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Electrifying Freight: Modeling the Decision-Making Process for Battery Electric Truck Procurement

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Abstract: As the transportation industry seeks sustainable alternatives to internal combustion engine trucks (ICET), understanding the dynamics behind battery electric truck (BET) adoption becomes essential. This paper explores the critical factors influencing the procurement decision for BET in the freight transportation sector, employing a novel combination of fuzzy logic and the Delphi method to bridge qualitative assessments and quantitative analysis. Through a comprehensive literature review and expert consultations via the Delphi method, the research identifies the barriers to BET adoption, including initial investment costs, charging infrastructure, and legislative clarity. Fuzzy logic is then applied to model these factors' impacts on the purchasing decision, translating subjective judgments into a structured analytical framework. This approach enables the assessment of BETs' viability against ICETs, considering the total cost of ownership (TCO), travel time (TT) ratios, and perceived social benefits. While economic factors primarily drive the purchasing decision, the study reveals that social utility also plays a crucial role. This research contributes to the sustainable transportation literature by offering a detailed model of the decision-making process for BET procurement, providing valuable insights for industry professionals, policymakers, and academics committed to advancing environmentally friendly freight solutions.

Keywords: battery electric trucks; fuzzy logic; Delphi method; purchasing decision

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1. Introduction

The concern regarding the adverse impacts of environmental pollution, particularly stemming from the degradation of the natural environment due to human activities, is escalating across the globe. This increasing awareness, especially in relation to air pollution and global warming, is compelling developed countries to embark on the formulation of comprehensive strategies, the establishment of clear roadmaps, and the setting of ambitious targets to mitigate these environmental challenges.

The transportation sector is a major source of global greenhouse gas emissions, responsible for 26% of CO_2 emissions in the United States [1], 19% in Latin America [2], and a notable 25% in Europe [3]. Within the transportation sector of Europe, heavy-duty vehicles stand out for their significant environmental impact, accounting for one quarter of the continent's greenhouse gas emissions [3]. The International Energy Agency (IEA) has highlighted that heavy-duty trucks are major consumers of oil in road cargo transportation, utilizing half of the oil consumed in this sector [4]. This evidence places the transportation sector, and specifically trucks, at the forefront of global efforts to reduce emissions. In the realm of air pollutant emissions, throughout their life cycle, BETs have been shown to outperform their conventional counterparts significantly [5], marking them as a key opportunity for substantial emission reductions.

As a response to the need for sustainable transportation solutions, academic research focusing on electric vehicles (EV), particularly in the context of urban passenger and light commercial vehicle applications, has seen a significant increase. However, the literature remains relatively limited regarding the deployment of electric trucks, with existing studies presenting diverse outcomes for critical parameters and threshold values across various countries [2,6].

The literature review reveals that prior research primarily emphasizes qualitative aspects, such as identifying and prioritizing criteria for the adoption of BETs. While this qualitative focus offers a foundational understanding of the factors influencing BET adoption, it lacks the detailed, quantitative data that are crucial for informed decision-making. To effectively contribute to the 2030 and 2050 greenhouse gas emission targets, there is a critical need for quantitative analysis that demonstrates how different criteria impact BET purchasing rates. Such data would not only facilitate accurate predictions of BET adoption based on specific criteria values but also guide necessary adjustments to these criteria or the implementation of targeted incentives to meet emission reduction goals. This gap in the literature highlights an urgent need for studies that bridge the divide between qualitative insights and quantitative decision-making tools in the context of BET adoption.

Given the identified gap in the literature, this study aims to develop a quantitative model to enhance decision-making in the procurement of BETs. It provides insightful contributions to the literature on sustainable transportation by presenting a comprehensive model for the decision-making process in the procurement of BETs. It delivers important insights for industry experts, policymakers, and scholars who are dedicated to promoting sustainable freight options.

The paper is organized as follows. Section 2 offers a comprehensive literature review on the adoption of electric freight vehicles (EFV) and the management of EV fleets. Section 3 elaborates on the methodologies utilized in this study, including the Delphi method and fuzzy logic, for the development of the analytical model. Section 4 details the comparison process for potential purchasers employing fuzzy logic, providing a step-by-step analysis. Section 5 summarizes the significant findings of the research, highlighting the implications for the advancement of sustainable transportation solutions and the role of BETs in this endeavor.

2. Literature Review

The literature review for this study was systematically conducted through an extensive search on the Google Scholar search engine. This enabled a comprehensive examination of scholarly articles by incorporating a diverse array of keywords. The following keywords were used for the search:

- "Battery electric vehicle" AND "long haul transportation";
- "Battery electric logistics vehicles" AND "long haul transportation";
- "Electric trucks" AND "long haul transportation";
- "Electric trucks" AND "lifetime costs";
- "Battery electric trucks" AND "life cycle emissions";
- "Electric vehicles" AND "logistic fleets".

After relevant publications were identified, the list was expanded by the citation links of the relevant publications (also known as snowballing). To ensure the exclusion of grey literature and maintain the credibility of our review, we focused predominantly on reputable sources, including book chapters from reputable publishers and doctoral dissertations that adhered to academic standards. Additionally, prominent reports from established organizations like the International Energy Agency were also considered due to their relevance and credibility in the field. This extensive strategy facilitated a systematic and thorough search and selection process to obtain relevant articles. The aim was to analyze the content of these articles, synthesizing the findings to provide a nuanced understanding of the factors that influence the purchasing decisions regarding EFVs.

2.1. EFV Adoption

From the analysis of the literature, several critical insights emerged.

- Initial Investment Cost: The literature consistently identifies the high initial investment cost associated with EFVs as the principal impediment to their broader adoption [7–13].
- Life Cycle Cost Analysis: Studies comparing BET and ICET based on life cycle costs suggest that these vehicle types may reach cost parity, particularly in contexts of long-distance freight transportation [5,6,14–19]. This parity indicates a shifting economic landscape favoring the adoption of EVs in certain sectors.
- Charging Infrastructure Investment: The significant investment required for the development of EFV charging infrastructure is highlighted as a notable disadvantage in comparison to the existing fuel infrastructure for ICET, impacting lifetime cost comparisons unfavorably for EFVs [10,20].
- Operational Costs: The operational cost advantage of BETs, attributed to the lower electricity costs compared to ICETs' fuel costs, potentially offsets the disadvantage presented by the higher initial investment costs. This balance is sensitive to projections of electricity and diesel prices, illustrating the economic complexities surrounding EFV adoption [2,7,10,21].
- Country-Specific Factors: Variations in factor costs, such as energy prices and infrastructure investments, across different countries lead to significant disparities in the economic break-even point between BETs and ICETs, suggesting that the viability of EFVs is contextually dependent on the national circumstances [2].
- Range and Charging Limitations: The operational range of EFVs on a single charge, particularly for long-distance transportation, and the prolonged charging times of BETs are identified as critical barriers to their widespread use [9,13,22–24]. These operational challenges necessitate advancements in battery technology and charging infrastructure to make EFVs more competitive.
- Battery Weight and Payload: The increased weight of batteries in BETs compared to diesel tanks in ICETs results in a payload loss, which is considered a disadvantage for the adoption of BETs. This highlights the need for technological innovations to improve the energy density of batteries [7,22].
- Route Planning Constraints: The introduction of BETs introduces additional constraints in route planning, including the battery range and the availability of charging stations. This necessitates a reevaluation of logistical strategies to accommodate these new variables [25].
- Technological Advancements: The promise of improvements in battery technology, including an increased range and reduced TCO through mass production, is seen as a key factor that could enhance the attractiveness of BETs [16].
- Service and Maintenance: The quality of service maintenance is an influential factor in the purchasing decisions regarding BETs, with expectations for service quality to match that of ICETs [7,22,26].
- Resale Value Concerns: Uncertainty surrounding the second-hand market value of BETs poses an obstacle to their adoption, impacting the TCO and financial considerations for potential buyers [7,11].
- Environmental Considerations: While BETs offer lower greenhouse gas emissions compared to ICETs, this environmental advantage alone is insufficient to drive widespread adoption. The desire for enhanced public relations and social responsibility is notable among carriers, yet economic and operational factors remain paramount [7,8,10,11,22].
- Long-Term Investment and Uncertainty: The purchasing of BETs is recognized as a long-term investment decision fraught with uncertainty. Despite the strategies and targets set by governments, carriers seek more concrete roadmaps and official legislative guidance to mitigate the risks associated with transitioning to BETs [7,11,12,20].

