct outcomes are observed between scaled and normalized data used in Istanbul case. While PROMETHEE typically does not necessitate such an approach, the results demonstrate that scaling and normalizing the data can significantly alter preference orders according the individual criteria, ultimately leading to divergent preference

rankings. However, this phenomenon was not observed in the Paris case, indicating that such outcomes may vary depending on the dataset.

- V-PARS and updated TOPSIS are the methods expected to be most similar for comparison. The reference points of TOPSIS are updated as the extreme points, independent of the data, as in V-PARS. As can be seen, somewhat similar rankings are obtained in both cases. However, this is not a situation that can be encountered in every application. Because in this comparison, while the effects of alternatives on each other are only in the data driven phase in V-PARS to create vectors, the alternatives are evaluated completely independently of each other in TOPSIS (no normalization throughout). For this reason, in an environment where the use of scaled data is accepted, the TOPSIS procedure cannot be preferred so that the alternatives affect each other. For scaled data, V-PARS is meaningful for preference ranking.

Overall, while the three methods provide similar overall rankings, the differences in how they process data—whether through scaling, normalization, distance, references or direction—can lead to notable shifts in rankings. This analysis highlights the importance of understanding the specific mechanics of each method when applying them to decision making scenarios.

If a comparative critique is to be conducted, it should be noted that, as observed in both cases, complete compatibility among all versions cannot be guaranteed. This discrepancy arises from the application of distinct methodologies to diverse datasets, which inevitably influences the results. It is essential to recognize that the pursuit of a superior method is inherently flawed. The unique steps and perspectives inherent in each technique inevitably lead to varying outcomes. When introducing a novel methodology, the primary objective should not be to assert its superiority over existing approaches, but rather to establish a fresh perspective on evaluation architecture.

In addition, to definitively claim that the results are unequivocally superior, a comprehensive refutation of the steps employed in other techniques would be necessary. The anticipated outcome is the generation of comparable outputs from similar methods and

versions. Solely relying on numerical results to proclaim a method as the best is a fallacy. MCDM methods serve as guiding tools, and the decision to select a particular alternative ultimately rests with the individual applying the technique. MCDM methods create value through their numerical operations.

8.3.3 Fuzzy versus Score Data in Subjective Evaluation

In the published article associated with this thesis (Çakır and Tolga, 2024b), subjective data are assessed using a range of 1-9 scores. Notably, the same survey results are expressed using different sets in the two studies. The article only exclusively evaluated the Paris City case, and different criterion weights are assigned directly without employing a specific methodology, deviating from the weights utilized in this study of PODER.

As illustrated in the Table 8.20, the preference rankings obtained are identical for all methods except TOPSIS with normalized or scaled data. Similar to the disparity observed between the Paris and Istanbul results in this thesis (Table 8.18 and Table 8.19), the article's findings do not lend methods to a fixed categorization. This discrepancy can be attributed to variations in data type and the precise values of the weights. Consequently, it is evident that even minor modifications can significantly influence the results and alter the comparative behavior of the techniques.

Table 8.20: Comparative results of V-PARS for Paris in the published article.

	Private Bike	**Private e-Scooter**	**Private e-Moped**	**Private e-Bike**
V-PARS (Scaled data) *-original-*	0.301 1	-0.322 4	-0.090 3	0.111 2
V-PARS (Normalized data)	0.480 1	-0.610 4	-0.181 3	0.311 2
TOPSIS (Normalized data) *-original-*	0.615 2	0.377 4	0.472 3	0.652 1
TOPSIS (Scaled data)	0.629 1	0.369 3	0.445 4	0.547 2
TOPSIS (Scaled data and updated references)	0.052 1	0.044 4	0.049 3	0.051 2
Fuzzy V-PARS (Scaled data) *-original-*	0.451 1	-0.521 4	-0.157 3	0.227 2

8.4 Limitations

While this study offers valuable insights into micromobility mode preferences, it is essential to acknowledge inherent limitations within the research methodology and its practical application. The following section provides a critical examination of these constraints, thereby enhancing the overall comprehension of the study's scope and findings.

8.4.1 Theorical Limitations

To develop the proposed procedures for future studies, some limitations and developing ideas are given in this subsection. The following remarks are important to discuss the proposed method in more detail.

PODER and V-PARS Phase 1: Expert Driven Model

As previously mentioned in Chapter 7, the procedures employed in Phase 1: Expert-Driven Model are identical for both PODER and V-PARS methodologies. Consequently, the subsequent analysis pertains to both models within the confines of this phase.

First of all, given that this is a multi-criteria decision-making method, it is necessary for the system to incorporate a minimum of two criteria. Intuitively, multiple alternatives and criteria are expected to be used in practice.

While recommending the adaptation of Nudge Theory for MCDM, it is necessary to draw attention to an inequality arising from the number of decision makers in the weighting system used in Table 5.1 and Table 5.2. For example, if there are many experts and few beginners in the system; the individual weight of each expert will be less than the beginners. This may seem like an unfair distribution due to the unbalanced distribution of the number of people, but since the category they belong to has a higher weight, their in-group weight in group decision making actually decreases. Since group decision still has a high weight, it would not be correct to say that the hierarchy has been disrupted. This study prioritized group hierarchy over individual hierarchy in the integration of Nudge Theory. Consequently, assigning individual weights and normalizing them would compromise the established group decision making framework. Group decisions within the category can also be examined separately. As a precaution, groups at higher levels of the hierarchy should be expected to have fewer people.

Evaluations in real life can include both objective and subjective evaluations. Therefore, it is necessary to create a balance for the mixed sets given here. It is difficult to combine objective data with subjective data in one system. In expert driven phase, since the definition ranges of objective and subjective data are different, it is necessary to scale the data before combining them. There is an important reason why normalization is not preferred here. As previously mentioned in Chapter 3, while normalization aims to standardize data onto a common scale, it inherently seeks to segregate outliers. The normalization formula is a statistical method used to scale down a dataset so that all variations fall within the interval of zero and one. It facilitates the representation of data points as values between zero and

one, where the largest data point is assigned a normalized value of one and the smallest a value of zero. The remaining data points are represented by decimal values proportional to their positions within the dataset range. This technique also enables the comparison of corresponding normalized values across multiple datasets, effectively mitigating the impact of variations in scale. However, this approach causes us to lose sight of the true positions of the data within its original scale. Data integrity need not be sacrificed, nor should it be required to conform to a particular distribution; rather, the data should be utilized in a manner that accurately reflects its real world significance. In MCDM techniques in the literature, only the data in the decision matrix is used when normalizing decision matrices. However, the definition range of the data is beyond the matrix data being processed. In other words, it is normalized based on the highest-lowest data in the matrix for applications. This means that the preference position may change if there is an alternative entry or exit into the system in preference ranking. However, the preference ranking, or preference evaluation should be made based on the position of the alternative itself, not on other data. The definition range includes the largest and smallest possible values and does not represent an ideal measurement. At some points, the min-max calculation can be synchronized with the scaling calculation. However, data scaling as standard usage fixes the actual location of the data in the system and preserves it throughout the entire system.

For subjective data, due to the novel nature of the proposed models and the unavailability of suitable data for constructing interval or ratio-based expressions, ordinary fuzzy sets are employed. As elaborated in Chapter 3 and Chapter 4, alternative approaches, such as probabilistic sets, score-based methods or advanced fuzzy set extensions, could be explored for handling qualitative data.

It is very important that the data in the data driven phase (*aggregated decision matrix*) is scaled, so, point data. The operations are done by reducing the combined matrix to one-dimensional data. The multidimensional environment mentioned in the method arise from the number of criteria. Because each alternative carries its value in the relevant criterion as a score value on the axes. If it is preferred to use this idea directly for multidimensional data, three approaches can be followed.

- Either these operations must be applied separately for each data dimension, and then a multidimensional data is obtained,
- Either the data should be reduced to a single dimension with the relevant function, so that the V-PARS procedure can be applied exactly,
- Or the points to be used to plot Euclidean vectors need to be specifically defined according to the geometric interpretation of the data. For example, if the data is a sphere rather than a point, special definitions must be proposed for the start and target points of the vectors to be drawn between the spheres.

The fact that Phase 1 is identical in both methods suggests a new perspective in MCDM. The data collection and decision matrix aggregation processes can be considered as "Phase 1: Expert-Driven Model", which can be treated as a separate procedure in MADM methods. While many MADM approaches share this initial phase, the differentiation among methods arises in how they process the aggregated decision matrices. This thesis, therefore, introduces the Expert-Driven Model as a distinct category, marking a novel contribution to the literature.

PODER Phase 2: Data Driven Model

The Phase 2 of the PODER method involves deriving criteria weights from the aggregated decision matrix generated in Phase 1.

