THE PREDICTION MODEL FOR ELECTRIC VEHICLES ADOPTION RATE IN MALAYSIA

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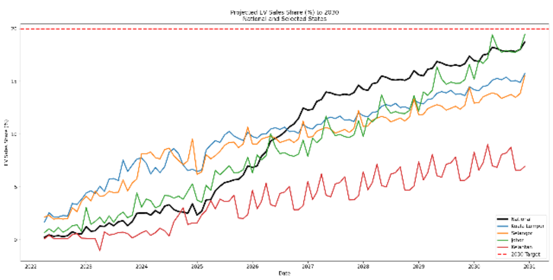
Graphical Abstract



Abstract

This comprehensive study presents an integrated analysis of electric vehicle (EV) adoption in Malaysia, combining behavioural research, advanced predictive modelling, and policy assessment to evaluate the country's readiness for sustainable transportation transition. The research employed a sequential mixed-methods approach, integrating a validated Theory of Planned Behaviour (TPB) survey with hybrid forecasting models to assess current adoption trends and project future scenarios through 2030. A two-phase TPB survey was conducted with a pilot test (n=50) and main survey (n=500), achieving excellent reliability across all constructs (Cronbach's α = 0.802-0.850). Advanced modelling framework combining SARIMAX, LSTM, and weighted ensemble approaches achieved excellent predictive accuracy at the national level (R^2 = 0.822). Key findings reveal that while Malaysia's EV market demonstrated 45.6% growth in Q1 2025, reaching 6,827 units, no region is projected to meet the 20% 2030 adoption target under current trajectories. Current infrastructure deployment stands at 4,161 charging stations, representing 41.6% progress toward 2025 targets. Behavioral analysis indicates perceived behavioral control as the primary barrier despite positive consumer attitudes. Strategic recommendations include accelerating rural charging infrastructure, extending fiscal incentives beyond 2025, and implementing targeted behavioural interventions.

Keywords

Electric vehicles, Malaysia, Theory of Planned Behaviour, SARIMAX, LSTM modelling

Introduction

Malaysia stands at a critical juncture in its transition toward sustainable transportation, with electric vehicles positioned as a cornerstone of the nation's climate and economic objectives. The National Energy Transition Roadmap (NETR) has established ambitious targets for EV adoption, aiming for 20% market share by 2030 and 80% by 2050. However, achieving these goals requires comprehensive understanding of the complex interplay between infrastructure readiness, consumer behaviour, policy effectiveness, and market dynamics.

The urgency of this transition is underscored by Malaysia's commitment to achieving carbon neutrality by 2050 and the need to reduce dependence on fossil fuel imports. The transportation sector, which accounts for approximately 25% of national energy consumption, represents a critical intervention point for achieving these sustainability goals. Furthermore, the global shift toward electric mobility presents both opportunities for industrial development and risks of technological obsolescence if Malaysia fails to adapt adequately.

Recent studies have highlighted the complexity of EV adoption patterns in emerging economies, where infrastructure limitations, economic constraints, and behavioral factors interact to influence consumer decisions. Unlike developed markets where EV adoption has been driven primarily by environmental consciousness and early adopter enthusiasm, emerging markets require more comprehensive intervention addressing practical barriers such as charging infrastructure, affordability, and consumer education.

This research addresses three interconnected objectives that collectively provide a comprehensive assessment of Malaysia's EV adoption landscape: first, to evaluate the current state of EV readiness encompassing infrastructure development, market demand patterns, and government policy effectiveness; second, to develop and validate robust prediction models integrating advanced statistical and machine learning techniques with behavioral and policy variables; and third, to validate adoption projections through behavioral analysis and case study examination, particularly focusing on regional variations across Malaysian states.

The methodological approach integrates primary behavioral research using validated TPB instruments with secondary data analysis of EV registrations, infrastructure deployment, and policy interventions. Advanced modeling techniques including SARIMAX time series analysis, LSTM neural networks, and ensemble methods are employed to develop robust forecasting capabilities. The integration of behavioral variables as exogenous factors in technical modeling represents a significant methodological innovation with broader applicability to transportation policy research.

This study extends prior EV adoption models by integrating behavioral constructs from the Theory of Planned Behavior (TPB) directly into hybrid predictive modeling. This approach not only quantifies behavioral drivers but also operationalizes them as exogenous predictors in forecasting algorithms, offering a replicable diagnostic framework for other Southeast Asian emerging markets.