2.2. EV Fleet Management

The review of the literature on EV fleet management was organized under several categories, including the application areas, methodologies, criteria, applications, and findings. This organized approach facilitated a structured analysis, the details of which are provided in the Electronic Supplementary Information (ESI†) in Tables S1 and S2 [27–46].

In summarizing the literature on EV fleet management, it becomes evident that economic considerations, particularly the TCO, play a crucial role in the decision-making process for EFV procurement. Feng et al. [47] analyzed the factors influencing EV adoption rates under two primary categories: perceived economic utility and perceived social utility. The analysis concluded that the perceived economic utility significantly determines the general propensity to purchase EVs, whereas perceived social utility may marginally elevate this propensity under certain conditions. The literature review illustrates that operational limitations, such as the range achievable on a single charge, act as barriers to the adoption of EFVs when these fall below specific threshold values. Such barriers are critical in the decision-making process and underscore the importance of addressing these challenges to facilitate the broader adoption of EFVs.

Although there is a significant amount of study on EVs, including BETs, for urban passenger and light commercial vehicle use, there is a lack of understanding of the aspects affecting the decision-making process when procuring BETs in the freight transportation industry. Prior research has shown different results and identified multiple important criteria and threshold values that affect the adoption of BETs. However, there is a lack of comprehensive models that combine these distinct aspects into a unified framework. Furthermore, although the current literature discusses specific obstacles such as the initial investment costs, charging infrastructure, and legislative clarity, there is a lack of research that utilizes a systematic methodology to measure and analyze how these barriers interact and influence purchasing decisions in a comprehensive manner. The objective of this study is to address this gap by utilizing a unique combination of fuzzy logic and the Delphi technique. This technique not only connects subjective assessments with quantitative analysis but also provides a comprehensive framework for the decision-making process in relation to BET procurement.

3. Research Methodology

This article develops a model for BET purchasing decisions by employing a combination of fuzzy logic and the Delphi method. Below, we elaborate on the methodologies applied.

3.1. Delphi Method

The Delphi method facilitates the derivation of a consensus among a group of experts through controlled feedback, ensuring the reliability of the collective judgment [48]. This study opted for the Delphi technique due to several compelling reasons. Unlike approaches that rely on a singular perspective, the Delphi method leverages the collective expertise of a panel, mitigating the risk of biased or erroneous individual opinions. Traditional roundtable discussions can be skewed by dominant voices, potentially compromising objectivity. The Delphi method circumvents this issue by ensuring anonymity; participants are exposed to others' responses without identifying information, allowing for unbiased self-reflection and evaluation [49]. The logistics of assembling experts in a single location, considering geographic dispersion, time, and financial constraints, further validate the preference for Delphi over face-to-face engagements [50]. While other crowdsourcing methods may involve a broader participant base, including laypersons, Delphi method's efficacy with a select group of experts is well documented across various fields [51].

The Delphi method is characterized by three principal features [52].

- Confidentiality/Anonymity: The identities of the contributing experts remain confidential, ensuring unbiased contributions.
- Sequentiality: The method involves multiple rounds of surveys, enhancing the depth and breadth of the consensus.

- Controlled Feedback/Statistical Group Reaction Analysis: This distinct aspect of the Delphi method facilitates consensus-building through iterative feedback and learning among participants.

The selection and diversity of experts are crucial for the success of the Delphi method. A panel comprising a wide range of perspectives is preferred, as heterogeneity among panelists enriches the discussion, leading to more nuanced and comprehensive outcomes [53]. To achieve a diverse panel, experts were chosen from various sectors, including industry, academia, and governmental bodies [54]. However, the Delphi method is not without its criticisms, particularly regarding the selection of experts. The variation in expertise levels across the survey's scope may lead to challenges, especially if the panel membership changes or if new experts are introduced in subsequent rounds [55].

For this study, the expert panel was carefully generated to encompass a broad spectrum of knowledge and experience relevant to BET decision-making. This included four senior managers from Turkey's leading international freight forwarding companies, ensuring industry insight. To capture the broader perspective of potential BET purchasers, including those managing their own fleets, senior managers from prominent logistics associations were also included. Additionally, two academics with extensive experience in logistics were invited to the panel to provide an academic viewpoint on industry trends and changes.

The inclusion of senior managers from international freight forwarders, along with top executives from logistics associations and seasoned academics, established a high-caliber, heterogeneous expert panel. To maintain consistency and avoid any disruption in the consensus-building process, no new members were introduced after the commencement of the study. The composition of the Delphi expert group is detailed in Table 1, reflecting a deliberate effort to ensure a balanced representation of all relevant stakeholders in the BET purchasing decision process.

Table 1. Expert group for Delphi study.

Stakeholder Group	Type of Organization/Department	Expert Position
Industry	International Freight Forwarder	Chief Executive Chairman
Industry	International Freight Forwarder	Director of Overseas Highways
Industry	International Freight Forwarder	Purchasing General Manager
Industry	International Freight Forwarder	Deputy General Manager
Academic	University/Transportation Technologies and Research Center	Professor
Academic	University/International Trade and Logistics Department	Professor
Policy Planner	Logistics Associations	Chief Executive Chairman
Policy Planner	Logistics Associations	Vice Chairman of the Board of Directors

3.2. Fuzzy Logic

We selected fuzzy logic as a methodological tool for this research due to its unique ability to model and quantify uncertain perceptions within the procurement decision-making process. This approach enables the transformation of subjective judgments and qualitative evaluations into a structured mathematical framework.

The foundational concept of fuzzy logic, introduced by Lotfi Zadeh through his seminal paper on 'Fuzzy Sets' in 1965 [56], revolutionized how we approach decision-making processes that involve ambiguity and uncertainty. Zadeh's innovative application of natural language terms to represent and manipulate data within fuzzy sets laid the groundwork for what is now known as fuzzy logic. Unlike classical binary logic, which is rigid in its classification of events as either true or false—akin to black and white—fuzzy logic introduces a gradient of possibility, acknowledging that real-world scenarios often embody elements of both truth and falsehood simultaneously [57,58].

In the context of purchasing decisions, alternatives are evaluated based on a spectrum of factors that are perceived differently by each buyer. Fuzzy logic is inherently equipped to handle this diversity in perception, allowing for the characterization of buyers' uncertain perceptions through varying degrees of membership. This variability is essential, as buyers frequently employ linguistic terms—such as "highly reliable", "moderately expensive", or "somewhat efficient"—to articulate their preferences and assessments. Fuzzy logic facilitates the translation of these qualitative descriptions into a quantitative analysis by associating linguistic variables with a range of membership degrees. This process enables the computation of quantitative outcomes based on the established rules of fuzzy logic [59].