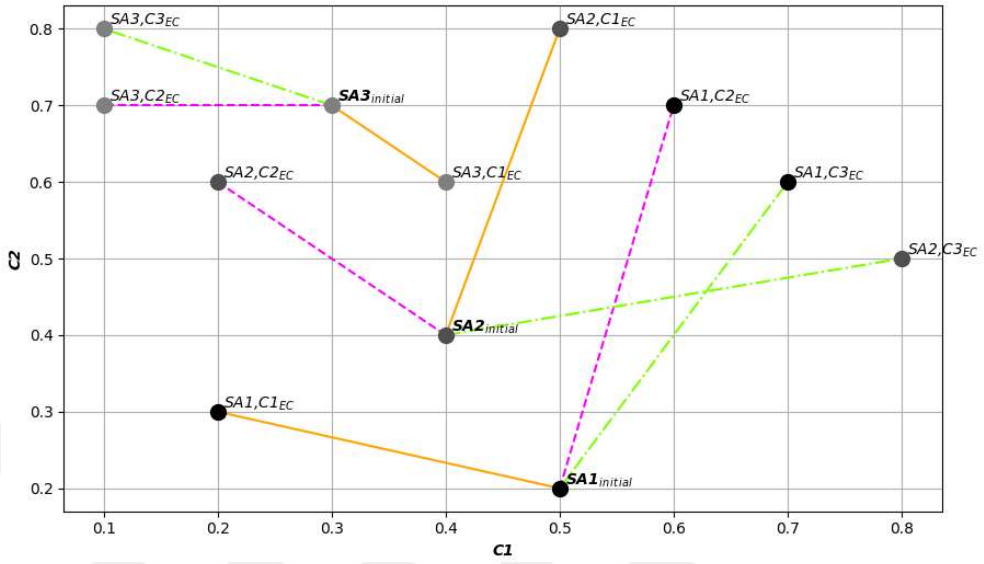
While drawing inspiration from the MEREC and SERA methodologies, the PODER model introduces distinct variations in its data riven phase. Unlike its predecessors, which operate exclusively on crisp or fuzzy sets, PODER integrates both quantitative and qualitative data within a unified framework. A preliminary step involves scaling all data to a standardized interval, rendering logarithmic transformations superfluous. The application of logarithmic functions to fuzzy numbers within the MEREC context is inappropriate given the fundamental differences between these data types. The original MEREC score formula, designed specifically for crisp numerical data, is not directly applicable to the diverse data structures encountered in the PODER model. Moreover, as supported by the comparisons made in the original article (Keshavarz-Ghorabaee et al., 2021); although

MEREC is introduced as a criterion weighting MCDM method, it is actually a data analysis method. SERA was previously proposed by the author of this research and emerged from the adaptation of the same concept by MEREC to fuzzy sets.

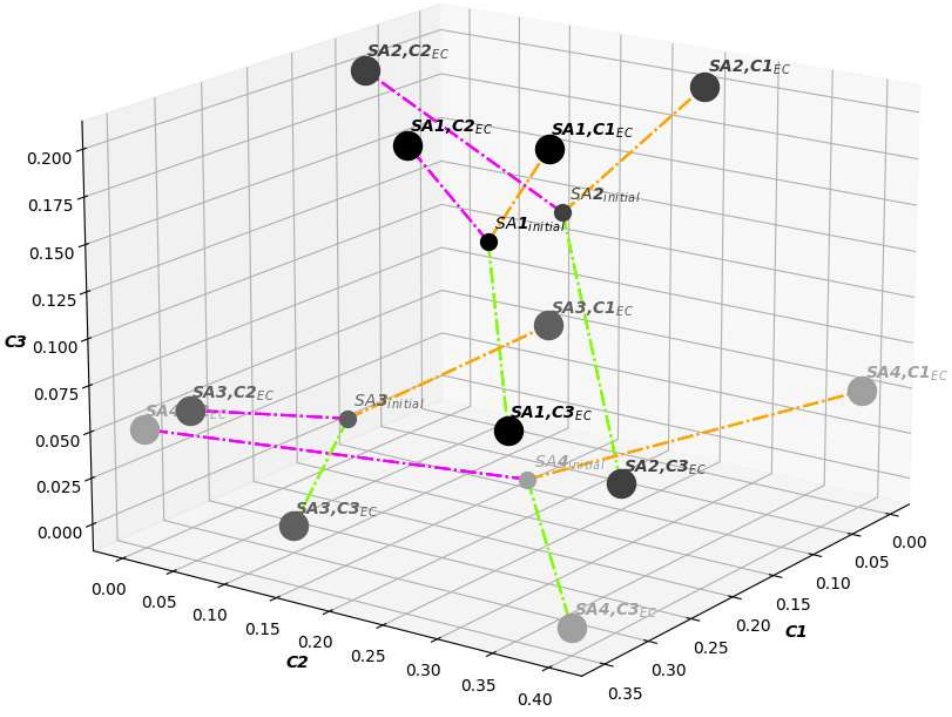
The PODER method employs Euclidean geometry, differentiating it from the Taxicab geometry (a.k.a. Manhattan). The decision environment is characterized as m-dimensional, with each alternative represented by a point defined by its corresponding criterion values. Therefore, the reference point is the alternative itself. Unlike MEREC, which implicitly operates in a one-dimensional environment due to its reliance on logarithmic function, PODER explicitly acknowledges the multidimensional nature of the decision problem. The concept of criteria extraction, adapted from MEREC, is modified in PODER to preserve the dimensionality of the space. Rather than eliminating a criterion (which means keeping the dimension number constant), its value is assigned as zero to prevent the collapse of data points onto an orthogonal axis. To maintain consistency in weight calculations, the remaining criteria weights are divided by *m-1*. While SERA applies *m-1* in the same manner, MEREC retains it as m. This approach ensures that the relative positions of alternatives within the m-dimensional environment can be observed when a criterion is effectively extracted from consideration. It is evident that the extraction of a criterion will reduce the dimensionality to $m-1$. However, since the evaluation is to be conducted in the context of $m-$dimensions, the distance expression in two different dimensional environments can be addressed by assigning a value of 0 to the missing dimension. The application of varying weights enhances the clarity of this change.

Sample illustrations of PODER in 2-dimensional and 3-dimensional environment are given separately in Figure 8.1. Note that the two examples are independent of one another. The cumulative distances of the lines of the same color correspond to the weight associated with the extraction of the relevant criterion from the system. The impact of criterion extraction on each alternative is duly considered by distance.

A fundamental distinction between PODER and existing methods lies in its adoption of Euclidean geometry and the associated distance metric. Unlike Manhattan distance, which is suitable for constrained environments, Euclidean distance is appropriate for un-



(a) 3 alternatives and 2 criteria (2-dimensional environment).



(b) 4 alternatives and 3 criteria (3-dimensional environment).

Figure 8.1: Sample geometric drawings of PODER.

constrained multidimensional spaces. By sequentially extracting criteria and calculating the resulting distance changes, PODER derives criteria weights based on their relative influence on the alternatives.

It is important to note that the normalization process employed in assigning weights (last step) differs from that utilized in the expert-driven phase. As the data in this instance is generated internally, normalization is applied to ensure comparability among criteria. Unlike traditional weighting methods that often rely on external data or subjective judgments, the PODER method leverages the inherent properties of the data to derive weights based on distance metrics, obviating the need for sorting or directional considerations.

V-PARS Phase 2: Data Driven Model

In developing the data driven phase of V-PARS, it is important to understand the following explanations.

In Voting Theory, alternatives are ranked, and the preferred alternatives are included in the system by preference aggregation methods. Borda Count (Borda, 1781) multiplyies the orders in preference and the number of preferences. Condorcet methods are based on pairwise comparison. As an extension of Condorcet (De Condorcet, 2014), the Kemeny-Young (Young, 1988a) use the distance of disagreements and Copeland (Copeland, 1951) integrates winners and losers (refer to Chapter 3). However, these concepts from Social Choice Theory are insufficient for direct comparison with MADM methods in the literature due to their reliance on individual votes and discrete distance calculations. By conceptualizing individuals as criteria and candidates as alternatives, and expressing ordinal preferences as continuous values, an extension to MCDM frameworks becomes feasible.

The V-PARS procedure represents a clear extension of the Borda Count. Unlike Condorcet methods, it does not rely on pairwise comparisons. However, similarities to Condorcet principles emerge when considering Kemeny–Young's distance-based approach and Copeland's winner-loser combination calculations. Instead of ordinal rankings as in Borda, V-PARS employs continuous preference distances, allowing for refined preference aggregation. Additionally, it incorporates disaggregation analysis, solidifying its founda-

tion. Since V-PARS operates beyond discrete settings, employing a vectorial framework is essential, ensuring that negative distances are logically managed. The development of V-PARS was driven by these theoretical advancements, offering a novel perspective within MCDM.

It is critical to say that while V-PARS draws inspiration from Social Choice Theory, it operates independently of Arrow's Impossibility Theorem. As a MADM methodology, V-PARS falls outside the scope of Social Choice Theory and cannot be evaluated within its framework. Its purpose is distinct, focusing on preference aggregation in a continuous, multi-criteria environment rather than adhering to the axiomatic constraints of collective decision-making.

