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Review of greenhouse gas life-cycle assessments of passenger cars in India

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SUMMARY

This study reviews six life-cycle greenhouse gas (GHG) emission assessments of passenger cars in India, focusing on three powertrain types: internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), and battery electric vehicles (BEVs). It finds that key differences in assumptions—especially concerning grid carbon intensity, test versus real-world energy use, and fuel type—are primary drivers of variation in reported GHG emissions. A statistical bootstrapping analysis showed that these three factors alone accounted for nearly 75% of the variance in life-cycle emission estimates across studies.

Based on these findings, researchers undertaking future assessments of life-cycle emissions from passenger cars in India could consider using dynamic grid carbon intensity values, accounting for hybrid vehicles, applying real-world energy consumption adjustments, and refining assumptions about biofuel blending and land-use change. A harmonized approach to life-cycle assessments can better support policymaking on fuel efficiency standards, zero-emission vehicle mandates, and incentives for cleaner technologies.

INTRODUCTION

In its Nationally Determined Contribution under the Paris Agreement, India pledged to achieve net-zero GHG emissions by 2070. The transportation sector is responsible for nearly 14% of India's total GHG emissions and is the fastest-growing sector in India in terms of annual GHG emissions (Kumar et al., 2022).

Approximately 3.9 million passenger cars were sold in India in fiscal year (FY) 2022–23, positioning the country as the third-largest passenger vehicle market after China and the United States. Despite the continued dominance of fossil fuel-powered vehicles, BEVs have begun to gain traction: as of 2023, the BEV sales share in India stood at 2% (Deo & Kaur, 2024). Battery electric vehicles will be critical to decarbonizing the transport sector; when powered by renewable energy, BEVs can significantly reduce the life-cycle emissions from passenger transport (Abdul-Manan et al., 2022).

Recent studies have assessed the life-cycle emissions of passenger cars of various powertrains. However, these studies have used varying assumptions (e.g., regarding emissions from battery production, biofuels, and electricity generation). This paper examines the conflicting findings in the existing literature on the life-cycle GHG emissions of passenger cars in India in order to provide a clearer picture for policymakers as they determine how best to pursue India's decarbonization goals.

We review six studies on the life-cycle emissions of passenger vehicles in India and analyze how differences in variables and assumptions contribute to variation in GHG emissions estimates. We explore how estimates of the life-cycle GHGs of BEV, HEV, and ICEV passenger cars in India vary across the selected studies, and identify which assumptions pertaining to the vehicle cycle, fuel cycle, and electricity grid might explain convergence or divergence in GHG estimates.

We begin by presenting the six studies selected for this analysis and describing our methodology. We next present our results in two ways: first by comparing descriptive

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statistics of key variables included in the studies, and subsequently by assessing the relative importance of these variables in explaining the studies' differing findings. We close by offering some concluding thoughts on policy implications and highlighting potential areas of future work.

STUDY SELECTION AND DESCRIPTIONS

A life-cycle assessment (LCA) is used to estimate emissions over a vehicle's entire lifetime. This includes both fuel cycle emissions—encompassing well-to-tank (WTT) emissions from fuel and electricity production and tank-to-wheel (TTW) emissions from consumption—and vehicle cycle emissions produced in vehicle manufacturing, operation, and maintenance. It also includes emissions associated with the end of a vehicle's useful life, such as those from recycling and disposal.

Following an extensive literature review, six studies of the life-cycle GHG emissions of passenger cars in India were selected for analysis based on their relevance to the Indian passenger car context. Table 1 gives a brief description of these studies, outlining the scope of emissions assessed and the functional unit of emissions analyzed. The functional units varied across studies, with most reporting emissions in grams or kilograms of CO_2-equivalent (CO_2e) per vehicle kilometer while Gadepalli et al. (2023) also assessed CO_2e per passenger kilometer.

Table 1

Summary of the six studies of passenger vehicle emissions considered in this analysis

Study	Description	Scope of GHG emissions considered for LCA	Functional unit
Electrifying passenger road transport in India requires near-term electricity grid decarbonization (Abdul-Manan et al., 2022)	Assessment of the impact of grid decarbonization on BEV emissions in India	Fuel and vehicle cycle	g CO_2e per vehicle km
A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars (Bieker, 2021)	Analysis of GHG emissions from BEVs and ICEVs globally, with a chapter on India	Fuel and vehicle cycle, indirect land-use change emissions from biofuel feedstocks, maintenance	g CO_2e per vehicle km
Comparative life cycle GHG emission analysis of conventional and electric vehicles in India (Das, 2022)	India-specific study comparing ICEVs and BEVs	Fuel and vehicle cycle	kg CO_2 per vehicle km
LCA and TCO analyses of BEVs, HEVs, and ICEs (Agarwal, 2023)	India-specific comparison of the cost and emissions of BEVs, HEVs, and ICEVs	Fuel and vehicle cycle	g CO_2e per km and g CO_2e per vehicle lifetime km
Life-cycle assessment of passenger transport: an Indian case study (Gadepalli et al., 2023)	India-specific case study-based LCA on different transport modes	Fuel and vehicle cycle	g CO_2e per vehicle km and g CO_2e per passenger km
Well-to-wheel analysis of energy efficiency & CO_2 emissions for hybrids & EVs in India: current trends & forecasting for 2030 (Nadola et al., 2023)	India-specific study on energy efficiency and CO_2 emissions	Fuel and vehicle cycle	g CO_2 per vehicle km

Table 2 summarizes the range of life-cycle emissions estimated across the six studies for three vehicle classes in India. The studies analyzed life-cycle emissions across different powertrains, fuel types, and vehicle classes, highlighting significant variability based on the fuel and energy mix.

Table 2

Minimum and maximum life-cycle emissions recorded across the six studies for different vehicle classes in India

Vehicle class	Indicator	Minimum	Maximum
Hatchback	Life-cycle emissions (g CO_2e/km)	131.5	257.2
	Powertrain	BEV	ICE
	Study	Bieker (2021)	Bieker (2021)
	Remarks	Powered by electricity, based on India's average power generation mix over 15 years starting from 2021	Fuelled by a blend of compressed natural gas (CNG) and biogas, assuming 5% biogas share from 2030 and 10% share from 2040
Sedan	Life-cycle emissions (g CO_2e/km)	90.0	325.0
	Powertrain	BEV	BEV
	Study	Nadola et al. (2023)	Abdul-Manan et al. (2022)
	Remarks	Powered by the electricity generation mix in 2030 from the Central Electricity Authority (CEA) optimistic scenario	Powered by the FY 2018–19 electricity generation mix of the western regional grid in India
Sport utility vehicle (SUV)	Life-cycle emissions (g CO_2e/km)	115.0	368.8
	Powertrain	BEV	BEV
	Study	Abdul-Manan et al. (2022)	Das (2022)
	Remarks	Powered by the FY 2018–19 electricity generation mix of the northeastern regional grid in India	Powered by electricity from India's FY 2018–19 generation mix

METHODOLOGY

The methodology for this analysis consists of two parts: a descriptive statistics analysis and a statistical bootstrapping analysis. The descriptive statistics analysis provided a basis to draw comparisons across LCA variables observed across the studies, while the bootstrapping analysis assessed how variables contributed to the variance in results. For the methods used to calibrate emissions estimates from each study across each phase and sub-phase of the life-cycle system boundary, see Appendix A.

DESCRIPTIVE STATISTICS ANALYSIS

The descriptive statistics analysis focused on seven categories of variables, shown in Table 3, to understand differences and alignments across the studies. Where available, metrics were recorded from all six studies to ensure standardization and comparability.

Table 3
Dependent and independent variables in the six studies

Type	Category	Variables
Dependent variable	**Life-cycle GHG emissions**	• Life cycle emissions (g CO_2e/km)
Independent variables	**Energy consumption**	• Test-cycle energy consumption (MJ/km) • Real-world energy consumption adjustment factor (> 1.00)
	Vehicle use	• Vehicle lifetime (years) • Total vehicle kilometers traveled (km) • Vehicle maintenance emissions (g CO_2e/km) • Annual mileage degradation over vehicle lifetime (km)
	Fuels	• Biofuel blend share (%) • Wheel-to-tank emissions, excluding indirect land-use change (g CO_2e/MJ) • Indirect land-use change emissions (g CO_2e/MJ) • Tank-to-wheel emissions (g CO_2e/MJ)
	Electricity mix	• Carbon intensity of electricity generation (g CO_2e/kWh or g CO_2e/MJ) • Transmission and distribution loss factor (energy lost per energy input)
	Battery production	• Battery capacity (kWh) • Market share of battery chemistries deployed in Indian market (% of GW-hr deployed) • Carbon intensity of battery production per unit of battery capacity, by battery chemistry and region of production (g CO_2e/kWh)
	Rest-of-vehicle production	• Kerb weight, excluding battery (kg) • Carbon intensity of vehicle production excluding battery per unit of weight (g CO_2e/kg)

We evaluated the estimated life-cycle emissions of vehicles of the same segment, powertrain, and fuel type, using a functional unit of GHG emissions per vehicle kilometer traveled (VKT) over the vehicle lifetime. Vehicles were classified into three segments—hatchbacks, sedans, and SUVs—to account for the distinct characteristics and operational profiles of each, which can significantly influence energy consumption and emissions. In terms of powertrains, we considered ICEVs, HEVs, and BEVs. Among fuel types, we considered gasoline, diesel, electricity, and alternative fuels like CNG.

The review captured variations in life-cycle GHG emissions across a wide range of scenarios arising from differing assumptions concerning the fuel and vehicle cycles. This granularity ensured that results were not generalized across vehicle types and technologies, providing actionable insights for policy and strategy development.[1]

We sourced data directly from the six studies to the extent possible; when data were not available, we consulted the sources cited in the study to retrieve the relevant information or assumptions. These included information from stakeholder engagements and other data from the International Energy Agency (IEA) *World Energy Outlook 2021* (IEA, 2021) and CEA reports (CEA, 2024a), sales data from Segment Y (2024), and passenger car data from the Society of Indian Automobile Manufacturers (SIAM; SIAM, 2024). In some instances, when direct data were unavailable, back-estimations were made using materials referenced in the reports. Attempts also were made to engage with the primary authors for clarifications and to address data gaps, though we did not receive responses from all authors.

BOOTSTRAPPING ANALYSIS

To assess how variables contributed to variance in results across the six studies, we used the random forest model. This machine learning algorithm constructs multiple decision trees during training and outputs the mode of classes (for classification tasks) or mean prediction (for regression tasks) of the individual trees (Breiman, 2001). Each individual tree is trained on a random subset of the data and variables by bootstrap sampling with replacement from the original dataset. After the individual decision trees are trained and each tree makes a prediction, the final prediction for regression tasks is the average of all the individual tree predictions. This approach allows the algorithm to handle complex, non-linear relationships in data, be relatively robust to outliers and noise, and provide variable importance rankings (Hastie et al., 2009). It was selected for our study due to its high predictive accuracy, applicability in multivariable regression, and ability to estimate variable importance (Genuer et al., 2010).

To illustrate how different analysis methods might create uncertainty and to provide multiple perspectives on variable importance, we also applied three other widely used approaches: correlation analysis, linear regression, and perturbation analysis. Those results are presented in Appendix B.

The variables and input data used in the bootstrapping analysis came from the six LCA studies under consideration. Some of the variables were combined or removed to avoid colinear effects between variables and to decrease the complexity of the analysis. The variables used for the analysis are shown as in Table 4. These inputs do not consider Nadola et al. (2023), which did not provide data on key vehicle specifications, like lifetime VKT and kerb weight, required for input into the bootstrapping analysis.
As the variables for the WTW emissions estimation might be disparate for different powertrains, two groups of inputs were considered: one including all powertrains, and one for just ICEVs and HEVs (i.e., excluding BEVs).

1 We depended on the author(s) of each study to select vehicles with approximately comparable utility (e.g., in terms of seating, range, and engine power); we did not make adjustments ourselves.

Table 4
Variables used for the bootstrapping analysis

	Bootstrapping analysis variables	Units
Dependent variable	**Life-cycle emissions**	g CO_2e/km
Independent variables	**Kerb weight**	kg
	Test-cycle energy consumption	MJ/km
	Real-world energy consumption adjustment factor	No unit (> 1.00)
	Vehicle lifetime	years
	Total VKT	km
	Vehicle maintenance	g CO2e/km
	Annual mileage degradation over vehicle lifetime	km
	Average biofuel blend share across vehicle lifetime	% biofuel
	WTT emissions of conventional fuel	g CO_2e/MJ
	WTT emissions of biofuel mix (including ILUC)	g CO_2e/MJ
	TTW emissions of conventional fuel	g CO_2e/MJ
	Emissions due to generation of electricity	g CO_2e/kWh
	Transmission and distribution losses	%
	Battery capacity	kWh
	Emissions intensity of battery	kg CO_2e/kWh battery
	Battery replacement during vehicle lifetime	Number

Note: The estimated WTT emissions of conventional fuel include any biofuel blending considered. Additionally, for reference, we separately analyzed the volumetric average of the vehicle's lifetime WTT emissions based on the biofuel mix considered.

RESULTS

DESCRIPTIVE STATISTICS ANALYSIS

In this section, we compare descriptive statistics of the LCA variables.

Life-cycle GHG emissions

Table 5 summarizes the characteristics of the sample of life-cycle emissions estimates in the six studies assessed in this report. We analyzed results from 112 unique combinations of vehicle class (hatchback, sedan, and SUV), powertrain (ICEV, HEV, and BEV), and fuel or electricity mix assumed in the respective studies.

Table 5
Sample characteristics of life-cycle emissions estimates

Vehicle segment		Hatchbacks			Sedans			SUVs		
Powertrain		ICE	HEV	BEV	ICE	HEV	BEV	ICE	HEV	BEV
Sample size		4	0	2	17	9	33	9	8	28
Life-cycle emissions (g CO_2e/km)	**Mean**	235.1	N/A	146.8	207.7	157.6	211.4	228.9	189.4	226.5
	Median	235.0	N/A	146.8	210.0	170.0	199.5	220.0	182.5	212.0
	Min	213.0	N/A	131.5	122.0	92.0	90.0	175.0	145.0	115.0
	Max	257.2	N/A	162.0	285.0	241.9	325.0	314.0	240.4	368.8

Of the six studies, only Bieker (2021) assessed emissions from hatchbacks, hence hatchbacks make up the smallest subset in the sample. None of the studies analyzed emissions from HEV hatchbacks; in FY 2023–24, hybrid powertrains were available exclusively in the sedan and SUV segments.[2]

Table 6 compares the estimated life-cycle emissions of BEVs with those of ICEVs and HEVs for the three vehicle classes. For hatchbacks, the lowest estimated life-cycle emissions of BEVs in the sample were 38.3% lower than the lowest estimated emissions of ICEVs, while the highest estimated life-cycle emissions of BEVs in the sample were 37% lower than the highest estimated emissions of ICEVs. For sedans and SUVs, the lowest estimated life-cycle emissions of BEVs were lower than those of ICEVs and HEVs, while the highest estimated life-cycle emissions of BEVs were higher than those of ICEVs and HEVs.

