

Research Paper

## Pathways to Electric Two-Wheeler Adoption in Emerging Markets: A Scoping Review and Empirical Validation of Consumer Behaviour

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### Abstract

The electrification of two-wheelers (E2Ws) is increasingly recognised as a high-impact decarbonisation strategy in emerging Asian markets, where motorcycles are the dominant mode of transport. However, the literature remains fragmented, and behavioural studies consistently report a persistent gap between stated adoption intentions and actual purchase behaviour. This study provides a robust empirical proxy to address these limitations through a two-phase hybrid approach: a scoping review and bibliometric analysis (ScoRBA) of 278 Scopus-indexed articles, synthesised using the PAGER framework, followed by empirical validation via a multi-model machine learning approach applied to a stated-preference dataset of 6,040 respondents from Solo, Indonesia. Bibliometric mapping identified three core socio-technical research clusters. The empirical analysis revealed a finding that departs substantially from prevailing assumptions: Perceived E-bike Quality, not financial incentives or operational costs, emerged as the dominant predictor of adoption. While initially identified via a baseline Decision Tree, this dominance was robustly validated across advanced ensemble algorithms and confirmed via SHAP analysis (Mean |SHAP Value| = 17.88%). Correctly situated within the technology perception dimension of the Technology Acceptance Model (TAM), this variable's dominance implies a sequential cognitive architecture: technology credibility must be established before economic evaluation becomes relevant. Consequently, policymakers in similar motorcycle-dominated transitional markets should prioritise quality certification and demonstration programmes before deploying purchase subsidies at scale.

**Keywords:** Electric two-wheelers; Scoping review; Machine learning; Technology acceptance; Consumer behaviour

## 1. Introduction

In emerging Asian economies, motorcycles are the primary mode of transport. In India and Indonesia alone, powered two-wheelers account for 75–83% of the total registered vehicle fleet [1], [2], [3], making electrification one of the most consequential levers available for transport-sector decarbonisation [4]. This is not merely a matter of scale. Unlike passenger cars, two-wheelers are the daily mobility backbone for low- and middle-income commuters. Consequently, adoption barriers in this segment carry direct equity

implications that extend well beyond environmental policies.

Despite this significance, the literature on E2W adoption remains notably fragmented [5], [6], [7]. Prior reviews have contributed useful groundwork, but most rely on narrative approaches or general EV frameworks that were not designed with two-wheelers or the socio-economic realities of emerging markets in mind (Table 1). However, the deeper problem is behavioural. Studies have reported high stated intentions to adopt E2Ws; however, market penetration in most Southeast Asian cities remains



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**Table 1.** Comparison of previous literature reviews on electric vehicle adoption

| Refs       | Scope      | Method                                               | Framework       | Gap Addressed                                                             |
|------------|------------|------------------------------------------------------|-----------------|---------------------------------------------------------------------------|
| [5]        | General EV | Narrative Review                                     | -               | Consumer preferences and economic factors                                 |
| [8]        | E2W        | Narrative Review                                     | -               | Electric motorcycle adoption intentions                                   |
| [9]        | General EV | Systematic Review                                    | -               | Adoption barriers and policy incentives                                   |
| [7]        | General EV | Systematic Review                                    | TEOP Dimensions | Holistic impacts across technology, environment, organization, and policy |
| This study | E2W        | ScoRBA + Multi-Model ML (DT, RF, XGBoost, GB) + SHAP | PAGER           | Integration of 3 socio-technical clusters & empirical validation          |

low. This intention-behaviour gap is not merely a statistical inconvenience; it signals that existing theoretical models are missing something fundamental about how consumers in these markets make adoption decisions.

To address these limitations, this study proposes an integrated, hybrid approach. First, we apply a Scoping Review and Bibliometric Analysis (ScoRBA) to comprehensively map the intellectual structure of the topic [10]. Subsequently, the Patterns, Advances, Gaps, Evidence for Practice, and Research Recommendations (PAGER) framework was used to translate the bibliometric data into actionable qualitative insights. Finally, to move beyond theoretical mapping and provide a robust empirical proxy for behavioural tendencies, this study validates the qualitative findings using a multi-model machine learning approach applied to a publicly available stated-preference dataset of 6,040 respondents from Solo, Indonesia [11], [12]. This dataset is particularly relevant because it captures the mobility characteristics and economic constraints of a typical motorcycle-dominated emerging market. Prior studies have typically separated scoping reviews from bibliometric mapping. In contrast, this study introduces a novel methodology that integrates a qualitative PAGER synthesis with a robust multi-model machine learning architecture. By benchmarking an interpretable baseline decision tree against advanced ensemble models and model-agnostic SHAP (SHapley Additive exPlanations) analysis, this study overcomes the single-algorithm biases frequently assumed in transitional markets [13]. The aim is not methodological novelty for its own sake, but rather to produce adoption insights that are both theoretically grounded and empirically resilient.

## 2. Methods

This section outlines the integrated two-phase methodology used in this study. The first phase employed a Scoping Review and Bibliometric Analysis (ScoRBA) guided by PRISMA-ScR principles and adapted for bibliometric database construction to systematically map the existing literature. The specific procedures for this qualitative mapping are outlined in Subsections 2.1 through 2.4. Subsequently, the second phase involves empirical validation to bridge the identified intention-behaviour gap. This validation utilised a secondary public dataset which was analysed using a machine learning classification approach, as detailed in Subsection 2.5.

### 2.1. Research Design

This study employed a Scoping Review and Bibliometric Analysis (ScoRBA) methodological design to comprehensively map the research landscape of E2W adoption. This approach was selected for its capacity to merge the strengths of a broad scoping review, ideal for identifying the extent of the literature, with quantitative bibliometric analysis, used to uncover the intellectual structure, trends, and key themes within the field [10]. To ensure transparency and replicability, this study adopts a PRISMA-ScR-informed reporting logic, adapting it specifically for the bibliometric database construction.

### 2.2. Data Source and Search Strategy

The Scopus search was conducted on September 2, 2025 using a predefined search string that combined terms related to electric two-wheelers and adoption behaviour. The final search string was, (TITLE-ABS-KEY ("electric motorcycle" OR "electric scooter" OR "electric two-

wheeler") AND TITLE-ABS-KEY (adoption OR diffusion OR acceptance OR uptake OR intention)) AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE, "English")). The search was limited to publications from 2015 to 2025 and refined using Scopus filters for subject area, document type, language, source type, and publication stage.

### 2.3. Selection Criteria and Screening Process

Stringent inclusion and exclusion criteria were applied to construct a bibliometric corpus. The inclusion criteria covered English-language peer-reviewed journal articles and conference papers published between 2015 and 2025, indexed in Scopus, and directly related to electric two-wheeler adoption, acceptance, diffusion, uptake, or purchase intention. The exclusion criteria eliminated editorials, book reviews, non-peer-reviewed documents, non-English publications, and studies not directly related to electric two-wheeler adoption or consumer behaviour.

The Scopus database search and eligibility filtering process yielded a final corpus of 278 records. It should be noted that the number of retained records remained unchanged across the subsequent filtering stages because the relevant eligibility restrictions, including publication year, subject area, document type, language, source type, and publication stage, were applied directly through the Scopus interface before data export. Consequently, no additional records were excluded during the post-export screening, and all

278 records were included in the bibliometric analysis and PAGER synthesis.

The article selection process was documented using a PRISMA-ScR-informed flow diagram adapted to the requirements of the bibliometric database. [Figure 1](#) illustrates the PRISMA-ScR-informed database construction process, and [Table 2](#) provides a detailed summary of the number of records retained and excluded at each filtering stage.

### 2.4. Data Analysis

To map the thematic landscape, a co-occurrence analysis of author keywords was conducted using VOSviewer software [14]. This methodology generates a network map where each node represents a keyword, and its size reflects its frequency of occurrence. The links between nodes signify that the keywords frequently appear together in the same publications, indicating a strong thematic relationship. VOSviewer's clustering algorithm then groups closely related nodes into coloured clusters, each representing a primary research domain. To ensure analytical rigor and relevance, the minimum keyword occurrence threshold was set to 5.

