Key Green Performance Indicators (KGPIs) for vehicle cleanliness evaluation: A buyer choice

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Abstract

This paper aims to develop a testing and scoring mechanism, to assess the buyers' behaviours on purchasing green vehicles. As there are various vehicle types with different emission properties presented in the current market, a Key Green Performance Indicator (KGPI) framework is designed to choose vehicles by comparing all the relevant factors affecting consumer choice on green vehicles, including different emission damages, buyer cost, car performance, and other incentives. The novelty of this paper is to combine all the factors to produce a unique single score to present vehicle cleanliness and guide buyer choices. The findings will provide useful information to guide buyers towards the cleanest available vehicles and promote the manufacturing of new cleaner vehicles to the market.

Keywords: Transport sustainability, Prioritizing vehicle cleanliness, Key Green Performance Indicators, Vehicle emission, Evidential reasoning, AHP, Vehicle customer choice, Vehicle cleanliness

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1. Introduction

Despite many efforts on vehicle emission control in the past decade, air quality in cities still needs to be further improved (Carrington, 2016). Air pollution is threatening public health, and governments need to do much more to replace old and dirty diesel vehicles. However, fleet renewal by real zero-emission technologies is facing economic challenges (Petroff and Riley, 2018) and technical difficulties (Vaughan, 2018). Waiting for all vehicles on the road to be replaced by electrified ones will take dozens of years at least. It is essential to develop practical and short-term solutions for reducing the impact of the existing internal combustion fleet (Aggarwal and Jain, 2016). One realistic answer is to provide incentives and guidance to the potential buyers of green vehicles by clarifying their definition of cleanliness (Dhar et al., 2017a).

Transport is recognised as a major source of greenhouse gases (GHG). For example, approximately a quarter of GHG emissions in the UK come from transport (Wassan et al., 2019). Also, transport is a source of pollution emissions, making the quality of ambient air poorer every day. Reducing GHG from transport will help the long-term goal of reducing the UK's GHG emissions by at least 80% of the 1990 level by 2050. For achieving this goal, several policies have been set up. For example, the drivers can get a discount on the price of brand new low-emission vehicles through a grant the government gives to vehicle dealerships and manufacturers. Also, drivers will be charged for driving their vehicles in a low emission zone (LEZ) in Greater London, if the cars cannot meet the emission requirements (Department for Transport, 2019). Therefore, buying a green car becomes a complicate decision.

To assist the decision making, previous studies on vehicle emissions evaluation have been conducted using multiple criteria assessments. For instance, a discrete choice model was established to analyse the relationship between purchasing power and CO2 reduction of vehicles (Achtnicht, 2012). Although showing the interest on the investigation of the effect of car emissions on buyer purchasing behaviour, such studies have not taken all influential factors into account. The factors influencing buyer choice include purchase price, fuel economy and reduction of different pollutions (Shi et al., 2016). To address this research gap, Dhar et al (2017b) proposed an Electric Vehicle Emissions Index (EVEI) into which non-emission factors were first incorporated. However, the investigated factors were not comprehensive, and the index was only applicable to electric vehicles, limiting its applicability on vehicle choice across different types and models in today's market. Furthermore, it is necessary to gather all the key factors from multiple stakeholder perspectives into one framework to understand the dynamics between buyer choice and transport authorities' policies (e.g. incentive).

To tackle this emerging issue, it is necessary to develop a new framework for comparing Internal Combustion Engine Vehicles (ICEV) and Alternative-Fuelled Vehicles (AFV) today available in the market. This paper aims to develop a new framework and undertake a study on a Key Green Performance Indicators (KGPIs) framework to prioritise different types of cars in terms of their cleanliness. It firstly describes a full set of KGPIs that appear in the relevant literature on vehicle emission. Secondly, it applies an evidential reasoning approach to develop the new KGPI methodology for prioritising vehicle cleanliness (PVC). Thirdly, it presents the questionnaire results and conducts a comparative analysis of the responses from different types of respondents. Lastly, it uses a set of real data to show the feasibility of the new method in evaluating the cleanliness of different vehicles. As a result, it presents the analysis of the state-of-the-art vehicle cleanliness/greenness studies, the identification of KGPIs influencing cleanliness incorporating buyer choice, and proposes a feasible solution to synthesising KGPIs of different features (i.e. qualitative and quantitative) for PVC. It combines the performance scores of different vehicles against the defined KGPIs to demonstrate which is cleaner and better in either selected KGPI(s) or overall performance. Its final aim is to aid emission reduction from the existing combustion-engine fleet and provide more insights to guide car buyers towards the cleanest available vehicles.

By constructing a KGPI framework, the understanding of green vehicle choices can be broadened, and the results can be insightful for buyers to choose, car manufacturers to produce and transport authorities to promote clean vehicles. Vehicle buyers will benefit from low running cost and various incentives, while manufactures can enjoy the improved competitiveness by introducing cleaner vehicles that meet the buyers' demands. National authorities will be able to use the results to rationalise incentive schemes and relevant policies to realise the purpose of reducing air pollution. All the three groups of stakeholders will be able to demonstrate a high degree of social responsibility.

The remaining part of this paper is organised as follows: Section 2 is the literature review. Section 3 describes the development of the KGPI framework based on a FER approach. Section 4 specifies a real case study to demonstrate the application of KGPI framework for vehicle purchase selection in the UK. Section 5 discusses the research findings and research implications. Section 6 presents the conclusions of this work.

2. Literature review

To implement a radical literature review of PVC using KGPIs, a systematic approach for articles searching and selection is set up. With reference to the bibliographical methodology used in recent systematic review studies (e.g. Wan et al., 2018, Poo et al., 2018, Luo and Shin, 2016). The data collection approach in this review are divided into three steps: Online database searching, article screening, final refining and analysing.

Firstly, PVC related papers from all of the peer-reviewed academic journals are collected on Web of Science Core Collection, which is one of the most popular and comprehensive multidisciplinary academic searching platforms (Hosseini et al., 2016, Luo and Shin, 2016, Wan et al., 2018). Different strings, such as the combination of the elements from the sets of "Emission, (Car or Vehicle or road transport), (Parameter or Indicator or Index or indices or model), (Clean or Cleanliness)", are inputted as the "Topic" items to perform the searching process. Throughout the searching process, "OR" function has been used to finish the journals collection. The search was completed in February 2018, covering the period from 2004 to 2018 - the whole period of modern electric vehicle (EV) series production (Baker, 2018). As a result, 224 relevant papers are finally identified.

Secondly, a two-step scanning process is conducted to ensure the relevance and quality of the selected articles. The first step is to filter out the peer-reviewed journals by eliminating non-peer-reviewed journals, book chapters, conference proceedings and editorial materials. The peer-reviewed journal papers were chosen for further analysis because it is the most acceptable type of documents for the scientific community (Bergström et al., 2015). The number of articles is thus reduced from 224 to 194. At the second stage, titles, keywords, and abstracts of the chosen 194 articles are assessed to confirm their relevance. For example, some materials related to pollutants from buildings (Lee et al., 2015) and road infrastructures (Amato et al., 2010), which are irrelevant to the aim of this work, are eliminated. After the second screening, the number of the selected articles is reduced to 174.

Finally, the full-text review of the refined 174 articles is carefully conducted. As a result, the articles, which have no aspect of transportation, are also eliminated. After the final refining process, 127 articles remain. The articles are analysed by the distribution of their publishing years, authors, journals, regions, transportation modes and research methods. The upward corresponding trends are found within the context of different research themes. Furthermore, the connections of leading authors through their collaborative papers are analysed, and all studies to guide the directions of further studies and better understanding of the innovative value of this study are ultimately compared.

2.1. Trend of studies

Figure 1 shows the publication distribution of the refined 127 articles in the period of 2004 – 2018 February. The most significant annual journal production is 26 papers in 2017, which is nearly triple comparing to that in 2012. The number of published papers is increasing rapidly. Such growth in published papers indicates that the research interests for vehicle emissions have a high priority on both national and international research agenda, in the last years. As 2018 is not over at the time of conducting this review, it can be reasonably foreseen that the number of relevant research papers will increase to keep the momentum. Consequently, it is expected that there will be more studies and relevant outcomes and publications related to vehicle emissions in this field in the next decade, given the emergency of emission control for climate change mitigation, and local air quality associated to health impacts.

