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# Battery Electric Vehicles and Plug-in Hybrid Electric Vehicles: Review of Integration, Machine Learning Applications, and Future Mobility Trends

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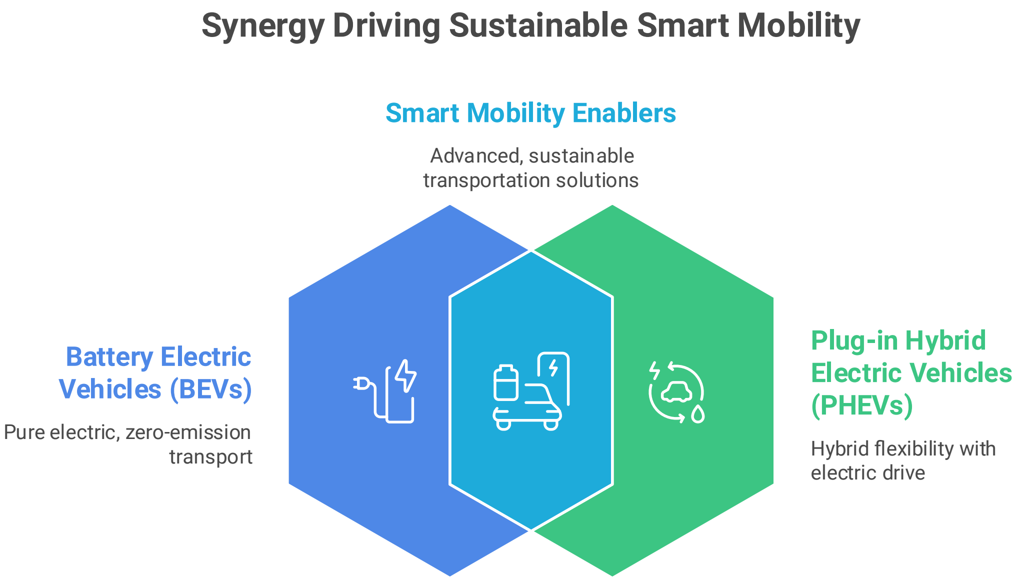
## HIGHLIGHTS

- Plug-in hybrid and battery electric vehicles enable sustainable smart mobility
- Advanced battery management systems improve safety, efficiency, and lifespan
- Machine learning optimizes battery health, charge control, and fault prediction
- Vehicle-to-grid systems enhance grid stability and renewable energy integration
- Integration of ML, BMS, and V2G supports low-carbon and intelligent mobility

## GRAPHICAL ABSTRACT




## ABSTRACT

Both Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are redefining the foundation of smart mobility, have accelerated the transition toward sustainable transportation. A BEV operates entirely on electrical energy stored in high-density batteries managed by advanced Battery Management Systems (BMS), offering benefits such as zero emissions, minimal maintenance, and smooth operation. In contrast, a PHEV combines internal combustion power with an electric drive, using its BMS to balance power delivery and maximize fuel efficiency. Together, BEVs and PHEVs serve as essential enablers of smart mobility, ensuring cleaner transportation and energy-efficient operation. Recent progress in Battery Management System (BMS) technology, coupled with Machine Learning (ML) applications, has significantly improved the monitoring, control, and optimization of battery health and performance. ML algorithms enable predictive analytics for state-of-charge, state-of-health, and degradation patterns, extending the lifespan of BEVs and PHEVs. Furthermore, there is enhancement in energy efficiency associated with Vehicle-to-Grid (V2G) systems since it allows BEVs and PHEVs to exchange power dynamically with the grid and supports renewable energy integration and grid stability. Through V2G and integration of renewable energy, electric vehicles evolve from passive energy consumers to active participants in a smart mobility ecosystem. Integration of ML within BMS facilitates adaptive energy control and intelligent fault detection in BEVs and PHEVs. This synergy improves operational safety while reducing life-cycle emissions. Additionally, renewable energy integration through solar and wind-powered V2G systems further strengthens the sustainability of smart mobility infrastructures. Despite challenges such as high battery costs, recycling, and infrastructure limitations, the combination of ML, BMS optimization, V2G interaction, and renewable energy integration ensures that BEVs and PHEVs will remain at the forefront of the global shift toward intelligent, sustainable, and low-carbon smart mobility systems.

**Keywords:** Battery Electric Vehicle (BEV); Plug-in Hybrid Electric Vehicle (PHEV); Machine Learning (ML); Vehicle-to-Grid (V2G); Battery Management System (BMS)

## Abbreviations

| Abbreviation | Full Term |
|---|---|
| AI | Artificial Intelligence |
| AC | Alternating Current |
| BESS | Battery Energy Storage System |
| BEV | Battery Electric Vehicle |
| BMS | Battery Management System |
| BIPV | Building Integrated Photovoltaic |
| BAPV | Building Attached/Applied Photovoltaic |
| $CO_2$ | Carbon Dioxide |
| DC | Direct Current |
| DG | Distributed Generation |
| EDLC | Electrochemical Double-Layer Capacitor |
| EV | Electric Vehicle |
| FAST | Future Automotive Industry Structure |
| GHG | Greenhouse Gas |
| HEV | Hybrid Electric Vehicle |
| ICE | Internal Combustion Engine |
| IoT | Internet of Things |
| kW | Kilowatt |
| Li-ion | Lithium-ion |
| ML | Machine Learning |
| NiMH | Nickel–Metal Hydride |
| PV | Photovoltaic |
| SOC | State of Charge |
| SOH | State of Health |
| STPV | Semi-Transparent Photovoltaic |
| SPD | Suspended Particle Device |
| V2G | Vehicle-to-Grid |
| V2H | Vehicle-to-Home |

| | |
|---|---|
| V2I | Vehicle-to-Infrastructure |
| V2P | Vehicle-to-Pedestrian |
| V2V | Vehicle-to-Vehicle |
| V2X | Vehicle-to-Everything |
| V2N | Vehicle-to-Network |
| B2G | Building-to-Grid |
| EVSE | Electric Vehicle Supply Equipment |
| MLP | Multi-Layer Perceptron |
| AIoT | Artificial Intelligence of Things |

## 1. Why Electric Vehicle?

The operation of electric vehicles (EVs) is feasible by connecting it to a charging station thereby drawing power from available grid [1]. The electricity storage requires rechargeable batteries which powers the electric motor that turns subsequently the wheels [2]. The charging of an EV is carried out by connection to public charging station or by using a home charger. Many charging stations exist on highways to maintain a full charge while travelling. In respect to home charging, to attain the greatest bargain, however, it is essential to find the proper EV power tariff that allows the consumer to minimize charging cost for overall bill reduction.

The distance that can be travelled on using single charge session varies by vehicle type. There is variation in distinct range, capacity of the battery, and performance for different models. The ideal EV must be one which the consumer can use for routine trips without needing to stop recharging. There are many varieties of EV. The vehicles that operate on electricity only are considered pure EVs, and some can also be powered in addition to gasoline or diesel, these are termed ‘hybrid’ EVs.

