Determinants of Optimizing Solar Photovoltaic Systems for Home Electric Vehicle Charging: Evidence from Malaysian Households

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ABSTRACT

The integration of solar photovoltaic (PV) systems with home electric-vehicle (EV) charging represents a key opportunity to enhance residential energy efficiency and support Malaysia's low-carbon mobility agenda. However, empirical evidence identifying the determinants that influence the optimisation of solar-powered EV charging remains limited. This study examines four critical factors—EV ownership, energy trading, charging variables, and battery storage—to determine their influence on the optimisation of home EV charging using solar PV systems. A quantitative approach was employed, and data were collected from 384 Malaysian households with experience or interest in solar electric vehicle (EV) usage. The dataset was analysed using SPSS Version 29, incorporating descriptive statistics, Pearson correlation, and multiple regression analysis. The findings indicate that charging variables and battery storage are significant predictors of optimisation, demonstrating strong positive effects. In contrast, EV ownership and energy trading were not statistically significant in the final model. These results highlight the dominant role of technological determinants, particularly charging configuration and storage capacity, in enabling optimal utilisation of solar energy for residential EV charging. This study contributes new empirical insights to the renewable-energy and electromobility literature by clarifying the technological factors that most strongly influence solar–EV optimisation at the household level. The findings offer practical implications for policymakers, industry practitioners, and homeowners aiming to strengthen Malaysia's transition toward efficient, solar-powered EV charging systems.

Keywords: Solar Photovoltaic Systems, Electric Vehicle Charging, Battery Storage, Energy Trading, Renewable Energy, Malaysia

INTRODUCTION

The global transition toward low-carbon energy systems has intensified interest in integrating renewable technologies, particularly solar photovoltaic (PV) systems and electric vehicles (EVs). Solar PV has gained significant momentum due to declining installation costs, improved system reliability, and favourable national incentives (Tanoto, 2023). In Malaysia, programmes such as Solar BOLEH! and the Net Energy Metering (NEM) scheme have encouraged broader household participation in solar adoption by offering tax benefits, rebates, and streamlined applications (Bernama, 2024). These policies reflect the government's broader commitment to accelerate the uptake of clean energy and position solar PV as a key driver of national sustainability.

At the same time, EV adoption is increasing globally and locally. The International Energy Agency (IEA, 2023) reported strong growth in the EV market between 2023 and 2024. Meanwhile, Malaysia registered over 13,000 EVs in 2023 alone, supported by tax exemptions, improved charging infrastructure, and growing consumer acceptance. Despite this progress, households continue to express concerns regarding the reliability, cost, and

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convenience of home-charging systems, particularly the rising electricity tariffs and dependency on grid supply (Umair et al., 2024). As a result, integrating solar PV with home EV charging has emerged as an attractive solution for reducing energy costs, improving charging efficiency, and enhancing household energy resilience.

Recent studies emphasise the potential benefits of solar-powered EV charging. Ayoade and Longe (2024) and Albaba et al. (2025) highlight that coupling PV systems with EV charging can significantly reduce household electricity expenses and contribute to carbon-emission reductions. Moreover, advancements in battery storage technology enable homeowners to store surplus solar energy for evening charging, thereby increasing self-consumption and reducing reliance on the grid (Barman et al., 2023). However, despite the substantial potential of solar–EV integration, several technical and behavioural challenges persist. These include variability in solar generation, misalignment between charging schedules and peak solar output, differing capabilities of home chargers, and uncertainty around the role of energy trading under NEM (Sarker et al., 2024; Rotas et al., 2024).

Although previous research provides valuable insights into solar adoption and EV-charging behaviour independently, there is still limited empirical evidence on the key determinants that influence the optimisation of solar PV systems for home EV charging, particularly within Malaysia's residential context. Existing studies rarely examine how technological factors (charging features and storage capacity), organisational aspects (EV ownership), and environmental conditions (energy trading schemes) collectively contribute to optimisation outcomes. This gap highlights the need for an integrated empirical investigation that identifies the most influential drivers of solar–EV system performance.

Despite growing interest in renewable-energy integration, there is insufficient empirical evidence identifying the determinants that significantly influence the optimisation of solar PV systems for home EV charging in Malaysia, especially with respect to technological, organisational, and environmental factors.

