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Comparative Analysis of Electrical and Autonomous Vehicles Using the COPRAS Method

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ABSTRACT

The rapid development of electric and autonomous vehicle technologies has increased the need for systematic evaluation methods to determine their performance, feasibility, and sustainability. This study employs the Multi-Criteria Decision-Making (MCDM) approach, specifically the Complex Proportional Assessment (COPRAS) method, to evaluate and rank conventional electric vehicles and autonomous electric vehicles based on multiple criteria. The assessment considers essential factors, including initial purchase cost, maintenance and operational expenses, safety features, environmental impact, technological advancement, energy efficiency, and infrastructure requirements. The COPRAS method provides a quantitative and objective framework for comparing alternatives and identifying the most suitable vehicle technology for future transportation systems. The findings reveal that autonomous electric vehicles demonstrate superior performance in terms of automation, safety, energy efficiency, and intelligent technological integration. However, their widespread adoption remains constrained by high initial investment costs and limited supporting infrastructure. In contrast, conventional electric vehicles offer a reliable, environmentally friendly, and economically accessible transportation alternative with fewer implementation challenges. The study concludes that autonomous electric vehicles represent a promising direction for future sustainable mobility, although infrastructure development and cost reduction are essential for their broader acceptance. The results provide valuable guidance for policymakers, automotive manufacturers, and consumers in making informed decisions regarding the adoption and development of sustainable and intelligent transportation technologies.

1. INTRODUCTION

Rapid advances in electrical engineering have contributed significantly to the development of autonomous vehicles. Electrical systems form the backbone of modern self-driving technology, providing the power, control, and communication needed for these vehicles to operate efficiently and safely. These technologies work together to collect and process real-time data so that vehicles can make decisions without human intervention. The electric powertrain in EVs, combined with advanced battery management systems, ensures optimal performance and energy efficiency .Companies and researchers are continuously working to improve battery technology, charging infrastructure, and autonomous driving algorithms to make self-driving cars more reliable and accessible. The shift toward electric and autonomous vehicles will not only reduce carbon emissions, but also pave the way for a future with fewer traffic accidents and improved mobility solutions. In conclusion, the combination of electric systems and autonomous technology is revolutionizing the automotive industry. As advances continue, these innovations will lead to a better, safer, and more sustainable transportation ecosystem. With

