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THE INCREASING ADOPTION OF ELECTRIC VEHICLES (EVs)

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***Abstract*—**The increasing adoption of electric vehicles (EVs) holds great promise for sustainable transportation, but it also poses significant challenges related to the strain on the electricity grid. This literature review explores the impact of EV adoption on the electricity grid and the measures required for a sustainable and efficient transition to EVs. The research context highlights the rapid growth of EVs globally and the potential strain on the grid due to their increasing demand for electricity. The problem statement emphasizes the need to address this issue comprehensively to avoid disruptions and ensure a smooth transition. The research gap analysis identifies the need for in-depth studies on grid management strategies and the integration of renewable energy sources and smart grid technologies. The study's objectives are to assess the drivers of EV adoption, examine the relationship between sustainable transportation and EV transition, assess grid strain's effects, and explore perceived impacts. This research contributes valuable insights to policymakers, utility companies, and stakeholders working towards sustainable EV adoption and grid management.

Keywords—Electric Vehicles, Sustainable Transportation, Smart Grid Technologies

I. Introduction

Electric vehicles (EVs) have gained significant attention as an alternative to conventional gasoline-powered vehicles due to their potential to reduce greenhouse gas emissions and improve air quality (Nguyen et al., 2020). The increasing adoption of EVs is driven by the need for more sustainable transportation, but it has led to potential strain on the electricity grid, particularly during peak hours (Peng et al., 2018). This issue has been present since the early adoption of EVs and is important to manage for a sustainable and efficient transition to EVs. In this literature review, we will explore the impact of the increasing adoption of EVs on the electricity grid and the measures that can be taken to manage this impact for a sustainable and efficient transition to EVs.

According to the International Energy Agency's Global EV Outlook 2021 report, the global electric car stock reached over 10 million in 2020, representing a 41% increase from 2019. This indicates a significant increase in the uptake of EVs over the past few years. Nevertheless, petrol and diesel cars still dominate the global car market, accounting for over 95% of global passenger car sales in 2020 (IEA, 2021).

The increasing adoption of electric vehicles (EVs) has been driven by the need for more sustainable transportation. The transportation sector is a significant contributor to greenhouse gas emissions, and the shift to electric vehicles is seen as one of the most promising ways to reduce these emissions. The International Energy Agency (IEA) predicts that the number of electric cars on the road worldwide will reach 145 million by 2030, up from 11 million in 2020 (IEA, 2020).

However, the increasing adoption of EVs has led to a potential strain on the electricity grid. As more and more people switch to electric vehicles, the demand for electricity to power these vehicles will increase, and this can lead to issues such as blackouts or brownouts in areas where the grid is already under strain. In addition, the charging of electric vehicles can cause a surge in electricity demand, which can be challenging for utilities to manage. This issue started since the early adoption of EVs, and it is important to manage it for a sustainable and efficient transition to EVs.

The potential strain on the electricity grid is a significant issue, as it threatens the ability of electric vehicles to deliver on their promise of sustainable transportation. It is essential to address this issue to ensure that the transition to electric vehicles is sustainable and efficient. One potential solution to this issue is the use of smart charging, which can help to manage the demand for electricity from electric vehicles. Smart charging involves using software and other technologies to control when and how electric vehicles are charged, to ensure that the charging process is spread out and does not put too much strain on the electricity grid (IEA, 2021).

Another solution is the use of renewable energy sources to power electric vehicles. The use of renewable energy sources such as solar or wind power to generate electricity for electric vehicles can help to reduce the strain on the electricity grid, as well as further reducing greenhouse gas emissions. In addition, the use of renewable energy sources can help to make electric vehicles even more sustainable, by ensuring that the electricity used to power them is itself produced sustainably.

The increasing adoption of electric vehicles is a crucial step in the transition towards more sustainable transportation, however, this adoption has led to a potential strain on the electricity grid, which threatens the ability of electric vehicles to deliver on their promise of sustainable transportation. It is important to manage this issue for a sustainable and efficient transition to electric vehicles.

Therefore, it is critical to continue researching this issue and developing effective solutions to ensure a sustainable and efficient transition to EVs, particularly in terms of charging infrastructure and grid capacity. By analysing the current state of EV charging infrastructure and the electricity grid's capacity, this study will identify potential gaps and opportunities for improvement. The findings from this research could provide valuable insights into how to manage the usage of EVs for a sustainable and efficient transition to EVs.