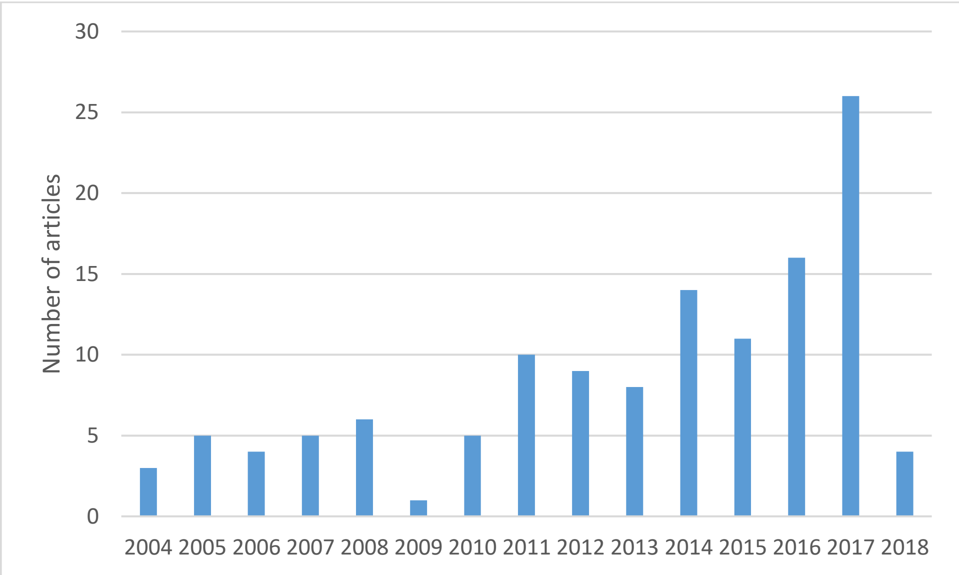

Figure 1 Trend of studies

2.2. Distribution by pollutants

This section compares the frequencies of pollutants mentioned in the 127 papers to draw some directions on KGPI framework construction. As the associated pollutants are easily quoted in articles, the contaminants are captured if they are mentioned in the analysis or modelling. Accordingly, Carbon dioxide (CO2), particulate matter (PM), nitrogen oxides (NOx), and carbon monoxide (CO) are the most investigated pollutants, and the illustrative numbers are 58, 43 and 38, respectively. As a result, 22 studies have mentioned the GHG emissions, rather than a single pollutant. Hydrocarbons (HC) are indicated in 19 papers, while Sulfur oxides (SOx) are referenced in 16 articles.

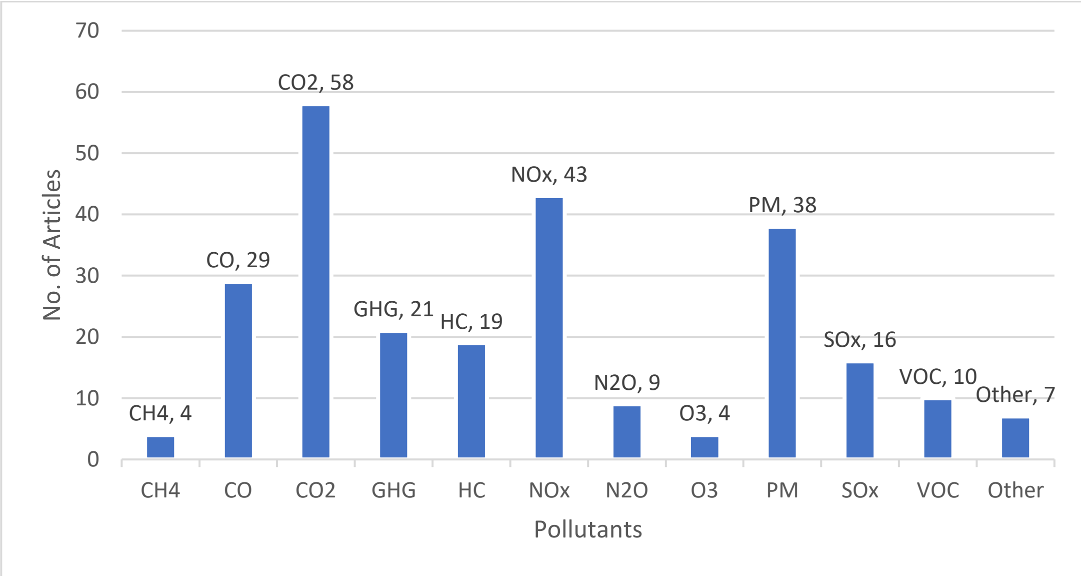

Figure 2 Distribution by pollutants

2.3. Distribution of research areas

For understanding the research focuses/topics of the previous studies, different categories are identified and classified as follows: Cleaner technology policy analysis, Congestion/routing analysis, Buyer choice analysis, Infrastructure analysis, Life cycle assessment (LCA), Public transport analysis, Regional analysis, Technology analysis.

Cleaner technology policy analysis is conducted to assess the outcome of a policy to control vehicle emission. The assessment can be evaluated economically or environmentally. Congestion/routing analysis is to use traffic engineering knowledge on reducing congestion as it makes vehicles emitting fewer pollutants. Buyer choice analysis explores studies that examine how customers decide on purchasing a car. LCA groups a type of studies on assessing the contaminants emitted from vehicles, from the cradle to the grave. Public transport analysis investigates how public transport assists in emission control. The regional analysis provides an overhead angle to observe the transportation pollutions in one region. The technology analysis will evaluate how new technologies can reduce pollution, while components like EV and AFV are excluded.

Table 1 Distribution of research topics

Research Area	2004 - 2008	2009 - 2013	2014 - 2018	Total	Occupancy
Cleaner technology policy analysis	3	1	18	22	17%
Congestion/ routing analysis	3	0	4	7	6%
Buyer choice analysis	4	3	5	12	9%
Infrastructure analysis	1	2	2	5	4%
Life cycle assessment (LCA)	0	0	5	5	4%
Public transport analysis	3	3	1	7	6%
Regional analysis	7	15	33	55	43%
Technology analysis	2	9	3	14	11%

Regional analysis represents 43% of the 127 articles. Policy analysis is the second largest group by 17% occupancy, while the buyer choice analysis is a marginal research area in the whole period, by presenting 12 papers (9%) of the total. The remaining categories have a descending order by occupancy: technology analysis, public transport analysis, congestion/routing analysis, infrastructure analysis and LCA. They are counting 11%, 6%, 6%, 4% and 4%, respectively. Furthermore, three periods (2004 – 2008, 2009 – 2013, and 2014 – 2018) have been defined to understand the trends of different research topics. It can be observed that cleaner technology policy analysis, regional analysis and LCA had a significant increase in occupancy with time. Public transport analysis and technology analysis decreased in their occupancy. The remaining research areas do not have apparent homogenous trends. In the meantime, it can be observed that there is still a clear research demand in terms of buyer choice analysis, particularly taking the need for controlling the existing internal combustion fleet into account. This also reflects the high demand on the collection of experimental evidence on effective emission control in a country, e.g. the UK.

2.4. Evaluation of the buyer choice analysis

A comparative analysis of buyer choice analysis has been undertaken. The analysis is further divided into three categories, including questionnaire surveying (Dill, 2004, Achtnicht, 2012, Graham-Rowe et al., 2012, Okushima, 2015, Hackbarth and Madlener, 2016), simulation modeling (Horne et al., 2005, BenDor and Ford, 2006, Potoglou and Kanaroglou, 2007, Burguillo-Cuesta et al., 2011, Simmons et al., 2015, Miotti et al., 2016) and indicator framework establishment (Dhar et al., 2017b).

For examining questionnaire surveying, Dill (2004) estimates the emissions reductions from accelerated vehicle retirement programs by a trade-off between pollutions and incentives. The following studies include more parameters into consideration. Graham-Rowe, et al. (2012) investigate the willingness of German car buyers on paying for EVs to mitigate CO2 emissions (Graham-Rowe et al., 2012). Okushima (2015) simulates the social influences for heterogeneous-agent sustainable mobility shift by the survey result. Hackbarth and Madlener (2016) provide a stated choice experiment for AFVs (Hackbarth and Madlener, 2016). In terms of simulation modelling, discrete choice modelling visualises personal transportation decisions (Horne et al., 2005). BenDor and Ford (2006) simulate a model to visualise the feebate scheme and scrappage incentives to reduce automobile gas emissions. One year later, Potoglou and Kanaroglou (2007) analyse the household’s purchasing demand for clean vehicles by a nested logit model. Burguillo-Cuesta, et al. (2011) establishe the econometric model of simultaneous equations for assessing the demand of diesel cars and diesel oil (Burguillo-Cuesta et al., 2011). Simmos et al. (2015) set up a benefit-cost assessment using sensitivity analysis for fuel economy and new vehicle technologies in the US market. One year later, Miotti et al. (2016) evaluate vehicle choices on buyers against climate change mitigation targets. For the study on indicator establishment, Ehar, et al. (2017b) create an alternative EVEI to quantify the GHG emissions of EVs.

From the above literature analysis, Table 2 reveals the eight factors influencing buyer choice. Exempted pollutants, fuel economy and purchase price are all crucial concerns affecting buyers' choice on green vehicles. Driving power and fuel availability are both apparent factors for choosing AFV cars. Furthermore, maintenance, driving range, incentives and refuelling/recharging time draw considerable attention from private vehicles buyers.