Global EV Adoption Patterns

International experience demonstrates that successful EV adoption requires coordinated intervention across multiple domains. Norway's achievement of over 80% EV market share by 2023 resulted from sustained fiscal incentives, comprehensive charging infrastructure, and strong environmental policy frameworks. Similarly, China's rapid EV adoption, reaching 35% market share by 2024, was driven by substantial government investment, manufacturing localization, and urban air quality concerns.

These international cases highlight the importance of policy consistency, infrastructure investment, and behavioral intervention in driving adoption. However, direct application of developed country experiences to emerging markets like Malaysia requires careful consideration of economic, cultural, and institutional differences. Recent research in Southeast Asian markets reveals common patterns of slow initial adoption followed by rapid acceleration once critical infrastructure and policy thresholds are achieved.

Theory of Planned Behavior Framework

The Theory of Planned Behavior, developed by Ajzen (1991), provides a robust theoretical foundation for understanding individual adoption decisions. The framework posits that behavioral intention is predicted by three primary constructs: attitude toward the behavior, subjective norm reflecting perceived social pressure, and perceived behavioral control indicating individual perception of ease or difficulty in performing the behavior.

For EV adoption research, this framework has been successfully extended to include additional constructs such as environmental concern, moral norms, and price value, providing comprehensive understanding of consumer decision-making processes. Recent applications in Malaysian contexts have demonstrated the framework's cultural appropriateness and predictive validity for technology adoption decisions.

Advanced Modeling Approaches

Contemporary EV adoption forecasting employs hybrid approaches combining traditional econometric methods with machine learning techniques. SARIMAX models effectively capture linear trends, seasonal patterns, and exogenous variable impacts, while neural network approaches excel at modeling complex nonlinear relationships. Recent developments in ensemble modeling demonstrate superior performance through optimal combination of complementary approaches.

METHODOLOGY

Research Design

This study employed a sequential mixed-methods research design integrating quantitative modeling with behavioral survey validation. The approach combined secondary data analysis of EV registrations, infrastructure deployment, and policy variables with primary behavioral research using validated TPB survey instruments.

The research framework consisted of four integrated phases: data collection and integration involving multi-source compilation including government statistics and infrastructure databases; behavioral survey implementation through two-phase TPB survey deployment; advanced modelling development using hybrid forecasting approaches; and validation through behavioural correlation analysis and case study examination.

Data Collection Framework

Secondary Data Sources

EV registration data comprising monthly vehicle registration records from January 2022 through May 2025 were obtained from official government sources, providing comprehensive coverage by state, model, and time. Charging infrastructure data was compiled from MEVnet dashboard, OpenChargeMap API, and government reports, providing monthly AC and DC charging station counts geocoded by location.

Policy variables were systematically encoded, including duty exemptions for CBU and CKD vehicles, road tax exemptions, infrastructure investment targets, and fiscal incentive programs. Economic indicators including monthly RON95 fuel prices were integrated to capture economic context.

Primary Survey Implementation

A comprehensive TPB-based questionnaire was developed comprising 40 items across eight behavioural constructs, measured using 5-point Likert scales. The two-phase validation protocol included a pilot test (n=50) involving cognitive interviews and reliability assessment, followed by a main survey (n=500) employing stratified sampling by state and demographics.

The pilot phase achieved acceptable to good reliability (Cronbach's α = 0.725-0.869) across all constructs, confirming instrument readiness. The main survey demonstrated excellent reliability (α = 0.802-0.850) with a 28.5% response rate from 1,754 initial contacts.

Advanced Modeling Framework

Model Architecture

The hybrid modelling approach integrated three complementary techniques: SARIMAX models configured with order (1,1,1) and seasonal order (0,1,1,12) to capture linear trends and seasonality; LSTM neural networks with 3-month lookback windows and 50 hidden units for nonlinear pattern recognition; and weighted ensemble optimization determining optimal combination weights through validation RMSE minimization.

