



Research paper

An integrated fuzzy decision-making framework for the evaluation of electric buses in public transportation: A case study in Istanbul, Türkiye

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ABSTRACT

Rapid urbanization and environmental concerns have accelerated the transition to sustainable public transportation alternatives in place of traditional internal combustion engine vehicles. Electric buses (EBs) are emerging as a competitive alternative due to their economic, social and environmental advantages. This study focuses on providing practical guidance for integrating sustainable EB solutions into urban transit networks. In this study, an integrated approach is proposed, encompassing a combined picture fuzzy logarithmic decomposition of criteria importance (PF-LODECI) and picture fuzzy alternative ranking technique based on adaptive standardized intervals (PF-ARTASI) methods to support the evaluation and selection of EBs under uncertainty. Unlike prior studies that often focus solely on economic or environmental criteria, this research adopts a comprehensive perspective by incorporating economic, technical, environmental, and social dimensions. A real-world case study in Türkiye is conducted; five electric bus alternatives are evaluated based on four main criteria and twenty-seven sub-criteria. Furthermore, the stability and consistency of the results obtained are confirmed through the implementation of a sensitivity analysis. In addition, the findings offer insights into the economic and welfare implications of electric bus adoption in large urban public transport systems, particularly in terms of cost efficiency, externality reduction, and service quality improvements.

1. Introduction

Rapid urbanization and increasing population densities in cities have led to numerous challenges, particularly in transport infrastructure. The extensive reliance on internal combustion engine vehicles has played a significant role in increasing traffic density and worsening air pollution in city environments (Hilmola, 2011). These social and technical issues highlight the need for policy makers and urban planners to encourage a shift from the private car to the public transport system. Public transport plays an important role in urban mobility. It reduces traffic congestion and provides accessible transport options for city dwellers. Among public transport modes, buses are cost-effective, flexible and often superior in terms of capacity and speed. With growing concerns about, greenhouse gas (GHG) emissions, climate change and fossil fuel

dependency, the transition to sustainable transport has become an urgent global priority. Within this context, public bus systems represent one of the most impactful intervention points for achieving rapid and large-scale emission reductions in urban mobility. According to the European Environment Agency, existing policies and initiatives are expected to result in greenhouse gas emissions from transport reaching 1990 levels by 2030. In addition to encouraging a modal shift to public transportation and active mobility modes, the majority of planned policies and measures in the transport sector concentrate on promoting low-carbon fuels or zero-emission technologies (EEA, 2025). Air pollution from emissions caused by fossil fuels emphasizes the significance of adopting alternative clean energy sources, such as utilizing electrification for public transportation (Varghese & Pradhan, 2025).

One of the most pressing issues in transport is sustainability.

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Sustainable transport refers to mobility solutions that not only meet current needs, but also protect the environment and human health, promote economic growth and ensure social equity (Deakin et al., 2002). In this context, the integration of environmentally friendly vehicles with advancing technology is essential. Many cities around the world have increasingly adopted electric buses due to their lower emissions and numerous economic and social benefits. The electrification of public transport, particularly through EBs, is gaining attention as an effective strategy to reduce carbon emissions and improve energy efficiency (Li et al., 2024; Maybury et al., 2022). China has the world's highest share of electric buses at 30%; this percentage is 2% across Europe, which has the second-largest electric bus fleet (IEA, 2025). The total number of buses classified as battery electric vehicles (BEVs) in Europe increased from 431 in 2015 to 29,190 in 2025 (EAFO, 2026). The growing adoption of EBs is largely driven by stricter environmental regulations aimed at reducing emissions in public transport (UITP, 2017). Electric buses not only help lower greenhouse gas emissions—particularly when fueled by renewable energy, but also consume less energy and generate much less noise compared to traditional diesel or petrol-powered buses (Mahmoud et al., 2016; Teoh et al., 2018). In addition to their benefits for the environment, EBs can have a competitive total cost of ownership when compared to alternative fuel sources due to their lower maintenance and fuel costs (Åslund & Pettersson-Löfstedt, 2023). The transition to sustainable transport has significant economic benefits, as EBs offer lower operating and maintenance costs. Many governments are actively promoting the introduction of electric buses, recognizing their long-term benefits. Studies suggest that electric buses will increasingly replace traditional fossil fuel-powered models over the next decade (Pagliaro & Meneguzzo, 2019). Furthermore, projections suggest that electric vehicles could account for up to 80% of total vehicle sales by 2040 (Li et al., 2018). Despite these promising trends, the practical implementation of electric bus systems remains a complex strategic decision that requires careful evaluation of multiple, interdependent criteria.

As cities continue to look for sustainable transport solutions, electric buses are expected to play a key role in shaping the future of urban mobility. The electrification of public transportation, particularly through electric buses (EBs), has emerged as a viable solution to reduce carbon footprints and enhance energy efficiency (Li et al., 2024; Maybury et al., 2022). However, the adoption and evaluation of EBs require a structured decision-making approach that accounts for multiple, often conflicting, criteria such as cost, technical feasibility, environmental impact, infrastructure readiness, and social acceptance (Varghese & Pradhan, 2025). Multi-criteria decision-making (MCDM) approaches have been extensively utilized in the fields of transportation planning and sustainability to enhance decision-making efficiency in intricate situations (Hamurcu & Eren, 2020; Pradhan et al., 2022). Traditional MCDM methods, while effective, often fail to fully capture the uncertainty and hesitation inherent in expert judgments. This limitation is particularly critical for electric bus selection, where decision-makers (DMs) must evaluate emerging technologies under incomplete data, evolving policy frameworks, and uncertain operational conditions. In order to address this gap, this study proposes a theoretically grounded model of decision-making that utilizes the LODECI and ARTAS methods under the picture fuzzy (PF) environment. These methods offer a refined approach to handling vagueness and ambiguity in assessments.

From a theoretical perspective, the selection of electric buses for urban public transport systems can be conceptualized as a socio-technical and sustainability-oriented decision problem. Such decisions simultaneously involve technological performance, economic feasibility, environmental impact, institutional arrangements, and social acceptance, which are widely recognized as core dimensions of sustainable transport planning (Deakin et al., 2002; Manzolli et al., 2022; Varghese & Pradhan, 2025). In this context, electric bus adoption cannot be evaluated solely through technical efficiency or cost-based criteria, but rather requires an integrated decision-making framework capable of

capturing trade-offs among multiple sustainability dimensions under uncertainty. This theoretical viewpoint provides the conceptual foundation for employing advanced multi-criteria decision-making approaches in sustainable public transport planning. This conceptualization directly motivates the use of advanced fuzzy MCDM approaches that can represent not only preferences, but also indecision and neutrality in expert evaluations.

Due to the intrinsic uncertainty that is characteristic of complex MCDM problems, the decision makers (DMs) may encounter difficulties in articulating their judgments in terms of unambiguous information. The fuzzy set (FS) theory, as proposed by Zadeh (1965), was developed as a theoretical framework to address the management of uncertainty in information processing. Subsequently, Atanassov (1986) pioneered the development of intuitionistic fuzzy sets (IFS) as an extension of fuzzy sets, providing a framework capable of yielding more flexible solutions when confronted with uncertainties. Cuong and Kreinovich (2013) proposed picture fuzzy sets (PFS) as an extension of IFS. As an extended version of FS, PFS have been considered to be a highly versatile and successful approach to addressing uncertainty in decision-making situations (Alshamrani et al., 2025). PFS has been utilized in a variety of research areas such as selection of healthcare waste disposal technique (Mishra et al., 2024), selection of blockchain platforms for the logistics sector (Rani et al., 2025), analyzing the performance of manufacturing sectors in relation to circular supply chain management (Saraji & Streimikiene, 2022), determination of the most appropriate technology to convert waste into energy (Kumar et al., 2023), assessment of software reliability (Yue, 2020) along with similar research subjects.

In the context of electric bus selection, expert evaluations frequently involve neutral or hesitant judgments due to incomplete operational data, evolving charging technologies, infrastructure readiness, and uncertain regulatory environments. Conventional fuzzy and intuitionistic fuzzy approaches are limited in explicitly representing such decision states. Picture fuzzy sets are particularly well suited to EB selection problems, as they simultaneously model positive, negative, neutral, and refusal degrees, thereby offering a more realistic and comprehensive representation of expert judgment structures in sustainable public transport planning. This methodological advantage of picture fuzzy sets over conventional and intuitionistic fuzzy approaches has been widely acknowledged in the decision-making literature, particularly for complex problems characterized by expert hesitation, neutrality, and ambiguous information (Cuong, 2014; Wei & Gao, 2018).

The motivation of this study stems from the urgent need for sustainable and efficient urban mobility solutions. Public transportation, while essential for reducing congestion and emissions, is heavily reliant on fossil fuels, making it a significant contributor to air pollution and environmental degradation (Manzolli et al., 2022). Although electric buses offer a promising alternative, transportation authorities face a critical challenge: how to systematically select the most appropriate electric bus model among many competing alternatives under uncertainty. The adoption of EBs offers a promising alternative, but selecting the most suitable model requires a methodical evaluation process that integrates diverse perspectives and technical considerations. Accordingly, the primary aim of this study is to develop a robust, theoretically grounded, and practically applicable decision-support framework for electric bus selection under uncertainty. Specifically, by integrating PF-LODECI and PF-ARTASI methods, this study seeks to determine reliable weights for a comprehensive set of sustainability-oriented criteria, and rank competing electric bus alternatives in a way that explicitly accounts for expert hesitation and neutrality. A real-world case study from Türkiye is used to demonstrate the applicability and policy relevance of the proposed framework. Previous studies on EB evaluation have primarily focused on either economic or environmental factors (Rodrigues & Seixas, 2022). Although more recent studies have begun to incorporate additional technical, social, or institutional dimensions, these criteria are often examined separately or represented through a limited number of sub-criteria, without a fully integrated

evaluation structure. This study addresses this limitation by simultaneously considering four main and twenty-seven sub-criteria within a unified picture fuzzy decision framework. These objectives are grounded in the theoretical assumption that sustainable electric bus selection constitutes a complex decision problem under uncertainty, where expert judgments cannot always be expressed in binary or fully confident terms. Accordingly, the proposed PF-based framework is designed to operationalize this theoretical assumption by explicitly modeling positive, negative, neutral, and refusal judgments within the decision-making process. This research integrates a broader set of criteria, including social and institutional aspects, to provide a more holistic assessment. By addressing these objectives, this study contributes to the advancement of sustainable transportation and decision-making methodologies, fostering a more environmentally friendly and efficient urban mobility system. The study aims to compare five different electric buses supplier based on four main criteria and twenty-seven sub-criteria and make appropriate choices. In this study, the public transportation of Türkiye is investigated. Therefore, the LODECI (Pala, 2024) and ARTASI (Pamucar et al., 2024) methods are integrated within the PF environment to select the most suitable alternative electric bus. The weights of the criteria are determined by PF-LODECI and then by using PF-ARTASI the alternatives are ranked. EB3 is determined as the best alternative according to the determined criteria for Türkiye.