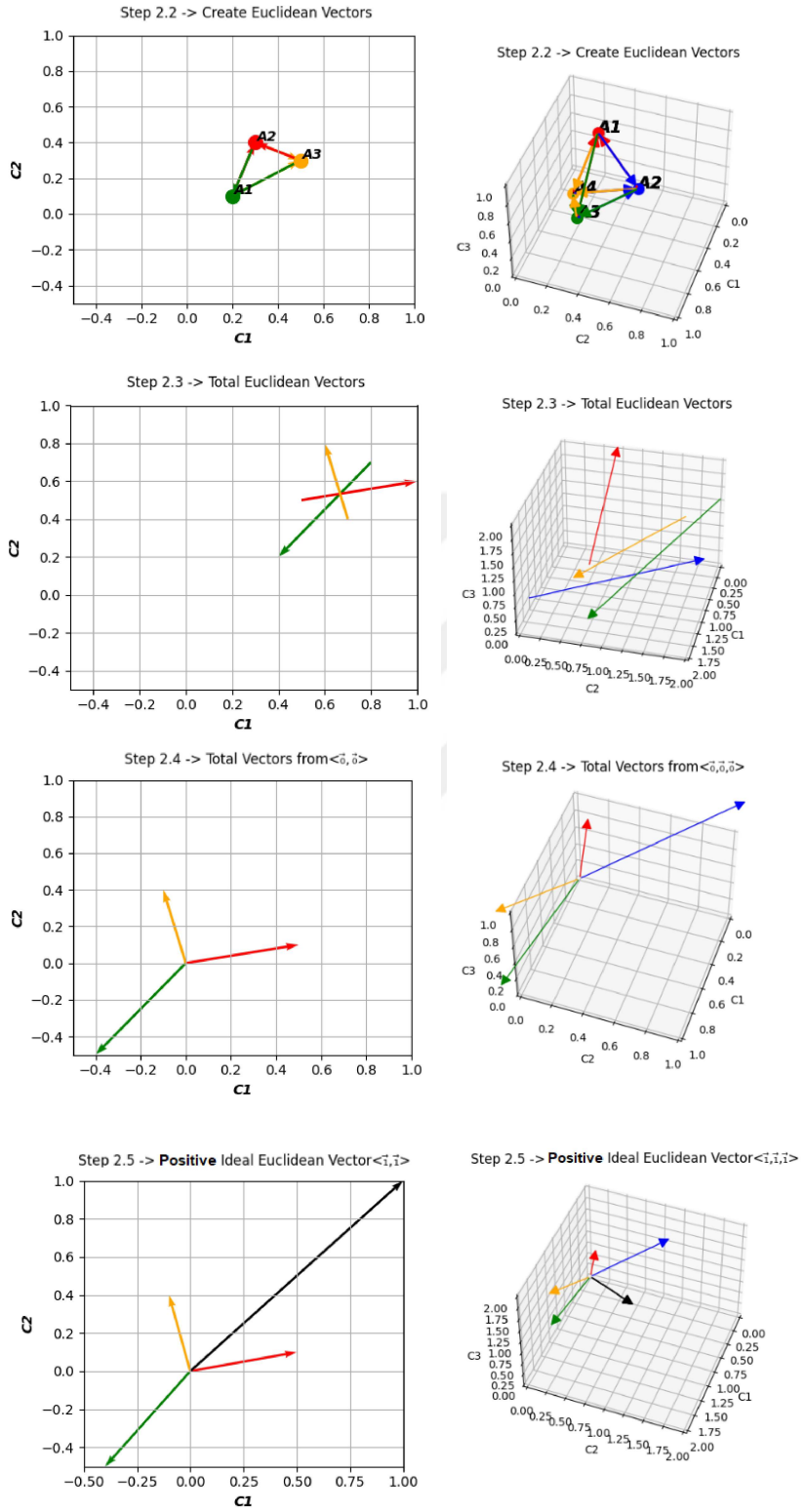
Back to the issue of the negative sign for non-preference, it is clear that this alone is insufficient for effectively integrating the concept of disagreement into MADM methods. PROMETHEE and TOPSIS encapsulate this idea to some extent. However, the methods in which preference ranking is integrated in MCDM are generally distance-based methods. Distance-based always operates relative to a reference point. This point can be ideal extreme solutions or average values. In this regard, Borda Count sets the reference point according to the highest choice, that is, the positive ideal solution. Because the ordinal order decreases according to hightest ordre. To include non-preference here, each alternative must be based on itself. Just using distance is insufficient because distance is always positive and does not indicate direction. In other words, the amount of distance only shows the effect, the information about whether it is preferred or not is missing. Therefore, in order to reach the actual preference value of the relevant alternative, it is necessary to investigate its position relative to other alternatives. Hence, an Euclidean vector-based evaluation emerges here. (*Note that the concept of vectors in this context differs significantly from traditional expressions used in MCDM literature, such as "DM vector" or "criterion vector". These expressions are typically used to represent pre-existing input data sets, but they do not align with the vector-based approach discussed here. In the V-PARS methodology, vectors are generated dynamically within the system, referencing points within Euclidean n-spaces in a multi-criteria environment. This process results in vectors that are not merely expressions of input data, but rather represent new structures*

created through system operations.)

The vector obtained by the sum of the Euclidean vectors that give the position of the other alternatives is the preference Euclidean vector of the relevant alternative. In preference ranking-based MCDM, evaluations have values and are ordered without the need for ordinal numbers unlike in Borda Count. Since we are in an m-dimensional environment, all preference Euclidean vectors can be in any directions. To compare, it is appropriate to search for the similarity according to the Euclidean vector $< \overrightarrow{0_1, 0_2, ..., 0_m; 1_1, 1_2, ..., 1_m} >$ (in short $< \overrightarrow{1_1, 1_2, ..., 1_m} >$). The Euclidean vector $< \overrightarrow{1_1, 1_2, ..., 1_m} >$ defines the positive ideal Euclidean vector. If an alternative has the preference Euclidean vector $< \overrightarrow{1_1, 1_2, ..., 1_m} >$ in the scaled (or normalized) data, it should have the highest value in all criteria, and the other alternatives should be in the $(0_1, 0_2, ..., 0_m)$ point, that is, their worst versions. This is too ideal to be true, but preference Euclidean vectors in different directions are compared with their similarity to this ideal. Figure 8.2 depicts examples for vector steps of V-PARS in 2-dimensional and 3-dimensional environment separately.

It is significant to note that it is not necessary to take a position according to the negative ideal Euclidean vector $< \overrightarrow{0_1, 0_2, ..., 0_m; -1_1, -1_2, ..., -1_m} >$. It is obvious that two ideal solutions are always clear. It does not change according to each data set in contrary of TOPSIS. Since there is a fixed reference each time, there is no need for a different reference. The negative ideal Euclidean vector can be chosen as the reference, but the only change is that the preference order is reversed. In general, similarity to the positive ideal in V-PARS has been accepted and is sufficient for evaluation. The reason why TOPSIS includes both ideal solutions is that positive and negative ideal solutions are imaginary points that arise on obtained data, and in fact the formulation is based on the normalization idea with respect to ideal points. There is no need for V-PARS, because it works with scaled data. It is evident that the V-PARS method consistently maintains the concept of scalarization throughout the entire process.

PROMETHEE also retains the concept of positive and negative preferences through the use of flows; however, the calculation of preference distances can be based on six distinct functions. Additionally, flows are not holistic. To create and compare a vector, it is es-



(a) 3 alternatives and 2 criteria (2-dimensional environment).

(b) 4 alternatives and 3 criteria (3-dimensional environment).

Figure 8.2: Sample geometric drawings of V-PARS.

sential to consider both positive and negative perspectives simultaneously. PROMETHEE addresses this separately by first calculating the positive flow and then the negative flow. The subsequent combination of these flows is fundamentally different from the process of creating vectors using the holistic approach in V-PARS.

Note that the metric to be used to measure the similarity of two vectors is important. In the literature, it is seen that Euclidean distance and cosine similarity are generally used in MCDM methods. However, it is not valid here since V-PARS works with vectors and takes direction information into account. There are three methods in the literature to compare the similarity of two vectors; Euclidean distance, cosine similarity and dot product.

Euclidean distance calculates the distance of two vectors without direction. So, it is always positive and expresses only one intensity. Cosine similarity is concerned with calculating the angle between vectors regardless of their magnitude. It does not contain direction information and evaluates the closeness of two vectors by looking at the angle between them. Dot product, on the other hand, keeps both direction information and evaluates magnitudes. Basically, dot product calculates the projection of one vector onto another vector and preserves the direction of the vector, that is, it can take a negative value. In V-PARS, the similarities of all other vectors to the positive Euclidean ideal vector can thus be compared to find the similarity to the vector $< \overrightarrow{1_1, 1_2, ..., 1_m} >$. As long as this idea is preserved, the use of similarity metrics including direction and magnitude can be explored. Therefore, dot product is used in V-PARS.