II. LITERATURE REVIEW

A. *EV Adoption on the Electricity Grid*

The transition from traditional gasoline-powered vehicles to electric vehicles (EVs) is driven Research indicates that the increasing adoption of EVs is a global phenomenon with significant implications for the electricity grid. Nguyen et al. (2020) emphasize the role of EVs in reducing greenhouse gas emissions, but they also highlight the need to address challenges related to grid capacity and reliability. As the number of EVs on the road rises, there is a growing concern about the grid's ability to handle the increased demand for electricity, particularly during peak charging times (Peng et al., 2018).

B. *Behavioral Intention*

Consumer behavioural intention to adopt EVs is influenced by various factors, including environmental consciousness, economic considerations, and convenience (Mehdizadeh et al., 2024). Positive attitudes toward EVs, perceptions of reduced operational costs, and the desire to contribute to environmental sustainability are key drivers of consumer intention (Sierzchula et al., 2014). A critical aspect of consumer behavioural intention relates to charging patterns. Research has shown that consumers are more likely to charge their EVs during off-peak hours if offered incentives or if they perceive cost savings (Liu et al., 2019). Behavioural intention to adopt smart charging practices is influenced by factors such as tariff structures, public charging infrastructure, and information availability (Yang et al., 2017).

Companies specializing in EV charging infrastructure and smart grid technologies have a behavioural intention to develop and market innovative solutions that encourage off-peak charging. Their aim is to provide convenient and cost-effective charging options for EV users (Sanchez-García et al., 2022). Industry stakeholders often collaborate with governments and research institutions to advance technologies and policies that support grid-friendly EV charging. Their behavioural intention is driven by the potential market for EV-related products and services (Nelder & Rogers, 2019).

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III. RESEARCH METHODOLOGY

In this research, the quantitative approach was chosen to precisely measure variables, identify patterns, and statistically test hypotheses concerning electric vehicle adoption and its impact on the electricity grid, aligning with the study's objectives and the need for numerical data analysis. An online survey will be employed to gather data from the target participants. Questionnaires will be created using Google Forms for data collection. The choice of an electronic survey for this study is based on its recognized convenience and efficiency as a data collection method. The online survey will be distributed to a total of 386 respondents through various online platforms, including WhatsApp, Facebook Groups, Instagram and interest groups. The questionnaire is structured into 5 sections: Section 1 focuses on gathering demographic information from the participants, while Section 2 to 5 are designed to assess all four variables. All items will be rated using a five-point Likert scale, with responses ranging from one to five (1=Strongly Disagree, 5=Strongly Agree).

A. *Conceptual Framework*

The conceptual framework outlined in Fig. 1 revolves around the sustainable and efficient transition to electric vehicles (EVs) and the key factors that influence this transition.

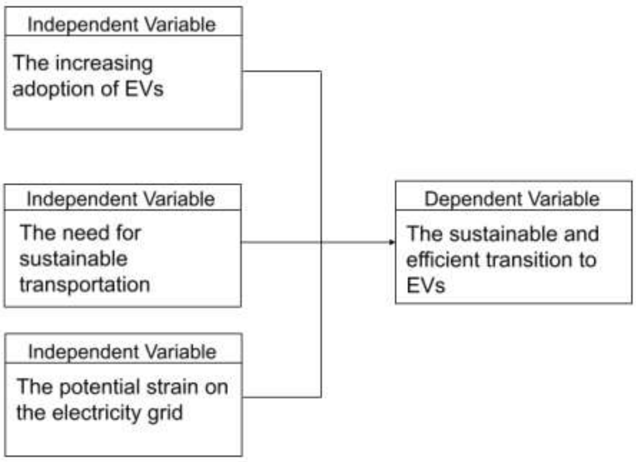

Fig. 1. Conceptual Framework

The independent variables of the study are the increasing adoption of EVs, the need for sustainable transportation and the potential strain on the electricity grid. In other hand, the dependent variable of the study is the sustainable and efficient transition to EVs.