This study makes several contributions to the field of sustainable transportation and fuzzy sets. The main contribution of this study is, unlike conventional approaches, that it considers a broad set of factors including economic, environmental, technical, institutional, and social dimensions, ensuring a holistic assessment of EBs. To the best of our knowledge, this study, which is the first to use the PFLA approach in the evaluation of sustainable public transport systems, is a pioneering initiative in the literature. Secondly, the proposed methodology is applied to an EB selection scenario in Türkiye, offering valuable insights for policymakers and urban planners. Another contribution of this research is, the robustness of the proposed model is validated through sensitivity analyses that ensures its reliability in diverse decision-making scenarios. These contributions address key gaps in the literature and provide a systematic approach to EB selection, emphasizing data-driven decision-making in sustainable transportation policies.

The following sections of the article are organized as follows: Section 2, provides a concise summary of the existing literature. Section 3, the case study is presented, the scope is defined, and the proposed methodologies are explained. Section 4 constructs a proposed electric bus performance evaluation framework using an integrated PF-LODECI & ARTASI approach and presents a case study in Türkiye using the proposed framework. Finally, section 5 concludes the study and provides some future research directions and implications for researchers in the field.

2. Related studies

In this section, a concise survey of the extant literature on electric vehicle (EV) evaluations and case studies of former research is provided, together with literature on the MCDM approaches used in EV selection.

2.1. Research and analysis of electric transportation

The heightened sensitivity to climate change, attributable to the escalating emissions of GHG, and the financial losses incurred from energy have prompted numerous countries to explore alternative energy sources in lieu of fossil fuels. Electrification of the transportation sector is being prioritized by many countries in order to support the transition to net zero, as decarbonization is assuming increasing importance (Maybury et al., 2022). The contemporary resurgence of EVs can be attributed to a number of factors, including advancements in battery technology, increased government focus on vehicle emissions and air

quality standards, and a growing awareness of environmental sustainability (Coffman et al., 2017). The adoption of EVs has been shown to offer numerous advantages, which include reduced carbon emissions, ease of use, high levels of intelligence, and the capacity to facilitate dynamic grid services through vehicle-to-grid (V2G) technology (Li et al., 2024). EVs represent a significant potential for achieving energy security and mitigating pollution (Navyasri et al., 2023). In view of the evidence that suggests battery electric vehicles (BEVs) are integral to improving air quality in urban areas, particularly in less developed countries whose cities rank among the most polluted and fastest growing, it can be concluded that the use of BEVs is recommended (Rajagopal et al., 2022). The decarbonization of the sector consisting of passenger transport vehicles (i.e. cars, motorcycles and buses), which account for approximately 45% of GHG, has the potential to play a very important role in reducing climate change and related ecological damage (Manzolini et al., 2022).

Cooney et al. (2013) emphasized that regional variations in electricity grid structures should be taken into account prior to recommending the implementation of EBs. Li (2016) provided insights into the crucial technical parameters of range and charging time, which significantly affect the operational capabilities of electric buses. Lajunen and Lipman (2016) carried out a comparative evaluation focusing on life cycle costs and carbon dioxide (CO₂) emissions across various bus types, including hybrid electric, natural gas, diesel, fuel cell hybrid, and fully electric models. The study indicated that fully electric buses have the potential to significantly reduce CO₂ emissions. Li et al. (2018) conducted a comprehensive analysis of emergent trends and innovative advancements in the adoption of electric buses. The study emphasized the importance of utilizing grants from national or international sources to offset the additional procurement costs associated with electric buses, and the role of tax incentives in facilitating these purchases. McCabe and Ban (2023) conducted a study on the optimum locations and dimensions of stop charging stations for EBs. Guschinsky et al. (2023) argued that the design of the charging infrastructure and the determination of battery sizes are strategic decisions, while charging planning for a fixed infrastructure is operational. According to Kumar and Cao (2024), the study of the charging management of electric vehicles as an energy hub (EH) in conjunction with the associated energy system necessitates a comprehensive understanding of their impacts on the power grid. Varghese and Pradhan (2025) proposed that the effective implementation of EBs can be facilitated by the imposition of fees on bus traffic operators and bus manufacturers. This can be achieved by the provision of charging infrastructure and the development of the technology. Behnia et al. (2024) have demonstrated, there are considerable challenges associated with the integration of EBs into an urban network. This necessitates further adjustments to the current bus scheduling process. Avenali et al. (2024) reported that the most frequently discussed subjects in the literature on EBs are operational management (e.g. energy consumption, charging planning), cost-benefit assessment, ecological and social dimensions. Zhong et al. (2024) proposed a unified optimization model that jointly schedules electric bus charging and energy storage system operations to improve cost efficiency under variable load conditions. Rodrigues and Seixas (2022) analyzed the sustainability of battery-electric buses. The researchers stated that the main technological obstacle to the widespread use of battery-electric buses is their limited driving range in comparison to conventional buses. Lim et al. (2025) analyzed South Korean households' acceptance and willingness to pay for urban bus electrification. Dindar et al. (2026) presented a degradation-aware and climate-specific techno-economic planning framework for electric bus systems that incorporates battery aging effects into total cost and greenhouse gas emission optimization, underscoring environmental and economic trade-offs in sustainable transit planning.

However, recent electric mobility literature emphasizes that non-technological factors such as policy incentives, institutional support mechanisms, and operational management strategies (e.g., charging

planning, fleet scheduling, and route optimization) play an equally critical role in the successful deployment and large-scale adoption of battery-electric buses. Taken together, these studies reveal that the current EB literature is dominated by technological, economic, and operational perspectives, while policy, institutional, and behavioral dimensions are often treated as secondary or supportive factors rather than integral components of the evaluation process. Moreover, most studies implicitly assume that decision-makers can express their preferences with confidence, even though EB deployment is typically characterized by uncertainty regarding battery performance, infrastructure readiness, and long-term regulatory stability. Although these recent studies significantly advance the operational, technological, and energy-system-oriented understanding of electric bus deployment, they do not provide a comprehensive decision-support framework that simultaneously integrates sustainability dimensions with expert behavioral uncertainty, such as neutrality, hesitation, and refusal. While these studies provide valuable insights into technological, economic, and operational aspects of electric buses, they predominantly examine these dimensions in isolation. In particular, none of these works addresses how multi-dimensional sustainability criteria can be weighted and ranked under picture fuzzy information, which remains a critical gap for strategic electric bus selection in public transport systems.

Consequently, the literature lacks a unified conceptual framework that simultaneously integrates sustainability dimensions with decision-makers' behavioral uncertainty and hesitation. This limitation becomes particularly evident in public transport contexts, where expert evaluations are often characterized by neutrality, indecision, or conflicting assessments due to evolving technologies and policy conditions.

2.2. The MCDM approaches to EV selection

With the focus on EVM steadily mounting, there has been a concomitant rise in the application of MCDM models to the evaluation and selection of EVs.

Das et al. (2019) employed a combination of Fuzzy AHP and EVAMIX techniques to evaluate and identify the most appropriate electric vehicle (EV) model for the Asian market, aiming to reflect the preferences of potential EV consumers. Similarly, Sonar and Kulkarni (2021) applied the AHP to obtain the relative importance of selection criteria and used the MABAC method to identify the optimal EV option. Hamurcu and Eren (2020) proposed an integrated AHP-TOPSIS framework for choosing suitable EBs in line with sustainable transportation goals. Bošković et al. (2023) introduced AROMAN method, which incorporates a two-step normalization process to facilitate the selection of EVs for last-mile delivery. Dwivedi and Sharma (2023) combined Shannon's entropy for determining criteria weights with the TOPSIS method to assess the available EVs. The results of the present investigation suggest that the popularity of electric vehicles has increased due to their battery capacity, peak speed, base price, maximum power, electric range, and quick charge time. In the study conducted by Hamurcu and Eren (2022) MOORA and TOPSIS were utilized for the evaluation of ideal EB choices for public transportation. Pradhan et al. (2022) proposed an integrated fuzzy-QFD-COPRAS model for the selection of EVs, with this model being developed with consideration of the challenges experienced in hilly terrain. In this instance, the Quality Function Deployment model is utilized to address the weighting of the criteria in accordance with customer feedback. Tian et al. (2023) presented a MCDM model to assist consumers in their EV purchase decisions. Golui et al. (2024) proposed the application of a new correlation-based fermatean fuzzy TOPSIS to MCDM processes for the selection of electric vehicles. Seth and Kartheek (2024) proposed a hybrid AHP and WASPAS methodology for selecting the most optimal EV from among the numerous models available in the Indian market, taking into account key factors such as charging time, torque, price, range, and battery power. Görçün et al. (2024) utilized an interval-valued intuitionistic fuzzy COPRAS model for industrial users to select electric vehicles. The analysis of the extant research findings

demonstrates that the pivotal factors in the decision-making process are the driving range, purchase price, and charging time. Although these MCDM models have significantly improved the rigor of EV and EB evaluation, most of them rely on crisp, fuzzy, or intuitionistic fuzzy environments that restrict expert opinions to limited forms of expression. In real-world EB selection, however, experts frequently express neutral, hesitant, or even abstaining judgments due to uncertainty about technology maturity, infrastructure deployment, and policy continuity. These behavioral features of expert decision-making are not adequately captured by conventional or intuitionistic fuzzy MCDM frameworks.

Despite the extensive application of MCDM techniques in EV and EB selection, existing approaches exhibit several methodological limitations when applied to complex public transport decisions. Conventional crisp and fuzzy MCDM models primarily rely on binary or membership-based judgments, while intuitionistic fuzzy approaches are restricted to membership and non-membership degrees. Such structures are insufficient to explicitly capture neutral, abstaining, or conflicting expert opinions, which frequently arise in EB selection due to uncertainties related to technology maturity, infrastructure readiness, and policy constraints.

2.3. Research gap and contributions

Despite the growing body of literature on electric buses and MCDM-based evaluation approaches, several important gaps remain unresolved. Firstly, although previous studies acknowledge multiple evaluation dimensions, most EB assessment frameworks do not simultaneously integrate economic, environmental, technical, institutional, and social criteria within a single decision-making structure. Instead, these dimensions are often treated separately or represented through a limited set of sub-criteria.