More specifically, Hilbert spaces extend the concepts of linear algebra and calculus from finite-dimensional Euclidean vector spaces to potentially infinite-dimensional spaces. A Hilbert space is formally defined as a vector space equipped with an inner product that induces a distance function, making it a complete metric space. It is a specific type of Banach space. A familiar example of a Hilbert space is the three-dimensional Euclidean vector space, which employs the dot product to measure the relationship between vectors (Kubrusly, 2003). The dot product has several key properties: it is symmetric, meaning the order of the vectors in multiplication does not affect the result; it is linear in its first

argument, allowing for scalar multiplication and addition; and it is positive definite, indicating that the dot product of a vector with itself is non-negative, with equality only when the vector is zero. These characteristics define the dot product as a real inner product, leading to the concept of a real inner product space. Importantly, every finite-dimensional inner product space qualifies as a Hilbert space, linking the dot product to fundamental aspects of Euclidean geometry, such as the length or norm of a vector (Young, 1988b). Refer to Chapter 3 for definitions of key terms.

It should also be noted that the magnitude of the vector is not the same as distance-based calculations in the literature. The magnitude and direction of the resulting projection vector in the dot product is affected by the location of the decision points, and thus the similarity score of the total vector tends to be lower compared to measurements of distance functions. Given the complementary nature of all vectors, it is expected that the sum of the final scores is zero.

8.4.2 Practical Limitations

The application cases present certain limitations. Although Paris has been a pioneering city in global transportation trials, the micromobility landscape has undergone significant changes following a 2023 referendum that resulted in the ban on vehicles operated by shared micromobility companies (Relman, 2023). Consequently, the focus of this study has shifted to personal micromobility vehicles, exploring how Parisians are adapting to this transition and how these privately owned modes continue to support the city's sustainability objectives.

In contrast, Istanbul provides a different perspective on micromobility. As a large city characterized by traffic congestion, Istanbul has embraced micromobility as a potential solution to its urban transportation challenges. Unlike Paris, which has imposed restrictions on shared micromobility and permits only the local bike-sharing program, Vélib', Istanbul continues to foster a vibrant market for shared micromobility services. This includes the local bike-sharing program, İSBİKE, which operates similarly to Vélib'. The diverse array of transportation options available in Istanbul renders it a dynamic case study for understanding the integration of micromobility within a complex urban environment.

Nevertheless, common private modes are selected for comparative analysis.

In the model application, the objective data are sourced from official municipal reports, which led to some criteria being based solely on subjective values (C_8 to C_{14} in Chapter 7). Given that the evaluation relied on a single official source, the objective data are accepted universally by all decision makers. To leverage the anchoring effect from Nudge Theory, decision-makers are presented with objective values while soliciting their subjective opinions. This approach aimed to facilitate more informed decision making through status assignment and anchoring.

The selection of decision makers involved consultations with various institutions. At this juncture, the choice of the individual responsible for implementing the case is of significant importance. Since this aspect may vary based on the specific case, it is feasible to select numerous decision makers from diverse categories. If this were a system design, the population of decision makers would expand, demonstrating an increasing distribution from experts to beginners. Including beginners—who represent new users with limited experience—would provide valuable insights for both customer satisfaction and user perspective evaluations. This thesis primarily observes the behavior of the proposed PODER and V-PARS approaches concerning evaluation and is not designed for a broad audience. Therefore, the population of decision makers is relatively limited. However, it is also essential to conduct evaluations using a larger, systematic approach that incorporates a diverse demographic distribution, as the proposed models are scalable.

The selection of criteria in this case has not been left solely to the decision makers. As a newly emerging research topic, obtaining data for micromobility assessment is inherently challenging. To establish a foundation for evaluation based on officially published data, criteria are determined in accordance with the framework of the European Union's 2050 sustainability targets.

8.5 Further Research

The proposed PODER and V-PARS methodologies introduce a novel geometric perspective to the established domain of Multi-Criteria Decision Making (MCDM). These methodologies extend the traditional boundaries of MCDM by incorporating dynamic adaptability and vector-based analysis, respectively, thereby addressing some of the critical limitations in conventional approaches. The proposed choice architecture presents an suitable design for establishing a real world customer-centric evaluation system. The PODER methodology exhibits a unique capability to accommodate dynamic changes in decision scenarios. This adaptability allows for criteria to be selectively included or excluded based on user preferences, making an advanced version of PODER particularly well-suited for applications that require real-time adjustments and feedback integration.

- **Navigation Systems:** One potential application of the PODER methodology is in navigation systems. Users can dynamically adjust route preferences based on real-time conditions, such as traffic congestion, road closures, or personal preferences for scenic routes. Additionally, users can provide feedback on their experiences, which can be used to further refine the criteria weights and improve future route recommendations. This dynamic adaptability not only enhances user satisfaction but also ensures that the decision making process remains relevant and responsive to changing conditions.

- **Hotel Selection Process:** Similarly, the hotel selection process can benefit from the adaptability of the PODER methodology. Customer satisfaction ratings can be integrated as individual decision maker weights within the PODER framework. This enables the system to dynamically adjust criterion weights based on user preferences and participation levels. For instance, if a particular user places a high value on amenities such as free Wi-Fi or complimentary breakfast, these importance can be emphasized in the decision making process. As a result, the system can provide personalized and relevant hotel recommendations, enhancing overall customer satisfaction.

In contrast, the V-PARS methodology ranks the preferences of alternatives rather than assigning numerical scores. This vector-based approach considers both the magnitude and direction of alternatives, providing a richer understanding of an alternative's positioning within the criteria space.

- **Optimal Route Identification:** In the context of navigation, the V-PARS methodology facilitates the identification of routes and vehicle options for specific journeys. By ranking alternatives based on user-defined criteria, V-PARS can help users select the most suitable route or vehicle without the need for detailed comparative evaluations. This approach simplifies the decision-making process and ensures that users receive the relevant recommendations based on their preferences and needs.
- **Accommodation Ranking:** Similarly, V-PARS can be employed to rank accommodation options based on customer preferences. By considering factors such as location, price, amenities, and customer reviews, V-PARS can provide a comprehensive ranking of available accommodations. This ranking helps users make informed decisions quickly and efficiently, without the need for extensive pairwise comparisons. This is particularly useful in scenarios where users have specific preferences and limited time to evaluate multiple options.
- **Development of Customer-Centric Evaluation Systems:** The proposed decision architecture, which integrates both the PODER and V-PARS methodologies, offers a promising framework for developing customer-centric evaluation systems in real-world applications. By leveraging the dynamic adaptability of PODER and the vector-based ranking capabilities of V-PARS, these methodologies can be applied across various (unlimited) domains to enhance decision making processes and improve user satisfaction.

Implementing these models in a computer program is recommended but involves considerable complexity. It is not enough to simply code the rules and ensure the program scales across different criteria and alternatives. The program must also accommodate various data types and their dimensions. For instance, this study uses ordinary fuzzy set,

but for uncertain data, expressions like probability, interval, score, or multidimensional fuzzy types might be preferred. Future research should focus on developing computer programs that address these requirements and use a programming approach appropriate for the subject matter.

By addressing these research directions, the proposed PODER and V-PARS methodologies can be further developed and refined to provide robust, adaptable, and user-centric decision making frameworks for a wide range of applications. This will contribute to the advancement of MCDM methodologies and their practical implementation in real world scenarios. Future research in the evaluation of micromobility modes using MCDM methodologies could focus on several key areas to enhance the robustness, applicability, and impact of these models.

- Firstly, there is a need to explore the integration of real-time data analytics with MCDM models. Incorporating real-time data from IoT devices, GPS tracking, and user feedback can provide dynamic and up-to-date inputs for decision-making, improving the accuracy and relevance of the evaluations. This approach would allow for adaptive decision making that can respond to changing urban mobility patterns and user preferences.

- Secondly, expanding the geographic scope of case studies can provide more comprehensive insights. While the current research focuses on Paris and Istanbul, future studies could include a wider variety of cities with different urban structures, cultural contexts, and levels of technological adoption. This would help in understanding the universal applicability of the proposed MCDM methodologies and identifying location specific factors that influence micromobility adoption and efficiency.

The future of micromobility in Paris and Istanbul is poised for significant evolution, shaped by distinct regulatory approaches and urban contexts, as well as emerging innovations. In Paris, the focus will likely shift towards enhancing personal micromobility through improved infrastructure and stringent regulations following the ban on shared

vehicles. Innovations such as smart bike-sharing systems, integrated mobility apps, and real-time data analytics will be crucial in streamlining user experiences and promoting safe practices. Although the first steps have been taken, Paris may explore partnerships with technology providers to create a seamless connection between micromobility and public transport, further bolstering its sustainability goals. Conversely, Istanbul is expected to expand its thriving market for shared services, adapting regulations to support innovation while ensuring public safety. The introduction of electric vehicles, GPS tracking, and automated fleet management systems will enhance service efficiency and user convenience.

Furthermore, initiatives that promote ecofriendly practices, such as solar powered charging stations for e-scooters, could significantly contribute to the city's environmental objectives. Both cities will need to foster public acceptance through education and targeted outreach, ensuring diverse demographic engagement. With thoughtful infrastructure investments and a focus on technological advancements, the unique strategies of Paris and Istanbul will not only address local transportation challenges but also provide valuable insights for urban mobility on a global scale.