Table 2 Factors influencing vehicle buyer choice

Journal articles	**Fuel economy**	**Maintenance cost**	**Pollution**	**Driving range**	**Fuel availability**	**Refuelling/ Recharging time**	**Power**	**Incentives**
(Dill, 2004)			v					v
(Horne et al., 2005)	v						v	
(BenDor and Ford, 2006)	v		v		v		v	v
(Potoglou and Kanaroglou, 2007)	v	v	v				v	v
(Burguillo-Cuesta et al., 2011)	v		v					

(Achtnicht, 2012)	v		v		v		v	
(Graham-Rowe et al., 2012)	v	v	v	v	v	v	v	
(Okushima, 2015)	v		v					
(Okushima, 2015)	v		v					
(Miotti et al., 2016)	v	v	v					
(Hackbarth and Madlener, 2016)	v		v	v	v	v		
(Dhar et al., 2017b)			v					
Total	10	3	12	2	4	2	5	3

* The pollution can be further breakdown to reflect the particular pollutants as shown in Figure 2.

2.5. Review of multiple-criteria decision analysis

Due to the involvement of multiple factors, PVC is in nature a multiple criteria decision making (MCDM) problem involving qualitative and quantitative parameters. Based on the work by Velasquez and Hester (2013) and Lee and Yang (2018), the major MCDM methods in the literature are reviewed against their individual advantages and disadvantages. The result is presented in Table 3.

Table 3 Advantages and disadvantage of the major MCDM methods

MCDA	**Advantages**	**Disadvantages**
Multi-Attribute Utility Theory (MAUT)	• Taking uncertainty into account; • Able to incorporate preferences.	• Requiring a lot of input; • Preferences need to be precise.
Analytic Hierarchy Process (AHP)	• Easy to use; • Scalable; • Not data intensive.	• Problems due to interdependence between criteria and alternatives; • Possibly inconsistencies between judgment and ranking criteria.
Case-Based Reasoning (CBR)	• Not data intensive; • Requiring little maintenance; • Improving over time; • Adapting changes in environment.	• Sensitive to inconsistent data; • Requiring many cases.
Data Envelopment Analysis (DEA)	• Capable of handling multiple inputs and outputs; • Efficiency can be analysed and quantified.	• Difficult to deal with incomplete dataset; • Assumes that all input and output are exactly known.
Evidential Reasoning (ER)	• Capable of handling different assessments	• Compulsory requirement to obtain decision-maker's true preferences.

	• Suitable to analysis incomplete dataset • Capable of delivering a result from multiple decision makers perspectives	
Fuzzy Set Theory	• Allowing for imprecise input; • Possible to compile with insufficient information.	• Difficult to develop fuzzy membership functions; • Requiring numerous simulations before use.
Simple Multi-Attribute Rating Technique (SMART)	• Simple; • Capable for combining any type of weight assignment technique; • Less effort by decision makers.	• Inconvenient procedure to consider the framework.
Goal Programming (GP)	• Capable of handling large-scale problems; • Producing infinite alternatives.	• Ability to weight coefficients; • Typically requiring to be used in combination with other MCDM methods to weight coefficients.
ELECTRE	• Taking uncertainty and vagueness into account.	• Its process and outcome can be difficult to explain in layman's terms; • Outranking causes the strengths and weaknesses of the alternatives not to be directly identified.
PROMETHEE	• Easy to use; • Does not require assumption that criteria are proportionate.	• No clear method by which to assign weights.
Simple Additive Weighting (SAW)	• Ability to compensate among criteria; • Intuitive to decision makers; • Calculation does not require complex computer programs.	• Estimates do not always reflect the real situation; • Result obtained may not be logical.
Technique for Order Preferences by Similarity to Ideal Solutions (TOPSIS)	• Easy to use and program; • The number of steps remains the same regardless of the number of attributes.	• Its use of Euclidean Distance does not consider the correlation of attributes; • Difficult to weight and keep consistency of judgment.

A KGPI framework requires a hierarchical structure to build and to accommodate the KGPIs of different features (i.e. qualitative and quantitative) for different types of vehicles. Corresponding KGPIs have been selected to assess each investigated vehicle independently. In the framework, the indicators at a higher level rely on the information from the lower levels. It is therefore essential to simulate the vehicle performance against individual indicators from the lowest level to the top level. In the process of assessing the vehicle cleanliness, there are two main uncertainties that decision-makers may encounter. Firstly, qualitative data and quantitative data are required to support the analysis together. Secondly, the subjective dataset may occur due to the lack of data for some specific vehicle types. Furthermore, multiple stakeholders are involved, and the understanding of their different perspectives on the PVC is essential for the goal of this study.

Evidential reasoning (ER) demands the transformation from quantitative to qualitative assessments (Yang and Singh, 1994). ER can effectively comply with uncertainties in data by the concept of degree of belief (DoB), and it can also aid the PVC decision from different perspectives against different indicators in the framework. Therefore, the ER approach is suitable for developing the KGPI framework. The core of this framework is an ER algorithm with the implementation the Dempster–Shafer (D–S) theory and modelling the hypothesis set, associating with the requirements and limitations of the accumulation of evidence (Liu et al., 2004). However, ER has no built-in algorithms to calculate the weight of each factor in the KGPI framework. Analytic Hierarchy Process (AHP) is used to collect the data and calculate the corresponding weights. AHP is applied through the following four steps: Determine the vector of criteria weights, calculating the matrix of option values, ranking the choices, and checking the consistency (Saaty, 1988). AHP is not only suitable for this framework as the corresponding dataset is not sufficient, but also can generate a weight for each KGPI by the decision maker's pairwise comparisons (Vaidya and Kumar, 2006). The combined ER-AHP method, having advantages of the two methods, has generated three main advantages to meet the requirements of constructing the KGPI framework as follows: Accommodation of both qualitative and quantitative data for a decision involving high uncertainty in data; Capability of coping with fuzzy and incomplete data; and Benchmarking of the decision alternatives against any criterion at any level of the decision hierarchy.

3. A new KGPI framework for PVC using ER

3.1 ER Algorithm within the context of the KGPI framework

In the KGPI framework, the indicators at a higher level rely on the information from the lower levels. It is therefore essential to simulate the vehicle performance against individual indicators from the lowest level to the top level. In the process of assessing vehicle cleanliness, decision-makers may encounter two main uncertainties, which are vagueness/fuzziness and incompleteness of the qualitative assessment. As discussed in Section 2.5, ER can competently deal with such uncertainties by its algorithm below. By connecting all input information and undertaking analysis, it is possible to combine different types of KGPIs into a framework and make a final decision. The following equations have integrated the newest ER algorithm within the KGPI context.

A represents the set with five linguistic assessment grades {"Slightly preferred (L_1)", "Moderately preferred (L_2)", "Average (L_3)", "Preferred (L_4)", "Extremely preferred (L_5)"}, which has been combined from two subsets A_1 and A_2

based on two different KGPIs. Let α represent belief degrees assigned to the linguistic grades (L) and ω represents the normalised relative weights of the two KGPIs.

$$A = \{\alpha_1 L_1, \alpha_2 L_2, \alpha_3 L_3, \alpha_4 L_4, \alpha_5 L_5\} \text{, where } \sum_{m=1}^{5} \alpha_m \le 1 \tag{1}$$

$$A_k = \{\alpha_{1,k} L_1, \alpha_{2,k} L_2, \alpha_{3,k} L_3, \alpha_{4,k} L_4, \alpha_{5,k} L_5\} \text{, where } \sum_{m=1}^{5} \alpha_{m,k} \le 1 \text{ and } k = 1, 2 \tag{2}$$

$$\sum_{k=1}^{2} \omega_k = 1 \tag{3}$$

$$M_{m,k} = \omega_1 \alpha_{m,k} \text{, where m = 1, 2, 3, 4, 5 and k = 1, 2} \tag{4}$$

Equation (1) represents the combined set with five linguistic assessment grades and equation (2) represents the corresponding KGPIs fuzzy sets from two subsets. The normalised relative weights of the two subsets are given in equation (3). The individual weighted DoB, M is then obtained by equation (4).

$$H_k = \bar{H}_k + \tilde{H}_k \text{, where k = 1, 2} \tag{5}$$

$$\bar{H}_k = 1 - \omega_k \text{, where k = 1, 2} \tag{6}$$

$$\tilde{H}_k = \omega_k \left(1 - \sum_{m=1}^{5} \alpha_{m,k}\right) \text{, where k = 1, 2} \tag{7}$$

Equations (5) to (7) represent the unassigned DoB (H) to $M_{m,1}$ and $M_{m,2}$, where m = 1, 2, 3, 4, 5. $\bar{H}$ represents the degree that the other KGPI subset can assist in the assessment and $\tilde{H}$ represents the possible DoB incompleteness in one subset A_1 or A_2.

$$a'_m = K\left(M_{m,1} M_{m,2} + M_{m,1} H_2 + H_1 M_{m,2}\right) \text{, where m = 1, 2, 3, 4, 5} \tag{8}$$

$$\bar{H}'_U = K\left(\bar{H}_1 \bar{H}_2\right) \tag{9}$$

$$K = \left(1 - \sum_{T=1}^{5} \sum_{\substack{R=1 \\ R \neq T}}^{5} M_{T,1} M_{R,2} \right)^{-1} \quad (10)$$

Let a'_m be the non-normalised combined DoB and $\bar{H}'_U$ be the non-normalised remaining belief unassigned after the DoB combination. They work together as the result of the synthesis of the belief degrees. K is a constant calculated by Equation (10). As a result, the combined degrees a_m can be obtained by the normalization process in Equations (11-12). They are generated by putting $\bar{H}'_U$ back to the all expressions, and H_U defines the normalised remaining unassigned DoB in the synthesised set.