Although co-citation analysis, bibliographic coupling, and thematic evolution mapping can provide additional insights into the intellectual structure of a research field, this study prioritised author-keyword co-occurrence analysis because its main purpose was to identify thematic domains

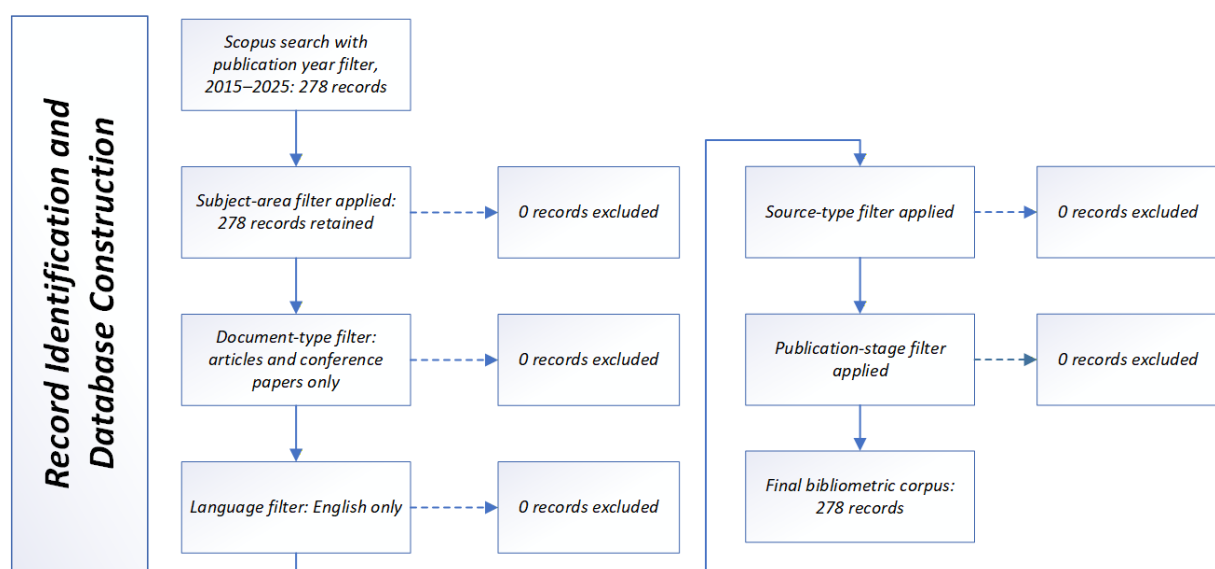


**Figure 1.** PRISMA-ScR flow diagram of the article selection process

**Table 2.** Scopus database construction and eligibility filtering process

| Stage                                     | Records Retained | Records Excluded | Explanation                                                                                       |
|-------------------------------------------|------------------|------------------|---------------------------------------------------------------------------------------------------|
| Scopus search with year filter, 2015–2025 | 278              | N/A              | Initial eligible records were retrieved using the final search query and publication year filter. |
| Subject-area filter                       | 278              | 0                | All retrieved records were within the selected subject area.                                      |
| Document-type filter                      | 278              | 0                | All records were articles or conference papers.                                                   |
| Language filter                           | 278              | 0                | All records were written in English.                                                              |
| Source-type filter                        | 278              | 0                | All records met the eligible Scopus source-type criteria.                                         |
| Publication-stage filter                  | 278              | 0                | All records met the eligibility criteria for publication.                                         |
| Duplicate checking                        | 278              | 0                | No duplicates were found because the corpus was retrieved from only one database.                 |
| Final corpus                              | 278              | 0                | All retained records were included in the bibliometric and PAGER analyses of this study.          |

that could be directly translated into empirical adoption variables for the subsequent machine learning phase. The absence of additional bibliometric network analyses is acknowledged as a methodological limitation and an opportunity for future research.

Following quantitative mapping and identification of thematic clusters via VOSviewer, the subsequent stage of analysis involved an in-depth qualitative synthesis. For this purpose, the PAGER framework was applied as an analytical guide [13]. Each previously identified cluster was further analysed by examining the constituent articles. The findings from these articles were systematically categorised into the five PAGER domains. This structured approach allows the review to not merely describe the literature, but also to generate actionable insights, highlight knowledge gaps, and formulate concrete recommendations for future research. To minimise subjective bias during the PAGER categorization process, the authors extracted the findings through iterative discussions to reach an inter-coder agreement. To enhance the transparency of PAGER synthesis, two authors independently coded the extracted findings into the five PAGER domains. Discrepancies in coding were discussed and resolved through consensus, with the third author acting as an adjudicator, when necessary. This iterative procedure was used to reduce individual interpretive bias and improve the consistency of the thematic categorization.

## 2.5. Empirical validation data source and analysis

To empirically assess the literature-derived themes, particularly those concerning consumer behaviour, operational costs, and range anxiety, this study utilised a secondary public dataset from a stated-preference survey conducted in Solo, Indonesia [11], [12]. This dataset is relevant because it captures the socioeconomic and mobility characteristics of a motorcycle-dominated urban context in Indonesia. The selection of Solo is strategically justified, as it represents a prototypical mid-sized emerging market city characterised by a transitional urban-suburban infrastructure and a heavy daily reliance on motorcycles for commuting. This high dependency mirrors the broader mobility patterns across Southeast Asia (such as in Vietnam, Thailand, and the Philippines), making this dataset a useful empirical context for exploring the dynamics of E2W adoption in motorcycle-dominated Southeast Asian cities.

The dataset comprises 6,040 choice observations from respondents, capturing demographic profiles (age, income, and gender) alongside vehicle attributes (e.g., maximum range, charging time, EV electricity cost, and comparative gasoline prices). To ensure a robust analysis, a Decision Tree classification algorithm with balanced class weights was employed. This machine learning technique was chosen for its ability to visually map critical decision nodes such as exact operational cost thresholds and range

limitations associated with consumers' willingness to adopt an electric two-wheeler.

To ensure the robustness and generalisability of the primary Decision Tree findings, four additional benchmark classifiers were trained under identical preprocessing conditions: Logistic Regression, Random Forest (n=200 estimators), XGBoost (n=200 estimators), and Gradient Boosting (n=200 estimators). These specific algorithms served as benchmarks to strike a balance between a linear baseline and robust ensemble prediction, whilst maintaining clear feature-importance interpretability. Support Vector Machine (SVM) was excluded from this comparative analysis, as the empirical objective required classifiers that naturally produce interpretable feature rankings to validate the earlier bibliometric themes. Class imbalance was consistently addressed across all models using balanced class weights or equivalent scale parameters. Furthermore, SHapley Additive exPlanations (SHAP) analysis [15] was applied to the Random Forest model to provide a model-agnostic, permutation-validated measure of feature importance, thereby mitigating the known susceptibility of single-tree importance scores to split-point artefacts.

## 2.6. Limitations of the Scoping Review and Bibliometric Analysis

This study acknowledges several methodological limitations inherent to the scoping review phase. First, exclusive reliance on the Scopus database may introduce publication bias, potentially excluding relevant grey literature or regionally indexed studies in platforms such as Web of Science (WoS) or Google Scholar. Furthermore, restricting the inclusion criteria to English-language articles may underrepresent the rich literature originating from major non-Anglophone E2W markets, such as China and Vietnam. Because the temporal scope concludes in September 2025, the publication data for the final year are only partially captured.

Second, a formal risk of bias assessment was not conducted because this study followed a scoping review design, whose primary purpose is to map the breadth, extent, and thematic structure of an emerging research field rather than to evaluate intervention effectiveness or synthesise causal effect sizes. This approach is consistent with the methodological orientation of

scoping reviews proposed by Arksey and O'Malley and the PRISMA-ScR. Nevertheless, baseline quality control was ensured by restricting the corpus to peer-reviewed publications indexed in Scopus, applying explicit inclusion criteria, and conducting iterative author discussions to minimise subjective interpretations during PAGER synthesis. The absence of formal quality scoring is acknowledged as a limitation, as it may restrict the ability to compare the methodological rigor of the individual studies.

## 3. Results and Discussion

### 3.1. Publication Trends and Descriptive Statistics

Analysis of annual scientific production reveals a surging research interest in Electric Two-Wheeler (E2W) adoption. [Figure 2](#) presents the publication trends from 2016 to September 2025. In the initial period (2016–2019), the number of publications was relatively low, ranging from four to eight articles per year. A significant upward trend began in 2020, with 15 publications, and continued to accelerate, peaking in 2024 with 78 articles. The 61 articles recorded as of September 2025 reflect an incomplete dataset for that year an expected limitation in bibliometric studies.

The bibliometric extraction reveals a robust and accelerating interest in Electric Two-Wheeler (E2W) adoption. As illustrated in [Figure 3](#), the geographical distribution of E2W research is overwhelmingly concentrated in Asia. Indonesia led the global scientific output with 208 publications, followed closely by India with 146 and China with 118. These empirical data strongly

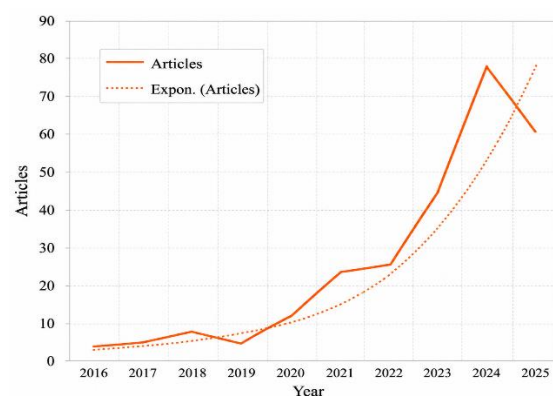


**Figure 2.** Annual scientific production trend

validate the premise introduced earlier: powered two-wheelers constitute the backbone of mobility in emerging Asian markets, thereby prompting a massive academic urgency to address local adoption and electrification challenges. In contrast, Western countries such as the USA (93 publications) and Italy (55 publications) show a relatively lower output, reflecting their car-centric mobility culture. Country production was calculated based on author affiliation occurrences; therefore, the total country counts may exceed the number of unique documents because a single publication can involve multiple countries.

