Energy Economics 158 (2026) 109322

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Balancing climate action for greater transport decarbonisation: An avoid-shift-improve driven network data envelopment analysis framework

Keyvan Hosseini [a,b], Saeed Assani [c], Agnieszka Stefaniec [d,*], Philippos Papaphilippou [e], Anna Charly [f], Brian Caulfield [b]

[a] *School of Health Sciences, University of Southampton, Southampton, United Kingdom*
[b] *Trinity Centre for Transport Research, Department of Civil, Structural and Environmental Engineering, Trinity College Dublin, Dublin, Ireland*
[c] *Department of Mathematics, Nanjing University of Aeronautics and Astronautics, Nanjing, China*
[d] *Department of Decision Analytics and Risk, Southampton Business School, University of Southampton, Southampton, United Kingdom*
[e] *School of Electronics and Computer Science, University of Southampton, Southampton, United Kingdom*
[f] *Department of Civil and Environmental Engineering, University of Liverpool, Liverpool, United Kingdom*

ARTICLE INFO

Keywords:
Sustainable transport
Avoid-shift-improve
Transport decarbonisation
Just transition
Data envelopment analysis
Stackelberg leader–follower game
Best-worst method

ABSTRACT

Transport decarbonisation requires allocating limited resources across competing strategies. The Avoid–Shift–Improve framework categorises these strategies to reduce transport's reliance on fossil fuels. This study develops an Avoid–Shift–Improve driven network data envelopment analysis (DEA) framework to measure county-level progress toward transport decarbonisation. The framework also serves as a decision-support tool for allocating resources efficiently to advance transport decarbonisation. Using data from Ireland's 26 counties, we integrate DEA with a Stackelberg leader–follower game and the best–worst method. The DEA component provides an objective, mathematically defined measure of relative efficiency. The best–worst method incorporates expert judgement on the economic and environmental impact of actions within the Avoid–Shift–Improve hierarchy. This hierarchical approach, reflecting expert consensus, prioritises transformational measures that reduce travel demand (Avoid), followed by strategies that shift remaining trips to low-carbon modes (Shift), while technological improvements (Improve) play a more limited role. Results reveal disparities in county performance. Dublin leads due to its relatively well-developed public transport and active mobility infrastructure. Smaller counties such as Longford and Leitrim also perform strongly despite their rural character. By contrast, large-area counties including Cork, Mayo, and Kerry underperform, reflecting structural challenges of dispersed settlement and high car dependency. The analysis highlights that larger counties achieve lower efficiency scores, while links with emissions and expenditure are weaker, underscoring the role of spatial scale and carbon lock-in in shaping outcomes. The framework is scalable to other regional and national contexts and can support economically rational, socially inclusive climate policy.

1. Introduction

Decarbonising transport requires allocating limited resources across competing interventions. It is indispensable to meeting climate commitments, yet progress remains slow given that internal-combustion-engine vehicles (ICEVs) still dominate personal and freight mobility. Their fossil-fuel dependence drives greenhouse-gas (GHG) emissions and distributes environmental, health, and social burdens unequally (Beltrán-Esteve and Picazo-Tadeo, 2015; LaMonaca and Ryan, 2022). Over recent decades, escalating car dependence and low-density urban expansion have locked in carbon-intensive travel patterns that are difficult and costly to reverse (Banister, 2008; Burgess, 2015; Hosseini and Stefaniec, 2023).

Ireland exemplifies the scale of the problem. While the State has pledged, under the Climate Action and Low Carbon Development (Amendment) Act, to reduce economy-wide emissions by 51% by 2030, it remains the third-highest per-capita emitter within the European Economic Area (Environmental Protection Agency (EPA), 2024a; Emissions Database for Global Atmospheric Research (EDGAR), 2024). Agriculture still accounts for most of national emissions, but the

---

* Corresponding author.
E-mail addresses: k.hosseini@soton.ac.uk (K. Hosseini), saeedassani@nuaa.edu.cn (S. Assani), a.stefaniec@soton.ac.uk (A. Stefaniec), p.philippos@soton.ac.uk (P. Papaphilippou), anna.charly@liverpool.ac.uk (A. Charly), brian.caulfield@tcd.ie (B. Caulfield).

https://doi.org/10.1016/j.eneco.2026.109322
Received 24 August 2025; Received in revised form 4 February 2026; Accepted 27 March 2026

transport share has more than doubled since 1990, reaching 21.4% in 2023 (Environmental Protection Agency (EPA), 2024b). Achieving the national target, therefore, hinges on rapid, deep cuts in transport-related CO_2.

Assessing decarbonisation options is not simply a technical exercise; transport decisions shape access to jobs, education, and healthcare, influence land values, and create long-term fiscal liabilities through congestion, pollution, and road maintenance (Marrero et al., 2021; Stefaniec et al., 2021). Effective assessment must therefore interrogate the political and institutional levers that translate strategy into action.

The Avoid–Shift–Improve (ASI) framework remains a valuable organising heuristic, yet its contribution currently lies less in the taxonomy itself and more in the policy adjustments that activate each pillar. Without credible fiscal, regulatory, and infrastructural measures, the framework risks becoming another abstract planning tool (Intergovernmental Panel on Climate Change (IPCC), 2022). Recent scholarship underscores this point: measures that merely 'improve' vehicles dominate funding, while demand-side measures that 'avoid' or 'shift' trips are routinely under-resourced (Joyashree Roy et al., 2021; Mårtensson et al., 2023). Past over-reliance on Improve measures alone has delivered limited progress, prompting a renewed emphasis on demand-side governance (Bongardt et al., 2019). Hence, sequencing matters: first reduce demand through Avoid, then redirect the remaining demand to low-carbon modes through Shift, and then decarbonise the motorised traffic that must still be moved through Improve (Creutzig et al., 2018; Wimbadi et al., 2021).

It should be noted that the three categories are not strictly separate and may overlap in several measures they represent. For instance, active mobility measures such as cycling can be classified under both the Avoid and Shift strategies. Furthermore, all Avoid actions, along with certain Shift measures, demand a reduction in consumption, whereas Improve measures are often framed as enabling more responsible forms of consumption by reducing emissions intensity through technological and operational efficiency improvements, rather than reducing demand. Since slowing down climate change and decarbonisation is the primary objective for the Avoid-Shift-Improve framework (Suomalainen, 2025), therefore, even if a particular measure does not contribute to other goals of sustainable urban transport and focuses solely on climate change mitigation, it is included in this framework. For instance, the electrification of private car fleets does not contribute to active and healthy lifestyles nor to reducing traffic congestion, but it arguably can reduce GHG emissions in urban areas (Charly et al., 2023; Hosseini and Stefaniec, 2023). Therefore, this electric vehicle (EV) penetration is categorised as an Improve measure (Creutzig et al., 2018; Wimbadi et al., 2021).

Previous studies have identified various sub-strategies within each Avoid-Shift-Improve strategy. Avoid strategies emphasise reducing travel demand and urban sprawl. Studies highlight teleworking as an effective measure (Dillman et al., 2021), along with compact city development, to promote densification and mixed land use (Lah, 2015; Roy et al., 2021). Other measures include smart logistics to optimise freight transport (Creutzig et al., 2018), improved pedestrian infrastructure (Creutzig et al., 2022), and enhanced cycling networks with designated bike lanes (Hidalgo and Huizenga, 2013; Hosseini et al., 2023). Shift strategies concentrate on transitioning toward more sustainable and low-carbon modes of transport. Research underscores the importance of public transport connectivity, including bus rapid transit systems and dedicated public transport lanes (Hidalgo and Huizenga, 2013). Additionally, shared mobility options, such as carpooling and micromobility services, can help reduce transport emissions (Hosseini et al., 2024; Creutzig et al., 2022). Integrated public transport infrastructure, including park-and-ride schemes (Roy et al., 2021); traffic zone regulations, such as congestion pricing, fuel taxes, and urban tolls (Nakamura and Hayashi, 2013); and the use of information and communication technologies for public transport, including automated fare collection (Wimbadi et al., 2021) further support modal shift. Improve measures aim to enhance vehicle and fuel efficiency. Research highlights the importance of expanding EV sales and charging infrastructure (Creutzig et al., 2018) and electrifying public transport fleets (Say et al., 2024; Dillman et al., 2021). Adopting clean energy vehicles, including hydrogen and biofuel-powered transport, is also critical (Zhu et al., 2023; Dalkmann and Brannigan, 2021). Further measures include promoting smaller, lightweight vehicles to enhance energy efficiency and reduce overall resource consumption (Stefaniec et al., 2025) and enforcing stricter technical inspection programmes and emission standards (Nakamura and Hayashi, 2013).

The ongoing debate between supporters of Avoid measures and their critics focuses on the feasibility and applicability of actions to reduce transport activities. Common ground exists in the understanding that reducing or avoiding travel mainly pertains to motorised transport. Avoiding walking or biking is less impactful, as these activities, which rely solely on human power, contribute minimally to emissions even when considering the whole-life impact of vehicles and infrastructure. Additionally, while restricting travel may be seen as limiting freedom or the right to move, which includes opportunities for social interactions, it is deemed reasonable to reduce excessive and energy-intensive travel given the climate emergency and its consequences. For instance, the use of private jets for leisure and business trips is often cited (Gössling et al., 2024). Moreover, despite the challenges in implementing Avoid measures, evidence suggests that they are more effective than Improve measures—and at least as effective as Shift measures—in delivering greater emissions reductions and additional benefits for well-being and nature (Zhang and Hanaoka, 2022). If, however, the effectiveness of measures is to be balanced against the investment, the Shift strategy emerges as the most viable and economical option for curbing CO_2 emissions in transportation. While the Improve strategy can also contribute to cutting emissions, it is less effective and more costly than Shift measures (Zhu et al., 2023). The Avoid strategy, particularly in its spatial redesign measures, is a long-term implementation option despite its unquestioned effectiveness.

Ireland has embedded the Avoid–Shift–Improve hierarchy in its transport decarbonisation strategy. The Climate Action Plan labels every transport action by pillar and highlights high-impact interventions such as road-space reallocation, demand-management pricing, and public-engagement campaigns to make low-carbon modes the default choice (Department of Climate, Energy and the Environment, 2024). Yet the Climate Change Advisory Council concludes that Avoid levers, such as compact-growth planning, distance-based road-user charging, and a comprehensive review of motoring taxes, are still at consultation stage, placing the sector on a trajectory to exceed its carbon budgets unless demand is curbed more aggressively (Climate Change Advisory Council, 2024). Hence, the Government employs Avoid–Shift–Improve as a practical organising framework, but its success will depend on accelerating the statutory and fiscal instruments that suppress car dependency before relying on technological improvements to reduce emissions from the trips that remain.

While this study adopts the term decarbonisation in line with dominant transport policy and academic discourse, it does not imply the complete elimination of fossil energy from the transport system. Within the Avoid–Shift–Improve framework, different actions contribute to emissions reduction through distinct mechanisms. Avoid and Shift measures deliver direct decarbonisation by reducing travel demand and high-carbon mobility. In contrast, EV-related Improve actions contribute conditionally and depend on the carbon intensity of the energy system. EV-related Improve actions are included because they represent one of the principal climate policy instruments currently adopted by governments and therefore form part of real-world transport strategies. In this study, however, such measures are deprioritised through lower weights, reflecting their more limited contribution to system-level decarbonisation. Electrification alone does not guarantee a fossil-free outcome where electricity generation remains carbon intensive.

Full decarbonisation also remains particularly challenging for sectors such as aviation, maritime transport, and long-haul freight, where technological alternatives are limited or uncertain (Gross, 2020). In this context, it is useful to distinguish between reductions in tailpipe (tank-to-wheel) emissions and emissions reductions assessed on a well-to-wheel basis (Challa et al., 2022). Electric vehicles act as a defossilisation measure at the vehicle level but do not inherently eliminate carbon emissions at the system level if electricity generation remains fossil based. In such cases, emissions are displaced upstream within the energy system rather than eliminated.

In Ireland, electric vehicles (EVs) accounted for an estimated 6.39% of the national vehicle fleet (Illahi et al., 2024), alongside government policy measures such as Vehicle Registration Tax relief and Benefit-in-Kind exemptions. Ireland's Climate Action Plan sets a target for EVs to represent 30% of the national vehicle fleet by 2030, corresponding to approximately 960,000 vehicles (Government of Ireland, 2025; Stefaniec et al., 2024). According to the Department of Transport (2025), 195,000 EVs were registered by the end of September 2025. Previous research on barriers to EV uptake in Ireland indicates that households often purchase EVs as a second or additional car rather than as a direct replacement for an internal combustion engine vehicle, which can limit their overall impact on reducing fossil fuel vehicle use (O'Neill et al., 2019). In addition, there has been growing criticism that the rollout of charging infrastructure does not match the scale of Ireland's national ambition (The Irish Times, 2026). While public charging infrastructure is expanding through state-led investment programmes, coverage and reliability remain uneven, particularly outside major urban areas.