Secondly, the majority of existing EB-focused MCDM studies rely on crisp, fuzzy, or intuitionistic fuzzy environments, which have limited capability to represent neutrality, hesitation, and refusal in expert judgments. Such limitations are particularly critical in public transport planning problems, where decision-makers often face conflicting information and incomplete knowledge. Thirdly, while advanced fuzzy extensions have been increasingly applied in MCDM research, there is a noticeable lack of methodological justification regarding their suitability for electric bus selection problems. Most existing studies adopt specific fuzzy environments without explicitly discussing why these approaches are appropriate for capturing the complexity and uncertainty inherent in EB evaluation. Furthermore, very few studies explicitly link the choice of fuzzy environment to the behavioral characteristics of expert decision-makers in public transport planning, such as neutrality, indecision, or refusal to provide precise judgments. This disconnect weakens the theoretical foundation of many existing EB-focused MCDM frameworks.

To address these gaps, this study proposes an integrated picture fuzzy LODCEI-ARTASI (PFLA) framework for electric bus selection. By simultaneously incorporating multi-dimensional sustainability criteria and explicitly modeling positive, negative, neutral, and refusal degrees of expert opinions, the proposed approach provides a more holistic and uncertainty-aware evaluation structure. This framework directly responds to the identified research gaps and establishes a clear link between the reviewed literature and the objectives of the present study. Accordingly, the novelty of this study does not stem solely from the inclusion of multiple evaluation dimensions, but from their simultaneous operationalization within an integrated picture fuzzy weighting and ranking framework, which has not been explicitly addressed in prior EB-focused MCDM studies. Furthermore, the integration of PF-LODECI and PF-ARTASI is specifically motivated by the need to ensure both robust criteria weighting and reliable alternative ranking under high uncertainty, addressing limitations observed in prior EB-focused MCDM studies that treat these stages independently.

3. Methodological architecture

The methodological architecture of the research conducted to accurately select EBs within the scope of sustainable public transportation is illustrated in Fig. 1. The methodological infrastructure encompasses LODECI and ARTASI methods, based on MCDM and picture fuzzy sets. The model, designated as PF-LODECI-ARTASI (PFLA), is comprised of two major stages. In the stage of determining the weight of the criteria, which constitutes one of these major stages, the PF-LODECI method is employed, while in the other stage, the PF-ARTASI method is applied to determine the optimal alternative. The subsections of the PFLA framework are presented in detail in Fig. 1.

In the next sections of this paper, the preliminaries of PFS are explained. Then, the PF-LODECI-ARTASI approach is detailed, which is the result of combining PFS with the LODECI and ARTASI methods, along with the steps involved in the method.

3.1. PFS: preliminaries

The concept of PFS provides more useful information when dealing with human opinions that encompass a broader range of responses, such as 'yes', 'abstain', 'no', and 'refusal'. A common example of this scenario is the voting process, where individuals can be divided into four categories: supporters, abstainers, opponents, and non-voters. PFS enhances the handling of ambiguity in judgment scores by employing independent membership functions (Cuong & Kreinovich, 2013; Cuong, 2014).

Definition 1. A PFS on a \tilde{Y} of the universe of discourse K is given by:

$$\tilde{Y} = \{ \langle k, (\lambda_{\tilde{Y}}(k), \mu_{\tilde{Y}}(k), \nu_{\tilde{Y}}(k)) \mid k \in K \} \tag{1}$$

where the function $\lambda_{\tilde{Y}}(k) : K \rightarrow [0, 1]$, $\mu_{\tilde{Y}}(k) : K \rightarrow [0, 1]$ and $\nu_{\tilde{Y}}(k) : K \rightarrow [0, 1]$ represent the degrees of positive, neutral, and negative membership of k in \tilde{Y} , respectively.

These functions are formulated in a rigorous manner while adhering to the condition that $0 \leq \lambda_{\tilde{Y}}(k) + \mu_{\tilde{Y}}(k) + \nu_{\tilde{Y}}(k) \leq 1$, which applies to all elements k belonging to set K . $\lambda_{\tilde{Y}} = 1 - (\lambda_{\tilde{Y}}(k) + \mu_{\tilde{Y}}(k) + \nu_{\tilde{Y}}(k))$ is defined as the degree of refusal membership of k in \tilde{Y} .

Definition 2. The preliminary computational operations of PFS are delineated in Eqs. (2)–(4) (Haktanir & Kahraman, 2022; Hussain et al., 2024):

$$\tilde{\alpha} \oplus \tilde{\beta} = \{ \lambda_{\tilde{\alpha}} + \lambda_{\tilde{\beta}} - \lambda_{\tilde{\alpha}} \lambda_{\tilde{\beta}}, \mu_{\tilde{\alpha}} \mu_{\tilde{\beta}}, \nu_{\tilde{\alpha}} \nu_{\tilde{\beta}} \} \tag{2}$$

$$\tilde{\alpha} \otimes \tilde{\beta} = \{ \lambda_{\tilde{\alpha}} \lambda_{\tilde{\beta}}, \mu_{\tilde{\alpha}} + \mu_{\tilde{\beta}} - \mu_{\tilde{\alpha}} \mu_{\tilde{\beta}}, \nu_{\tilde{\alpha}} + \nu_{\tilde{\beta}} - \nu_{\tilde{\alpha}} \nu_{\tilde{\beta}} \} \tag{3}$$

$$c. \tilde{\alpha}^c = \{ (1 - (1 - \lambda_{\tilde{\alpha}})^c), \mu_{\tilde{\alpha}}^c, \nu_{\tilde{\alpha}}^c \} \text{ for } c > 0, \tag{4}$$

$$\tilde{\alpha}^c = \{ \lambda_{\tilde{\alpha}}^c, (1 - (1 - \mu_{\tilde{\alpha}})^c), (1 - (1 - \nu_{\tilde{\alpha}})^c) \} \text{ for } c > 0. \tag{5}$$

Definition 3. Let $\tilde{Y}_j = \langle \lambda_{\tilde{Y}_j}, \mu_{\tilde{Y}_j}, \nu_{\tilde{Y}_j} \rangle$ ($j = 1, 2, \dots, n$) be a set of picture fuzzy numbers (PFNs), and $\varpi = \varpi_1, \varpi_2, \dots, \varpi_n$ be the weight vector, with $\varpi_j \in [0, 1]$ and $\sum_{j=1}^n \varpi_j = 1$. The Picture Fuzzy Weighted Arithmetic operator (PFWA) is defined as follows (Haktanir & Kahraman, 2022; Hussain et al., 2024):

$$PFWA_{\varpi} = \left\{ 1 - \prod_{j=1}^n (1 - \lambda_{\tilde{Y}_j})^{\varpi_j}, \prod_{j=1}^n \mu_{\tilde{Y}_j}^{\varpi_j}, \prod_{j=1}^n \nu_{\tilde{Y}_j}^{\varpi_j} \right\} \tag{6}$$

Definition 4. When considering $\tau_{\tilde{Y}} = 1 - \lambda_{\tilde{Y}} - \mu_{\tilde{Y}} - \nu_{\tilde{Y}}$; the following score function can be utilized to defuzzify PFNs (Dağdılar & Özkan, 2024):

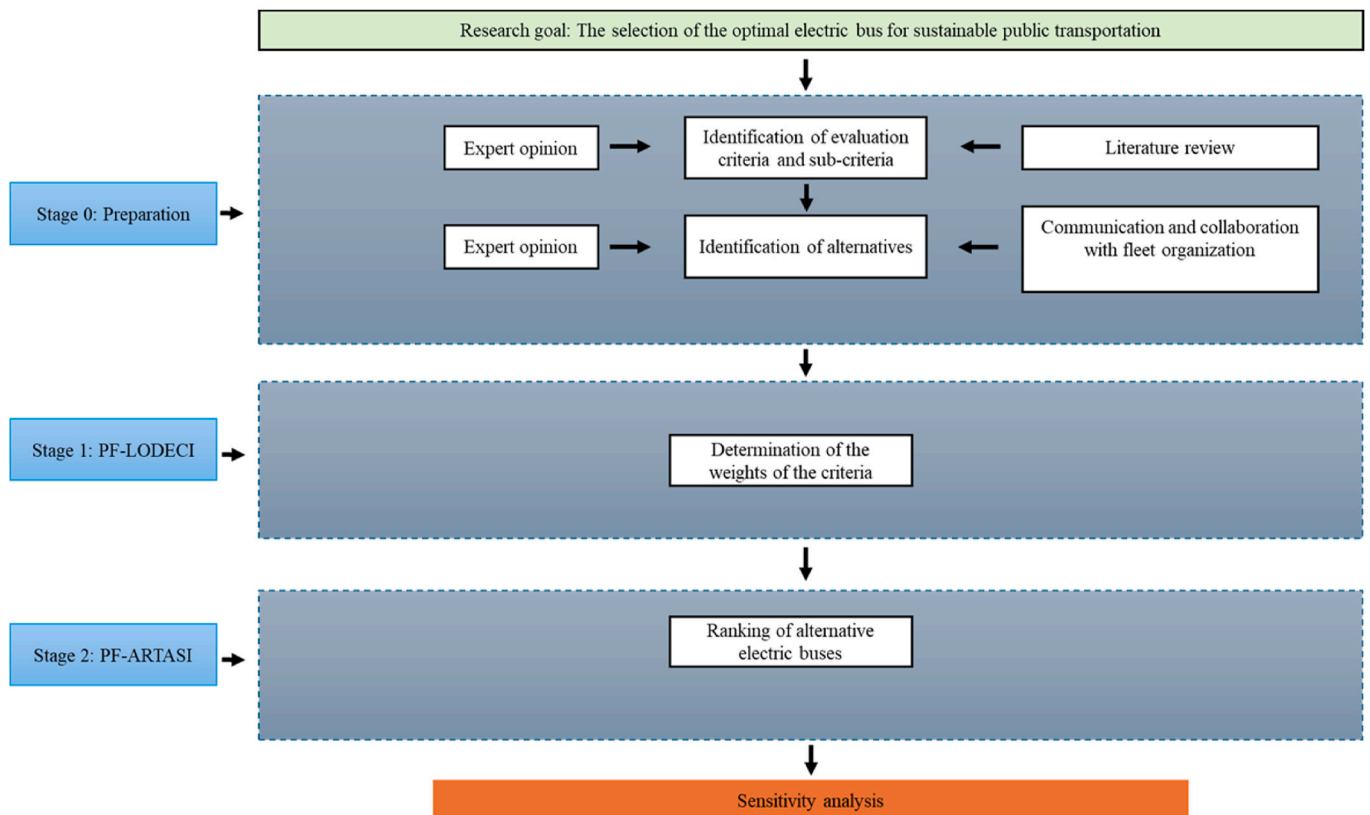


Fig. 1. PFLA methodology.