Table 6
Life-cycle emissions of BEVs relative to ICEVs and HEVs

Vehicle class	Powertrain comparison	Life-cycle emissions (g CO_2e/km)	
		Min	Max
Hatchbacks	BEV relative to HEV	N/A	N/A
	BEV relative to ICE	-38.3%	-37.0%
Sedans	BEV relative to HEV	-2.2%	34.4%
	BEV relative to ICE	-26.2%	14.0%
SUVs	BEV relative to HEV	-20.7%	53.4%
	BEV relative to ICE	-34.3%	17.5%

For BEVs, the large variation in estimated emissions is attributable to differing assumptions concerning the electricity grid over the lifetime of the vehicle, including as it relates to the share of renewable energy in the grid mix. We compare the grid-related assumptions across the six studies in subsequent sections.

Energy consumption

Parameters related to energy consumption include fuel and electricity consumption rates. In this section, we compare the assumptions of vehicle cycle-related parameters across the studies. We assess energy consumption by vehicle class (hatchback, sedan, and SUV) to allow representative comparisons across the data.

Bieker (2021) did not analyze HEVs, as these vehicles had limited market share in India at that time (0.01%). In FY 2023–24, however, hybrid sales in the country almost equaled BEV sales with 91,008 units, representing 0.4% of passenger car sales.[3] To enable comparison with the other studies, which analyzed HEV sedans and SUVs, we assumed emissions values for these vehicles for Bieker (2021) based on the top-selling HEVs in the fleet using the methodology in that paper.[4]

2 The sample of hatchback vehicles in Bieker (2021) comprised four fuel types: petrol with biofuels, diesel with biofuels, CNG with a methane slip of 1.8 g CO_2e/km combined with biofuels, and CNG with a methane slip of 30 g CO_2e/km. The maximum life-cycle emissions value was recorded for the sample with methane slip of 30 g CO_2e/km. The scenario for vehicles sold in 2030 is not included in this analysis. Sales data for FY 2023-24 was provided by Segment Y Automotive Intelligence Pvt Ltd.

3 Based on data from Segment Y Automotive Intelligence Pvt Ltd.

4 Among HEV sedans, the Toyota Camry Hybrid and Honda City HEV were analyzed. For HEV SUVs, the Maruti Suzuki Grand Vitara, Toyota Urban Cruiser Hyryder, Toyota Innova Hycross, and Maruti Suzuki Invicto were considered. Collectively, these six models accounted for 98% of strong hybrid sales in FY 2023–24 according to data provided by Segment Y Automotive Intelligence Pvt. Ltd.

Table 7 shows the mean values of test-cycle energy consumption—which refers to the energy a vehicle uses when tested under standardized driving conditions, typically in a controlled laboratory setting—assumed in each study, by vehicle class and powertrain. Figure 1 illustrates the distribution of test-cycle energy consumption values assumed across the six papers.

Table 7

Mean test-cycle energy consumption values assumed in each study, in MJ/km

Study	Hatchback			Sedan			SUV		
	ICE	HEV	BEV	ICE	HEV	BEV	ICE	HEV	BEV
Abdul-Manan et al. (2022)	–	–	–	1.8	–	0.5	1.7	–	0.4
Bieker (2021)	1.7	–	0.4	1.7	1.3	0.6	2.0	1.3	0.3
Das (2022)	–	–	–	2.1	–	–	–	–	1.0
Agarwal (2023)	–	–	–	1.8	1.1	–	1.8	1.2	0.4
Gadepalli et al. (2023)	–	–	–	2.1	–	0.5	–	–	–
Nadola et al, (2023)	–	–	–	1.7	1.2	0.6	–	–	–

Notes: Dashed cells indicate data were not available.

Figure 1

Distribution of test-cycle energy consumption values assumed across studies

Note: The top and bottom edges of each box show the lower and upper quartiles, meaning the box covers the middle 50% of the data. The line inside each box marks the median, and the cross represents the mean.

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For sedans and SUVs, the spread in energy consumption values is more prominent for ICEVs than for HEVs. Moreover, there is considerable variation in values for battery-electric SUVs. For BEV SUVs, Das (2022) reported a value of 1 MJ/km (27.8 kWh/100 km), much higher than other values in the dataset, corresponding to the energy consumption reported for the Hyundai Kona EV. The Hyundai Kona EV is also modeled as a representative BEV in Agarwal (2023), which reported an energy consumption value nearly 50% lower, at 0.5 MJ/km (12.9 kWh/100km). For comparison, the manufacturer-reported energy consumption of the 2022 Hyundai Kona EV in India is 0.3 MJ/km (8.6 kWh/100 km)(*Hyundai Kona Electric*, 2022)

Real-world driving conditions often differ from the conditions in standardized test cycles. To address this, a real-world adjustment factor is used. The adjustment factor is a correction applied to test results to account for variations in driving behaviour, road conditions, and environmental factors to reflect actual on-road performance. 2 illustrates the distribution of real-world adjustment factors used for the test-cycle consumption values assumed across all studies, by powertrain.

Figure 2
Distribution of real-world adjustment factors assumed across studies

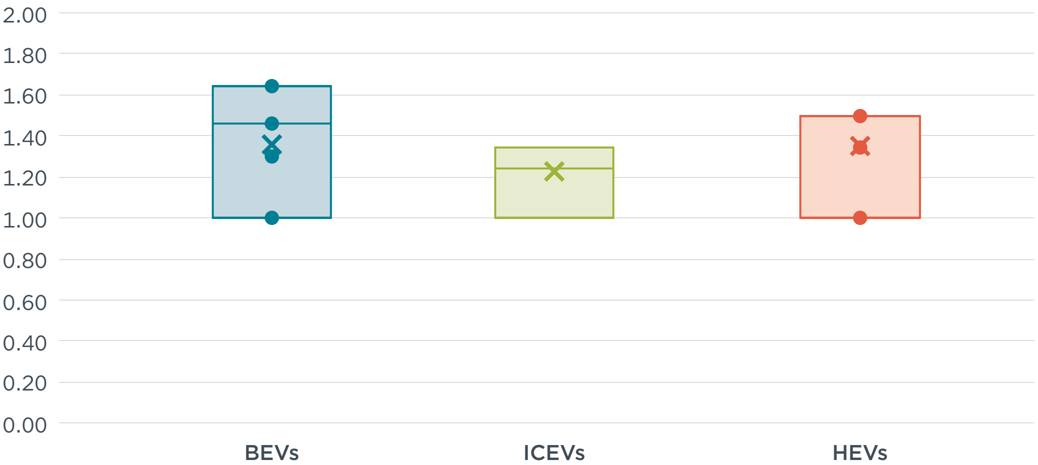

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Table 8 shows the mean values of energy consumption adjustment factors for each study by powertrain. In several studies, adjustment factors applied for BEVs were higher than those applied for ICEVs and HEVs. For BEVs, Bieker (2021) applied an adjustment factor of 1.34, accounting for 15% charging losses, to the Modified Indian Driving Cycle (MIDC) energy consumption values.[5] None of the other studies referenced charging losses when estimating the energy consumption of BEVs. Abdul-Manan et al. (2022) applied a real-world adjustment factor of 1.46 for BEVs, which includes a 40% correction from test-cycle energy consumption values and an additional 6% temperature adjustment factor reflecting ambient conditions in India. Across all studies, the average real-world adjustment factor for ICEVs was 1.24 and for HEVs was 1.27. The highest real-world adjustment factor for ICEVs was 1.34 (Agarwal, 2023; Bieker, 2021) and for HEVs was 1.50 (Bieker, 2021).

5 The MIDC is based on a standardized driving pattern representing typical urban and highway driving conditions in India. The maximum speed in the MIDC cycle is set to 90 km/h.

Table 8
Mean real-world adjustment factors for energy consumption in each study, by powertrain

Study	Hatchback			Sedan			SUV		
	ICE	HEV	BEV	ICE	HEV	BEV	ICE	HEV	BEV
Abdul-Manan et al. (2022)	–	–	–	1.2	–	1.5	1.2	–	1.5
Bieker (2021)	1.3	–	1.6	1.3	1.5	1.6	1.3	1.5	1.6
Das (2022)	–	–	–	1.0	–	–	–	–	1.0
Agarwal (2023)	–	–	–	1.3	1.3	–	1.3	1.3	1.3
Gadepalli et al. (2023)	–	–	–	1.0	–	1.0	–	–	–
Nadola et al. (2023)	–	–	–	1.0	1.0	1.0	–	–	–
Range of real-world adjustment factors across studies	1.3	–	1.6	1.0–1.3	1.0–1.5	1.0–1.6	1.2–1.3	1.3–1.5	1.3–1.6

Note: Dashed cells indicate data were not available.

Vehicle use indicators

Vehicle use indicators represent how much mileage is accrued by a vehicle over its useful life based on assumptions of total VKT, vehicle lifetime, and mileage degradation. 9 shows the distribution of these assumptions across the studies.

Table 9
Lifetime VKT, vehicle lifetime, and mileage degradation factor assumed in each study

Study	Vehicle class	Lifetime VKT	Vehicle lifetime (years)	Mileage degradation factor
Abdul-Manan et al. (2022)	Sedan and SUV	200,000	16	–
Bieker (2021)	Hatchback and sedan	165,000	15	3.0% per year
	SUV	188,000	15	3.0% per year
Das (2022)	Sedan and SUV	160,000	15	–
Agarwal (2023)	Sedan and SUV	200,000	10	–
Gadepalli et al. (2023)	Sedan	181,500	15	–

Note: Dashed cell indicated data were not available.

The six studies applied relatively uniform values of vehicle use indicators across all powertrains. While most studies assumed vehicle lifetimes of 15–16 years, Agarwal (2023) assumed a shorter 10-year lifetime; along with Abdul-Manan et al. (2022), Agarwal (2023) also assumed the highest lifetime VKT, of 200,000 for sedans and SUVs. Only Bieker (2021) considered a mileage degradation factor, which increases the estimated GHG intensity of vehicles by shifting some mileage from later years, which are characterized by less carbon-intense fuel and electricity supply, to the near-term, where both are dominated by fossil fuels.

Carbon intensity of fuels

Conventional fuels analyzed in the studies included gasoline, diesel, and CNG. Bieker (2021) and Nadola et al. (2023) also considered biofuel blending as part of their fuel scenarios. Bieker (2021) modeled a dynamic fuel blend of ethanol in gasoline, biodiesel in diesel, and biomethane in CNG over the vehicle lifetime.

In Bieker's scenario, shares of ethanol in gasoline start at a 5% volumetric blend in 2020 and increase to 20% by 2040. The share of cellulosic ethanol within the fuel blend from second-generation sources like agricultural residues and energy crops also gradually increases from 0% in 2020 to 15% by 2040, with molasses-based ethanol staying constant at 5% throughout the projection. The biofuel assumptions in the study are based on India's 2018 National Policy on Biofuels and feature high shares of sustainable cellulosic ethanol for blending in gasoline, used cooking oil (UCO) and municipal solid waste (MSW) for blending in diesel, and biogas for blending in CNG. Agarwal (2023) considered three scenarios for ethanol blending, assuming constant blend shares of 10%, 20%, and 30% over the vehicle lifetime with all ethanol being produced from sugarcane.

Bieker (2021) was the only study to consider biofuel blending with diesel and CNG. For diesel, Bieker assumed that UCO-based biodiesel and MSW-based syndiesel collectively make up 5% of diesel use in 2040. For CNG, Bieker assumed sewage-based biomethane blending shares increase from 0% in 2020 to 10% by 2040.

Table 10 presents the various biofuel blending scenarios considered across the six studies. For Bieker (2021), a lifetime average biofuel blend rate is reported based on weighting the progressively increasing biofuel blend rates with the progressively decreasing mileage of the vehicle assumed over the lifetime.

Table 10
Biofuel blending scenarios in each study

Study	Ethanol		Biodiesel / syndiesel		Biomethane	
	Average lifetime blend rate	Feedstock	Average lifetime blend rate	Feedstock	Average lifetime blend rate	Feedstock
Abdul-Manan et al. (2022)	–	–	–	–	–	–
Bieker (2021)	12.0%	Molasses, agricultural residue, energy crops	2.0%	UCO, MSW	3.7%	Sewage
Das (2022)	–	–	–	–	–	–
Agarwal (2023)	10%, 20%, 30%[a]	Sugar-cane	–	–	–	–
Gadepalli et al. (2023)	–	–	–	–	–	–
Nadola et al. (2023)	–	–	–	–	–	–

[a] Gasoline-ethanol blend scenarios are 10%, 20%, and 30%.
Note: Dashed cells indicate data were not available.

Table 11 presents the upstream WTT emission factors associated with conventional fuels and biofuels used in each study, and Figure 3 illustrates the distribution across studies. CNG values depicted in Figure 3 assume a 100-year global warming potential (GWP) for methane.[6] Only two studies, Bieker (2021) and Agarwal (2023), considered biofuel blending, and only Bieker reported ILUC emissions associated with various biofuel feedstocks. For the other studies, we estimated these emission factors based on the available data. In some cases, this involved making reasonable estimations by assuming values pertaining to the property of fuel, such as calorific value or density.

6 GWP is a measure of how much heat 1 ton of a given GHG absorbs over a given time period relative to the same amount of CO_2.

Wherever such assumptions were required in the absence of directly available WTT values, we used fuel property data based on Bieker (2021).