For fully battery electric vehicles (BEVs), they solely run on electricity, thus, all their power is received when they are plugged in to charge. The operation does not require gasoline or diesel to operate and therefore it does not cause pollution like conventional automobiles. For the plug-in hybrid, these vehicles run mostly on electricity plus its traditional fuel engine, allowing users to utilize gasoline or diesel if the battery runs out. When operating on gasoline, these automobiles will emit emissions, however when operating on electricity, they will not. The batteries of plug-in hybrids vehicles (PHEVs) can be recharged by being hooked into an electrical source. As for hybrid-electric vehicles (HEVs), these vehicles run primarily on diesel or gasoline but also have an electric battery which is recharged by regenerative braking to allow the users to switch between operating the internal combustion engine (ICE) and 'EV mode’ with a switch button. These automobiles cannot be plugged into an electrical outlet and run on either diesel or gasoline.

Note that the EVs contain fewer moving components and parts in comparison with internal combustion engine vehicles (ICEVs). There are several components responsible for EV movement: (i) Electric Engine/Motor – this provides the necessary force to turn the wheels and it can be a DC or AC, although AC motors are more common; (ii) Inverter – this component converts DC electric current to AC; (iii) Drivetrain – EVs feature a single-speed transmission that transmits motor power to the wheels; (iv) Batteries – store the electricity needed to power an electric vehicle. The greater the battery's kW rating, the longer its range, and; (v) Charging system – this connect to the battery or EV charging station to charge battery.

Figure 1 shows comparison between the relative life-cycle greenhouse gas (GHG) emissions of different types of vehicles, highlighting the key environmental benefits of transitioning to electric mobility. ICEVs exhibit the highest emissions due to fuel combustion. BEVs powered by electricity from fossil-based grids still generate emissions during power generation, but their overall footprint remains less compared to conventional vehicles. The lowest emissions are achieved when BEVs are charged utilizing renewable energy sources like wind or solar. The figure emphasizes that the environmental advantage of BEVs increases as electricity generation becomes cleaner and more sustainable.

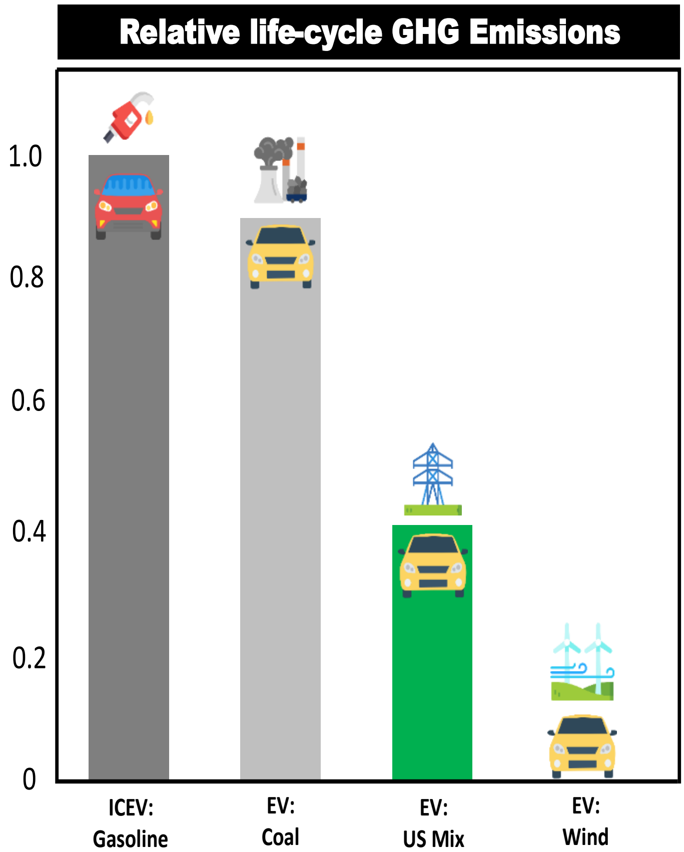



**Figure 1**. Comparison of relative life-cycle GHG emissions from ICEV and EVs, showing significant reductions when EVs are powered by renewable energy sources.

In general terms, BEVs are attributed to having low cost of maintenance due to fewer moving parts of the vehicle, and they are also more environmentally friendly since they utilise less or no fossil fuels at all. Basically, some categories of BEVs uses nickel metal hydride batteries or lead acid [3], presently, lithium-ion batteries are regarded as norm for modern battery for BEVs because of their better energy retention and improved durability [4]. Efforts are made to improve the safety of these batteries despite their improved efficiency because they are still liable to thermal runaway.

## 2. Battery Electric Vehicle (BEV)

Presently, BEVs have a restricted range. Charging stations are required for BEVs, yet there is a considerable paucity of infrastructures. While this issue is manageable in an urban setting, long-distance travel necessitates properly placed recharge stations. Unlike gasoline-powered vehicles, BEVs require hours to fully recharge.

In comparison to ICEs, BEVs that are battery-powered have minimal maintenance-required moving components. Benefits of a BEV include lower and almost silent sound with no spark plugs, clutch, exhaust, or transmission since rechargeable batteries are used instead of fossil fuels. Charging BEVs can be done at home overnight, providing sufficient range for typical trips. However, for longer trips or trips with numerous steep ascents can necessitate recharging the battery packs prior to reaching destination, although regenerative braking and driving downhill can assist offset this by charging the battery packs. Charge times for electric vehicles often range between 30 minutes and over 12 hrs. This depends on the speed of the charging station and the battery's capacity. In the actual world, electric car range is one of the main issues, but there is industry backed research working to address the issue.

Recently, battery technology has significantly been advanced and have improved in terms of the charging speed, energy density, and overall performance [5-7]. Innovations like solid-state batteries [8-10], silicon anodes [11, 12], and advanced battery management systems (BMS) [13-15] therefore paving way for higher energy efficiency and longer driving ranges. Furthermore, the development of ultra-fast charging infrastructure [16, 17] and wireless charging technologies [18, 19] aims to make recharging as convenient as refueling conventional vehicles.

In addition to technological improvements, governments and automotive manufacturers are collaborating to expand public charging networks and offer incentives that encourage the adoption of electric mobility. Policies promoting zero-emission vehicles, combined with declining battery costs, are making BEVs increasingly accessible to consumers. Integration with renewable energy sources, such as solar and wind, further enhances the environmental benefits of BEVs by enabling cleaner and sustainable charging alternatives.

Moreover, the incorporation of smart technologies plus Internet of Things (IoT) connectivity which makes it possible for real-time monitoring of battery health, route optimization, and predictive maintenance, thereby increasing reliability and reducing operational costs. As challenges continue to be addressed through research such as battery degradation, range limitations, and infrastructure gaps, BEVs are positioned to play a crucial role in achieving global carbon neutrality and reshaping the future of sustainable transportation.

