Market and Policy Dynamics in Forecasting Fuel Cell Vehicle Adoption in Malaysia: The Role of Technology Readiness, Infrastructure Development, and Policy Intervention

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ABSTRACT

This study examines the adoption of fuel cell vehicles (FCVs) in Malaysia in line with the National Energy Transition Roadmap (NETR) and Hydrogen Economy and Technology Roadmap (HETR). Despite strong policy direction, FCV adoption remains low due to high costs, limited hydrogen infrastructure, and low market readiness. Forecasting FCV growth is also challenging due to limited and incomplete local data.

To address this, this study develops a forecasting framework combining regression analysis and logistic growth modelling. Data from 2019 to 2023, including electric vehicle (EV) sales, EV charging infrastructure, gross domestic product (GDP) per capita, and sustainable and responsible investment (SRI) are used as proxy indicators. Missing data are handled using imputation techniques to improve reliability.

Two scenarios are analysed: a market-driven model and a policy-driven model. The market-driven scenario shows slow adoption, reaching only 288 FCVs by 2070. In contrast, the policy-driven scenario, which includes government support such as infrastructure expansion, incentives, and fleet conversion, shows a significant increase to 4,259 FCVs over the same period.

The results show that infrastructure availability and cost are the main factors influencing FCV adoption, while economic indicators and investment trends have a smaller impact. Overall, the findings suggest that without strong policy intervention, FCV adoption in Malaysia will remain limited. This study provides a practical framework to support policy and investment decisions for hydrogen mobility development.

Keywords: Fuel Cell Vehicle, Forecast Model, Imputation Regression, Logistic Growth, Energy Policy.

INTRODUCTION

Malaysia is transitioning towards a hydrogen economy to address environmental challenges and strengthen long-term energy security. In line with its commitment to the Paris Agreement (United Nations Framework Convention on Climate Change (UNFCCC), 2016), the government introduced the National Energy Transition Roadmap (NETR) (Malaysia Ministry of Economy, 2023) and the Hydrogen Economy and Technology Roadmap (HETR) (Malaysia Ministry of Science, Technology and Innovation, 2023) to support decarbonisation and economic sustainability. These frameworks target a 45% reduction in carbon intensity by 2030, with hydrogen positioned as a key enabler of this transition (Malaysia Ministry of Economy, 2023).

The HETR outlines strategies to expand hydrogen production, strengthen research and development, and accelerate the commercialisation of hydrogen technologies through industry collaboration and policy support (Malaysia Ministry of Science, Technology and Innovation, 2023). At the same time, the NETR introduces structural reforms such as the Third-Party Access (TPA) framework, which enhances market competitiveness and supports renewable energy integration (L. Siaw Wan, C. Jack, C. L. Ong, 2023). While these initiatives provide a strong policy foundation, their effectiveness depends on the development of a viable hydrogen ecosystem supported by investment, infrastructure, and market readiness (C. Andrew, C. Edward, V. Jasmine, 2023).

The transportation sector plays a central role in this transition, with fuel cell vehicles (FCVs) offering a low-emission alternative to conventional vehicles (C. Mendez, M. Contestabile, Y. Bicer, 2023). Existing studies show that FCV adoption is influenced by environmental benefits, cost competitiveness, and infrastructure availability (Z. Chen, R. Kleijn et al, 2026). In developed markets such as Japan, adoption has been largely driven by strong policy support and economic incentives (W. Akihiro, L. Jonathan, 2021). In contrast, studies in Malaysia indicate that adoption is more closely linked to socio-demographic factors, safety perceptions, and public awareness of hydrogen technology (N. Norafneeza, et al, 2023) (Angelina F. Ambrose, Abul Quasem Al-Amin, Rajah Rasiah, R. Saidur, Nowshad Amin, 2017). This suggests that in emerging markets, behavioural and social factors play a more significant role alongside policy and cost considerations.

Although FCVs have strong potential to reduce greenhouse gas emissions and support a low-carbon transport system (Aryanpur, V., Rogan, F, 2024), their adoption remains limited due to several structural challenges. These include insufficient hydrogen refuelling infrastructure, high production and ownership costs, and uncertainties surrounding technology maturity. Previous studies highlight that overcoming these barriers requires coordinated efforts between policymakers, industry players, and technology providers to develop a complete and scalable hydrogen ecosystem (M. Asghari et al., 2025) (M. S. Herdem, J. Nathwani, 2024).

From a forecasting perspective, the adoption of FCVs in emerging markets is difficult to assess due to limited historical data. Previous research suggests that proxy indicators can be used to represent market readiness and adoption potential (Burke AF, Zhao J, Miller MR, Fulton LM, 2024). Electric vehicle (EV) market trends are commonly used as a reference, as they reflect consumer acceptance of alternative vehicle technologies and broader shifts in mobility behaviour (M. S. Bindhya, N. V. Madhusoodanan Kartha et al, 2025) (A. Pamidimukkala, S. Kermanshachi et al, 2023). In addition, macroeconomic indicators such as Gross Domestic Product (GDP) influence purchasing power and investment capacity (S. B. Arzova, B. Ş. Şahin, 2024), while green investment trends indicate the level of financial support for green technologies (T. Pimonenko, T. Tambovceva, 2021). Together, these factors provide a useful basis for modelling adoption behaviour in the absence of direct FCV data.

Previous studies on alternative vehicle adoption have applied a range of forecasting approaches, including regression analysis, system dynamics models, and diffusion-based models such as the Bass and logistic growth models (R. R. Kumar et al, 2022) (S.P.Shepherd, 2014). Regression models are commonly used to identify relationships between adoption and influencing factors such as GDP, infrastructure, and policy variables, providing interpretable insights into key drivers (A. C. Ruoso, J. L. Duarte Ribeiro, 2022) (C. Xia, 2024). In contrast, diffusion models capture the dynamic nature of technology adoption, particularly the transition from early adoption to market maturity through S-curve behaviour (R. R. Kumar et al, 2022) (T. V. Ramadoss , J. H. Lee et al, 2025). However, many of these studies are primarily focused on developed markets and often rely on complete datasets, limiting their applicability in emerging markets such as Malaysia where data availability remains constrained. Furthermore, most existing approaches apply single-model techniques and do not integrate both statistical relationships and adoption dynamics within a unified framework (C. Domarchi, E. Cherchi, 2023).

However, existing studies present several limitations. First, most research focuses on developed countries and does not fully capture the socio-economic and infrastructural conditions in Malaysia. Second, many forecasting models rely on incomplete datasets and do not adequately address missing data issues, which reduces prediction accuracy. Third, key determinants such as market dynamics, infrastructure development, and public perception

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are often analysed separately rather than within an integrated framework. Additional factors including consumer awareness, technology readiness, environmental perception, and fuel affordability are also recognised as influencing FCV adoption (Syed Mansor, S. M. F. & Anuar, H. S., 2025), although consistent Malaysian datasets for these variables remain limited. This limits the ability to capture the combined effects that influence FCV adoption (Q. Zhang, J. Chen, T. Ihara, 2024). Data imputation techniques have been identified as a practical approach to improve model reliability by addressing these data gaps (J. Yousef, M. Mohammad Zakaria et al, 2024).

This study addresses these limitations by developing an integrated forecasting model for FCV adoption in Malaysia. The model incorporates key variables including EV market trends, GDP per capita, infrastructure readiness, and green investment or Sustainable and Responsible Investment (SRI) performance, while applying data imputation techniques to improve data completeness and reliability. In addition, this study introduces a dual-scenario approach by comparing market-driven and policy-driven adoption pathways. The market-driven model reflects organic adoption trends, while the policy-driven model evaluates the impact of targeted government interventions such as incentives, infrastructure expansion, and fleet conversion strategies (W. Guo, W. Xia et al, 2024).