9 CONCLUSION

This dissertation introduces and elaborates on the foundational concepts of Multi-Criteria Decision Making (MCDM), emphasizing the imperative of robust decision making frameworks to address complex challenges characterized by conflicting criteria. It provides a comprehensive justification for the development of novel MCDM methodologies, particularly within the domain of urban transportation and micromobility. By identifying significant gaps in existing distance-based MCDM approaches, such as the absence of decision-centric reference points and the under-utilization of vector-based perspectives, the dissertation establishes a robust foundation for its research objectives and contributions. The proposed choice architecture constitutes a viable framework for the development of a customer-centric evaluation system in real world applications.

The primary objectives of this research encompass the development of two innovative MCDM methodologies: the POndération sur la Distance par ExtRaction (PODER) and the Vector-Based Preference Ranking System (V-PARS). The research contributions are multifaceted, encompassing the introduction of novel methodologies, the integration of Social Choice Theory and Nudge Theory, and the practical application of these frameworks to the evaluation of micromobility vehicles. This comprehensive approach includes a rigorous theoretical foundation, mathematical formulation, and empirical application, culminating in a robust framework for evaluating and ranking alternatives.

A substantial portion of the dissertation is devoted to a comprehensive review of existing MCDM methods, with a particular focus on distance-based approaches. This review encompasses theoretical underpinnings, common techniques, and diverse applications across various disciplines. The research considers the strengths and limitations of these methods, emphasizing the criticality of selecting appropriate distance metrics and reference points. Furthermore, the potential of vector-based methods in MCDM is explored, highlighting their capacity to consider both magnitude and direction, and their suitability for similarity assessments. Additionally, the incorporation of principles from Social Choice Theory, such as the idea of Borda Count, Kemeny-Young Approach and

Copeland Method, is examined to enhance MCDM methodologies. The dissertation also reviews the application of Nobel Prize-winning Nudge Theory in decision making processes, demonstrating its potential to improve decision quality through subtle guidance.

The PODER methodology introduces the concept of criterion extraction distance within a Euclidean n-spaces, thereby refining criteria weighting by considering both relative distances and criterion importance. Conversely, the V-PARS methodology integrates vector-based elements and principles from Social Choice Theory, offering a nuanced evaluation of alternatives by considering both magnitude and direction. The integration of Nudge Theory into the decision gathering processes for both methodologies constitutes a novel contribution. By designing decision making processes that incorporate subtle nudges, the research enhances the overall efficacy of MCDM procedures, fostering more informed and rational choices. This integration supports decision making by anchoring and assigning status to decision makers, guiding them towards conceptial outcomes.

The complexities associated with normalization and scaling in MCDM procedures, particularly when handling both precise (crisp) and uncertain (fuzzy) data, are comprehensively addressed in this dissertation. A robust framework incorporating diverse normalization techniques is developed to ensure accurate representation of decisions across various data types. This framework is essential for standardizing data and facilitating comparable decision making.

The practical relevance of the proposed methodologies is demonstrated through case studies focused on micromobility modes in Paris and Istanbul. These case studies involve evaluating micromobility vehicles within the context of the European Union's 2050 targets. The preference ranking results show some distinct contrasts between Paris and Istanbul in micromobility preferences. Paris is suitable for traditional mobility, with Private Bikes and e-Bikes ranking highest, while new generation mode like e-Scooter is viewed less favorably. Istanbul prioritizes Private Bikes ranking highest as Paris, in contrast, electric vehicle like e-Moped is ranking lower. These differences highlight the cities' varied urban dynamics, infrastructure, and cultural attitudes towards micromobility solutions. By considering economic, environmental, social, and technical factors, the research provides a

holistic assessment of micromobility vehicles. The findings from these case studies offer valuable insights for policymakers and stakeholders, contributing to sustainable micromobility decisions.

In conclusion, this dissertation makes significant contributions to the field of MCDM by introducing novel methodologies, integrating different advanced theoretical frameworks, and demonstrating practical applications in the evaluation of micromobility modes. Additionally, several novel publications to the scholarly literature outlined in Biographical Sketch are provided. The research addresses critical gaps in existing methods and provides a robust foundation for sustainable urban transportation planning. Future research directions are proposed to further explore and refine these methodologies, emphasizing the need for continued innovation and application in real world contexts. vector-based MADM has established its own branch within the field, enabling the development of new extensions within this subcategory. The overall significance of this research lies in its potential to influence and improve decision making processes in complex and dynamic environments, ultimately contributing to the advancement of MCDM and urban transportation planning.

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APPENDICES

Appendix A Micromobility Modes Evaluation Questionaires

This appendix presents the "Micromobility Modes Evaluation Questionnaire," designed to gather insights on user experiences and preferences regarding various micromobility modes.

The questionnaire is presented in three languages—Turkish, English, and French—to ensure accessibility and inclusivity for diverse populations. Informed Voluntary Consent Form" and the "Post-Participation Information Form" are also included as follows.

MİKROMOBİLİTE MODLARI DEĞERLENDİRME ANKETİ

Araştırmacı tarafından belirlenen karar grubu: .....……..

Kişisel bilgiler

Yaş :…….
Cinsiyet :……...
Eğitim Durumu : …….
Meslek : ……
Mikromobilite modları/servisleri üzerine deneyimi (yıl): …….

Lütfen şehrinizdeki mikromobilite modlarının ilgili kriterle ilişkisi/yeterliliği konusunda "*düşük-orta-yüksek*" görüşlerden birini seçerek aşağıdaki tabloyu doldurunuz. Bilgi amaçlı olarak her mod için bazı resmi ölçüm değerleri (nesnel değerler) verilmiştir.

Kod	***Kriter***	***Mikromobilite Modu***		***Nicel Veriler***	***Nitel Değerlendirme***
C_1	Ortalama yaşam süresi	A_1	*Özel Bisiklet*	30 yıl	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	3 yıl	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	7 yıl	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	10 yıl	Düşük / Orta / Yüksek
C_2	Şarj süresi	A_1	*Özel Bisiklet*	*gerekli değil*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	5 saat	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	8 saat	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	4 saat	Düşük / Orta / Yüksek
C_3	Tek şarjla maksimum sürüş menzili	A_1	*Özel Bisiklet*	150 km	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	50 km	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	65 km	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	100 km	Düşük / Orta / Yüksek

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C_4	Hız Limiti	A_1	*Özel Bisiklet*	20 km/s	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	25 km/s	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	30 km/s	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	25 km/s	Düşük / Orta / Yüksek
C_5	Haftada en az bir kez kullanım oranı	A_1	*Özel Bisiklet*	0.57 (oran)	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	0.61 (oran)	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	0.73 (oran)	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	0.87 (oran)	Düşük / Orta / Yüksek
C_6	Kaza Oranı	A_1	*Özel Bisiklet*	0.15 (oran)	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	0.26 (oran)	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	0.15 (oran)	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	0.51 (oran)	Düşük / Orta / Yüksek
C_7	Mod değiştirme oranı	A_1	*Özel Bisiklet*	0.12 (oran)	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*	0.23 (oran)	Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*	0.08 (oran)	Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*	0.14 (oran)	Düşük / Orta / Yüksek
C_8	Güvenlik	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek

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		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_9	Zamandan tasarruf	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_{10}	Rahatlık	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_{11}	Sağlık yararı	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_{12}	Çevresel gürültü	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek

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		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_{13}	Eko-Tasarım	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek
C_{14}	Düşük karbon emisyonu (Sürdürülebilirlik)	A_1	*Özel Bisiklet*	*Veri mevcut değildir*	Düşük / Orta / Yüksek
		A_2	*Özel e-Skuter*		Düşük / Orta / Yüksek
		A_3	*Özel e-Moped*		Düşük / Orta / Yüksek
		A_4	*Özel e-Bisiklet*		Düşük / Orta / Yüksek

Değerli görüşleriniz için içtenlikle teşekkür ederiz.

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BİLGİLENDİRİLMİŞ GÖNÜLLÜ RIZA FORMU

Bu araştırma, Endüstri Mühendisliği Bölümü öğretim elemanlarından Arş. Gör. Esra ÇAKIR ve Prof. Dr. Çağrı TOLGA tarafından yürütülen bir çalışmadır. Bu form sizi araştırma koşulları hakkında bilgilendirmek için hazırlanmıştır.

Çalışmanın Amacı Nedir? Araştırmanın amacı yaşadığınız şehirdeki mikromobilite araçlarını belirtilen kriterlere göre değerlendirilmesi ve yeni geliştirilen karar verme yöntemleri uygulanarak elde edilen görüşlere/verilere göre bir öncelik sıralamasının elde edilmesidir. Araştırmaya katılmayı kabul ederseniz, sizden beklenen, anket sorularını yanıtlamanızdır. Bu çalışmaya katılım ortalama olarak 3 dakika sürmektedir.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz? Anketteki soruları yanıtlayarak.

Sizden Topladığımız Bilgileri Nasıl Kullanacağız? Araştırmaya katılımınız tamamen gönüllülük temelinde olmalıdır. Ankette, sizden kimlik veya kurum belirleyici hiçbir bilgi istenmemektedir. Cevaplarınız tamamıyla gizli tutulacak, sadece araştırmacılar tarafından değerlendirilecektir. Katılımcılardan elde edilecek bilgiler toplu halde değerlendirilecek ve bilimsel yayımlarda kullanılacaktır. Sağladığınız veriler gönüllü katılım formlarında toplanan kimlik bilgileri ile eşleştirilmeyecektir.