$a_m = a'_m / \left(1 - \bar{H}'_U\right)$, where m = 1, 2, 3, 4, 5 (11)

$$H_U = \tilde{H}_U / \left(1 - \bar{H}'_U\right) \quad (12)$$

KGPIs have different numbers of linguistic grades. In order to synchronise the linguistic terms, a fuzzy mapping technique is presented for distributing DoBs based on the utility theory. From Figure 3, a fuzzy utility mapping example is given to the modeling from a fuzzy input to a fuzzy output (Yang et al., 2009a). There are three levels involved in the example, including “Selection control options (SCO)”, “Other incentives”, “Car Scrappage Scheme”. “SCO” and “Other incentives” have the same sets of five linguistic variables, and “Car Scrappage Scheme” has a set of 2 linguistic variables. More explanations of the linguistic grades are found in Section 4.1.

w represents the normalised weights of each criterion at the same level and under the same upper-level criterion. The values B attached to the links connecting two levels are the DoB, which presents the relationships between linguistic variables of different-level KGPIs. The sum of the belief values from one linguistic variable must equal one. For example, the parameter “Car Scrappage Scheme” with “No” expression indicates that the level of the attribute ‘Other incentives’ can be 0.4 ($B_{s=1}^{oi=1}$) “Slightly preferred”, 0.4 ($B_{s=1}^{oi=2}$) “Moderately preferred”, and 0.2 ($B_{s=1}^{oi=3}$) “Average” without the presence of other evidence. The assignment of such belief degrees is obtained by the utility theory or expert judgements (Yang et al., 2009b).

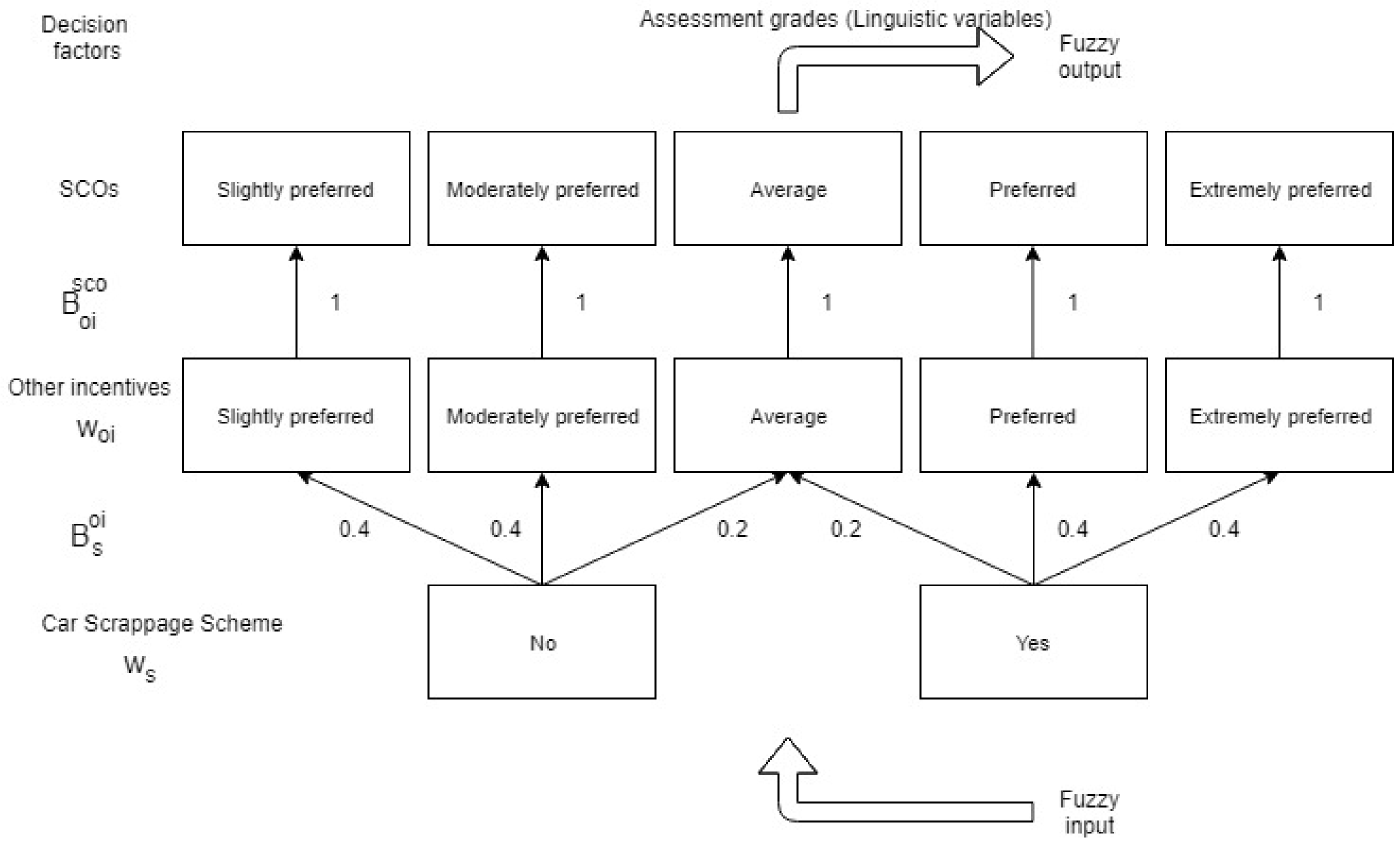

Figure 3 An example of transforming fuzzy input to output

Suppose each I^i ($i=1,2$) represents the fuzzy sets associated with the criterion "Car Scrappage Scheme"; each I^{oi} ($i=1,2,...,5$) presents the corresponding fuzzy input of the criterion "Other incentives" transformed from the "Car Scrappage Scheme" related fuzzy input I^i; and O^{sco} ($sco=1,2...,5$) presents the fuzzy output transformed from I^{oi}. Assume w_{sco} is the relative weight associated with the fuzzy output transformed from the fuzzy input. w_{oi} and w_s represent the weights of criteria "Other incentives" and "Car Scrappage Scheme" respectively.

$$O^{sco} = \sum_{oi=1}^{5} I^{oi} B_{oi}^{sco} = \sum_{oi=1}^{5} \left(\sum_{i=1}^{2} I^i B_i^{oi} \right) B_{oi}^{sco} \tag{13}$$

$$\sum_{sco=1}^{5} O^{sco} = 1 \tag{14}$$

$$w^{sco} = w_{oi} \times w_s \tag{15}$$

The above fuzzy mapping transformation process is also applicable to quantitative factors at the lowest level of the KGPI hierarchy. The only difference lies in the input data for the quantitative factors will be processed first to transform them into the probabilities to the pre-defined quantitative grades. For instance, a set of numerical grades {60, 180, 300, 420, 540 (hp)} can be used to evaluate "Engine Power". If an investigated car has an engine power at 360hp, then it can be described as [0% 60, 0% 180, 50% 300, 50% 420, 0% 540(hp)]. Such a result can be then used as the input into the mapping process to transform it to the equivalent output expressed by the linguistic grades of the top-level indicator.

3.2 A new KGPI framework for PVC

The new KGPI framework for PVC is outlined by the following five steps.

1) Identifying the KGPIs

The first step is to define the specific PVC problem in detail using decision trees. The decision tree is chosen as it is much easier to use compared with other methods such as decision tables (Yang et al., 2009b). In the selection of clean vehicles, buyers do not always fully understand what the car specifications they need most. A decision tree can help observe the system along with all the KGPIs involved, and it is also possible to observe the relationships between all KGPIs. Furthermore, it is flexible enough to add or modify data or layer found during the vehicle selection process (Sen and Yang, 1995).