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recent technological advances advancing rapidly, it is worth revisiting whether electric propulsion and autonomy are sufficiently developed to support a fully functional on-demand air transport system. This system must provide a service at a cost that attracts a wide range of passengers, while ensuring a strong capacity for profitable operations. A vehicle system can only be considered truly "autonomous. This article examines the convergence of autonomous vehicles, ride-sharing, ride-hailing services, and electric vehicles, analyzing their potential impact on the utility industry's business model. It begins with a brief overview of autonomous vehicle (AV) technologies and shared mobility concepts, highlighting how the emergence of shared autonomous electric vehicles (SAEVs) could lead to widespread adoption of electrified transportation. In addition, recent developments, including the rise in electric vehicle (EV) sales and growing car-sharing participation, are examined for their significant impact on greenhouse gas emissions and energy consumption .This article examines the convergence of autonomous vehicles, ride-sharing, ride-hailing services, and electric vehicles, analyzing their potential impact on the utility industry's business model. It begins with a brief overview of autonomous vehicle (AV) technologies and shared mobility concepts, highlighting how the emergence of shared autonomous electric vehicles (SAEVs) could lead to widespread adoption of electrified transportation. In addition, recent developments, including the rise in electric vehicle (EV) sales and growing car-sharing participation, are examined for their significant impact on greenhouse gas emissions and energy consumption. Although the idea of driverless vehicles has been around for decades, high costs have prevented mass production. Rather than following the conventional linear development model, this paper introduces a new parallel roadmap for improving automotive E/E architectures. This approach seeks to address the misconceptions associated with the traditional continuous roadmap by proposing two distinct development paths: a domain-based path and a zone-based path, each tailored to the varying needs of OEMs and Tier 1 suppliers. The widespread adoption of electric vehicles (EVs) will significantly transform freight transportation operations, not only because of their significant environmental benefits, but also because of the potential decline in ownership-based business models driven by technology obsolescence costs. Autonomous vehicles (AVs) will further reduce operating costs and accelerate the shift towards ownership-free business models. These technological advances will have profound implications for existing industry players, eroding their competitive advantage and requiring them to adopt new business models. The increasing integration of autonomous vehicle features has added complexity to vehicle systems, raising concerns about compliance with safety standards and regulations. The growing reliance on artificial intelligence (AI) algorithms for ADAS functions such as mapping, perception, and sensor processing has introduced challenges related to performance, predictability, and reliability, especially in dealing with unexpected situations. The automotive industry is undergoing rapid transformation driven by the integration of AI into driver assistance and autonomous systems. This research examines key aspects of this technological transformation, including advances in cognitive systems, safety algorithms, sensor fusion techniques, and decision-making algorithms. As autonomous vehicles (AVs) become a key component of future mobility, it is essential to assess their environmental and sustainability impacts. This study specifically analyzes the effect of AVs on urban air quality, focusing on Knox levels on a major avenue in a medium-sized Portuguese city. In recent years, the impact of AV adoption on personal mobility and freight transport has received considerable attention. The development of AVs has been fueled by advances in artificial intelligence and real-time data processing. While early AVs had limited situational awareness, continued technological advances have significantly improved their capabilities. Over the past decade, significant efforts from both research and industry have led to significant advances in AV technology. However, most studies focus on a single aspect, such as environmental impacts, often overlooking other important impacts, which may provide an incomplete picture. This work also explores recent applications of block chain technology to improve autonomous vehicle performance, particularly in areas such as data security, integration, and distributed decision-making. In addition, it explores various AV models and emphasizes the role of block chain in improving reliability and efficiency within autonomous systems. In the coming decades, autonomous vehicles (AVs) are set to transform the transportation industry, offering a safe and convenient mobility solution. A key example of this shift is General Motors' partnership with Lift to develop an autonomous taxi service. While electric powertrains have already been successfully integrated into the market, autonomous driving technology is anticipated to become commercially viable within the next ten years. Most path-tracking (PT) studies have primarily concentrated on steering control, as AVs require path-tracking controllers (PTCs) that ensure safe and stable operation, even in extreme driving conditions. Initially, much of the research in PT steering control focused on driver modeling. However, in autonomous electric vehicles (EVs), the torque vector controller (TVC) functions independently, receiving automatic