Katılımınızla ilgili bilmeniz gerekenler: Çalışmamız günlük hayatta karşılaşılması muhtemel olağan risklerin ötesinde bir risk içermemektedir. Katılım sırasında sorulardan ya da herhangi başka bir nedenden ötürü kendinizi rahatsız hissederseniz cevaplama işini yarıda bırakıp çıkmakta serbestsiniz. Böyle bir durumda çalışmayı uygulayan kişiye, çalışmadan çıkmak istediğinizi söylemek yeterli olacaktır. Çalışma sonunda, bu araştırmayla ilgili sorularınız cevaplanacaktır.

Araştırmayla ilgili daha fazla bilgi almak isterseniz: Bu çalışmaya katıldığınız için şimdiden teşekkür ederiz. Araştırma hakkında daha fazla bilgi almak için Endüstri Mühendisliği Bölümü öğretim üyelerinden Prof. Dr. Çağrı TOLGA (E-posta: ctolga@gsu.edu.tr) ile iletişim kurabilirsiniz.

Yukarıdaki bilgileri okudum ve bu çalışmaya tamamen gönüllü olarak katılıyorum.

(Formu doldurup imzaladıktan sonra uygulayıcıya geri veriniz).

İsim Soyad **Tarih** **İmza**

Anonim

KATILIM SONRASI BİLGİ FORMU

Bu araştırma daha önce de belirtildiği gibi Endüstri Mühendisliği Bölümü öğretim elemanlarından Arş. Gör. Esra ÇAKIR ve Prof. Dr. Çağrı TOLGA tarafından yürütülen bir çalışmadır. Çalışmanın amacı yaşadığınız şehirdeki mikromobilite araçlarını belirtilen kriterlere göre değerlendirilmesi ve yeni geliştirilen karar verme yöntemleri uygulanarak elde edilen görüşlere/verilere göre bir öncelik sıralamasının elde edilmesidir.

Bu araştırmanın temel beklentisi, grup karar verme ve Çok Kriterli Karar Verme (MCDM) yöntemlerini kullanarak mikromobilite araçlarının sistematik bir şekilde değerlendirilmesi ve sıralanmasıdır. Avrupa Komisyonu'nun 2050 hedefleri doğrultusunda, sürdürülebilir ve çevre dostu ulaşım çözümlerinin ön planda olduğu bir geleceği desteklemek amaçlanmaktadır (European Commission, 2018). Literatürde, MCDM yöntemlerinin, farklı kriterler ve paydaş görüşlerini bir araya getirerek daha dengeli ve objektif kararlar almayı sağladığı belirtilmiştir (Triantaphyllou, 2000; Öztürk et al., 2020). Ayrıca, mikromobilite araçlarının şehir içindeki rolünü ve etkisini değerlendiren çalışmalar, bu araçların trafik yönetimi ve çevresel sürdürülebilirlik üzerindeki potansiyel katkılarını ortaya koymaktadır (Aldred et al., 2021). Araştırma, bu bağlamda, araçların belirlenen kriterlere göre sıralanmasıyla, şehir içi ulaşım sistemlerinin daha etkili bir şekilde optimize edilmesine katkıda bulunmayı hedeflemektedir.

Bu çalışmadan alınacak ilk verilerin 31.12.2024 sonunda elde edilmesi amaçlanmaktadır. Elde edilen bilgiler sadece bilimsel araştırma ve yazılarda kullanılacaktır. Bu araştırmaya katıldığınız için tekrar çok teşekkür ederiz.

Araştırmanın sonuçlarını öğrenmek ya da daha fazla bilgi almak için aşağıdaki isimlere başvurabilirsiniz.

Prof. Dr. Çağrı TOLGA (E-posta: ctolga@gsu.edu.tr)

Referanslar:

- European Commission. (2018). *A European Strategy for Low-Emission Mobility.* Brussels: European Commission.
- Triantaphyllou, E. (2000). *Multi-Criteria Decision Making Methods: A Comparative Study.* Springer.
- Öztürk, M., Karahan, E., & Aydın, N. (2020). *Application of MCDM Techniques in Transportation: A Review.* Journal of Transportation Engineering.
- Aldred, R., et al. (2021). *Micromobility and its Role in Sustainable Urban Transport.* Transportation Research Part D: Transport and Environment.

MICROMOBILITY MODES EVALUATION QUESTIONNAIRE

Decision group designated by the investigator: .....……..

Personal information

Age :…….
Sex :……..
Latest diploma : ……...
Profession : ……..
Experience with micromobility modes/services (years) :……..……

Please fill in the table below by choosing one of the opinions "*low-medium-high*" on the relationship/adequacy of micromobility modes in your city with respect to the relevant criterion. For information purposes, some official measurement values (objective values) are provided for each mode.

Code	***Criterion***	***Micromobility Mode***		***Quantitative Data***	***Qualitative Evaluation***
C_1	Average lifespan	A_1	*Private Bike*	30 years	Low / Medium / High
		A_2	*Private e-Scooter*	3 years	Low / Medium / High
		A_3	*Private e-Moped*	7 years	Low / Medium / High
		A_4	*Private e-Bike*	10 years	Low / Medium / High
C_2	Charging time	A_1	*Private Bike*	*no need*	Low / Medium / High
		A_2	*Private e-Scooter*	5 hours	Low / Medium / High
		A_3	*Private e-Moped*	8 hours	Low / Medium / High
		A_4	*Private e-Bike*	4 hours	Low / Medium / High
C_3	Maximum driving range in one charge	A_1	*Private Bike*	150 km	Low / Medium / High
		A_2	*Private e-Scooter*	50 km	Low / Medium / High
		A_3	*Private e-Moped*	65 km	Low / Medium / High
		A_4	*Private e-Bike*	100 km	Low / Medium / High

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C_4	Speed Limit	A_1	*Private Bike*	20 km/h	Low / Medium / High
		A_2	*Private e-Scooter*	25 km/h	Low / Medium / High
		A_3	*Private e-Moped*	30 km/h	Low / Medium / High
		A_4	*Private e-Bike*	25 km/h	Low / Medium / High
C_5	Usage rate at least once a week	A_1	*Private Bike*	0.57 (rate)	Low / Medium / High
		A_2	*Private e-Scooter*	0.61 (rate)	Low / Medium / High
		A_3	*Private e-Moped*	0.73 (rate)	Low / Medium / High
		A_4	*Private e-Bike*	0.87 (rate)	Low / Medium / High
C_6	Accident Rate	A_1	*Private Bike*	0.15 (rate)	Low / Medium / High
		A_2	*Private e-Scooter*	0.26 (rate)	Low / Medium / High
		A_3	*Private e-Moped*	0.15 (rate)	Low / Medium / High
		A_4	*Private e-Bike*	0.51 (rate)	Low / Medium / High
C_7	Intermodality Rate	A_1	*Private Bike*	0.12 (rate)	Low / Medium / High
		A_2	*Private e-Scooter*	0.23 (rate)	Low / Medium / High
		A_3	*Private e-Moped*	0.08 (rate)	Low / Medium / High
		A_4	*Private e-Bike*	0.14 (rate)	Low / Medium / High
C_8	Security	A_1	*Private Bike*	*No data available*	Low / Medium / High

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		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_9	Saving time	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_{10}	Comfort	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_{11}	Health benefit	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_{12}	Environmental noise	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		

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					Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_{13}	Eco-Design	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High
C_{14}	Low carbon emission (Sustainability)	A_1	*Private Bike*	*No data available*	Low / Medium / High
		A_2	*Private e-Scooter*		Low / Medium / High
		A_3	*Private e-Moped*		Low / Medium / High
		A_4	*Private e-Bike*		Low / Medium / High

We sincerely thank you for your valuable feedback.

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VOLUNTARY INFORMED CONSENT FORM

This research is a study conducted by Res. Asst. Esra ÇAKIR and Prof. Dr. Çağrı TOLGA, faculty members of the Department of Industrial Engineering. This form has been prepared to inform you about the research conditions.

What is the Purpose of the Study? The purpose of the research is to evaluate micromobility vehicles in your city according to the specified criteria and to obtain a priority order according to the opinions/data obtained by applying newly developed decision-making methods. If you agree to participate in the research, what is expected from you is to answer the survey questions. Participation in this study takes an average of 3 minutes.

How Will We Ask You to Help Us? By answering the questions in the survey.

How Will We Use the Information We Collect From You? Your participation in the research must be completely voluntary. No information that identifies you or identifies your institution is requested in the survey. Your answers will be kept completely confidential and will be evaluated only by the researchers. The information obtained from the participants will be evaluated collectively and will be used in scientific publications. The data you provide will not be matched with the identity information collected in the voluntary participation forms.

What you need to know about your participation: Our study does not involve any risks beyond the normal risks that are likely to be encountered in daily life. If you feel uncomfortable during participation due to the questions or any other reason, you are free to leave the task halfway through and leave. In such a case, it will be sufficient to tell the person implementing the study that you want to leave the study. Your questions about this research will be answered at the end of the study.