Furthermore, an analysis of the most relevant sources, presented in Figure 4, indicates that the discourse on E2W adoption is predominantly hosted by high-impact journals focusing on environmental sustainability and transportation policy. Sustainability (Switzerland) emerged as the leading outlet with 16 published articles, followed by Transport Policy (eight articles) and Transportation Research Record (eight articles). The prominence of these specific journals alongside others, such as Transportation Research Part D: Transport and Environment (seven articles), underscores the interdisciplinary nature of E2W research. This trend highlights that E2W adoption has evolved from a narrow automotive engineering issue into a complex socio-technical transition, intersecting vehicle technology, macro-environmental sustainability, and equitable policy frameworks.

### 3.2. Co-occurrence Analysis of Author Keywords

Co-occurrence analysis of the author keywords delineated the intellectual structure of the literature, identifying three distinct thematic clusters. Each cluster, represented by a different colour in the network visualisation (Figure 5), reflects an interconnected yet distinct research domain. A summary of each cluster is provided in Table 3.

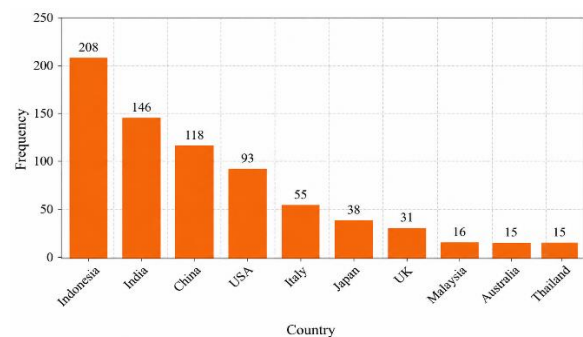


Figure 3. Countries' scientific production

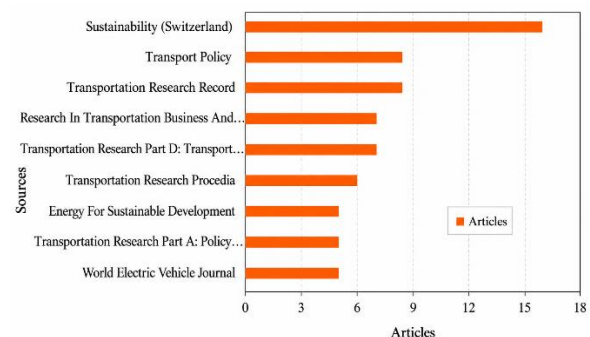


Figure 4. Most relevant sources

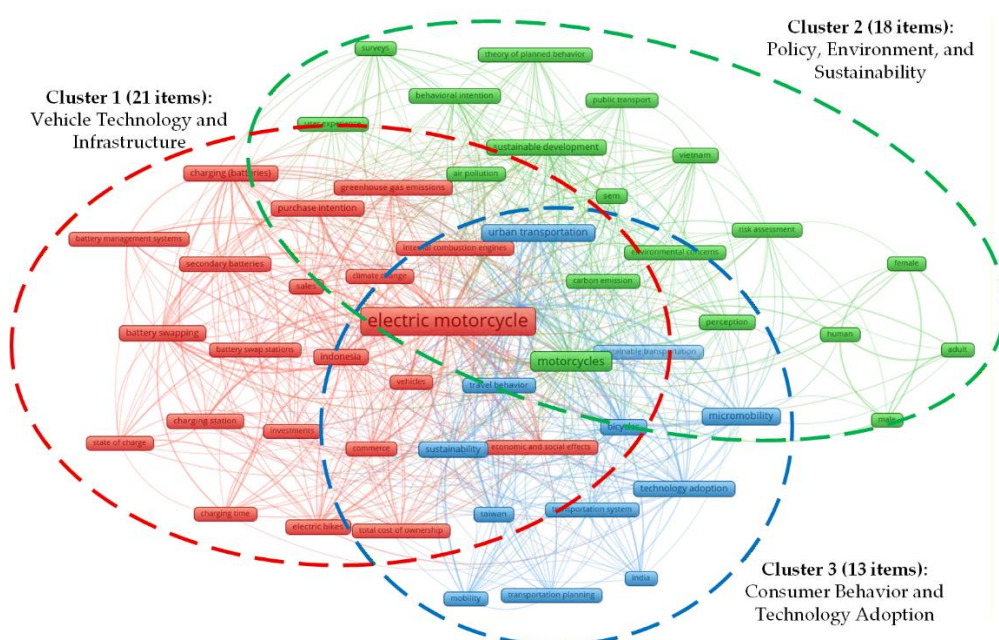
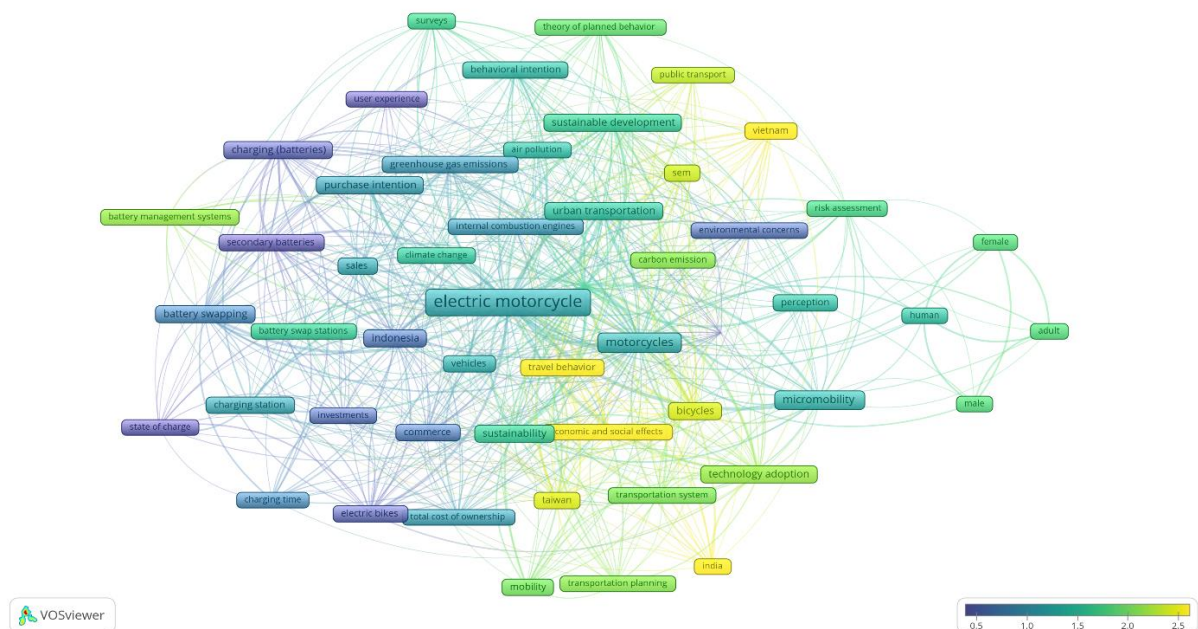


Figure 5. VOSviewer thematic network map

**Table 3.** Three primary clusters and themes in E2W adoption research

| Cluster | Theme                                      | Description                                                                                                                                                                                      |
|---------|--------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Red     | Vehicle Technology and Infrastructure      | This cluster is centred on the technical aspects of E2Ws, including research on battery performance, driving range, management systems, and charging infrastructure.                             |
| Green   | Policy, Environment, and Sustainability    | This cluster covers the broader macro-context, focusing on the environmental impact of electric vehicle adoption, the role of government regulation, and public perceptions of sustainability.   |
| Blue    | Consumer Behaviour and Technology Adoption | This cluster specifically investigates user-side factors, such as purchase intention, socio-demographic characteristics, and motivations and barriers for consumers in adopting this technology. |

**Figure 6.** Keyword overlay visualisation of thematic evolution

To further enhance the bibliometric depth and capture the thematic evolution of the field, a temporal overlay visualisation was generated (Figure 6). The colour gradient, ranging from dark blue (older publications) to yellow (recent publications), illustrates a clear evolutionary trajectory in E2W research. Early studies (dark blue nodes) were predominantly foundational, focusing heavily on technical limitations and infrastructure, such as charging (batteries), state of charge, and battery swapping. As the field matured (green nodes), the focus shifted towards environmental impact and fundamental behavioural models, evidenced by keywords like air pollution, sustainable development, and theory of planned behaviour.