Ireland's recent energy profile also shows gradual progress toward renewables alongside a continued reliance on fossil fuels, particularly in the transport sector. In 2024, renewable sources accounted for 14.6% of Ireland's primary energy, while 93% of transport energy consumption remained fossil fuel–based. In the electricity sector, fossil fuel–based sources accounted for 45.3% and renewables accounted for 40.0% of generation, with natural gas as the dominant source (41.8%), followed by wind (32.1%) and net electricity imports (13.9%). This mix reflects progress in renewable electricity generation alongside continued reliance on gas for system stability (Sustainable Energy Authority of Ireland, 2025). Together, these figures provide background context for the role of EVs within Ireland's transport and energy system.

The core intention of this research is to analyse strategies focused on mitigating dependency on private cars by developing a decarbonisation assessment framework to examine the transport sector based on the Avoid-Shift-Improve framework. This model combines network DEA with a Stackelberg competition game (objective assessment) and the best-worst multi-criteria decision-making method (BWM; subjective assessment) through decomposition and composition processes, using Ireland as the test study area. In particular, this research aims to evaluate the efforts toward carbon-neutral mobility in 26 counties of Ireland, considering measures to progress toward decarbonisation in travel behaviour, transport planning and technological advancement. The diverse actions defined within the proposed Avoid-Shift-Improve framework are distilled into a concise set of indicators to facilitate the quantitative assessment. This framework allows for the quantification of the effects of implementing these measures and for the comparison of the results, which can lead to balancing the policies and strategies regionally and guiding efficient allocation of resources to achieve greater emissions reductions. The motivation for this comparative analysis is to pinpoint disparities, illuminate best practices, and identify areas that require intervention to advance sustainable mobility throughout the region. This work addresses the needs and challenges facing Ireland, but also mirrors the global agenda for sustainable mobility, underscoring its broader applicability.

2. Method and data

Governments prioritise various actions to achieve emissions reduction and balance the decarbonisation goals with other objectives, including equity, sustainability, and just transitions (International Energy Agency (IEA), 2021). Categorising the actions and evaluating efforts toward them establishes a coherent framework to assess measures across the Avoid-Shift-Improve strategies. Additionally, comparing the effectiveness of these plans provides a feedback loop, enabling the redesign of plans and targets. Such a structured approach to monitoring progress toward sustainable transport is critical in the context of a climate emergency, where there is a pressing need for effective and swift action nationwide. This section describes how DEA, a powerful mathematical performance measure, was used in conjunction with BWM and the Stackelberg competition game to provide a reliable assessment based on this proposed evaluation framework.

2.1. Best-worst method for subjective assessment

Multi-criteria decision-making (MCDM) techniques are developed to tackle decision-making and appraisal challenges involving a set of criteria. Among the various MCDM approaches, the Best-Worst MCDM (BWM), developed by Rezaei (2015), stands out as a linear mathematical method based on pairwise comparisons for determining weights in MCDM problems. Since its inception, BWM has been increasingly adopted in science and engineering applications due to its precision, simplicity, and reliability (Torkayesh et al., 2021). Researchers have employed BWM across various sustainability applications, appreciating its fewer required pairwise comparisons and its capacity to manage inconsistencies that arise from these comparisons. The reader is referred to several applications of BWM in the transport sustainability realm (Rezaei et al., 2018; Thompson et al., 2024; Foroozesh et al., 2022; Rezaei et al., 2017).

The BWM was selected over alternative weighting approaches such as the Analytic Hierarchy Process (AHP) and entropy-based methods for several reasons related to the design and objectives of this study. First, BWM requires substantially fewer pairwise comparisons than AHP, which reduces cognitive burden on respondents with highly specialised expertise, who are often scarce, busy, and difficult to recruit (Huang et al., 2024). While BWM is designed to produce and structure expert judgement efficiently, entropy-based weighting methods derive weights primarily from data variability rather than expert judgement and are therefore less well suited to capturing normative policy priorities and expert judgement, which are central to the objectives of this study. Second, BWM incorporates an explicit consistency measure, enabling the reliability of expert judgements to be assessed and reported (Roy, 2023). Third, the structured design of BWM helps mitigate behavioural biases commonly observed in pairwise comparison methods. Anchoring bias arises when early or prominent reference points unduly influence subsequent judgements, while equalising bias reflects a tendency to assign similar importance to criteria despite substantive differences in their relevance. By requiring experts to explicitly identify the most and least important criteria and to evaluate all others relative to these reference points, BWM reduces the influence of such biases and promotes clearer discrimination among criteria (Rezaei et al., 2022; Li et al., 2024; Rezaei et al., 2024).

In this study, BWM is applied within the Avoid-Shift-Improve framework to prioritise actions according to their impact and feasibility. It is crucial for government investment decisions to identify which decarbonisation strategies and measures are more impactful and inclusive in decreasing anthropogenic reliance on fossil fuels. This method was utilised to engage transport experts to validate the importance of strategies aimed at decarbonising the passenger transport system.

The application of BWM serves a two-fold purpose: Firstly, to shed light on which of the Avoid, Shift, or Improve strategies should receive more priority in the Stackelberg competition based on expert insights, and secondly, to determine weights for the subjective composition of the decarbonisation score across each strategy, ultimately producing a unified decarbonisation score for each county. By engaging experts to prioritise decarbonisation actions, the study aligns theoretical models with practical insights. This approach ensures that the evaluation metrics are grounded in expert consensus, thereby enhancing the relevance, applicability and acceptability of the research findings. This novel integration of the Avoid-Shift-Improve framework and BWM distinguishes this study, showcasing its unique approach to tackling decarbonisation through a structured, expert-driven weighting methodology.

Rezaei (2015) describes the five steps of BWM as follows: In the initial step, a set of criteria is identified and specified. The second step involves the experts identifying the most and least favourable criteria within the set. In the third step, experts conduct pairwise evaluations for each criterion to establish the preference of the most prominent criterion relative the others using a nine-point scale, resulting in a best-to-other vector where each element represents the preference of the best criterion over another criterion, and the preference of the best criterion over itself is always one. The fourth step involves performing pairwise comparisons between the other criteria and the least favourable one, leading to an other-to-worst vector, where each element signifies the preference of a criterion over the least favourable, and the self-preference of the worst criterion also set at one. Finally, the fifth step involves calculating optimal weights for all criteria using the previously obtained comparison outcomes.

In accordance with the steps outlined above, a questionnaire based on the BWM, detailing the nine actions mentioned in Fig. 1, was developed and distributed to ten experts to gather their insights for determining weights. To ensure the derivation of reliable weights, it is crucial that respondents possess comprehensive knowledge of sustainable urban transportation and transport engineering. To incorporate both professional and academic perspectives, three of the ten experts were employed by the National Transport Authority of Ireland and were involved in transport modelling and policy implementation, while the remaining seven were affiliated with universities or research institutes as academic researchers in transportation-related divisions. The academic experts included senior researchers at chair and professor levels, as well as associate professor and assistant professor levels, all holding doctoral qualifications in relevant fields.

2.2. Network DEA model for objective assessment

2.2.1. Decomposing the black-box into a network model

Introduced by Charnes et al. (1978), DEA provides a robust nonparametric method to evaluate the relative efficiency of decision-making units (DMUs) that operate employing various inputs and outputs. Further, network DEA is developed by Färe and Primont (2012) to address the need for capturing internal operations and interdependencies within complex systems that feature hierarchical structures. The application of network DEA is an advanced extension of the conventional DEA model, allowing for a more granular analysis by considering the internal structure of the DMUs. DEA is extensively documented in the literature for measuring sustainability and decarbonisation across various segments of the transportation sector in regional, national, and international case studies (See et al., 2025; Charles and Emrouznejad, 2024; Sandhiya and Gajanand, 2024; Stefaniec et al., 2020; Stefaniec et al., 2021; Michali et al., 2021; Zhang et al., 2024). In the context of this study, each Irish county represents a DMU,

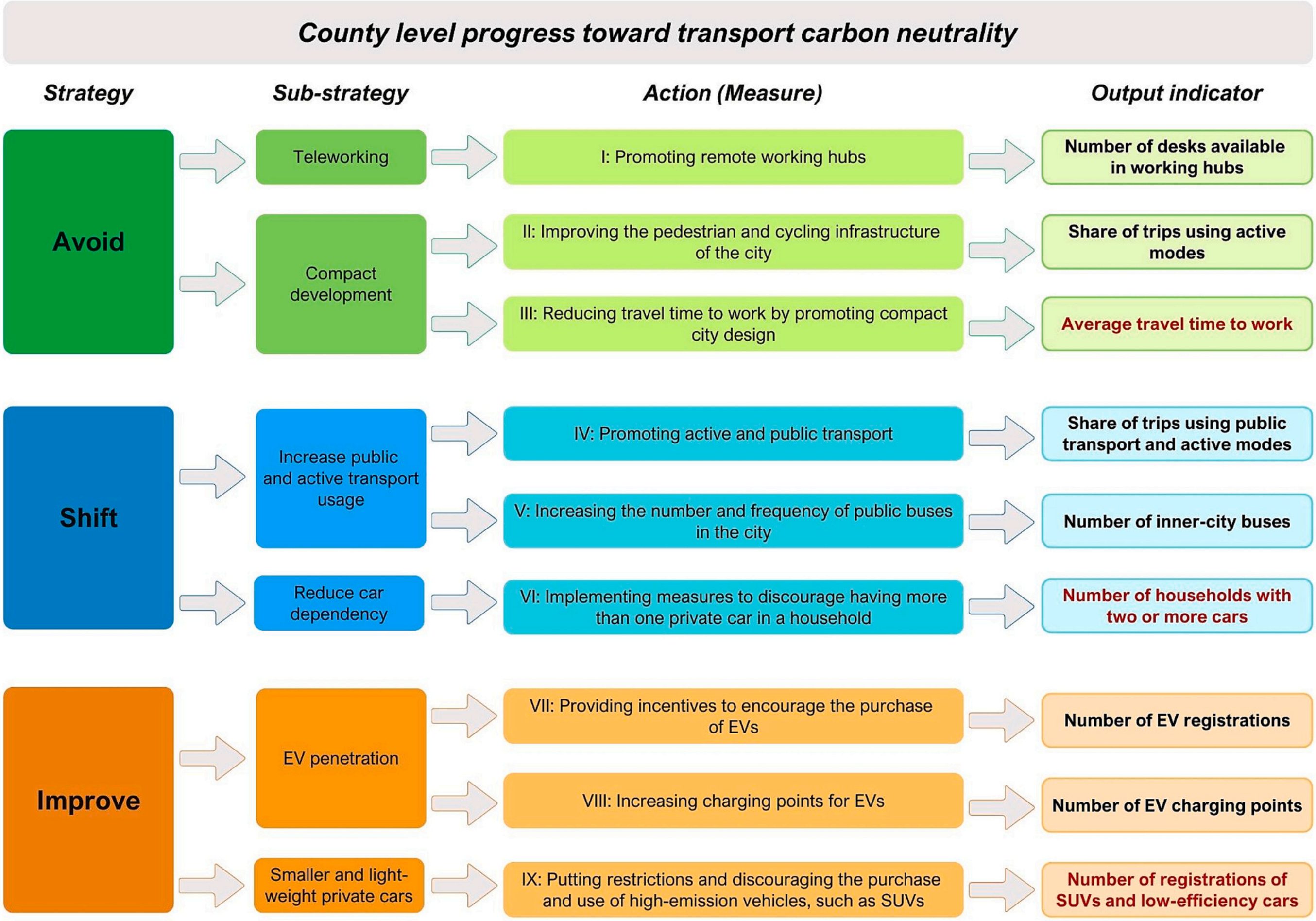

Fig. 1. Illustration of the proposed decarbonisation appraisal Network DEA framework, consisting of three subunits corresponding to Avoid, Shift, and Improve strategies, respectively. The strategy is then linked to its corresponding sub-strategies and actions, and measurable indicators are defined that serve as outputs to the model (Undesirable outputs are denoted by red).

and their decarbonising transport performances are evaluated relative to each other based on the proposed framework (Fig. 1).

In this section, we build our proposed models to compute the overall decarbonisation scores of the system and the scores of the internal processes Avoid, Shift, and Improve by generalising the model of Chen and Delmas (2012) from the black-box DEA model in the envelopment form into a network DEA model in the multiplier form.