The application of fuzzy logic in this research extends beyond mere theoretical significance. It provides a pragmatic tool to deal with the complexities inherent in procurement decisions, where multiple factors and subjective perceptions must be balanced. By employing fuzzy logic, this study offers a particular approach to understanding and modeling the decision-making process, capturing the nuances of human judgment and the inherent ambiguities of purchasing decisions. Through this methodology, the research aims to provide a more accurate and comprehensive analysis of the factors influencing the adoption and procurement of BET, translating the intricate structure of buyer perceptions and preferences into actionable insights [47].

4. Results

In this analysis, the focus is narrowed to considering only BETs as the principal alternative to ICETs in the freight vehicle market. This decision is predicated on the current landscape of the transportation industry in Europe, where ICETs are the predominant choice for logistics and freight operations [60]. The rationale behind highlighting BETs as the sole significant alternative to ICETs stems from several key developments within the automotive sector. These include notable advancements in EV technologies, particularly in the domain of battery efficiency and capacity, alongside significant investments in both the production of EVs and the infrastructure supporting their operation. The shift towards BETs is further supported by the growing emphasis on sustainability and environmental stewardship within the transportation industry, aligning with global efforts to reduce carbon emissions and mitigate climate change's impacts. Consequently, while other alternative fuel types exist, BETs are singled out in this study due to their emerging prominence and potential to fundamentally transform the logistics and freight transportation paradigm, positioning them as the most viable and strategic alternative to conventional ICETs in the foreseeable future [22].

The literature review conducted as part of this research underscored the pivotal role of economic factors in the decision-making process when purchasing freight vehicles. These factors, which include but are not limited to the TCO, operational and maintenance costs, and fuel or energy consumption, are identified as primary considerations that significantly influence the choice between BET and ICET. It is evident from the synthesis of the available studies that the economic viability of BETs, when considered over the life cycle of the vehicle, plays a crucial role in determining their adoption rate within the industry.

In addition to economic considerations, social factors also play a role in influencing the purchasing decision regarding BETs. The increasing societal awareness regarding environmental issues and the social responsibility of businesses to contribute to sustainable practices add an important dimension to the decision-making process. While the direct impact of social factors on the purchasing ratio of BETs may be limited, they nonetheless contribute to creating a favorable context for the adoption of EVs. This includes considerations such as corporate image enhancement, compliance with environmental regulations, and the potential to leverage BET adoption in marketing strategies to appeal to environmentally conscious consumers.

4.1. Specifying Problem and Defining Linguistic Variables

In this study, the factors influencing BET purchasing decisions are categorized and discussed under the following themes: (1) barriers, (2) perceived economic utility, and (3) perceived social utility. This structured approach provides a comprehensive understanding of the multidimensional considerations impacting the adoption of BETs in the freight transportation sector.

4.1.1. Determining Input and Output Variables

To ensure a comprehensive understanding and approach to the problem, individual online meetings were organized with each expert team member, during which summaries of the literature were shared and discussed. It was established early in these discussions that the primary output variable of interest would be the BET purchasing ratio within Turkey, aiming to quantify the adoption rate of BETs in comparison to traditional ICETs.

Barriers

The initial focus of the Delphi method's first round was on identifying barriers that could potentially hinder the adoption of BETs. The experts were presented with a series of factors derived from the literature review, inviting their insights on whether these factors should be included, revised, or expanded upon within the model as barriers. The following factors were discussed:

- The driving range of BETs [9,13,22,23];
- The disparity in the number of charging stations and gas stations [10–13,20];
- The service maintenance quality specific to BETs [7,22,26];
- The clarity and effectiveness of legislation relevant to BETs [7,11,12,20].

These four factors were unanimously approved to be included in the model as significant barriers, with no additional barriers suggested for inclusion.

Economic Factors

Acknowledging the literature review's findings, economic factors were addressed as a critical determinant influencing the BET purchasing decision. The experts were asked to evaluate and provide feedback on a list of economic factors, deliberating on their inclusion, removal, or modification within the model:

- The TCO ratio between BET and ICET [5,6,12–19];
- The TT ratio between BET and ICET [9,24].

The discussion acknowledged that BET batteries, due to their lower energy density, are heavier, leading to payload loss—an important consideration for the TCO calculation of BETs. Thus, a consensus was reached to include payload loss due to the battery weight in the TCO evaluation, alongside the previously mentioned factors, without suggesting any additional economic factors.

Social Factors

The dialogue around social factors encompassed the perception and positioning of BETs within the broader context of corporate social responsibility and public relations. The experts were presented with three topics from the literature for discussion:

- A corporate inclination towards BETs as part of a positive public relations strategy [7,8,10,11,22];
- Purchasing decision-makers' environmental sensitivity and its impact on BET adoption [7,8,10,22];
- Anticipated legal regulations (including incentives, penalties, and restrictions) driven by environmental considerations in the EU and Turkey [20].

It was collectively decided that the expected legal regulations, initially considered under social factors, should instead be categorized as economic factors, particularly within the TCO calculations under incentives and penalties. Consequently, these regulations were reclassified, and the remaining two factors were affirmed for inclusion, without any further additions.

The finalized structure of the BET purchasing decision model, along with the defined factors, emerged from a comprehensive consensus among all expert group members, as illustrated in Figure 1. This model serves as a foundational framework to understand the dynamics and considerations influencing the adoption of BETs in Turkey, incorporating barriers, economic factors, and social influences as key determinants.

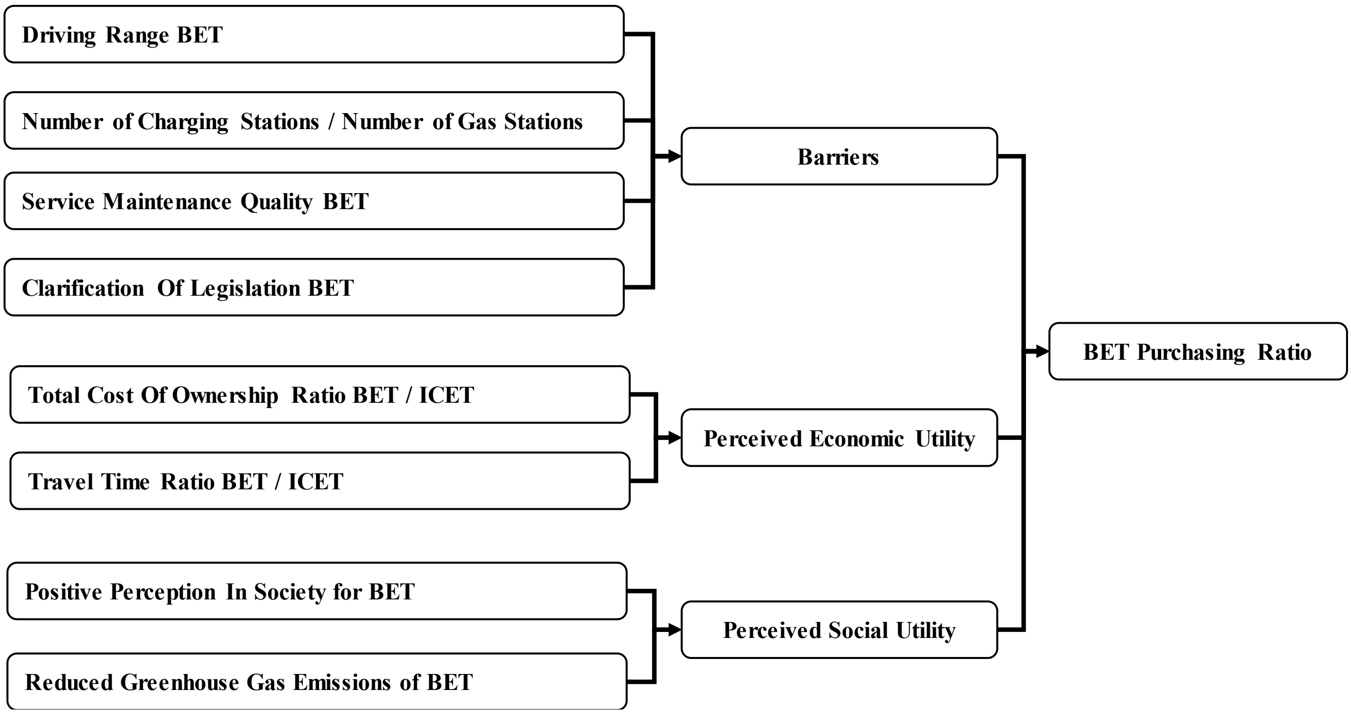


Figure 1. Determinants of BET purchasing decision.