In parallel with these advancements, the global shift toward sustainable urban mobility has accelerated deployment of ‘smart charging’ solutions and vehicle-to-grid (V2G) systems. Through V2G technology, BEVs are no longer passive consumers of electricity but become active participants in the power grid. During periods of low demand, BEVs can draw power to charge their batteries, and during peak hours, they can feed stored energy back into the grid. This bidirectional energy exchange improves grid stability, supports renewable energy integration, and provides financial incentives for EV owners.

Machine learning (ML) and the integration of artificial intelligence (AI) is another emerging trend used in EV energy management systems. Adoption of these technologies enable precise prediction of driver behavior, traffic conditions, and energy consumption, helping optimize power allocation and extend battery lifespan. Predictive models based on ML can also forecast charging demand patterns across cities, allowing power utilities to plan infrastructure more effectively and reduce grid stress.

It is noteworthy that social and environmental implications of BEV adoption are substantial. By reducing dependence on fossil fuels, BEVs contribute to cleaner air and lower urban noise levels, improving overall public health. The electrification of transport also stimulates innovation in battery recycling and second-life applications, such as repurposing used BEV batteries for stationary energy storage in buildings or microgrids.

While challenges such as inadequate charging infrastructure mostly in the rural areas and high initial costs exist [20-22], plus battery material sustainability remain, the continuous improvement in energy technologies and policy frameworks indicates a promising trajectory. The convergence of digitalization, renewable energy, and electrified transportation is expected to redefine mobility in the 21$^{st}$ century, steering society toward a more resilient, low-carbon future.

## 3. Plug-in Hybrid Electric Vehicles (PHEV)

Rather than relying only on an electric motor, the HEVs further combine battery and gasoline (or diesel) power [23, 24]. This makes them suitable for long-distance driving as the driver can switch to using fuel rather than having to seek charging stations. HEVs have similar disadvantages to ICEVs, including maintenance requirements, pollutants, engine noise, and gasoline cost. Additionally, their battery packs are smaller, leading to shorter coverage range.

However, PHEVs provides necessary transitional technology between the conventional ICEVs and tBEVs. They allow users to experience the merits of electric driving without the limitations of range coverage anxiety. During short commutes or city driving, PHEVs operation can be entirely on electric power, reducing fuel consumption and emissions. After the battery depletion, the internal combustion engine then automatically engages, ensuring continuous mobility even when charging stations are unavailable.

Figure 2 shows an overview in comparison between the three main categories of electric-powered vehicles: PHEV, HEV, and BEV. The illustration demonstrates the transition from fossil fuel dependency to full electric reliance, with corresponding reductions in GHG emissions. HEVs depend primarily on internal combustion with limited electric assistance, PHEVs offer dual energy sources with plug-in charging capability, and BEVs operate solely on stored electrical energy, producing zero tailpipe emissions. This comparison highlights the progressive shift toward sustainable and low-emission mobility.

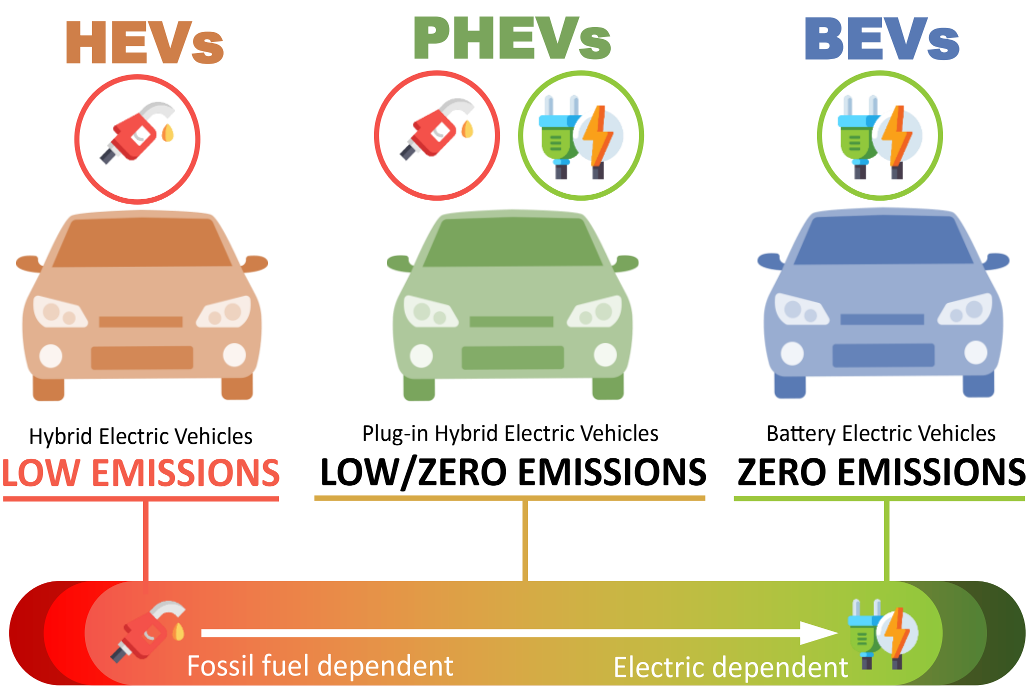



**Figure 2**. Comparison between HEV, PHEV, and BEV showing the transition from fossil fuel dependence to full electric operation and corresponding reduction in emissions.

Figure 3 depicts the continuum of vehicle electrification, ranging from ICEV on the left to fully battery (BEV) on the right. As the figure shows, vehicles transition from larger engines and fuel dependency to larger batteries and greater electric power utilization. HEV and PHEV occupy the middle ground, combining both fuel-based and battery-driven systems. This progression highlights the role of PHEVs as an intermediate step toward full electrification, balancing range, efficiency, and environmental benefits.

Recently, PHEV technology development has focused on improving battery capacity, charging efficiency, and hybrid control systems to achieve higher performance and lower emissions. The integration of regenerative braking [25], intelligent energy management [26, 27], and advanced thermal control [28] helps optimize the power interaction between the engine and the electric motor, enhancing overall efficiency. Moreover, PHEVs can be charged through standard household outlets or fast chargers, offering users flexibility in how they refuel their vehicles.

Despite their advantages, PHEVs still face criticism for their environmental impact when driven predominantly in gasoline mode. Real-world fuel economy often depends on driving habits and charging frequency. If drivers neglect to recharge regularly, the vehicle functions more like a conventional hybrid, diminishing its environmental benefits. Furthermore, the complexity of dual maintenance of electric drivetrain and a combustion engine increases manufacturing and servicing costs compared to BEVs.