The main contribution of this study lies in integrating statistical modelling with policy scenario analysis within a unified framework tailored to Malaysia's context. By combining regression analysis with logistic growth modelling, this study provides a more practical and data-driven approach for forecasting FCV adoption in emerging markets. The findings aim to support policymakers, industry stakeholders, and investors in designing strategies to accelerate Malaysia's transition towards a hydrogen-based transportation system.

Figure 1 illustrates the conceptual framework of this study, showing the relationship between proxy indicators, modelling approach, and FCV adoption outcomes. The framework integrates market, economic, infrastructure, and investment factors within a dual-scenario forecasting approach.

METHODOLOGY

The overall analytical framework of this study is presented in Figure 1. Building on this framework, the methodology consists of three stages: (i) identification of proxy variables, (ii) data processing and imputation, and (iii) forecasting using regression and logistic growth models.

Due to the limited availability of long-term FCV-specific datasets in Malaysia, proxy variables were used to represent market readiness, infrastructure development, economic conditions, and investment support. Similar proxy-based approaches are commonly applied in forecasting studies involving emerging technologies and early-stage transportation systems where direct market data remain limited. Although proxy variables may introduce uncertainty in long-term forecasting, they provide a practical and systematic approach for evaluating early-stage FCV adoption trends within the Malaysian context.

FCV Forecast Parameters

Malaysian EV Market

EV sales data from 2019 to 2023 are used as an independent variable (X_1) to represent market readiness. The dataset, shown in Figure 2, captures the rapid growth in EV adoption in Malaysia, particularly after 2022, and reflects increasing consumer acceptance of alternative vehicle technologies.

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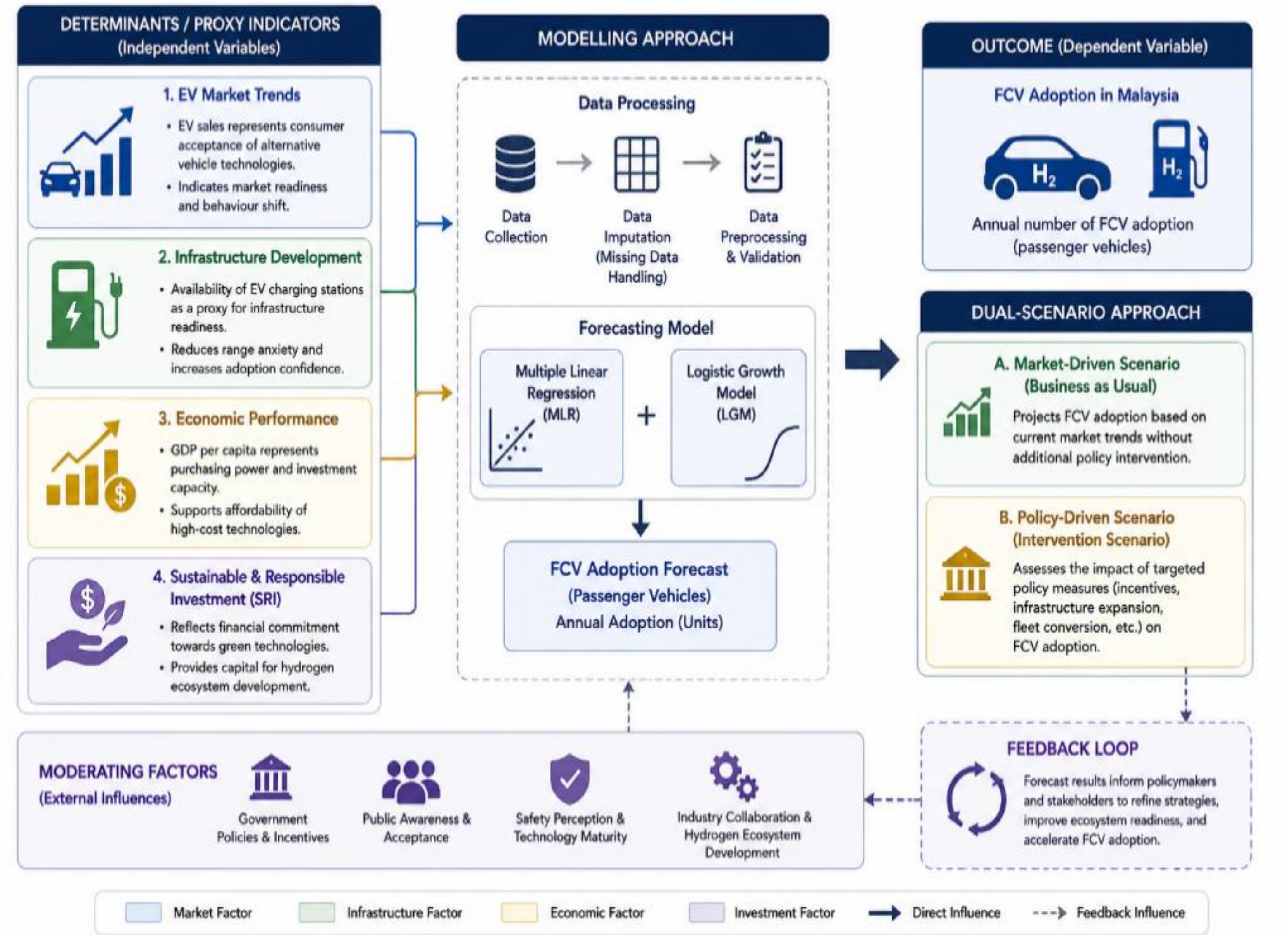

Fig. 1. Conceptual Framework for FCV Adoption Forecasting in Malaysia

Electric Vehicle Charging Stations

The number of EV charging stations is used as an independent variable (X_2) to represent infrastructure development. The dataset indicates an increase from 90 units in 2019 to 1,430 units in 2023 (J. Sammy, 2016), reflecting the rapid expansion of supporting infrastructure for alternative vehicle adoption.

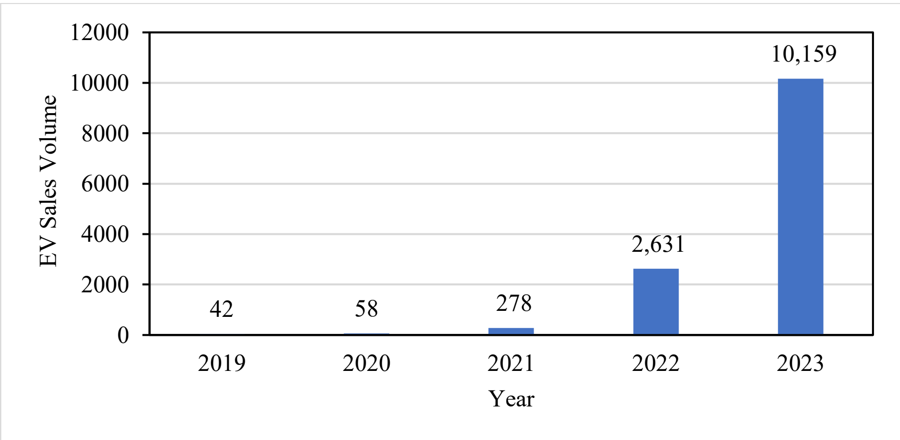

Fig. 2. Malaysia EV market sales trend overview (A. Kisok, 2023) (P. Tan, 2023)

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Malaysia's Policies and Initiatives

Policy and investment indicators, particularly Sustainable and Responsible Investment (SRI), are used as an independent variable (X_4) to represent financial and regulatory support. Relevant policy frameworks are summarised in Table 1, including the Hydrogen Economy and Technology Roadmap (HETR), which supports hydrogen technology deployment (Malaysia Ministry of Science, Technology and Innovation, 2023).