The most recent literature (yellow nodes) reveals a distinct pivot towards specific emerging market contexts (Vietnam, India, Taiwan) and

real-world mobility integration, highlighted by terms such as travel behaviour and economic and social effects. This temporal evolution provides additional support for the empirical focus of the current study, suggesting that the current research frontier has increasingly moved beyond basic technological feasibility towards understanding socio-economic behaviours in specific transitional markets.

### 3.3. In-depth Analysis and PAGER Synthesis

This section presents an in-depth analysis and discussion of each thematic cluster identified previously. Utilising the PAGER framework, each cluster was dissected to identify patterns, advances, gaps, evidence for practice, and research recommendations, aligning with the journal's guidelines to present an idea-driven review.

### 3.3.1. Cluster 1: Vehicle technology and infrastructure

The comprehensive PAGER analysis findings for the Vehicle Technology and Infrastructure cluster, detailing the patterns, advances, gaps, evidence for practice, and research recommendations, are summarised in [Table 4](#). The foundational pillar of E2W adoption relies heavily on the continuous advancement of battery technology and corresponding mechanical infrastructure. Historically, the transition from conventional lead-acid batteries to advanced lithium-ion (Li-ion) variants has marked a significant leap in E2W energy density, weight reduction, and overall driving range [16], [17], [18], [19]. However, recent literature emphasises that diverse Li-ion chemistries such as Lithium Iron Phosphate (LiFePO<sub>4</sub>) and Nickel Manganese Cobalt (NMC) present distinct trade-offs between thermal stability and energy capacity [20], [21]. Studies set in tropical and emerging markets have highlighted thermal degradation as a critical barrier; extreme ambient temperatures coupled with intensive urban commuting patterns significantly accelerate battery aging and reduce operational reliability [22], [23], [24], [25], [26]. Consequently, the compact architecture of E2Ws has driven recent technical focus toward developing robust thermal management and heat dissipation systems [27], [28].

To mitigate these physical degradation issues and enhance user trust, the integration of intelligent Battery Management Systems (BMS) has become a vital research trajectory. A prevalent pattern in the literature is the utilisation of operational data to estimate the State of Health (SoH) and State of Charge (SoC) of E2W batteries

[27], [29], [30], [31]. While earlier studies relied on straightforward equivalent circuit models, recent advancements have increasingly deployed machine learning algorithms such as Decision Trees, Random Forests, and Artificial Neural Networks to provide high-precision predictive maintenance diagnostics [32], [33], [34]. Despite these algorithmic advances, a critical gap remains: current predictive models often lack generalisability across diverse battery chemistries and validation using longitudinal, real-world operational data [35], [36], [37]. Addressing this gap by benchmarking ensemble machine learning models against varied environmental conditions is crucial for developing onboard BMS that can prevent sudden battery failures and optimise the lifecycle of E2Ws [38], [39], [40], [41].

Equally critical to the advancement of onboard vehicle technology is the development of an accessible and reliable charging infrastructure. The literature reveals a robust debate concerning the optimal energy replenishment mechanism for E2Ws: conventional plug-in charging versus Battery Swapping Stations (BSS) [42], [43]. While plug-in charging remains the most common method for private users, studies consistently report that prolonged charging times and the scarcity of public charging infrastructure in densely populated urban areas act as primary deterrents to widespread adoption [44], [45], [46], [47]. To circumvent these challenges, BSS has emerged as a disruptive and highly efficient alternative, particularly in regions where E2Ws are heavily utilised for commercial purposes, such as ride-hailing and last-mile delivery services [48], [49], [50]. Research demonstrates that BSS significantly reduces energy replenishment time from several

**Table 4.** PAGER analysis results for Cluster 1: Vehicle technology and infrastructure

| Domain                   | Findings and Analysis                                                                                                                                                                                               |
|--------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Patterns                 | The dominant application of Machine Learning (ML) algorithms (e.g., Support Vector Machines, Neural Networks) for estimating the State of Health (SoH) within Battery Management Systems (BMS).                     |
| Advances                 | Significant improvements in SoH prediction accuracy have been achieved by utilising advanced ensemble methods, such as Random Forest, alongside the successful integration of IoT for real-time battery monitoring. |
| Gaps                     | Limited cross-validation of predictive models across diverse battery chemistries (e.g., LFP vs. NMC) and a lack of generalisability under extreme tropical temperatures.                                            |
| Evidence for Practice    | Manufacturers should adopt IoT-enabled predictive maintenance systems to optimise battery lifecycle management and reduce warranty-claim numbers.                                                                   |
| Research Recommendations | Future studies must empirically validate ML-based BMS algorithms across diverse battery chemistries under varied climatic conditions, specifically in emerging markets.                                             |

hours to merely a few minutes, mitigating "range anxiety" and enhancing the operational efficiency of E2W fleets [51], [52], [53].

Despite their operational advantages, the deployment of BSS introduces complex mechanical and logistical challenges that dominate recent research agendas. From an engineering standpoint, standardising battery pack dimensions and ensuring connector interface durability under high-frequency swapping cycles remain formidable challenges [54], [55]. Furthermore, the literature highlights the necessity of optimising the spatial distribution of swapping cabinets to minimise user detour distances while maximising station utilisation rates [56], [57], [58]. Consequently, advanced mathematical modelling and heuristic algorithms such as Genetic Algorithms and Particle Swarm Optimisation are increasingly employed to solve complex facility location problems associated with BSS networks [59], [60]. Addressing these infrastructure challenges is paramount, as the transition from private ownership to "Battery-as-a-Service" (BaaS) models hinges entirely on the mechanical reliability and strategic placement of these swapping ecosystems [2], [61], [62].

### 3.3.2. Cluster 2: Policy, environment, and sustainability

The comprehensive PAGER analysis findings for the Policy, Environment, and Sustainability cluster are systematically summarised in Table 5. The transition towards electric micro-mobility is inextricably linked to the design and implementation of macro-level government interventions. A substantial portion of the literature in this cluster evaluates the efficacy of various policy instruments ranging from direct financial subsidies to operational tax exemptions in accelerating E2W adoption [63], [66], [67], [68]. Historically, governments in emerging markets have heavily relied on upfront purchase subsidies to lower the initial sticker price of E2Ws, which remains significantly higher than conventional Internal Combustion Engine (ICE) motorcycles [69], [70], [71]. However, recent longitudinal policy evaluations indicate a paradigm shift; evidence suggests that operational incentives, such as reduced electricity tariffs for home charging, parking fee waivers, and road tax exemptions, often exert a more sustained positive

impact on consumer retention and long-term usage than one-off purchase discounts [1], [72], [73], [74]. Consequently, formulating a balanced, mixed-policy package that simultaneously addresses both acquisition and operational barriers has been identified as a critical determinant for successful market penetration [75], [76], [77].

To objectively measure the economic viability of these policies, researchers increasingly rely on Total Cost of Ownership (TCO) modelling. TCO analyses provide a comprehensive mathematical framework that compares the lifetime expenses of E2Ws against ICE motorcycles, factoring in depreciation, battery replacement costs, and fluctuating energy prices [78], [79], [80], [81]. The literature reveals that while E2Ws incur higher initial capital costs, their lower per-kilometre energy consumption and minimal mechanical maintenance requirements allow them to reach a financial break-even point within an average of three to five years of intensive urban use [82], [83]. Furthermore, when TCO models are integrated with Life Cycle Assessment (LCA) frameworks, the literature exposes a critical debate regarding the actual "green" credentials of E2Ws [65], [84], [85]. Studies emphasise that the net environmental benefit of E2W adoption is heavily contingent upon the carbon intensity of the national power grid; in countries where electricity generation is still dominated by coal, the reduction in tailpipe emissions is partially offset by upstream greenhouse gas emissions [86], [87], [88], [89].