The terms used in Figure 1 are defined below.

- *BET Purchasing Ratio:* The proportion of BETs among all new truck sales, indicating the market penetration of BETs compared to traditional trucks.
- *Barriers:* Elements that could potentially hinder the adoption of BETs by acting as impediments or deterrents.
- *Driving Range of BETs:* The maximum distance (in kilometers) that a BET can travel on a full charge, a critical factor in assessing the vehicle's operational feasibility.
- *Number of Charging Stations:* The total count of EV charging stations, reflecting the infrastructure's capability to support BET operations.
- *Number of Gas Stations:* The total count of gasoline and diesel fuel stations in Turkey, indicative of the existing refueling infrastructure for ICETs.
- *Service Maintenance Quality for BETs:* The extent to which BETs can match ICETs in terms of service maintenance, including aspects such as roadside assistance and the availability of service points, ensuring comparable post-sale support.
- *Clarification of Legislation for BETs:* The degree to which legislation relevant to BETs, including incentives and regulatory frameworks, is clearly published and enforced, influencing the legal and operational landscape for BET adoption.
- *Perceived Economic Utility:* The subjective evaluation by purchasers of the economic benefits and drawbacks associated with BETs versus ICETs, encompassing costs, savings, and financial incentives.
- *TCO for BETs:* The comprehensive cost calculated for the ownership of a BET, incorporating the initial purchase cost, value-added tax (VAT), excise duty, maintenance expenses, insurance fees, motor vehicle tax, total electricity costs, and additional costs attributable to payload loss, minus any incentives and resale value. Payload loss is included in the TCO calculation through the following formula: payload loss = (electricity cost BET + maintenance cost BET) * (payload capacity ICET/payload capacity BET—1).

- *TCO for ICETs:* The aggregate cost of owning an ICET, including the purchase price, VAT, excise duty, maintenance costs, insurance fees, motor vehicle tax, total diesel fuel expenses, and penalties, offset by the vehicle's sales revenue.
- *TCO Ratio (BET/ICET):* A comparative metric evaluating the TCO of a BET against an ICET, offering insights into the relative economic efficiency of adopting BETs.
- *TT Ratio (BET/ICET):* The ratio comparing the total travel time of BETs, inclusive of driving and charging times, to that of ICETs, considering driving and refueling times, highlighting operational efficiency differences.
- *Positive Perception in Society of BETs:* The degree to which companies adopt BETs in their fleets as part of a positive public relations strategy, reflecting societal approval and corporate responsibility.
- *Reduced Greenhouse Gas Emissions of BETs:* The favorable view of individuals and decision-makers towards purchasing BETs, motivated by environmental concerns and the potential for significant reductions in greenhouse gas emissions compared to ICETs.

4.1.2. Defining Linguistic Variables

Social Factors

Linguistic expressions for social factors were not directly determined, acknowledging that while social factors influence the BET purchasing decision, it is primarily driven by economic considerations.

The experts were asked about how the perceived social utility might augment the BET purchasing ratio, influenced chiefly by economic utility. Three response options were provided, "no effect", "moderate effect", and "high effect", with corresponding mathematical percentages requested for the latter two. The consensus set the effects at 10% for a "moderate effect" and 20% for a "high effect". The "moderate effect" was unanimously chosen for both the "positive perception in society for BETs" and the "reduced greenhouse gas emissions of BETs" factors, leading to the formulation of the perceived social utility equation as the sum of these two factors.

Economic Factors

Given the leading importance of economic utility in the BET purchasing decision, fuzzy logic was employed to encapsulate and measure this dimension.

- *TCO Ratio BET/ICET:* To quantify subjective perceptions of the TCO ratio, the experts were initially asked to map these perceptions to linguistic terms ranging from "very low" to "very high". In the subsequent Delphi round, feedback on these terms was refined using quartile data from the collective responses. This iterative process culminated in the second round with agreement on the linguistic terms, adopting median values for the model. The specific linguistic values for the TCO ratio are detailed in Table 2. Figure A1 in Appendix A presents the membership function formulas for the TCO ratio.
- *TT Ratio BET/ICET:* The experts were asked to associate their perceptions of the travel time ratio with the terms "medium", "high", and "very high", deliberately excluding "low" and "very low" due to the presupposition that the BET charging times would not be shorter than the ICET refueling times. The second Delphi round adjusted these values based on quartile feedback, reaching a consensus and adopting the median values for inclusion in the model. The agreed-upon linguistic expressions for the TT ratio are provided in Table 3. The TT ratio membership function formulas are listed in Figure A2 in Appendix A.
- *Perceived Economic Utility:* The expert group deliberated on appropriate linguistic terms to describe the perceived economic utility, achieving a consensus in the second Delphi round. The agreed linguistic expressions are enumerated in Table 4, providing a nuanced framework for an understanding of the economic considerations influencing

BET adoption. The membership function formulas for the perceived economic utility are shown in Figure A3 in Appendix A.

Barriers

Barriers were defined as limit values rather than specific linguistic expressions. These limit values, as determined by consensus within the expert group, represented the critical points below which BETs ceased to be a viable option in the truck purchasing decision process.

- *Clarification of Legislation for BETs:* The expert group agreed that the pivotal limit for this factor was the comprehensive publication and implementation of all regulations and procedures pertinent to the purchasing, usage, and charging infrastructure for BETs.
- *Service Maintenance Quality for BETs:* A unanimous agreement was reached that achieving parity in service maintenance quality with ICETs represented the essential limit value for this factor.
- *Driving Range for BETs:* During the first Delphi round, the focus was on identifying the desirable driving range. The second round involved sharing the quartile values (Q1, median, Q3) from the initial round with each expert, prompting a reevaluation of the driving range. With a consensus achieved in the second round, the median value of 500 km was selected for inclusion in the model.
- *Ratio of Charging Stations to Gas Stations:* Initially, the experts were asked to evaluate the ratio of charging to gas stations. Following a similar procedure to the driving range assessment, a consensus in the second round led to the adoption of the median ratio of 0.50 in the model.

4.2. Determining Fuzzy Sets

Various geometrical shapes can be employed to represent fuzzy sets, each with their own advantages in modeling expert knowledge and facilitating computational processes. Among these, the triangular shape is particularly valued for its ability to significantly streamline calculations without compromising the accuracy in representing expert insights [57]. Due to its balance between computational simplicity and effective knowledge representation, a triangular configuration was chosen as the preferred shape for the fuzzy sets within this study. This decision aimed to optimize the efficiency of the computations while accurately capturing and applying the nuanced understanding of the experts in the model.

Table 2. Linguistic scales of term set for TCO ratio BET/ICET (represented by c).