Table 1. Malaysia's vision and framework overview in energy transition

Year	Policy	Key Initiative	Relevant Bodies	Status
2011	Feed-in Tariff scheme (Sustainable Energy Development Authority (SEDA), 2011) (Ministry of Energy, Green Technology and Water (KeTTHA), 2017)	Guaranteed price for RE producers	SEDA	Active
2011	Larger Scale Solar PV Program (LSS) (Sustainable Energy Development Authority (SEDA), 2011)	100% tax exemption on investment/CAPEX in GT	SEDA	Active
2011	Low Carbon Cities 2030 Challenge (LCCC) (Malaysia Ministry of Energy, Green Technology and Water, 2011)	Local council to develop & implement plans to reduce GHG emission to 40%	MGTCCC	On Going
2014	Green Investment Tax Allowance (GITA) and Green Income Tax Exemption (GITE) (Malaysia Green Technology and Climate Change Corporation, 2014)	100% Income tax exemptions from green business	Malaysia Green Technology and Climate Change Corporation (MGTCCC)	Active
2017	National Green Technology Policy (NGTP) (Ministry of Energy, Green Technology and Water (KeTTHA), 2017)	Financial incentives, regulatory support & capacity building	Ministry of Energy, Green Technology and Water (KeTTHA)	Active
2019	Green Technology Master Plan (GTMP) (Malaysia Prime Minister's Office, 2019)	a) Identifies GT development key areas i.e. energy efficiency, renewable energy, and waste management. b) Targets for green technology adoption in various sectors, such as buildings, transportation, and manufacturing.	Prime Minister's Office (PMO)	Active
2019	National Climate Change Policy (NCCP) (Prime Minister's Office, 2019)	Reduce 40% (2030) of GHG emission, relative on 2005 levels	PMO	Active
2022	National Energy Policy (NEP) (Economic Planning Unit, Prime Minister's Department, 2022)	Target for RE at 5% (2005), 31% (2025), 40% (2035)	Ministry of Economy (MOE)	Active
2023	Renewable Energy Act (REA) (Sustainable Energy Development Authority (SEDA), 2023)	100% income tax exemption, subsidies on feed-in tariff & net metering.	Sustainable Energy Development Authority (SEDA)	Active
2023	National Energy Transition Roadmap (NETR) (Malaysia Ministry of Economy, 2023)	To liberalise power sector by establishing third-party access (TPA)	MOE	On going
2023	Hydrogen Economy Roadmap (Malaysia Ministry of Science, Technology and Innovation, 2023)	Plans & strategies to develop hydrogen economy	MOSTI	On going

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Green technology investment growth in Malaysia

SRI data are used to capture investment trends in sustainable sectors. As shown in Figure 3, SRI increased by 19% in 2021, reaching USD 4.3 billion (L. Nam Soon, R. Abdul Rauf et al, 2022), indicating growing financial support for green technologies.

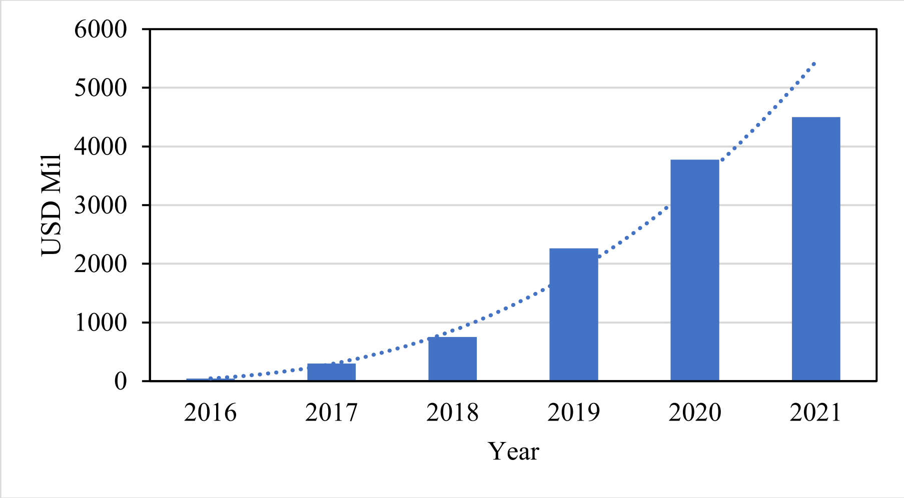

Fig. 3. Overview of Sustainable Responsible Investment (SRI) Sukuk in Malaysia

Economic Implications and Policy Support

GDP per capita is used as an independent variable (X_3) to represent economic conditions. The dataset, presented in Figure 4, reflects Malaysia's economic growth and its potential influence on technology affordability, purchasing power and investment capacity.

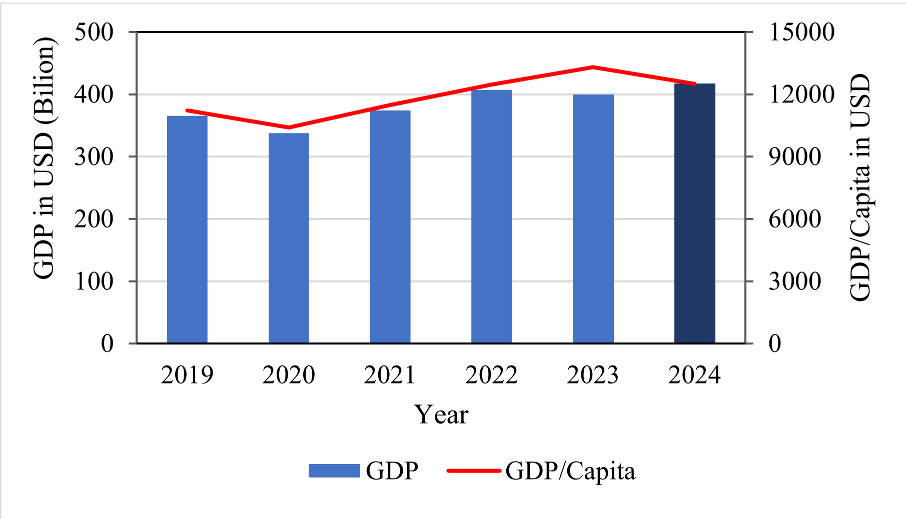

Fig. 4. Malaysia GDP and GDP per capita growth trend (Department of Statistics Malaysia, 2024)

Note: forecasted

Addressing Data Gaps in Forecasting Models

To address incomplete datasets, data imputation techniques are applied to improve reliability. Methods such as random forest imputation, regression-based imputation, and deep learning approaches are considered (J. Yousef, M. Mohammad Zakaria et al, 2024). These approaches are particularly useful for emerging technology studies where historical datasets remain limited and incomplete. The use of imputation techniques improves dataset consistency and reduces potential bias caused by missing values.

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The Clustered Random Forest (ClusteredRF) method, which integrates DBSCAN clustering with random forest algorithms, is used to enhance data consistency (N. Subhashish, M.K. Pabitra, 2025). Random forest-based imputation methods are suitable for handling small and incomplete datasets because they are capable of preserving nonlinear relationships between variables while improving prediction stability. Additional approaches, including flexible predictive frameworks and longitudinal regression tree methods, are also considered to improve model robustness (J. Mina et al, 2023).

FCV Forecast Model

The forecasting framework integrates multiple linear regression and logistic growth models. Regression analysis is used to identify relationships between FCV adoption and influencing variables, while the logistic growth model captures long-term adoption patterns, including initial growth, acceleration, and saturation phases. The integration of both models allows short-term variable relationships and long-term technology diffusion behaviour to be evaluated within a single forecasting framework. The summary of the regression analysis applications are as Table 2.