$$\lambda'_{\bar{Y}} = \lambda_{\bar{Y}} + \frac{\mu_{\bar{Y}}}{2} \tag{7}$$

$$v'_{\bar{Y}} = v_{\bar{Y}} + \frac{\mu_{\bar{Y}}}{2} \tag{8}$$

The defuzzified value (SF) is calculated by Eq. (9):

$$SF = \lambda'_{\bar{Y}} + \frac{1 + \lambda'_{\bar{Y}} - v'_{\bar{Y}}}{2} \tau_{\bar{Y}} \tag{9}$$

3.2. The proposed model

This section presents a description of the LODECI-ARTASI hybrid model, which is based on PFS. This model is proposed to evaluate MCDM problems systematically and to incorporate PFS information. The PFLA model has been conceptualized as a framework to address decision-making in complex real-world scenarios. Let $A_i (i = 1, \dots, m)$ be alternatives, $C_j (j = 1, \dots, n)$ be criteria and decision-makers $\mathfrak{D}\mathfrak{M}_k (k = 1, \dots, q)$ for the MCDM problem. The steps of the PFLA hybrid model are elucidated as follows: The utilization of PF-LODECI to the evaluation of criteria weighting:

Step 1: Each alternative $A_i (i = 1, \dots, m)$ and each criterion $C_j (j = 1, \dots, n)$ are evaluated by each decision-maker ($\mathfrak{D}\mathfrak{M}_k$) using the linguistic scale shown in Table 1. To generate the initial decision matrix $\tilde{\delta}^{(\mathfrak{D}\mathfrak{M}_k)} = [\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}]_{m \times n}$, the linguistic terms (LTs) are transformed into corresponding PFNs by deploying Table 1.

Step 2: The aggregated decision matrix ($\tilde{\delta} = [\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}]_{m \times n}$) is computed by utilizing the PFWA operator in Eq. (6). Herein, $\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)} = (\lambda_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k), \mu_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k), v_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k))$. In Eq. (6), the decision maker's weight is denoted as $\varpi_k = (\varpi_1, \varpi_2, \dots, \varpi_q)$, with $\varpi_k \in [0, 1]$ and $\sum_{k=1}^q \varpi_k = 1$.

$$PFWA(\tilde{\delta}^{(\mathfrak{D}\mathfrak{M}_1)}, \tilde{\delta}^{(\mathfrak{D}\mathfrak{M}_2)}, \dots, \tilde{\delta}^{(\mathfrak{D}\mathfrak{M}_q)}) = \bigoplus_{k=1}^q \varpi_k \tilde{\delta}^{(\mathfrak{D}\mathfrak{M}_k)} = \left\{ \left(1 - \prod_{k=1}^q (1 - \lambda_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k))^{\varpi_k}, \prod_{k=1}^q (\mu_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k))^{\varpi_k}, \prod_{k=1}^q (v_{\tilde{\delta}_{ij}^{(\mathfrak{D}\mathfrak{M}_k)}}(k))^{\varpi_k} \right) \mid k \in K \right\} \tag{10}$$

Step 3: The calculation of the crisp values is achieved through the utilization of Eq. (11). Subsequently, establish the crisp decision matrix ($\mathfrak{C} = [\mathfrak{C}_{ij}]_{m \times n}$).

$$SF(\tilde{\delta}_{ij}) = \lambda'_{\tilde{\delta}_{ij}} + \frac{1 + \lambda'_{\tilde{\delta}_{ij}} - v'_{\tilde{\delta}_{ij}}}{2} \tau_{\tilde{\delta}_{ij}} \tag{11}$$

Step 4: The computation of the normalized decision matrix ($\mathfrak{N} = [\mathfrak{N}_{ij}]_{m \times n}$) using Eq. (12).

$$\mathfrak{N}_{ij} = \begin{cases} \frac{\mathfrak{C}_{ij}}{\mathfrak{C}_{ij}^{max}} & \text{if } j \in \text{benefit criteria} \\ \frac{\mathfrak{C}_{ij}^{min}}{\mathfrak{C}_{ij}} & \text{if } j \in \text{cost criteria} \end{cases} \text{ for } (i = 1, \dots, m; j = 1, \dots, n) \tag{12}$$

Table 1
Linguistic scale for PFNs (Korucuk et al., 2023).

Linguistic terms	PFNs		
	λ	μ	v
Extremely low (EL)	0	0	1
Very low (VL)	0.1	0.3	0.6
Low (L)	0.2	0.3	0.5
Middle low (ML)	0.3	0.3	0.3
Below middle (BM)	0.4	0.2	0.3
Middle (M)	0.5	0.2	0.2
Above middle (AM)	0.6	0.2	0.2
Middle high (MH)	0.7	0.1	0.1
High (H)	0.8	0.1	0.1
Very high (VH)	0.9	0	0.1
Extremely high (EH)	1	0	0

Step 5: Obtain the decomposition value matrix ($\Delta = [\Delta_{ij}]_{m \times n}$) deploying Eq. (13).

$$\Delta_{ij} = \max\{|\mathfrak{N}_{ij} - \mathfrak{N}_{rj}|\} \text{ for } r \neq i \text{ and } (r = 1, 2, \dots, m; i = 1, \dots, m; j = 1, \dots, n) \tag{13}$$

Step 6: Obtain the logarithmic decomposition value matrix ($\Gamma = [\Gamma_j]_n$) deploying Eq. (14).

$$\Gamma_j = \ln\left(1 + \frac{\sum_{i=1}^m \Delta_{ij}}{m}\right) \text{ for } i = 1, \dots, m; j = 1, \dots, n \tag{14}$$

Step 7: The computation of the criteria weight matrix ($\mathfrak{W} = [\mathfrak{W}_j]_n$) employing Eq. (15).

$$\mathfrak{W}_j = \frac{\Gamma_j}{\sum_{j=1}^n \Gamma_j} ; (j = 1, 2, \dots, n) \tag{15}$$

The utilization of PF-ARTASI to rank the alternatives.

Step 8: The crisp decision matrix ($\mathfrak{C} = [\mathfrak{C}_{ij}]_{m \times n}$) determined in Step 3, represents an initial decision matrix for the PF-ARTASI method.

Determine the matrix of absolute maximum values ($\mathfrak{C}^{max} = [\mathfrak{C}_{ij}^{max}]_n$) and the matrix of absolute minimum values ($\mathfrak{C}^{min} = [\mathfrak{C}_{ij}^{min}]_n$) via Eqs. (16) and (17), respectively, utilizing a crisp decision matrix.

$$\mathfrak{C}_{ij}^{max} = \left(\max_{1 \leq i \leq m} (\mathfrak{C}_{ij}) \right) + \left\{ \max_{1 \leq i \leq m} (\mathfrak{C}_{ij}) \right\}^{1/m} \text{ for } (i = 1, \dots, m; j = 1, \dots, n) \tag{16}$$

$$\mathfrak{C}_{ij}^{min} = \left(\min_{1 \leq i \leq m} (\mathfrak{C}_{ij}) \right) - \left\{ \min_{1 \leq i \leq m} (\mathfrak{C}_{ij}) \right\}^{1/m} \text{ for } (i = 1, \dots, m; j = 1, \dots, n) \tag{17}$$

Step 9: The next step in the process is the implementation of the standardized decision matrix, which is comprised of two sub-steps.

Step 9 (i): The first-level standardized decision matrix ($\mathfrak{F} = [\mathfrak{F}_{ij}]_{m \times n}$) is obtained through the utilization of Eq. (18).

$$F_{ij} = \frac{\psi^u - \psi^l}{\zeta_j^{max} - \zeta_j^{min}} \zeta_{ij} + \frac{\zeta_j^{max} \psi^l - \zeta_j^{min} \psi^u}{\zeta_j^{max} - \zeta_j^{min}} \text{ for } (i = 1, \dots, m; j = 1, \dots, n) \tag{18}$$

where ζ_j^{max} and ζ_j^{min} denote the absolute maximum and minimum values, respectively, ψ^l and ψ^u indicate the lower and upper bounds of the standardized interval, respectively, while ζ_{ij} denotes the initial decision matrix value. Furthermore, the values in the standardized $[\psi^l, \psi^u]$ values are equal [1100] (Pamucar et al., 2024).

Step 9 (ii): The second-level standardized decision matrix ($S = [S_{ij}]_{m \times n}$) is obtained via Eq. (19).

$$S_{ij} = \begin{pmatrix} (-F_{ij} + \max_{1 \leq i \leq m} F_{ij} + \min_{1 \leq i \leq m} F_{ij}); \text{ if } j \in \text{cost criteria} \\ (F_{ij}); \text{ if } j \in \text{benefit criteria} \end{pmatrix} \tag{19}$$

Step 10: Determining the utility level of alternatives in relation to ideal and anti-ideal values consists of two subsequent sub-steps.

Step 10 (i): The calculation of the utility level for the ideal matrix ($\Delta^+ = [\Delta_{ij}^+]_{m \times n}$) is achieved through the utilization of Eq. (20) as follows:

$$\Delta_{ij}^+ = \left(\frac{S_{ij}}{\max_{1 \leq i \leq m} S_{ij}} \mathfrak{W}_j \psi^u \right) \text{ for } (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{20}$$

where $\psi^u = 100$ and \mathfrak{W}_j are criterion weights.

Step 10 (ii): The calculation of the utility level for the anti-ideal matrix ($\Delta^- = [\Delta_{ij}^-]_{m \times n}$) is achieved through the utilization of Eq. (21) as follows:

$$\Delta_{ij}^- = -\mathbb{I}_{ij} + \max_{1 \leq i \leq m} \mathbb{I}_{ij} + \min_{1 \leq i \leq m} \mathbb{I}_{ij} \text{ for } (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{21}$$

where \mathbb{I}_{ij} is the degree of usefulness. \mathbb{I}_{ij} derived from Eq. (22).

$$\mathbb{I}_{ij} = \left(\left(\frac{\min_{1 \leq i \leq m} S_{ij}}{S_{ij}} \mathfrak{W}_j \psi^u \right) \right) \text{ for } (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{22}$$

where $\mathfrak{B}^u = 100$ and \mathfrak{W}_j are criterion weights.