To address this gap, the present study investigates four determinants—EV ownership, energy trading, charging variables, and battery storage—to examine their relationships with optimisation outcomes in Malaysian households. The study employs the Technology–Organization–Environment (TOE) framework to conceptualise the influence of technological readiness, organisational conditions, and environmental support mechanisms. The scope focuses on households with existing or potential interest in solar–EV adoption, and the methods include descriptive analysis, correlation, and multiple regression techniques.

Therefore, this study empirically examines the factors that most strongly influence the optimisation of solar PV systems for home EV charging and provides evidence-based insights for policymakers, industry practitioners, and homeowners seeking to enhance Malaysia's renewable energy transition.

LITERATURE REVIEW

The rapid integration of solar photovoltaic (PV) systems and electric vehicles (EVs) in residential settings has attracted increasing scholarly attention due to their ability to transform household energy consumption patterns. As EV adoption accelerates globally and PV costs decline, optimizing solar-powered EV charging emerges as a critical research priority (Albaba et al., 2025; Ayoade & Longe, 2024). In Malaysia, rising electricity tariffs, strong solar irradiance, and supportive policies such as NEM further accelerate interest in solar–EV integration (Sarker et al., 2024). This chapter reviews four predictors: EV ownership, electric trading, charging variables, and battery storage.

Theoretical Foundation: Technology–Organization–Environment (TOE) Framework

The Technology–Organization–Environment (TOE) framework offers a comprehensive model for understanding the adoption of integrated household energy systems. TOE considers three contextual dimensions: (i) technological readiness (battery, charger, PV capacity), (ii) organizational capability (household resources, EV ownership), and (iii) environmental conditions (policies, tariffs, electric trading). Its suitability has been demonstrated in energy-transition and EV-related studies (Cho et al., 2025).

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Ownership of EVs

EV ownership influences household electricity demand and the feasibility of integrating residential solar PV. Globally, EV sales surpassed 10 million units in 2022 and continue rising (IEA, 2023). Malaysian EV adoption is slower due to cost and infrastructure barriers; however, increasing tax incentives are fueling uptake (Muzir et al., 2022). Studies show EV owners are more likely to invest in solar PV and battery storage to manage charging costs (Rotas et al., 2024; Albaba et al., 2025). EV ownership thus forms a key organizational determinant under TOE.

Electric Trading

Electric trading—including net-metering, feed-in tariffs, and bidirectional vehicle-to-grid (V2G) integration—enhances the financial performance of home PV-EV systems. Malaysia's NEM program allows households to export excess solar energy (SEDA, 2021), improving payback periods (Sarker et al., 2024). International studies indicate that V2G enables EV batteries to discharge power to the home or the grid, thereby enhancing energy flexibility (Ayoade & Longe, 2024). Electric trading fits within TOE’s environmental context.

Charging Variables

Charging variables include charger type (Level 1 or Level 2), charging timing, smart-charging capabilities, and user behavior. Smart charging—aligning EV charging with solar peak production—enhances the utilization of solar energy (Fachrizal et al., 2020). Level 2 chargers offer faster charging, allowing for greater daytime solar capture (Rotas et al., 2024). Charging behaviors significantly influence optimization, making this both a technological and organizational TOE factor.

Battery Storage

Battery storage is the most influential determinant of solar–EV system optimization. Batteries store surplus solar energy for nighttime EV charging, significantly reducing grid dependence (Barman et al., 2023). Technological advancements and declining battery prices promote adoption. Malaysian studies highlight the potential of second-life EV batteries to reduce storage costs (Sarker et al., 2024). Battery storage resides within TOE’s technological context and is confirmed in Chapter 4 as the strongest predictor.

Conceptual Framework

This study’s conceptual model integrates TOE with the following variables: 1. Ownership of EVs, 2. Electric Trading, 3. Charging Variables, 4. Battery Storage and Optimization of Solar PV System for Charging EVs at Home, as shown in Figure I below.