Below, the model of Chen and Delmas (2012) is presented in envelopment form. Assume K is the number of DMUs under assessment, each utilising M inputs to generate N desirable outputs and B undesirable outputs. Specifically, DMU_0 (“0” denotes the DMU under assessment) consumes a certain amount of input M $(x_{m0}, m = 1, 2, \dots, M)$ to generate a certain amount of desirable output N $(y_{n0}, n = 1, 2, \dots., N)$, and a certain amount of undesirable output B $(u_{b0}, b = 1, 2, \dots, B)$; these are all known and positive values. The eco-inefficiency model of Chen and Delmas (2012) under constant returns to scale (CRS) and output orientation is given as follows:

$$\max \frac{1}{N+B}\left(\sum_{n=1}^{N}\frac{g_n^y}{y_{n0}} + \sum_{b=1}^{B}\frac{g_b^u}{u_{b0}}\right) \tag{1}$$

$$s.t. \sum_{k=1}^{K}\lambda_k x_{ik} \le x_{i0}, for\ i = 1, \dots, M, \tag{2}$$

$$\sum_{k=1}^{K}\lambda_k y_{nk} \ge y_{n0} + g_n^y, for\ n = 1, \dots, N, \tag{3}$$

$$\sum_{k=1}^{K}\lambda_k u_{bk} \le u_{b0} - g_b^u, for\ b = 1, \dots, B, \tag{4}$$

$$\lambda_k \ge 0, g_n^y \ge 0, g_b^u \ge 0, for\ all\ k, n, b, \tag{5}$$

where λ_k denotes a nonnegative and nonzero intensity variable for each DMU_k, indicating the importance of DMU_k in establishing the efficient frontier. The variables g_n^y and g_b^u represent the excess and shortfall of desirable and undesirable output, respectively. The objective function in Eq. (1) maximises the average proportional improvement in both desirable and undesirable outputs relative to the observed outputs of the DMU under evaluation, DMU_0. The input constraints in Eq. (2) guarantee that the projected inputs do not exceed the observed inputs of the DMU under evaluation. The desirable output constraints in Eq. (3) ensure that the projected desirable outputs are at least as large as the observed outputs plus the corresponding improvement. In contrast, the undesirable output constraints in Eq. (4) ensure that the projected undesirable outputs are at most equal to the observed undesirable outputs minus the corresponding improvement. The non-negativity constraints in Eq. (5) ensure that all variables are non-negative. Therefore, $\left(g_n^{y^*}, g_b^{u^*}, \lambda_k^*\right)$ denotes the optimal solution of Eqs. (1)–(5). Here, we consider the output orientation to be consistent with our target. Thus, the direction $\left(g_n^y = y_{n0}, g_b^u = u_{b0}\right)$ has been chosen.

The model of Chen and Delmas (2012) has a dual multiplier form. Eqs. (1)–(5) are written in the enveloped form using the intensity variable. By converting Eqs. (1)–(5) to their equivalent dual multiplier form, using the dual theory (Färe and Primont, 2012), we have:

$$\min \sum_{i=1}^{m} v_i x_{i0} - \sum_{n=1}^{N} w_n y_{n0} + \sum_{b=1}^{B} q_b u_{b0} \tag{6}$$

$$s.t. (N+B)\sum_{n=1}^{N} w_n \ge \frac{1}{y_{n0}}, for\ n = 1, \dots, N, \tag{7}$$

$$(N+B)\sum_{b=1}^{B} q_b \ge \frac{1}{u_{b0}}, for\ b = 1, \dots, B, \tag{8}$$

$$\sum_{i=1}^{m} v_i x_{ik} - \sum_{n=1}^{N} w_n y_{nk} + \sum_{b=1}^{B} q_b u_{bk} \ge 0, for\ k = 1, \dots, K, \tag{9}$$

$$v_i, w_n, q_b \ge 0, for\ all\ i, n, b. \tag{10}$$

In Eqs. (6)–(10), v_i, w_n, and q_b represent the shadow prices of inputs, desirable outputs, and undesirable outputs, respectively. The objective function in Eq. (6) minimises the weighted sum of inputs, desirable outputs, and undesirable outputs. Eq. (7) represents the dual constraints associated with g_n^y while Eq. (8) represents the dual constraints associated with g_b^u. The dual constraints involving λ_k are given in Eq. (9), which ensure that the weighted sum of inputs, desirable outputs, and undesirable outputs for each DMU is non-negative.

Eqs. (6)–(10) are designed to represent a black-box decision system. In our case, we have three processes connected in parallel, so we need to write Eqs. (6)–(10) in their corresponding network model.

To better reflect real-world dynamics, we propose a parallel subunit network DEA model rather than a multistage (series) structure. In this parallel structure, three processes operate independently, each using its inputs to generate outputs without intermediate measures or connections between them. This is the key distinction between a parallel and a series network. In practical terms, government policies often address these processes simultaneously rather than sequentially. A series network would imply that the second stage depends on the outcomes of the first stage – meaning intermediate measures link each stage. However, this is not applicable in our case. For instance, the number of Sport Utility Vehicles (SUVs) purchased is not a direct consequence of having a high or low number of remote working hubs in a given county, nor does a low or high number of these hubs lead to buying more or fewer SUVs. One of the advantages of a parallel network structure is that each process can be analysed independently, producing outputs without requiring inputs from another process. This allows for simultaneous assessment, rather than waiting for one stage to complete before the next begins. Regarding the relative importance of subunits (Avoid, Shift, Improve), the leader-follower approach can be applied to either network structure – parallel or series – as it does not inherently depend on the choice of network design.

Here, the dual multiplier model of Chen and Delmas (2012), Eqs. (6)–(10) is generalised to a network model in dual multiplier form. Assume that each DMU_0 utilises a certain amount of inputs mp (x_{mp0}) in each process $P(p = 1, 2, 3)$ where the sum of the inputs of all sub-units is x_{m0}. In addition, each process produces a specific amount of desirable output np $\left(y_{np0}, p = 1, 2, 3\right)$, and a specific amount of undesirable output bp $(u_{bp0}, p = 1, 2, 3)$; these are all known and positive values. In other words, the system is inhomogeneous from the output side as each process produces different types of outputs. Here, all processes consume the same types of inputs.

The proposed network model of the whole system, overall efficiency, is given as follows:

$$\beta_0^{System} = \min \sum_{i=1}^{m} v_i x_{i0} - \sum_{p=1}^{3}\sum_{np=1}^{Np} w_{np} y_{np0} + \sum_{p=1}^{3}\sum_{bp=1}^{Bp} q_{bp} u_{bp0} \tag{11}$$

$$s.t. (N+B)\sum_{np=1}^{Np} w_{np} \ge \frac{1}{y_{np0}}, for\ n = 1, \dots, N, p = 1, 2, 3, \tag{12}$$

$$(N+B)\sum_{bp=1}^{Bp} q_{bp} \ge \frac{1}{u_{bp0}}, for\ b = 1, \dots, B, p = 1, 2, 3, \tag{13}$$

$$\sum_{i=1}^{m} v_i x_{ik} - \sum_{p=1}^{3}\sum_{np=1}^{Np} w_{np} y_{npk} + \sum_{p=1}^{3}\sum_{bp=1}^{Bp} q_{bp} u_{bpk} \ge 0, for\ k = 1, \dots, K, \tag{14}$$

$$v_i, w_{np}, q_{bp} \ge 0, for\ all\ i, n, b, p. \tag{15}$$

Eq. (11) extends Eq. (2) to a parallel network DEA model and minimises the weighted sum across all three processes (Avoid, Shift, Improve). Each process p has its own desirable outputs y_{np0} and undesirable outputs u_{bp0}. Eqs. (12) and (13) extend the normalisation constraints in Eqs. (7) and (8) to each process p for the desirable and undesirable outputs, respectively. Eq. (14) represents the feasibility constraint for each DMU_k across all processes. The System efficiency score for the DMU under evaluation is computed as $\varnothing_0^{System*} = 1/\left(1 + \beta_0^{System*}\right)$ which takes values between 0 and 1. A score of 1 indicates full system efficiency.

2.2.2. Establishing subunit hierarchy using the Stackelberg competition

Since we aim to attach more importance to the first criterion Avoid than the other two criteria and attach importance to the second criterion Shift more than the third one Improve based on the BWM results, we apply a leader-follower approach developed by Stackelberg (1934). First, the decarbonisation score of Avoid is calculated by keeping the efficiency of the whole System, calculated from Eqs. (11)–(15), unchanged (see Eqs. (16)–(21)). Second, the decarbonisation score of Shift will be calculated by keeping the System's efficiency, calculated from Eqs. (11)–(15), and Avoid efficiency, calculated from Eqs. (16)–(21), unchanged (see Eqs. (22)–(28)). Third, the Improve decarbonisation score will be calculated by restricting the System's score and the scores of Avoid and Shift unchanged (see Eqs. (29)–(36)).

The following equations delineate the efficiency model for the Avoid strategy:

$$\beta_0^{Avoid} = \min \sum_{i=1}^{m1} v_i x_{i0} - \sum_{n1=1}^{N1} w_{n1} y_{n10} + \sum_{b1=1}^{B1} q_{b1} u_{b10} \tag{16}$$

$$s.t.(N+B) \sum_{np=1}^{Np} w_{np} \geq \frac{1}{y_{np0}}, for\ n = 1, \ldots, N, p = 1, 2, 3, \tag{17}$$

$$(N+B) \sum_{bp=1}^{Bp} q_{bp} \geq \frac{1}{u_{bp0}}, for\ b = 1, \ldots, B, p = 1, 2, 3, \tag{18}$$

$$\sum_{i=1}^{m1} v_i x_{ik} - \sum_{n1=1}^{N1} w_{n1} y_{n1k} + \sum_{b1=1}^{B1} q_{b1} u_{b1k} \geq 0, for\ k = 1, \ldots, K, \tag{19}$$

$$\beta_0^{System*} = \sum_{i=1}^{m} v_i x_{i0} - \sum_{p=1}^{3} \sum_{np=1}^{Np} w_{np} y_{np0} + \sum_{p=1}^{3} \sum_{bp=1}^{Bp} q_{bp} u_{bp0}, \tag{20}$$

$$v_i, w_{np}, q_{bp} \geq 0, for\ all\ i, n, b, p. \tag{21}$$

The efficiency score of the Avoid process for DMU under evaluation the is computed as $\varnothing_0^{Avoid*} = 1/\left(1 + \beta_0^{Avoid*}\right)$. Eqs. (17) and (18) represent the normalisation constraints and are identical to those in Eqs. (12) and (13). The difference lies in Eq. (19), which represents the feasibility constraint of the Avoid process for each DMU K. In addition, Eq. (20) fixes the overall system score to the optimal value $\beta_0^{System*}$ obtained from Eq. (11), ensuring that improvements in Avoid efficiency do not worsen the System efficiency.

The same logic is applied in calculating the efficiency of Shift and Improve processes. Eqs. (26) and (27) ensure that the Shift efficiency is improved without worsening the efficiencies of the System and Avoid processes, which are fixed at the values obtained from Eqs. (11) and (16), respectively. Similarly, Eqs. (33)–(35) ensure that Improve efficiency is enhanced without worsening the efficiencies of the System, Avoid, and Shift processes, which are calculated from Eqs. (11), (16), and (22), respectively.

The following equations delineate the efficiency model for the Shift strategy:

$$\beta_0^{Shift} = \min \sum_{i=1}^{m2} v_i x_{i0} - \sum_{n2=1}^{N2} w_{n2} y_{n20} + \sum_{b2=1}^{B2} q_{b2} u_{b20} \tag{22}$$

$$s.t.(N+B) \sum_{np=1}^{Np} w_{np} \geq \frac{1}{y_{np0}}, for\ n = 1, \ldots, N, p = 1, 2, 3, \tag{23}$$

$$(N+B) \sum_{bp=1}^{Bp} q_{bp} \geq \frac{1}{u_{bp0}}, for\ b = 1, \ldots, B, p = 1, 2, 3, \tag{24}$$

$$\sum_{i=1}^{m2} v_i x_{ik} - \sum_{n2=1}^{N2} w_{n2} y_{n2k} + \sum_{b2=1}^{B2} q_{b2} u_{b2k} \geq 0, for\ k = 1, \ldots, K, \tag{25}$$

$$\beta_0^{System*} = \sum_{i=1}^{m} v_i x_{i0} - \sum_{p=1}^{3} \sum_{np=1}^{Np} w_{np} y_{np0} + \sum_{p=1}^{3} \sum_{bp=1}^{Bp} q_{bp} u_{bp0}, \tag{26}$$

$$\beta_0^{Avoid*} = \sum_{i=1}^{m1} v_i x_{i0} - \sum_{n1=1}^{N1} w_{n1} y_{n10} + \sum_{b1=1}^{B1} q_{b1} u_{b10}, \tag{27}$$

$$v_i, w_{np}, q_{bp} \geq 0, for\ all\ i, n, b, p. \tag{28}$$

The efficiency score of the Shift process for the DMU under evaluation is computed as $\varnothing_0^{Shift*} = 1/\left(1 + \beta_0^{Shift*}\right)$.