Feature Engineering

Comprehensive feature engineering included temporal variables with 1 until 3-month lags for key indicators, policy encoding as binary flags and numeric values, behavioral integration through state-level TPB construct means, and model categorization using one-hot encoding for best-selling vehicles.

```
# Key Feature Engineering Implementation
def prepare_modeling_dataset():
    # Temporal features
    lagged_features = create_lagged_variables(
        ['ev_registrations',
'charging_stations'],
        lags=[1,2,3]
    )

    # Policy encoding
    policy_variables = encode_policy_scenarios(
        duty_exemptions, tax_incentives,
infrastructure_targets
    )

    # Behavioral integration
    tpb_state_means =
aggregate_tpb_by_state(survey_data)

    # Model features
    best_selling_models =
encode_categorical_models(top_5_monthly)

    return integrated_dataset

# Model Training Pipeline
def train_hybrid_models(dataset):
    # SARIMAX implementation
    sarimax_model = SARIMAX(
        endog=dataset['ev_share'],
        exog=dataset[exog_vars],
        order=(1,1,1),
        seasonal_order=(0,1,1,12)
    ).fit()

    # LSTM implementation
    lstm_model = Sequential([
        LSTM(50, dropout=0.2,
return_sequences=False),
        Dense(1, activation='linear')
    ])
```

```
    lstm_model.compile(optimizer='adam',
loss='mse')

    # Ensemble optimization
    optimal_weights =
optimize_ensemble_weights(
        sarimax_predictions, lstm_predictions,
validation_data
    )

    return sarimax_model, lstm_model,
optimal_weights
```

Validation Protocol

Model validation employed multiple metrics including RMSE for prediction accuracy, MAE for robustness assessment, and R^2 for explanatory power. Rolling window time series cross-validation ensured stability and prevented overfitting, while regional performance assessment enabled geographic variability analysis.

RESULTS AND ANALYSIS

Infrastructure and Market Assessment

Current infrastructure analysis reveals 4,161 public charging stations deployed by May 2025, comprising 2,857 AC and 1,304 DC chargers, representing 41.6% progress toward the 10,000-station 2025 target. Geographic distribution shows substantial urban-rural disparities with over 60% concentration in Selangor, Kuala Lumpur, Penang, and Johor.

Market performance demonstrates remarkable growth with 45.6% increase in Q1 2025 registrations (6,827 units vs. 4,689 in Q1 2024), achieving 3.86% market penetration. Proton e.MAS 7 leads with 3,399 units year-to-date 2025, validating domestic manufacturing viability, while Tesla Model Y's May 2025 resurgence demonstrates continued premium segment demand.

Behavioral Survey Results

The TPB survey validation achieved exceptional success with all constructs demonstrating excellent reliability in the main survey (α = 0.802-0.850). Notable improvements from pilot to main survey included Purchase Intention (0.772 → 0.816) and Personal Innovativeness (0.725 → 0.836), validating larger sample benefits.

Table 1: TPB Construct Reliability and Mean Scores

Construct	Pilot α	Main α	Mean Score	Interpretation
Purchase Intention	0.772	0.816	3.68	Moderate intent
Attitude	0.813	0.830	4.02	Positive perception
Subjective Norm	0.858	0.842	3.87	Social support
Perceived Behavioral Control	0.869	0.850	3.41	Primary barrier
Environmental Concern	0.815	0.802	4.16	High motivation
Moral Norm	0.833	0.829	3.92	Strong obligation
Price Value	0.802	0.813	3.48	Cost sensitivity
Personal Innovativeness	0.725	0.836	3.79	Moderate openness

Environmental Concern emerged as the strongest driver (4.16/5), while Perceived Behavioral Control represented the primary barrier (3.41/5), indicating that despite positive attitudes, practical concerns limit adoption confidence.

Model Performance Analysis

The weighted ensemble approach achieved excellent predictive performance with national-level R^2 of 0.822, RMSE of 0.518, and MAE of 0.415. State-level performance varied significantly, reflecting data quality and market maturity differences.

Table 2: Model Performance by Region

Region	RMSE	MAE	R^2	Performance Level
National	0.518	0.415	0.822	Excellent
Kuala Lumpur	1.282	1.036	0.653	Good
Selangor	2.104	1.328	0.461	Moderate
Johor	1.161	0.856	0.637	Good
Kelantan	1.092	0.760	0.476	Acceptable

The ensemble optimization successfully combined SARIMAX linear trend capture with LSTM nonlinear pattern recognition, achieving superior performance through data-driven weight determination.

2030 Adoption Projections

Comprehensive projection analysis reveals no region currently on track to achieve the 20% 2030 target under current trajectories. National projections indicate 12.71% adoption, representing a 7.29 percentage point gap.