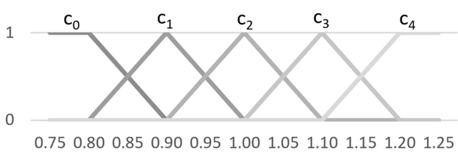
Linguistic Variable	Triangular Fuzzy Number	Figure of Membership Function
c_0 = very low	(0, 0.8, 0.9)	
c_1 = low	(0.8, 0.9, 1.0)	
c_2 = medium	(0.9, 1.0, 1.1)	
c_3 = high	(1.0, 1.1, 1.2)	
c_4 = very high	(1.1, 1.2, ∞)	

Table 3. Linguistic scales of term set for TT ratio BET/ICET (represented by t).

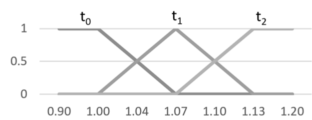
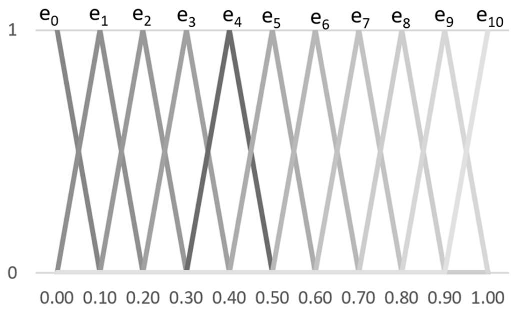
Linguistic Variable	Triangular Fuzzy Number	Figure of Membership Function
t_0 = medium	(0, 1.0, 1.07)	
t_1 = high	(1.0, 1.07, 1.13)	
t_2 = very high	(1.07, 1.13, ∞)	

Table 4. Linguistic scales of term set for perceived economic utility (represented by e).

Linguistic Variable	Triangular Fuzzy Number	Figure of Membership Function
e_0 = zero percent	(0, 0.0, 0.1)	
e_1 = very very low	(0, 0.1, 0.2)	
e_2 = extremely low	(0.1, 0.2, 0.3)	
e_3 = very low	(0.2, 0.3, 0.4)	
e_4 = low	(0.3, 0.4, 0.5)	
e_5 = medium	(0.4, 0.5, 0.6)	
e_6 = high	(0.5, 0.6, 0.7)	
e_7 = very high	(0.6, 0.7, 0.8)	
e_8 = extremely high	(0.7, 0.8, 0.9)	
e_9 = very very high	(0.8, 0.9, 1.0)	
e_{10} = hundred percent	(0.9, 0.9, 1.0)	

4.3. Construction of Fuzzy Rules

During the third Delphi round, the members of the expert panel were tasked with estimating the purchasing ratio of BETs in Turkey across all possible pairings of linguistic expressions for the TCO ratio and the TT ratio. This exercise aimed to assess the combined impact of economic and operational factors on the likelihood of BET adoption.

To refine these predictions and ensure a robust consensus, the fourth Delphi round involved a detailed review process. Each expert was presented with the quartile data (Q1, median, Q3) compiled from the collective forecasts of the group, alongside their individual contributions from the previous round. This method facilitated a reflective evaluation, encouraging the experts to review their estimates considering broader group insights and any divergence in perspectives.

The iterative Delphi process concluded after the fourth round, with a consensus emerging among the expert group regarding the formulation of the fuzzy rules. These rules, representing a synthesized agreement on how various TCO and TT linguistic expressions influence the BET purchasing ratio, are encapsulated and presented in Table 5. This culmination of expert deliberation provides a comprehensive framework for an understanding of the nuanced interplay between economic feasibility and operational efficiency in shaping the adoption of BETs in Turkey.

Table 5. Fuzzy rules.

Rule	IF	AND	THEN
	TCO Ratio BET/ICET	**TT Ratio BET/ICET**	**Perceived Economic Utility**
1	very low (c_0)	medium (t_0)	very very high (e_9)
2	very low (c_0)	high (t_1)	very very high (e_9)
3	very low (c_0)	very high (t_2)	extremely high (e_8)
4	low (c_1)	medium (t_0)	extremely high (e_8)
5	low (c_1)	high (t_1)	very high (e_7)
6	low (c_1)	very high (t_2)	high (e_6)
7	medium (c_2)	medium (t_0)	high (e_6)
8	medium (c_2)	high (t_1)	medium (e_5)
9	medium (c_2)	very high (t_2)	low (e_4)
10	high (c_3)	medium (t_0)	very low (e_3)
11	high (c_3)	high (t_1)	extremely low (e_2)
12	high (c_3)	very high (t_2)	very very low (e_1)
13	very high (c_4)	medium (t_0)	extremely low (e_2)
14	very high (c_4)	high (t_1)	very very low (e_1)
15	very high (c_4)	very high (t_2)	very very low (e_1)

In the evaluation of conditions where multiple criteria intersect, particularly for the "AND" operation within fuzzy logic, the product method is selected as the preferred approach due to its ability to accurately reflect the conjunctive relationships between factors. This method multiplies the membership values of the involved fuzzy sets, thereby capturing the interactions between different variables in a nuanced and mathematically sound manner.

Consider an example involving the TCO ratio and the TT ratio, denoted as (x) and (y), respectively. Let us say that (x), the TCO ratio, has a membership value of 0.4. Similarly, (y), the TT ratio, holds a membership value of 0.6. When these two factors, (x) (TCO ratio) and (y) (TT ratio), are analyzed conjointly to determine their combined effect on the perceived economic value of a BET, denoted as (z), the "AND" operation is conducted as follows:

IF	x is c2	(0.4)
AND	y is t1	(0.6)
THEN	z is e5	(0.24)

$$\mu_{e5}(z) = \mu_{c2}(x) \times \mu_{t1}(y) = 0.4 \times 0.6 = 0.24.$$

This result, 0.24, represents the combined membership degree for the perceived economic utility based on the intersection of the TCO and TT criteria. By applying the product method, we achieve a nuanced understanding of how these two factors jointly influence the economic attractiveness of BETs, enabling a more informed and comprehensive analysis.

4.4. Encoding Fuzzy Sets, Fuzzy Rules, and Procedures to Perform Fuzzy Inference in Expert System

Fuzzy sets serve the critical function of transforming input variables into outputs within the framework of fuzzy inference, enabling nuanced decision-making that accommodates uncertainty and gradation. While Mamdani-style inference is widely recognized for its intuitive nature and ease of understanding, it calculates the centroid of a two-dimensional shape to determine the output values. This process, although effective, tends to be computationally demanding due to its requirement for integration over the shape to find the centroid, potentially slowing down the inference process in complex systems.

In contrast, Sugeno (or Takagi–Sugeno–Kang) inference, introduced by Sugeno in 1985, streamlines this computation by adopting a simpler approach to defining the output of fuzzy rules. Instead of a variable function, Sugeno inference uses a fixed single spike (a singleton) as the membership function for the consequent of a rule [61]. This method simplifies the calculation of the system's output, making it computationally more efficient, especially for control systems and modeling applications where speed and precision are paramount.

The implementation of fuzzy rules in the zero-order Sugeno fuzzy model adheres to the structure IF (x) is (A), AND (y) is (B), THEN (z) is (k), where (k) is a constant value. This formulation stipulates that the output of each fuzzy rule is a constant, enabling the straightforward aggregation of these outputs. The crisp, or precise, output is then determined through the calculation of the weighted average of these singletons [57], taking into account the degree of matching (or firing strength) of each rule.