Table 2. Regression analysis applications overview

Focus Area	Method	Variables	Application	Reference
Forecasting transportation demand	Regression analysis with stacking ensemble models	GDP, population, passenger/vehicle travel distances	Predicting transportation energy demand	(H. Julia, C.M. Yasin et al, 2023)
Predicting transportation on-time delivery	Predictive analytics based on historical dataset	Historical dataset	Improving resource allocation	(A.D. Rafael, W.O. Kenneth, 2020)
Prediction for urban transport	Regression analysis based on traffic current flow structure	Traffic flow data	Improving fuel consumption for end users	(R.Sathiyaraj, A. Bharathi, 2020)
Sales forecasting	Methodical approaches	Advertising expenditure, sales outcomes	Guiding effective marketing strategies	(N. Flori, 2024)
Marketing strategies	Regression analysis	Advertising expenditure, sales outcomes	Understanding relationship between variables to guide marketing strategies	(L. Michael, 2023)
New product adoption	Bass model estimation	Coefficients of innovation and imitation	Predicting new product adoption	(M.L Journey, n.d.)

Regression Model Specification

The model is formulated using multiple linear regression to evaluate the relationship between FCV adoption and selected variables:

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a. Independent Variables:
i. X_1 – EV sales trend
ii. X_2 – EV charging station status
iii. X_3 – GDP per capita performance
iv. X_4 – Government incentives/SRI performance

b. Dependent Variable
i. Y_i - FCV adoption

The dataset used in this study is compiled from government reports, financial institutions, academic journals, and official automotive statistics, covering the period from 2019 to 2023.

Multiple Linear Regression Model

The relationship between FCV adoption and the independent variables is expressed as:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \quad (1)$$

where Y_i represent the dependent variable, β_0 represent the intercept, $\beta_{1\sim5}$ represent the coefficients for related independent variables and $X_{1\sim5}$ represent the independent variables and *i* as the number of forecasting years.

Estimation of Regression Coefficients

The regression coefficients are estimated using the least squares method, which minimises the sum of squared differences between observed and predicted values:

$$\beta_i = \frac{\sum_{i=1}^{n}(x_1 - \bar{x})(y_1 - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (2)$$

$$\beta_0 = \bar{Y} - \beta_1 \bar{X} \quad (3)$$

Where β_i is the estimated coefficient for independent variable *X,* β_0 as the estimated intercept, *n* as the number of data points, X_i and Y_i as the individual data points for the independent and dependent variables while $\bar{X}$ and $\bar{Y}$ are the means of the respective independent and dependent variables.

The estimation was performed using statistical software in Excel (Regression analysis) where those formulas estimates the slope (β_i) and intercept (β_0) by minimizing the sum of squared differences between the observed and predicted values.

Where β_i is the estimated coefficient for independent variable X, β_0 as the estimated intercept, *n* as the number of data points, X_i and Y_i as the individual data points for the independent and dependent variables while $\bar{X}$ and $\bar{Y}$ are the means of the respective independent and dependent variables.

The estimation was performed using statistical software in Excel (Regression analysis) where those formulas estimates the slope β_i and intercept β_0) that minimize the sum of squared differences between the observed and predicted values of the dependent variable.

Correlation Analysis (Multiple R)

The strength of the relationship between variables is evaluated using the Pearson correlation coefficient. The Multiple R value represents the overall correlation between the dependent variable and the set of independent variables.

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$$\boldsymbol{R} = \frac{\sum(\boldsymbol{X_i}-\bar{\boldsymbol{X}})(\boldsymbol{Y_i}-\bar{\boldsymbol{Y}})}{\sqrt{\sum(\boldsymbol{X_i}-\bar{\boldsymbol{X}})^2 \sum(\boldsymbol{Y_i}-\bar{\boldsymbol{Y}})^2}} \quad (4)$$

The value of R ranges between -1 and 1, indicating the strength and direction of the linear relationship. A higher absolute value indicates a stronger relationship between variables. In this study, the Multiple R analysis is used to evaluate the overall influence of the selected proxy variables on FCV adoption trends and to assess the suitability of the forecasting model.

Model Significance Testing (ANOVA)

Analysis of Variance (ANOVA) is used to evaluate the statistical significance of the regression model. The test assesses whether the independent variables collectively explain variations in FCV adoption.

The hypotheses are defined as:

- Null hypothesis (H_0): $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$
- Alternative hypothesis (H_1): At least one $\beta_i \neq 0$

A significance level of $\alpha = 0.05$ is applied. If the Significance F-value obtained from the ANOVA test is less than 0.05, the null hypothesis is rejected. This indicates that the model is statistically significant and that at least one independent variable has a meaningful influence on FCV adoption. The ANOVA analysis also provides an indication of the overall reliability of the regression framework in explaining variations in FCV adoption under the selected market and policy conditions.

RESULTS AND DISCUSSIONS

Regression statistic of independent variables

The regression results, summarised in Table 3, show varying degrees of influence of the selected variables on FCV adoption.

Table 3. Regression statistic overview

Description	EV sales trend	EV charging trend	Economic indicator	SRI
Multiple R	0.968	0.823	0.756	0.828
R Square	0.937	0.678	0.572	0.686
Adjusted R- square	0.916	0.570	0.429	0.581
Standard error	0.646	1.466	1.690	1.448
Observations	5	5	5	5

EV sales exhibit the strongest relationship, with a Multiple R value of 0.968 and an Adjusted R^2 of 0.916. This indicates that market readiness, reflected through EV adoption trends, explains a substantial portion of the variation in FCV uptake.

EV charging infrastructure also shows a strong positive relationship (Multiple R = 0.823), although its Adjusted R^2 of 0.570 suggests that infrastructure alone does not fully explain adoption behaviour. This implies that infrastructure must be complemented by cost reductions and policy support.

GDP per capita demonstrates a moderate relationship (Multiple R = 0.756; Adjusted R^2 = 0.429), indicating that economic conditions support adoption but are not the primary driver.

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Similarly, SRI shows moderate explanatory power (Multiple R = 0.828; Adjusted R^2 = 0.581), suggesting that investment supports technology development and ecosystem growth but has limited direct influence on immediate FCV adoption.

Overall, the results indicate that behavioural and market-driven factors have stronger explanatory power than macroeconomic and investment variables. The findings also reflect the current early-stage condition of Malaysia's hydrogen mobility ecosystem, where market acceptance and infrastructure readiness remain more influential than broader economic or investment indicators in determining FCV adoption trends.

Analysis of Variance (ANOVA)

The statistical significance of the model is evaluated using ANOVA, as presented in Table 4 and illustrated in Figure 5.