If you would like to receive more information about the study: Thank you in advance for participating in this study. You can contact Prof. Dr. Çağrı TOLGA (E-mail: ctolga@gsu.edu.tr), a faculty member of the Department of Industrial Engineering, for more information about the study.

I have read the information above and I am participating in this study completely voluntarily.

(Please return the form to the implementer after filling out and signing it).

Name Surname **Date** **Signature**

Anonymous

POST-PARTICIPATION INFORMATION FORM

As mentioned before, this research is a study conducted by Res. Asst. Esra ÇAKIR and Prof. Dr. Çağrı TOLGA, faculty members of the Department of Industrial Engineering. The aim of the study is to evaluate micromobility vehicles in the city you live in according to the specified criteria and to obtain a priority ranking according to the opinions/data obtained by applying newly developed decision-making methods.

The main expectation of this research is to systematically evaluate and rank micromobility vehicles using group decision-making and Multi-Criteria Decision Making (MCDM) methods. In line with the 2050 goals of the European Commission, it is aimed to support a future in which sustainable and environmentally friendly transportation solutions are at the forefront (European Commission, 2018). It has been stated in the literature that MCDM methods enable more balanced and objective decisions to be made by bringing together different criteria and stakeholder opinions (Triantaphyllou, 2000; Öztürk et al., 2020). In addition, studies evaluating the role and impact of micromobility vehicles in cities reveal their potential contributions to traffic management and environmental sustainability (Aldred et al., 2021). In this context, the research aims to contribute to the more effective optimization of urban transportation systems by ranking the vehicles according to the determined criteria.

The first data to be obtained from this study is intended to be obtained by the end of 31.12.2024. The information obtained will only be used in scientific research and articles. Thank you again for participating in this research.

You can contact the following names to learn the results of the research or get more information.

Prof. Dr. Çağrı TOLGA (E-mail: ctolga@gsu.edu.tr)

References:

- European Commission. (2018). *A European Strategy for Low-Emission Mobility.* Brussels: European Commission.
- Triantaphyllou, E. (2000). *Multi-Criteria Decision Making Methods: A Comparative Study.* Springer.
- Öztürk, M., Karahan, E., & Aydın, N. (2020). *Application of MCDM Techniques in Transportation: A Review.* Journal of Transportation Engineering.
- Aldred, R., et al. (2021). *Micromobility and its Role in Sustainable Urban Transport.* Transportation Research Part D: Transport and Environment.

QUESTIONNAIRE DE EVALUATION DES MODES MICROMOBILITÉS

Groupe de décision désigné par l'enquêteur : .....……..

Informations personnelles

Âge :…….
Sexe :…….
Dernier diplôme : ……
Profession : ……..
Expérience sur les modes/services de micromobilité (années) : ……..…….

Veuillez remplir le tableau ci-dessous en choisissant l'une des opinions « *faible-moyen-élevé*» sur la relation/adéquation des modes de micromobilité dans votre ville par rapport au critère pertinent. À titre informatif, quelques valeurs de mesures officielles (valeurs objectives) sont fournies pour chaque mode.

Code	***Critère***	***Mode Micromobilité***		***Données Quantitatives***	***Évaluation Qualitative***
C_1	Durée de vie moyenne	A_1	*Vélo privé*	30 ans	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	3 ans	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	7 ans	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	10 ans	Faible / Moyen / Élevé
C_2	Temps de charge	A_1	*Vélo privé*	*pas besoin*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	5 heures	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	8 heures	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	4 heures	Faible / Moyen / Élevé
C_3	Autonomie maximale en une seule charge	A_1	*Vélo privé*	150 km	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	50 km	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	65 km	Faible / Moyen / Élevé

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		A_4	*Vélo électrique privé*	100 km	Faible / Moyen / Élevé
C_4	Limitation de vitesse	A_1	*Vélo privé*	20 km/h	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	25 km/h	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	30 km/h	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	25 km/h	Faible / Moyen / Élevé
C_5	Taux d'utilisation au moins une fois par semaine	A_1	*Vélo privé*	0.57 (taux)	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	0.61 (taux)	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	0.73 (taux)	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	0.87 (taux)	Faible / Moyen / Élevé
C_6	Taux d'accidents	A_1	*Vélo privé*	0.15 (taux)	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	0.26 (taux)	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	0.15 (taux)	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	0.51 (taux)	Faible / Moyen / Élevé
C_7	Taux d'intermodalité	A_1	*Vélo privé*	0.12 (taux)	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*	0.23 (taux)	Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*	0.08 (taux)	Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*	0.14 (taux)	Faible / Moyen / Élevé

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C_8	Sécurité	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_9	Gagner du temps	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_{10}	Confort	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_{11}	Bénéfice pour la santé	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_{12}	Bruit ambiant	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé

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		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_{13}	Eco-conception	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé
C_{14}	Faible émission de carbone (Durabilité)	A_1	*Vélo privé*	*Aucune donnée disponible*	Faible / Moyen / Élevé
		A_2	*Trottinette électrique privée*		Faible / Moyen / Élevé
		A_3	*Cyclomoteur électrique privé*		Faible / Moyen / Élevé
		A_4	*Vélo électrique privé*		Faible / Moyen / Élevé

Nous vous remercions sincèrement pour vos avis précieux.

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FORMULAIRE DE CONSENTEMENT VOLONTAIRE ÉCLAIRÉ

Cette recherche est une étude menée par l'assistante de recherche Esra ÇAKIR et le Prof. Dr. Çağrı TOLGA, membres du corps professoral du Département de génie industriel. Ce formulaire a été préparé pour vous informer des conditions de recherche.

Quel est le but de l'étude ? Le but de la recherche est d'évaluer les véhicules de micromobilité dans votre ville selon les critères spécifiés et d'obtenir un ordre de priorité en fonction des avis/données obtenus en appliquant des méthodes de prise de décision nouvellement développées. Si vous acceptez de participer à la recherche, ce que l'on attend de vous, c'est de répondre aux questions de l'enquête. La participation à cette étude prend en moyenne 3 minutes.

Comment allons-nous vous demander de nous aider ? En répondant aux questions du sondage.

Comment allons-nous utiliser les informations que nous collectons auprès de vous ? Votre participation à la recherche doit être entièrement volontaire. Aucune information permettant de vous identifier ou d'identifier votre institution n'est demandée dans l'enquête. Vos réponses resteront totalement confidentielles et seront évaluées uniquement par les chercheurs. Les informations obtenues auprès des participants seront évaluées collectivement et seront utilisées dans des publications scientifiques. Les données que vous fournissez ne seront pas comparées aux informations d'identité collectées dans les formulaires de participation volontaire.

Ce que vous devez savoir sur votre participation : Notre étude ne comporte aucun risque au-delà des risques normaux susceptibles d'être rencontrés dans la vie quotidienne. Si vous vous sentez mal à l'aise pendant la participation à cause des questions ou pour toute autre raison, vous êtes libre d'abandonner la tâche à mi-chemin et de partir. Dans un tel cas, il suffira d'informer la personne réalisant l'étude que vous souhaitez quitter l'étude. Vos questions sur cette recherche trouveront réponse à la fin de l'étude.

Si vous souhaitez recevoir plus d'informations sur l'étude : Merci d'avance de votre participation à cette étude. Vous pouvez contacter le Pr. Dr. Çağrı TOLGA (E-mail : ctolga@gsu.edu.tr), membre du corps professoral du Département de génie industriel, pour plus d'informations sur l'étude.

J'ai lu les informations ci-dessus et je participe à cette étude de manière entièrement volontaire.

(Veuillez retourner le formulaire au responsable de la mise en œuvre après l'avoir rempli et signé).

Nom Prénom	**Date**	**Signature**
Anonyme		

FORMULAIRE D'INFORMATION APRÈS PARTICIPATION

Comme mentionné précédemment, cette recherche a été menée par l'assistant de recherche Esra Çakir et Prof. Dr. Çağrı TOLGA, les membres du corps professoral du Département de génie industriel. Le but de l'étude est d'évaluer les véhicules de micromobilité dans votre ville selon les critères spécifiés et d'obtenir un classement prioritaire en fonction des avis/données obtenus en appliquant des méthodes de prise de décision nouvellement développées.

L'objectif principal de cette recherche est d'évaluer et de classer systématiquement les véhicules de micromobilité en utilisant les méthodes de prise de décision de groupe et de prise de décision multicritère (MCDM). Conformément aux objectifs de la Commission européenne pour 2050, il vise à soutenir un avenir où les solutions de transport durables et respectueuses de l'environnement sont au premier plan (European Commission, 2018). Il est indiqué dans la littérature que les méthodes MCDM permettent de prendre des décisions plus équilibrées et objectives en réunissant différents critères et points de vue des parties prenantes (Triantaphyllou, 2000 ; Öztürk et al., 2020). De plus, des études évaluant le rôle et l'impact des véhicules de micromobilité dans la ville révèlent les contributions potentielles de ces véhicules à la gestion du trafic et à la durabilité environnementale (Aldred et al., 2021). Dans ce contexte, la recherche vise à contribuer à une optimisation plus efficace des systèmes de transport urbain en triant les véhicules selon des critères déterminés.