The following equations delineate the efficiency model for the Improve strategy:

$$\beta_0^{Improve} = \min \sum_{i=1}^{m3} v_i x_{i0} - \sum_{n3=1}^{N3} w_{n3} y_{n30} + \sum_{b3=1}^{B3} q_{b3} u_{b30} \tag{29}$$

$$s.t.(N+B) \sum_{np=1}^{Np} w_{np} \geq \frac{1}{y_{np0}}, for\ n = 1, \ldots, N, p = 1, 2, 3, \tag{30}$$

$$(N+B) \sum_{bp=1}^{Bp} q_{bp} \geq \frac{1}{u_{bp0}}, for\ b = 1, \ldots, B, p = 1, 2, 3, \tag{31}$$

$$\sum_{i=1}^{m3} v_i x_{ik} - \sum_{n3=1}^{N3} w_{n3} y_{n3k} + \sum_{b3=1}^{B3} q_{b3} u_{b3k} \geq 0, for\ k = 1, \ldots, K, \tag{32}$$

$$\beta_0^{System*} = \sum_{i=1}^{m} v_i x_{i0} - \sum_{p=1}^{3} \sum_{np=1}^{Np} w_{np} y_{np0} + \sum_{p=1}^{3} \sum_{bp=1}^{Bp} q_{bp} u_{bp0}, \tag{33}$$

$$\beta_0^{Avoid*} = \sum_{i=1}^{m1} v_i x_{i0} - \sum_{n1=1}^{N1} w_{n1} y_{n10} + \sum_{b1=1}^{B1} q_{b1} u_{b10}, \tag{34}$$

$$\beta_0^{Shift*} = \sum_{i=1}^{m2} v_i x_{i0} - \sum_{n2=1}^{N2} w_{n2} y_{n20} + \sum_{b2=1}^{B2} q_{b2} u_{b20}, \tag{35}$$

$$v_i, w_{np}, q_{bp} \geq 0, for\ all\ i, n, b, p. \tag{36}$$

The efficiency score of the Improve process for the DMU under evaluation is computed as $\varnothing_0^{Improve*} = 1/\left(1 + \beta_0^{Improve*}\right)$. The notation used in the proposed model is summarised in Table 1.

2.3. Python implementation

To compute the decarbonisation scores and weights based on the proposed network DEA model, a series of linear systems are constructed and resolved using a Python program. The PuLP library, a linear programming modeler developed in Python (Mitchell et al., 2011), is employed for solving these systems. PuLP serves primarily as an interface to various linear programming solvers installed on the system. In this instance, the Python script utilises the GNU Linear Programming Kit

Table 1
Notation for the Avoid–Shift–Improve network DEA framework.

Symbol	Description
$k = 1,\ldots,K$	Index of decision-making units (DMUs), where each DMU represents a county
$i = 1,\ldots,m$	Index of inputs
$p = 1,2,3$	Index of ASI strategies: Avoid ($p = 1$), Shift ($p = 2$), Improve ($p = 3$)
$np = 1,\ldots,N_p$	Index of desirable outputs within strategy p
$bp = 1,\ldots,B_p$	Index of undesirable outputs within strategy p
x_{i0}	Amount of input i for the DMU under evaluation
y_{n0}	Amount of desirable output n for the DMU under evaluation
u_{b0}	Amount of undesirable output input b for the DMU under evaluation
λ_k	Intensity variable for DMU k
x_{ik}	Amount of input i used by DMU k
y_{npk}	Desirable output np produced by DMU k under strategy p
u_{bpk}	Undesirable output bp produced by DMU k under strategy p
v_i	Weight (multiplier) assigned to input i
w_{np}	Weight (multiplier) assigned to desirable output np under strategy p
q_{bp}	Weight (multiplier) assigned to undesirable output bp under strategy p
N_p	Number of desirable outputs in strategy p
B_p	Number of undesirable outputs in strategy p
M	Number of inputs
N	Total number of desirable outputs across all strategies
B	Total number of undesirable outputs across all strategies
$\beta_0^{System*}$	Optimal value of the system-level DEA objective function for the DMU under evaluation
$\varnothing_0^{System*}$	System decarbonisation score of the DMU under evaluation
β_0^{Avoid*}	Optimal value of the Avoid subunit for the DMU under evaluation
$\varnothing_0^{Avoid*}$	Avoid decarbonisation score of the DMU under evaluation
β_0^{Shift*}	Optimal value of the Shift subunit for the DMU under evaluation
$\varnothing_0^{Shift*}$	Shift decarbonisation score of the DMU under evaluation
$\beta_0^{Improve*}$	Optimal value of the Improve subunit for the DMU under evaluation
$\varnothing_0^{Improve*}$	Improve decarbonisation score of the DMU under evaluation

(GLPK) as the underlying solver. Moreover, the results are consistent when the script uses the internal solver, specifically version 2.10.3 of the CBC (COIN-OR Branch-and-Cut) solver.

The algorithm implemented in the script operates as follows. Initially, the data are parsed from a comma-separated value (.csv) file that organises the dataset in a tabular format. This import process is performed separately for the Avoid, Shift, and Improve models, and the dataset is stored in memory. Each model, such as Avoid, is implemented as a standalone function but receives the output of other calls when necessary. For instance, Shift uses Avoid's weights in its constraints to adhere to the leader-follower Stackelberg competition approach. Each model-function calls the linear solver K times, where K is the number of counties. After the K calls, a weights table for all counties is collectively completed for the specific model-function. This is returned as a single attribute to be reused by consecutive models where appropriate in a recursive fashion. Each time a weights table is finalised, it is printed into the standard output and subsequently transferred to a spreadsheet format.

The software was selected primarily based on practicality, as different versions and packages offer largely equivalent functionality, particularly with regard to the solver options available within PuLP. The specific software packages used include "python-pulp 2.8.0–1", "glpk 5.0–2", and "python 3.12.3–1" from the Arch User Repository (AUR), and the operating system is Arch Linux with a custom kernel based on version 6.1.58.

2.4. Indicators and data sources

Based on a comprehensive literature review, this research outlines sub-strategies and actions aligned with each of the three Avoid, Shift, and Improve strategies. In total, nine actions were considered as options, with each trio of actions corresponding to one of the strategies, respectively. Then, the most suitable indicators representing each action based on the availability of data were selected (Fig. 1).

Regarding the Avoid strategy, the number of desks available in working hubs is chosen to represent teleworking. It is noteworthy that remote working hubs are shared office environments that provide workspaces for remote workers, start-ups, small and medium-sized enterprises, and corporates. These hubs offer facilities ranging from individual desks to meeting rooms and conference spaces, thus facilitating teleworking while reducing commuting needs (Western Development Commission (WDC), 2026). A desk refers to a workstation within a remote working hub, used by one person. The share of trips using active modes (%) illustrates how the urban areas have achieved densifications and compact development. Conversely, the average travel time to work (in minutes) is associated with dispersed development and is designated as undesirable output for Avoid.

In the case of Shift strategy, the share of trips utilising public transport and active modes (%) and number of inner-city buses have both been chosen as desirable outputs to demonstrate increased usage of public and active transport. The number of households with two or more cars is negatively associated with the reduction in car dependency, as higher car ownership indicates greater car usage, and therefore it is treated as undesirable output in the model.

Finally, within the Improve strategy, the number of EV registrations, together with the number of EV charging points, represent increased EV penetration and enhanced fleet efficiency. In contrast, the number of registrations for SUVs and other low-efficiency vehicles contradicts the trend toward smaller and lightweight private cars, which are indicative of higher energy efficiency. All private car registrations with engines over 2000 cc are included in this undesirable indicator. Notably, in 2023 and 2024, SUVs constituted 48% and 54%, respectively, of all vehicles sold worldwide, with sales showing an upward trajectory compared to previous years. 95% of the SUVs currently on the road—both new and older models—are burning fossil fuels. This trend directly contributes to heightened fossil fuels consumption and higher carbon emissions, exacerbating the environmental impact. In the European market, the demand for SUVs has surpassed those of EVs, contradicting earlier projections that anticipated a decline in SUV popularity (International Energy Agency (IEA), 2024; BBC News, 2025).

In relation to data sources, the most up-to-date data for selected inputs and outputs was drawn from multiple Irish databases, including the Central Statistics Office (CSO, 2026), Western Development Commission (Western Development Commission (WDC), 2026), Official Statistics of the Irish Motor Industry (SIMI, 2026), Local Property Tax (Local Property Tax (LPT), 2026) and Regional Development Monitor (Regional Development Monitor (RDM), 2025). proposed network DEA model incorporates two inputs – population density and local authority expenditure on road transport – to capture, respectively, structural/spatial conditions and the fiscal resources devoted to the road mobility system and also compensate for variations in outputs that may stem from differences in size and population of the counties. This adjustment ensures a standardised assessment of each county's performance. These inputs normalise the model, enabling an accurate comparison of decarbonisation across different regions. A summary of the descriptive statistics for the collected data is presented in Table 2.

Regarding inputs, network DEA can incorporate either subunit-specific inputs or shared inputs across some or all subunits (Stefaniec et al., 2020). Theoretically, incorporating shared inputs increases the complexity of mathematical calculations, requiring nonlinear modelling. This approach also presents challenges because solving nonlinear models necessitates generating values for shared inputs among the three processes and testing multiple allocation combinations, many of which may not be realistic in practice. In real-world applications, shared input proportions may be difficult to determine, making simplicity an essential consideration. A model that is easier to work with is more practical for real-world decision-making. Assigning a fixed input level to each process at the outset allows each process to operate independently, without competing for resources. In this study, population density

Table 2
Descriptive statistics of indicators in DEA model.

	Min	Max	Mean	Std. Dev.
Inputs				
County population density (persons per km^2)	22.09	1567.04	116.99	297.73
Local authority expenditure on road transport (million € per year)	17.50	258.77	52.07	52.03
Outputs				
Number of desks available in working hubs	32.00	6896.00	703.73	1359.66
Share of trips using active modes (%)	10.90	29.50	16.10	4.75
Average travel time to work (minutes)	23.40	35.20	28.48	3.25
Share of trips using public transport and active modes (%)	12.10	40.40	19.33	5.95
Number of inner-city buses	109.00	3139.00	416.61	585.72
Number of households with two or more cars	5308.00	154,811.00	26,656.35	30,825.95
Number of EV registrations	8.00	639.00	102.65	122.28
Number of EV charging points	139.00	26,136.00	2101.27	5030.98
Number of registrations of SUVs and low-efficiency cars	69.00	10,892.00	941.12	2112.54

(persons per km^2), and local authority expenditure on road transport (million euros per year), are designated as shared inputs. While population density is inherently non-rivalrous, expenditure is in practice a rivalrous resource. However, due to the absence of disaggregated data on its allocation across Avoid, Shift, and Improve strategies, we adopt the simplifying assumption of treating expenditure as non-rivalrous, meaning that its allocation to one subunit does not reduce its availability for others. For instance, EV ownership does not prevent the same population from walking or cycling for certain trips. Similarly, an increase in the number of desks available in working hubs does not necessarily affect the share of trips using active modes. Both these indicators can increase independently, as expanding remote working facilities does not limit opportunities for active travel, nor does a rise in active travel reduce the utility or demand for remote working spaces. The same logic is extended here to transport expenditure to maintain model tractability, although we acknowledge this as a simplification. However, if disaggregated investment data were available, the model could be adapted to incorporate expenditure as a rivalrous shared input, which would more accurately reflect the competition among strategies for limited financial resources.

3. Results, discussion and policy insights

The primary contribution of this work lies in its innovative integration of network DEA with Stackelberg leader-follower equilibrium and BWM. This model was developed to address a gap, as no existing DEA model accounts for the hierarchical importance of subunits within a parallel structure. We also incorporate expert judgement, thus ensuring an assessment that captures the complex dynamics of policy implementation and its effectiveness in reducing transport carbon emissions across Irish counties.