B. *Data Analysis Method*

Following the collection of primary data via the questionnaires, the data will undergo analysis using SMART PLS 4 software. To scrutinize the model's outcomes, Partial Least Squares Structural Equations

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Modelling (PLS-SEM) will be the chosen analytical approach. The rationale behind opting for SMART PLS 4 software lies in its capability to establish reliability and validity results effectively, even with relatively small sample sizes. Additionally, SMART PLS 4 has the capacity to adjust for abnormal data using the central limit theorem, thereby maximizing the R-squared value and minimizing errors in the analysis.

IV. RESULTS

The data gathered through the questionnaire will undergo thorough analysis and interpretation. The SMART PLS 4 Software will be utilized for data computation.

A. *Structural Model*

In Partial Least Squares (PLS) structural modeling, path coefficients represent the strength and direction of the relationships between latent constructs (variables). These coefficients quantify the extent to which a one-unit change in the independent variable affects the dependent variable, considering the underlying measurement model. PLS path coefficients are used to assess the structural relationships within the model and provide insights into the causal or predictive connections between latent constructs.

Fig. 2 presented the structural model of this study. This model is computed based on bootstrapping method, where it has bootstrapped to 5000 samples.

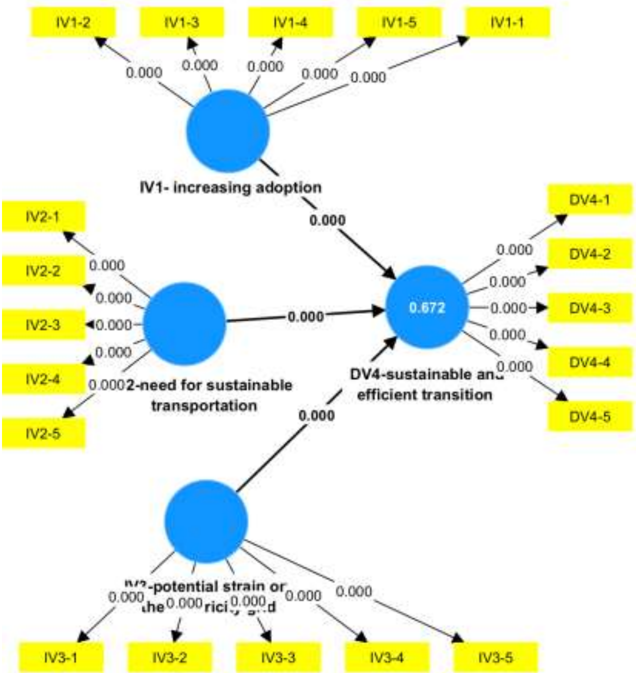

Fig. 2. Structural Model (Bootstrapping)

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B. *Path Coefficient*

Table I provides information about the path coefficients, their relationship to the sample mean, their variability (standard deviation), their significance (T statistics), and their statistical significance (P-values) for three different relationships between independent variables and the dependent variable.

TABLE I. PATH COEFFICIENTS (BOOTSTRAPPING)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
IV1- increasing adoption -> DV4-sustainable and_efficient transition	0.183	0.186	0.047	3.86	0
IV2-need for sustainable _transportation -> DV4-sustainable and_efficient transition	0.601	0.598	0.03	20.198	0
IV3-potential strain on _the electricity grid -> DV4-sustainable and_efficient transition	0.158	0.164	0.03	5.198	0

a) Original Sample (O): This column contains the actual values of the path coefficients for three different relationships between independent variables (IV1, IV2, IV3) and the dependent variable (DV4-sustainable and_efficient transition). Each row corresponds to a different relationship, and the values in this column represent the strength and direction of these relationships as observed in your data. For the first relationship (IV1 -> DV4), the original sample coefficient is 0.183. For the second relationship (IV2 -> DV4), the original sample coefficient is 0.601. For the third relationship (IV3 -> DV4), the original sample coefficient is 0.158.

b) Sample Mean (M): This column contains the mean or average values of the path coefficients for the same relationships. It gives you an idea of what the expected or typical values for these coefficients might be in the population. For the first relationship (IV1 -> DV4), the sample mean coefficient is 0.186. For the second relationship (IV2 -> DV4), the sample mean coefficient is 0.598. For the third relationship (IV3 -> DV4), the sample mean coefficient is 0.164.