In this research, the Sugeno style of inference was chosen to conduct fuzzy inference, due to its computational efficiency and effectiveness in handling the complexities of modeling perceived economic utility. The formula for the calculation of perceived economic utility within this framework was established on the basis of Sugeno inference, allowing for a precise and expedient evaluation of the economic factors that influence the decision-making process.

$$\begin{aligned}\text{Perceived Economic Utility} = {} & [\mu_{e0}(z) \times e_0 + \mu_{e1}(z) \times e_1 + \mu_{e2}(z) \times e_2 + \\ & \mu_{e3}(z) \times e_3 + \mu_{e4}(z) \times e_4 + \mu_{e5}(z) \times e_5 + \mu_{e6}(z) \times e_6 + \mu_{e7}(z) \times e_7 + \mu_{e8}(z) \times e_8 + \\ & \mu_{e9}(z) \times e_9 + \mu_{e10}(z) \times e_{10}]/[\mu_{e0}(z) + \mu_{e1}(z) + \mu_{e2}(z) + \mu_{e3}(z) + \mu_{e4}(z) + \mu_{e5}(z) + \\ & \mu_{e6}(z) + \mu_{e7}(z) + \mu_{e8}(z) + \mu_{e9}(z) + \mu_{e10}(z)]\end{aligned} \tag{1}$$

4.5. BET Purchasing Ratio

For BETs to be considered a viable option in the truck purchasing decision-making process, it is imperative that they surpass the established limit values for each identified barrier. These barriers act as preliminary filters, ensuring that only those BETs meeting the necessary criteria can be evaluated further for potential adoption. Once these thresholds are exceeded, the decision to purchase a BET is influenced primarily by the perceived economic utility, complemented by the impact of perceived social utility.

Perceived economic utility emerges as the cornerstone in determining the likelihood of choosing BETs over traditional options. This factor encapsulates the financial rationale behind the decision, considering the costs and benefits from a long-term ownership perspective. It quantifies the economic attractiveness of BETs, underlining the importance of cost-effectiveness and financial incentives in swaying purchasing decisions.

Perceived social utility, on the other hand, enhances the purchasing ratio of BETs by adding value through societal and environmental considerations. While its influence is secondary to that of economic utility, perceived social utility amplifies the appeal of BETs by aligning with broader social and environmental goals, such as reducing carbon footprints and promoting sustainability. This factor acknowledges the growing importance of corporate social responsibility and public perception in business decisions, especially those related to environmental impacts.

Accordingly, the BET purchasing ratio can be modeled through an equation that integrates these considerations, illustrating the symbiotic relationship between economic and social utility in influencing purchasing decisions. The formula is given by Equation (2):

$$\text{BET Purchasing Ratio} = \text{Perceived Economic Utility} \times (1 + \text{Perceived Social Utility}) \quad (2)$$

This equation reflects the nuanced interplay between the economic and social factors, where the base economic utility of BETs is enhanced by the additional value derived from their perceived social benefits. Through this formulation, it becomes evident that while economic considerations lay the foundation for the adoption of BETs, the incorporation of social utility factors can significantly elevate their attractiveness and adoption rate within the market.

An illustrative example is provided in Appendix B to demonstrate the application of the model.

5. Discussion

The results of our study underscore the pivotal roles of economic and social considerations in the decision-making framework for the acquisition of BETs within the freight vehicle sector. This agrees with the previous literature, which highlights the TCO, as well as operational and maintenance expenses, as the primary influence on vehicle selection in logistics operations.

Our findings support the premise that the economic feasibility of BETs has a significant impact on their market acceptance. In accordance with the findings of Nykvist and Nilsson [62], we acknowledge that reducing the costs of batteries could potentially make BETs economically competitive with traditional ICETs in the near future. Moreover, Nurhadi [63] highlights that when the total life cycle costs—including significant savings in fuel and maintenance—are considered, BETs emerge as economically advantageous despite their higher initial purchase prices. Our findings extend this analysis by incorporating the economic implications of payload loss due to the battery weight in the TCO calculation, providing a more specific insight into the economic challenges faced by BETs in freight operations. Looking ahead, the ongoing advancements in battery technology and energy density are likely to mitigate these payload issues [64], potentially enhancing the economic attractiveness of BETs. However, the volatility of raw material prices and the scalability of battery production remain as potential economic challenges that could influence the future trajectory of BET adoption [65].

It has been estimated that, when mass produced, battery electric vehicles will provide a significant cost advantage over their competitors, including diesel and hydrogen fuel cell vehicles, in a comparison of tractors for semi-trailers [16]. On the other hand, it has been stated that, based on a technical and economic analysis, hydrogen fuel cell electric vehicles' weight and costs are much less sensitive to an increased range than batteries. Therefore, hydrogen fuel cell electric trucks are identified as a promising technology for future truck decarbonization scenarios [66]. Although hydrogen fuel cell electric vehicles (HFCEVs) represent a promising technology for long-haul transportation, they were excluded from this study due to their current developmental stage. However, it is important to recognize that future advancements in technology could position HFCEVs as a significant alternative in the transportation sector.

Our analysis also reveals the substantial impact of social factors, particularly the increasing public and corporate awareness of environmental issues. Although the direct impact of these social factors on BET purchasing decisions may be moderate, they contribute significantly to creating a favorable environment for the adoption of electric vehicles. As societal expectations continue to evolve, companies may face increasing pressure to demonstrate real progress in sustainability, not merely in vehicle acquisition but across all operations. Additionally, advancements in corporate social responsibility strategies and public relations campaigns could further enhance the marketability and societal acceptance of BETs [67].

The identified barriers to BET adoption include the limited driving range, the imbalance in the number of charging versus gas stations, and concerns about the service maintenance quality and legislative clarity. These issues align with the challenges documented in the literature [68–70], recognized as significant obstacles that could impede the transition from ICETs to BETs. Addressing these barriers is essential in securing the viability and competitiveness of BETs in the freight sector. Future advancements in charging infrastructure and regulatory frameworks are anticipated to mitigate these barriers. For instance, the development of ultra-fast charging technology and the expansion of charging networks could decrease range concerns. Similarly, clearer and more favorable legislation could accelerate BET adoption by providing stronger incentives for businesses to transition their fleets. Additionally, ongoing improvements in service networks and maintenance training specifically tailored to BETs will be crucial to ensure that they can compete with ICETs in terms of operational reliability and serviceability.

Driver satisfaction was not incorporated into the model, as evidenced in Table S2, where the predominant criteria across most studies focused on economic and social factors. While driver satisfaction plays a significant role in the purchase of passenger vehicles, its impact on the decision to purchase BETs appears to be limited. Most users report satisfactory technical performance for BETs, and the quietness of the vehicle is often highlighted as a positive feature [7]. Several operators have noted that BETs offer a pleasant, comfortable, and enjoyable driving experience [16]. However, range anxiety is cited as a primary source of stress among drivers [16,28]. It has been observed that some group members appreciate using electric vehicles, whereas others express dissatisfaction with how these vehicles are introduced or operated within their organizations. Both groups have expressed frustration over the lack of prior information during the initial implementation phase [28]. Although driver satisfaction is not a principal factor in purchasing decisions for BETs, involving drivers in the planning process is crucial for smooth implementation and to address potential concerns effectively.

6. Conclusions

This study contributes significantly to the understanding of the factors influencing the adoption of BETs in the freight transportation sector. By employing fuzzy logic and the Delphi method, it provides a comprehensive model that captures the complex decision-making process involved in the procurement of BETs. The study emphasizes the role of economic and social utility in influencing purchasing decisions, focusing on the interaction between cost concerns and the perceived value of environmental sustainability.

For industry experts and policymakers, this study provides important insights into the constraints and drivers of BET adoption. The findings highlight the importance of addressing both the economic feasibility and the social/environmental attractiveness of BETs in order to increase their market adoption. Managers in the transportation and logistics industries can use this model to assess the possible benefits and obstacles to incorporating BETs into their fleets, taking into account the TCO, operational efficiency, and societal implications. Furthermore, policymakers can extract guidelines for the development of policies and incentives that are consistent with the goal of expediting the transition to sustainable transportation solutions.