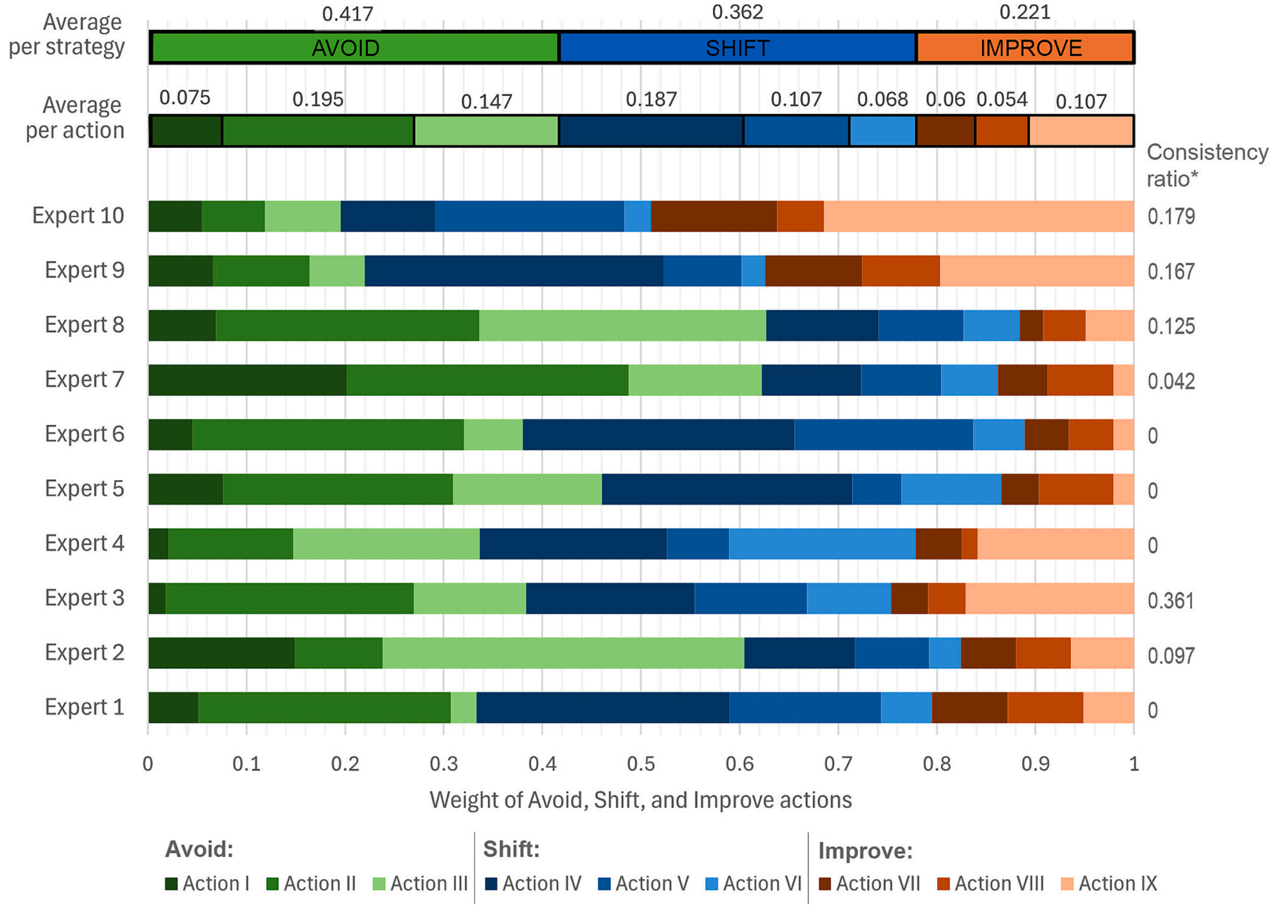

Fig. 2. The average and expert-level weights derived from BWM.
* The consistency ratios report the level of consistency in the experts' pairwise comparisons.

Fig. 2 shows the weights derived from the experts' assessments of the actions in the proposed model derived from BWM. The average weights indicate that Action II is considered by the experts to have the highest impact and feasibility relative to the other actions. Conversely, Actions VIII and VII, which are associated with EV penetration, are deemed the least impactful according to the experts' perspectives. The average consistency ratio is 0.097, and notably, four out of the ten consistency ratios are zero, suggesting that the weights calculated are highly reliable (see Rezaei et al., 2017). Experts, in their responses to the BWM questionnaire, assigned the highest weighting to the Avoid strategy with a value of 0.417, ranking it first. This was followed by Shift with a weighting of 0.362 and Improve at 0.221. This is consistent with the established framework of Avoid-Shift-Improve and shows the alignment of experts with state-of-the-art understanding of climate policy. Therefore, in developing our proposed leader-follower Stackelberg competition-based network DEA, we position Avoid as the leader. This is followed sequentially by Shift, and then Improve (For numerical results, see Appendix A).

These findings also demonstrate where the opinions of experts lie between the transformational and incremental changes in addressing the climate emergency in the transport sector. In the BWM results, the Avoid strategy received the highest weighting, followed by Shift and then Improve. These findings underscore a recognised need to facilitate transformational changes within the current urban transport regime, which relies heavily on private vehicles, rather than limiting efforts to incremental adaptations, such as transitioning to EVs. Therefore, there is a need to move away from incrementalism and focus more on formulating transformational climate and transport policies (Kulovesi and Oberthür, 2020; Hosseini and Stefaniec, 2023).

Avoid strategy focuses on changes in transport demand, while Shift and Improve concentrate on changes in types of services (Joyashree Roy et al., 2021). The outcomes of the BWM questionnaire indicate that reducing transport demand is more important than adopting strategies that maintain the existing demand but make the transport supply more sustainable and decarbonised. This outcome aligns with prior literature (Caulfield et al., 2022; Creutzig et al., 2022) that suggests prioritising the avoidance of unnecessary trips and transforming modes of travel, which are essential for achieving carbon neutrality in transportation and are often more effective than merely improving vehicle technology or fuel efficiency.

Regarding the prioritisation of Shift measures over Improve actions, it should be noted that human needs are an anthropogenic constant and limited in number, whereas the means to satisfy these needs are virtually limitless. Contrary to the assumption that human needs are infinite, this assumption actually pertains more to satisfiers (means) rather than the needs themselves (Spangenberg and Lorek, 2019). Recent research has highlighted that by using private cars (both ICEVs and EVs), users inflict harm on others (Braun and Randell, 2025; Hosseini and Stefaniec, 2023). Consequently, incentives for these satisfiers should not be prioritised over sustainable and inclusive alternatives, such as active travel modes, public transport, and shared mobility. Given that Shift measures are more inclusive—meaning they benefit a broader and more diverse range of users and provide equitable benefits across different socioeconomic groups—they should be assigned greater weight than Improve actions.

Table 3 presents the outcomes of the proposed framework. The decarbonisation progress scores, which vary from 0 to 1, facilitate the ranking of the 26 counties by decomposing scores from Network DEA (Eqs. (11)–(15)) into individual scores for the Avoid, Shift, and Improve criteria. Subsequently, expert judgements are integrated, calculating the overall decarbonisation score by aggregating the three hierarchical scores into a single system score, utilising weights derived from the BWM. In the network DEA model, DMUs achieving a score of 1 are deemed efficient. Furthermore, higher efficiency scores indicate superior performance between DMUs. Thus, the model differentiates and identifies higher-performing counties, although the highest-performing counties all have score 1. Conversely, lower scores indicate relatively poorer performance. The average efficiency score was also computed using arithmetic means to distinguish counties with above-average decarbonisation scores from those with scores.

These performance scores do not merely provide rankings; they represent a structured way to allocate limited resources across competing decarbonisation strategies. By linking operational research methods with indicators that reflect both economic and environmental

Table 3
Avoid, shift, improve, and system decarbonisation scores of Irish counties.

County	Overall score (objective)	Decomposition by Stackelberg competition model			Overall score with expert weights (subjective)	County rank
		Avoid	Shift	Improve		
Carlow	0.652	0.658	0.816	0.535	0.688	10
Cavan	0.495	0.535	0.401	0.512	0.481	21
Clare	0.612	0.755	0.270	0.679	0.563	17
Cork	0.285	0.466	0.067	0.226	0.268	26
Donegal	0.773	0.685	1.000	0.721	0.807	6
Dublin (4 regions)	0.945	1.000	1.000	0.845	0.966	1
Galway	0.576	1.000	0.113	0.405	0.547	18
Kerry	0.483	0.532	0.209	0.614	0.433	24
Kildare	0.695	0.538	0.509	1.000	0.630	12
Kilkenny	0.615	0.664	0.590	0.576	0.618	14
Laois	0.858	0.888	0.596	1.000	0.807	5
Leitrim	0.782	1.000	1.000	0.387	0.864	3
Limerick	0.563	0.778	0.267	0.518	0.536	19
Longford	0.822	1.000	1.000	0.499	0.889	2
Louth	0.845	0.693	1.000	0.913	0.853	4
Mayo	0.450	0.570	0.201	0.482	0.417	25
Meath	0.455	0.522	0.380	0.428	0.450	22
Monaghan	0.708	0.701	1.000	0.519	0.769	8
Offaly	0.663	0.950	0.594	0.383	0.696	9
Roscommon	0.465	0.485	0.344	0.525	0.443	23
Sligo	0.653	0.796	0.424	0.645	0.628	13
Tipperary	0.516	0.740	0.231	0.453	0.492	20
Waterford	0.608	0.804	0.375	0.540	0.591	16
Westmeath	0.823	0.942	0.505	0.900	0.775	7
Wexford	0.740	0.769	0.308	1.000	0.653	11
Wicklow	0.681	0.545	0.440	1.000	0.608	15
Arithmetic mean	0.645	0.731	0.525	0.627	0.633	–

priorities, the model offers evidence that can guide policymakers toward cost-efficient and carbon-neutral transport planning.

Although the performance scores among counties are unevenly distributed, some patterns emerge from the outcomes (Table 3). The results indicate Dublin is the frontrunner in decarbonising transport performance; this is attributed to its relatively extensive public transport network and active travel infrastructure. This observation showcases the centralised development paradigm in Ireland, wherein a vast portion of resources, investments, and infrastructural development are disproportionately allocated to the capital city, to some degree to the detriment of other regions (Moore-Cherry and Tomaney, 2019; Aontú, 2025; Irish Examiner, 2024). Dublin is followed by Longford County, located in north-central Ireland, which serves as an access point to the Northern and Western regions. The Longford County Council developed a comprehensive local transportation plan, enacting substantial initiatives to advance the sustainability of urban transport in this area (Longford County Council (Longfordcoco), 2023).

Counties like Mayo, Roscommon, Kerry, and Tipperary, ranked 20th or lower in decarbonising transportation (Table 3), correspond to the least densely populated areas in Ireland, whereas Dublin is by far the densest region. Dispersed settlement patterns pose challenges to decarbonising urban transport. Gaur et al. (2024) found that transport GHG emissions are 52% lower in Ireland's most densely populated regions compared to those with the lowest population densities. Key indicators for identifying patterns of dispersion include population density, as mentioned earlier, and accessibility to common amenities. Steckel et al. (2017) noted that access to services tends to be higher in densely populated urban areas. In relation to this, the average distance from residential dwellings to everyday amenities including supermarkets, general practitioners, primary and secondary schools, pharmacies, and post offices is notably greater in counties like Roscommon, Mayo, Kerry, and Cavan, while the shortest distances are found in Dublin. Therefore, in counties with dispersed settlement patterns, people frequently travel long distances to access such services. Although walking and cycling can cover shorter distances, realising and encouraging a modal shift from passenger cars for longer travels necessitates infrastructure improvements. Specifically, the provision of public transport and the establishment of shared electric mobility hubs that offer access to e-cargo bikes and e-bikes are essential to effectively decarbonise these journeys (Hosseini et al., 2023; Anburuvel et al., 2022; Wong et al., 2023).

Cork, Mayo, and Kerry, which rank the poorest for transport decarbonisation, are also among the largest counties by area in Ireland. These counties are recognised as rural, characterised by dispersed settlement patterns, low population density, and several peninsulas. These characteristics make the deployment of sustainable transport infrastructure challenging and could explain the high usage of private cars in these areas compared to their peers (Kerry County Council (Kerrycoco), 2022). For instance, fewer than 1% of commuters in Mayo utilise public transportation (Mayo County Council (Mayococo), 2021), and less than 1% of commuters in Cork County use bicycles to commute, with sustainable transport usage falling and car usage increasing (Cork County Council (Corkococo), 2022). This unsustainable transportation pattern is also reflected in Cork City's low ranking among European small to medium-sized cities for local and international connections (Ryan et al., 2024).

Fig. 3 reveals that counties' progress in the Shift paradigm lags behind their achievements in the Avoid and Improve criteria. Decarbonisation of transport in the context of the first two criteria, particularly Shift, is more closely linked to the availability of infrastructure than to individual decisions based on cost analysis and behavioural change. This aligns with the findings reported by Javaid et al. (2020) and Mattauch et al. (2015), who recognised infrastructure as the primary determinant of net-zero transition in transport. They concluded that investments in infrastructure can impact substitution elasticity and should form a crucial part of the policy actions to address carbon lock-in (Unruh and Carrillo-Hermosilla, 2006). In Ireland, private automobility has become deeply entrenched, posing significant challenges to transitioning to new systems. This entrenchment is due to various factors, including centralised development, which results in non-Dublin regions receiving lower budgets for infrastructure upgrades, dispersed settlement patterns, and the predominance of large rural areas that complicate the viability of active, shared, and public transport options. Additional obstacles include regulatory barriers and societal inertia. Such infrastructure lock-in can impede decarbonisation efforts by obstructing the adoption of newer, more efficient, or environmentally friendly technologies and practices.