Table 11

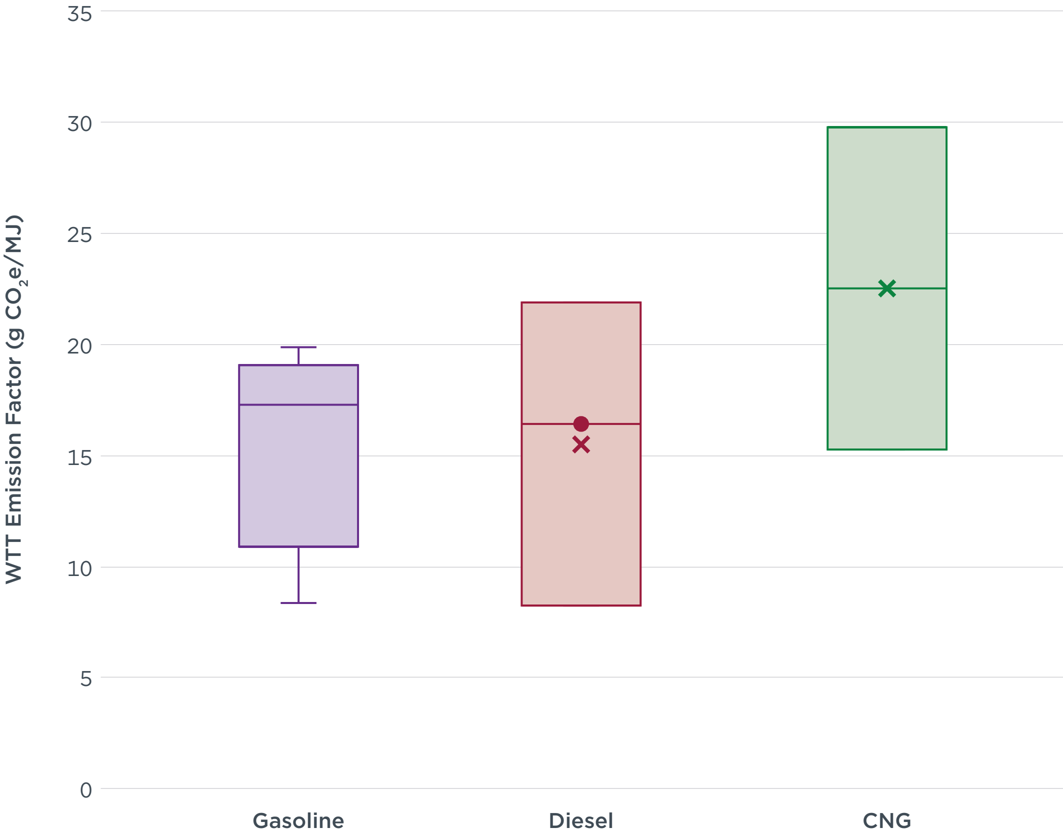
Upstream WTT emission factors in each study

Study	Gasoline (g CO_2e/MJ)	Diesel (g CO_2e/MJ)	CNG (g CO_2e/MJ)
Abdul-Manan et al. (2022)	17.3	16.4	–
Bieker (2021) (inlcudes ILUC)	19.9	21.9	29.8 (20-year GWP) and 15.3 (100-year GWP)
Das (2022)	–	–	–
Agarwal (2023)	18.2	–	–
Gadepalli et al. (2023)	13.5	–	–
Nadola et al. (2023)	8.4	8.2	15.0
Range of upstream WTT emissions across the studies	8.4–19.9	8.2–21.9	15.0–29.8

Note: Dashed cells indicate data were not available.

Figure 3

Distribution of upstream WTT emission factors for conventional fuels assumed across studies



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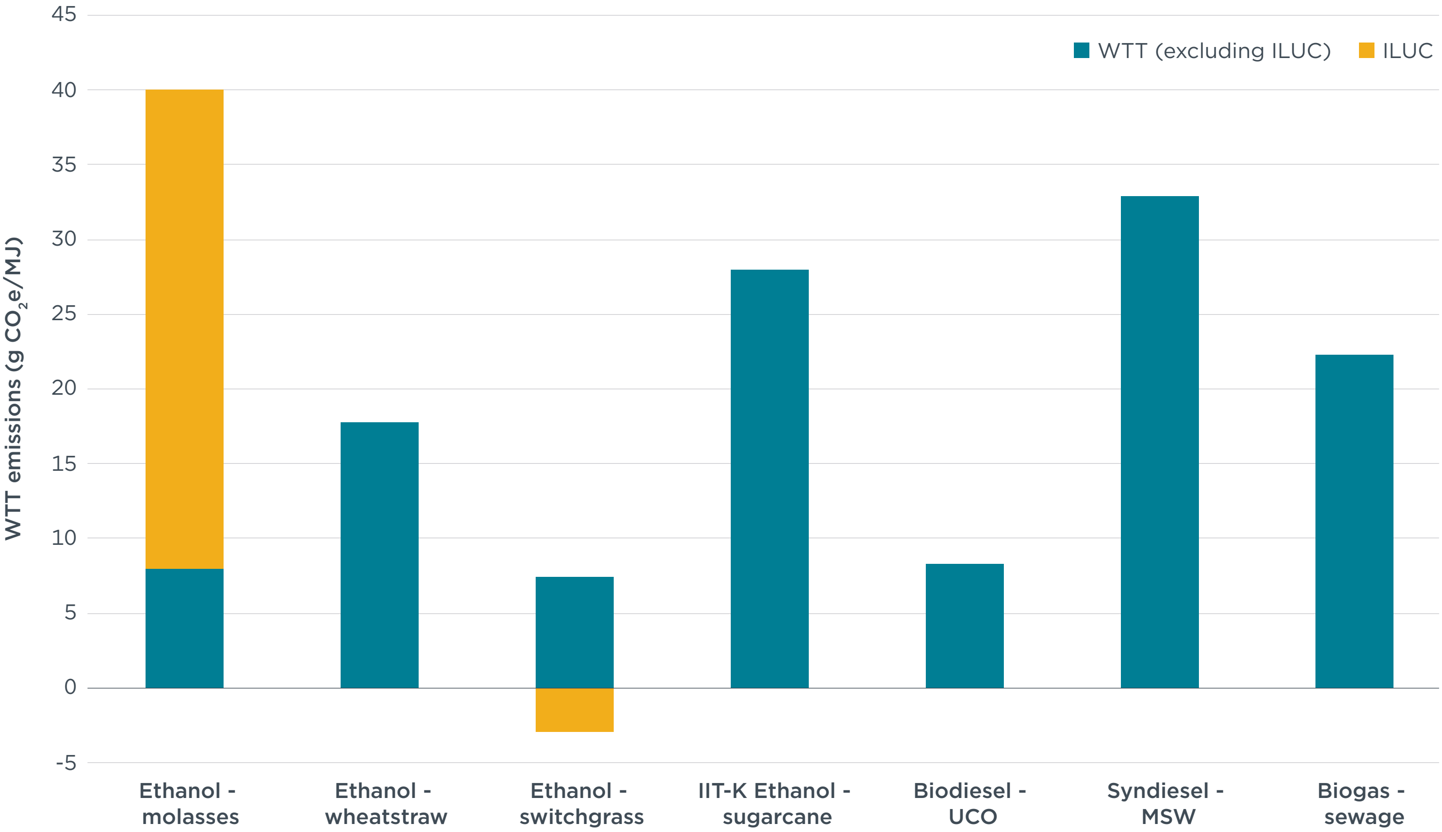
There are large spreads in the upstream WTT emission factor values for diesel and CNG. For diesel, the lowest WTT emission factor for diesel is 8 g CO_2e/MJ (Nadola et al., 2023), while the highest is 22 g CO_2e/MJ (Bieker, 2021). Among the studies, only Bieker provided the WTT emission factors for CNG and considered two GWP scenarios.

As shown in the figure above, the values range from a minimum of 15.3 (based on a 100-year GWP) to a maximum of 29.8 (based on a 20-year GWP). When considering a 20-year GWP, the upstream WTT emission factor for CNG is higher than that of both gasoline and diesel (Bieker, 2021).

Figure 4 shows the upstream emission factors for biofuels assumed in the studies, including ILUC emissions where appropriate.[7] Bieker (2021) estimated WTT emissions for biofuels including ILUC emissions, while Agarwal (2023) made no reference to ILUC emissions. It is expected that food-based biofuels such as sugarcane ethanol, which is considered in Agarwal (2023), will have sizeable ILUC emissions associated with their production.

Figure 4

Upstream WTT emission factors for biofuels assumed across studies



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In 2022, the Indian Government amended its National Policy on Biofuels, bringing forward the 20% ethanol blending target from 2030 to 2025. As of FY 2023–24, India is reported to have achieved 12% ethanol blending (Ashokan, 2024). While the amended policy does not explicitly outline a feedstock strategy to meet the accelerated target, scaling supply will likely entail supplementing sugar-based feedstock with ethanol produced from corn, broken rice, and surplus rice feedstocks, which can be associated with significant ILUC emissions. Further, the Indian government is also promoting flex-fuel vehicles, which run ethanol blend shares between 85% and 100%, as part of a “multi-fuel” decarbonization strategy for the transport sector. At higher ethanol blend

7 When biofuel blending is taken into account, WTT emissions also include ILUC emissions associated with the amount of biofuels used. ILUC occurs when agricultural resources are diverted to fuel production, leading to global land cover changes and, consequently, GHG emissions.

levels, more food and feed may be needed, which could lead to unintended land-use issues and sustainability concerns.

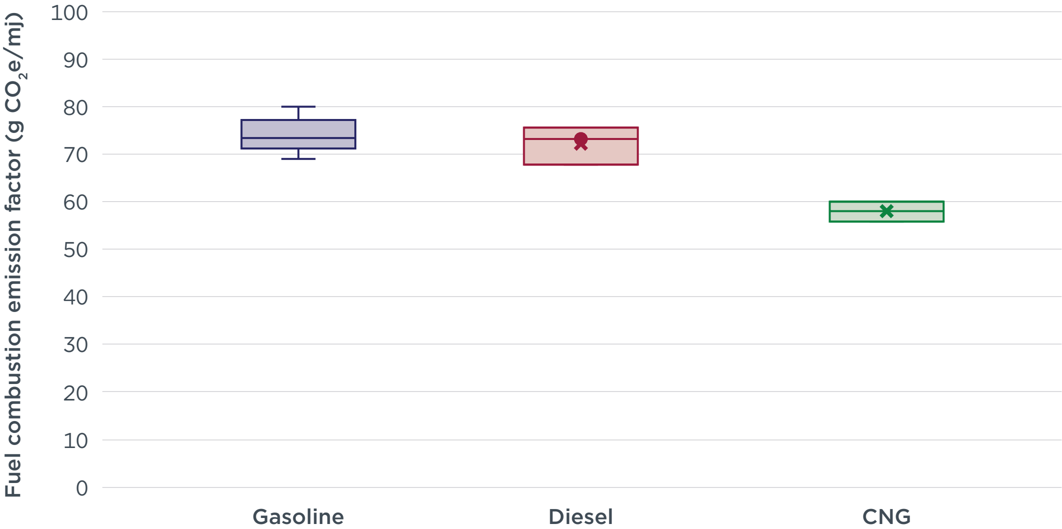
Table 12 summarizes the TTW emission factors for fuel combustion for each conventional fuel considered, while Figure 5 illustrates the distribution of TTW emission factors for fuel combustion across the six studies. The emission factors are observed to be relatively consistent across all studies. For CNG-powered cars, there can be sizeable additional emissions associated with methane slip.

Table 12
TTW emission factors used in each study

Study	Gasoline (g CO_2e/MJ)	Diesel (g CO_2e/MJ)	CNG (g CO_2e/MJ)
Abdul-Manan et al. (2022)	74.3	75.6	–
Bieker (2021)	73.4	73.2	60.0
Das (2022)	–	–	–
Agarwal (2023)	80.0	–	–
Gadepalli et al. (2023)	69.0	–	–
Nadola et al. (2023)	73.3	67.7	55.9
Range of TTW emissions	73.3–80.0	67.7–75.6	55.9–60.0

Note: Dashed cells indicate data were not available.

Figure 5
TTW emission factors for fuel combustion across studies



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Only Bieker (2021) and Nadola et al. (2023) analyzed CNG powertrains in their studies. Unlike Nadola et al., Bieker explicitly accounted for the additional emissions from methane slip associated with the combustion of CNG. In the absence of methane slip data from Indian passenger cars, Bieker assumed methane slip emission factors based on data for Euro 6 cars in the European Union (2 g CO_2e/km, assuming a 100-year GWP), while noting that methane slip from passenger cars in other markets are reported to be much higher. The large variability in emission factors for methane slip highlights the need for India-specific emission factors to be considered in future work.

For biofuels, TTW emissions are assumed to be zero on account of a biogenic feedstock credit that offsets emissions in proportion to the volumetric blend share assumed in the fuel mix. In theory, biogenic feedstocks will still result in TTW emissions of nitrous oxide and methane, resulting in non-zero TTW emissions. As BEVs have zero emissions at the tailpipe, TTW emissions from BEVs are zero.

Carbon intensity of electricity supply

The carbon intensity of electricity generation is a crucial factor in determining the overall emissions of electric vehicles. In India, electricity is generated from a diverse mix of energy sources, including coal, natural gas, hydropower, nuclear, wind, and solar, each with different carbon intensities. Table 13 summarizes the grid supply emissions assumed in each study.

Table 13

Assumptions of electricity grid carbon intensity in each study

Studies	Sample size of grid scenarios	Carbon intensity (g CO_2e/kWh)			
		Mean	Median	Minimum	Maximum
Abdul-Manan et al. (2022)	24	879.1	922.7	501.1	1080.0
Bieker (2021)	2	653.4	653.4	560.9	745.9
Das (2022)	3	1260.0	1329.8	1050.1	1400.0
Agarwal (2023)	1	975.6			
Nadola et al. (2023)	3	803.9	864.0	612.0	936.0
Gadepalli et al. (2023)	3	634.3	588.9	523.1	790.9

Among the six studies considered, Abdul-Manan et al. (2022) featured the most extensive range of grid scenarios, including variations in charging times (day or night) across two seasons (summer and winter). They also incorporated scenarios assuming annual carbon intensity reductions ranging from 0.5% to 1.5% relative to the baseline, and covered different regional grids within India. Bieker's (2021) approach modelled the carbon intensity of the grid as the weighted average grid emissions intensity over the vehicle's lifetime based on data from the IEA and Intergovernmental Panel on Climate Change life-cycle emissions factors (Stocker et al., 2013).

Assuming a single carbon intensity value does not account for changes in the Indian energy mix over time. Bieker (2021), however, adopted a dynamic approach, considering the average carbon intensity over a vehicle's lifetime based on projections from the IEA *World Energy Outlook*—specifically, the Stated Policies Scenario (STEPS) and Sustainable Development Scenario (SDS). Das (2022) applied values from the International Renewable Energy Agency (IRENA)'s 2030 scenario. Nadola et al. (2023), meanwhile, applied both NITI Aayog's 2030 scenario and the CEA's optimistic scenario. Apart from Agarwal (2023), most studies explored multiple grid scenarios.