Step 11: The determination of the aggregate degree of utility of the alternatives for the ideal value matrix ($A^+ = [A_i^+]_m$) and the anti-ideal value matrix ($A^- = [A_i^-]_m$) is achieved through the use of Eqs. (23) and (24), respectively.

$$A_i^+ = \sum_{j=1}^n \Delta_{ij}^+ \text{ for } (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{23}$$

$$A_i^- = \sum_{j=1}^n \Delta_{ij}^- \text{ for } (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{24}$$

Step 12. The final utility function matrix ($U = [U_i]_m$) is calculated using Eq. (25) as follows:

$$U_i = \{A_i^+ + A_i^-\} \{ \beta f(A_i^+)^{\lambda} + (1 - \beta) \cdot f(A_i^-)^{\lambda} \}^{1/\lambda}; \beta \in [0, 1]; \lambda \in [1, +\infty] \tag{25}$$

where $f(A_i^+)$ and $f(A_i^-)$ denote additive functions and calculated as

$f(A_i^+) = \frac{A_i^+}{A_i^+ + A_i^-}$ and $f(A_i^-) = \frac{A_i^-}{A_i^+ + A_i^-}$, respectively. Subsequently, the maximum value in the final utility functions matrix is determined the optimal alternative.

4. Case location

The implementation of the proposed methodology was conducted through a selection of Istanbul, Türkiye's most populous metropolis, as the designated pilot area. This city is distinguished by a sophisticated public transport system, integrating a wide range of modes including public buses, ferries, rail systems, Marmaray, tram line, and bus rapid transit. The Istanbul Strait is a major transit route connecting the Sea of Marmara to the Black Sea, divides the metropolis into two sides: European and Asian. According to the results of Address Based Population Registration System 2024, the population of Istanbul is 15.701.602 (Turkish Statistical Institute, 2024). In recent years, the city of Istanbul has sought to enhance its urban transport system in a manner that is economically viable, socially inclusive, and environmentally sustainable. This objective has been pursued through the implementation of substantial investments. IETT (Istanbul Electricity, Tramway and Tunnel General Management), as the municipal public bus operator of Istanbul, delineated a vision to lead the way as an eco-friendly public bus authority. The IETT fleet comprises a total of 3516 public buses, of which 702 are allocated to bus rapid transit (BRT) services, with the remainder utilized for conventional bus operations. According to data from 2024, the total number of bus and BRT trips in Istanbul is approximately 7.8 million, with a cumulative distance traveled of 241 million kilometers. Furthermore, the number of journeys is recorded to be 678 million (IETT, 2024).

In conversations with the managers of IETT, it was stated that a vehicle converted from a different fuel type to an electric bus underwent trial runs on a flat, non-sloping route along the YENİKAPI-BEYAZIT-KAPALI ÇARŞI route (see Fig. 2). In this context, the aim of the current study is to serve as a guide for IETT in order to facilitate the evaluation of electric buses in its future projections.

4.1. Data description

In view of the environmental consequences of greenhouse gas (GHG) emissions from public transportation, the adoption of electric vehicles (EVs) within this sector is of the utmost importance. This importance is further heightened by the contribution of GHG emissions to declining air quality and climate change caused by global warming. A real-case study was conducted to facilitate evidence-based validation of the practical execution of the PFLA model. In contemplating the intricacies inherent in EBs, seven decision-makers ($\mathfrak{D}\mathfrak{M}_1, \mathfrak{D}\mathfrak{M}_2, \dots, \mathfrak{D}\mathfrak{M}_7$) have been involved in the execution of the proposed hybrid model, with a focus on sustainable public transportation. To ascertain the optimal choice for the bus type selection problem based on the provided criteria, transportation experts were selected from a public bus transportation company in Istanbul. In order to ensure a comprehensive perspective, seven DMs with a minimum of ten years of experience were selected from various departments of the company. The departments encompass transportation planning, innovation, bus maintenance and repair, strategy development, transportation technologies, intelligent transportation systems, fleet management, and purchasing. Before distributing blank evaluation tables to the relevant DMs via email, a comprehensive briefing was provided to them, outlining the definitions and criteria of the PFLA model. In instances where ambiguity arose, prompt meetings were scheduled to address the issue in question. A more comprehensive information of the DMs participating is provided in Table 2.

A comprehensive literature review was conducted in addition to consultations with the experts detailed in Table 2 to conduct this research process. Google Scholar and Web of Science research platforms



Fig. 2. Test route for EBs.

Table 2
The details of the DMs.

No	Area of expertise	Area of current work	Year of experience
DM ₁	Industrial Engineer	Bus field management	16
DM ₂	Mechanical Engineer	Vehicle maintenance and repair	19
DM ₃	Mechanical Engineer	Vehicle maintenance and repair	21
DM ₄	Public Transportation Senior Manager	Intelligent transportation systems	18
DM ₅	Public Transportation Manager	Public transportation	16
DM ₆	Transportation Planning Manager	Transportation technologies	16
DM ₇	Fleet Management Manager	Bus field management	14

were utilized to review books, articles, and conference proceedings that exhibited potential for utilization as references in the study. An initial search on the Google Scholar and Web of Science research platforms using the keywords "electric bus" "selection" and "public transportation" produced a wide range of publications, including journal articles, conference proceedings, and books, during the identification phase. Using the keywords "fuzzy" and "MCDM" the search was refined during the screening stage, and only publications that were more pertinent to the research field were included in the data set. Following a thorough evaluation, studies that are directly pertinent to the subject matter have been identified through the utilization of predetermined inclusion and exclusion criteria. The purpose of the review was twofold: first, to

identify relevant studies that could be used as a basis for the study, and second, to determine the selection criteria.

The inclusion criteria were as follows: (1) Focus on electric buses or sustainable public transportation, (2) Application of fuzzy set and/or MCDM methods, (3) Studies addressing electric vehicle selection, (4) Studies contributing to experimental, conceptual, or methodological aspects, (5) Full texts of articles published in peer-reviewed journals or related databases, (6) Full texts of articles available in English.

The exclusion criteria are as follows: (1) Studies whose full text is not accessible, (2) Studies that do not include explicit details regarding the methodological approach and resultant findings, (3) Studies written in languages other than English.

In accordance with the aforementioned points, the criteria were determined through consultations with a team of experts consisting of decision-makers, as detailed in Table 2, focus group discussions, and a review of the existing literature. In this context, four main criteria (MC) and twenty-seven sub-criteria (Sub-C) constituted the first stage of the hierarchical structure. The main criteria consist of economic (C1), environmental (C2), technical (C3), and social (C4) factors. The following Tables (3 and 4) present a comprehensive list of the relevant criteria, together with the relevant references and explanations.

The second stage of the hierarchical structure is the identification of alternatives. Following consultations with IETT managers and the opinions of the expert team consisting of decision-makers, five electric bus alternatives (EB1, EB2, EB3, EB4, EB5) were identified based on the inclusion criteria that had been determined. In this context, the inclusion criteria for the selection of EBs alternatives were as follows: (1) Market Availability/Technological Maturity: Models currently operating commercially and available for sale in Europe or Türkiye, (2)

Table 3
Factors influencing EB selection decisions.

MC	Sub-C	Type	References
Economic (C1)	Affordability (C11)	Benefit	Babar et al. (2021)
	After sales service (C12)	Benefit	Büyüközkan and Uztürk (2020)
	Fuel economy (C13)	Benefit	Tian et al. (2023), Biswas and Das (2018), Biswas et al. (2019), Babar et al. (2021), Patil and Majumdar (2021)
	Maintenance&repairment cost (C14)	Cost	Büyüközkan and Uztürk (2020), Jaller and Otay (2021)
	Operating cost (C15)	Cost	Büyüközkan and Uztürk (2020), Patil and Majumdar (2021), Pradhan et al. (2022)
	Price (C16)	Cost	Biswas et al. (2019), Ziemba (2020), Stopka et al. (2022), Wei and Zhou (2023)
	Brand reputation (C17)	Benefit	Büyüközkan and Uztürk (2020), Jaller and Otay (2021), Ozdagoglu et al. (2022), Khan et al. (2020)
Environmental (C2)	Energy consumption (C21)	Cost	Ecer (2021), Ren et al. (2021), Stopka et al. (2022), Ziemba (2021), Turoń et al. (2022)
	Fuel consumption (C22)	Cost	Tian et al. (2023), Ozdagoglu et al. (2022)
	Environment friendly performance (C23)	Benefit	Wei and Zhou (2023)
	CO ₂ saving (tonnes/year) (C24)	Benefit	Onat et al. (2016)
	GHG emissions (C25)	Cost	Onat et al. (2016), Khan et al. (2020)
Noise production (C26)	Cost	Süt et al. (2019), Patil and Majumdar (2021)	
Technical (C3)	Battery capacity (C31)	Benefit	Ecer (2021), Pradhan et al. (2022), Sonar and Kulkarni (2021), Ziemba (2021)
	Charging time (min) (C32)	Cost	Pradhan et al. (2022), Ren et al. (2021), Sonar and Kulkarni (2021), Wei and Zhou (2023), Ziemba (2021), Jaller and Otay (2021)
	Max speed (C33)	Benefit	Ecer (2021), Ziemba (2020), Ziemba (2021), Patil and Majumdar (2021)
	Power (C34)	Benefit	Ecer (2021), Pradhan et al. (2022), Ren et al. (2021), Stopka et al. (2022), Tian et al. (2023), Ziemba (2021), Turoń et al. (2022), Süt et al. (2019)
	Range (C35)	Benefit	Das et al. (2019), Ecer (2021), Pradhan et al. (2022), Ren et al. (2021), Sonar and Kulkarni (2021), Stopka et al. (2022), Ziemba (2021),

Table 3 (continued)

MC	Sub-C	Type	References
Social (C4)	Torque (C36)	Benefit	Turoń et al. (2022), Biswas and Saha (2019), Patil and Majumdar (2021), Das et al. (2019)
	Appearance/Design (C37)	Benefit	Tian et al. (2023), Süt et al. (2019), Büyüközkan and Uztürk (2020), Ren et al. (2021)
	Passenger capacity (C38)	Benefit	Biswas and Das (2018), Das et al. (2019), Büyüközkan and Uztürk (2020), Ziemba (2021)
	Employment opportunities (C41)	Benefit	Khan et al. (2020)
	Trust (C42)	Benefit	Bakioglu and Atahan (2021), Wei and Zhou (2023)
	Responsibility (C43)	Benefit	Wei and Zhou (2023)
	Satisfaction (C44)	Benefit	Wei and Zhou (2023)
	Secondary market development (C45)	Benefit	Ren et al. (2021), Büyüközkan and Uztürk (2020)
	Barrier-free transportation (C46)	Benefit	Süt et al. (2019)

Segment Diversity: In addition to 12-m standard city buses, 18-m articulated models, (3) Range: Models with a range between 300 km and 400 km, (4) Garage Charging: Compatibility with garage overnight charging (depot charging) infrastructure, (5) Operational Performance: Models with positive hill start capability test performance under load, taking into account Istanbul's geographical conditions (slope, humidity, etc.), (6) Purchase price: Models with acceptable initial purchase costs, (7) Power and Battery Capacity: Approximately 120 kW - 250 kW motor power and 350 kWh - 450 kWh battery capacities for 12-m vehicles. EBs that fail to meet the inclusion criteria outlined above are excluded from the selection alternatives.