Overemphasising the importance of actions related to EV adoption under the Improve criteria in policy formulations can exacerbate the lock-in effect of car dependence (Mattioli et al., 2020), which impedes the effective implementation of measures at the Avoid and Shift levels. This perpetuates car-oriented rather than people-oriented settlements, leading to urban sprawl, increased traffic jams, and greater demand for road networks and parking areas. These developments negatively impact urban living experiences and contribute to the further loss of

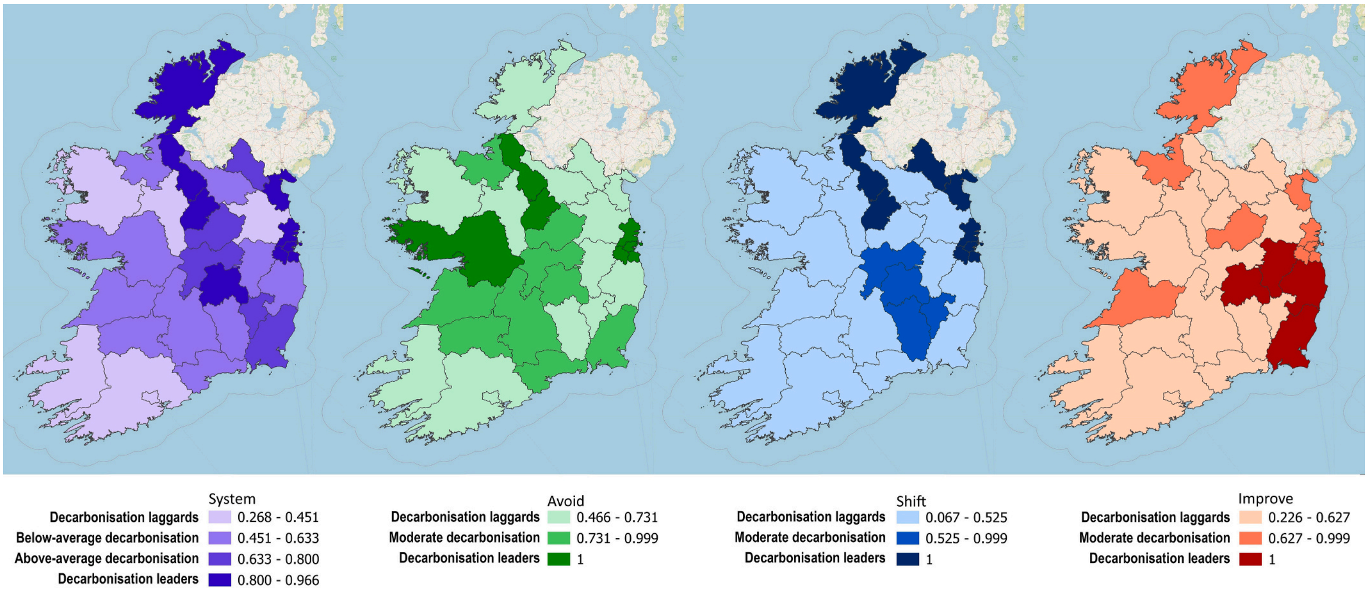

Fig. 3. Decarbonisation progress across counties in Ireland, depicting Avoid, Shift, Improve, and overall system performances.

ecosystems and biodiversity (Hosseini and Stefaniec, 2023).

The outcomes derived from the proposed model offer a comprehensive view of decarbonisation progress in Ireland, and provide an informative snapshot that can assist transport decision-makers by reflecting detailed insights. There are a few patterns that could be noted for addressing passenger transport in Ireland from the systemic perspective. Focusing on the Avoid, Shift, and Improve outputs that were fed into the DEA model, it can be identified that there exist certain mechanisms that amplify the transport trends over time, either by promoting sustainable transport or deepening car dependency. Car dependency is one of the most significant reinforcing mechanisms that prevents the transition toward more sustainable transport. As households acquire more cars, congestion increases, leading to pressure for road expansion and further public investment in car infrastructure. More road capacity makes driving more attractive, which in turn reinforces higher car ownership and reduces demand for public and active transport. This process strengthens car dependency over time. However, compact development and increased teleworking can reduce congestion, thereby weakening this loop. Expanding bus networks and promoting modal shift also counteract car dependency. Encouraging the use of smaller, more efficient vehicles, as well as increasing the adoption of EVs, can help limit emissions despite an overall increase in vehicle ownership.

In contrast to car dependency, the growth in sustainable mobility positively reinforces the effect on the transport system. Increased investment in public and active transport infrastructure leads to greater usage of public transportation and active mobility, which in turn reduces congestion and makes these modes more attractive. Higher ridership generates more ticket revenue, enabling further service improvements. As public transport and active travel options enhance, even more people shift away from private car use, reinforcing a cycle of sustainable transport growth. Improved public transport reliability helps lower average commute times, making these modes more appealing. A greater share of public and active transport trips sustains this positive effect, encouraging further investment in public transport Besides the mechanisms that drive long-term change, constraints exist that slow or limit sustainable transport growth. For public transport investment, a bottleneck occurs when public transport demand outpaces infrastructure capacity. Increased investment in public transport improves service quality, leading to more ridership and reinforcing modal shift. However, if demand surpasses available infrastructure, capacity constraints limit further growth, creating a bottleneck that prevents continued improvements. Without compact development, long commutes place additional strain on public transport systems, reducing efficiency. Increasing the number of buses and expanding services help prevent this constraint.

To further examine determinants of county performance, Spearman rank correlations were conducted between decarbonisation scores and contextual indicators (Table 4). Results show a strong negative correlation with county area (−0.745), indicating that larger counties underperform in decarbonisation efficiency. This likely reflects the structural challenges of dispersed settlement patterns, longer travel distances, and higher dependence on private cars. A modest but statistically significant negative relationship was also found with transport-related CO_2 emissions (−0.409), suggesting that higher-performing counties tend to achieve lower emissions overall. Local authority expenditure on road transport exhibited a modest but significant negative correlation (−0.478), suggesting that higher spending is not associated with greater efficiency. This likely reflects the orientation of expenditure, where funds devoted to road expansion and maintenance may reinforce car dependency rather than support sustainable modes. By contrast, neither county population density nor county population showed significant correlations with system scores, underscoring that demographic scale alone does not determine decarbonisation performance. This is consistent with our modelling approach, which incorporates density as an input to control for structural variation across counties, but demonstrates that efficiency outcomes depend more on structural constraints such as county size, settlement dispersion, and the persistence of carbon lock-in in car-dependent regions. Taken together, these findings emphasise that territorial scale, emissions intensity, and expenditure orientation are more influential than density or population per se in shaping county-level outcomes.

In the context of systemic thinking, counties with high decarbonisation scores, such as Dublin, Longford, and Leitrim, have reinforced the growth in sustainable mobility and increased their EV adoption, while weakening their car dependency and reducing investment in new roads. These counties have benefited from strong investment in public transport, compact development, and policies that promote EV adoption. Conversely, counties with lower decarbonisation scores, such as Cork and Mayo, remain trapped in the car dependency loop and the road investment. These counties have struggled to shift away from private car reliance and have not made significant investments in public or active transport. For these regions, breaking car dependency and prioritising public transport investment are essential actions for achieving long-term transport sustainability.

Dublin, with an overall score of 0.966, exemplifies this trend through strong performance across Avoid, Shift, and Improve criteria. In terms of Avoid (1.000), Dublin benefits from compact urban development, which minimises the need for long car commutes, thereby weakening the need for road expansion. Additionally, high teleworking adoption further reduces congestion. In the Shift (1.000) dimension, Dublin's investment in public transport infrastructure, including buses, Luas tram system, trains, and cycling networks, reinforces sustainable mobility. Also, increased public transport funding leads to higher ridership, generating greater revenue and enabling further service improvements. Under Improve (0.845), Dublin is actively investing in EV adoption. However, despite these efforts, or rather because of a great focus to electrify the private car fleet rather than replace it with other transport modes, congestion remains a challenge, slowing further emissions reductions. Strategically, Dublin's success demonstrates that reinforcing public transport expansion and EV adoption leads to better decarbonisation performance, yet the public transport bottleneck remains a constraint due to capacity limitations. Timely action on public transport investment is needed to enable further emissions reduction.

4. Limitations and directions for future research

The proposed model is flexible but is constrained by the availability of data for actions and corresponding indicators that must be available for all counties to be included in the model. Therefore, we selected only

Table 4
Spearman's correlation coefficients between overall decarbonisation scores (subjective) and contextual indicators.

	County CO_2 emissions from transport (2019)*	Local authority expenditure on road transport (million € per year)	County Geographical area (km^2)	County population	County population density (persons per km^2)
Decarbonisation scores	−0.409[b]	−0.478[b]	−0.745[a]	−0.313	0.189

a Correlation is significant at 1%.
b Correlation is significant at 5%.
* Excludes CO_2 emissions from national navigation and fishing, international navigation, and international aviation (MapEIre.dk, 2024).

those indicators that were uniformly accessible across all counties. For instance, shared micromobility is limited in Ireland, existing to some extent only in Dublin, Limerick, Galway, and nine other towns (Irish Cycle, 2023) but is rare in other parts of the country. Consequently, it could not be considered as one of the indicators in this model, as the penalty of 0 for other counties would be too severe. Therefore, future adaptations of the proposed model in regions with established shared micromobility and mobility hubs should include these elements as part of the Shift criteria.

Another limitation of this study was that although Dublin comprises four council areas, the majority of the selected indicators were only available for Dublin as a whole, without regional-level detail. This lack of granularity limits the ability to capture variations across the different regions within Dublin. However, presenting data for Dublin as a whole does provide a comprehensive overview that could highlight overarching trends and issues affecting the entire city.

Many of the indicators considered, such as those related to working hubs and EVs, are relatively new and lack historical data for tracking changes over time following the introduction of policies and interventions by local governments. However, changes associated with these indicators could be compared in future research, allowing for the design of dynamic frameworks and system to assess whether trends are moving in a positive or negative direction.

A further limitation concerns the treatment of local authority expenditure on road transport. In reality, this expenditure is a rivalrous input—funds allocated to one strategy (e.g., EV charging) cannot simultaneously support another (e.g., cycling infrastructure). In this study, however, it was modelled as a shared, non-rivalrous input to ensure consistency and comparability across counties, given the absence of disaggregated expenditure data by Avoid, Shift, and Improve strategies. This modelling choice maintains tractability while still capturing the influence of financial capacity on decarbonisation performance. Future research could refine the framework by incorporating more detailed expenditure breakdowns, which would enable an even more realistic representation of budgetary trade-offs across strategies.

5. Conclusion

This work marks the first attempt to measure transport decarbonisation progress at the national level, employing a quantitative approach within the Avoid-Shift-Improve framework. The proposed model utilises network DEA in conjunction with Stackelberg competition game theory and BWM. This combination provides a robust and comprehensive framework for evaluating and prioritising decarbonisation mobility strategies. It aligns the different components of sustainable mobility, ensuring a cohesive approach to addressing the multifaceted challenges of urban transport. The framework demonstrates how progress can be quantified and how scarce resources might be directed to maximise decarbonisation gains.

The model considers nine actions and their corresponding indicators, with six indicators deemed desirable and three undesirable. The first three actions represent Avoid; the second three pertain to Shift, and the final three are associated with Improve (Fig. 1). A data collection process was undertaken to gather up-to-date data for each indicator across all Irish counties. Further depth is added to the analysis through the application of BWM, which engages transportation experts to weigh the relative importance of each action within the Avoid-Shift-Improve framework. It should be noted that while the proposed network DEA framework can assign objective weights to the three components of the model, BWM provides a means to allocate subjective weights, reflecting expert perspectives.

Results from BWM indicate a strong preference for transformational changes with the Avoid strategy receiving the highest weighting at 0.417, followed by Shift at 0.362, and Improve at 0.221. This suggests a move toward systemic changes that reduce reliance on private vehicles rather than incremental adaptations like transitioning to EVs. The prioritisation of Shift measures over Improve actions reflects an understanding that the means to satisfy human needs are extensive, advocating for more inclusive transport options such as active travel modes and public transport. In this way, the study underscores the importance of a hierarchical implementation of the Avoid-Shift-Improve strategies, recommending a focus on Avoid and Shift strategies to reduce travel necessity and promote sustainable and inclusive transport modes.

The outcome from the network DEA model indicates that Dublin outperforms the other counties in Ireland in terms of transport decarbonisation. This reflects a centralised development pattern where significant resources and investments are concentrated in the capital, at the expense of other regions. The findings highlight challenges due to dispersed settlement patterns in rural counties such as Mayo, Roscommon, Kerry, and Tipperary. These counties rank low in decarbonisation efforts and display high private car usage, driven by their sparse populations and limited infrastructure for sustainable transport modes. Such conditions foster an infrastructure lock-in, where entrenched reliance on private vehicles and insufficient infrastructure investment obstruct the progression toward carbon neutrality in transportation. The results from the model underscore the critical role of infrastructure development in achieving decarbonisation and provide insights for urban planners and policymakers on which mitigation policies are more effective and inclusive, and should therefore be prioritised. Moreover, the results highlight the necessity for more evenly distributed investment throughout the country to facilitate transport carbon neutrality.