The highest carbon intensity of grid supply value was assumed in Das (2022), which considered a static electricity mix based on the FY 2018–19 grid. The lowest value was in Gadepalli et al.'s (2023) ambitious scenario, which assumed a 53% fossil fuel generation mix by 2030, emphasizing the substantial emission reductions achievable with greater integration of renewables into the grid. Among studies that assumed static mixes, Abdul-Manan et al.'s (2022) analysis of the FY 2018–19 electricity mix in the northeastern grid also showed a notably low carbon intensity, underscoring regional variations in grid emissions based on the specific energy sources in use.

Table 14 summarizes the grid scenario assumptions in the six studies. Each study used different scenarios for the generation mix over the vehicle lifetime. Among constant generation scenarios, which assumed the generation mix remains unchanged over time, fossil fuel shares varied even when they used the same CEA data for the 2018–19 generation mix: Abdul-Manan et al. (2022) assumed 81% fossil fuel and Das (2022) assumed 78%. Similarly, using the same 2020–21 CEA data, Agarwal (2023) assumed a fossil fuel share of 79%, while Gadepalli et al. (2023) assumed 76%.

Among dynamic scenarios, in which the generation mix changes over time, Nadola et al. (2023) and Das (2022) adopted the most conservative projections of the fossil fuel share for 2030. As noted above, Bieker (2021) included two scenarios from the IEA's *World Energy Outlook*: STEPS and SDS. STEPS represents the current policy framework, including policies under development. Under this scenario, India surpasses the targets outlined in its Nationally Determined Contribution under the Paris Agreement. Meanwhile, the SDS scenario examines how India could achieve a significant increase in clean energy investments to enable an early emissions peak followed by a rapid decline, aligning with the long-term goal of net-zero emissions while advancing progress on various sustainable development objectives.

Table 14 categorizes the scenarios in each study into three groups by ambition in phasing out fossil fuels: conservative, optimistic, and ambitious/aggressive. Conservative scenarios project the fossil fuel share to range between 65% and 70% by 2030. Optimistic scenarios assume it will be between 50% and 65% by 2030. Ambitious/aggressive scenarios assume the share will drop below 50% by 2030.

The CEA's National Electricity Plan (NEP) for 2022–2032 projects a significant shift in India's energy mix (CEA, 2024b). The fossil fuel share is anticipated to decline from 61% in FY 2026–27 to 51% by FY 2031–32. As of 2024, renewable energy accounted for 46.3% of total installed capacity (Ministry of New and Renewable Energy, 2024).

Table 14

Grid scenarios in India's NEP and the six studies, highlighting fossil generation mix over vehicle lifetime

Scenario	Used by study	Scenario source	Years of vehicle operation	Fossil generation share	Average carbon intensity of electricity (g CO_2e/kWh)
NEP	—	CEA	-	Declines to 61% in 2026–27 and 51% in 2031–32.	548.0
Constant generation mix scenarios					
Constant 2018–2019 mix	Abdul-Manan et al. (2022)	CEA	2018–2019	81% (constant)	778.9
	Das (2022)	CEA	2018–2019	78% (constant)	1,400.0
Constant 2019–2020 mix	Nadola et al. (2023)	CEA	2019–2020	75% (constant)	775.7
	Agarwal (2023)	CEA	2019–2020	79% (constant)	820.5
	Gadepalli et al. (2023)	ITF-World Bank	2020	76% (constant)	791.0
Conservative scenarios					
Reference	Das (2022)	IRENA	2030	Increases to 82% in 2030	1,330.0
2030 Conservative	Nadola et al. (2023)	NITI Aayog	2030	Declines to 70% in 2030	744.8
REmap	Das (2022)	IRENA	2030	Declines to 65% in 2030	1,050.0
Optimistic scenarios					
STEPs	Bieker (2021)	IEA	2021–2035	Declines to 69% in 2025 and 59% in 2030	746.0
IPS	Gadepalli et al. (2023)	ITF-World Bank	2030	Declines to 65% in 2025 and 53% in 2030	589.0
Optimal Generation Mix	Abdul-Manan et al. (2022)	CEA	2030	Declines to 60% in 2029–30	568.1
Ambitious/aggressive scenarios					
SDS	Bieker (2021)	IEA	2021–2035	Declines to 41% by 2030	561.0
Net-zero	Gadepalli et al. (2023)	ITF-World Bank	2030	Declines to 46% by 2030	523
2030 Aggressive	Nadola et al. (2023)	CEA	2030	Declines to 56% by 2030	556.9

Transmission and distribution (T&D) losses refer to the energy lost as electricity is transmitted from power plants to end-users due to resistance in transmission lines and inefficiencies in distribution networks (Bhatt & Singh, 2021). Table 15 presents the assumptions of T&D losses across the studies. Four out of six studies assumed a standard loss of or near 19%. Gadepalli et al. (2023) assumed a substantially lower value for T&D losses, of 4.9%, implying a far more limited gap between electric power supplied and electric power consumed. Variations in T&D loss assumptions impact the overall carbon intensity calculations, as higher T&D losses translate to greater emissions per unit of electricity delivered to end-users. As of FY 2022–23, India's T&D losses stood at 17.68% (CEA, 2024a). Efforts are underway to reduce these losses to 12–15% by FY 2025–26 under the Government's Revamped Distribution Sector Scheme (Ministry of Power, 2023a).

Table 15

Sample characteristics of T&D loss assumptions in each study

Studies	Sample size of grid scenarios	Mean	Median	Minimum	Maximum
Abdul-Manan et al. (2022)	24	19.0%			
Bieker (2021)	2	19.0%			
Das (2022)	3	19.0%			
Agarwal (2023)	1	18.9%			
Gadepalli et al. (2023)	3	4.9%			
Nadola et al. (2023)	3	16.0%	16.0%	10.0%	21.0%

Carbon intensity of battery production

The carbon intensity of battery production is primarily influenced by the materials that make up the battery cells and pack. Lithium-ion batteries, the most widely used battery type in BEVs, are distinguished based on cathode chemistries: lithium cobalt oxide (LCO), lithium manganese oxide (LMO), lithium cobalt oxide (LCO), nickel manganese cobalt (NMC), lithium iron phosphate (LFP), and nickel cobalt aluminum (NCA). NMC batteries are further sub-classified based on the ratio of nickel, manganese, and cobalt used in the cathode. While first generation NMC batteries contained equal shares of all three cathode materials (NMC 111), the development of next generation NMC batteries has been characterized by increasing nickel content to increase energy density while lowering cobalt content. NMC 811 batteries are the latest and most energy dense NMC variant on the market to date.

Table 16 shows the mean battery capacity values for HEVs and BEVs assumed in each study and Figure 6 illustrates the distribution across studies.

Table 16

Mean battery capacity values used in each study by vehicle class and powertrain type

Study	Hatchback		Sedan		SUV	
	HEV (kWh)	BEV (kWh)	HEV (kWh)	BEV (kWh)	HEV (kWh)	BEV (kWh)
Abdul-Manan et al. (2022)	–	–	–	0.5	–	0.4
Bieker (2021)	–	23	1.2	23	1.1	32.3
Das, 2022	–	–	–	–	–	39.2
Agarwal (2023)	–	–	5.9	–	5.9	34.7
Gadepalli et al. (2023)	–	–	–	40	–	–
Nadola et al. (2023)	–	–	–	–	–	–

Note: Dashed cells indicate data were not available.

Figure 6

Distribution of battery capacity values across studies

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For BEV sedans, the average assumed battery capacity across the studies was 23 kWh, while the highest was 40 kWh. For BEV SUVs, the average was 34 kWh while the highest was 39 kWh. For context, in FY2023–24, the sales-weighted average battery capacity was 23 kWh for BEV hatchbacks, 31 kWh for BEV sedans, and 35 kWh for BEV SUVs.[8]

HEVs are also equipped with a small battery pack. Of the six studies, only Bieker (2021) set out assumptions concerning HEV battery capacity. Agarwal (2023) did not directly report the capacity of HEV batteries, but based on the reported battery weight (49 kg) and battery density (120 Wh/kg), we estimated that sedans and SUVs were assumed to be equipped with a 5.88 kWh battery. Based on data from Segment Y, the two models considered in Agarwal (2023)—the Honda City eHEV sedan and the Maruti Suzuki Grand Vitara SUV—are equipped with much smaller batteries, in the range of 0.7–0.8 kWh.

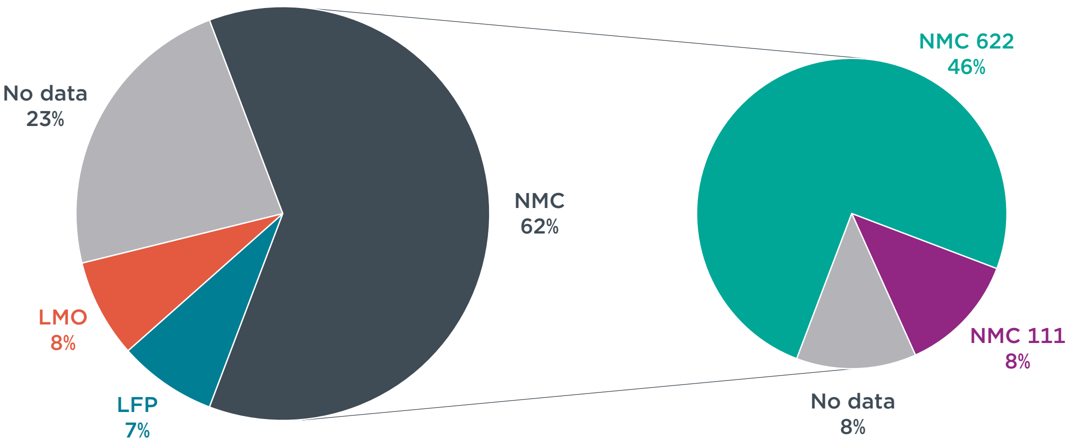
Figure 7 illustrates the BEV battery assumptions in the reviewed literature. In the dataset, 62% of representative models considered were assumed to be equipped with

8 These values are based on data provided by Segment Y Automotive Intelligence Pvt. Ltd.

NMC batteries, 8% with LMO, and 7% with LFP. Among NMC battery chemistries, 46% of the vehicles assessed ran on NMC 622 and 8% used NMC 111.

Figure 7

Battery chemistry shares among representative BEV models across studies



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In 2023, LFP was the most prevalent battery chemistry in the Indian passenger car market (Stellarix, 2024). That year, 90% of sales of the top 11 highest selling BEV cars in India—which in turn represented 90% of total BEV sales—were of LFP-powered vehicles, with NMC-powered vehicles making up the remaining 10%.[9] LFP batteries are projected to maintain high market shares of near 60% in India's BEV market by 2030 (Moerenhout et al., 2023). Future LCAs of passenger cars in India might therefore consider including scenarios with higher market shares of LFP batteries.

Figure 8 presents the assumptions of carbon intensity of battery production in each of the six studies, while Table 17 illustrates the distribution across studies.

Table 17

Assumed carbon intensity of battery production in each study by battery chemistry

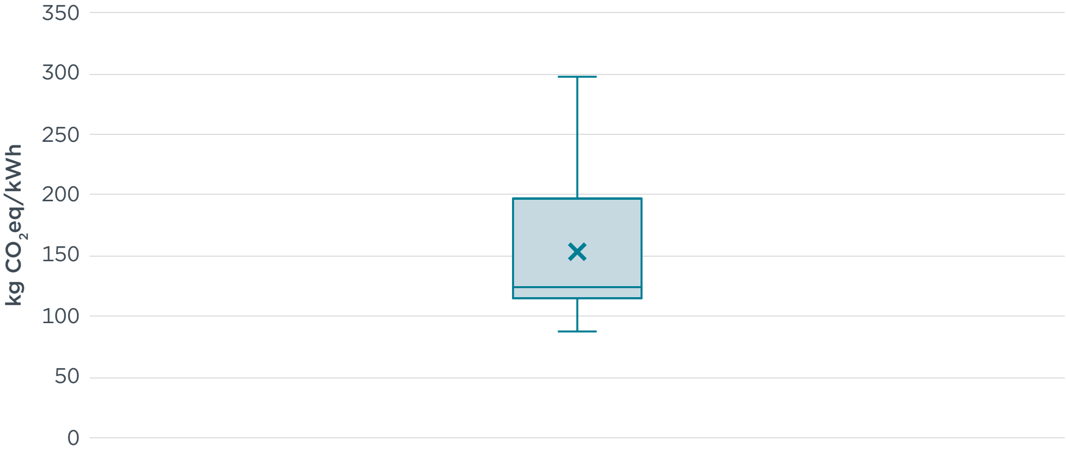
Study	Battery chemistry	Carbon intensity of battery production (kg CO_2eq/kWh)
Abdul-Manan et al. (2022)	NMC 622	124.5
Bieker (2021)	NMC 622	68.0
Das (2022)	NMC	164.0
	LMO	88.0
	LFP	297.0
Agarwal (2023)	–	123.0
Gadepalli et al. (2023)	NMC 111	93.0

Note: Dashed cells indicate data were not available.

9 These values are based on sales data for FY 2023–24 provided by Segment Y Automotive Intelligence Pvt Ltd.

Figure 8

Distribution of carbon intensity of battery manufacturing assumed across studies



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Most studies assumed that modeled BEVs were equipped with NMC batteries, though a wide range of emission factors for NMC battery manufacturing was observed across the dataset. Das (2022) assumed the highest emission factor for NMC battery production at 164 kg CO_2e/kW, while Bieker (2021) assumed the lowest, at 68 kg CO_2e/kWh.

Table 18 presents the carbon intensity of battery production values alongside the assumptions concerning battery replacement in the vehicle lifetime for each study.

Table 18

Battery replacement assumptions in each study

Study	Battery replacement assumption	Carbon intensity (kg CO_2e/kWh)
Gadepalli et al. (2023)	1 replacement	93.0
Abdul-Manan et al. (2022)	1 replacement	124.5
Agarwal (2023)	1 replacement	123.0
Bieker (2021)	No replacement	68.0
Das (2022) – NMC	No replacement	164.0
Das (2022) – LFP	No replacement	297.0
Das (2022) – LMO	No replacement	88.0

Gadepalli et al. (2023), Abdul-Manan et al. (2022), and Agarwal (2023) considered scenarios with one battery replacement over the lifetime of the BEV. Bieker (2021) assumed no battery replacement is needed because lithium-ion batteries are typically considered to reach the end of their useful life when they reach 70%–80% of their initial capacity. In rigid battery durability tests, NMC batteries have been demonstrated to sustain more than 80% of their initial capacity after 3,000–5,000 equivalent full cycles and LFP batteries have been shown to remain above that value even after 5,000–6,000 equivalent full cycles. For light-duty BEVs with a range of 200–400 km, a battery lifetime of 3,000–5,000 equivalent full cycles would correspond to a mileage of 600,000–2,000,000 km. This is several times higher than an average LDV lifetime mileage of 150,000–300,000 km (Bieker, 2021; Li et al., 2024).