Table 4. Analysis of variance overview

Independent variables	Description	df	SS	MS	F	Significance F
EV sales trend	Regression	1	18.74	18.74	44.79	0.0068
	Residual	3	1.26	0.42		
EV charging trend	Regression	1	13.55	13.55	6.31	0.0868
	Residual	3	6.45	2.15		
Economic indicator	Regression	1	11.43	11.43	4.00	0.1392
	Residual	3	8.57	2.86		
SRI	Regression	1	13.71	13.71	6.54	0.0834
	Residual	3	6.29	2.10		

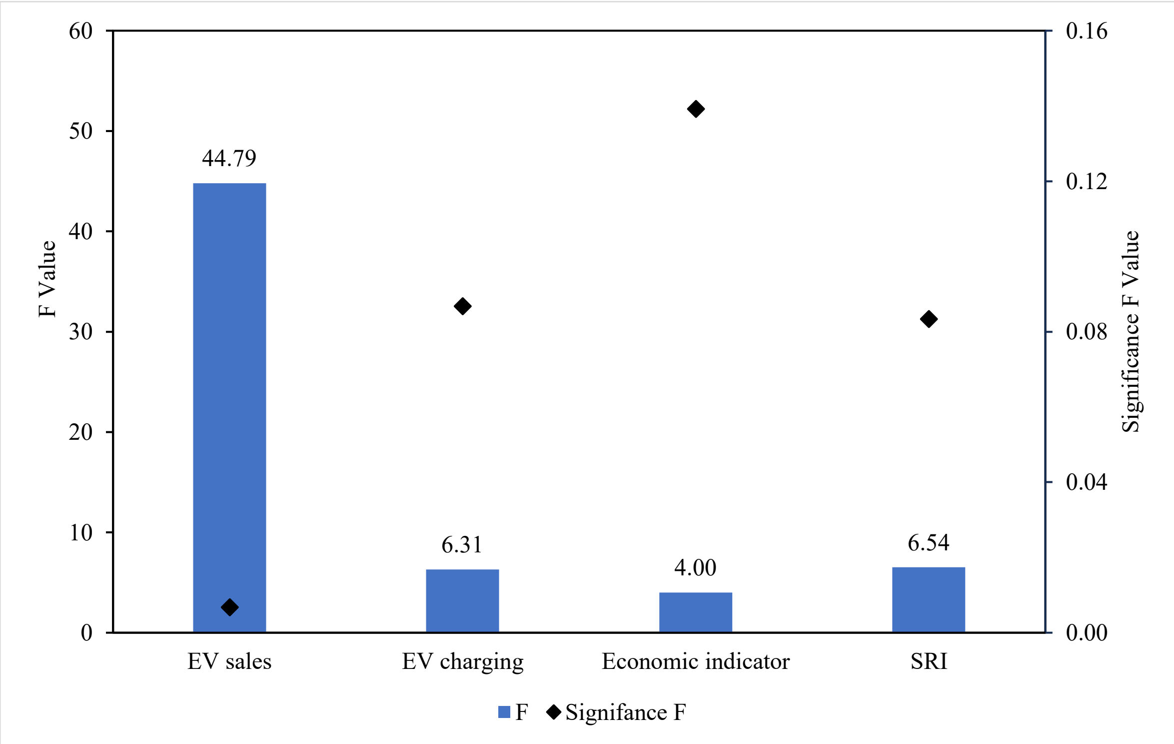

Fig. 5. The Significance F impact of independent variables

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EV sales show strong statistical significance (F = 44.79; Significance F = 0.0068 < 0.05), confirming their reliability as a predictor.

In contrast, SRI (Significance F = 0.0834) and GDP (Significance F = 0.1392) are not statistically significant at the 5% level. This indicates that although these variables show correlation, their contribution becomes weaker when evaluated within the overall forecasting model.

These findings highlight the importance of distinguishing between correlation strength and statistical significance when interpreting regression results. This may reflect the current early-stage development of Malaysia's FCV ecosystem, where market readiness and infrastructure expansion remain more immediate drivers of adoption compared to broader macroeconomic and investment indicators.

Regression coefficient analysis

Table 5 presents the regression coefficients, providing insight into the relative influence of each variable.

Table 5. Regression coefficients overview

Independent variables	Description	Coefficients	Standard Error	t-Stat	P-Value
EV sales trend	Intercept	-0.3119	0.3495	-0.8928	0.4378
	EV sales	**0.0005**	7.443E-05	6.6928	**0.0068**
EV charging trend	Intercept	-1.2621	1.1141	-1.1329	0.3396
	EV Charge	**0.0035**	0.0014	2.5113	**0.0868**
Economic indicator	Intercept	-16.631	8.8449	-1.8803	0.1566
	Economic indicator	**0.0015**	0.0007	2.0001	**0.1392**
SRI	Intercept	-2.6238	1.5576	-1.6846	0.1907
	SRI	**7.694E-09**	3.008E-09	2.5580	**0.0834**

EV charging infrastructure has the largest coefficient (0.0035), indicating the strongest direct impact on FCV adoption. This confirms that infrastructure availability is a key enabling factor.

GDP per capita follows with a coefficient of 0.0015, suggesting a moderate influence through purchasing power, affordability and investment capacity.

EV sales, despite showing strong correlation earlier, have a smaller coefficient (0.0005), indicating that they function more as an indirect indicator of market readiness rather than a direct driver.

SRI has a negligible coefficient (7.69×10^{-9}), suggesting minimal direct impact within the current model.

The p-values reinforce these findings, with EV sales showing strong significance (p = 0.0068), while infrastructure (p = 0.0868), GDP (p = 0.1392), and SRI (p = 0.0834) exhibit weaker statistical significance.

This highlights that variables may be influential in different ways either directly through coefficients or indirectly through behavioural trends. The findings suggest that physical infrastructure development remains a more

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immediate requirement for FCV adoption in Malaysia compared to broader financial and investment-related indicators.

Overall interpretation

The results indicate that infrastructure development is the most critical factor influencing FCV adoption, followed by economic conditions. EV sales serve primarily as an indicator of market readiness rather than a direct driver.

The limited impact of SRI suggests that financial investment alone is insufficient without supporting infrastructure and policy alignment.

These findings emphasise that FCV adoption is influenced by multiple interacting factors, rather than a single dominant factor. The findings also suggest that FCV adoption in Malaysia remains highly dependent on ecosystem readiness, particularly the availability of supporting infrastructure and technology accessibility. While broader economic and investment indicators contribute to long-term market development, early-stage adoption appears to be driven more strongly by practical considerations such as infrastructure availability, affordability, and consumer confidence. This reflects the current maturity level of Malaysia's hydrogen mobility ecosystem, where infrastructure development remains a prerequisite for wider FCV adoption. A summary of the relative influence is presented in Figure 6.