steering angle inputs from the PTC and generating a reference yaw rate, which the TVC must then track to maintain vehicle stability This study fills an important gap by analyzing two distinct control system architectures for obstacle avoidance using a validated vehicle simulation model. Despite advances in battery technology, progress has not kept pace with the increasing demands for extended range and computational power. This problem is particularly pronounced in autonomous electric vehicles (EVs), where energy-intensive sensors and real-time processing units such as GPUs place additional strain on battery systems. The performance evaluations in this study rely on datasets that form the basis for validating algorithm designs. The analysis begins by assessing the ability of a machine learning algorithm to predict time-series data. Using these predictions, the study explores charging station allocation algorithms and scheduling strategies for AVs, comparing them to existing methods and previous research. In addition, the Symbioses demo car, which has three driving modes, highlights autonomous driving (AD) as a revolutionary approach that represents the future of mobility. This method allows the vehicle to make autonomous driving decisions without human supervision or intervention. This cognitive process, called "assertion," improves the reliability of artificial intelligence (AI) in AVs, alleviating user anxiety and reducing uncertainty. Passengers can receive real-time feedback from the vehicle's central processing unit, providing reassurance while in transit. To be effective, these signals should primarily consist of auditory cues, providing clear and relevant information at appropriate times without being intrusive or overwhelming .Electric vehicles (EVs) are defined as cars that run solely on battery power, excluding hybrid models. Research has highlighted their environmental and energy efficiency benefits, as they produce zero local emissions of pollutants and greenhouse gases. Furthermore, when charged using renewable energy sources, EVs significantly reduce global emissions. An autonomous vehicle (AV) is a self-driving car that operates without human intervention, representing a significant milestone in modern transportation. AVs integrate computer-based systems to handle driving tasks and are designed with the following key objectives: (1) improving vehicle safety, (2) reducing accidents, (3) reducing fuel consumption, (4) freeing up driving time, (5) expanding market opportunities, and (6) reducing emissions and air pollution. However, AVs rely on advanced sensors, complex software, and sophisticated architectures to manage complex driving situations. A major challenge is that current sensor technologies struggle to process large amounts of data quickly enough to detect and react to dangerous situations with high accuracy. Autonomous vehicles (AVs) rely on a combination of sensors and advanced devices to ensure they stay on track, avoid obstacles, and develop situational awareness, helping them assess their environment and make informed driving decisions. However, despite their potential benefits, there are uncertainties about their development, costs, travel impact, consumer demand, and overall benefits. Significant advances are still needed before AVs can reliably navigate complex urban environments, severe weather conditions such as heavy rain and snow, unmapped or unpaved roads, and areas with limited wireless connectivity. Before they can achieve widespread commercial adoption, AVs must undergo extensive testing and regulatory approvals. Early AV models entering the market are expected to be expensive, have performance limitations, and introduce new risks and costs. These factors could discourage consumers, especially if AVs are unreliable in bad weather or on unmapped roads. An important factor in transportation planning is whether AVs will increase or decrease total vehicle travel and traffic congestion. The impact could be positive or negative, depending on how the technology evolves and integrates with existing infrastructure. Autonomous vehicles (AVs) have the potential to increase overall vehicle travel by allowing non-drivers to travel independently, improving travel convenience and comfort, reducing operating costs, creating empty trips, and encouraging longer trips and urban sprawl. While this additional mobility may provide some consumer benefits, it also introduces significant external costs. As a result, much of this increased travel may be economically inefficient, as the associated costs may outweigh the potential benefits.

2. MATERIALS AND METHODS

To address the challenges of selection, classification, and ranking, various decision-making approaches are used, particularly multi-criteria decision-making (MCDM) techniques. However, no single method has been universally accepted as the most effective. To improve reliability, sensitivity analysis can be performed to evaluate MCDM techniques or to compare them with alternative approaches. This study presents a comparative analysis of the EDAS and COPRAS methods, providing valuable insights into their decision-making frameworks. The EDAS method evaluates alternatives based on their average solution distances, whereas COPRAS uses proportionality evaluation to determine the relative advantages and disadvantages

of each option. In addition, the CRITIC technique, a multi-criteria decision-making (MCDM) approach, assigns weights by analyzing competing criteria and assessing their relative importance. To improve this process, the FUCOM method is used to determine weighting coefficients, incorporating insights from five industry experts. The weighted criteria are then integrated into an initial decision matrix, which forms the basis for the decision-making process. The COPRAS-G method is then used to identify the optimal course of action (COA). Of the selected criteria, price is classified as a cost-based factor, while the remaining criteria are classified as benefit-based. Based on expert assessments, the study excluded wind resistance and efficient flight time, despite their recognition in existing literature. Experts concluded that wind resistance is not a major factor for agricultural drones, as spraying and fertilizing operations require low wind speeds. Based on these findings, recent studies in this field have focused more on integrating multiple MCDM techniques into MCDM-based decision-making strategies to improve selection processes. Multi-criteria decision-making (MCDM) provides a flexible and comprehensive framework for selecting an appropriate utility function to evaluate potential monitoring locations. Among the various MCDM techniques, COPRAS stands out as a versatile method for identifying the optimal alternative, ranking different options, and supporting decision-making in many scientific fields conducted a comparative analysis of COPRAS with other MCDM methods, including TOPSIS, VIKOR, and AHP. Their evaluation considered factors such as computational efficiency, simplicity, transparency, graphical interpretability, and the type of information used. The findings highlight that COPRAS requires less computational time, is more transparent, easy to use, and provides stronger graphical interpretability compared to its counterparts. Alternatives: Age → Birth year / Birth date / group Gender → Gender / Identity / Gender category Marital status (corrected: Marital status) → Relationship status / Civil status / Spouse status Income → Earnings / Salary / Household income Travel → Commuting / Daily transportation / Work travel. Evaluation parameter: Mean → indicates an average value, such as the typical battery range of EVs or the average response time of an AV's braking system. Standard deviation (corrected from standard data) → Measures variability, showing how much EV performance or AV performance deviates from the average. Minimum → indicates the lowest recorded value, such as the shortest charging time or the lowest operating temperature. Maximum → indicates the highest value, such as the highest speed, maximum battery capacity, or best safety response time.