Das (2022) was the only study to explicitly consider battery recycling; however, there are insufficient data to infer the extent of recycling credits. Bieker (2021) did not account for battery recycling credits, and assumed that in the 2035–2050 timeframe, battery recycling ecosystems globally will mature and can potentially result in lowering of battery production emissions by 14%–50%. None of the studies considered the use of batteries in second life applications, which can further lower the production emissions attributed to the vehicle cycle for BEVs.

Carbon intensity of vehicle production

The carbon intensity of vehicle production includes emissions associated with the production of glider and powertrain systems, maintenance, and any end-of-life recycling credits applied from material recycling of scrapped vehicles.

Table 19 shows the mean values of kerb weights by powertrain type where available, and Figure 9 shows the distribution of vehicle kerb weights assumed across the six studies. For sedans and SUVs, a large spread in kerb weight within each vehicle class was observed across all studies, with HEV sedans and SUVs assumed to be heavier than corresponding BEVs. (As all HEVs sold in India in FY 2023–24 were sedans and SUVs, HEVs were not analyzed in the hatchback segment.) Based on SIAM vehicle classifications, in which hatchbacks and sedans are classified into six sub-segments based on length and engine displacement and SUVs into another six sub-segments based on length and vehicle price, all HEV sedans in the sample belong to the (relatively heavier) premium and executive segment, whereas all BEV sedans pertain to the smaller compact and super-compact segments.[10] Similarly, HEV SUVs in the sample include top-selling models from the larger UV4 segment, while most BEV SUVs are from the subcompact UV1 segment. Ideally, for an LCA comparison across powertrains, it is important to ensure that the vehicles compared are from similar weight classes, which is not reflected in the study sample analyzed.

Table 19

Mean values of kerb weights by powertrain

Study	Sedan			SUV		
	ICE (kg)	HEV (kg)	BEV (kg)	ICE (kg)	HEV (kg)	BEV (kg)
Abdul-Manan et al. (2022)	1,113.0	–	1,408.0	1,271.0	–	1,400.0
Das (2022)	1,455.0	–	1,685.0	–	–	–
Agarwal (2023)	1,110.0	1,280.0	–	1,240.0	1,290.0	1,388.0
Gadepalli et al. (2023)	1,300.0	–	1,240.0	–	–	–

Note: Dashed cells indicate data were not available.

10 Car sub-segments are mini, compact, super-compact, mid-size, executive, and premium, and SUV sub-segments are UVC, UV1, UV2, UV3, UV4, UV5. While the SIAM classification for SUVs is powertrain-agnostic, the classification for hatchbacks and sedans is partly based on engine displacement. Based on our discussions with SIAM officials, SIAM has not updated its methodology to extend the classification system to BEVs (e.g., by using battery capacity in lieu of engine displacement). For BEV sedans and hatchbacks, we have arrived at SIAM classifications using length-based thresholds only.

Figure 9

Distribution of kerb weights assumed for each powertrain type across studies

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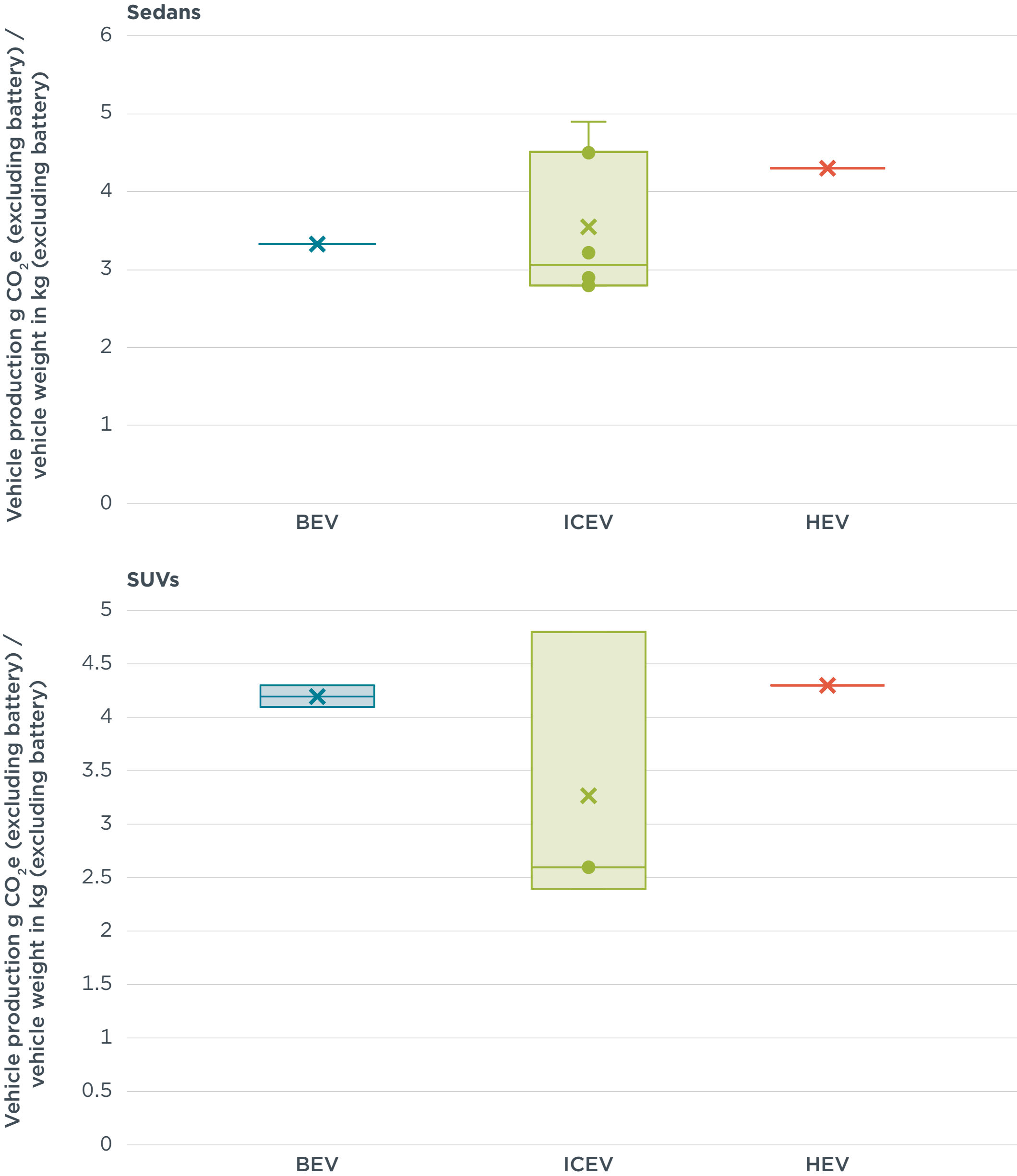
Figure 10 illustrates the variation in the carbon intensity of vehicle production assumed across the six studies, expressed in terms of CO_2e emissions normalized to the weight of the vehicle, excluding battery weight. In the case of BEVs, the carbon intensities of battery production and any battery recycling credits are excluded.

Figure 10

Distribution of carbon intensity of vehicle production assumed across studies



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A wide variance was observed in vehicle manufacturing emission factors, particularly for ICEVs in the sedan and SUV segments. There is a lack of sufficient context available in the studies to explain this wide variance.

Table 20 shows the mean values of carbon intensity of vehicle production for each study. While no data are available from Bieker (2021) or Nadola et al. (2023), Agarwal (2023) and Das (2022) assumed average vehicle manufacturing emissions of between 4 and 5 kg CO_2e/kg, while Gadepalli et al. (2023) and Abdul-Manan et al. (2022) assumed values near 3 kg CO_2e/kg.

Table 20

Mean carbon intensity of vehicle production values by powertrain, in kg CO_2e/kg

Study	Hatchback			Sedan			SUV		
	ICE	HEV	BEV	ICE	HEV	BEV	ICE	HEV	BEV
Abdul-Manan et al. (2022)	–	–	–	2.8	–	–	2.5	–	–
Bieker (2021)	–	–	–	–	–	–	–	–	–
Das (2022)	–	–	–	4.7	–	–	–	–	–
Agarwal (2023)	–	–	–	4.5	4.3	–	4.8	4.3	4.2
Gadepalli et al. (2023)	–	–	–	3.2	–	3.3	–	–	–
Nadola et al. (2023)	–	–	–	–	–	–	–	–	–

Note: Dashed cells indicate data were not available.

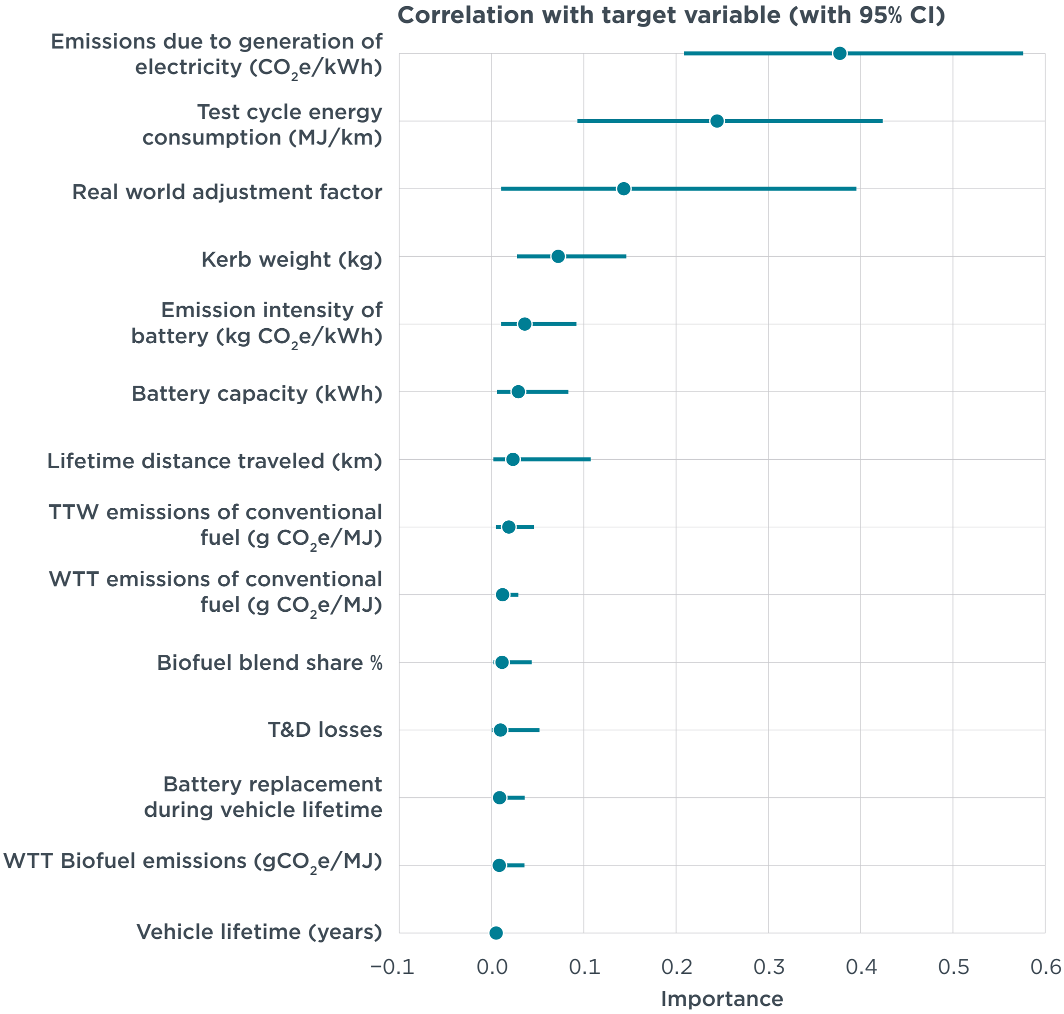
STATISTICAL ANALYSIS

A bootstrapping analysis using random forest algorithms was applied to assess the relative importance of different variables in explaining the variance of GHG intensity across studies. Figure 11 shows the results of this analysis using all the inputs for the three powertrains. The dots show the mean importance, and the lines represent the 95% confidence interval. The aggregation of importance values of all variables is 1.

According to the analysis, the most important variables were electricity generation emissions (i.e., grid carbon intensity), test-cycle energy consumption, and real-world energy consumption adjustment factor. These three variables together explained about three-quarters (77%) of the variance across studies.