The framework developed in this research may be pertinent for application in real-world studies using the Avoid-Shift-Improve framework within transport and other sustainability-focused contexts. It is adaptable to assessment frameworks that require prioritisation across multiple criteria, since it incorporates a leader–follower dynamic among multiple system components. By explicitly framing transport decarbonisation as a problem of allocating limited resources across competing strategies, the study also provides a decision-support tool that links operational research methods with policy-relevant indicators. The proposed framework is scalable beyond Ireland and can be extended to other regions, supporting just transitions to carbon neutrality.

CRediT authorship contribution statement

Keyvan Hosseini: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Funding acquisition. **Saeed Assani:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Agnieszka Stefaniec:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Philippos Papaphilippou:** Writing – original draft, Validation, Software, Methodology, Investigation, Writing – review & editing, Funding acquisition. **Anna Charly:** Writing – original draft, Validation, Investigation, Formal analysis, Conceptualization, Writing – review & editing. **Brian Caulfield:** Writing – review & editing, Validation, Supervision, Resources, Data curation, Conceptualization, Investigation, Writing – original draft.

Declaration of competing interest

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

Acknowledgement

This study was funded by the Sustainability and Resilience Institute (SRI), University of Southampton, under the CORDIAL Project. The sponsor neither had any direct involvement in the conduct of this work nor had any influence on the decision to publish this research paper. The authors wish to acknowledge David Murphy of the Western Development Commission for providing data and constructive insights related to the remote working hubs.

Appendix A

Table A.1
Weights derived from BWM.

Experts	Avoid			Shift			Improve			Consistency ratio
	Action I	Action II	Action III	Action IV	Action V	Action VI	Action VII	Action VIII	Action IX	
Expert 1	0.051	0.256	0.026	0.256	0.154	0.051	0.077	0.077	0.051	0.179
Expert 2	0.149	0.089	0.367	0.112	0.075	0.032	0.056	0.056	0.064	0.167
Expert 3	0.018	0.252	0.114	0.171	0.114	0.085	0.038	0.038	0.171	0.125
Expert 4	0.021	0.126	0.189	0.189	0.063	0.189	0.047	0.016	0.158	0.042
Expert 5	0.076	0.234	0.151	0.254	0.050	0.101	0.038	0.076	0.021	0.000
Expert 6	0.045	0.275	0.060	0.275	0.181	0.052	0.045	0.045	0.021	0.000
Expert 7	0.202	0.286	0.135	0.101	0.081	0.058	0.050	0.067	0.021	0.000
Expert 8	0.069	0.267	0.291	0.114	0.086	0.057	0.024	0.043	0.049	0.361
Expert 9	0.066	0.098	0.056	0.303	0.079	0.024	0.098	0.079	0.197	0.097
Expert 10	0.055	0.064	0.077	0.096	0.192	0.027	0.128	0.048	0.315	0.000
Average	0.075	0.195	0.147	0.187	0.107	0.068	0.060	0.054	0.107	0.097
Strategy's weights		0.417			0.362			0.221		–

Data availability

Data will be shared upon request.

References

Anburuvel, A., Perera, W.U.L.D.P., Randeniya, R.D.S.S., 2022. A demand responsive public transport for a spatially scattered population in a developing country. Case Stud. Transp. Policy 10 (1), 187–197. https://doi.org/10.1016/j.cstp.2021.12.001.

Aontú, 2025. Regional Development. https://aontu.ie/regional-development [Accessed 29/06/2025].

Banister, D., 2008. The sustainable mobility paradigm. Transp. Policy 15 (2), 73–80. https://doi.org/10.1016/j.tranpol.2007.10.005.

BBC News, 2025. Small Electric Cars were Said to be the Future – But SUVs Now Rule the Road [Accessed 19/03/2025]. https://www.bbc.co.uk/news/articles/c778ekg64mjo.

Beltrán-Esteve, M., Picazo-Tadeo, A.J., 2015. Assessing environmental performance trends in the transport industry: eco-innovation or catching-up? Energy Econ. 51, 570–580. https://doi.org/10.1016/j.eneco.2015.08.018.

Bongardt, D., Stiller, L., Swart, A., Wagner, A., 2019. Sustainable Urban Transport: Avoid-Shift-Improve (ASI). German International Cooperation Society (GIZ).

Braun, R., Randell, R., 2025. Automobility violence: the case for adopting tobacco public health policies. Appl. Mobil. 1–23. https://doi.org/10.1080/23800127.2025.2477939.

Burgess, E.W., 2015. The growth of the city: An introduction to a research project. In: The City Reader. Routledge, pp. 212–220.

Caulfield, B., Furszyfer, D., Stefaniec, A., Foley, A., 2022. Measuring the equity impacts of government subsidies for electric vehicles. Energy 248. https://doi.org/10.1016/j.energy.2022.123588.

Central Statistics Office (CSO), 2026. https://www.cso.ie/en/releasesandpublications/ep/p-cpr/censusofpopulation2022-preliminaryresults/geographicchanges/ [Accessed 24/05/2025].

Challa, R., Kamath, D., Anctil, A., 2022. Well-to-wheel greenhouse gas emissions of electric versus combustion vehicles from 2018 to 2030 in the US. J. Environ. Manag. 308, 114592. https://doi.org/10.1016/j.jenvman.2022.114592.

Charles, V., Emrouznejad, A., 2024. DEA-based index systems for addressing the united nations SDGs. Environ. Sci. Pol. 162, 103950. https://doi.org/10.1016/j.envsci.2024.103950.

Charly, A., Thomas, N.J., Foley, A., Caulfield, B., 2023. Identifying optimal locations for community electric vehicle charging. Sustain. Cities Soc. 94, 104573. https://doi.org/10.1016/j.scs.2023.104573.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.

Chen, C.M., Delmas, M.A., 2012. Measuring eco-inefficiency: a new frontier approach. Oper. Res. 60 (5), 1064–1079. https://doi.org/10.1287/opre.1120.1094.

Climate Change Advisory Council, 2024. https://www.climatecouncil.ie/councilpublications/annualreviewandreport/AR2024-Transport-final.pdf [Accessed 20/05/2024].

Cork County Council (Corkococo), 2022. Cork County Development Plan 2022–2028. https://www.corkcoco.ie/sites/default/files/2022-04/transport-and-mobility-pdf.pdf.

Creutzig, F., Roy, J., Lamb, W.F., Azevedo, I.M.L., Bruine De Bruin, W., Dalkmann, H., Edelenbosch, O.Y., Geels, F.W., Grubler, A., Hepburn, C., Hertwich, E.G., Khosla, R., Mattauch, L., Minx, J.C., Ramakrishnan, A., Rao, N.D., Steinberger, J.K., Tavoni, M., Ürge-Vorsatz, D., Weber, E.U., 2018. Towards demand-side solutions for mitigating climate change. Nat. Clim. Chang. 8 (4), 268–271. https://doi.org/10.1038/s41558-018-0121-1.

Creutzig, F., Niamir, L., Bai, X., Callaghan, M., Cullen, J., Díaz-José, J., Figueroa, M., Grubler, A., Lamb, W.F., Leip, A., Masanet, E., Mata, É., Mattauch, L., Minx, J.C., Mirasgedis, S., Mulugetta, Y., Nugroho, S.B., Pathak, M., Perkins, P., Ürge-Vorsatz, D., 2022. Demand-side solutions to climate change mitigation consistent with high levels of well-being. Nat. Clim. Chang. 12 (1), 36–46. https://doi.org/10.1038/s41558-021-01219-y.

Dalkmann, H., Brannigan, C., 2021. Transport and climate change. In: Sustainable Transport: A Sourcebook for Policy-makers in Developing Cities. https://doi.org/10.1016/b978-0-08-102671-7.10620-7.

Department of Climate, Energy and the Environment, 2024. Climate Action Plan 2024 (CAP24). https://www.gov.ie/en/department-of-climate-energy-and-the-environment/publications/climate-action-plan-2024/ [Accessed 18/03/2025].

Department of Transport, 2025. Ireland Reaches Major Milestone in the Transition EVs Now on Irish Roads. Department of Transport Ireland. https://www.gov.ie/en/department-of-transport/press-releases/ireland-reaches-major-milestone-in-the-transition-to-electric-with-196000-evs-now-on-irish-roads/.

Dillman, K., Czepkiewicz, M., Heinonen, J., Fazeli, R., Árnadóttir, Á., Davíðsdóttir, B., Shafiei, E., 2021. Decarbonization scenarios for Reykjaviks passenger transport: the combined effects of behavioural changes and technological developments. Sustain. Cities Soc. 65 (September 2020). https://doi.org/10.1016/j.scs.2020.102614.

Emissions Database for Global Atmospheric Research (EDGAR), 2024. GHG Emissions of All World Countries Report. https://edgar.jrc.ec.europa.eu/report_2024?vis=ghgpop#data_download [Accessed 04/05/2025].

Environmental Protection Agency (EPA), 2024a. Latest Emissions Data. https://www.epa.ie/our-services/monitoring–assessment/climate-change/ghg/latest-emissions-data/ [Accessed 28/06/2025].

Environmental Protection Agency (EPA), 2024b. Ireland is Projected to Exceed its National and EU Climate Targets. https://epa.ie/news-releases/news-releases-2024/ireland-is-projected-to-exceed-its-national-and-eu-climate-targets.php [Accessed 13/04/2025].

Färe, R., Primont, D., 2012. Multi-Output Production and Duality: Theory and Applications. Springer Science & Business Media.

Foroozesh, F., Monavari, S.M., Salmanmahiny, A., Robati, M., Rahimi, R., 2022. Assessment of sustainable urban development based on a hybrid decision-making approach: group fuzzy BWM, AHP, and TOPSIS–GIS. Sustain. Cities Soc. 76, 103402. https://doi.org/10.1016/j.scs.2021.103402.

Gaur, A., McGuire, J., O'Riordan, V., Curtis, J., Daly, H., 2024. Dispersed settlement patterns can hinder the net-zero transition: evidence from Ireland. Energ. Strat. Rev. 51, 101296. https://doi.org/10.1016/j.esr.2024.101296.

Gössling, S., Humpe, A., Leitão, J.C., 2024. Private aviation is making a growing contribution to climate change. Commun. Earth Environ. 5 (1), 666. https://doi.org/10.1038/s43247-024-01775-z.

Government of IrelandGovernment of Ireland. Climate Action Plan 2025. https://assets.gov.ie/static/documents/c491032e/DECC_Climate_Action_Plan_2025_Main_Report_-_Final_Web.pdf.

Gross, S., 2020. The Challenge of Decarbonizing Heavy Transport. Foreign Policy. Brookings Institution, Washington, D.C., United States.

Hidalgo, D., Huizenga, C., 2013. Implementation of sustainable urban transport in Latin America. Res. Transp. Econ. 40 (1), 66–77. https://doi.org/10.1016/j.retrec.2012.06.034.

Hosseini, K., Stefaniec, A., 2023. A wolf in sheep's clothing: exposing the structural violence of private electric automobility. Energy Res. Soc. Sci. 99 (March), 103052. https://doi.org/10.1016/j.erss.2023.103052.

Hosseini, K., Stefaniec, A., O'Mahony, M., Caulfield, B., 2023. Optimising shared electric mobility hubs: insights from performance analysis and factors influencing riding demand. Case Stud. Transp. Policy 13, 101052. https://doi.org/10.1016/j.cstp.2023.101052.

Hosseini, K., Choudhari, T.P., Stefaniec, A., O'Mahony, M., Caulfield, B., 2024. E-bike to the future: scalability, emission-saving, and eco-efficiency assessment of shared electric mobility hubs. Transp. Res. Part D: Transp. Environ. 133, 104275. https://doi.org/10.1016/j.trd.2024.104275.

Huang, H., Metzger, D.J., Siskos, E., Burgherr, P., 2024. Analyzing Swiss energy policy through a fuzzy BWM-PROMETHEE approach: A socio-political multi-criteria decision analysis. In: The International Workshop on Best-Worst Method. Springer Nature Switzerland, Cham, pp. 1–21. https://doi.org/10.1007/978-3-031-76766-1_1.

Illahi, U., Choudhari, T.P., Charly, A., O'Mahony, M., Caulfield, B., 2024. Driving green change: commercial sector adopting electric vehicles in Ireland. Transp. Res. Part D: Transp. Environ. 135, 104398. https://doi.org/10.1016/j.trd.2024.104398.

Intergovernmental Panel on Climate Change (IPCC), 2022. Climate Change 2022: Mitigation of Climate Change. https://www.ipcc.ch/report/ar6/wg3/ [Accessed 04/04/2025].