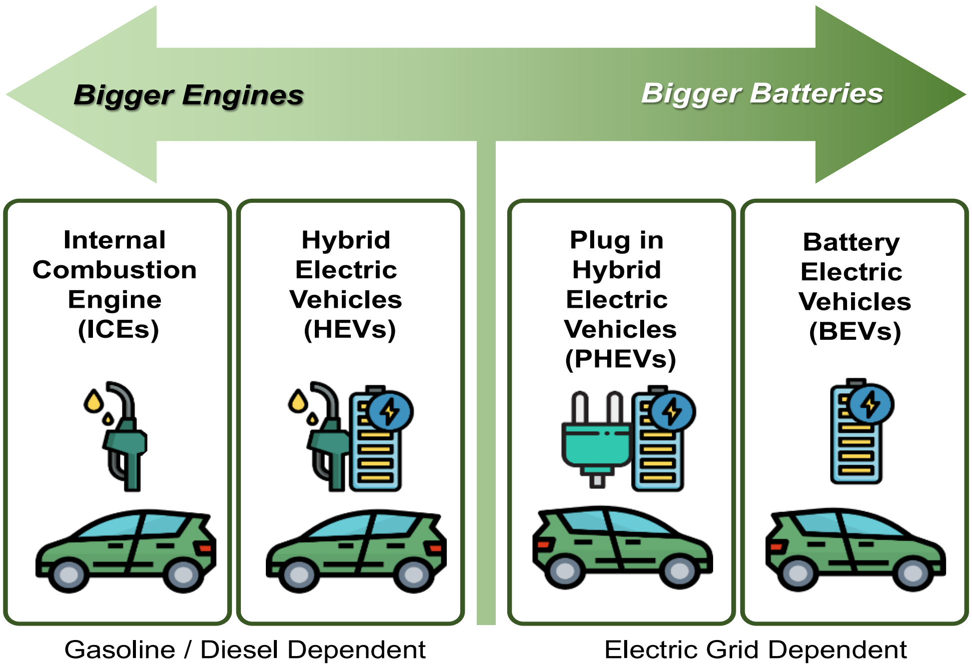



**Figure 3**. Classification of vehicles along the electrification spectrum, from ICEV to HEV, PHEV, and BEV, illustrating major trade-off between engine size and battery capacity.

Nevertheless, PHEVs play a very important role in accelerating adoption of electric mobility by familiarizing consumers with electric driving while leveraging existing refueling infrastructure. In markets where charging networks are still developing, PHEVs offer a practical and adaptable solution that bridges the gap toward a fully electrified transportation ecosystem. With continued advances made in battery technology in recent times in addition to supportive government incentives, it is expected that PHEVs in the next generation will deliver longer electric ranges, lower emissions, and enhanced fuel efficiency, further contributing to the global transition toward sustainable mobility.

## 4. Machine Learning-Driven Transformation in Electric Vehicles: Enhancing Efficiency, Sustainability, and Smart Mobility

The transportation industry is the cause of majority of GHG emissions and environmental damage [29]. E-mobility applications like EVs [30], hybrid locomotives, as well as other battery-energy storage systems [31] can enhance the transportation industry. The capacity of the energy storage system is among the most important components of electric vehicles and smart grid technologies [32-35]. The rising technology in electricity transmission and distribution lines is the smart grid.

Figure 4 illustrates the life-cycle emission stages associated with EV production and operation. It highlights key emission sources, including mining, drilling, processing, transportation, and electricity generation. The diagram also differentiates between material-related emissions and those from the vehicle's fuel cycle, emphasizing that while electric vehicles eliminate tailpipe emissions, upstream activities still contribute to carbon output. These visual underscores the importance of integrating renewable energy and sustainable materials in the EV supply chain to achieve true carbon neutrality.

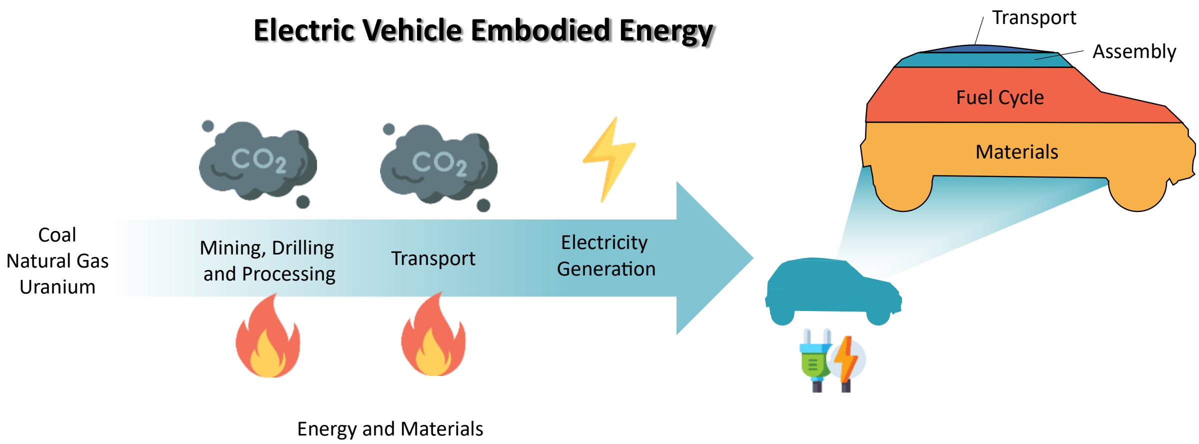



**Figure 4**. Life-cycle emissions of electric vehicles showing carbon dioxide ($CO_2$) release during mining, processing, transportation, and electricity generation, along with contributions from materials and the fuel cycle.

Figure 5 illustrates the primary sources of transportation-related emissions and their environmental consequences. Both on-road (cars, trucks, and motorcycles) and non-road (aircraft, trains, ships, and industrial machinery) vehicular emission of pollutants like smog, soot, and $CO_2$. These emissions contribute to adverse health impacts, reduced quality of air humans breathe, and broader climate change effects. The figure 5 below underscores the urgent need for clean transportation technologies, such as EVs, to mitigate the sector's environmental footprint.