In this section, all KGPIs mentioned in Table 2 are considered to merge into a single common KGPI framework. In this process, several factors associated with their purchase price, fuel economy, maintenance cost, pollution, driving range, fuel availability, refuelling/recharging time, power and incentives, affects the selection of vehicles. Due to the different nature between different types of cars, some of the indicators are born to be subjective. For dealing with the characteristic of incompleteness in subjective data, the above ER approach is, for the first time, applied within the context of vehicle cleanliness analysis.

2) Setting the KGPI grades

In this step, all KGPIs are appropriately graded for buyer choice by objective values or subjective judgements. For those criteria with objective quantitative input, numerical grades are developed. For example, a set of numerical grades {60, 180, 300, 420, 540 (hp)} can be used to evaluate "Engine Power". For those criteria with subjective qualitative input, various sets of linguistic terms are defined with a set of linguistic terms {“Slightly preferred”, “Moderately preferred”, “Average”, “Preferred”, “Extremely preferred”}.

3) Evaluating vehicles using KGPIs

The lowest-level KGPIs are defined as the indicators without any sub-criteria presented in the hierarchy. They are the input dataset for the evaluation to find out how well a candidate vehicle is suitable for a car purchaser. The evaluation can be conducted successfully if the assessors have enough data or confidence in using subjective judgements. If the dataset is incomplete, the result can be described by DoB belonging to either numerical grades or linguistic terms. Other location measurement techniques such as linear, bi-linear, non-linear, and judgmental (Lee and Yang, 2018, Yang et al., 2009a) can be implemented to produce DoB distributed to different grades.

4) Transforming from the low-level to top-level indicators

By the evaluation from the lowest level KGPIs, the transformation takes place by the combination of datasets and weights. The process details are shown in Section 3.1 (e.g. Figure 3). By using the equivalent rules and weights, different vehicles can be assessed against the lowest level KGPIs and then the initial evaluation against the lowest level KPGIs can be transformed to be expressed by the grades of the top-level KGPI.

5) Synthesising all assessments using the ER algorithm for selecting the cleanliest car

The evaluation data of an investigated vehicle with regards to each lowest level KGPI is inputted into an ER-based calculation software for calculating the overall cleanliness score of the vehicle. The software is called Intelligent Decision System via ER, IDS, and it is Windows-based software, developed based on the ER algorithm in Section 3.1 (Yang and Xu, 2000). The function includes constructing a model, defining alternatives, setting up criteria, and performing different assessments according to the buyers’ requirements. It is capable of changing the weights of KGPIs to reflect the different scenarios/preference owned by different buyers.

After dataset of each chosen vehicle is imparted, the final score at the highest level and the corresponding ranking takes place. Their preferences can be ranked according to the final utility value of each investigated vehicles. In this process, the final utility value is obtained by assigning a utility value to each grade of the top-level KGPI using a linear function (Yang et al., 2009b). By following the steps above, the potential buyers can choose the most suitable vehicle from the results via IDS.

4. The KGPI framework: A real case study

A case study with six selected vehicles representing different types of vehicles is conducted to demonstrate the KGPI framework in this section. The selected car alternative vehicles include various fuel types, also taking the driving incentives variety by locations into account. The result shows that the framework is powerful to accommodate the decisions varying from different locations, stakeholders, and fuel types. Following the KGPI framework in Section 3.2, the case study is conducted in six steps as follows.

1) Identifying all the KGPIs

First, we have identified the relevant factors influencing vehicle cleanliness by carrying out a systematic literature review. 127 related journal papers are collected on Web of Science Core Collection and grouped to perform the review. Eight factors on vehicle buyer choice have been investigated. They include fuel economy, maintenance cost, pollution (incl. different pollutants/emission factors), driving range, fuel availability, refuelling/ recharging time, power, and incentives. Secondly, we have further purified all the pollution/emission factors from the industry best practice, such as Emissions Analytics (Emissions Analytics Limited, 2013) and Next Green Car (Next Green Car Ltd, 2019). Thirdly, a pilot study was held online between June 2018 and March 2019, involving eight professions from the UK Connected Places Catapult (previously known as Transport Systems Catapult), universities, and engineering consultancies. Each of them has at least five-year working experience in green transport, vehicle emissions and/or air quality. For obtaining the consensus among the eight experts, three-round debates and discussions were conducted, which helped ensure the robustness of the hierarchy containing the most important KGPIs in a rational structure. The first round is for constructing the framework based on the literature review and industrial practices taken place in Jun 2018, and the second and third rounds are for choosing and refining suitable indicators, and they were held in September 2018 and March 2019, respectively. During the discussions, both the factor contents and their presentations were carefully addressed. Finally, the hierarchy was used in a large-scale survey to evaluate the weights of the influencing factors. In the survey, participants have been invited to provide their comments on the possible inclusion of new important factors and exclusion of trivial factors.

For evaluating the weights of the indicators, sixty-three public responses and seven responses from technical and governmental bodies have been collected, and the geometric mean is used to present a single value to calculate the weights of the indicators using AHP. The questionnaire is designed on Jisc online platform and distributed by emails. Also, categories of respondents have been defined by demography related questions included in the questionnaire: "Londoners" (6), "North West England" (21), "Preferring green car" (14), "Preferring non-green car" (30), "Single" (27), "Married" (32), "With children" (19), "No Children" (4), "Purchased a car before 2012" (10), "Purchased a car after 2012"(31), and "No car" (22). The pairwise comparisons are conducted between people from the general public and those from technical and governmental bodies separately in order to analyse the perspectives of different stakeholders. The detailed calculation (incl. consistent ratio) and results are presented and discussed in Section 5.

The hierarchy is constructed as shown in Figure 4 based on the weight assignments generated from the questionnaire result. The pilot group found that the buyer choice is influenced by national transport policies and the actual locations of the users. After careful discussion among them, it is decided to design a real experiment in Section 4 and discuss the results Section 5. It can demonstrate the KGPI framework on one hand and show that there are weight differences between each customer on the other hand. The chosen KGPIs are the most significant ones taken under consideration for this analysis from different stakeholders (e.g. buyers, transport authorities, innovation/technology transfer agencies). The description of each indicator, including the data sources used to support their evaluation, is given as follows.

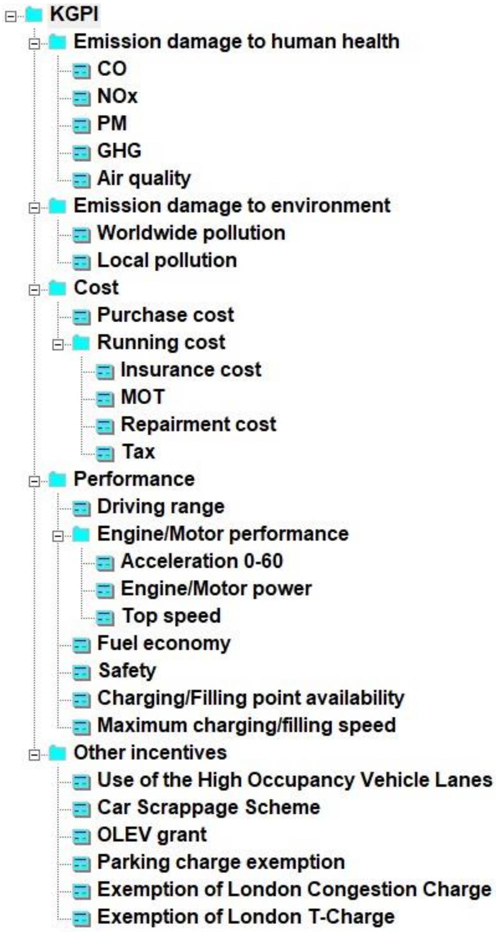

Figure 4 The KGPI framework

i) Emission damage to human health

In the analysis of Section 2.2, several pollutants are highly concerned by academic scholars and pilot team. In this study, CO, NOx, PM, and GHG are chosen. CO2 is exempted from this group but is counted as the main GHG by motor driving. In terms of CO, NOx and GHG, the real-world emission data is collected from Emission Analytics. Emission indicators are chosen from the Next Green Car (NGC) (Next Green Car Ltd, 2018). GHG, includes CO2, CH4, and N2O. Motor vehicles also emit pollutants, such as carbon dioxide that contributes to global climate change. Air quality related indicators include NOx, HCs, CO, PM10, and SOx. These pollutants react with nitrogen oxides under sunlight to form ground-level ozone, which is a primary ingredient in smog. At the ground level, this gas can irritate the respiratory system, causing coughing, choking, and reducing lung capacity.

ii) Emission damage to the environment

Emission damage to the environment is separated from human health because car purchasers usually concern about the health and environment differently. GHG contributes to worldwide pollution, and the pollutants affecting air quality contribute to local pollution. NGC (2018) dataset is used to define the indicators in the category.