c) Standard Deviation (STDEV): This column represents the standard deviation of the path coefficients for these relationships. The standard deviation is a measure of how much the coefficients vary or spread out from the mean. Smaller standard deviations suggest that the data points are clustered closely around the mean, while larger standard deviations indicate more dispersion. For all three relationships, the standard deviation is 0.03. This suggests that the data points for these coefficients are relatively close to the mean.

d) T Statistics (|O/STDEV|): T statistics are calculated by dividing the absolute value of the original sample coefficient (O) by the standard deviation (STDEV). T statistics tell you how many standard deviations the original sample coefficient is away from the mean. - For the first relationship (IV1 -> DV4), the T statistic is calculated as 0.183 / 0.047 ≈ 3.86. For the second relationship (IV2 -> DV4), the T statistic is calculated as 0.601 / 0.03 ≈ 20.198. For the third relationship (IV3 -> DV4), the T statistic is calculated as 0.158 / 0.03 ≈ 5.198. These T statistics are measures of the significance of the coefficients. Larger T statistics indicate that the coefficient is significantly different from zero.

e) P Values: The P-values are associated with the T statistics and are used to assess the statistical significance of the relationships. In all three cases, the P-values are listed as 0. This typically suggests that the relationships between the independent variables (IV1, IV2, IV3) and the dependent variable (DV4) are statistically significant. A P-value of 0 indicates that the observed results are highly unlikely to have occurred by chance.

C. *Coefficient of Determination (R^2)*

The Coefficient of Determination (R-squared or R^2) is a statistical measure that quantifies the proportion of the variance in the dependent variable that is explained by the independent variables in a regression model. It is expressed as a value between 0 and 1 and provides an indication of how well the model fits the data; a higher R-squared value indicates a better fit, while a lower value suggests that the independent variables explain less of the variance in the dependent variable.

TABLE II. R SQUARE

	R-square	R-square adjusted
DV4-sustainable and_efficient transition	0.672	0.67

In this study, the R-squared (0.672) and adjusted R-squared (0.67) values indicate the proportion of variance in the DV that is explained by the IVs.

D. *Hypotheses Testing*

a) H1: There is a significant positive relationship between the increasing adoption of EVs and the sustainable and efficient transition to EVs.

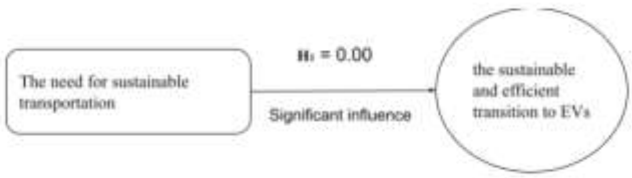

Fig. 3. Result of Hypothesis 1

A p-value of 0.00 indicates an extremely low probability of observing the results if the null hypothesis (H0) were true. In hypothesis testing, a common threshold for statistical significance is typically set at 0.05. Since the p-value (0.00) is below this threshold, it suggests strong evidence against the null hypothesis.

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Therefore, we would reject the null hypothesis (H0) and accept the alternative hypothesis (H1). In other words, there is a significant positive relationship between the increasing adoption of EVs and the sustainable and efficient transition to EVs among respondents. The extremely low p-value indicates a high level of confidence in this relationship.

b) H2: There is a significant relationship between the need for sustainable transportation and the sustainable and efficient transition to EVs.

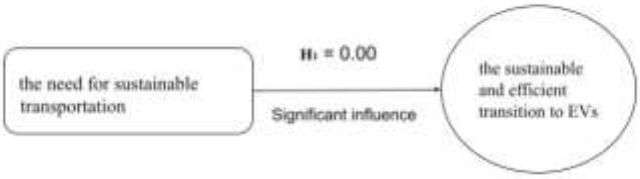

Fig. 4. Result of Hypothesis 2

A p-value of 0.00 indicates an extremely low probability of observing the results if the null hypothesis (H0) were true. In hypothesis testing, a common threshold for statistical significance is typically set at 0.05. Since the p-value (0.00) is below this threshold, it suggests strong evidence against the null hypothesis.