Table 3: 2030 Adoption Projections vs. Targets

Region	2030 Projection	Target	Gap	Achievement Status
National	12.71%	20.0%	-7.29%	Below Target
Kuala Lumpur	14.03%	20.0%	-5.97%	Below Target
Selangor	15.23%	20.0%	-4.77%	Below Target
Johor	10.47%	20.0%	-9.53%	Below Target
Kelantan	9.55%	20.0%	-10.45%	Below Target

Urban centres demonstrate smaller gaps but still fall substantially short, while rural states face critical adoption challenges requiring intensive intervention.

While national-level forecasts indicate positive momentum, several states—particularly Kelantan, Johor, and other rural regions—display substantially lower projected adoption rates, these disparities likely stem from differences in charging infrastructure density, income distribution, and policy outreach. Limited access to public charging stations and lower household purchasing power reduce perceived behavioral control, a construct identified as the dominant barrier in the TPB analysis. In contrast, urban centers such as Kuala Lumpur and Selangor benefit from higher infrastructure availability, policy visibility, and greater environmental awareness, explaining their relatively higher but still sub-target projections. This divergence highlights that infrastructure and behavioral readiness must advance concurrently to achieve equitable nationwide EV adoption.

Discussions

Infrastructure-Behavior Correlation

Statistical analysis confirms strong positive correlation ($r = 0.72$) between charging station density and regional adoption rates. Each additional station per 100,000 population correlates with 0.3% increase in market share, validating infrastructure investment prioritization.

Perceived Behavioral Control shows direct relationship with infrastructure accessibility, with states having higher charging density demonstrating significantly higher PBC scores. This correlation validates the causal mechanism linking infrastructure development to consumer confidence.

Policy Effectiveness Assessment

Fiscal incentive analysis reveals measurable adoption impacts with 40% temporary increases during announcement periods and 15-20% higher baseline rates during extended incentive periods. However, policy effectiveness varies by consumer segment: higher-income consumers respond more to percentage-based incentives, while middle-income consumers require absolute-value subsidies.

The time-limited nature of current incentives creates both opportunities and risks, generating adoption urgency while threatening market disruption post-expiry. International experience suggests gradual phase-out outperforms abrupt termination in maintaining momentum.

Regional Development Patterns

Urban centres benefit from infrastructure advantages and higher policy awareness, while rural regions face compounding barriers including limited charging access, lower incomes, and reduced technology exposure. This urban-rural disparity requires differentiated intervention strategies addressing local conditions and capabilities.

Economic development indicators correlate strongly with adoption readiness, suggesting EV policy integration with broader regional development planning would optimize intervention effectiveness.

```
# Policy Impact Analysis Code
def analyze_policy_impact(registration_data,
policy_periods):
    """Quantify policy intervention effects on
adoption rates"""

    # Baseline vs. policy period comparison
    baseline_periods = registration_data[
        ~registration_data['policy_active']
    ]
    policy_periods = registration_data[
        registration_data['policy_active']
    ]

    # Calculate effect sizes
    baseline_mean =
baseline_periods['ev_registrations'].mean()
    policy_mean =
policy_periods['ev_registrations'].mean()
    effect_size = (policy_mean - baseline_mean)
/ baseline_mean
```

```
    # Statistical significance testing
    t_stat, p_value = ttest_ind(
        policy_periods['ev_registrations'],
        baseline_periods['ev_registrations']
    )

    return {
        'effect_size': effect_size,
        'p_value': p_value,
        'baseline_mean': baseline_mean,
        'policy_mean': policy_mean
    }

# Behavioral Correlation Analysis
def
behavioral_infrastructure_correlation(survey_da
ta, infrastructure_data):
    """Analyze relationship between PBC and
infrastructure availability"""

    # Merge survey and infrastructure data by
state
    merged_data = survey_data.merge(
        infrastructure_data,
        on='state',
        how='inner'
    )

    # Calculate correlations
    pbc_infrastructure_corr = merged_data[
        ['pbc_mean',
'charging_stations_per_capita']
    ].corr().iloc[0,1]

    # Regression analysis
    model = LinearRegression()
    X =
merged_data[['charging_stations_per_capita']].v
alues
    y = merged_data['pbc_mean'].values
    model.fit(X, y)

    return {
        'correlation': pbc_infrastructure_corr,
        'regression_coef': model.coef_[^0],
        'r_squared': model.score(X, y)
    }
```

POLICY RECOMMENDATIONS

Infrastructure Development Strategy

Immediate rural deployment acceleration through highway corridor development and community centre installations addresses geographic equity concerns. Urban enhancement requires high-rise residential solutions and workplace charging expansion to improve accessibility.