Beyond technical and economic calculations, recent advancements in this cluster highlight the profound impact of macro-socioeconomic factors, particularly wealth disparity, on adoption trajectories. Studies indicate that generic, blanket subsidy programmes often disproportionately benefit middle-to-upper-income demographics, thereby risking the exacerbation of mobility inequality in developing nations [90], [91], [92]. To ensure a just and equitable socio-technical transition, current literature underscores the need for targeted fiscal interventions prioritising low-income commuters and regions with lagging adoption rates [93], [94]. Moreover, the role of environmentalism often assumed to be a primary driver of green purchasing has been structurally redefined; it frequently acts not as a direct behavi

**Table 5.** PAGER analysis results for Cluster 2: Policy, environment, and sustainability

| Domain                   | Findings and Analysis                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |
|--------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Patterns                 | A dominant pattern is research evaluating the impact of government policy instruments (e.g., subsidies, fiscal incentives) on E2W adoption [63], [64]. Studies often test the role of environmentalism constructs (awareness, concern) as psychological drivers of adoption [41], [65].                                                                                                                                                                                                                                                         |
| Advances                 | The role of environmentalism is better understood; its effect is often indirect, mediated by awareness of green policies [65]. The analysis of incentive effectiveness shows that operational subsidies (e.g., electricity tariffs) are often preferred by users over upfront purchase subsidies [64]. Research has begun to reveal that adoption policies are significantly shaped by macro factors like wealth inequality, risking an uneven mobility transition [1].                                                                         |
| Gaps                     | The majority of studies are cross-sectional, lacking evidence from longitudinal studies that can track the real-world impact of policies over time [41], [65]. The generalisability of findings is limited due to the specific geographical scope of primary studies [41], [64]. There is a lack of research comparing the effectiveness of mixed policy packages.                                                                                                                                                                              |
| Evidence for Practice    | Evidence suggests that incentive policies must be designed with an equity perspective, for instance, by targeting low-income demographics and regions to prevent mobility inequality [1]. Policy marketing and communication should focus on raising awareness of existing green policies, as this is an effective mediator for activating consumers' environmental values [65]. To foster mass adoption, policymakers should prioritise instruments that lower the initial sticker price and operational costs [2].                            |
| Research Recommendations | Conduct longitudinal studies and quasi-experimental policy designs to assess the actual behavioural effects of regulatory shifts. Integrate the Total Cost of Ownership (TCO) and Life Cycle Assessment (LCA) into dynamic models for holistic policy evaluation [65]. Undertake cross-national comparative studies with different market structures to test the universality of findings [1], [41]. Integrate Total Cost of Ownership (TCO) and Life Cycle Assessment (LCA) of emissions into policy evaluations for a more holistic view [2]. |

oural trigger, but rather as a distal psychological variable that must be activated through aggressive public awareness campaigns regarding green policies [95], [96], [97], [98].

### 3.3.3. Cluster 3: Consumer behaviour and technology adoption

The specific qualitative insights and PAGER analysis findings regarding the Consumer Behaviour and Technology Adoption cluster are presented in Table 6. The final cluster investigates the psychological, social, and instrumental determinants that govern consumer behaviour towards E2W adoption. A prevalent pattern within this domain is the application of classic technology acceptance frameworks, most notably the TPB, Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), to decode user purchase intentions [100], [101], [102], [103], [104]. However, recognising the unique socio-technical nature of electric mobility, recent literature has significantly extended these foundational models. Scholars have increasingly incorporated context-

specific constructs such as range anxiety, perceived charging infrastructure availability, and national cultural dimensions to enhance the predictive power of these models in emerging markets [99], [105], [106], [107], [108]. Furthermore, studies reveal that product observability and cultural compatibility, such as the vehicle's ability to accommodate local commuting habits and varying payload requirements, are often weighted more heavily by consumers than pure ecological benefits [109], [110], [111], [112].

Despite the proliferation of behavioural studies, a critical methodological limitation persists within this cluster: the overwhelming reliance on stated-preference data gathered through cross-sectional surveys [64], [113], [114], [115]. The literature frequently highlights an "intention-behaviour gap," wherein a high stated intention to purchase an E2W does not proportionately translate into actual market sales or revealed-preference behaviour [116], [117], [118]. This discrepancy underscores the urgent need for longitudinal studies capable of tracking

the conversion from cognitive intention to actual physical adoption over time [119], [120], [121], [122]. To capture these non-linear adoption dynamics, researchers are beginning to advocate for the transition from static structural equation modelling to dynamic simulation approaches, such as Agent-Based Modelling (ABM) and System Dynamics, which can simulate the complex interplay of word-of-mouth effects, peer influence, and changing policy landscapes [123], [124], [125], [126].

Beyond individual psychology, recent literature underscores the necessity of embedding adoption models within specific socio-spatial and demographic contexts. Adoption barriers differ drastically between dense urban centres and sprawling suburban commuter belts; suburban

users exhibit higher sensitivity to battery range and top-speed performance due to longer daily travel distances [127], [128], [129]. Additionally, macro-economic factors such as wealth inequality and limited access to consumer credit have been identified as structural bottlenecks that prevent lower-income demographics from participating in the E2W transition, regardless of their personal environmental values [130], [131]. To circumvent these financial barriers, a growing sub-section of this cluster explores the viability of alternative business models, such as E2W sharing services and "Battery-as-a-Service" (BaaS) leasing schemes, which lower the barrier to entry and shift the paradigm from vehicle ownership to mobility usership [132], [133], [134].

**Table 6.** PAGER analysis results for Cluster 3: Consumer behaviour and technology adoption

| Domain                   | Findings and Analysis                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|--------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Patterns                 | A prevalent pattern is the use of technology acceptance theories like the Theory of Planned Behaviour (TPB) and the Unified Theory of Acceptance and Use of Technology (UTAUT) as foundational research frameworks [8], [99]. Research methodologies are dominated by quantitative surveys using stated preference to measure user intentions [8], [64]. The primary focus is the identification of psychological and instrumental factors influencing purchase intention [8].                                                                                                                                              |
| Advances                 | Classic models like UTAUT have been extended to include new contextual variables, such as national culture, enhancing their explanatory power [99]. Analysis has evolved from individual factors to macro socio-economic factors, like wealth inequality, which has been shown to influence regional adoption rates [1]. Research focus has broadened from private ownership intention to usage intention in new business models like sharing services [6].                                                                                                                                                                 |
| Gaps                     | A critical methodological flaw exists as most studies heavily rely on stated-preference data (intention) rather than revealed-preference data (actual adoption behaviour). Furthermore, the specific causal mechanisms linking macro-level factors (e.g., wealth inequality) to individual adoption have been underexplored [8], [64]. The generalisability of findings is limited as samples are often specific (e.g., university students, single cities) [6], [64]. The specific causal mechanisms behind macro-level findings (e.g., exactly how inequality affects credit access for E2Ws) are not fully explored [1]. |
| Evidence for Practice    | Incentive policies are most effective when they focus on lowering the initial sticker price and subsidising operational costs [2], [64]. User acquisition heavily depends on enhancing service compatibility with local lifestyles and mobility needs (e.g., convenient access, helmet availability) [6]. Policy design needs an equity perspective, targeting low-income demographics to ensure a just mobility transition [1].                                                                                                                                                                                            |
| Research Recommendations | Conduct longitudinal studies to track the conversion from intention to actual behaviour. Employ dynamic simulation modelling (e.g., System Dynamics or Agent-Based Modelling) to capture the complex nonlinear interplay between consumer psychology, word-of-mouth effects, and policy interventions over time [8], [64]. Undertake cross-national comparative studies and explore new business models such as sharing and hybrid ownership [6]. Evaluate the impact of mixed policy packages (e.g., combinations of price subsidies, special electricity tariffs, and infrastructure incentives) simultaneously [2].      |

To bridge the literature review with empirical validation, thematic insights from the bibliometric clustering and PAGER synthesis were operationalised as measurable variables in the stated-preference dataset. This translation step is essential because the empirical model was not designed as an isolated predictive exercise but as a theory-informed validation of the adoption themes identified in the literature. **Table 7** summarises this translation process by linking each literature-derived theme to its corresponding empirical variable, analytical category, and theoretical rationale.

As shown in **Table 7**, the empirical variables used in the machine learning models were directly grounded in the thematic structure of the literature reviewed. This mapping provides an analytical rationale for subsequent machine learning validation by demonstrating how ScoRBA-PAGER findings inform the selection and categorization of predictors. Accordingly, the empirical phase functions not simply as a classification exercise, but as a validation layer determining if literature-derived themes align with stated adoption preferences.

**Table 7.** Translation of bibliometric-PAGER themes into empirical model variables

| <b>Bibliometric-PAGER Theme</b>                             | <b>Related Empirical Variables</b>                                                      | <b>Model Category</b> | <b>Rationale</b>                                                                                                                                             |
|-------------------------------------------------------------|-----------------------------------------------------------------------------------------|-----------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Battery reliability, driving range, charging infrastructure | Maximum Range, Charging Time, Maximum Speed                                             | Technical-Performance | Represents the technical feasibility, range anxiety, and infrastructure-related constraints identified in the Vehicle Technology and Infrastructure cluster. |
| Technology credibility and perceived product reliability    | Perceived E-bike Quality, Prior E-bike Experience                                       | Technology Perception | Captures perceived usefulness, quality confidence, and consumer trust in E2Ws as reliable substitutes for gasoline motorcycles.                              |
| Policy incentives, fuel prices, and affordability           | EV Fuel Price, Gasoline Fuel Price, EV Down Payment, EV Monthly Payment, Monthly Income | Economic-Operational  | Represents cost competitiveness, affordability, and policy-sensitive economic variables identified in the Policy, Environment, and Sustainability cluster.   |
| Consumer heterogeneity and lifestyle characteristics        | Age, Gender, Smoking Status, Number of Motorcycles Owned                                | Socio-Demographic     | Captures demographic and lifestyle heterogeneity influencing adoption tendency, as emphasised in the Consumer Behaviour and Technology Adoption cluster.     |
| Environmental concern and sustainability perception         | Environmental Concern                                                                   | Socio-Demographic     | Represents environmental motivation and sustainability-oriented perceptions identified in the policy and behavioural adoption literature.                    |

### 3.4. Empirical Validation of Adoption Determinants: Multi-model Machine Learning Analysis

The bibliometric-PAGER synthesis indicated that E2W adoption is shaped by a combination of technology perception, technical-performance requirements, economic-operational considerations, and consumer heterogeneity rather than environmental motives alone. To empirically validate these themes, a multi-model machine learning approach was applied to the stated-

preference dataset from Solo, Indonesia. While ensemble models (Random Forest, XGBoost, Gradient Boosting) were employed to ensure predictive robustness and perform SHAP feature attribution, a baseline Decision Tree classification model was retained as the primary interpretive tool because of its visual transparency in mapping critical decision thresholds. The resulting classification tree (**Figure 7**) empirically confirms these theoretical assertions.