iii) Cost

Cost is defined as all relevant expenses and divided into purchasing cost and running cost. Purchasing cost includes retail price and first-year tax, while running cost includes insurance cost, Ministry of Transport (MOT) test, maintenance cost, and tax after the first year. Retail price and taxes are found from the NGC website, and insurance cost is quoted from car insurance companies (Thatcham Research, 2019; Warranty Direct, 2019). Maintenance cost is quoted from the reliability index provided from Warranty Direct, and MOT test cost is quoted from the Department for Transport (DfT) (Department for Transport, 2019).

iv) Performance

Performance is relating to all engine and motor specifications of vehicles. Engine/motor performance can be further divided into Acceleration time for 0-60 mile/hour, Engine/motor power, and Top speed. Engine/motor performance, fuel economy and safety datasets are collected from the NGC website. The remaining three KGPIs, driving range, charging/filling point availability and maximum charging/filling speed are only for AFVs. Petrol and diesel vehicles have no concerns about refuelling. Therefore, the conditions of those vehicles on these three KGPIs will go to a linguistic term of the highest score “Extremely preferred” in the assessment. Moreover, the charging/filling point availability varies between different locations, so the charging point density is chosen as the KGPI, and the relevant data is collected from NGC (2019).

v) Other incentives

There are several incentives that are found available in the UK. The following incentives affect buyer decisions. Car scrappage scheme, exemption from London Congestion Charge, and exemption from London T-charge are specific to London, and the scrappage scheme are provided by vehicle companies.

- Use of High Occupancy Vehicle Lanes: Ability to use the High Occupancy Vehicle Lane by an electric/hybrid vehicle (Vaughan, 2016).
- Car scrappage scheme: The UK vehicle scrappage scheme is a scheme that was introduced by the government in 2009 to encourage citizens to purchase a new vehicle and scrap an old one that they have owned for more than 12 years (Transport for London, 2019). Also, several car brands provide their own schemes.
- OLEV grant: The government offers grants to promote the use of electric and hybrid vehicles via the Office of Low Emission Vehicles (OLEV) by a grant scheme for installation of electric vehicle charging infrastructure (Department for Transport, 2019).
- Parking charge exemption: Ability to benefit from reduced parking or metered fees as an electric/hybrid vehicle (Smith, 2018).
- Exemption from London Congestion Charge: The Congestion Charge is a daily charge for driving a vehicle within the charging zone between 07:00 and 18:00, Monday to Friday in London. (Department for Transport, 2019).
- Exemption from London T-charge: Older vehicles driving in central London need to pay an extra daily charge if they cannot meet minimum Euro emission standards. This is exclusive to the Congestion Charge (Department for Transport, 2019).

2) Setting the KGPI grades

The definitions of KGPI grades are referring to available references or domain experts' knowledge. The first and second level assessment grades have been defined in five grades (e.g. "Slightly preferred", "Moderately preferred", "Average", "Preferred", "Extremely preferred"}. Third level KGPIs are characterized by different sets of assessment grades for facilitating raw data collection. For example, "CO" has ten assessment grades, from A++ to H, based on Emissions Analytics (2013). Some KGPIs, such as Car Scrappage Scheme, have binary grades in nature.

3) Evaluating six candidate vehicles using the lowest level indicators

Considering the availability of the car performance data and domain expert suggestions, six vehicles from different brands are chosen in a real case study as follows.

- JAGUAR E-Pace 2.0D I4 180PS AWD
- BMW M2 Competition DCT
- VW Passat Saloon 2.0 TDI SE Business 150PS
- AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic
- NISSAN LEAF Acenta 40kWh Auto
- Tesla Model X Long Range AWD Auto

The vehicle performance data for evaluation are collected from different sources, including Emission Analytics and NGC. The range of each assessment grades is set up with regards to the practical norms. For instance, the five grades of engine power are defined as {60, 180, 300, 420, 540(hp)}. If the engine power of a candidate vehicle is ranged between two defined grades, a linear distribution is applied, and two assessment grades with the DoBs are used to describe the candidate vehicle.

NISSAN LEAF Acenta 40kWh Auto is taken as an example to show the raw data against the 26 lowest level KGPIs in Table 4. As some criteria are geographical sensitive, the case focuses on a buyer from Great London.

Table 4 The raw data of NISSAN LEAF Acenta 40kWh Auto

Lowest level KGPIs	**Sources from**	**Unit**	**Value**	**Lowest grade**	**Highest grade**
CO	EQUA Index	N/A	A+	H	A++
NOx	EQUA Index	N/A	A+	H	A+
PM	Department for Transport	g/km	0	0.25	0
GHG	Next Green Car	N/A	22	90	10
Air quality	Next Green Car	N/A	19	90	10
Worldwide pollution	Next Green Car	N/A	22	90	10
Local pollution	Next Green Car	N/A	19	90	10
Purchase cost	Next Green Car	£	36995	125000	25000
Insurance cost	Insurance group	N/A	21	45	5
MOT cost	Next Green Car	£	54.85	90	10
Maintenance cost	Reliability index	N/A	89	250	50
Second-year tax	Next Green Car	£/year	0	400	0
Driving range	Next Green Car	miles	168	50	450 or ICEV *
Acceleration time for 0-60 miles/hour	Next Green Car	Second	7.9	15	3
Engine/Motor power	Next Green Car	hp	148	60	540
Top speed	Next Green Car	mph	90	20	180
Fuel economy	Next Green Car	Real MPG/MPGe	>100	20	100

Safety	NCAP Safety Rating	N/A	5 stars	1	5
Charging/Filling point availability	Zap-Map	Charging points in 100 km^2	397.265	5	≥25 or ICEV *
Maximum charging/filling speed	Next Green Car	N/A	Yes	No	Yes or ICEV *
Use of the high-occupancy vehicle lane	Department for Transport	Binary	Yes	No	Yes
Car Scrappage Scheme	Department for Transport	Binary	Yes	No	Yes
OLEV grant	Department for Transport	Binary	Yes	No	Yes
Parking charge exemption	Department for Transport	Binary	Yes	No	Yes
Exemption of London Congestion Charge	Department for Transport	Binary	Yes	No	Yes
Exemption of London T-Charge	Department for Transport	Binary	Yes	No	Yes

* Petrol and diesel vehicles have no concerns about refuelling. Thus, the condition of those vehicles on these three KGPIs will go to a linguistic term of the highest score “Extremely preferred”.

4) Transforming the evaluation from the lowest-level criteria to top-level criteria

Transformation by equivalent rules in Figure 3 is used in this section to transform the raw data in Table 4 and expressed them by the five grades of the top-level KGPI in Table 5. For example, “Acceleration 0-60”, “Engine/Motor power”, and “Top speed” have the assessment grades as {15, 12, 9, 6, 3 (Sec)}, {60, 180, 300, 240, 540 (hp)}, and {20, 60, 100, 140, 180 (mph)} respectively. Using the raw data in Table 4, the vehicle performance against the three indicators are transformed as {0% L1, 0% L2, 63.3% L3, 36.7% L4, 0% L5}, {26.7% L1, 73.3% L2, 0% L3, 0% L4, 0% L5} and {0% L1, 0% L2, 40% L3, 60% L4, 0% L5}, respectively.

Table 5 The transformation of the evaluation of NISSAN LEAF Acenta 40kWh Auto to the highest level KGPI lowest-level criteria

KGPIs	**Assessment grades**
CO	0% L1, 0% L2, 0% L3, 44.4% L4, 55.6% L5
NOx	0% L1, 0% L2, 0% L3, 0% L4, 100% L5
PM	0% L1, 0% L2, 0% L3, 0% L4, 100% L5
GHG	0% L1, 0% L2, 0% L3, 60% L4, 40% L5
Air quality	0% L1, 0% L2, 0% L3, 45% L4, 55% L5
Worldwide pollution	0% L1, 0% L2, 0% L3, 60% L4, 40% L5
Local pollution	0% L1, 0% L2, 0% L3, 45% L4, 55% L5
Purchase cost	0% L1, 0% L2, 0% L3, 47.98% L4, 52.02% L5
Insurance cost	0% L1, 0% L2, 60% L3, 40% L4, 0% L5
MOT cost	0% L1, 0% L2, 100% L3, 0% L4, 0% L5
Maintenance cost	0% L1, 0% L2, 44% L3, 78% L4, 22% L5
Second-year tax	0% L1, 0% L2, 45% L3, 0% L4, 100% L5

Driving range	0% L1, 12% L2, 88% L3, 0% L4, 0% L5
Acceleration 0-60	0% L1, 0% L2, 63.3% L3, 36.7% L4, 0% L5
Engine/Motor power	26.7% L1, 73.3% L2, 0% L3, 0% L4, 0% L5
Top speed	0% L1, 0% L2, 40% L3, 60% L4, 0% L5
Fuel economy	0% L1, 0% L2, 0% L3, 0% L4, 100% L5
Safety	0% L1, 0% L2, 0% L3, 0% L4, 100% L5
Charging/Filling point availability	0% L1, 0% L2, 0% L3, 0% L4, 100% L5
Maximum charging/filling speed	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
Use of the high-occupancy vehicle lane	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
Car Scrappage Scheme	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
OLEV grant	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
Parking charge exemption	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
Exemption of London Congestion Charge	0% L1, 0% L2, 20% L3, 40% L4, 40% L5
Exemption of London T-Charge	0% L1, 0% L2, 20% L3, 40% L4, 40% L5