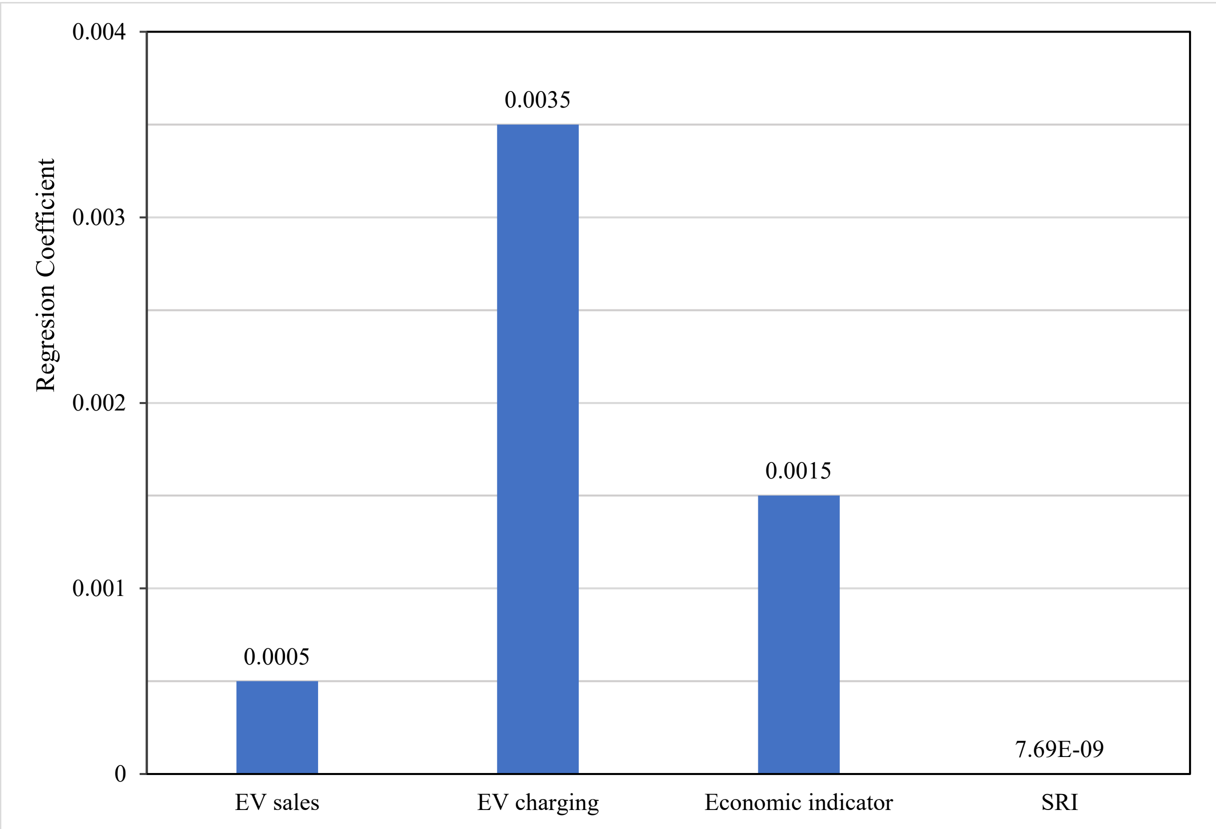

Fig. 6. Coefficient β_i overview

FCV Adoption Forecast: Market-Driven vs Policy-Driven Scenarios

FCV adoption in Malaysia is projected from 2030 to 2070 under two scenarios: a market-driven baseline and a policy-driven pathway.

The market-driven scenario reflects organic growth based on current trends, while the policy-driven scenario incorporates cost reductions, infrastructure expansion, and government intervention.

The results show that FCV adoption follows a logistic (S-curve) pattern, with slow initial growth, acceleration as enabling conditions improve, and eventual stabilisation. This adoption behaviour is consistent with emerging transportation technologies, where infrastructure readiness, affordability, and policy support strongly influence the transition from early adoption to wider market penetration.

Market-Driven Adoption - Baseline Projection

The baseline projection is presented in Figure 7.

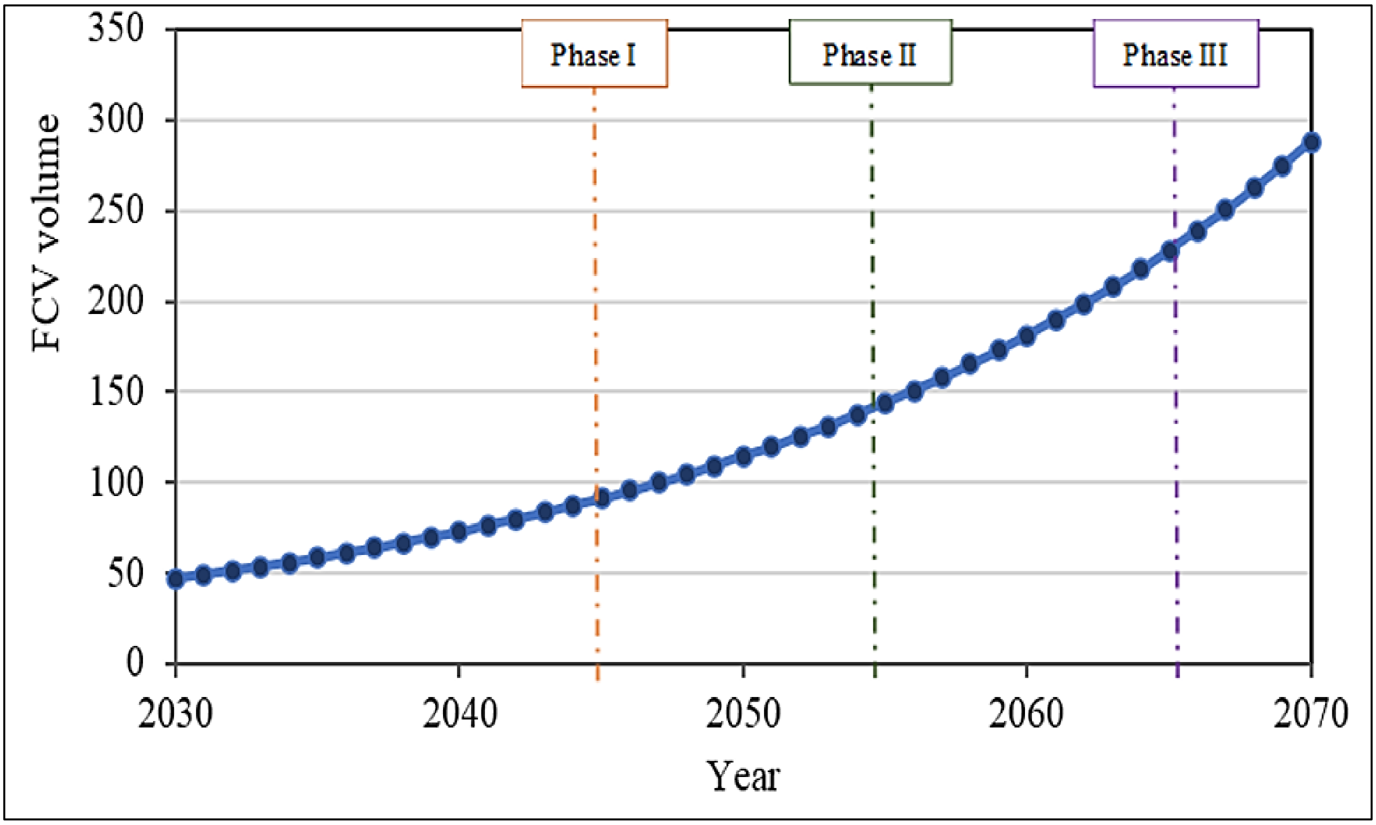

Fig. 7. Forecasted FCV adoption based on Market-Driven model

FCV adoption increases gradually but remains limited throughout the forecast period. Three phases are observed:

Phase I (2030–2045): Early Adoption

Adoption remains limited due to insufficient hydrogen refuelling infrastructure, high vehicle and hydrogen production costs, and low public familiarity with FCV technology, reaching approximately 91 vehicles by 2045.

Phase II (2045–2055): Acceleration

Expansion of hydrogen infrastructure and gradual cost reductions improve accessibility and market confidence, increasing adoption to 115 vehicles by 2050 and 144 by 2055.

Phase III (2055–2070): Growth Phase

Adoption reaches 181 vehicles by 2060 and exceeds 288 by 2070. Although adoption continues to increase, the projected values remain relatively low compared to the overall Malaysian transport market, reflecting the early-stage development of the hydrogen mobility ecosystem and the long lead time required for infrastructure and market maturation.

These findings indicate that a purely market-driven pathway is unlikely to achieve large-scale FCV adoption without stronger infrastructure investment, cost reduction strategies, and long-term policy support.

Policy-Driven Adoption Scenario

The baseline results highlight a clear limitation: market forces alone are not strong enough to drive rapid FCV adoption. This aligns with global evidence showing that early-stage clean technologies require policy support to overcome cost and infrastructure barriers. This is particularly relevant in Malaysia, where hydrogen infrastructure and FCV market ecosystems are still in the early stages of development, limiting large-scale adoption under purely market-driven conditions

In a policy-driven scenario, adoption is expected to accelerate significantly due to:

i. targeted financial incentives (e.g. subsidies, tax reductions)
ii. rapid expansion of hydrogen refuelling infrastructure
iii. regulatory support and fleet mandates
iv. increased private sector participation

Under these conditions, the adoption trajectory becomes significantly steeper, particularly during the transition from early adoption to acceleration phases. This reflects the role of policy in reducing uncertainty, improving affordability, and enabling infrastructure development. The findings suggest that policy intervention acts primarily as an enabling mechanism by accelerating infrastructure deployment, improving affordability, and strengthening public and industry confidence in hydrogen mobility technologies.