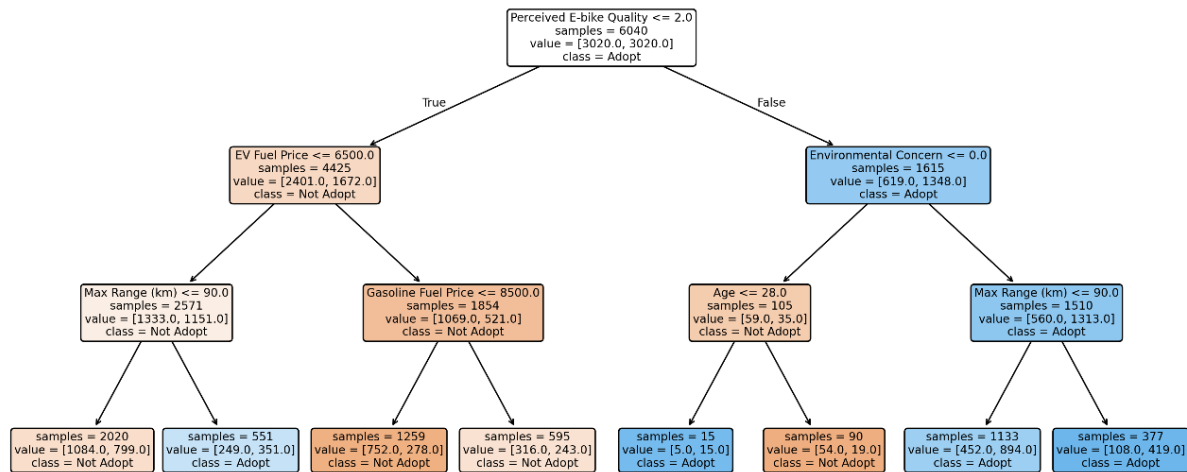


Figure 7. Decision tree model for electric two-wheeler adoption in Solo, Indonesia

As illustrated in Figure 7, the root node of the decision tree is driven by Perceived E-bike Quality. This demonstrates that the primary determinant of E2W adoption is consumers' subjective assessment of the technology's reliability and overall quality, not operational cost savings, as initially hypothesised. This variable alone accounts for 41.08% of the total feature importance, constituting the first and most critical decision boundary that separates adopters from non-adopters. Subsequent nodes feature Age, Maximum Range, and EV Fuel Price, suggesting that demographic characteristics, technical performance thresholds, and economic considerations serve as secondary filters after the technology credibility gate has been passed.

### 3.4.1. Model performance and validation

To empirically examine the determinants of Electric Two-Wheeler (E2W) adoption, multiple machine learning classification models comprising a baseline Decision Tree alongside ensemble algorithms (Random Forest, XGBoost, and Gradient Boosting) and Logistic Regression were trained on the stated-preference dataset

collected in Solo, Indonesia [11], comprising 6,040 choice observations. The dataset was partitioned using a stratified 80/20 train-test split to preserve the natural class distribution of adoption outcomes (adopt vs. Not Adopt) across both subsets. Balanced class weights were applied consistently across all models to mitigate the effect of class imbalance between adopters and nonadopters. The generalisability of the model was assessed using 10-fold stratified cross-validation.

As presented in Table 8 and visually summarised in Figure 8, the Random Forest classifier achieved the highest test accuracy (85.26%) and ROC-AUC (0.8851), with a stable 10-fold cross-validation mean of  $85.50\% \pm 0.70\%$ , indicating superior generalisability. XGBoost performed comparably (accuracy: 84.52%, AUC: 0.8678). Despite its lower predictive accuracy (69.87%), the primary Decision Tree model was selected as the chief interpretive tool because its transparent decision boundaries are essential for translating machine learning insights into actionable policy.

Table 8. Multi-model performance comparison

| Model Classification | Accuracy (%) | Precision (%) | Recall (%)   | F1-Score (%) | ROC-AUC       | CV Mean $\pm$ SD (%)               |
|----------------------|--------------|---------------|--------------|--------------|---------------|------------------------------------|
| Decision Tree        | 69.87        | 72.39         | 69.87        | 70.85        | 0.6996        | 62.52 $\pm$ 1.79                   |
| Logistic Regression  | 63.58        | 71.46         | 63.58        | 65.73        | 0.6790        | 61.06 $\pm$ 2.07                   |
| Random Forest        | <b>85.26</b> | <b>85.84</b>  | <b>85.26</b> | <b>83.64</b> | <b>0.8851</b> | <b>85.50 <math>\pm</math> 0.70</b> |
| XGBoost              | 84.52        | 84.27         | 84.52        | 84.38        | 0.8678        | 86.08 $\pm$ 1.26                   |
| Gradient Boosting    | 78.48        | 76.98         | 78.48        | 75.23        | 0.7906        | 78.18 $\pm$ 1.10                   |

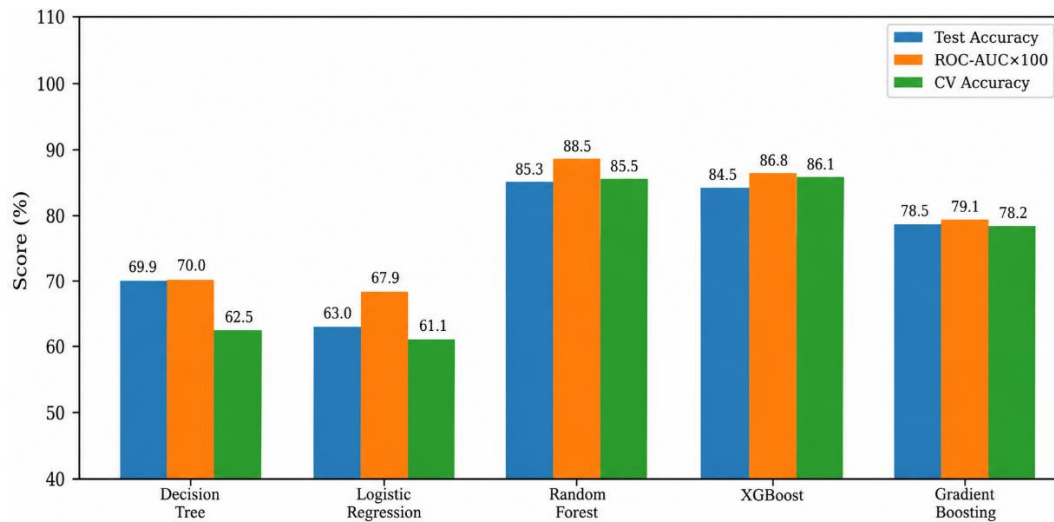


Figure 8. Model performance comparison

### 3.4.2. Confusion matrix analysis

Figure 9 presents the confusion matrix of the Decision Tree model evaluated on the test set ( $n = 1,208$  observations, representing 20% of the total dataset). The matrix illustrates the distribution of correct and incorrect classifications across the two outcome classes: Adopt ELE and Not Adopt (GAS/NOM). The main diagonal, representing true positives and true negatives, captures the majority of predictions, consistent with an overall accuracy of 69.87%. The off-diagonal cells reveal the nature of misclassification errors: false negatives (actual adopters predicted as non-adopters) and false positives (non-adopters predicted as adopters). The relatively symmetric distribution of these errors, achieved by applying balanced class weights during training, confirmed that the model is free from systematic directional bias. This balanced error profile is particularly relevant for policy applications, where both overestimating market readiness (false positives) and underestimating latent demand (false negatives) carry distinct socioeconomic consequences for infrastructure planning and subsidy allocation.