This work theoretically enhances the use of fuzzy logic in transportation research by showcasing its effectiveness in modeling complex decision-making processes that entail a significant level of ambiguity and subjective assessment. This study enhances the existing body of knowledge on sustainable transportation by offering a systematic method of understanding the elements that impact the adoption of EVs in corporate settings. In addition, the combination of fuzzy logic and the Delphi method introduces a new approach for future research in this field, providing a strong foundation for an understanding of the complex nature of procurement decisions.

Although this study provides important insights into the BET procurement process, it has several limitations. The model's dependence on expert judgment, while useful, may introduce biases that could impact the generalizability of the findings. Moreover, the ever-changing nature of technology and policy environments implies that the elements that influence the adoption of BET are subject to change, which could affect the model's applicability in the future. The study's focus on Turkey as a case study also limits its direct relevance to other geographical contexts with different legislative, economic, and infrastructural conditions.

Future scholarly work should focus on longitudinal analyses to monitor the evolving economic landscape of BETs and the impact of policy measures across diverse geographical regions. Such studies would enrich our understanding of the sustainability and enduring viability of BETs as a predominant option in freight transportation.

Future studies are needed to broaden the model's scope and address its limitations in multiple ways. Including multiple countries with different transportation ecosystems in the research would improve the understanding of the contextual factors that influence the adoption of BETs, offering a more comprehensive global perspective. It is essential to continuously monitor the progress in battery technology and EV infrastructure. Future studies could investigate the effects of these advancements on the financial and functional feasibility of BETs, potentially altering the factors that influence procurement choices. Additionally, future research might prioritize investigating the influence of regulations and incentives on the adoption of BETs, offering evidence-based suggestions for policymakers seeking to facilitate the shift towards sustainable freight transportation.

One potential approach is to utilize the established fuzzy logic model as a basis for a system dynamics simulation. This methodology would enable the examination of multiple scenarios including diverse characteristics, providing a valuable understanding of how changes in technology, laws, and market conditions could impact the adoption rates of BETs in the long run.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16093801/s1, Table S1: EV Fleet Management Literature Summary, Table S2: Electric Vehicle Fleet Management Criteria Literature Summary, Table S3: EFV Adoption Literature Summary.

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Appendix A. Fuzzy Rules

Linguistic Variable	Functions
c_0 = very low	$\mu_{c0}(x) = \begin{cases} 1 & \text{if } x \le 0.8 \\ \dfrac{0.9 - x}{0.9 - 0.8} & \text{if } x \in (0.8, 0.9) \\ 0 & \text{if } x \ge 0.9 \end{cases}$
c_1 = low	$\mu_{c1}(x) = \begin{cases} 0 & \text{if } x \le 0.8 \\ \dfrac{x - 0.8}{0.9 - 0.8} & \text{if } x \in (0.8, 0.9) \\ \dfrac{1.0 - x}{1.0 - 0.9} & \text{if } x \in (0.9, 1.0) \\ 0 & \text{if } x \ge 1.0 \end{cases}$
c_2 = medium	$\mu_{c2}(x) = \begin{cases} 0 & \text{if } x \le 0.9 \\ \dfrac{x - 0.9}{1.0 - 0.9} & \text{if } x \in (0.9, 1.0) \\ \dfrac{1.1 - x}{1.1 - 1.0} & \text{if } x \in (1.0, 1.1) \\ 0 & \text{if } x \ge 1.1 \end{cases}$
c_3 = high	$\mu_{c3}(x) = \begin{cases} 0 & \text{if } x \le 1.0 \\ \dfrac{x - 1.0}{1.1 - 1.0} & \text{if } x \in (1.0, 1.1) \\ \dfrac{1.2 - x}{1.2 - 1.1} & \text{if } x \in (1.1, 1.2) \\ 0 & \text{if } x \ge 1.2 \end{cases}$
c_4 = very high	$\mu_{c4}(x) = \begin{cases} 0 & \text{if } x \le 1.1 \\ \dfrac{x - 1.1}{1.2 - 1.1} & \text{if } x \in (1.0, 1.1) \\ 1 & \text{if } x \ge 1.2 \end{cases}$

Figure A1. TCO ratio BET/ICET membership function.

Linguistic Variable	Functions	Linguistic Variable	Functions
t_0 = medium	$\mu_{t0}(y) = \begin{cases} 1 & \text{if } y \leq 1.0 \\ \frac{1.07 - y}{1.07 - 1.0} & \text{if } y \in (1.0, 1.07) \\ 0 & \text{if } y \geq 1.07 \end{cases}$	t_2 = very high	$\mu_{t2}(y) = \begin{cases} 0 & \text{if } y \leq 1.07 \\ \frac{y - 1.07}{1.13 - 1.07} & \text{if } y \in (1.07, 1.13) \\ 1 & \text{if } y \geq 1.13 \end{cases}$
t_1 = high	$\mu_{t1}(y) = \begin{cases} 0 & \text{if } y \leq 1.0 \\ \frac{y - 1.0}{1.07 - 1.0} & \text{if } y \in (1.0, 1.07) \\ \frac{1.13 - y}{1.13 - 1.07} & \text{if } y \in (1.07, 1.13) \\ 0 & \text{if } y \geq 1.13 \end{cases}$		

Figure A2. TT ratio BET/ICET membership function.

Linguistic Variable	Functions
e_0 = zero percent	$\mu_{e0}(z) = \begin{cases} 1 & \text{if } z \leq 0.0 \\ \frac{0.1 - z}{0.1} & \text{if } z \in (0, 0.1) \\ 0 & \text{if } z \geq 0.1 \end{cases}$
e_1 = very very low	$\mu_{e1}(z) = \begin{cases} 0 & \text{if } z \leq 0 \\ \frac{z}{0.1} & \text{if } z \in (0, 0.1) \\ \frac{0.2 - z}{0.2 - 0.1} & \text{if } z \in (0.1, 0.2) \\ 0 & \text{if } z \geq 0.2 \end{cases}$
e_2 = extremely low	$\mu_{e2}(z) = \begin{cases} 0 & \text{if } z \leq 0.1 \\ \frac{z - 0.1}{0.2 - 0.1} & \text{if } z \in (0.1, 0.2) \\ \frac{0.3 - z}{0.3 - 0.2} & \text{if } z \in (0.2, 0.3) \\ 0 & \text{if } z \geq 0.3 \end{cases}$
e_3 = very low	$\mu_{e3}(z) = \begin{cases} 0 & \text{if } z \leq 0.2 \\ \frac{z - 0.2}{0.3 - 0.2} & \text{if } z \in (0.2, 0.3) \\ \frac{0.4 - z}{0.4 - 0.3} & \text{if } z \in (0.3, 0.4) \\ 0 & \text{if } z \geq 0.4 \end{cases}$
e_4 = low	$\mu_{e4}(z) = \begin{cases} 0 & \text{if } z \leq 0.3 \\ \frac{z - 0.3}{0.4 - 0.3} & \text{if } z \in (0.3, 0.4) \\ \frac{0.5 - z}{0.5 - 0.4} & \text{if } z \in (0.4, 0.5) \\ 0 & \text{if } z \geq 0.5 \end{cases}$
e_5 = medium	$\mu_{e5}(z) = \begin{cases} 0 & \text{if } z \leq 0.4 \\ \frac{z - 0.4}{0.5 - 0.4} & \text{if } z \in (0.4, 0.5) \\ \frac{0.6 - z}{0.6 - 0.5} & \text{if } z \in (0.5, 0.6) \\ 0 & \text{if } z \geq 0.6 \end{cases}$
e_6 = high	$\mu_{e6}(z) = \begin{cases} 0 & \text{if } z \leq 0.5 \\ \frac{z - 0.5}{0.6 - 0.5} & \text{if } z \in (0.5, 0.6) \\ \frac{0.7 - z}{0.7 - 0.6} & \text{if } z \in (0.6, 0.7) \\ 0 & \text{if } z \geq 0.7 \end{cases}$
e_7 = very high	$\mu_{e7}(z) = \begin{cases} 0 & \text{if } z \leq 0.6 \\ \frac{z - 0.6}{0.7 - 0.6} & \text{if } z \in (0.6, 0.7) \\ \frac{0.8 - z}{0.8 - 0.7} & \text{if } z \in (0.7, 0.8) \\ 0 & \text{if } z \geq 0.8 \end{cases}$
e_8 = extremely high	$\mu_{e8}(z) = \begin{cases} 0 & \text{if } z \leq 0.7 \\ \frac{z - 0.7}{0.8 - 0.7} & \text{if } z \in (0.7, 0.8) \\ \frac{0.9 - z}{0.9 - 0.8} & \text{if } z \in (0.8, 0.9) \\ 0 & \text{if } z \geq 0.9 \end{cases}$
e_9 = very very high	$\mu_{e9}(z) = \begin{cases} 0 & \text{if } z \leq 0.8 \\ \frac{z - 0.8}{0.9 - 0.8} & \text{if } z \in (0.8, 0.9) \\ \frac{1.0 - z}{1.0 - 0.9} & \text{if } z \in (0.9, 1.0) \\ 0 & \text{if } z \geq 1.0 \end{cases}$
e_{10} = hundred percent	$\mu_{e10}(z) = \begin{cases} 0 & \text{if } z \leq 0.9 \\ \frac{z - 0.9}{1.0 - 0.9} & \text{if } z \in (0.9, 1.0) \\ 0 & \text{if } z \geq 1.0 \end{cases}$