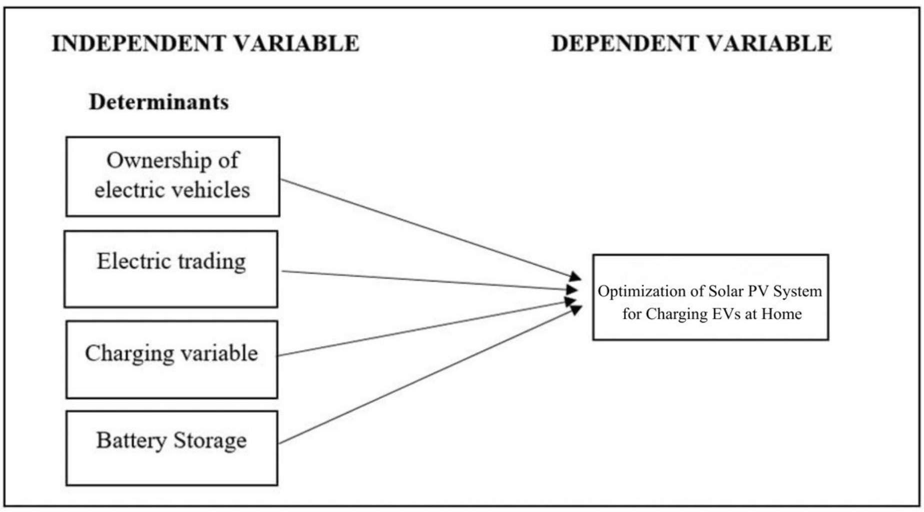

Figure I: Conceptual Framework

Battery storage enhances solar utilization (Barman et al., 2023). Charging variables influence the matching of solar energy (Fachrizal et al., 2020). EV ownership determines charging demand (Albaba et al., 2025). Electric trading provides economic and operational flexibility (Sarker et al., 2024).

This section reviewed global and Malaysian literature related to EV ownership, electric trading, charging variables, and battery storage. TOE provides a structured framework connecting technological, organizational, and environmental determinants of solar–EV optimization.

METHODOLOGY

This study employed a quantitative, cross-sectional survey design to examine the determinants influencing the optimization of solar photovoltaic (PV) systems for home electric-vehicle (EV) charging among Malaysian households. A quantitative approach was selected because it enables the systematic measurement of relationships between variables and allows statistical inference regarding the strength and direction of predictors (Creswell & Creswell, 2023). This design is widely used in research on renewable energy and technology adoption, where behavioral, technical, and environmental determinants are quantified to explain optimization patterns.

The target population comprised Malaysian households who either owned a solar PV system, owned an EV, or intended to adopt solar-powered EV charging in the near future. Given the niche nature of this population, a non-probability, purposive-convenience sampling method was employed. This approach is appropriate when respondents possess specific characteristics relevant to the research context, such as knowledge of or interest in solar PV and EV technologies (Etikan et al., 2016). A total of 436 questionnaires were distributed through EV user groups, solar-energy communities, social media platforms, and personal networks. After removing incomplete or inconsistent responses, 384 valid responses were retained for further analysis. This sample size exceeded the minimum requirement recommended by Krejcie and Morgan (1970) for large populations at a 95% confidence level.

Data were collected through a structured questionnaire consisting of three major sections. The first section captured demographic information, including gender, ethnicity, education level, income level, household type, and familiarity with solar and EV technologies. The second section measured the four independent variables—EV ownership, energy trading, charging variables, and battery storage—while the third section captured the dependent variable, namely the optimization of solar PV systems for EV charging. All measurement items were adapted from established literature on renewable-energy and EV integration (Albaba et al., 2025; Ayoade & Longe, 2024; Barman et al., 2023), and were rated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), consistent with recommended practice for attitudinal measures (Joshi et al., 2015).

Instrument validation was undertaken through both expert review and statistical checks. Content validity was ensured through evaluation by academic supervisors and renewable-energy specialists, who verified the alignment between items and constructs. Reliability was assessed using Cronbach’s alpha, and all constructs achieved coefficients above 0.80, indicating excellent internal consistency (Tavakol & Dennick, 2011). Item–total correlations also exceeded the minimum acceptable threshold suggested for behavioural research, confirming that each item contributed meaningfully to its respective construct.