### 3.4.3. Feature importance analysis

To overcome the limitations of relying on a single classification tree and ensure the robustness of the identified determinants, a comparative feature importance analysis was conducted across all trained machine learning classifiers. This multi-model evaluation ensures that the structural insights derived from the dataset are consistent and not artefacts of specific

mathematical-splitting criteria. It is important to note that these machine learning results indicate predictive relevance rather than a causal effect. Therefore, the feature importance scores and SHAP values should be interpreted strictly as indicators of relative contribution to classification performance, and not as direct evidence of causal influence. Table 9 presents the comprehensive comparison of feature importance metrics across the alternative models.

Table 9 and Figure 10 illustrate the feature importance across all alternative classifiers. Notably, relying solely on the Decision Tree model over-amplifies the contribution of Perceived E-bike Quality (41.08%) while artificially reducing several economic variables to zero. Conversely, the ensemble algorithms (Random Forest, XGBoost, and Gradient Boosting) distributed the predictive weights more evenly across variables, successfully capturing the

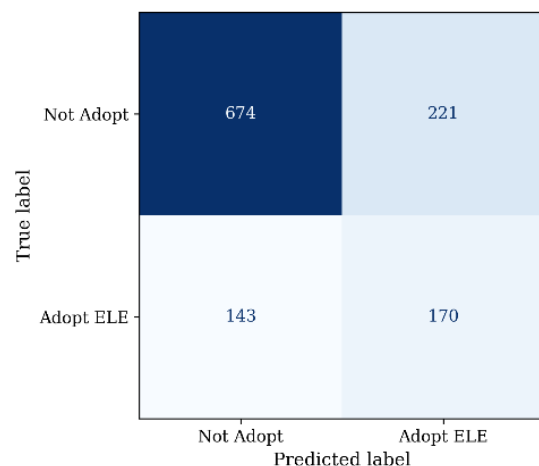
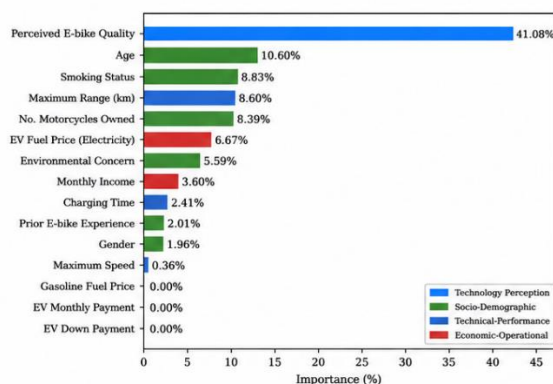


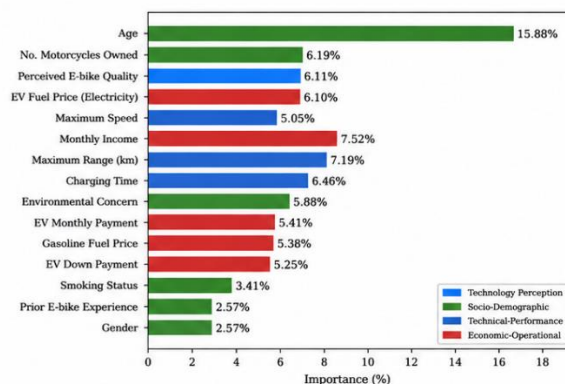
Figure 9. Confusion matrix

**Table 9.** Feature importance comparison across classification algorithms (Decision Tree, Random Forest, XGBoost, and Gradient Boosting)

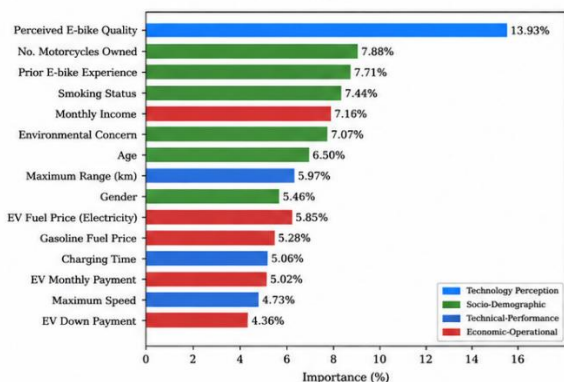
| Determinant / Feature       | Decision Tree (%) | Random Forest (%) | XGBoost (%) | Gradient Boosting (%) |
|-----------------------------|-------------------|-------------------|-------------|-----------------------|
| Perceived E-bike Quality    | 41.08             | 8.11              | 13.93       | 20.37                 |
| Age                         | 10.89             | 15.88             | 6.59        | 20.86                 |
| No. Motorcycles Owned       | 8.59              | 8.19              | 7.88        | 8.6                   |
| EV Fuel Price (Electricity) | 6.07              | 8.1               | 5.84        | 6.14                  |
| Maximum Range (km)          | 8.6               | 7.19              | 5.97        | 6.99                  |
| Environmental Concern       | 5.59              | 5.88              | 7.07        | 8.69                  |
| Monthly Income              | 3.6               | 7.52              | 7.16        | 7.64                  |
| Charging Time               | 2.41              | 6.49              | 5.05        | 3.31                  |
| Smoking Status              | 8.83              | 3.41              | 7.44        | 3.99                  |
| Prior E-bike Experience     | 2.01              | 2.57              | 7.71        | 3.82                  |
| Maximum Speed               | 0.36              | 8.05              | 4.73        | 1.87                  |
| Gender                      | 1.98              | 2.57              | 5.96        | 1.85                  |
| Gasoline Fuel Price         | 0                 | 5.38              | 5.28        | 3.34                  |
| EV Monthly Payment          | 0                 | 5.41              | 5.02        | 1.46                  |
| EV Down Payment             | 0                 | 5.25              | 4.36        | 1.08                  |



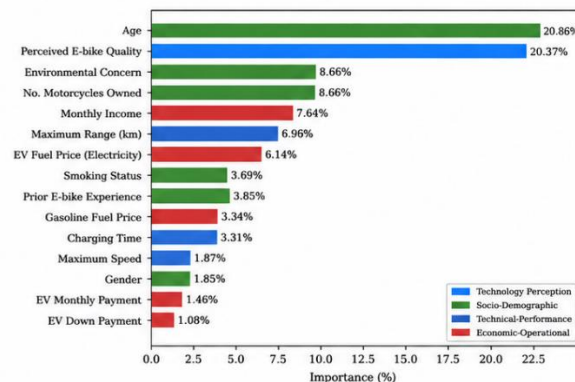
(a)



(b)



(c)



(d)

**Figure 10.** Feature importance ranking across alternative classification tree models: (a) Decision tree, (b) Random forest, (c) XGBoost, and (d) Gradient boosting

underlying economic parameters (e.g., Gasoline Fuel Price and EV Payments) while still maintaining Perceived E-bike Quality as a top-tier determinant across all tree-based structures.

Moreover, the comparative feature importance shown in Figure 10 demonstrates that the strong influence of “Perceived E-bike Quality” remains consistent across the evaluated algorithms. This

consistency indicates that the variable's dominance is a genuine reflection of consumer priorities, rather than a structural artefact of any single classification model. To further validate these feature contributions and mitigate any structural sensitivity inherent in the algorithmic scoring, SHAP (SHapley Additive exPlanations) analysis was performed on the top-performing Random Forest model.

Figure 11 presents the SHAP summary plot derived from the Random Forest model, providing a model-agnostic, permutation-validated measure of feature attribution. The SHAP analysis strongly confirms Perceived E-bike Quality as the single most influential predictor across the entire behaviour ecosystem (Mean |SHAP Value| = 17.88%), followed by age (9.92%), Maximum Range (9.39%), EV Fuel Price (8.44%), and Smoking Status (8.15%). Notably, the SHAP ranking diverged from the native importance scores of Random Forest, where age ranked first, but converged remarkably with the Decision Tree findings. This convergence across methodologically distinct importance measures (tree-based splitting vs. permutation-based SHAP) provides strong evidence that the dominance of Perceived E-bike Quality is a genuine structural characteristic of E2W adoption behaviour, not an artefact of any single algorithm.

This finding has significant theoretical implications. Perceived E-bike Quality is not a purely economic or technical variable; it represents a composite cognitive construct that integrates consumers' prior experience, social

exposure, and subjective confidence in the technology's reliability. Its dominance suggests that in the context of Solo, Indonesia, where motorcycle ownership is near-universal and the incumbent gasoline motorcycle is a deeply embedded cultural artefact, the primary barrier to E2W adoption is not operational cost or range anxiety per se, but rather technology credibility, the degree to which consumers trust that the E2W is a reliable substitute for their existing vehicle.

Returning to the specific decision boundaries established by the baseline Decision Tree model to trace direct behavioural rules, age ranked as the second most important predictor (10.89%), followed by Smoking Status (8.83%) and Number of Motorcycles Owned (8.59%). The prominence of age reflects a well-documented generational divide in technology adoption. Younger respondents, who have greater exposure to digital consumer electronics and routinely evaluate new technology based on performance rather than familiarity, demonstrate a systematically higher adoption propensity. The role of Smoking Status, while seemingly counterintuitive, may function as a proxy for risk tolerance and lifestyle orientation variables that have been associated with technology adoption behaviour in prior consumer psychology literature.