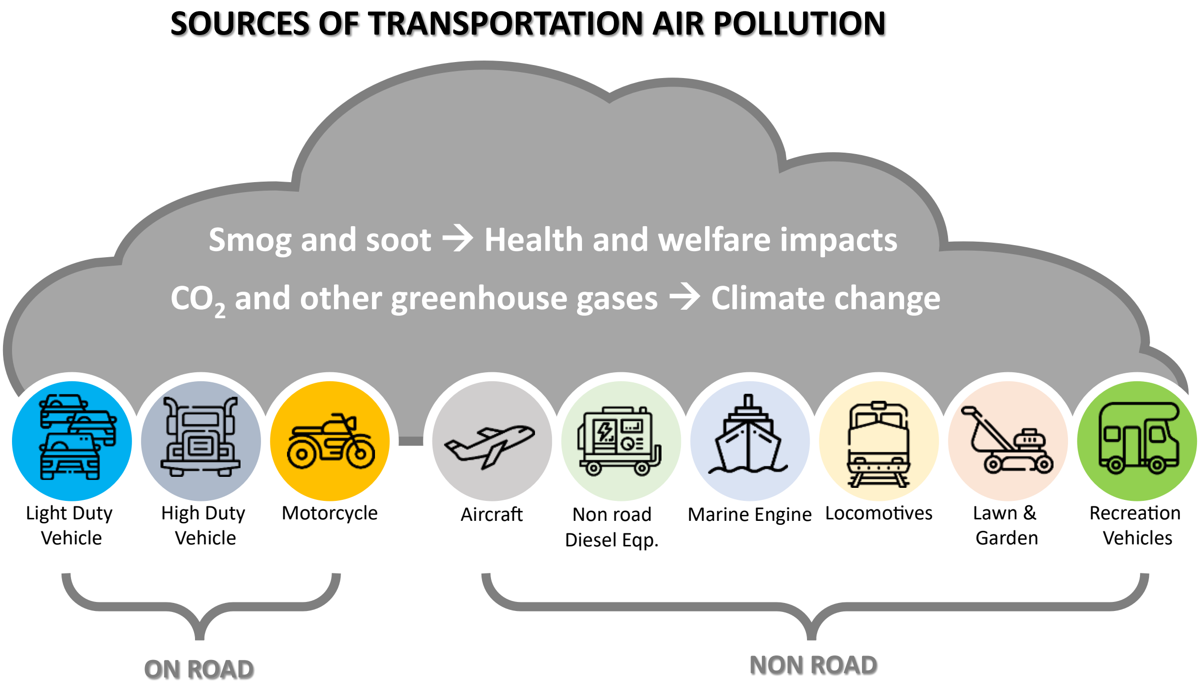



**Figure 5**. On-road and non-road sources of transportation emissions contributing to smog, soot, and $CO_2$ release, leading to health impacts and climate change. Adapted from Bawa, et al. [36]

There are various batteries available on the market for diverse uses involving energy storage. Figure 6 illustrates the comparative relationship among major energy storage technologies commonly used in EV systems, including fuel cells, rechargeable batteries, and supercapacitors. The chart positions these technologies based on their specific energy which represents the energy stored per unit mass and specific power (rate of energy dissipation).

On the left, fuel cells are shown to provide enormous specific energy but low specific power relatively, giving them suitability for long-range applications where sustained energy delivery is required. Rechargeable batteries occupy the central region, balancing both specific energy and specific power. Within this category, nickel–metal hydride (NiMH), lead-acid, and lithium-ion batteries are arranged according to their performance, with lithium-ion batteries achieving the best trade-off among factors like energy density, power output, and life-cycle efficiency.

To the right, supercapacitors similarly called electrochemical double-layer capacitors, (EDLCs) are characterized by their extremely high specific power but low specific energy. This enables them to deliver quick bursts of power, ideal for acceleration, regenerative braking, or transient load leveling. Hybrid systems combining lithium-ion batteries and supercapacitors are also depicted, offering a compromise that enhances both energy and power performance. Electrolytic capacitors appear at the lower right corner, representing devices with very high power density but negligible energy storage capacity, mainly used for backup or filtering applications.

Overall, the figure emphasizes that no single energy storage technology can fulfill all performance requirements simultaneously. Therefore, hybrid configurations that integrate fuel cells, batteries, and supercapacitors are often employed in advanced electric vehicle architectures to achieve optimal efficiency, reliability, and responsiveness across different driving conditions.

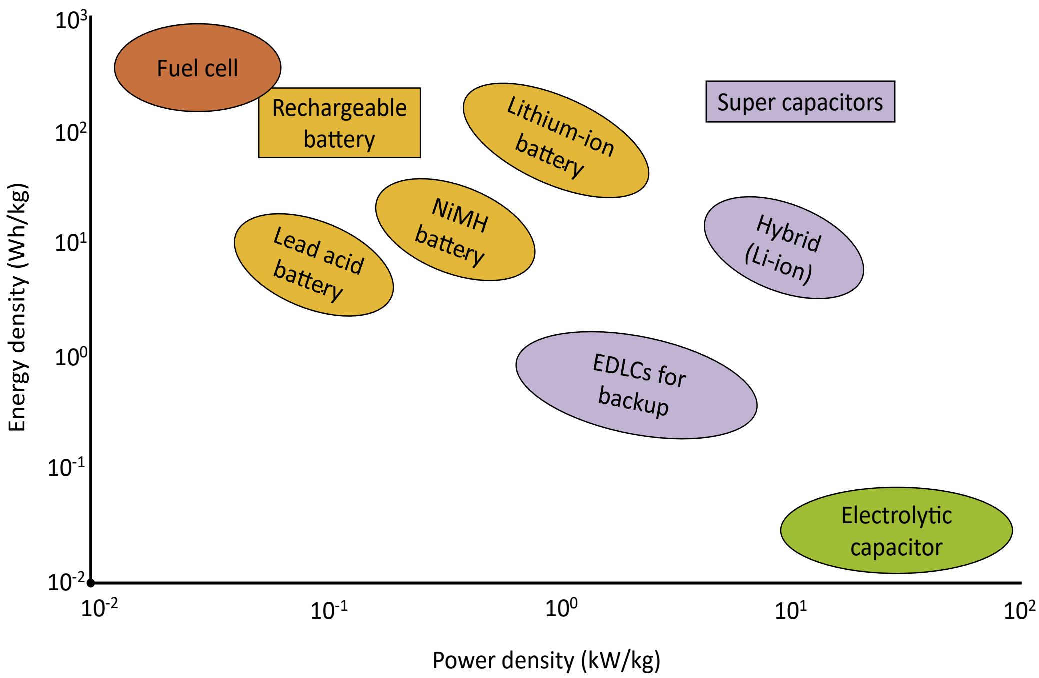



**Figure 6**. Comparative plot of energy storage and power delivery technologies for electric vehicle applications, illustrating the trade-off between specific energy and

specific power. Fuel cells are shown for reference as energy converters, while batteries (lead-acid, NiMH, Li-ion), supercapacitors (EDLCs), electrolytic capacitors, and hybrid systems are positioned according to their performance characteristics. Adapted from Verma, et al. [37]

As a result of its volumetric and gravimetric density, high hourly efficiency, and long life, EV producers selects lithium-ion batteries the main energy storage technology for electric vehicles [38, 39]. However, temperature control of batteries is critical for EV applications [40]. Internationally, EV charging stations are mostly used, and the ports number at private and public charging stations has increased [41]. In Belgium, two EVs with different battery capacities were examined. Reportedly, the grid usage for EVs causes fluctuations in power supply, grid control problems, and poor electricity quality [42]. Currently, novel research is being conducted to convert buildings from energy consumers to energy producers through the integration of renewable energy systems with storage systems [43-48]. Instead of pumping photovoltaic energy into the grid, it can be stored in batteries [49, 50]. Additionally, battery energy storage availability can enable the incorporation of electrically actuated smart windows into buildings [51, 52].