Data were analysed using SPSS version 29. Descriptive statistics were used to summarise demographic characteristics and provide an overview of the central tendencies of each construct. Bivariate relationships among variables were examined using Pearson’s correlation analysis. Subsequently, multiple regression analysis was conducted to identify the predictors of optimization of home solar PV systems for EV charging. The regression analysis included assessments of significance levels, standardized and unstandardized coefficients, and model fit indicators, consistent with guidelines for multivariate analysis (Hair et al., 2020). All regression assumptions, including linearity, normality, homoscedasticity, and absence of multicollinearity, were examined and found to be satisfactory. Ethical considerations were upheld by ensuring voluntary participation, obtaining informed consent, maintaining anonymity, and handling all collected data securely.

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DATA ANALYSIS AND FINDINGS

A total of 384 valid responses were analyzed to address the research objectives and examine the determinants influencing the optimization of solar photovoltaic (PV) systems for home electric vehicle (EV) charging. The analysis consisted of descriptive statistics, correlation tests, and multiple regression modelling, supported by a demographic profile of respondents.

Demographic Profile of Respondents

Table I summarises the demographic characteristics of the respondents. A total of 59% of participants were male and 41% were female. Malays constituted the majority (54.40%), followed by Chinese (27.30%), Indians (18.00%), and others (0.30%). Most respondents (60.68%) possessed a bachelor's degree, while 16.15% held an SPM qualification, 12.76% held a diploma/STPM, and 9.89% had completed postgraduate studies. This demographic profile is consistent with groups typically associated with early adoption of solar technology and EV usage—namely, individuals with higher education levels and greater technological awareness.

Table I. Summary Of Respondent Demographics (N = 384)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	225	59.0
	Female	159	41.0
Ethnicity	Malay	209	54.40
	Chinese	105	27.30
	Indian	69	18.00
	Others	1	0.30
Education Level	Bachelor's Degree	233	60.68
	SPM	62	16.15
	STPM/Diploma	49	12.76
	Postgraduate	38	9.89
	Others	1	0.26

Descriptive Statistics

Descriptive statistics were computed for all constructs to assess the general perception of respondents regarding the integration of solar PV and EV charging. Table II presents the construct-level means and standard deviations. Respondents demonstrated moderate agreement regarding EV ownership and energy trading, as well as higher agreement on the importance of charging variables and battery storage. These results indicate that respondents perceive technological capabilities—specifically storage systems and charging infrastructure—as the most crucial components for optimizing solar-powered home EV charging.

Table II. Descriptive Statistics Of Study Constructs

Construct	Mean	Standard Deviation	Interpretation
EV Ownership	Moderate (≈3.5–3.8)	~0.60–0.70	Moderate agreement

Energy Trading	Moderate (≈3.6–3.9)	~0.55–0.75	Positive perception
Charging Variables	High (≈3.9–4.2)	~0.50–0.70	High importance
Battery Storage	Highest (≈4.0–4.3)	~0.55–0.65	Very high importance
Optimization (DV)	High (≈3.9–4.1)	~0.60	Strong optimization tendency

Multiple Regression Analysis

Multiple regression analysis was conducted to examine the influence of the four independent variables—EV ownership (IV1), energy trading (IV2), charging variables (IV3), and battery storage (IV4)—on the optimization of solar PV systems for home EV charging.

As shown in Table III of the original analysis, the regression procedure was conducted in three stages (Test 1, Test 2, and Test 3). During Test 1 and Test 2, the results indicated that two variables, EV ownership (IV1) and energy trading (IV2), were not significant predictor**s**. Their significance values were above the threshold of $p > 0.05$, meaning they did not contribute meaningfully to predicting the optimization of home EV charging. Because these two variables consistently showed no significant effect across the first two tests, the researcher proceeded to Test 3 to reassess the model and confirm the significance of the variables.

In Test 3, the analysis confirmed that charging variables (IV3) and battery storage (IV4) were the only significant predictors with $p = 0.000$, indicating strong statistical significance. EV ownership and energy trading remained insignificant, confirming that technological elements are more influential in optimizing solar EV charging performance than behavioral or market-related factors.