*L1 = Slightly preferred, L2 = Moderately preferred, L3 = Average, L4 = Preferred, L5 = Greatly preferred

5) Synthesising all evaluations using the ER algorithm and its calculation software IDS for PVC

By transforming all the raw data of 6 candidate vehicles, the ER approach and its IDS software are used to synthesise them and obtain their overall results in Figure 5. For example, the synthesized result of NISSAN LEAF Acenta 40kWh Auto is {2.28% L_1, 2.73% L_2, 11.91% L_3, 30.67% L_4, 50.54% L_5, 1.88 % Unknown}. For ranking the 6 vehicles, the five grades are given their utility values as {0, 0.25, 0.5, 0.75, 1}. The DoB belonging to unknown is assigned to L_1 and L_5 respectively for the worst and best scenarios, respectively. The ranking can be realized by comparing the average utility values (average of two values indicating the best and worst scenarios). As a result, the ranking of the 6 vehicles is shown in Figure 6, revealing that Nissan LEAF is the best and BMW M2 is the worst in terms of the overall vehicle cleanliness analysis.

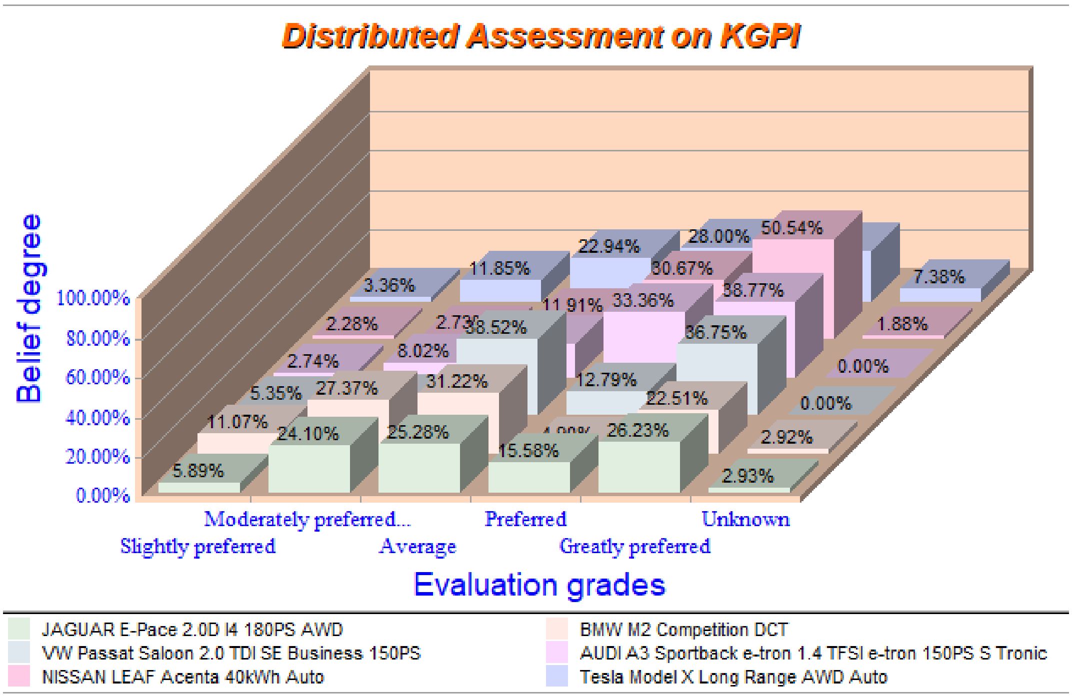

Figure 5 The overall estimations of the selected six vehicles

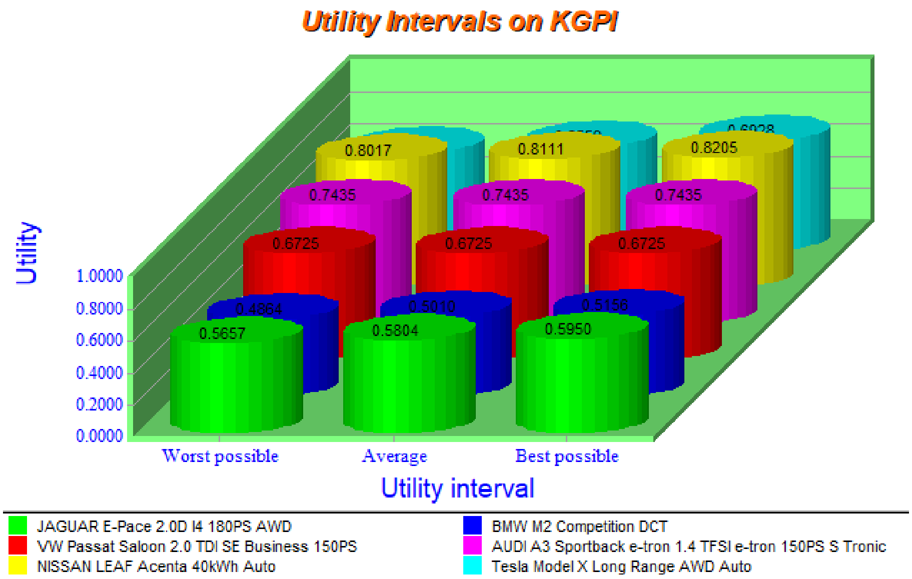

Figure 6 Ranking of the selected six vehicles

5. Discussions on the research findings

There is no ideal vehicle choice for all buyers as each of them may have different weights (preference) against all KGPIs. Therefore, the result obtained in Section 4 can only represent an integrated result taking both buyers and other stakeholder groups (e.g. transport authorities) opinions into account. The following sections provide insights on the choice of different respondent groups by redistributions of the AHP weight results. Then, the result shows the variations on the vehicle choices to meet the common expectation from different stakeholder groups. By computing the indicator weights from the separated data with regards to different stakeholder groups, the characterised relative weights are calculated and shown in Table 6 to 9. Then, vehicle cleanliness is analysed from the viewpoints of “General public”, “Technical and governmental bodies”, “Londoners”, and “North West England”, respectively in Table 10 to 11.

5.1. Comparing the different weights of the KGPIs between the two groups of “general public” and “technical and governmental bodies”

Table 6 reveals the weights of the second level KGPIs. It indicates that the leading factor for the “General public” and “Technical and governmental bodies” is “Buyer cost”. However, the second leading factor for the “General public” is “Emission damage to the environment”, while for “Technical and governmental bodies” is “Car performance”. It means that a buyer, when deciding to purchase a green car, pays much more attention to environment protection than car performance. Transport authorities and manufacturers should adapt their strategies on environment protection (e.g. GHG reduction) to rationalise their policies and bring cleaner cars to the market.

Table 6 Relative weights of second level factors between General public and Technical and governmental bodies

Factor	**General public**	**Rank**	**Technical and governmental bodies**	**Rank**
Emission damage to human health	0.201	3	0.157	3
Emission damage to the environment	0.203	2	0.099	5
Buyer cost	0.259	1	0.348	1
Car performance	0.184	4	0.266	2
Other incentives	0.154	5	0.130	4

The findings on the weight analysis of the 26 lower level KGPIs indicate that buyers and technical and governmental bodies have very consistent understanding and perspectives. The main difference is twofold. In terms of “emission damage to human health”, the leading factor from buyers is “CO”, followed by “NOx”. However, the “Technical and governmental bodies” group evaluates “PM” and “Air quality” are the two most important factors. As far as performance is concerned, buyers concern more on “Safety” and “charging/filling point availability”, while governmental bodies consider “Fuel economy” with a priority. Such findings can aid transport authorities to adjust their green policies to meet buyers’ needs better.

5.2 Comparing the different weights of the KGPIs between the two groups of “Greater London” and “North West England”

The rational to investigate the difference between “Greater London” and “North West England” is to see how the geographical locations and the economy affect green vehicle choice. In the UK, Greater London is the most developed and North West England is relatively less developed as far as economy is concerned. London is one of the pioneering cities to introduce various emission control policies (e.g. congestion charge) in the world.

Table 7 shows the weights of the second level factors based on the separate data from Greater London and North West England. It is apparent that Greater London responses focus more on “Emission damage to the environment”, while North West England responses are more “Buyer cost” oriented. The finding supports the positive effect of emission control policies on public awareness of environment protection and green vehicle choice.