Figure 7 illustrates the percentage share of electric vehicle adoption across selected countries worldwide. The data highlights Norway as the global leader with the highest EV market penetration, followed by nations like Netherlands, China, the United Kingdom, and Germany. The map underscores the uneven distribution of electric vehicle uptake, reflecting variations in national policies, charging infrastructure, incentives, and public awareness. It emphasizes the critical role of government support and technological readiness in accelerating global EV deployment.

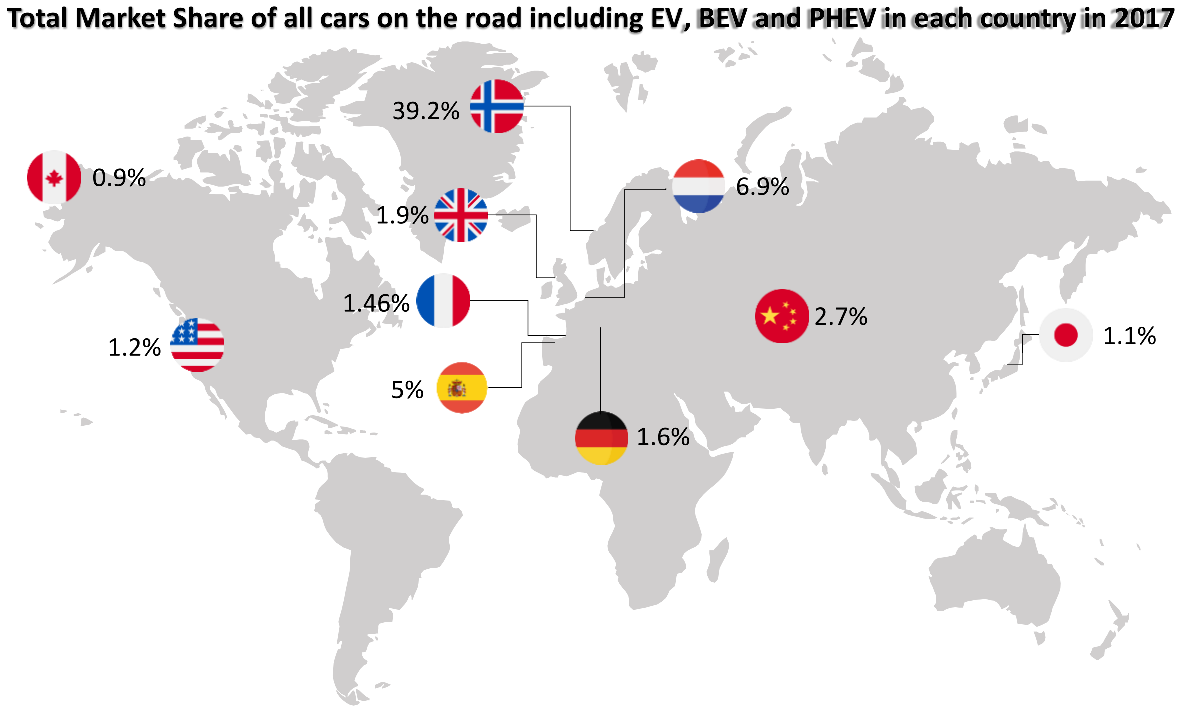



**Figure 7**. Global distribution of electric vehicle adoption rates showing market penetration percentages by country, with Norway leading the transition toward electric mobility followed by the Netherlands, China, Germany, and the United Kingdom.

The automotive sector is presently experiencing a period of profound transformation. Based on 2018 edition of the future automotive industry structure (FAST) study [53], reported by Oliver Wyman in conjunction with the German Automotive Association, presented seven major factors which will influence this industry within the next ten Years ranging through 2030 as a result of the use of digitization, AI, and ML. These identified elements are (i) autonomous vehicles, (ii) Linked vehicles, (iii) digital industry, (iv) electric mobility (v) new pay-per-use distribution channels, (vi) changes in customer structure, and (vii) new concepts for Human–Machine Interface. Figure 8 illustrates five emerging trends shaping the electric vehicles (EVs) future: smart power distribution, wireless charging, vehicle-to-home (V2H) in addition to V2G integration policies, and autonomous driving technologies. These advancements represent both challenges and also provides opportunities in the ongoing evolution of EV systems. They aim to enhance operational efficiency, connectivity, and sustainability while supporting intelligent grid interaction and user convenience within next-generation mobility frameworks.

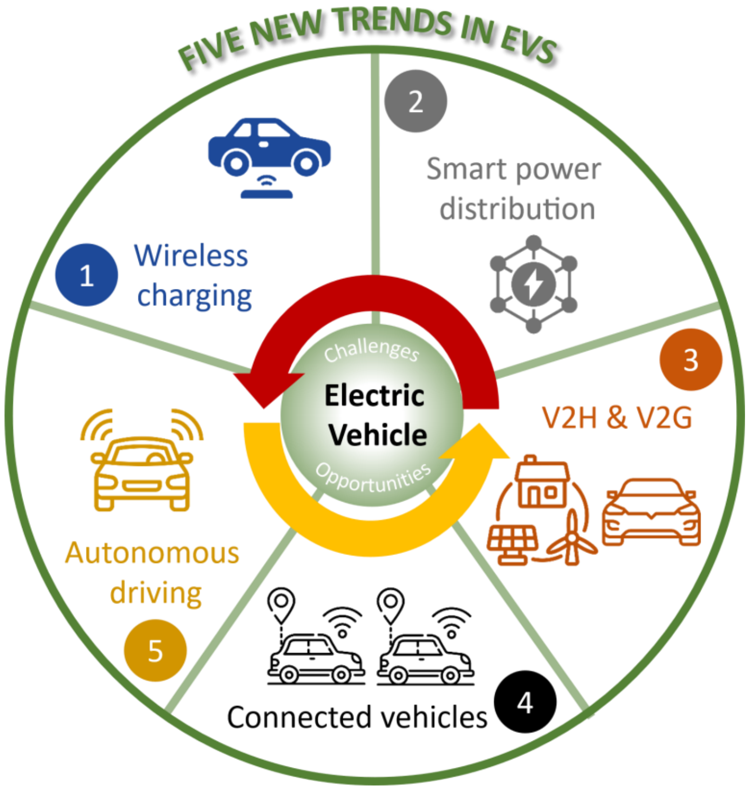



**Figure 8**. Five new technological trends in electric vehicles highlighting key areas of innovation: wireless charging, V2H/V2G integration, and autonomous driving, representing the challenges and key opportunities in the continously changing EV ecosystem.