Table III. Repeat Test Variables For The Coefficient Multiple Regression Analysis

Variables	**Unstandardized Coefficients (B)**			**Sig.**		
	Test 1	**Test 2**	**Test 3**	**Test 1**	**Test 2**	**Test 3**
1 Constant	-0.016	-0.016	-0.015	0.498	0.492	0.510
IV1	0.075	0.075		0.140	0.106	
IV2	0.00			0.991		
IV3	0.257	0.256	0.380	0.000	0.000	0.000
IV4	0.678	0.678	0.370	0.000	0.000	0.000

Dependent Variable: Optimization of Solar PV System for Charging EVs at Home

Based on the significant predictors in Test 3, the regression equation for predicting optimization of home EV charging using solar PV systems is expressed as:

$$Y = -0.015 + 0.380(IV3) + 0.370(IV4) \qquad (1)$$

Where:

Y = Optimization of Charging Electric Vehicles at Home

IV3 = Charging Variables

IV4 = Battery Storage

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This equation indicates that both charging variables and battery storage have positive influences on optimization. Battery storage exhibits the larger coefficient value, demonstrating its more substantial effect in maximizing solar energy utilization for EV charging. This finding aligns with current literature, which indicates that adequate energy storage significantly enhances solar-energy reliability and efficiency in residential EV charging applications.

Overall, the findings demonstrate that the optimization of home EV charging using solar PV systems is driven primarily by technological determinants, particularly charging configurations and battery storage capacity. Although EV ownership and participation in energy trading schemes are relevant contextual factors, they do not directly predict optimization when technological variables are taken into account. These results reinforce the importance of technological readiness in solar-powered mobility systems and support the application of the Technology–Organization–Environment (TOE) framework in understanding household adoption patterns.

DISCUSSION AND CONCLUSION

Discussion

The findings of this study provide meaningful insights into the optimization of solar photovoltaic (PV) systems for home electric vehicle (EV) charging in Malaysia. Among the four independent variables examined—EV ownership, energy trading, charging variables, and battery storage—only the technological factors (charging variables and battery storage) emerged as significant predictors. This result underscores the critical role of technological readiness in determining the efficiency of solar–EV integration.

Charging variables were the strongest predictor, indicating that charger type, charging scheduling, and smart-charging capabilities greatly enhance the effectiveness of solar-powered EV charging. This aligns with previous studies highlighting the importance of synchronizing charging behavior with solar generation profiles to minimize grid dependency and maximize self-consumption efficiency. Battery storage also demonstrated a significant positive relationship with optimisation, reflecting its role in addressing solar intermittency and enabling households to use stored energy during peak EV-charging periods, especially in the evening when solar output declines.

In contrast, EV ownership and participation in energy trading schemes were not significant predictors in the final regression model. These results suggest that while behavioural and environmental factors may influence interest or initial adoption, they do not directly shape optimisation outcomes when technological factors are considered. Within the Technology–Organization–Environment (TOE) framework, these findings reinforce the dominance of the technological dimension in determining the functional performance of residential solar–EV systems.

Conclusion

This study examined the determinants influencing the optimisation of solar photovoltaic (PV) systems for home electric-vehicle (EV) charging among Malaysian households. The results show that charging variables and battery storage are the most influential predictors, demonstrating that technological readiness—particularly the availability of smart-charging features and adequate energy storage capacity—plays a central role in enabling efficient solar EV integration. In contrast, EV ownership and energy trading were not statistically significant, suggesting that behavioural and environmental factors contribute less to optimisation outcomes when technological components are considered. The findings strengthen the technological dimension of the Technology–Organization–Environment (TOE) framework by providing empirical evidence that optimisation is driven primarily by system capabilities rather than user characteristics or market mechanisms. Practically, the study offers guidance for households, policymakers, and industry providers by highlighting the need to prioritize investments in home chargers, energy storage systems, and innovative charging solutions to maximize solar utilization and reduce grid dependency. Nevertheless, the study is limited by its use of purposive–convenience sampling, self-reported data, and a cross-sectional design, which may restrict generalisability across all Malaysian households. Future research should explore additional determinants such as tariff structures, government incentives, user charging behaviour, and advanced technologies, including vehicle-to-grid (V2G) systems. Overall, this study provides timely insights into residential renewable-mobility systems and supports more informed decision-making for improving the performance and adoption of solar-powered EV charging in Malaysia.