Figure A3. Perceived economic utility membership function.

Appendix B. An Illustrative Example

This exemplary application is presented to demonstrate the model's calculations using hypothetical assumptions.

If	(Barrier1 >= Limit1) AND (Barrier2 >= Limit2) AND (Barrier3 >= Limit3) AND (Barrier4 >= Limit4)
Then	BET Purchasing Ratio = Perceived Economic Utility × (1 + Perceived Social Utility)
Else	BET Purchasing Ratio = 0

- **Barriers**

Barriers	Actual	Limit		Result
Barrier 1: Driving Range BET	= 600 km	>=	500 km	Ok
Barrier 2: # of Charging Stations/# of Gas Stations	= 0.6	>=	0.5	Ok
Barrier 3: Service Maintenance Quality BET	Same as ICET	=	Same as ICET	Ok
Barrier 4: Clarification of Legislation BET	Published	=	Published	Ok

As all the barriers are equal or above the limit values, we can calculate the BET purchasing ratio.

- **Perceived Economic Utility**
    - **TCO ratio BET/ICET**

Assume that the trucks will be operated for 1,000,000 km over the next 10 years before being sold in the secondary market.

TCO BET =	PurchasingCost_BET (+180,000)
	+ VAT and ExciseDuty_BET (+50,000)
	+ MaintenanceCost_BET (+30,000)
	+ InsuranceCost_BET (+30,000)
	+ MotorVehicleTax_BET (+10,000)
	+ TotalElectricityCost_BET (+180,000)
	+ PayloadLoss_BET (60,000)
	− SalesRevenue_BET (10,000)
TCO BET =	530,000 USD
TCO ICET =	PurchasingCost_ICET (+150,000)
	+ VAT_ExciseDuty_ICET (+40,000)
	+ MaintenanceCost_ICET (+30,000)
	+ InsuranceCost_ICET (+30,000)
	+ MotorVehicleTax_ICET (+10,000)
	+ TotalDieselCost_ICET (+250,000)
	− SalesRevenue_ICET (−10,000)
TCO ICET =	500,000 USD
TCO Ratio BET/ICET=	530,000 USD/500,000 USD = 1.06

TCO Ratio BET/ICET Membership Function (Figure A1)

$\mu_{c0}(x) = 0$, $\mu_{c1}(x) = 0$, $\mu_{c2}(x) = 0.4$, $\mu_{c3}(x) = 0.6$, $\mu_{c4}(x) = 0$

- **Travel Time Ratio BET/ICET**

Travel Time BET = Driving Time + Charging Time = 9 + 2 = 11 h
Travel Time ICET = Driving Time + Refueling time = 9 + 1 = 10 h
Travel Time Ratio BET/ICET = 11/10 = 1.1

TT Ratio BET/ICET Membership Function (Figure A2)

$\mu_{t0}(y) = 0$, $\mu_{t1}(y) = 0.5$, $\mu_{t2}(y) = 0.5$

Fuzzy Rules (Table 5)

IF	x is c2(0.4), AND y is t1(0.5) THEN z is e5(0.2)	$\mu_{e5}(z) = \mu_{c2}(x) \times \mu_{t1}(y) = 0.4 \times 0.5 = 0.2$
IF	x is c2(0.4), AND y is t2(0.5) THEN z is e4(0.2)	$\mu_{e4}(z) = \mu_{c2}(x) \times \mu_{t2}(y) = 0.4 \times 0.5 = 0.2$
IF	x is c3(0.6), AND y is t1(0.5) THEN z is e2(0.3)	$\mu_{e2}(z) = \mu_{c3}(x) \times \mu_{t1}(y) = 0.6 \times 0.5 = 0.3$
IF	x is c3(0.6), AND y is t2(0.5) THEN z is e1(0.3)	$\mu_{e1}(z) = \mu_{c3}(x) \times \mu_{t2}(y) = 0.6 \times 0.5 = 0.3$

Perceived Economic Utility = $[\mu_{e0}(z) \times e_0 + \mu_{e1}(z) \times e_1 + \mu_{e2}(z) \times e_2 + \mu_{e3}(z) \times e_3 + \mu_{e4}(z) \times e_4 + \mu_{e5}(z) \times e_5 + \mu_{e6}(z) \times e_6 + \mu_{e7}(z) \times e_7 + \mu_{e8}(z) \times e_8 + \mu_{e9}(z) \times e_9 + \mu_{e10}(z) \times e_{10}]/[\mu_{e0}(z) + \mu_{e1}(z) + \mu_{e2}(z) + \mu_{e3}(z) + \mu_{e4}(z) + \mu_{e5}(z) + \mu_{e6}(z) + \mu_{e7}(z) + \mu_{e8}(z) + \mu_{e9}(z) + \mu_{e10}(z)]$
Perceived Economic Utility = $[0.3 \times 0.1 + 0.3 \times 0.2 + 0.2 \times 0.4 + 0.2 \times 0.5]/[0.03 + 0.06 + 0.08 + 0.10] = 0.27$

- **Perceived Social Utility**

Perceived Social Utility = Positive Perception in Society for BET + Reduced Greenhouse Gas Emissions of BET
Positive Perception in Society for BET = 0.1
Reduced Greenhouse Gas Emissions of BET = 0.1
Perceived Social Utility = 0.1 + 0.1 = 0.2

- **BET Purchasing Ratio**

BET Purchasing Ratio = Perceived Economic Utility × (1 + Perceived Social Utility)
BET Purchasing Ratio = 0.27 × (1 + 0.2)
BET Purchasing Ratio = 0.324

Using the hypothetical assumptions outlined above, the model presented in the article predicts a BET sales ratio of 32.4%. This exemplary application is provided solely to demonstrate how the model's calculations are performed.

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