Table 7 Relative weights of the second level factors between responses from Greater London and North West England

Factor	Greater London	Rank	North West England	Rank
Emission damage to human health	0.196	2	0.154	5
Emission damage to the environment	0.266	1	0.180	4
Buyer cost	0.166	5	0.238	1
Car performance	0.189	3	0.225	2
Other incentives	0.183	4	0.203	3

In terms of the lower level KGPIs, the responses on the factor importance from Greater London and North West England are very different. For instance, in the category of “Emission damage to human health”, the leading factor from the Greater London responses is “PM”, and that from the North West England responses is “Air quality”. In terms of “running cost”, the leading factor from the Greater London responses is “Insurance cost”, and that from the North West England responses is “Fuel duty”. When “other incentives” are considered, “Exemption from London Congestion Charge” and “Exemption from London T-charge” are the two leading factors from London, which is followed by “Parking charge exemption”. In North West England, “OLEV grant” is the leading factor.

5.3 Comparing relative weights between responses from “Preferring AFVs” and “Preferring ICEVs”

ICEVs and AFVs will co-exist in the current market for a few decades until all the ICEVs are replaced by AFVs. During this period, it is necessary to understand the different views on the KGPIS from the two groups choosing AFVs and ICEVs, respectively.

Table 8 reveals the weights of the second level KGPIs assigned by the two groups. The first leading factor from the "AFVs" responses is "Buyer cost" while the one from the "ICEVs" is "Emission damage to human health". It reflects the higher cost of the available AFVs in the current market. The key to drive higher proportion of AFVs is to reduce their high costs by the joint effort from all the stakeholder groups.

Table 8 Relative weights of the second level factors from the "ICEVs" and "AFVs" groups

Factor	**ICEVs**	**Rank**	AFVs	**Rank**
Emission damage to human health	0.206	2	0.224	1
Emission damage to the environment	0.203	3	0.222	2
Buyer cost	0.273	1	0.214	3
Car performance	0.178	4	0.200	4
Other incentives	0.139	5	0.140	5

Because of the different features of ICEVs and AFVs, the focuses of the two groups significantly vary. For instance, in the categories of "Car performance" and "Safety", both groups give the fourth and the fifth priorities. However, "AFVs" pay more attention to "Charging/fueling point availability", "Maximum charging/fueling speed" and "Driving range" than the factors such as "Fuel economy", which ICEVs concern the most.

5.4 Comparing relative weights between responses from different car ownership types against different registration years

This section is to investigate the change of car owners' perception on the importance of the KGPIs. Table 9 disclosed the change based on the three groups who own cars registered before 2012, after 2012 and no car (upon 2018). Obviously, the new buyers concern the most on "Emission damage to human health", followed by "Buyer cost", which is evaluated as the most important KGPI by the other two groups who own cars now. Furthermore, both "before 2012" and "no car" groups assign high importance to emission damage related KGPIs, while the group of "after 2012" assigns more weight to "Car performance" and "Other incentives". It is probably because before 2012, there were not lots of incentives available in the market when the group of "before 2012" purchased a car, they did not consider much on "other incentives"

KGPIs. For the group of "after 2012", the purchasing decision is also dependent on "Buyer cost". In the past few years, public awareness of environmental protection due to extreme weathers causes the increasing importance of emission damage related KPGIs.

Table 9 Relative weights of the second level factors to top-level factors between responses from different car ownership types

Factor	Before 2012	Rank	After 2012	Rank	No car	Rank
Emission damage to human health	0.222	2	0.154	5	0.260	1
Emission damage to the environment	0.211	3	0.178	4	0.223	3
Buyer cost	0.261	1	0.273	1	0.231	2
Car performance	0.158	4	0.213	2	0.159	4
Other incentives	0.147	5	0.182	3	0.126	5

5.5 Car cleanliness analyses from different respondent groups

In this section, the different weights of the KGPIs from the above analysis are used in the ER and its IDS software to find out the car cleanliness degrees to different respondent groups.

1) The General public and Technical and governmental bodies

The assessments of the six selected vehicles by the General public and Technical and governmental bodies are presented in Table 10. The vehicle cleanliness is ranked by comparing their average utility values. For both respondent groups, NISSAN LEAF Acenta 40kWh Auto is the best choice, and AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic is the second-best choice.

Table 10 Ranking comparison of the 6 selected vehicles by General public and Technical and governmental bodies

	General public				**Technical and governmental bodies**			
Vehicle options	Worst possible	Average	Best possible	Rank	Worst possible	Average	Best possible	Rank
JAGUAR E-Pace 2.0D I4 180PS AWD	0.5657	0.5804	0.5950	5	0.5461	0.5639	0.5818	5
BMW M2 Competition DCT	0.4864	0.5010	0.5156	6	0.4889	0.5066	0.5243	6
VW Passat Saloon 2.0 TDI SE Business 150PS	0.6725	0.6725	0.6725	3	0.6668	0.6668	0.6668	4

AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic	0.7435	0.7435	0.7435	2	0.7209	0.7209	0.7209	2
NISSAN LEAF Acenta 40kWh Auto	0.8017	0.8111	0.8205	1	0.8141	0.8212	0.8283	1
Tesla Model X Long Range AWD Auto	0.6190	0.6559	0.6928	4	0.6312	0.6779	0.7246	3

2) Greater London and North West England

The assessments of the six selected vehicles by Great London and North West England are presented in Table 11. “Exemption from London Congestion Charge” and “Exemption from London T-charge” are two London-only factors. They have been exempted (assigned a zero weight) in the North West England KGPI framework. NISSAN LEAF Acenta 40kWh Auto and AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic are the top two choices for both respondent groups. However, their preference degrees in Greater London is higher than those in North West England.

Table 11 Ranking comparison of the 6 selected vehicles by responses from Greater London and North West England

	Greater London				**North West England**			
Vehicle options	Worst possible	Average	Best possible	Rank	Worst possible	Average	Best possible	Rank
JAGUAR E-Pace 2.0D I4 180PS AWD	0.5281	0.5446	0.5611	5	0.5196	0.5439	0.5682	5
BMW M2 Competition DCT	0.4631	0.4796	0.4960	6	0.4733	0.4971	0.5210	6
VW Passat Saloon 2.0 TDI SE Business 150PS	0.6571	0.6571	0.6571	4	0.6482	0.6482	0.6482	3
AUDI A3 Sportback e-tron 1.4 TFSI e-tron 150PS S Tronic	0.7684	0.7684	0.7684	2	0.6731	0.6731	0.6731	2
NISSAN LEAF Acenta 40kWh Auto	0.8409	0.8409	0.8409	1	0.7498	0.7498	0.7498	1
Tesla Model X Long Range AWD Auto	0.6862	0.7084	0.7306	3	0.5503	0.5874	0.6244	4

6 Conclusion

This paper proposes a new KGPI framework via an advanced ER-AHP hybrid approach, to support decision makers (the general public or buyers), as well as technical and governmental bodies, to rationalize their car choice analysis with a focus on vehicle emission reduction. The framework has been developed to provide the potential decision makers with a single value on each vehicle to guide them towards clean vehicles. While new technologies such as EVs and AFVs make contributions to reducing vehicle emissions, the KGPIs can be applied to aid choice between ICEVs and AFVs. For the general public, it is useful for guiding buyers’ choice on relatively greener cars against the existing internal combustion fleets. In addition, KGPI is vital as, using the same structure but deriving different indicators' weights and preferences, it can be used by technical/manufacturer to evaluate new vehicles brought into the market and generate a comparable result to benchmark those from the existing ones.

From an academic perspective, the first contribution of this study is to generate a single score on a car purchasing decision for a single person or buyers' group. The current non-single factor scheme is not helpful because it cannot provide a final decision involving the factors from multiple dimensions (e.g. emissions) and multiple stakeholders of interest of conflict. Secondly, social factors, including the governmental policies and charging point availability, are first considered in vehicle cleanliness analysis and in the same decision-making framework. They are essential as emphasised in the current literature. However, the difficulty of combing such social factors and emission attributes has yet to be coped within previous relevant studies. Thirdly, fuzzy evidential reasoning (FER) is applied to this new topic with real case studies. This study has incorporated qualitative data, and subjective expert evaluations to compensate the incompleteness and unavailability of the objective data. In this process, experts can use linguistics terms with a belief structure (such as 80% "Preferred" and 20% "Extremely preferred") to define qualitative factors. Fourthly, multiple stakeholder perspectives on car purchasing are considered in this paper. A comparative analysis between buyers and the other stakeholder groups, takes place to observe the different understanding in car purchasing decision among them for rational policymaking.

In future, more questionnaires will be distributed for collecting new data for sensitivity analysis, which can help provide useful insights for tailor-made decisions for potential car buyers. Finally, policymakers and manufacturers having different perspectives on buyer choice decisions can make use of the framework to promote green car initiatives and policies by enhancing performances and providing suitable incentives.

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