The study adhered to the established ethical guidelines, with all participating experts, who were adult professionals, providing informed consent prior to involvement. The relevant experts were informed about the evaluation forms, the scope of their participation, and the purpose for which their contributions would be used. The protection of personal data attracted particular attention. The implementation of these procedures ensured the protection of the experts' privacy, maintained ethical principles, and ensured the establishment of an environment characterized by openness and trust.

4.2. The implementation of the methodology

This subsection provides a comprehensive exposition of the implementation steps for the proposed PFLA hybrid model to rank the EBs.

- *Determination of the weighting of criteria utilizing the PF-LODECI method*
Step 1. The construction of a hierarchical structure is an essential first step, followed by the evaluation of each alternative based on predetermined criteria. The proposed model's hierarchical structure (see Fig. 3) is constructed based on recent studies in the literature and experts' views.

Each decision-maker evaluated each criterion utilizing LTs presented in Table 1. The results of these evaluations are provided in Table S.1 in Appendix. Thereafter, employing Table 1, the LTs are converted into PFNs. The matrices corresponding to PFNs.

Table 4
Explanations of criteria.

	Sub-criteria	Explanations	
Economic	Affordability	Reasonable cost of purchasing an EV, including the initial purchase price, financing options, and potential government incentives	
	After-sales service	Refers to the availability and quality of maintenance and repair services for electric vehicles after they are purchased, including factors such as the availability of certified repair shops, availability of spare parts, and overall customer support, which can influence the ownership experience and long-term cost of owning an EB.	
	Fuel Economy	In the context of EB, fuel economy refers to the energy efficiency of the vehicle, typically measured in terms of miles per kilowatt-hour (kWh) or equivalent fuel economy metrics, which can affect the cost of operating the vehicle and the overall range it can achieve on a single charge.	
	Maintenance & repairment cost	Refers to the cost of maintaining and repairing an EB, including routine maintenance such as battery maintenance, tire rotation, and other service needs, as well as potential repair costs in case of breakdowns or accidents	
	Operating cost	Refers to the ongoing costs associated with operating an EB, such as electricity charging costs, insurance premiums, taxes, and other miscellaneous expenses, which can affect the overall cost of ownership and affordability of an EB.	
	Price	Refers to the cost of purchasing an EV, which includes the initial purchase price, as well as any additional costs such as taxes, registration fees, and other charges.	
	Brand reputation	Refers to the reputation of the brand or manufacturer of the EV, which can influence the resale or salvage value of the vehicle, as well as the overall perception of reliability and quality, which can affect the long-term economic viability of owning an EB.	
	Environmental	Energy consumption	The amount of energy used by an EV to power its motor and operate its various systems, which affects the efficiency and overall performance of the vehicle.
		Fuel consumption	Fuel consumption of EB refers to the energy usage of the vehicle, typically measured in kilowatt-hours (kWh) per unit of distance traveled, since electric bus do not use traditional fossil fuels as a source of energy.
		Environment friendly performance	The overall impact of an EV on the environment, taking into consideration factors such as emissions, resource usage, and ecological footprint, which can affect the sustainability and environmental performance of the vehicle.
CO ₂ saving (tonnes/year)		The release of CO ₂ gas into the atmosphere as a result of vehicle operation, which is a pollutant known to contribute to air pollution and climate change.	
GHG emissions		In the context of electric bus GHG emissions (greenhouse gas emissions such as CO ₂ , methane (CH ₄), and nitrous oxide (N ₂ O)) typically refer to the emissions associated with the generation of electricity used to charge and power the electric bus, as well as	

Table 4 (continued)

	Sub-criteria	Explanations
Technical	Noise production	emissions associated with manufacturing, transportation, and end-of-life disposal of the vehicle. Electromobility provides passengers with a quieter driving experience and contributes to the reduction of noise pollution in urban environments.
	Battery capacity	The amount of energy that an electric bus battery can store, determining how much distance the vehicle can travel on a single charge.
	Charging time	It is the required time to charge an electric bus battery from empty to full.
	Max Speed	Represents the highest achievable speed of an electric vehicle, indicating its performance capabilities and potential for highway driving.
	Power	Refers to the output power of an electric vehicle's motor, determining its acceleration and overall performance.
	Range	Represents the total distance an EV can travel on a single charge, affecting its practicality for long-distance driving and daily commutes.
	Torque	Refers to the twisting force generated by an electric vehicle's motor, influencing its acceleration and towing capabilities
	Appearance/Design	Refers to the visual aesthetics and overall design of an EB, which can influence consumer preferences and market appeal
	Passenger Capacity	It is an important consideration for bus selection as it directly impacts the capacity of the bus to transport passengers efficiently, meeting the demand of the intended route or service.
	Social	Employment opportunities
Trust		The trust-based association between a supplier and GAPBs (Governmental, Academic, Public, and Business) involves reliable and transparent collaboration in providing goods or services
Responsibility		The contentment resulting from the self-regulation of a business.
Satisfaction		Customer satisfaction-related performance level.
Secondary market development		Expansion or progress of markets related to the buying, selling, or trading of used or pre-owned vehicles and their associated parts, accessories, and services, create new job sector.
Barrier-free transportation		Accessible transportation options for individuals with disabilities or special needs, through features such as low-floor boarding, wheelchair ramps or lifts, priority seating, audible or visual announcements, and other accommodations that promote equal access and usability for all passengers.

Step 2: $\tilde{\delta} = [\tilde{\delta}_{ij}^{\mathfrak{D}V_k}]_{m \times n}$ matrix is calculated using the PFWA aggregation operator presented in Eq. (10). Refer to Table S.2 in the Appendix for this matrix.

Step 3: $\mathfrak{C} = [\mathfrak{C}_{ij}]_{m \times n}$ matrix is calculated using $SF(\tilde{\delta}_{ij})$ function presented in Eq. (11). This matrix is provided in Table 5.

Step 4: $\mathfrak{N} = [\mathfrak{N}_{ij}]_{m \times n}$ matrix is computed using Eq. (12). Refer to Table S.3 in the Appendix for this matrix.

Step 5: $\Delta = [\Delta_{ij}]_{m \times n}$ matrix is computed using Eq. (13). Refer to Table S.4 in the Appendix for this matrix.

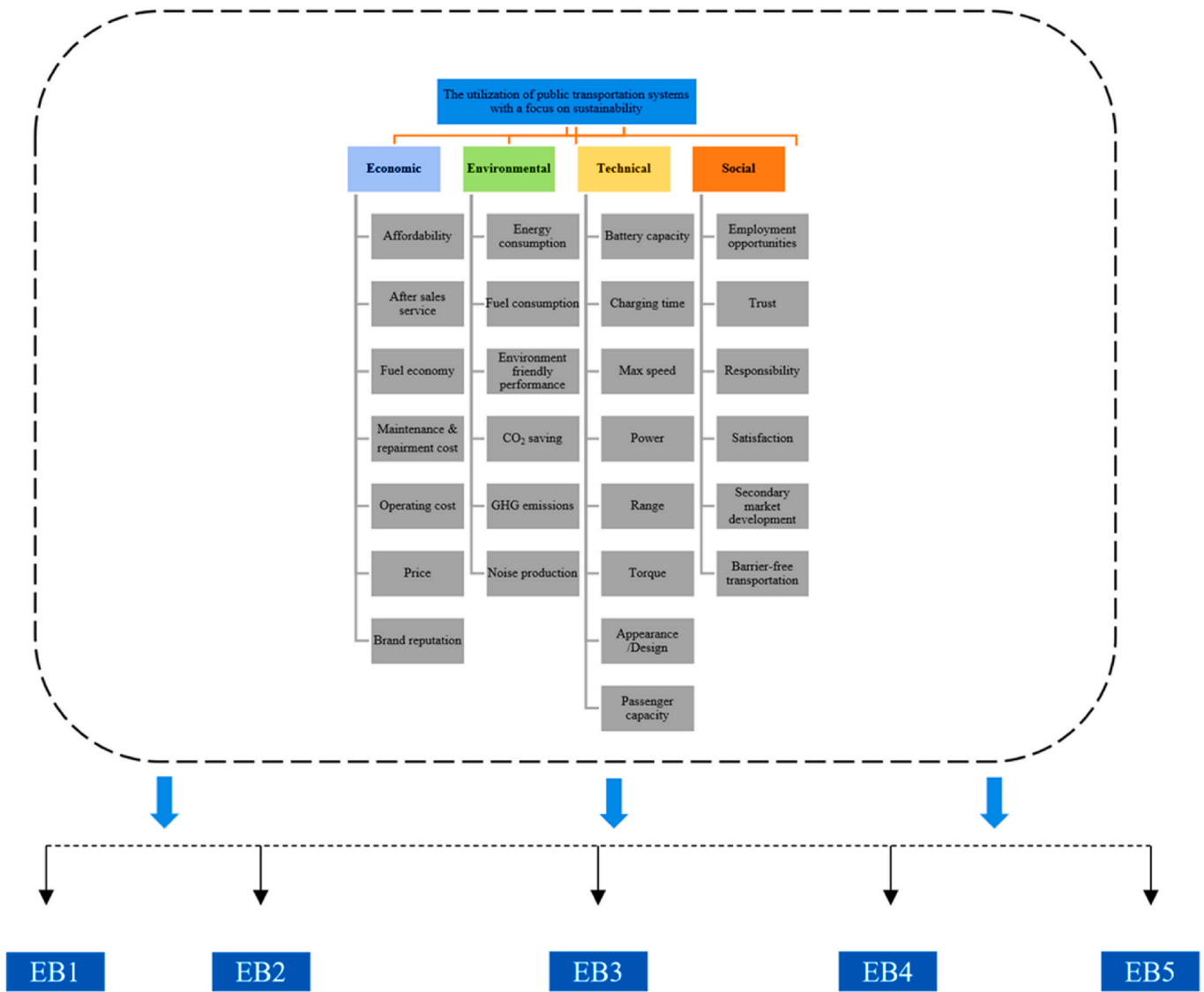


Fig. 3. Structure in hierarchy for the proposed model.

Step 6: $\Gamma = [\Gamma_j]_n$ matrix is computed using Eq. (14). Refer to Table S.5 in the Appendix for this matrix.

Step 7: $\mathfrak{B} = [\mathfrak{B}_j]_n$ matrix is computed using Eq. (15). This matrix is given in Table 6.