Figure 11

Importance of variables using inputs for ICEVs, BEVs, and HEVs



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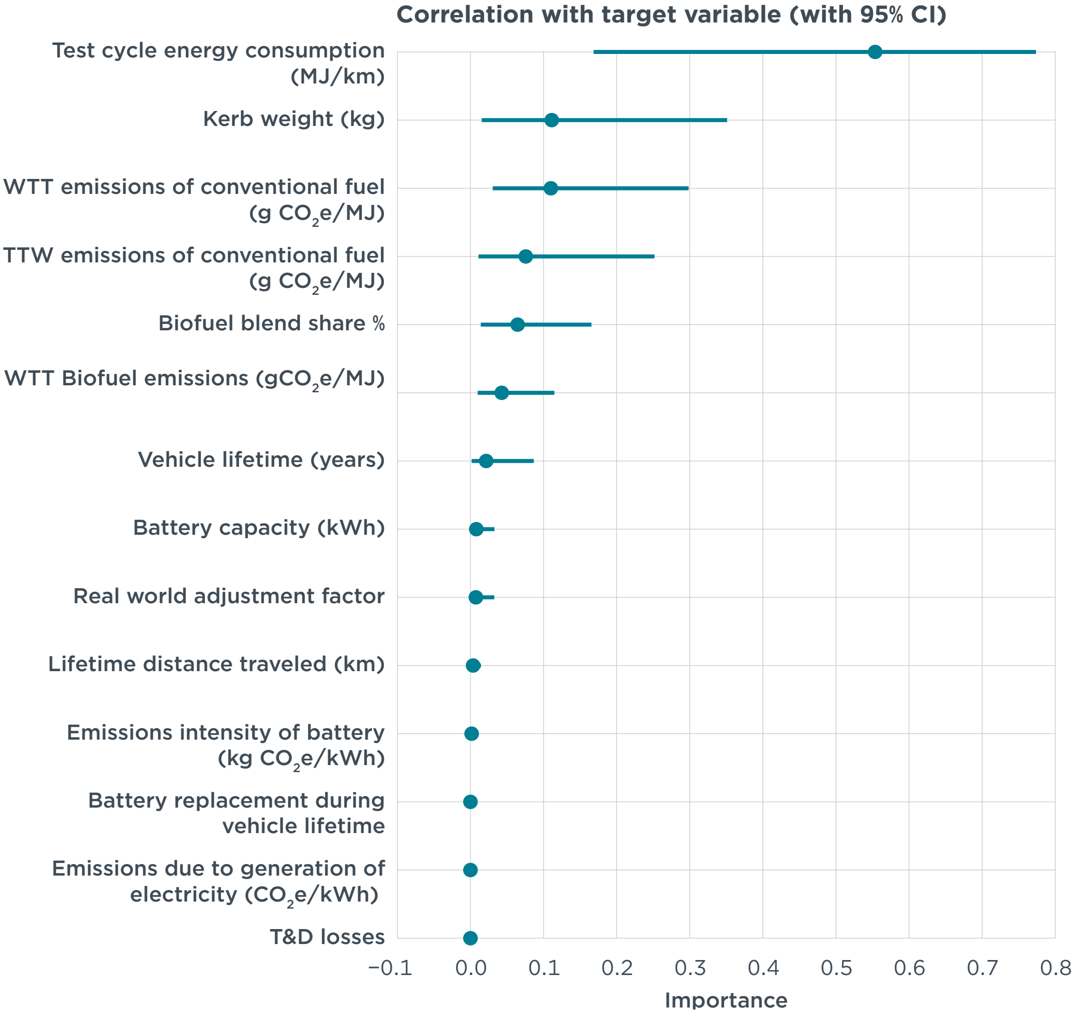
The electricity generation emissions variable primarily impacts the life-cycle emissions of BEVs, while the test-cycle energy consumption and real-world energy consumption adjustment factor variables shape the WTW emissions of all powertrains, notably hybrids. The kerb weight, emissions intensity of battery production, and VKT variables are the next most important, accounting for 0.13 of importance on average—though large and overlapping confidence intervals due to the small sample size complicate direct comparison.[11]

The key variables for estimating WTW emissions might vary for different powertrains, and the importance results depend heavily on the inputs. Figure 12 shows the importance results for only ICEVs and HEVs. Excluding BEVs, the most important variables are test-cycle energy consumption, WTT emissions of conventional fuels, and vehicle kerb weight. The mean importance of these three variables sums to 0.78, with the test-cycle energy consumption accounting for more than half of the observed variance.

11 Moreover, some variables that might be important might not be identified, as random forest relies heavily on the input dataset. For example, T&D loss could affect the emissions from electricity, but four of the six studies assumed a standard value of 19% for T&D loss. With such little difference in input values,T&D loss will not be considered to cause significant change in the dependent variable.

Figure 12

Importance of variables excluding BEVs



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Intuitively, variables concerning electricity generation and batteries are insignificant, as factors such as the grid carbon intensity and T&D losses will not notably impact the WTW emissions of vehicles powered by fossil fuels. Biofuel-related variables become comparatively more important when BEVs are excluded, with the biofuel blend share and WTT biofuel emissions variables accounting for a combined importance of 0.11. However, the uncertainty of the importance results increases significantly when excluding BEVs: The 95% confidence interval ranges expand, and the average deviation from the mean value increases from 75% to 86% for the confidence interval lower limit and from 205% to 235% for confidence interval upper limit. The R^2 value, meanwhile, decreases from 0.89 to 0.18. This occurs because the sample population of vehicle classification, powertrain, and fuel type narrows to 31 rows, which might not be adequate for analysis with 14 variables.

The results of other statistical techniques mentioned in the methods section—correlation analysis, linear regression, and perturbation analysis—are presented in Appendix B.

DISCUSSION

Our comparative and statistical analyses highlighted considerable differences in methods and assumptions for the LCA approach across the six studies. When we evaluated all three powertrains in the sample, our bootstrapping analysis found that varying assumptions in grid carbon intensity, test-cycle energy consumption, and the real-world energy consumption adjustment factor explained about three-quarters of the variance in GHG intensity across the six studies. Differences in assumptions for the three next most important variables—kerb weight, emissions intensity of battery production, and VKT—were found to be less important. Considering only ICEV and HEV powertrains, test-cycle energy consumption, upstream WTT emissions, and vehicle kerb weight were the most important variables.

These findings support the following conclusions and recommendations regarding ways to improve future LCAs of passenger cars in India.

Use appropriate and dynamic assumptions for grid carbon intensity. India's CEA has forecast that the emissions intensity of electricity generation will drop from 0.82 kg CO_2/kWh in 2020 to between 0.41 and 0.47 kg CO_2/kWh in 2030 (Ministry of Power, 2023b). Modeling a static carbon intensity for the electricity grid mix over a vehicle's lifetime ignores the expected decarbonization of the grid due to an increasing share of non-fossil energy sources and likely inflates life-cycle emissions of BEVs. Future LCA studies could incorporate dynamic grid carbon intensity scenarios to provide a more accurate assessment of emission reductions over time. Studies that do not reflect this improvement will generate overly pessimistic results for BEVs.

Capture the growing impact of hybrid technology by including HEVs in LCA studies. Hybrid vehicles are significantly more fuel-efficient than ICE vehicles. In India, HEV sales have grown rapidly—rising by 310% in 2023 compared with 2022, followed by another 29.8% increase in 2024 (Segment Y, 2024). Given this substantial growth and their improved fuel efficiency, it is important to include HEVs in future LCA studies of passenger vehicles to understand the environmental impacts and benefits, especially in terms of energy efficiency.

Apply an appropriate real-world energy consumption adjustment factor to distinguish test-cycle versus real-world fuel consumption. Research shows that there is a substantial difference between test-cycle and real-world fuel consumption. Using a real-world conversion factor for test-cycle values would provide greater analytical clarity for researchers. Real-world adjustment factors for BEVs would ideally consider lab-to-road differences, charging losses, and a temperature adjustment to account for ambient environmental conditions in India.

For consistent comparison when evaluating different powertrains, parameters related to vehicle size should be representative. This is particularly important in the sedan and SUV segments, which encompass a wide range of vehicle sizes. Sales-weighted average specifications for vehicle sizing parameters should be used instead of relying on representative models. If representative models are used, variances can be reduced by selecting models within the same vehicle class as defined by SIAM to ensure consistent comparisons across powertrains.

Vary the WTT carbon intensity of liquid fuels appropriately with robust assumptions on biofuel blending and ILUC emissions*.* As the Government of India pursues its ethanol blending target of 20% by 2025 and seeks to promote flex-fuel pathways beyond E20 for passenger cars, future LCA assessments of Indian passenger vehicles could account for increasing shares of biofuels. In addition, given the importance of ILUC as a driver of biofuel WTT emissions, including ILUC in this analysis is critical to accurately assessing the relative merits of biofuels.

CONCLUSIONS AND POLICY IMPLICATIONS

This study reviewed six LCA studies of passenger cars in India, highlighting wide variation in reported GHG emissions. Through an analysis of these papers' modeling assumptions related to vehicle and fuel cycle emissions, we identified three variables that explained about three-quarters of the variance in life-cycle GHG intensity: grid carbon intensity, test-cycle energy consumption, and the real-world energy consumption adjustment factor.

Das (2022) assumed the highest carbon intensity of grid supply, at 1,400 g CO_2e/kWh. This study used a static electricity mix based on FY 2018–19 data. In contrast, the ambitious scenario in Gadepalli et al. (2023), which assumed a 53% fossil fuel generation mix by 2030, had the lowest carbon intensity, at 523 g CO_2e/kWh.

There was wide variation in energy consumption values for BEVs, especially in the SUV segment. Das (2022) used a value of 27.78 kWh/100 km for BEV SUVs, which was much higher than other values in the dataset. This high value was linked to the Hyundai Kona EV. Agarwal (2023) modelled the same vehicle as a representative BEV but reported a much lower energy consumption value of 12.85 kWh/100 km.

Bieker (2021) applied an adjustment factor of 1.34 to MIDC test energy consumption values for BEVs. This factor accounted for 15% charging losses. No other study considered charging losses when estimating BEV energy consumption. Abdul-Manan et al. (2022) used a real-world adjustment factor of 1.46 for BEVs, which included a 40% correction from test-cycle energy consumption values and an additional 6% adjustment for Indian ambient temperatures. For ICEVs, the average real-world adjustment factor across all studies was 1.24, while for HEVs, it was 1.27. The highest assumed real-world adjustment factor was 1.34 for ICEVs (Agarwal, 2023; Bieker, 2021). Bieker (2021) assumed the highest factor for HEVs at 1.50.

These findings suggest that LCAs are likely to yield distorted results when they do not account for the evolving electricity grid mix, use unrepresentative vehicle models, or rely on unrealistic energy consumption values. Studies that report unusually high BEV emissions may fail to reflect the projected decarbonization of India's grid or assume unreasonably high real-world energy consumption values. Conversely, studies that underestimate ICEV and HEV emissions may rely on overly optimistic test-cycle values or neglect upstream emissions from conventional fuel production. Future LCAs can address these inconsistencies to ensure more representative results.

Beyond methodological implications, these findings translate into several policy considerations. First, given that grid carbon intensity is a primary driver of the life-cycle emissions of BEVS, the Government of India could consider continued grid decarbonization efforts in parallel to scaling up BEV sales. Abhyankar et al. (2023) projected that India's least-cost pathway to meeting incremental energy demand by 2030 consists primarily of 465 GW of renewable energy capacity and 60–63 GW of battery storage. Aligning electrification strategies with this trajectory can maximize the GHG reduction benefits of BEVs.

Second, the importance of test-cycle energy consumption for life-cycle emissions estimates underscores the need for stringent fuel efficiency policies. Strengthening corporate average fuel consumption standards and introducing fiscal measures such as emissions-linked taxation can incentivize vehicle manufacturers to improve vehicle efficiency and steer consumer demand toward lower- and zero-emission vehicles. These policies could also incorporate flexibility mechanisms to support cost-effective technology transitions while deterring non-compliance.

Third, the significant influence of real-world adjustment factors on emission estimates highlights a need for better data collection on real-world fuel and energy consumption across all powertrains. One approach would be to require on-board fuel and energy consumption meters (OBFCMs), as mandated in the European Union since 2021.[12] India could consider a similar mandate, ensuring real-world consumption data is collected through vehicle on-board data ports, telemetry, and periodic technical inspections. This data can enhance transparency, refine future LCAs, and inform evidence-based policy design.

Lastly, findings from this study suggest that WTT emissions from biofuels, particularly first-generation ethanol, can significantly exceed those of conventional fuels due to ILUC effects. Given India's accelerated ethanol blending target (E20 by 2025) and potential flex-fuel pathways, a careful assessment of feedstock strategies will be critical to identifying sustainable, cost-efficient solutions. Similarly, methane slip emissions from CNG vehicles, which have been found to be significantly higher in some regions, warrant India-specific real-world data collection and analysis.

By identifying the key variables shaping LCA outcomes, this study lays the groundwork for developing a consensus LCA for BEVs, HEVs, and ICEVs in India. Such an analysis could help inform the design of fuel consumption standards, OBFCM requirements, zero-emission vehicle sales regulations, and fiscal policies like incentives and taxes to drive the adoption of cleaner vehicle technologies.

12 Although BEVs are currently exempt from EU OBFCM requirements, they will be included from the introduction of Euro 7 regulations, due in late 2026. For BEVs, it is particularly important to identify the extent of energy losses attributed to on-board charging systems and determine whether these losses are accounted for in real-world consumption data.

REFERENCES

Abdul-Manan, A., Zavaleta V, G., Agarwal, A., Kalghatgi, G., & Amer, A. (2022). Electrifying passenger road transport in India requires near-term electricity grid decarbonisation. Nature Communication, 13(1). https://doi.org/10.1038/s41467-022-29620-x

Abhyankar, N., Mohanty, P., Deorah, S., Karali, N., Paliwal, U., Kersey, J., & Phadke, A. (2023). India's path towards energy independence and a clean future: Harnessing renewable edge for cost-effective energy independence by 2047. *The Electricity Journal*, *36*(5). https://www.sciencedirect.com/science/article/pii/S1040619023000404?via%3Dihub

Agarwal, A. (2023). *LCA and TCO analyses of BEVs, HEVs and ICEVs*. Indian Institute of Technology Kanpur. https://greenmobility-library.org/public/single-resource/REw5WWhBOXUrQ3Z4MnU4cXNDTmJCUT09

Ashokan, A. (2024, June). India's ethanol production gradually shifts from sugar to maize and rice. *Hindustan Times*. https://www.hindustantimes.com/business/indias-ethanol-production-gradually-shifts-from-sugar-to-maize-and-rice-101719462155575.html

Bhatt, B., & Singh, A. (2021). Power sector reforms and technology adoption in the Indian electricity distribution sector. *Energy*, *215*(Part A). https://www.sciencedirect.com/science/article/abs/pii/S0360544220319046

Bieker, G. (2021). *A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars*. The International Council on Clean Transportation. https://theicct.org/publication/a-global-comparison-of-the-life-cycle-greenhouse-gas-emissions-of-combustion-engine-and-electric-passenger-cars/

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Central Electricity Authority. (2024a, May). *All India electricity statistics: General review 2024*. https://cea.nic.in/wp-content/uploads/general/2024/General_Review_2024_2.pdf

Central Electricity Authority. (2024b, October). *National electricity plan*. https://cea.nic.in/wp-content/uploads/notification/2024/10/National_Electricity_Plan_Volume_II_Transmission.pdf

Das, J. (2022). Comparative life cycle GHG emission analysis of conventional and electric vehicles in India. *Environment, Development and Sustainability*, *24*, 13294–13333. https://doi.org/10.1007/s10668-021-01990-0

Deo, A., & Kaur, H. (2024). *Role of fuel efficiency norms in accelerating sales of electric vehicles in India*. International Council on Clean Transportation. https://theicct.org/wp-content/uploads/2024/06/ID-175-%E2%80%93-India-FE-policy_final.pdf

Enviraj Consulting. (n.d.). *Ethanol blend mileage reduction chart*. https://oer.enviraj.com/general/ethanol-blend-mileage-reduction-chart/

Gadepalli, R., Ollivier, G., Fernando, M., & Sohu, V. (2023). *Life-cycle assessment of passenger transport, An Indian case study*. International Transport Forum and The World Bank. https://www.itf-oecd.org/life-cycle-assessment-passenger-transport-indian-case-study