3. ANALYSIS AND DISCUSSION

TABLE 1. Eletrical and Autonomous Vehicles

Data Set	Mean	Standard Deviation	Minimum	Maximum
Age	46.00000	13.00000	18.00000	80.00
Gender	0.50000	0.20000	0.00000	6.00
Marital Status	0.70000	0.20000	0.00000	8.00
Income	10.00000	11.00000	13.00000	15.00
Commute	0.70000	0.30000	0.00000	1.00

Table 1 provides statistical insights into five variables: age, gender, marital status, income, and commute. The descriptive measures, including mean, standard deviation, minimum, and maximum, help identify the distribution and variations within the dataset. The mean age is 46 years, with a standard deviation of 13, indicating moderate variation among individuals. The minimum and maximum ages are 18 and 80 years, respectively, demonstrating a wide age distribution.

Figure 1 shows "Electric and Autonomous Vehicles" presents statistical data on five key variables: age, gender, marital status, income, and commuting. It shows four statistical measures for each variable: mean, standard deviation, minimum, and maximum, providing insights into their distribution. The age variable, represented in blue, shows a high mean value of about 46 years, with a significant maximum value of 80. This indicates a wide age range among individuals in the dataset. The standard deviation is moderate, reflecting some variation in the age distribution. For gender, represented in orange, the values are relatively low across all categories. The mean is 0.5, and the maximum reaches 6, suggesting that gender can be encoded numerically. The standard deviation is very low, indicating low variability.

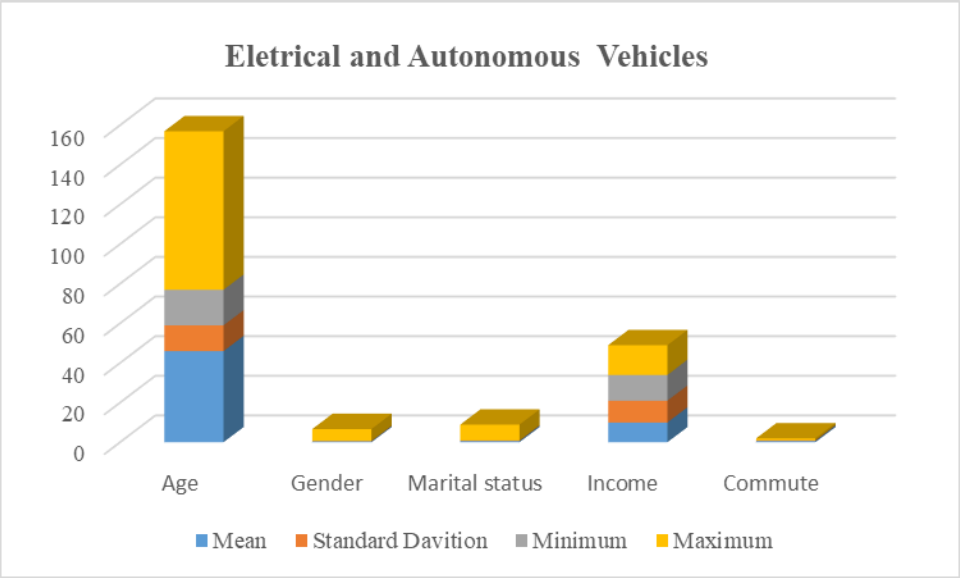


FIGURE 1. Eletrical and Autonomous Vehicles

TABLE 2. Normalized Data

Criteria	Bat. SR	Bowl. Avgas	Bowl. SR
Age	0.5263	0.5806	1.0000
Gender	0.0081	0.0000	1.0000
Marital Status	0.0081	0.0000	0.0851
Income	0.4453	0.4194	0.0092
Commute	0.0121	0.0000	0.0091