International Energy Agency (IEA), 2021. Net Zero by 2050. https://www.iea.org/reports/net-zero-by-2050 [Accessed 06/04/2025].

International Energy Agency (IEA), 2024. SUVs are Setting New Sales Records each year – and so are their Emissions. https://www.iea.org/commentaries/suvs-are-setting-new-sales-records-each-year-and-so-are-their-emissions [Accessed 07/04/2025].

Irish Cycle, 2023. Stationless Bicycle Share: 6 years after Dublin's first, Two More Cities and 9 Towns, but not Cork Yet. https://irishcycle.com/2023/08/11/stationless-bicycle-share-6-years-after-dublins-first-two-more-cities-and-8-town-but-not-cork-yet/.

Irish Examiner, 2024. Edgar Morgenroth: Spending between the Regions Needs More Clarity. https://www.irishexaminer.com/business/economy/arid-41365339.html [Accessed 12/07/2025].

Javaid, A., Creutzig, F., Bamberg, S., 2020. Determinants of low-carbon transport mode adoption: systematic review of reviews. Environ. Res. Lett. 15 (10), 103002. https://doi.org/10.1088/1748-9326/aba032.

Kerry County Council (Kerrycoco), 2022. Kerry County Development Plan 2022–2028. http://docstore.kerrycoco.ie/KCCWebsite/planning/devplan/volonewritten.pdf.

Kulovesi, K., Oberthür, S., 2020. Assessing the EUs 2030 climate and energy policy framework: incremental change toward radical transformation? Rev. Eur. Comp. Int. Environ. Law 29 (2), 151–166. https://doi.org/10.1111/reel.12358.

Lah, O., 2015. The barriers to low-carbon land-transport and policies to overcome them. Eur. Transp. Res. Rev. 7 (1). https://doi.org/10.1007/s12544-014-0151-3.

LaMonaca, S., Ryan, L., 2022. The state of play in electric vehicle charging services – a review of infrastructure provision, players, and policies. Renew. Sust. Energ. Rev. 154, 111733. https://doi.org/10.1016/j.rser.2021.111733 [Accessed 05/02/2025].

Li, Y., Tsang, Y.P., Lee, C.K.M., Chen, Z.S., 2024. A survey of fuzzy best-worst group decision-making process toward human centricity. IEEE Trans. Fuzzy Syst. 32 (6), 3302–3318. https://doi.org/10.1109/TFUZZ.2024.3379555.

Local Property Tax (LPT), 2026. http://localauthorityfinances.com/spending/carlow-2024/ [Accessed 01/06/2025].

Longford County Council (Longfordcoco), 2023. Longford Town Local Transport Plan. October 2023. https://www.longfordcoco.ie/services/planning/longford-transport-plan-ltp-and-active-travel-strategy/longford-transport-plan.pdf.

MapEIre.dk, 2024. MapEIre.dk: Spatial Results. https://projects.au.dk/mapeire/spatial-results/download#2019_GHG_LocalAuthorities [Accessed 05/04/2025].

Marrero, Á.S., Marrero, G.A., González, R.M., Rodríguez-López, J., 2021. Convergence in road transport CO_2 emissions in Europe. Energy Econ. 99, 105322. https://doi.org/10.1016/j.eneco.2021.105322.

Mårtensson, H.B., Larsen, K., Höjer, M., 2023. Investigating potential effects of mobility and accessibility services using the avoid-shift-improve framework. Sustain. Cities Soc. 96, 104676. https://doi.org/10.1016/j.scs.2023.104676.

Mattauch, L., Creutzig, F., Edenhofer, O., 2015. Avoiding carbon lock-in: policy options for advancing structural change. Econ. Model. 50, 49–63. https://doi.org/10.1016/j.econmod.2015.06.002.

Mattioli, G., Roberts, C., Steinberger, J.K., Brown, A., 2020. The political economy of car dependence: A systems of provision approach. Energy Res. Soc. Sci. 66, 101486. https://doi.org/10.1016/j.erss.2020.101486.

Mayo County Council (Mayococo), 2021. Mayo County Development Plan 2021–2027. https://consult.mayo.ie/en/consultation/draft-mayo-county-development-plan-2021-2027/chapter/06-movement-transport.

Michali, M., Emrouznejad, A., Dehnokhalaji, A., Clegg, B., 2021. Noise-pollution efficiency analysis of European railways: a network DEA model. Transp. Res. Part D: Transp. Environ. 98, 102980. https://doi.org/10.1016/j.trd.2021.102980.

Mitchell, S., O'Sullivan, M., Dunning, I., 2011. Pulp: A Linear Programming Toolkit for Python, 65. The University of Auckland, Auckland, New Zealand, p. 25.

Moore-Cherry, N., Tomaney, J., 2019. Spatial planning, metropolitan governance and territorial politics in Europe: Dublin as a case of metro-phobia? Eur. Urban Reg. Stud. 26 (4), 365–381. https://doi.org/10.1177/0969776418783832.

Nakamura, K., Hayashi, Y., 2013. Strategies and instruments for low-carbon urban transport: an international review on trends and effects. Transp. Policy 29, 264–274. https://doi.org/10.1016/j.tranpol.2012.07.003.

O'Neill, E., Moore, D., Kelleher, L., Brereton, F., 2019. Barriers to electric vehicle uptake in Ireland: perspectives of car-dealers and policy-makers. Case Stud. Transp. Policy 7 (1), 118–127. https://doi.org/10.1016/j.cstp.2018.12.005.

Regional Development Monitor (RDM), 2025. https://rdm.geohive.ie/ [Accessed 23/05/2025].

Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57. https://doi.org/10.1016/j.omega.2014.11.009.

Rezaei, J., Hemmes, A., Tavasszy, L., 2017. Multi-criteria decision-making for complex bundling configurations in surface transportation of air freight. J. Air Transp. Manag. 61, 95–105. https://doi.org/10.1016/j.jairtraman.2016.02.006.

Rezaei, J., van Roekel, W.S., Tavasszy, L., 2018. Measuring the relative importance of the logistics performance index indicators using best worst method. Transp. Policy 68, 158–169. https://doi.org/10.1016/j.tranpol.2018.05.007.

Rezaei, J., Arab, A., Mehregan, M., 2022. Equalizing bias in eliciting attribute weights in multiattribute decision-making: experimental research. J. Behav. Decis. Mak. 35 (2), e2262. https://doi.org/10.1002/bdm.2262.

Rezaei, J., Arab, A., Mehregan, M., 2024. Analyzing anchoring bias in attribute weight elicitation of SMART, swing, and best-worst method. Int. Trans. Oper. Res. 31 (2), 918–948. https://doi.org/10.1111/itor.13171.

Roy, P.K., 2023. Enriching the green economy through sustainable investments: an ESG-based credit rating model for green financing. J. Clean. Prod. 420, 138315. https://doi.org/10.1016/j.jclepro.2023.138315.

Roy, J., Some, S., Das, N., Pathak, M., 2021. Demand side climate change mitigation actions and SDGs: literature review with systematic evidence search. Environ. Res. Lett. 16 (4). https://doi.org/10.1088/1748-9326/abd81a.

Ryan, M., Noonan, L., Doyle, E., Linehan, D., 2024. Cork city, Ireland: a blueprint for transformation in second-tier urban centres. Cities 153, 105289. https://doi.org/10.1016/j.cities.2024.105289.

Sandhiya, E., Gajanand, M.S., 2024. Context-dependent evaluation of electric vehicles and charging infrastructure in an emerging economy. Transp. Res. Part D: Transp. Environ. 137, 104490. https://doi.org/10.1016/j.trd.2024.104490.

Say, K., Csereklyei, Z., Brown, F.G., Wang, C., 2024. The economics of public transport electrification: the charging dilemma. Energy Econ. 135, 107648. https://doi.org/10.1016/j.eneco.2024.107648.

See, K.F., Guo, Y., Yu, M.M., 2025. Measuring energy and CO_2 efficiency of global airlines using dynamic network DEA under natural and managerial disposability framework. Energy Econ. https://doi.org/10.1016/j.eneco.2025.108788, 108788.

Spangenberg, J.H., Lorek, S., 2019. Sufficiency and consumer behaviour: From theory to policy. Energy Policy 129, 1070–1079. https://doi.org/10.1016/j.enpol.2019.03.013.

Stackelberg, H.V., 1934. Marktform und Gleichgewicht. Julius Springer, Vienne.

Steckel, J.C., Rao, N.D., Jakob, M., 2017. Access to infrastructure services: global trends and drivers. Util. Policy 45, 109–117. https://doi.org/10.1016/j.jup.2017.03.001.

Stefaniec, A., Hosseini, K., Xie, J., Li, Y., 2020. Sustainability assessment of inland transportation in China: a triple bottom line-based network DEA approach. Transp. Res. Part D: Transp. Environ. 80, 102258. https://doi.org/10.1016/j.trd.2020.102258.

Stefaniec, A., Hosseini, K., Assani, S., Hosseini, S.M., Li, Y., 2021. Social sustainability of regional transportation: an assessment framework with application to EU road transport. Socio Econ. Plan. Sci. 78, 101088. https://doi.org/10.1016/j.seps.2021.101088.

Stefaniec, A., Brazil, W., Whitney, W., Zhang, W., Colleary, B., Caulfield, B., 2024. Examining the long-term reduction in commuting emissions from working from home. Transp. Res. Part D: Transp. Environ. 127, 104063. https://doi.org/10.1016/j.trd.2024.104063.

Stefaniec, A., Egan, R., Hosseini, K., Caulfield, B., 2025. The challenge of making EVs just affordable enough: assessing the impact of subsidies on equity and emission reduction in Ireland. Res. Transp. Econ. 109, 101495. https://doi.org/10.1016/j.retrec.2024.101495.

Suomalainen, E., 2025. Driving change or stuck in place? Mobility justice in finnish and European transport policy. Ambio 1–14. https://doi.org/10.1007/s13280-025-02283-w.

Sustainable Energy Authority of Ireland, 2025. Energy in Ireland 2025 Report. https://www.seai.ie/sites/default/files/publications/Energy-in-Ireland-2025.pdf [Accessed 20/01/2026].

The Irish Times, 2026. Ireland Needs to Get Serious on EV Charging Infrastructure. Chatten, O. https://www.irishtimes.com/business/2026/01/12/ireland-needs-to-get-serious-on-ev-charging-infrastructure/ [Accessed 25/01/2026].

The Official Statistics of the Irish Motor Industry (SIMI), 2026. https://stats.beepbeep.ie/ [Accessed 05/05/2025].

Thompson, E.A., Alimo, P.K., Abudu, R., Lu, P., 2024. Towards sustainable freight transportation in Africa: complementarity of the fuzzy Delphi and best-worst methods. Sustain. Futur. 8, 100371. https://doi.org/10.1016/j.sftr.2024.100371.

Torkayesh, A.E., Pamucar, D., Ecer, F., Chatterjee, P., 2021. An integrated BWM-LBWA-CoCoSo framework for evaluation of healthcare sectors in eastern Europe. Socio Econ. Plan. Sci. 78, 101052. https://doi.org/10.1016/j.seps.2021.101052.

Unruh, G.C., Carrillo-Hermosilla, J., 2006. Globalizing carbon lock-in. Energy Policy 34 (10), 1185–1197. https://doi.org/10.1016/j.enpol.2004.10.013.

Western Development Commission (WDC), 2026. Connected Hubs. https://connectedhubs.ie/nationalhubsmap.html [Accessed 18/06/2025].

Wimbadi, R.W., Djalante, R., Mori, A., 2021. Urban experiments with public transport for low carbon mobility transitions in cities: a systematic literature review (1990–2020). Sustain. Cities Soc. 72 (July 2020). https://doi.org/10.1016/j.scs.2021.103023.

Wong, R.C.P., Yang, L., Szeto, W.Y., 2023. Comparing passengers satisfaction with fixed-route and demand-responsive transport services: empirical evidence from public light bus services in Hong Kong. Travel Behav. Soc. 32, 100583. https://doi.org/10.1016/j.tbs.2023.100583.

Zhang, R., Hanaoka, T., 2022. Cross-cutting scenarios and strategies for designing decarbonization pathways in the transport sector toward carbon neutrality. Nat. Commun. 13 (1), 3629. https://doi.org/10.1038/s41467-022-31354-9.

Zhang, W., Wu, X., Chen, J., 2024. Low-carbon efficiency analysis of rail-water multimodal transport based on cross efficiency network DEA approach. Energy 305, 132348. https://doi.org/10.1016/j.energy.2024.132348.

Zhu, Y., Ma, H., Sha, C., Yang, Y., Sun, H., Ming, F., 2023. Which strategy among avoid, shift, or improve is the best to reduce CO_2 emissions from sand and gravel aggregate transportation? J. Clean. Prod. 391 (January), 136089. https://doi.org/10.1016/j.jclepro.2023.136089.