Key Insights and Policy Implications

The comparison between market-driven and policy-driven scenarios highlights several key insights. First, infrastructure availability is a critical enabler of FCV adoption. Without sufficient hydrogen refuelling stations, adoption remains limited regardless of consumer interest or economic conditions. This is consistent with earlier regression results, which identified infrastructure as a significant influencing factor.

Second, cost reduction is essential for scaling adoption. High vehicle costs remain a major barrier, and without targeted policy support, adoption is likely to progress slowly.

Third, market readiness alone is insufficient. Although EV trends indicate increasing acceptance of alternative vehicles, this does not directly translate into FCV adoption without supporting infrastructure and aligned policy measures.

Finally, the projected adoption levels under the market-driven scenario remain significantly below national targets outlined in the NETR and HETR, particularly the targets of 2% Total Industry Volume (TIV) by 2030 and 10% by 2050. This gap highlights the need for stronger and more coordinated policy intervention.

The findings also suggest that FCV adoption in Malaysia depends on the simultaneous development of infrastructure, affordability, regulatory support, and public confidence, rather than relying on a single policy or market factor alone. Overall, the findings indicate that policy-driven strategies are necessary to accelerate FCV adoption in Malaysia, particularly during the early and acceleration phases. Without such interventions, FCVs are likely to remain a niche transportation technology within the broader transportation sector.

Policy-Driven Forecasting Using Logistic Growth Model

To evaluate the potential acceleration of FCV adoption under policy intervention, this study applies a logistic growth model, which is widely used to represent technology diffusion patterns (L. Michael, 2023) (M.L Journey, n.d.). Unlike linear regression, which assumes constant growth, the logistic model captures the typical S-curve behaviour of emerging technologies, slow initial adoption, rapid acceleration, and eventual market saturation.

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The logistic growth function is defined as:

$$y = \frac{K}{1 + e^{-b(t-t_0)}} \tag{5}$$

- y = FCV adoption at time t
- K= market saturation level
- b= growth rate
- t_0= inflection point (year of maximum growth rate)

For this study, the parameters are defined as follows:

- Market saturation (K) = 5,000 units by 2070, representing a realistic upper limit under strong policy support and infrastructure expansion.
- Growth rate (b) = 0.07, reflecting accelerated adoption driven by cost reductions, policy incentives, and global trends in alternative vehicle markets.
- Inflection year (t_0) = 2045, corresponding to the expected scaling of hydrogen infrastructure under Malaysia's NETR and HETR frameworks.

The selected parameters are intended to represent a conservative but policy-supported adoption scenario within the Malaysian context. The market saturation level was selected to reflect the current early-stage condition of Malaysia's hydrogen mobility ecosystem, where infrastructure availability, vehicle affordability, and public adoption remain limited compared to more mature FCV markets such as Japan and South Korea. The growth rate parameter reflects a moderate acceleration scenario influenced by policy intervention, infrastructure expansion, and gradual reductions in hydrogen and vehicle costs. The inflection year is aligned with the anticipated scaling period of hydrogen infrastructure development under the NETR and HETR implementation timeline.

Forecast Results and Scenario Comparison

The comparison between market-driven and policy-driven scenarios is presented in Figure 8.

The baseline (market-driven) scenario projects a total of 288 FCVs by 2070, indicating that organic market growth alone is insufficient to drive large-scale adoption.

In contrast, the policy-driven scenario shows a substantial increase in adoption, reaching approximately 1,296 units by 2030, 3,769 units by 2050, and 4,259 units by 2070. This represents a significant acceleration compared to the baseline, particularly after the inflection point around 2045.

The results confirm that policy intervention plays a critical role in shifting the adoption curve from gradual growth to rapid expansion. However, even under this accelerated scenario, adoption remains below the HETR target of 10% Total Industry Volume (TIV) by 2050, indicating that current policy assumptions may still be insufficient.

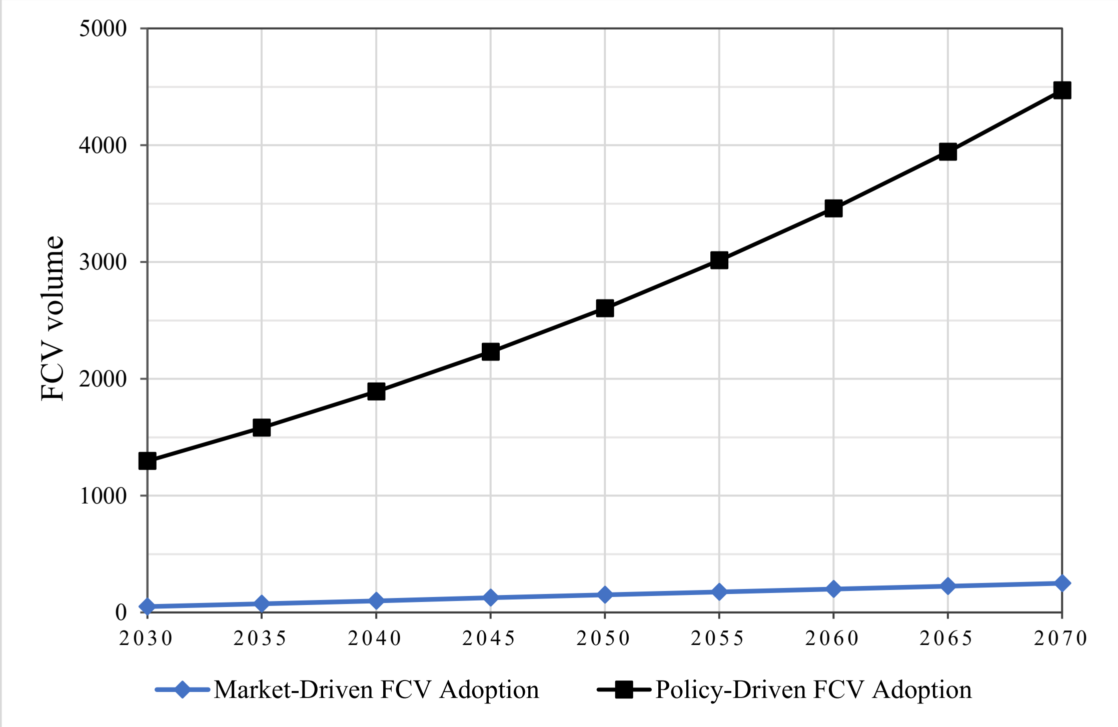

Fig.8. Comparison of Market against Policy Driven FCV adoption forecast

The relatively conservative adoption trajectory reflects the current maturity level of Malaysia's hydrogen mobility ecosystem, where infrastructure availability, hydrogen supply chains, vehicle affordability, and consumer readiness remain under development. Although policy intervention significantly improves adoption potential, large-scale FCV penetration is still constrained by the long implementation timeline required for hydrogen infrastructure deployment and market ecosystem expansion.

Implications of the Forecast

The findings highlight that affordability is a key driver of FCV adoption. The rapid growth of the EV market, particularly with the introduction of lower-cost models, demonstrates how price reductions can significantly accelerate adoption. A similar trend is expected for FCVs if production costs decrease through economies of scale, technological advancements, and targeted subsidies.