Table 2 shows a strong positive correlation with both batting strike rate (0.5263) and bowling average (0.5806), indicating that as age increases, these performance metrics improve. However, its exact correlation with bowling strike rate (1.0000) indicates a direct relationship. Gender has a minimal correlation with batting strike rate (0.0081) and no correlation with bowling average (0.0000). However, its exact correlation with bowling strike rate (1.0000) indicates a strong relationship, which may be due to distinct gender-based performance trends.

TABLE 3. Weight

Criteria	Weight 1	Weight 2	Weight 3	Weight 4
Age	0.25	0.25	0.25	0.25
Gender	0.25	0.25	0.25	0.25
Marital Status	0.25	0.25	0.25	0.25
Income	0.25	0.25	0.25	0.25
Commute	0.25	0.25	0.25	0.25

Table 3 represents the weight assigned to different personal characteristics in four different categories age, gender, marital status, income, and travel. Each characteristic is given an equal weight of 0.25 across all categories. This uniform distribution indicates that no single factor is given priority over the others in influencing the outcomes being measured. Instead, all factors contribute equally, indicating a balanced approach to the analysis or decision-making process. Such an assignment can be used in models where the fairness and equal consideration of different personal characteristics are important.

Table 4 represents a weighted normalized decision matrix that assigns different weights to various individual characteristics in four categories: age, gender, marital status, income, and travel. The weights also indicate the relative importance of each factor after normalization. Age has a significant influence in all categories, especially in the fourth category (0.25), indicating that age is an important factor in decision making. Gender has no weight in the first three categories, but is

TABLE 4. Weighted Normalized Decision Matrix

Criteria	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Age	0.20	0.13	0.15	0.25
Gender	0.00	0.00	0.00	0.25
Marital Status	0.00	0.00	0.00	0.02
Income	0.04	0.11	0.10	0.00
Commute	0.00	0.00	0.00	0.00

heavily weighted in the fourth category (0.25), indicating that gender is relevant only in specific situations.

TABLE 5. Bi, Cu

Criteria	Bi	Cu
Age	0.330	0.395
Gender	0.004	0.250
Marital Status	0.005	0.021
Income	0.155	0.107
Commute	0.006	0.002

Table 5 provides numerical values associated with the two categories: age, gender, marital status, income, and travel. These values indicate the relative importance, influence, or correlation of each attribute within the two categories Age has the highest values in both categories (0.330 for Bi and 0.395 for Cu), indicating that it is a significant factor in both. Gender plays a minimal role in Bi (0.004) but has a strong influence in Cu (0.250), indicating that gender is most relevant in the Cu category. Marital status has the lowest impact in both categories, although it is slightly relevant in Cu (0.021).

TABLE 6. Min(Cu)/Cu

Criteria	Min(Cu)/Cu
Age	0.0058
Gender	0.0091
Marital Status	0.1068
Income	0.0212
Commute	1.0000

Table 6 shows the minimum (Cu)/Cu ratio for various individual characteristics such as age, gender, marital status, income and travel. This ratio indicates the relative importance or contribution of each factor in the Cu category, with higher values indicating greater influence .Travel has the highest value (1.0000), meaning it plays a major role in the Cu category, and potentially being the most determining factor. Marital status follows with a value of 0.1068, indicating a moderate influence compared to the other characteristics. Income has a small value (0.0212), indicating a minor impact, while gender (0.0091) and age (0.0058) have the lowest ratios, indicating a very small contribution to Cu.