In this growing context, the paradigm of Internet of Things can be utilised by using increasingly accurate, smaller, and more potent networked sensors. Consequently, automobiles are rapidly equipped with a range of sensors which will monitor various components and situations, like the driving style, the engine, and climatic conditions. Thus, these sensors result in the collection of vast data quantities regarding the vehicle, which may be examined to identify trends and patterns. In fact, the significant influence of big data also applies to the automotive industry, where vehicle data can be utilised in a variety of ways like enhanced real-time analytics and predictive maintenance. These developing paradigms and technologies are particularly intriguing in relation to electric vehicle category, whose growth is fueled by considerations such as a reduced environmental effect, a faster and more practically precise motor torque generation, and lower long-term ownership costs. For that reason, the data streams acquired by leveraging networked sensors could provide a unique opportunity to alleviate popular "range anxiety," issues which is the concern that a BEVs battery could completely deplete during a trip [54-56], leaving the driver stranded.

Machine learning is an AI which permits software applications to exhibit more accuracy in the prediction of outcomes even when explicitly not programmed to act so [57-62]. The historical data is used by ML algorithms as input in the prediction of novel output values. It is used in areas like fraud detection [63-65], spam filtering [66-68], detection of malware threat [69-71], business process automation (BPA) [72] as well as in predictive maintenance [73-78].

Machine learning is very necessary as it gives enterprises perspective on customer behavior and operational patterns of the business, in addition to supporting the innovative products development. Many worlds' top companies like Google, Uber, and Facebook, make ML an integral aspect of their operations and therefore make ML to become an important competitive factor for many companies. Characterizations of classical ML is based on how fast and accurate an algorithm learns to carry out predictions effectively. The four basic approaches used include: supervised learning [79-81], unsupervised learning [82, 83], semi-supervised learning [84-87] and finally reinforcement learning [88-91]. The algorithm chosen by data scientists to use mainly depends on the type of data which they intend to predict.

## 5. Integration of Machine Learning in Electric Vehicle Systems for Grid Stability and Improved Performance

The integration of ML into EV systems [92-94] has become a promising direction to address current limitations and optimize performance, battery management, and grid interaction. ML algorithms can be applied in EVs for predicting battery degradation [95-97], estimate state-of-charge (SOC) [98-100] and [101-103] and enhance thermal management systems [104-106]. By analyzing historical driving patterns, environmental conditions, and charging behaviors, ML models can forecast energy consumption more accurately, which helps reduce range anxiety and improve route planning.

Moreover, ML-based predictive analytics can assist in real-time energy optimization between EVs and charging infrastructure, enabling smart charging strategies which can minimize the impact on the grid at peak demand period. This concept extends to V2G systems, where electric vehicles not only consume but also supply energy back to the grid when required. Reinforcement learning algorithms has the potential to dynamically schedule charging and discharging operations, maintaining grid stability and reducing electricity costs.

Figure 9 presents the Vehicle-to-Everything (V2X) communication network, which integrates electric vehicles into a broader intelligent transport and energy ecosystem. V2X enables vehicles to interact dynamically with multiple entities, involving other vehicles (V2V), devices (V2D), pedestrians (V2P), infrastructure (V2I), the power grid (V2G), homes (V2H), and communication networks (V2N). This interconnected system supports enhanced road safety, efficient energy exchange, autonomous driving, and optimized traffic flow—fundamental components of future smart mobility and intelligent transportation systems.

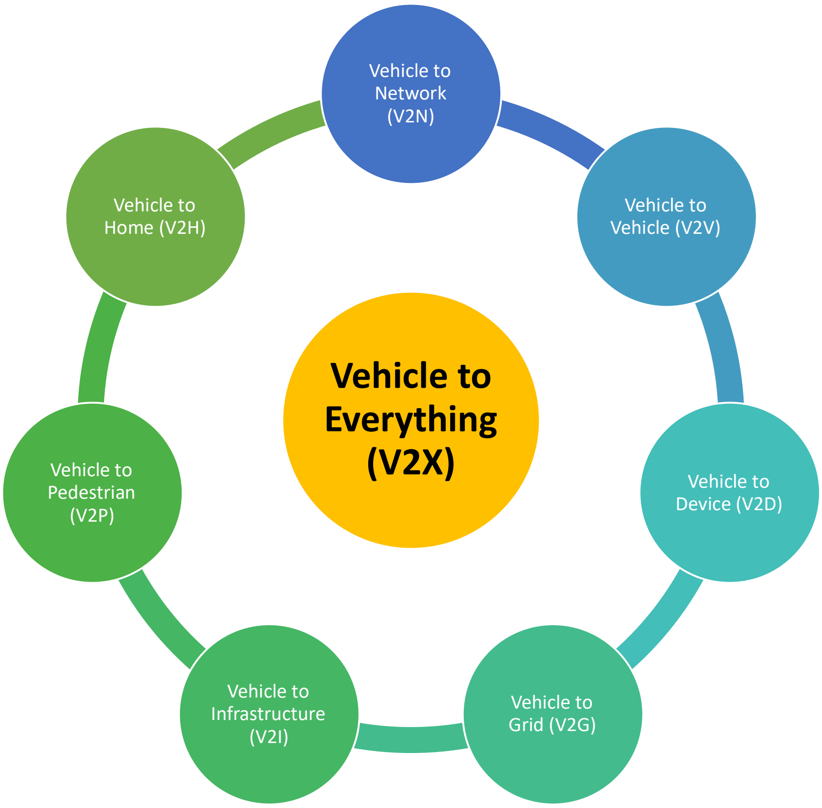



**Figure 9**. Overview of V2X communication framework connecting vehicles with networks, devices, infrastructure, pedestrians, homes, and the grid to enable intelligent, interconnected, and energy-efficient mobility systems. Adapted from Veza, et al. [107]

In addition, supervised and unsupervised learning techniques can be employed to detect anomalies in powertrain systems, predict component failures, and enhance safety through autonomous fault diagnosis. With continuous advancements in sensors [108-110], data acquisition [111], and computational power [112-114], EVs are evolving into intelligent energy entities capable of interacting seamlessly within the smart grid ecosystem.

## 6. Conclusion: BEVs and PHEVs

Battery Electric Vehicles and PHEVs represent two critical pathways toward decarbonizing the global transportation sector. BEVs eliminate direct emissions by relying entirely on electricity, offering superior energy efficiency, minimal maintenance, and compatibility with energy from renewable sources like solar. PHEVs, on the other hand, serve as a transitional technology, enabling users to experience electric mobility while mitigating range anxiety through the availability of internal combustion engines. Both technologies have benefited significantly from advances in battery design, management systems, and charging infrastructure.

The integration of AI and ML has further revolutionized EV performance optimization, energy management, and predictive maintenance. Through the analysis of large datasets derived from connected sensors and driving patterns, ML algorithms enhance range prediction accuracy, improve charging coordination, and optimize battery life. Furthermore, emerging V2G and IoT technologies are transforming EVs into active components of smart grids, supporting grid stability and integration of renewable energy.