Infrastructure development also plays a critical role. The expansion of HRS is necessary to support adoption, as limited infrastructure remains one of the main barriers. Without sufficient refuelling access, consumer confidence and market growth will remain constrained.

In addition, fuel price competitiveness is essential. Hydrogen must become a viable alternative to conventional fuels in terms of cost and availability. While green hydrogen production technologies are improving, further cost reductions are required to support widespread adoption.

Policy interventions, although not the sole driver, act as an enabler by reducing uncertainty, improving affordability, and accelerating infrastructure development. Measures such as fleet conversion programmes, public transport integration, and industry partnerships can further strengthen adoption. For example, the deployment of hydrogen-powered buses and trains can serve as early use cases, improving public confidence and demonstrating operational feasibility.

Overall, the findings suggest that successful FCV adoption in Malaysia will depend on the coordinated development of infrastructure, fuel affordability, technology accessibility, regulatory support, and public acceptance within a gradually maturing hydrogen mobility ecosystem.

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External Factors Influencing FCV Adoption

FCV adoption in Malaysia is influenced by broader external factors, including political, economic, social, technological, environmental, and legal conditions. A summary of these factors is presented in Figure 9.

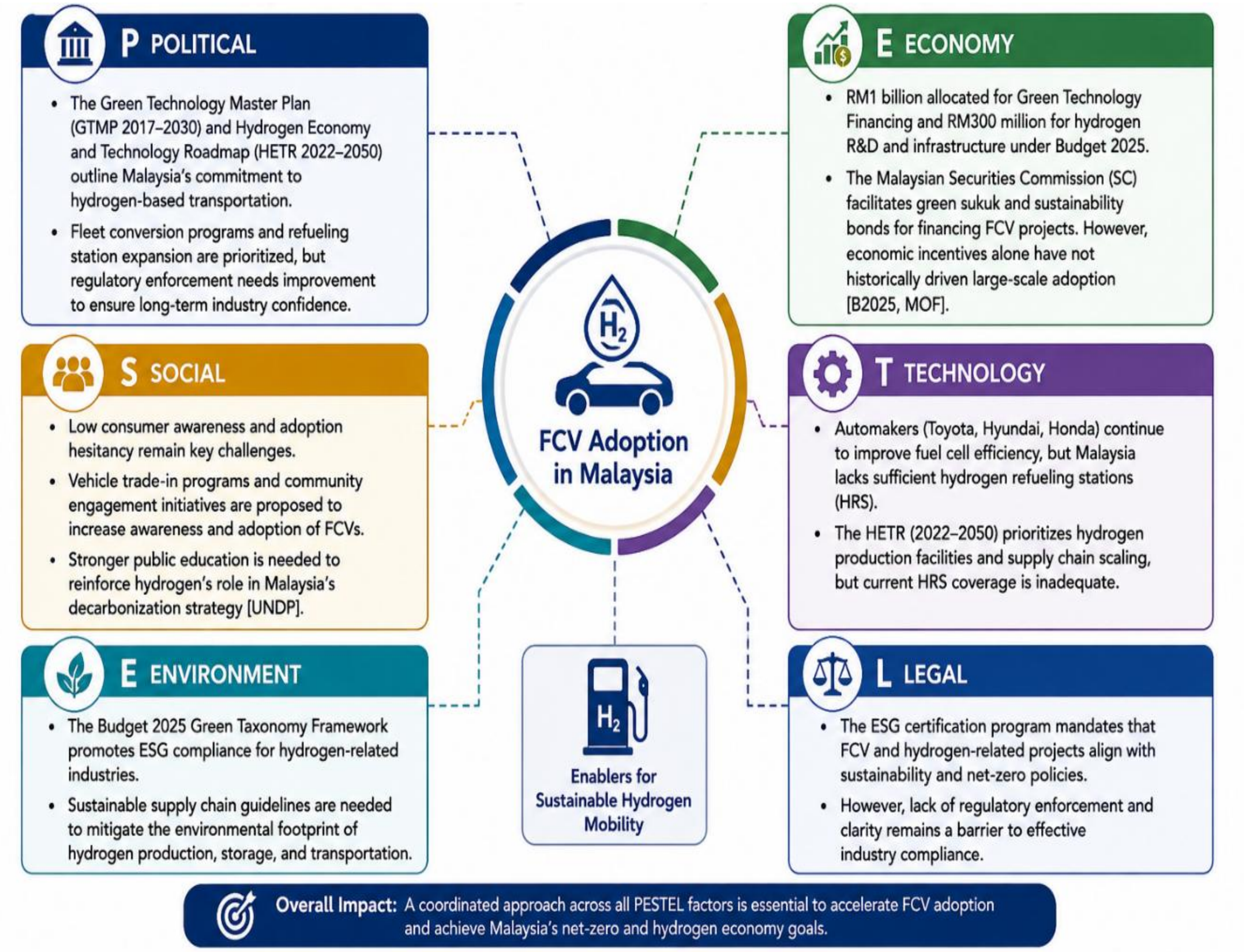

Fig.9. PESTEL Analysis on FCV growth in Malaysia

The PESTEL framework highlights that FCV adoption is not determined by a single factor, but by the interaction of policy support, economic conditions, technological readiness, environmental priorities, and regulatory frameworks. This reinforces the need for a coordinated and multi-dimensional strategy to support the hydrogen mobility transition. The interaction of these external factors also contributes to forecasting uncertainty, particularly in emerging markets where policy direction, infrastructure readiness, consumer acceptance, and technology maturity continue to evolve over time.

CONCLUSIONS

This study presents a forecasting framework for Fuel Cell Vehicle (FCV) adoption in Malaysia by integrating market, infrastructure, economic, and policy-related variables. Given the limited availability of direct FCV data, the model utilises proxy indicators such as EV market trends, infrastructure development, GDP per capita, and Sustainable and Responsible Investment (SRI) to estimate adoption behaviour. The results show that FCV adoption in Malaysia is likely to remain limited under a purely market-driven trajectory, with only gradual growth observed over the forecast period. This conservative adoption trajectory reflects the current early-stage maturity of Malaysia's hydrogen mobility ecosystem, where infrastructure readiness, fuel affordability, and consumer acceptance remain under development.

The comparison between market-driven and policy-driven scenarios highlights the critical role of policy intervention in accelerating adoption. While the baseline projection indicates slow uptake, the policy-driven model demonstrates that cost reduction, infrastructure expansion, and targeted incentives can significantly shift the adoption curve. However, even under an accelerated scenario, projected adoption levels remain below the targets outlined in the National Energy Transition Roadmap (NETR) and Hydrogen Economy and Technology Roadmap (HETR), indicating that current strategies may require further strengthening.

The findings confirm that infrastructure availability and affordability are the primary determinants of FCV adoption. The development of hydrogen refuelling stations, reduction in vehicle and fuel costs, and improved supply chain efficiency are essential to support large-scale deployment. In addition, financial and regulatory support plays an enabling role by reducing uncertainty and encouraging private sector participation.

From a policy perspective, a coordinated approach is required to build a complete hydrogen ecosystem. This includes expanding hydrogen infrastructure, promoting early adoption through fleet conversion programmes, and ensuring that hydrogen fuel becomes cost-competitive with conventional energy sources. Strengthening local hydrogen production, particularly through low-carbon technologies such as renewable-powered electrolysis, will also be critical to achieving both economic and environmental objectives.

Finally, this study contributes to the literature by providing a data-driven and context-specific forecasting framework for FCV adoption in an emerging market. Future research should focus on improving model accuracy through the integration of real-time data, dynamic policy variables, and technological advancements. A more adaptive modelling approach will be necessary to support long-term planning and ensure Malaysia's successful transition towards a sustainable hydrogen-based transportation system.

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