Medium-term strategy should establish integrated networks addressing both quantity and quality requirements, with private sector engagement through investment incentives and regulatory streamlining ensuring sustainable development.

Fiscal Policy Optimization

Incentive extension through 2027 with graduated reduction rather than abrupt termination maintains market momentum while ensuring fiscal sustainability. Administrative simplification through digital platforms and enhanced communication improves incentive accessibility and effectiveness.

Targeted subsidies for sub-RM100,000 vehicles broaden market access, while enhanced warranty programs address consumer confidence barriers regarding battery performance and maintenance costs.

Behavioral Intervention Programs

Consumer education addressing knowledge gaps about EV operation and maintenance, combined with hands-on experience programs, directly targets perceived behavioral control barriers. Peer support networks and community ambassador programs leverage positive social influence mechanisms identified in the survey analysis.

TECHNICAL IMPLEMENTATION FRAMEWORK

Data Pipeline Architecture

The comprehensive data integration system processes multiple real-time sources including government registration databases, charging infrastructure APIs, and survey platforms. The Python-based pipeline ensures data quality through automated validation and cleaning procedures.

```
    # Real-time Data Integration Pipeline
class EVAdoptionDataPipeline:
    def __init__(self):
        self.data_sources = {
            'registrations': RegistrationAPI(),
            'infrastructure':
ChargingStationAPI(),
            'surveys': SurveyDatabase(),
            'policy': PolicyTracker()
        }

    def fetch_and_process(self):
        """Main pipeline execution"""
        raw_data = {}

        # Fetch from all sources
        for source, api in
self.data_sources.items():
            raw_data[source] =
api.fetch_latest()

        # Data cleaning and validation
        clean_data =
self.clean_and_validate(raw_data)

        # Feature engineering
```

```
        engineered_data =
self.engineer_features(clean_data)

        # Model update
        updated_models =
self.update_models(engineered_data)

        return updated_models

    def engineer_features(self, data):
        """Advanced feature engineering"""
        features = {}

        # Temporal features
        features['lagged_registrations'] =
self.create_lags(
            data['registrations'], [1, 2, 3]
        )

        # Policy encoding
        features['policy_variables'] =
self.encode_policies(
            data['policy']
        )

        # Infrastructure metrics
        features['infrastructure_density'] =
self.calculate_density(
            data['infrastructure']
        )

        return features
```

Model Deployment and Monitoring

The production modelling system incorporates automated retraining capabilities and performance monitoring to ensure continued accuracy as market conditions evolve. Real-time prediction APIs enable policy makers to assess intervention impacts dynamically.

Limitations And Future Research

Study Limitations

Data availability constraints include urban bias in infrastructure reporting and potential gaps in government data collection systems. Methodological assumptions regarding constant exogenous variables post-2025 introduce uncertainty into long-term projections.

Cross-sectional survey design limits behavioral change tracking, while TPB framework constraints may not capture emotional or habitual influences fully. Geographic focus on four states may not represent full national diversity.

Future Research Directions

Longitudinal behavioral studies tracking attitude and intention evolution over time would enhance understanding of adoption dynamics. Advanced modelling approaches including deep learning architectures and causal inference methods offer opportunities for improved accuracy.

Regional comparative studies across Southeast Asian markets would identify transferable lessons and context-specific factors, while environmental impact assessment would provide crucial sustainability validation.

Conclusion

This comprehensive analysis reveals Malaysia's EV adoption landscape presents both significant opportunities and substantial challenges. While remarkable growth momentum with 45.6% Q1 2025 increases and emerging domestic manufacturing success demonstrate market potential, fundamental gaps in infrastructure, policy sustainability, and consumer readiness threaten 2030 target achievement.

The integration of behavioral, technical, and policy analysis provides unprecedented insight into adoption dynamics. The validated TPB framework confirms positive consumer attitudes and strong environmental motivation, but identifies perceived behavioral control as the primary barrier requiring coordinated intervention across infrastructure, affordability, and education domains.

Advanced modelling results demonstrate excellent national-level predictive accuracy while revealing substantial regional variations requiring targeted strategies. No region currently projects to meet 2030 targets under current trajectories, indicating needs for accelerated intervention across multiple domains.

The methodological framework successfully integrates behavioral science with advanced predictive modelling, establishing new standards for transportation policy research and providing replicable approaches for similar analyses in emerging markets. Strategic implementation of infrastructure acceleration, policy enhancement, and behavioral intervention programs offers pathways toward achieving national EV adoption goals and sustainable transportation transformation.

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