Despite these advances, there are other challenges such as high battery production costs, limited infrastructure in rural regions, and environmental concerns related to battery recycling. Nonetheless, the continuous collaboration among researchers, policymakers, and industry stakeholder's points toward a sustainable and intelligent transportation ecosystem that will underpin future mobility.

Figure 10 summarizes the main barriers slowing widespread EVs adoption are categorized into five key groups: infrastructural, financial, behavioral, technological, and external barriers. Technological challenges include limitations in EV technology, range, and reliability. Infrastructure barriers relate to the shortage of charging stations and lack of maintenance networks. Financial barriers such as high purchase cost and uncertain resale value discourage consumers, while behavioral barriers reflect skepticism toward safety and benefits. External barriers, including dependence on raw materials and insufficient government incentives, further slow EV market growth. Together, these interconnected issues highlight the complexity of transitioning to sustainable mobility systems.

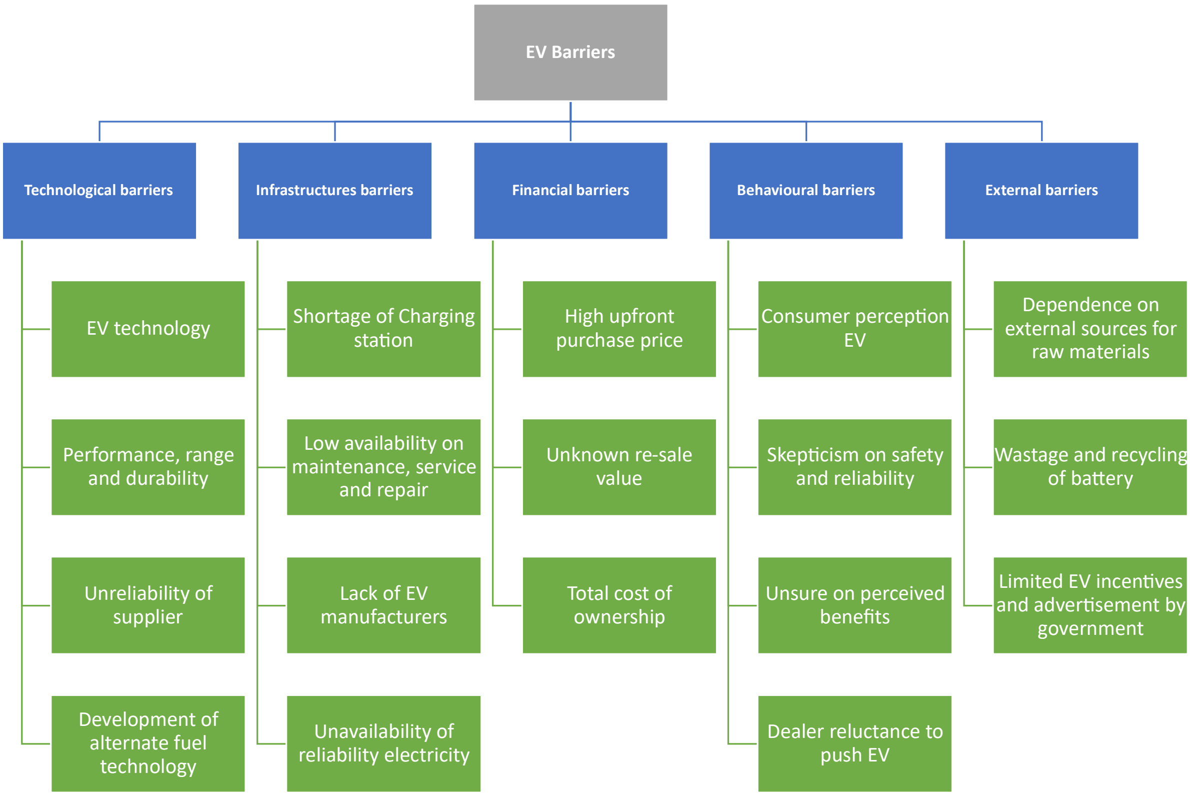



**Figure 10**. Classification of barriers to EV adoption, showing technological, infrastructural, financial, behavioral, and external challenges that collectively influence the pace of EV market penetration.

## 7. Future BEVs and PHEVs Research Directions

### 7.1. Advanced Battery Materials and Recycling Technologies

Future research must focus on developing next-generation battery components with improved chemistries like sodium-ion, solid-state, and lithium-sulfur systems. In parallel, sustainable recycling methods and circular economy models must be established to recover valuable materials and reduce environmental impact.

### 7.2. Artificial Intelligence for Battery and Energy Management

AI-driven battery management systems with capability of real-time learning, fault prediction, and dynamic optimization will be crucial. Reinforcement learning and federated learning approaches could more so enhance distributed charging coordination and V2G operations.

### 7.3. Smart Charging Infrastructure and Grid Integration

Studies should explore intelligent charging algorithms that incorporate renewable energy availability, grid demand, and dynamic pricing models. The integration of V2G and building-to-grid (B2G) concepts can further strengthen energy resilience and reduce carbon intensity.

### 7.3. Hybrid Powertrain Optimization and Control

For PHEVs, multi-objective optimization models should be developed to balance electric and fuel energy consumption, enhance regenerative braking recovery, and minimize life-cycle emissions under varying driving conditions.

### 7.4. Lifecycle Assessment and Policy Frameworks

Comprehensive life-cycle analyses comparing BEVs, PHEVs, and emerging technologies (such as hydrogen fuel cells) are essential for guiding policy decisions. Research on global policy harmonization, incentives, and carbon accounting mechanisms can accelerate EV adoption.

### 7.5. Cybersecurity and Data Privacy in Connected EVs

As EVs become further connected, future studies must address cybersecurity risks in vehicle communication networks, ML algorithms, and grid interfaces to ensure operational safety and user trust.

### 7.6. Integration of Renewable Energy and Smart Cities

Future work should examine how EVs can be integrated into smart city ecosystems, leveraging solar-powered charging hubs, digital twins, and real-time mobility data analytics to achieve urban sustainability goals.

## 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.

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## Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

## CRediT Authorship Contribution Statement

M.I.: Conceptualization, Supervision, Manuscript preparation, Writing – original draft.
A.S.: Reference validation, Writing – original draft, Review and editing.
F.A.: Data curation, Formal analysis, Visualization, Writing – original draft.
A.C.O.: Conceptualization, Methodology, Writing – original draft.
A.Y.K.: Conceptualization, Supervision, Writing – original draft.
A.L.H.: Visualization, Review and editing, Writing – Review & Editing.
O.D.S.: Reference validation, Writing – Review & Editing.
M.Z.A.: Validation, Writing – Review & Editing.
R.G.J.: Project Administration, Writing – Review & Editing
M.F.M.S.: Supervision, Writing – Review & Editing.

All authors have read and agreed to the published version of the manuscript.

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