As demonstrated in Table 5, the most significant main criterion is Economic (0.405), followed by Social (0.340), Technical (0.163), and Environmental (0.092). In addition, the most prominent five sub-criteria are; Trust (C42; 0.0868), Brand reputation (C17; 0.0830), After sales service (C12; 0.0749), Price (C16; 0.0644), and Satisfaction (C44; 0.0635). The findings indicate that the economic factor is the most significant main criterion, accounting for 40.5%. Furthermore, the study demonstrates that trust in manufacturers and brand reputation are crucial factors in the adoption of electric buses.

• *Computing the ranking of EBs via the PF-ARTASI method*

Step 8: $\mathfrak{C}^{max} = [\mathfrak{C}_j]_n$ and $\mathfrak{C}^{min} = [\mathfrak{C}_j]_n$ matrices are computed using Eqs. (16) and (17), respectively. Table 7 provides details of these matrices.

Step 9 (i): $F = [F_{ij}]_{m \times n}$ matrix is computed using Eq. (18). Refer to Table S.6 in the Appendix for this matrix.

Step 9 (ii): $\mathfrak{S} = [\mathfrak{S}_{ij}]_{m \times n}$ matrix is computed using Eq. (19). Refer to Table S.7 in the Appendix for this matrix.

Step 10 (i): $\Delta^+ = [\Delta^+_{ij}]_{m \times n}$ matrix is computed using Eq. (20). Refer to Table S.8 in the Appendix for this matrix.

Step 10 (ii): $\Delta^- = [\Delta^-_{ij}]_{m \times n}$ matrix is computed using Eq. (21). Refer to Table S.9 in the Appendix for this matrix.

Step 11: Utilizing Eqs. (23) and (24), the aggregate degree of utility for the alternatives is calculated for both $A^+ = [A^+_{ij}]_m$ and $A^- = [A^-_{ij}]_m$ matrices. Refer to Table S.10 in the Appendix for this matrix.

Step 12: $\mathfrak{U} = [\mathfrak{U}_i]_m$ matrix is calculated utilizing equation (24) ($\beta = 0.5$ and $\lambda = 1$). This matrix is given in Table 8. The most judicious choice is the maximum value of $[\mathfrak{U}_i]_m$.

The PFLA model results indicate that EB3 is the best appropriate alternative. Subsequently, EB4, EB2, EB1, and EB5 are listed in Table 7.

4.3. Analysis of sensitivity

In this subsection, an analysis of the model's sensitivity is conducted across nine scenarios (s1, s2, ..., s9). These scenarios involve the variation of the parameter β within the utility function (see Eq. (24)). In the

Table 5

$\mathbb{C} = [\mathbb{C}_{ij}]_{m \times n}$ matrix.

	EB1	EB2	EB3	EB4	EB5
C11	0.743	0.572	0.626	0.701	0.832
C12	0.548	0.671	0.817	0.830	0.525
C13	0.590	0.677	0.707	0.749	0.572
C14	0.546	0.489	0.563	0.572	0.583
C15	0.626	0.582	0.700	0.701	0.575
C16	0.714	0.546	0.682	0.701	0.844
C17	0.665	0.815	0.841	0.815	0.489
C21	0.606	0.634	0.634	0.606	0.621
C22	0.634	0.660	0.634	0.671	0.655
C23	0.645	0.645	0.681	0.671	0.639
C24	0.606	0.634	0.671	0.645	0.598
C25	0.634	0.660	0.645	0.681	0.606
C26	0.634	0.660	0.660	0.660	0.634
C31	0.634	0.645	0.697	0.671	0.686
C32	0.606	0.634	0.662	0.634	0.667
C33	0.598	0.639	0.645	0.634	0.598
C34	0.660	0.671	0.671	0.671	0.660
C35	0.598	0.645	0.645	0.606	0.598
C36	0.606	0.645	0.721	0.705	0.606
C37	0.723	0.749	0.749	0.749	0.626
C38	0.645	0.660	0.660	0.660	0.634
C41	0.692	0.692	0.754	0.749	0.680
C42	0.636	0.731	0.876	0.834	0.468
C43	0.598	0.709	0.754	0.749	0.535
C44	0.606	0.731	0.805	0.754	0.553
C45	0.710	0.681	0.589	0.662	0.765
C46	0.671	0.582	0.517	0.543	0.740

Table 6

$\mathbb{W} = [\mathbb{W}_j]_n$ matrix.

	W_j	Rank	W_j	Rank	W_j	Rank		
C11	0.0590	8	C23	0.0142	22	C36	0.0360	13
C12	0.0749	3	C24	0.0225	16	C37	0.0389	12
C13	0.0488	9	C25	0.0220	17	C38	0.0096	26
C14	0.0353	14	C26	0.0105	24	C41	0.0232	15
C15	0.0396	11	C31	0.0198	18	C42	0.0868	1
C16	0.0644	4	C32	0.0188	19	C43	0.0617	6
C17	0.0830	2	C33	0.0174	21	C44	0.0635	5
C21	0.0105	25	C34	0.0043	27	C45	0.0431	10
C22	0.0125	23	C35	0.0182	20	C46	0.0614	7

initial scenario (s0), the value of β was designated as 0.5, and in each subsequent scenario, the value of the parameter β was incrementally increased by one unit. The results' sensitivity to varying values is tested. The results of the sensitivity analysis scenarios (SASc) are illustrated in Fig. 4. The variations in the ranking of the EB alternatives are visualized in Fig. 4a, while the changes in their utility functions are graphically represented in Fig. 4b.

When Fig. 4 is analyzed, it becomes evident that the EB's rankings remain consistent across varying values.

Table 7

$(\mathbb{C}^{max} = [\mathbb{C}_j]_n)$ and $(\mathbb{C}^{min} = [\mathbb{C}_j]_n)$ matrices.

Criteria	C^{max}	C^{min}	Criteria	C^{max}	C^{min}	Criteria	C^{max}	C^{min}
C11	1.7960	-0.3220	C23	1.6066	-0.2753	C36	1.6576	-0.2988
C12	1.7934	-0.3543	C24	1.5943	-0.3041	C37	1.6927	-0.2843
C13	1.6927	-0.3220	C25	1.6066	-0.2988	C38	1.5803	-0.2792
C14	1.4804	-0.3779	C26	1.5803	-0.2792	C41	1.6990	-0.2460
C15	1.6318	-0.3199	C31	1.6271	-0.2792	C42	1.8495	-0.3908
C16	1.8101	-0.3401	C32	1.5894	-0.2988	C43	1.6990	-0.3471
C17	1.8067	-0.3779	C33	1.5615	-0.3041	C44	1.7628	-0.3350
C21	1.5463	-0.2988	C34	1.5943	-0.2602	C45	1.7134	-0.3106
C22	1.5943	-0.2792	C35	1.5615	-0.3041	C46	1.6812	-0.3597

5. Conclusion and policy recommendations

Research on electrification of public transportation fleets is relatively new and emerging, and our understanding of the consequences of policy decisions and their impacts locally and globally remain limited to date.

There is growing amount of literature in time and pricing strategies for electrified urban transportation modes, however, the relationship between vehicles and systems selected, criteria used and their performance outcomes is not widely reported and remain sparse. This study proposes a theoretical model that integrates the four major categories and evaluative criteria. The paper's contribution to the extant corpus is substantiated by the validation of the framework utilizing the PFLA methodology.

It is clear from technology development trends and environmental regulations globally that the public transportation is going through a major transformation towards electrification of vehicles. Foremost in the cycle is the conversion of fleets of buses, especially for cities and municipalities, from conventional ICE buses to electric buses. Adoption of sustainable transportation for cities bring a set of important parameters such as economic, environmental, technical, and social dimensions to consider in their decision-making processes in this transformation to EBs. A host of issues comes up such as power-grid infrastructure investments, battery-charging stations and range, maintenance cycles, operational performance of electric bus systems and new potential business models from secondary market opportunities that may develop as a result of planned transformation. This study proposes a systematic approach, incorporating a comprehensive set of criteria deemed pertinent to local requirements. The study employs a sophisticated decision-making framework, termed PFLA, to guide the selection process for EBs. This was demonstrated with a case study from Türkiye where some EBs were studied in detail projecting results based on set of factors and sub-criteria selected in the proposed framework. The weighting of these parameters can be varied based on local needs and state of regulations.

This study aims to establish a holistic evaluation approach for EB alternatives to provide guidance on sustainability in public transportation. In this study, the PF-LODECI and PF-ARTASI methods were combined and implemented in a real-world case study focusing on Türkiye. The evaluation process involved the consideration of four main criteria and twenty-seven sub-criteria, encompassing economic, environmental, technical, and social considerations.

The PFLA model results indicate that EB3 is the best appropriate alternative. Subsequently, EB4, EB2, EB1 and EB5 are listed. The established order (EB3 > EB4 > EB2 > EB1 > EB5) aligns closely with

Table 8

$\mathbb{U} = [\mathbb{U}_i]_m$ matrix.

Alternatives	U_i	Rank
EB1	89.7075	4
EB2	93.7857	3
EB3	95.1717	1
EB4	95.1461	2
EB5	86.0782	5