Genuer, R., Poggi, J.-M., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, *31*(14), 2225–2236. https://doi.org/10.1016/j.patrec.2010.03.014

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer. https://doi.org/10.1007/978-0-387-84858-7

Hyundai. (2022). *All-new Kona Electric* [Brochure]. https://dmassets.hyundai.com/is/content/hyundaiautoever/KONA-EV-Brochurepdf

International Energy Agency. (2021). *World energy outlook 2021.* https://www.iea.org/reports/world-energy-outlook-2021

Kumar, C. (2023, February). What is E20 petrol, and how will it affect your vehicle. *Times of India*. https://timesofindia.indiatimes.com/india/what-is-e20-petrol-and-how-will-it-affect-your-vehicle/articleshow/97671950.cms

Kumar, M., Shao, Z., Braun, C., & Bandivadekar, A. (2022). *Decarbonizing India's road transport: A meta-analysis of road transport emission models*. The International Council on Clean Transportation. https://theicct.org/publication/decarbonizing-india-road-transport-may22/

Li, E., Bieker, G., & Sen, A. (2024). *Electrifying road transport with less mining*. The International Council on Clean Transportation. https://theicct.org/wp-content/uploads/2024/12/ID-206-%E2%80%93-Battery-outlook_report_final.pdf

Ministry of Power. (2023a, February 9). *Government of India launches Revamped Distribution Sector Scheme (RDSS) to reduce the aggregate technical & commercial (AT&C) losses to pan-India levels*. https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1897764

Ministry of Power. (2023b, May 31). *Central Electricity Authority notifies the National Electricity Plan for the period of 2022-32* [Press release]. https://www.pib.gov.in/PressReleaseIframePage.aspx?PRID=1928750

Moerenhout, T., Goel, S., Bansal, A., Saxena, A., Brunelli, K., Jiang, C., Lee, L., Nilson, A., Wang, Q., Xu, & Xu, H. (2023). *India's potential in the midstream of battery production*. International Institute for Sustainable Development. https://www.iisd.org/publications/report/india-potential-midstream-battery-production

Nadola, Y., Krishna, U., Pramanik, S., M, H., & RV, R. (2023). *Well-to-wheel analysis of energy efficiency & CO2 emissions for hybrids & EVs in India: Current trends & forecasting for 2030*. https://www.researchsquare.com/article/rs-3086492/v1

NITI Aayog. (2024). *Benefits of electric vehicles*. https://e-amrit.niti.gov.in/benefits-of-electric-vehicles#:~:text=Fully%20electric%20vehicles%20have%20zero,dioxide%20than%20the%20average%20EV

Segment Y. (2024). *Sales of passenger cars in India* [Dataset]. https://www.segmenty.com/India.html

SIAM. (2024). *Automobile domestic sales trends* [Dataset]. https://www.siam.in/statistics.aspx?mpgid=8&pgidtrail=14

Stellarix. (2024, October 2). *India as an emerging manufacturing hub for EV battery*. https://stellarix.com/insights/articles/india-as-an-emerging-manufacturing-hub-for-ev-battery/

Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., & Midgley, P.M. (Eds.) (2013). *Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar5/wg1/

U.S. Energy Information Administration. (n.d.). *Frequently asked questions (FAQs): How much ethanol is in gasoline, and how does it affect fuel economy?* https://www.eia.gov/tools/faqs/faq.php?id=27&t=10#:~:text=The%20energy%20content%20of%20denaturant,does%20not%20contain%20fuel%20ethanol

APPENDIX A. EMISSION CALCULATIONS

The full life-cycle emissions associated with a given vehicle powertrain and fuel combination are assessed through several distinct phases within the system boundary.

Well-to-wheel emissions encompass the emissions associated with the propulsion energy pathways from fuel or electricity production to their use in a vehicle. They include well-to-tank (WTT) emissions associated with the extraction, production, and transportation of fuel or electricity to the point where it is ready for use, as well as tank-to-wheel (TTW) emissions produced during the use of the vehicle due to the consumption of energy.

Cradle-to-grave emissions cover the entire life-cycle of the vehicle, from production to end-of-life. These include emissions from raw material extraction, manufacturing of vehicle components, vehicle assembly, and transport to the point of delivery to the end-user. They also include end-of-life phase emissions in the form of recycling and material recovery, which reduce the need for new raw materials and lower the vehicle's overall emissions footprint.

WTT emissions

The WTT emissions associated with fuel consumption of ICEV and HEV models from all studies were calibrated against the following estimation method:

> **WTT emissions (g CO_2e/km) = Carbon intensity of fuel production (g CO_2e/MJ) * Fuel lower heating value (MJ/l) * Fuel consumption rate (L/100 km) * Real-world adjustment factor / 100**

The lower heating value is a property of the fuel and denotes the amount of energy that is released when a fuel is combusted and water vapor is emitted. The carbon intensity of fuel production refers to emissions associated with the extraction, production, and transportation and distribution of the fuel, including any fuel leakages. Fuel consumption rates denote test-cycle values of fuel consumption, which were adjusted using a real-world adjustment factor.

In the case of a multi-fuel blend, we considered the volumetric averages of carbon intensity of all fuels in the blend. Further, the WTT emissions also included additional ILUC emissions associated with the quantities of biofuels consumed. For BEVs, WTT emissions comprise the emissions associated with the generation, transmission, and distribution of electricity to the point of charge. Electricity consumption rates were based on test-cycle values adjusted for a real-world factor and include any assumed charging losses.

TTW EMISSIONS

The TTW emissions associated with fuel consumption in ICEV and HEV models from all studies were calibrated against the following estimation method:

> **TTW emissions (g CO_2e/km) = Carbon intensity of fuel combustion (g CO_2e/MJ) * Fuel lower heating value (MJ/l) * Fuel consumption rate (L/100 km) * Real-world adjustment factor / 100 + Methane slip emission factor (g CO_2e/km) * Lifetime distance traveled (km)**

Most studies applied a real-world adjustment to test values of fuel consumption rates, though the values differed across studies. Additionally, only two studies (Bieker, 2021; Agarwal, 2023) considered scenarios for biofuel blending with conventional fuel, although neither study accounted for any increase in fuel consumption as a result of fuel blending. For context, researchers have estimated that volumetric fuel efficiency of ICEVs (in km/L) can fall by 3% when gasoline is blended with 10% ethanol (U.S. Energy Information Administration, n.d.), 6% when it is blended with 20% ethanol (Kumar, 2023), and 10% when it is blended with 30% ethanol (Enviraj Consulting, n.d.) due to the lower heating value of those ethanol blends. Additionally, wherever biofuel blending was considered in the sample, we assumed an offset of zero emissions on account of biogenic sources in the TTW emissions against the volume of conventional fuel displaced.

For CNG vehicles, TTW emissions also include GHG emissions from methane slip. Only two studies included CNG-powered vehicles in their analysis (Bieker, 2021; Nadola et al., 2023), and only Bieker (2021) reported methane slip emissions in addition to emissions from CNG combustion. For BEVs, TTW emissions were considered to be zero as BEVs have zero emissions at the tailpipe.

CRADLE-TO-GRAVE EMISSIONS

The cradle-to-grave emissions associated with production of the vehicle and battery were calibrated against the following estimation method:

Cradle to grave emissions = Emissions from vehicle production + End-of-life vehicle recycling credits + Maintenance emissions from parts and fluids replacements.

Most studies reported emissions from vehicle production for the whole vehicle, including the battery as applicable, as follows:

Vehicle manufacturing emissions = Vehicle manufacturing emission factor (kg CO_2e/kg kg) * Kerb weight (kg) + End-of-life recycling credits

Where battery production emissions were reported separately, as in Bieker (2021), or where an additional kWh-based emission factor for battery production was also reported, emissions specifically resulting from battery production were estimated separately as follows:

Battery manufacturing emissions = Battery replacement multiplier * Battery manufacturing emission factor (kg CO_2e/kWh) * Battery capacity (kWh) + End-of-life recycling credits

Three studies (Gadepalli et al., 2023; Abdul-Manan et al., 2022; Agarwal, 2023) accounted for a replacement of the BEV battery during the vehicle lifetime. Only Bieker (2021) and Agarwal (2023) considered emissions associated with vehicle maintenance or replacement of key parts and consumables like lubricants, coolants, and tires, as follows:

Maintenance emissions = Maintenance emission factor (g CO_2e/km) * Vehicle lifetime (km)

APPENDIX B. FULL STATISTICAL ANALYSIS RESULTS

This appendix summarizes the results of other statistical tests applied in this study. The results of the random forest method, which were judged to be most robust, are summarized in the main body.

The other tests comprised a correlation analysis, linear regression coefficient analysis, and perturbation analysis. A correlation analysis measures the strength and direction of linear relationships between variables, and is usually useful in early exploratory analysis and when linear relationships are expected. A linear regression quantitively evaluates the relationship between dependent and independent variables, and is most appropriate when relationships are predominantly linear and features are relatively independent. A perturbation analysis is usually used to understand model sensitivity to input changes.

The results of these tests are shown in Figures B1 through B6. Some methods yielded importance trends similar to those found using the random forest method, while others showed a different direction. For example, when using all inputs, the results of the correlation analysis resembled those of the random forest, with the electricity generation emissions variable, test-cycle energy consumption variable, and real-world energy consumption adjustment factor variable showing the strongest correlation with WTW emissions. Using the linear coefficient method, the electricity generation emissions variable, WTT emissions of conventional fuel variable, and battery capacity variable had the largest coefficients. For the perturbation analysis, kerb weight showed the third-largest impact on prediction accuracy, behind electricity generation emissions and test-cycle energy consumption.

When limiting the analysis to ICEVs and HEVs, the four methods all identified test-cycle energy consumption as a significant factor. In addition, the linear regression and correlation analysis ranked the TTW emissions of conventional fuels in the top three most important variables, while the random forest method ranked it fourth.

These differences show that importance values are specific to the particular dataset and modelling task and may not be generalizable to other contexts. Additionally, the importance metric does not necessarily imply causation, as there may be complex interactions and confounding factors that influence the predictive power of each feature.