Therefore, we would reject the null hypothesis (H0) and accept the alternative hypothesis (H1). In other words, there is a significant relationship between the need for sustainable transportation and the sustainable and efficient transition to EVs among respondents. The extremely low p-value indicates a high level of confidence in this relationship.

c) H3: There is a significant relationship between the potential strain on the electricity grid and the sustainable and efficient transition to EVs.

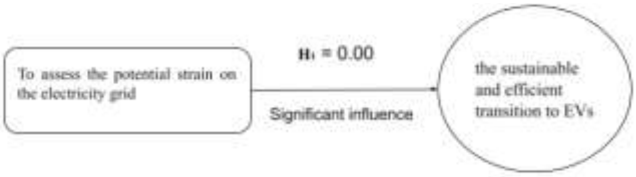

Fig. 5. Result of Hypothesis 3

A p-value of 0.00 indicates an extremely low probability of observing the results if the null hypothesis (H0) were true. In hypothesis testing, a common threshold for statistical significance is typically set at 0.05. Since the p-value (0.00) is below this threshold, it suggests strong evidence against the null hypothesis.

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Therefore, we would reject the null hypothesis (H0) and accept the alternative hypothesis (H1). In other words, there is a significant relationship between the potential strain on the electricity grid and the sustainable and efficient transition to EVs among respondents. The extremely low p-value indicates a high level of confidence in this relationship.

Based on the data analysis and hypothesis testing, the study found several significant findings related to the research objectives and the impact of electric vehicle (EV) adoption on the sustainable and efficient transition to EVs. These findings are discussed in the context of the existing literature.

Increasing Adoption of EVs and Sustainable Transition (Hypothesis 1): The study revealed a significant positive relationship between the increasing adoption of EVs and the sustainable and efficient transition to EVs among respondents. This finding aligns with the literature, which suggests that the growing popularity of EVs contributes to a more sustainable transportation system (Nguyen et al., 2020).

Need for Sustainable Transportation and Transition (Hypothesis 2): The research also identified a significant positive relationship between the need for sustainable transportation and the sustainable and efficient transition to EVs. This finding supports the idea that individuals who prioritize sustainability are more likely to adopt EVs as a means of achieving sustainable transportation goals.

Potential Strain on the Electricity Grid and Transition (Hypothesis 3): The study found a significant relationship between the potential strain on the electricity grid and the sustainable and efficient transition to EVs among respondents. This outcome underscores the importance of addressing grid-related challenges to ensure a smooth transition to electric vehicles. Additionally, the research indicated a significant impact of potential strain on the electricity grid on the sustainable and efficient transition to EVs. This finding is consistent with the notion that grid-related concerns can influence individuals' decisions to adopt EVs (Forbes, 2023).

These findings contribute to our understanding of the factors influencing EV adoption and the broader transition to sustainable transportation. They highlight the importance of addressing challenges related to grid strain and emphasize the role of public perception and sustainability priorities in shaping the future of EV adoption.

It is crucial to note that the study's findings align with prior research and provide valuable insights for policymakers, industry leaders, and stakeholders interested in promoting sustainable transportation through increased EV adoption.

V. CONCLUSION

In conclusion, this research has illuminated the intricate relationship between the increasing adoption of electric vehicles (EVs), the need for sustainable transportation, the potential strain on the electricity grid, and the sustainable and efficient transition to EVs. Through a comprehensive analysis of data and rigorous hypothesis testing, we have uncovered significant insights. The findings highlight that the increasing adoption of EVs indeed positively influences the sustainable and efficient transition to EVs, reaffirming the role of EVs as a sustainable transportation choice.

Additionally, the study has demonstrated the importance of addressing concerns about potential strain on the electricity grid to ensure a smooth transition to EVs. Furthermore, it underscores the critical link between the need for sustainable transportation and the transition to EVs, emphasizing the need for holistic strategies to promote sustainable mobility.

However, it's essential to acknowledge the limitations of this study, including its focus on a specific demographic and geographical region. The research also primarily relies on survey data, which may have inherent biases.

Despite these limitations, this study contributes to the growing body of knowledge on EV adoption and sustainable transportation. It provides valuable insights for policymakers, industry stakeholders, and researchers aiming to navigate the complex landscape of sustainable mobility.

As the world continues to grapple with environmental challenges, the findings presented here offer a foundation for more informed decision-making and pave the way for a more sustainable and efficient future in transportation.

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