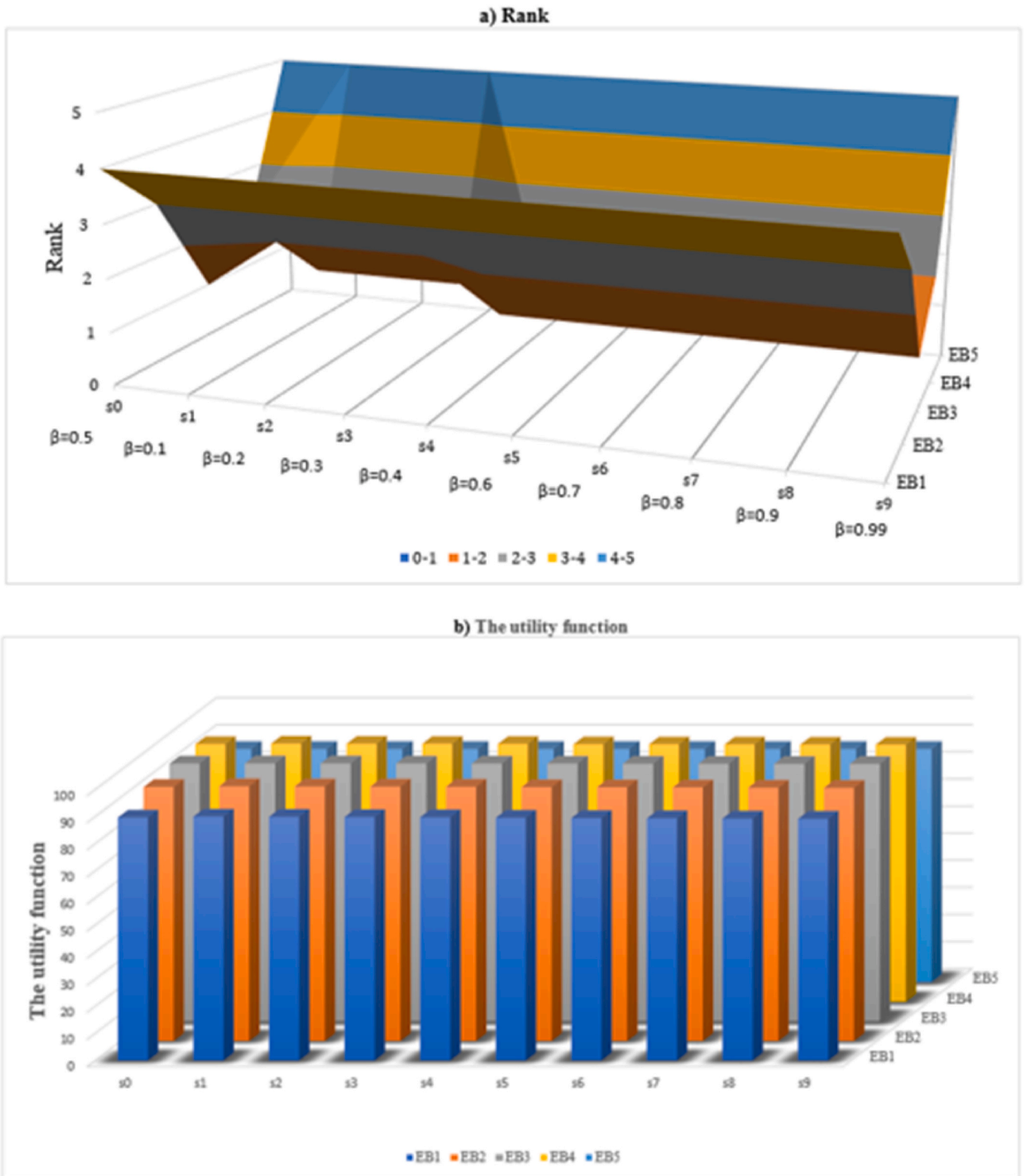


Fig. 4. The results of the SASc.

empirical evidence. EB3 is a widely prevalent electric bus model in Europe, demonstrating proficiency in technical, economic, and social domains. It possesses a range of 350-400 km, substantial battery capacity, robust service infrastructure, and a trusted brand reputation. A body of research has demonstrated that trust has a significant impact on the adoption of electric vehicles and the development of intent in this area (Eccarius & Chen, 2024; Kumar et al., 2026). EB4 excels in

operational reliability due to its minimal energy usage and comprehensive maintenance network. EB2 excels in the environmental and social categories due to its sustainable performance and brand reputation. However, its ranking is third due to its elevated price. EB1 is economically viable and energy-efficient, although it possesses constraints in range and servicing infrastructure. EB5 has the lowest position because to its failure to completely adhere to European standards

and its constrained service support, notwithstanding its cost advantage. This scenario illustrates that the model's theoretical findings correspond with prevailing market conditions and operational data.

The findings indicate that the process of selecting EBs is a complex, multifaceted decisional matter. In this context, technological maturity, life-cycle costs, environmental sustainability, and policy alignment are the most decisive factors. The model proposed for municipalities and transportation authorities supports data-driven, systematic, and sustainable decision-making processes, providing long-term environmental, economic, and social benefits.

5.1. Managerial implications

The shift from internal combustion engine (ICE) buses to EBs represents a crucial advancement in the pursuit of intelligent and sustainable urban transportation. In this transition process, politicians and local authorities must make strategic decisions by evaluating the appropriateness of existing infrastructure, legal frameworks, and financial capacity.

The study's findings indicate that the EB3 and EB4 models represent the most balanced choices regarding technological reliability, maintenance, and after-sales support. Consequently, public transportation operators seeking to rejuvenate their fleets should favor manufacturers with a robust local service network, durable batteries, and high brand reliability.

These findings highlight two key management priorities for decision-makers.

1. Fleet renewal decisions must consider not only initial investment costs but also life-cycle performance.
2. Technology selection should align with local infrastructure, energy supply security, and service continuity.

The adoption of EBs is profoundly influenced by emission regulations, incentive frameworks, charging infrastructure, and tax policies. The extensive implementation of V2X (Vehicle-to-Everything) technology will facilitate the development of transportation systems connected with smart city infrastructure.

The main benefits of V2X-based electric bus systems from a management perspective are as follows.

- Ensuring driver and pedestrian safety by improving traffic safety,
- Reducing CO₂ emissions and time losses by optimizing traffic flow,
- Contributing to the national economy by increasing energy efficiency,
- Improving passenger comfort and barrier-free access,
- Ensuring more effective use of existing transportation infrastructure,
- Supporting data sharing security and operational integrity.

Consequently, the conversion to electric buses should be regarded not merely as a modernization of transportation but also as an essential element of the smart city paradigm. This transition will enhance social welfare while promoting environmental and economic sustainability.

5.2. Economic and welfare implications of electric bus adoption

Electric bus (EB) adoption in urban public transport systems should be evaluated not only in terms of technical feasibility or environmental performance, but also from a transportation economics and welfare perspective. In urban transport economics, welfare effects arise through changes in public expenditures, operating and maintenance costs, externalities, service quality, accessibility, and long-term system efficiency. Accordingly, the results obtained from the proposed PFL-LODECI-ARTASI (PFLA) framework provide a structured basis for discussing the broader economic and societal welfare implications of electric bus deployment. From a public finance perspective, the

prominence of institutional and economic criteria such as government tax reductions, incentive mechanisms, and supportive policy frameworks highlights the decisive role of fiscal instruments in facilitating EB adoption. Although electric buses generally entail higher upfront investment costs than conventional internal combustion engine buses, their lower operating and maintenance costs over the vehicle life cycle can significantly improve cost efficiency in the long run. When combined with tax exemptions and public incentive schemes, these cost advantages may alleviate long-term budgetary pressures on municipalities and improve the allocative efficiency of public transport investments. Beyond direct budgetary impacts, electric buses generate substantial positive externalities that contribute to overall social welfare. Zero tailpipe emissions reduce local air pollutants such as nitrogen oxides (NOx) and fine particulate matter (PM), which are closely associated with respiratory and cardiovascular diseases and premature mortality. As a result, public health improvements represent one of the most significant welfare gains of EB deployment. For example, [Maizlish et al. \(2022\)](#) estimate health and climate benefits of up to USD 207,200 per bus when replacing older diesel models in large metropolitan areas. In addition, electric buses significantly reduce noise pollution, contributing to more peaceful urban environments, lower stress levels, and improved traffic safety. Over their operational lifetime, a single electric bus can prevent approximately 181 tons of CO₂-equivalent emissions compared to a conventional diesel bus. From the user perspective, electric buses enhance passenger welfare by offering smoother ride quality, quieter operation, and improved service reliability. These attributes increase passenger comfort and satisfaction while providing a less stressful working environment for drivers. Improved service quality can increase public transport attractiveness, encourage modal shifts away from private vehicle use, and reduce congestion-related costs. Such effects generate additional welfare gains through travel time savings, improved accessibility, and more efficient utilization of existing transport infrastructure.

Despite these advantages, the welfare effects of electric bus adoption are not unambiguously positive in the short run. High upfront investment costs, particularly for vehicles and charging infrastructure, remain a major barrier. [Giagnorio et al. \(2024\)](#) argue that in certain contexts, electric buses may not yet be welfare-improving, as reductions in external costs may not fully offset higher supply-side costs associated with battery systems and charging infrastructure. Moreover, large-scale EB deployment may require power grid upgrades, while operational challenges such as range limitations especially under cold climate conditions or heavy traffic can necessitate additional vehicles or route adjustments to maintain service frequency. Further considerations include the environmental and social impacts associated with battery production and raw material extraction, which account for a substantial share of vehicle costs and may involve environmental degradation and labor-related concerns in specific regions ([Demiryürek et al., 2023](#)). Additionally, the overall environmental performance of electric buses depends on the electricity generation mix used for charging, emphasizing the importance of system-level coordination between transport and energy policies.

Overall, the welfare effects of electric buses in large urban areas are predominantly positive, particularly with respect to public health, environmental quality, and user comfort. However, realizing these societal benefits requires addressing upfront investment barriers, infrastructure development, and system-level integration challenges. [Fan et al. \(2020\)](#) state that governments should appropriately raise subsidies for domestic electric vehicle consumers and decrease tariffs applied to imported electric vehicle manufacturers, which would contribute to improving social welfare.

5.3. Limitations of the study and future research

As with all studies of this nature, the findings and their implications for the parties responsible for making the decision should be interpreted

with prudence due to certain limitations. This study relies on perceptual evaluations and expert-based analytical judgments to assess system or product-level performance, which may not fully capture the complete reality—particularly across the five segments analyzed. To reduce potential bias, future research could benefit from incorporating diverse data sources and complementary methods. Although the PFLA model applied here satisfies many of the commonly accepted criteria, there remains potential for refinement. For instance, the incorporation of additional indicators or control variables may improve the model's comprehensiveness and accuracy.

In the process of identifying potential economic and social variables, it is crucial to recognize that the variables selected in this study may not fully align with all underlying assumptions. To gain deeper insights into the organizations examined, a future qualitative investigation such as conducting interviews with experts across various domains including strategic, managerial, technical, operational, and user perspectives could provide valuable complementary information. The urgent need for sustainable and efficient urban mobility solutions pivoted EBs as major winners in adoption to greener transportation from mostly economic perspective as battery costs continually go down. In this study a limited number of models have been analyzed, and a large a set of vehicles and technologies/models can be assessed.

The technical performance and economic considerations allow for shift from ICE to electric versions of transport vehicles. However, the fuel-cell (H2) based electric vehicles/buses are developed that enable greater energy densities and driving range than pure BEVs. Currently, EBs are significantly cheaper to acquire and operate compared to Hydrogen-Buses. These will be competing options in the future and cost-benefit parameters will have to be addressed as the infrastructure for hydrogen generation/storage becomes more feasible.

CRediT authorship contribution statement

Veysel Tatar: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Berk Ayvaz:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation. **Emine Elif Nebati:** Writing – original draft, Visualization, Resources. **Bahadır Tunaboylu:** Writing – review & editing, Writing – original draft. **Selim Zaim:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.retrec.2026.101765>.

Data availability

Data will be made available on request.

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