RESULTS OF CORRELATION COEFFICIENT, LINEAR REGRESSION, AND PERTURBATION ANALYSES WITH ALL INPUTS

Figure B1

Correlation analysis results with all inputs

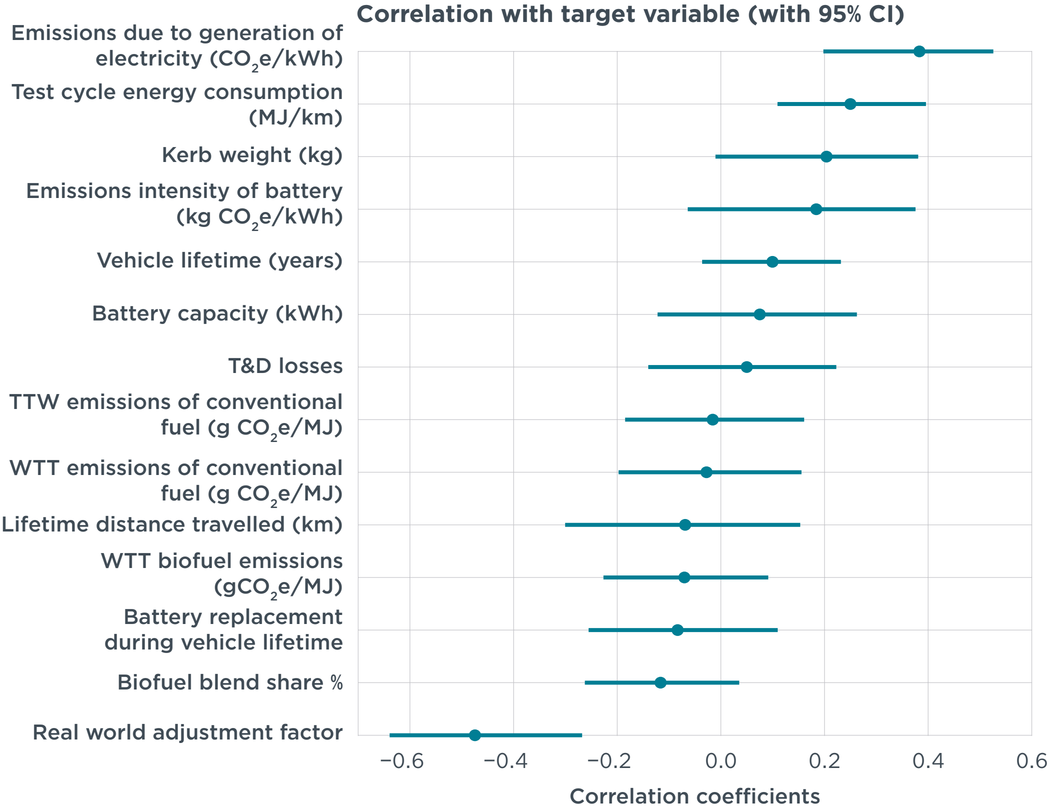

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Figure B

Linear regression analysis results with all inputs

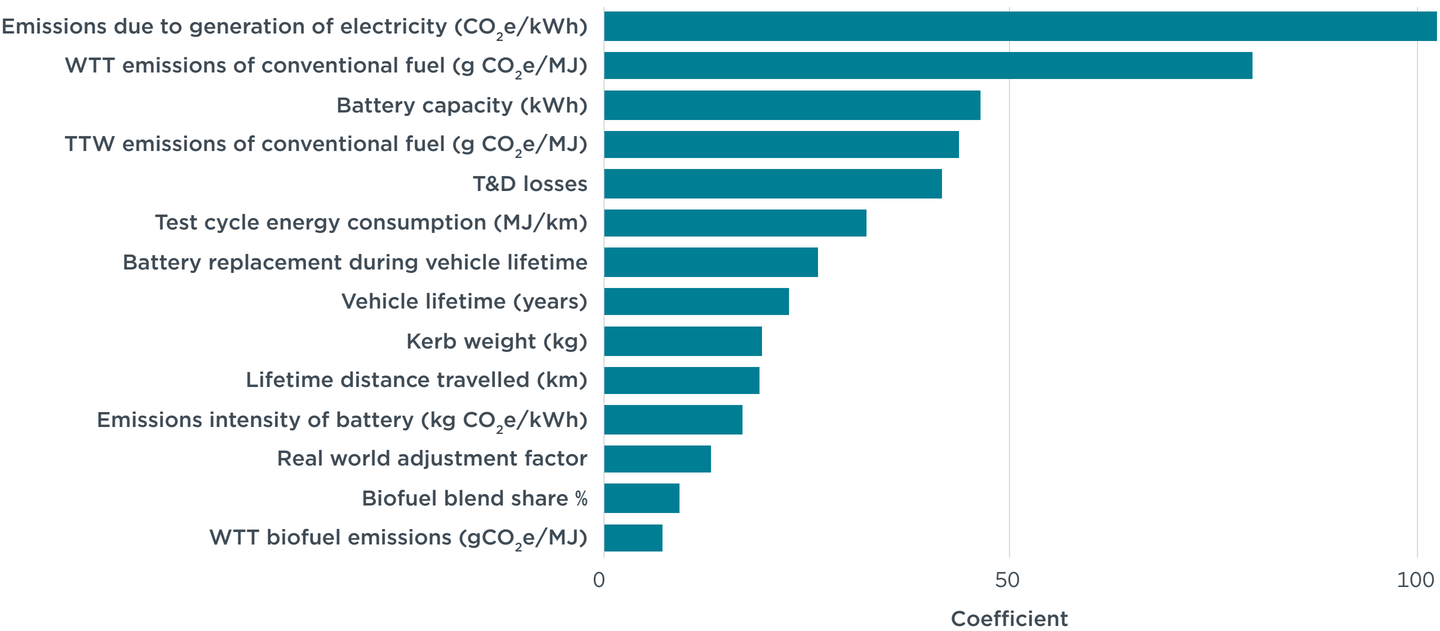

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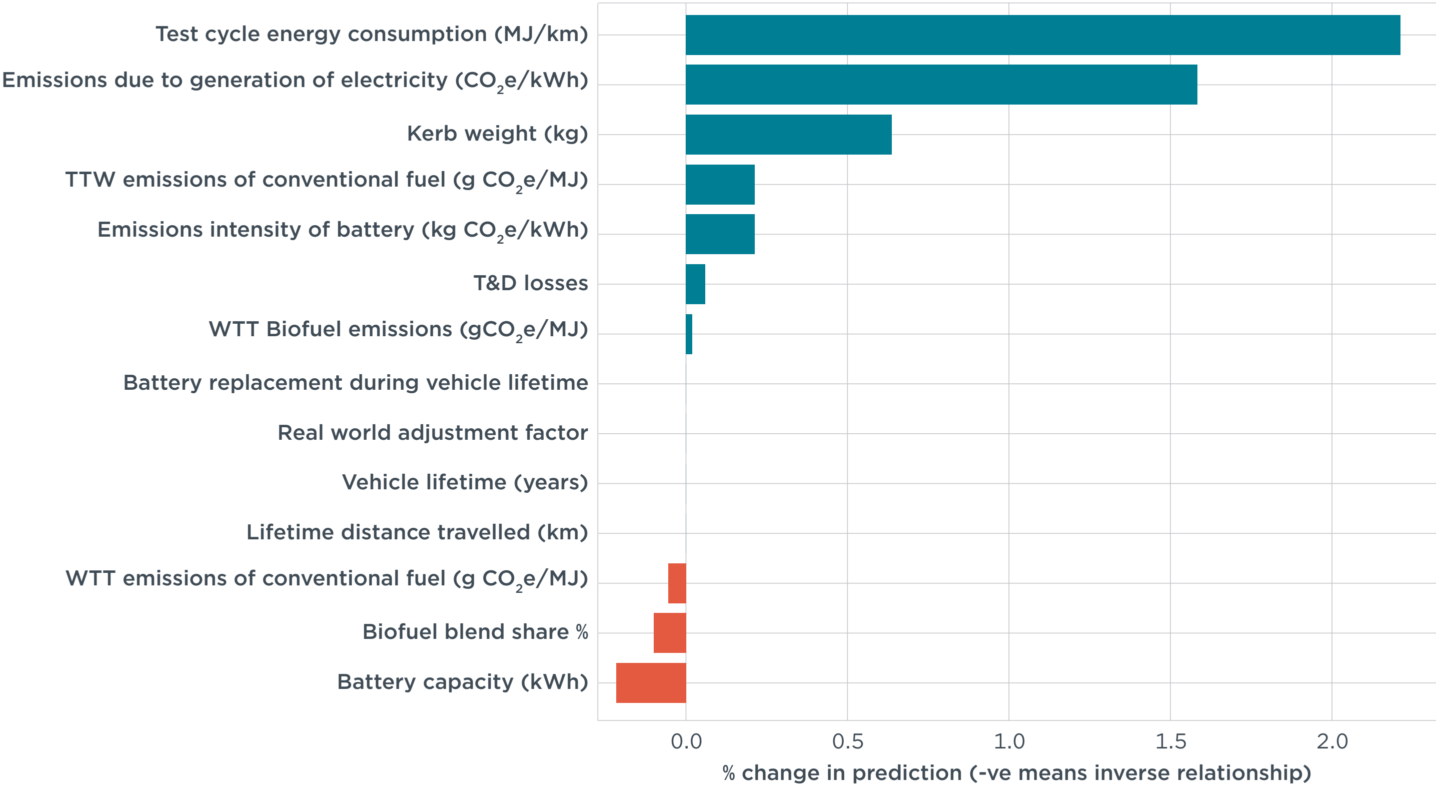
Figure B3

Perturbation analysis results with all inputs



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RESULTS OF CORRELATION COEFFICIENT, LINEAR REGRESSION, AND PERTURBATION ANALYSES WITH ALL INPUTS EXCLUDING BEVS

Figure B4

Correlation analysis results with inputs excluding BEVs

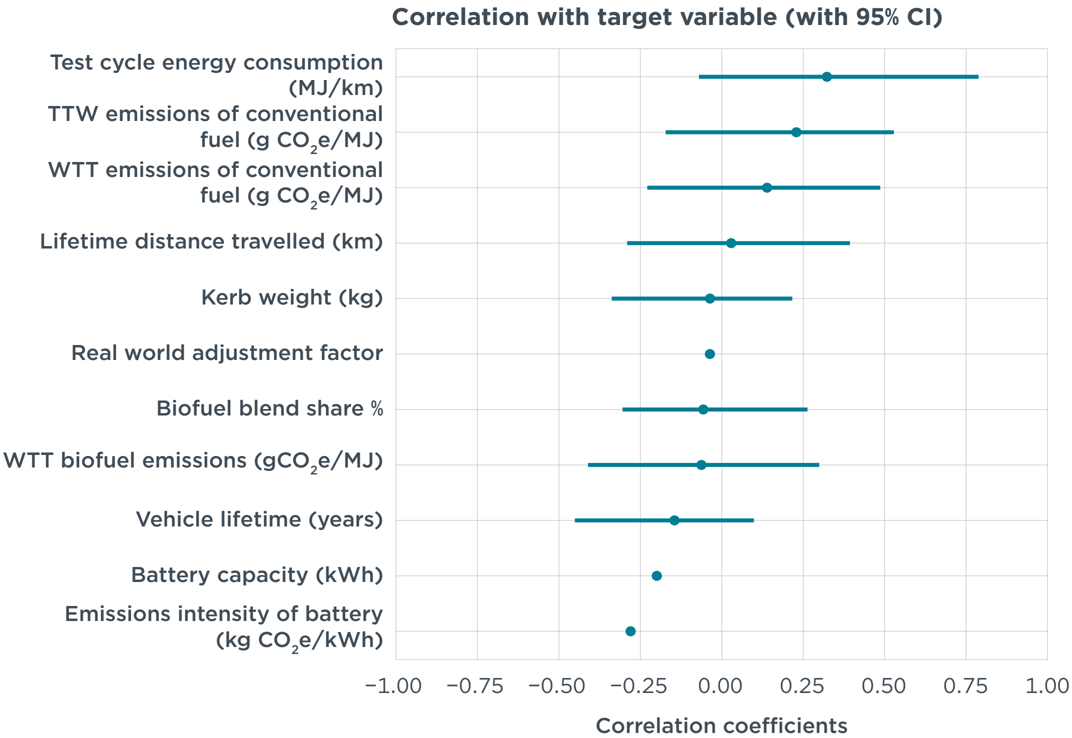

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Figure B5

Linear regression analysis results with inputs excluding BEVs

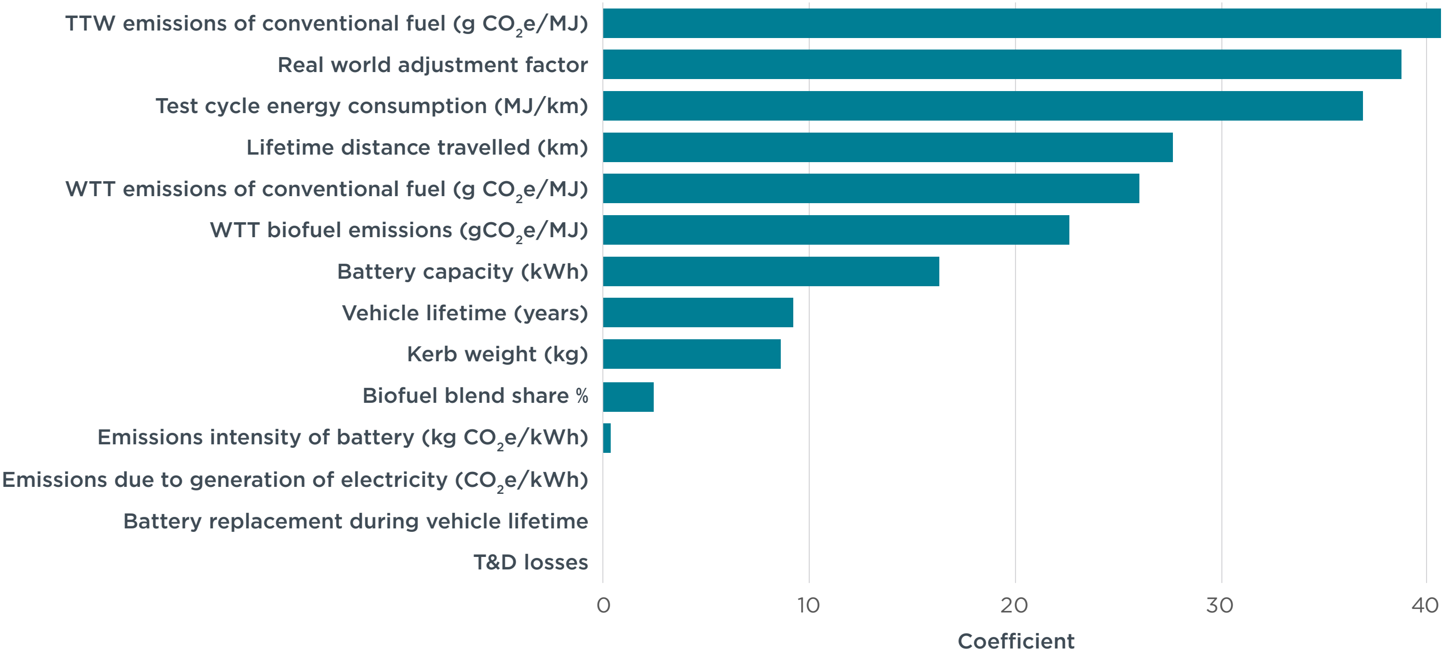

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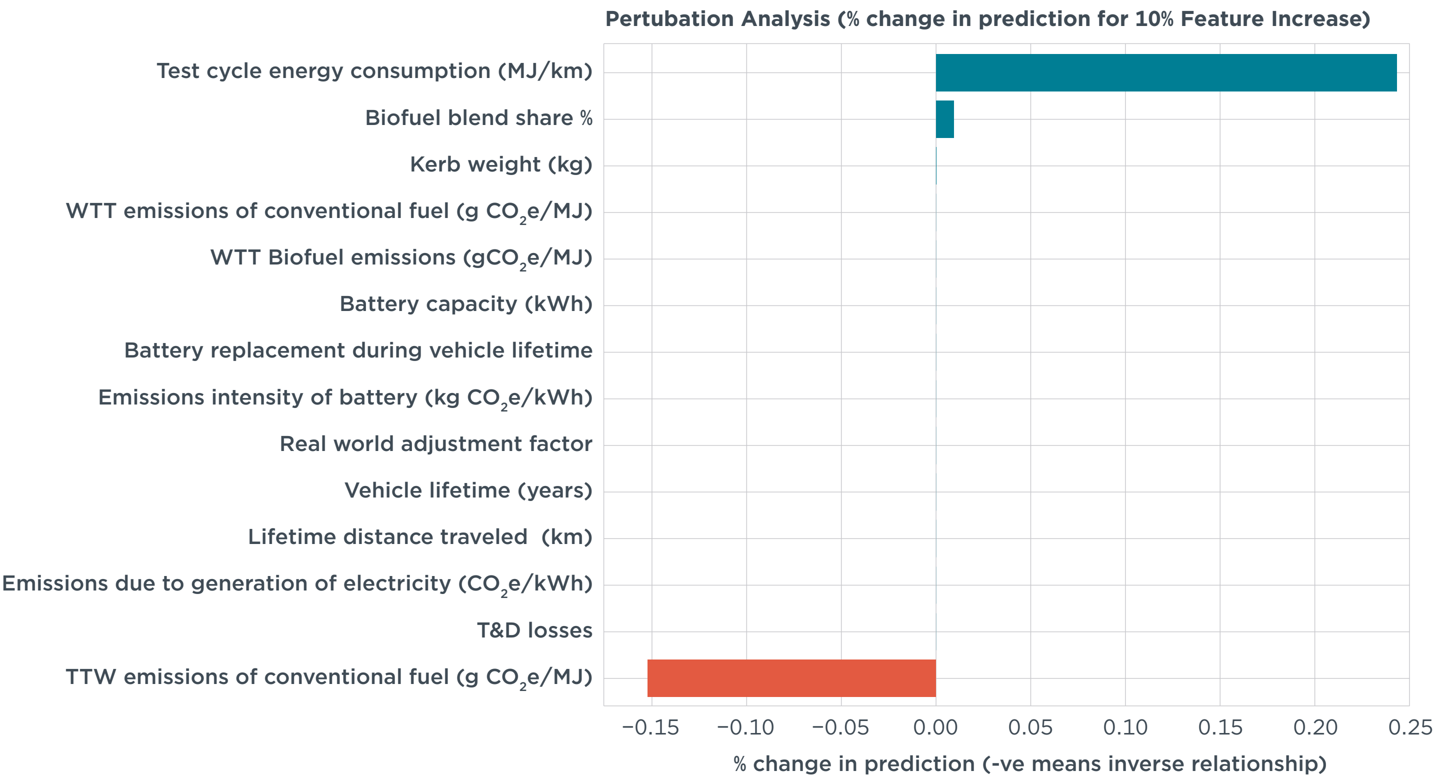
Figure B6

Perturbation analysis results with inputs excluding BEVs



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