Il est prévu d'obtenir les premières données de cette étude d'ici la fin du 31.12.2024. Les informations obtenues seront utilisées uniquement dans le cadre de recherches et d'articles scientifiques. Merci encore beaucoup d'avoir participé à cette recherche.

Vous pouvez contacter les noms ci-dessous pour connaître les résultats de la recherche ou obtenir plus d'informations.

Prof. Dr. Çağrı TOLGA (E-mail : ctolga@gsu.edu.tr)

Références :

- European Commission. (2018). *A European Strategy for Low-Emission Mobility.* Brussels: European Commission.
- Triantaphyllou, E. (2000). *Multi-Criteria Decision Making Methods: A Comparative Study.* Springer.
- Öztürk, M., Karahan, E., & Aydın, N. (2020). *Application of MCDM Techniques in Transportation: A Review.* Journal of Transportation Engineering.
- Aldred, R., et al. (2021). *Micromobility and its Role in Sustainable Urban Transport.* Transportation Research Part D: Transport and Environment.

Appendix B Approvals from the Ethics Committee

Given that personal opinions were utilized in the implementation of this doctoral thesis and its accompanying article, official permission was obtained from the Scientific Research and Publication Ethics Committee of Galatasaray University. The committee confirmed that there are "no ethical or scientific objections" regarding the method employed for information collection, as detailed in the following documents.

T.C.
GALATASARAY ÜNİVERSİTESİ REKTÖRLÜĞÜ
Bilimsel Araştırma ve Yayın Etiği Kurulu

Sayı : E-65364513-650-83799 21.10.2024
Konu : 2024/11-04 no'lu Etik Kurulu Kararı hk.

Sayın Prof. Dr. Abdullah Çağrı TOLGA
Endüstri Mühendisliği Bölüm Başkanlığı - Öğretim Üyesi

Bilimsel Araştırma ve Yayın Etiği Kurulunun 21.10.2024 tarih ve 2024/11 sayılı toplantısında alınan 04 no'lu kararı aşağıda yer almaktadır.

4. Mühendislik ve Teknoloji Fakültesi Öğretim Üyesi Prof. Dr. A. Çağrı Tolga'nın sorumlu araştırmacı olduğu 2024 / 030 protokol kodlu "İKİ YENİ ÇÖKV YAKLAŞIMI "PODER" VE "V-PARS": PARİS VE İSTANBUL'DA MİKROMOBİLİTE MODLARININ DEĞERLENDİRİLMESİ" başlıklı Esra Çakır'ın doktora tezi çalışması hakkında incelenmesi talep edilen 25.09.2024 tarihli başvuru dilekçesi ve ekleri Prof. Dr. Gülçin Büyüközkan Feyzioğlu tarafından değerlendirildi ve rapor görüşüldü.

Yapılan görüşme sonucunda çalışmanın başvuru dosyasında belirlenen kapsamda yapılmasında etik ve bilimsel açıdan sakınca bulunmadığına oy birliğiyle karar verildi.

Bilgilerinizi rica ederim.

Prof. Dr. Enver Murat ENGİN
Kurul Başkanı

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Kurul Başkanı

T.C.
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Konu : 2024/11-03 no'lu Etik Kurulu Kararı hk.

Sayın Prof. Dr. Abdullah Çağrı TOLGA
Endüstri Mühendisliği Bölüm Başkanlığı - Öğretim Üyesi

Bilimsel Araştırma ve Yayın Etiği Kurulunun 21.10.2024 tarih ve 2024/11 sayılı toplantısında alınan 03 no'lu kararı aşağıda yer almaktadır.

3. Mühendislik ve Teknoloji Fakültesi Öğretim Üyesi Prof. Dr. A. Çağrı Tolga'nın sorumlu araştırmacı olduğu 2024 / 029 protokol kodlu "Vektör Tabanlı Öncelik Yardımlı Sıralama Sistemi: Paris'teki Mikromobilite Modlar Üzerine Uygulama" başlıklı çalışması hakkında incelenmesi talep edilen 25.09.2024 tarihli başvuru dilekçesi ve ekleri Prof. Dr. Gülçin Büyüközkan Feyzioğlu tarafından değerlendirildi ve rapor görüşüldü.

Yapılan görüşme sonucunda çalışmanın başvuru dosyasında belirlenen kapsamda yapılmasında etik ve bilimsel açıdan sakınca bulunmadığına oy birliğiyle karar verildi.

Bilgilerinizi rica ederim.

Prof. Dr. Enver Murat ENGİN
Kurul Başkanı

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Kep Adresi:galatasarayuniversitesi@hs01.kep.tr

Bilgi için: Enver Murat ENGİN
Kurul Başkanı

BIOGRAPHICAL SKETCH

Esra ÇAKIR [redacted] She received the first B.S. degree in Computer Engineering in 2017 (first in her class), the second B.S. (2018) and M.S. degrees (2020) in Industrial Engineering from the Galatasaray University. She completes the Ph.D. in Industrial Engineering from the Galatasaray University with this doctoral thesis.

During her doctoral studies, she worked as a researcher at Università di Corsica Pasquale Paoli (2022), Université Paris Dauphine (2023) and Université de Lorraine (2024). Her research interest includes the fields of fuzzy sets, MCDM, optimization and graph theory. Her publication record includes over 50 scholarly works, encompassing SCI articles, book chapters, and conference papers. Her research activities extend across multiple research groups, laboratories, and projects.

[redacted]

For a comprehensive overview of her academic credentials, please refer to https://avesis.gsu.edu.tr/ecakir.

Academic studies pertinent to this doctoral dissertation

This thesis has contributed to the scholarly literature through the following publications, competitions, and research initiatives:

- ***Article:***
  - E. Çakır and A. Çağrı Tolga, "Vector-Based Preference Aided Ranking System (V-PARS): Application on Micromobility Modes in Paris," in IEEE Access, 2024, DOI: 10.1109/ACCESS.2024.3505138. (Çakır and Tolga, 2024b)

- ***Conference Paper:***

  - E. Çakır, "Criteria Weighting of Micromobility Modes via Extracted Framework Element Effect (EFEE) Methodology," 2024 Systems and Information Engineering Design Symposium (SIEDS), Virginia, United States Of America, pp.195-199, 2024. (Çakır, 2024a)
  - E. Çakır and Ç. Tolga, "New Multi Criteria Decision Making Methodology EFEE under Uncertainty on Paris City Micromobility," International Conference on Intelligent and Fuzzy Systems (INFUS 2024). Cham: Springer Nature Switzerland, pp.1-8, 2024. (Çakır and Tolga, 2024a)
  - E. Çakır, "Micromobility Evolution of Istanbul," 13.Ulusal Lojistik ve Tedarik Zinciri Kongresi (ULTZK 2024), Afyonkarahisar, Turkey, 2024. (Çakır, 2024d)
  - E. Çakır, "Novel Criteria Weighting Methodology EFEE: A Case of Micromobility Modes Assessment in Istanbul," 10th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2024), Angers, France, pp.1-5, 2024. (Çakır, 2024e)
  - E. Çakır, "Fuzzy Criteria Weighting of Micromobility Modes via Extracted Framework Element Effect (Fuzzy-EFEE) Methology," 27th International Conference On Multiple Criteria Decision Making (MCDM 2024), Hammamet, Tunisia, 2024. (Çakır, 2024b)
  - E. Çakır, "Reviewing Micromobility Modes of Paris City by novel MCDM Approach: EFEE," 33rd European Conference on Operational Research (EURO 2024), Copenhagen, Denmark, 2024. (Çakır, 2024f)
  - E. Çakır, "Micromobility Evaluation in İstanbul: A Critical Review," 3rd International Graduate Research Symposium (IGRS'24) , İstanbul, Turkey, pp.1-5, 2024. (Çakır, 2024c)

Note that an earlier version of the PODER method was published in conference proceedings under the name EFEE prior to the publication of the thesis.

- ***Competition:***

  – E. Çakır, "Évaluation des Alternatives de Micromobilité à l'Aide de Nouvelles Approaches Décisionnelles Multicritères ," Competition on *"Ma These en 180 Secondes"*, 4th prize, Istanbul, Turkey, May-2024.

  – E. Çakır, "Evaluating Micromobility Alternatives Using Novel Mcdm Approaches," Competition on *"Young Professionals - Pitch Competition"* of IEEE-RTSI 2024, Politecnico di Milano Polo Territoriale di Lecco, Italy, September-2024.

- ***Research:***

  – L' Université de Corse Pascal Paoli, 2022, Corte-France
  Laboratory Sciences Pour l'Environnement, UMR CNRS 6134 SPE, Group: IT Simulation and Ubiquitous Systems

  – L'Université Paris Dauphine – PSL, 2023, Paris-France
  Laboratoire d'analyse et modélisation de systèmes pour l'aide à la décision (LAMSADE)

  – L'Université de Lorraine, 2024, Metz-France
  Laboratoire de Conception, Optimisation et Modélisation des Systèmes (LCOMS)