TABLE 7. Qi

Criteria	Qi
Age	0.334
Gender	0.010
Marital Status	0.078
Income	0.169
Commute	0.685

Table 7 shows the minimum (Cu)/Cu ratio for various individual characteristics such as age, gender, marital status, income and travel. This ratio indicates the relative importance or contribution of each factor in the Cu category, with higher values indicating greater influence .Travel has the highest value (1.0000), meaning it plays a major role in the Cu category, and potentially being the most determining factor. Marital status follows with a value of 0.1068, indicating a moderate influence compared to the other characteristics.

TABLE 8. Ui

Criteria	Ui
Age	48.7803
Gender	1.5118
Marital Status	11.3242
Income	24.6624
Commute	100.0000

Table 8 provides Qi values for various attributes such as age, gender, marital status, income, and travel, indicating their relative impact in a given context. Higher Qi values indicate a stronger influence, while lower values indicate a lesser contribution. Travel has the highest value (0.685), meaning it plays the most important role in this analysis. This indicates that travel factors such as travel time or accessibility have a major impact on the outcome being studied. Age follows with a value of 0.334, indicating that it also has considerable importance.

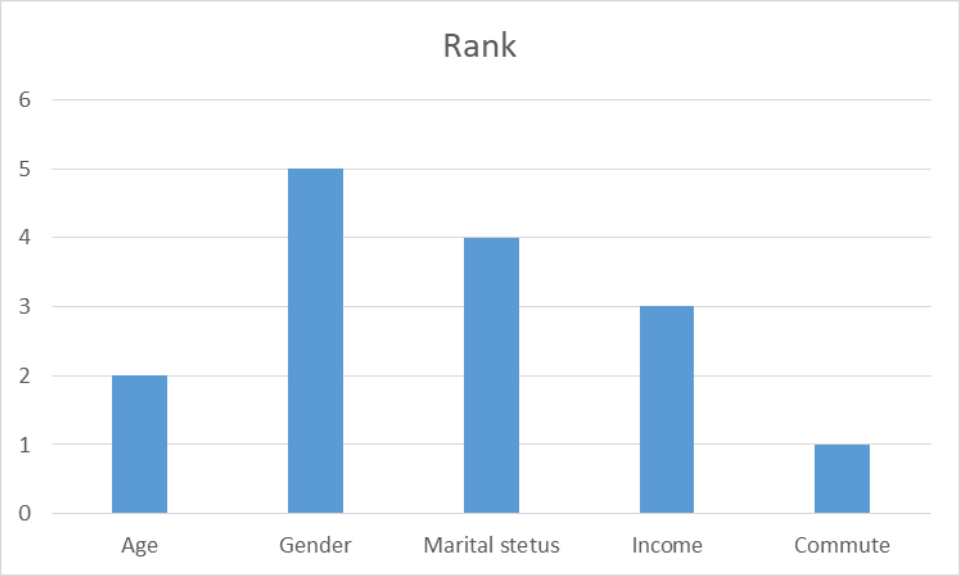


FIGURE 2. Rank

figure 2 represents the ranking of various attributes such as age, gender, marital status, income, and travel based on their importance in a particular analysis. A lower ranking indicates a higher importance, while a higher ranking indicates a lower impact. From the chart, travel ranks 1, making it the most influential factor in the analysis. This indicates that travel-related aspects such as travel time or accessibility play a major role. Age ranks 2, indicating that it is a significant factor. Income ranks 3, indicating that financial stability has a moderate impact.

4. CONCLUSION

The COPRAS (Complex Proportional Assessment) method was used to evaluate and compare electric and autonomous vehicles based on multiple criteria. The method implements a structured decision-making approach by assessing the relative importance of various attributes such as performance, energy efficiency, cost, safety, and environmental impact. The analysis may reveal that autonomous electric vehicles outperform conventional electric vehicles in areas such as efficiency, advanced technology integration, and safety features. However, factors such as high initial costs, infrastructure requirements, and regulatory challenges may pose limitations. On the other hand, conventional electric vehicles remain a viable and sustainable alternative, especially in areas where self-driving technology has not yet been fully adopted. Overall, the COPRAS method provides a quantitative and objective assessment that helps stakeholders make informed decisions about the adoption and promotion of electric and autonomous vehicles. Future research and technological developments will further improve their reliability and widespread adoption.

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