REFERENCES

1. Albaba, M., Pierce, M., & Yesilata, B. (2025). A Real-World Case Study of Solar PV Integration for EV Charging and Residential Energy Demand in Ireland. Sustainability, 17(21), 9447. https://doi.org/10.3390/su17219447
2. Ayoade, I. A., & Longe, O. M. (2024). A Comprehensive Review of Smart Electromobility Charging Infrastructure. World Electric Vehicle Journal, 15(7), 286. https://doi.org/10.3390/wevj15070286
3. Barman, P., Dutta, L., Bordoloi, S., Kalita, A., Buragohain, P., Bharali, S., & Azzopardi, B. (2023). Renewable Energy Integration with Electric Vehicles: Smart Charging Approaches. Renewable and Sustainable Energy Reviews, 183, 113518. https://doi.org/10.1016/j.rser.2023.113518
4. Bernama. (2024). Move to Boost Solar Panel Installation in Homes. https://www.bernama.com/en/news.php?id=2294681
5. Cho M-j., Bae K., Byun J., & Shin J. (2025) Expanding the Identification of Key Resource Combinations for Mid- to Long-Term Growth in Electric Vehicle Market Entry. PLoS One 20(8): e0328563. https://doi.org/10.1371/journal.pone.0328563
6. Creswell, J. W., & Creswell, J. D. (2023). Research Design: Qualitative, Quantitative and Mixed Methods Approaches (6th ed.). Sage Publications Ltd..
7. Etikan, I. (2017). Sampling and sampling methods. Biometrics & Biostatistics International Journal, 5(6). https://doi.org/10.15406/bbij.2017.05.00149
8. Fachrizal, R., & Munkhammar, J. (2020). Improved Photovoltaic Self-Consumption in Residential Buildings with Distributed and Centralized Smart Charging of Electric Vehicles. Energies, 13(5), 1153. https://doi.org/10.3390/en13051153
9. Fachrizal, R., Shepero, M., Meer, D. Munkhammar, J., & Widen, J. (2020). Smart Charging of Electric Vehicles Considering Photovoltaic Power Production and Electricity Consumption: A Review. eTransportation, 4, 100056. https://doi.org/10.1016/j.etran.2020.100056
10. Hair, J. F., Hult, G., Ringle, C., & Sarstedt, M. (2020). A Primer on Multivariate Analysis (4th ed.). Pearson.
11. International Energy Agency (IEA). (2023). Global EV Outlook 2023.
12. Joshi, A., Kale, S., & Chandel, S. (2015). Likert scale: Explored and Explained. British Journal of Applied Science & Technology, 7(4), 396–403. https://doi.org/10.9734/bjast/2015/14975.
13. Krejcie, R. V., & Morgan, D. W. (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement, 30, 607–610.
14. Muzir, N. A. Q., Mojumder, M. R. H., Hasanuzzaman, A., & Selvaraj, J.. (2022). Challenges of Electric Vehicles and Their Prospects in Malaysia: A Comprehensive Review. Sustainability, 14(14), 8320. https://doi.org/10.3390/su14148320
15. Rotas, R., Iliadis, P., Nikolopoulos, N., & Tomboulides, A. (2024). Evaluating Synergies between Electric Vehicles and Photovoltaics: A Comparative Study of Urban Environments. World Electric Vehicle Journal, 15(9), 397. https://doi.org/10.3390/wevj15090397
16. Sarker, M. T., Haram, M. H. S. M., Shern, S. J., Ramasamy, G., Farid, F. A. (2024). Readiness of Malaysia PV System to Utilize Energy Storage System with Second-Life Electric Vehicle Batteries. Energies, 17(16), 3953. https://doi.org/10.3390/en17163953
17. SEDA. (2021). Malaysia Renewable Energy Roadmap. https://www.seda.gov.my/reportal/myrer/
18. Tanoto, Y. (2023). Cost-Reliability Trade-offs for Grid-connected rooftop PV in Emerging Economics: A Case of Indonesia's Urban Residential Households. Energy, 285. https:// DOI: 10.1016/j.energy.2023.129388
19. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd
20. Umair, M., Hidayat, N. M.,Ali, N. H. N., Nasir, N. S. M., Hakomori, T., & Abdullah, E. (2024). A Review of Malaysia's Current State and Future in Electric Vehicles. Journal of Sustainable Development of Energy, water and Environment Systems, 12(4), 1120522. http://dx.doi.org/10.13044/j.sdewes.d12.0522