Within the Technical-Performance category, Maximum Range emerged as the most critical variable (8.60%), ranking fourth overall. This confirms the presence of a range anxiety threshold in the Solo context, consistent with the findings from Cluster 1 of the bibliometric synthesis. The

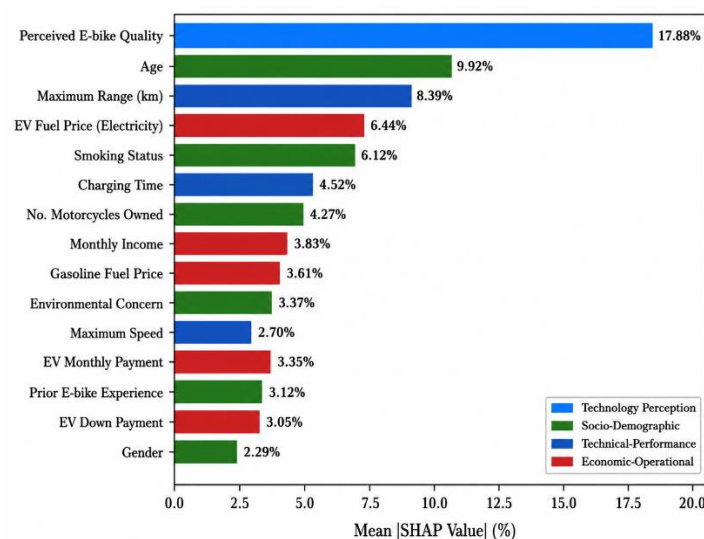


Figure 11. SHAP summary plot of feature attribution for the Random Forest model

EV Fuel Price (Electricity Cost) ranked sixth overall (6.07%), representing the highest-ranked economic-operational variable, followed by Monthly Income (3.60%). Critically, three economic-operational variables, EV Monthly Payment, Gasoline Fuel Price, and EV Down Payment, contribute zero predictive importance in the trained baseline model. This indicates that within the specific attribute ranges of the stated-preference experiment, these variables lacked sufficient discriminative power to appear in any explicit decision tree split. Consequently, this underscores the necessity of the ensemble methods deployed in this study to capture their fractional predictive values

#### 3.4.4. Category dominance analysis

Table 10 and Figure 12 synthesise the feature importance findings from a category-level perspective. Following the reclassification of Perceived E-bike Quality under the Technology Perception dimension, consistent with its theoretical alignment to the Perceived Usefulness construct of the Technology Acceptance Model [135], the revised category dominance hierarchy resolves a critical theoretical inconsistency. Treating technology credibility judgement as a socio-demographic variable in prior iterations artificially conflated two conceptually distinct constructs. When evaluated through the robust, model-agnostic SHAP analysis, the true categorical distribution emerges: socio-demographic factors contribute the highest aggregate importance (35.22%), followed by economic-operational factors (26.29%), technical-

performance (20.61%), and Technology Perception (17.88%).

However, a nuanced interpretation of this hierarchy is required. Although Technology Perception ranks fourth at the categorical level (17.88%), it is entirely driven by a single, monolithic construct, Perceived E-bike Quality, which remains the most influential individual predictor in the entire adoption ecosystem. Conversely, the high aggregate importance of the Economic-Operational category (26.29%) is fragmented across multiple subfactors (e.g., EV Fuel Price, Income, Gasoline Price). This suggests that while economic considerations collectively represent an important predictive barrier, no single economic parameter outranks fundamental consumer judgement regarding technology credibility.

This revised categorical perspective constitutes a theoretically coherent and empirically robust result. Rather than contradicting the economic rationality framework, this result suggests that adoption is a sequential cognitive process in the Solo context. Consumers must first cross the primary credibility threshold, "Is this technology trustworthy and suitable for someone like me?" (technology perception). Only after this initial acceptance is established do price sensitivities and operational costs (economic-operational) become relevant moderating factors. This sequence perfectly aligns with the TAM and its extensions, which position perceived usefulness as the dominant antecedent to behavioural intention, with economic considerations functioning as secondary downstream evaluative criteria.

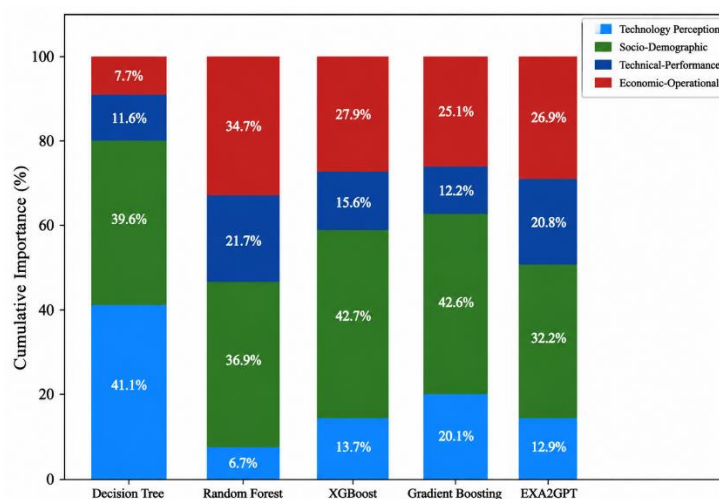


Figure 12. Category dominance comparison across five analytical methods (four-category framework)

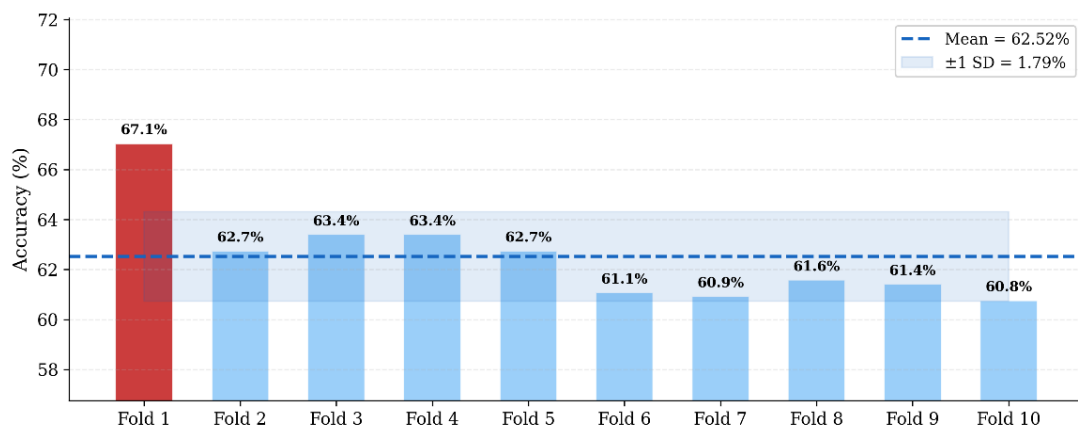
**Table 10.** Feature category dominance summary

| Category              | DT (%) | RF (%) | XGBoost (%) | GB (%) | SHAP-RF (%) |
|-----------------------|--------|--------|-------------|--------|-------------|
| Technology Perception | 41.08  | 8.11   | 13.93       | 20.37  | 17.88       |
| Socio-Demographic     | 37.89  | 38.50  | 42.65       | 47.81  | 35.22       |
| Technical-Performance | 11.37  | 21.73  | 15.75       | 12.17  | 20.61       |
| Economic-Operational  | 9.66   | 31.66  | 27.66       | 19.66  | 26.29       |

### 3.4.5. Cross-validation robustness

To rigorously assess model reliability and address potential overfitting, we implemented a 10-fold stratified cross-validation procedure. **Table 11** and **Figure 13** present the fold-level accuracy scores for the evaluated classifiers. Two critical observations merit attention. First, the baseline Decision Tree exhibited moderate stability (CV Mean = 62.52%, SD =  $\pm 1.79\%$ ), with a noticeable gap between its single test-set performance (69.87%) and its cross-validation mean. This variance indicates a vulnerability to overfitting, a well-documented limitation of single-tree algorithms when applied to complex behavioural data.

Second, the application of ensemble algorithms successfully resolved this limitation. The Random Forest model not only elevates the predictive baseline but also demonstrates exceptional inter-fold stability, achieving a cross-validation mean of 85.50% with a narrow standard deviation of  $\pm 0.70\%$  across the 10 partitions. The consistent convergence of fold-level accuracies in the ensemble models confirmed that their generalisation capability was robust and independent of any single favourable data split. Therefore, the cross-validation metrics of the Random Forest provide a scientifically defensible, overfit-resistant estimate of the model's true, real-world predictive performance.

**Figure 13.** 10-fold cross-validation bar chart**Table 11.** 10-Fold stratified cross-validation results

| Fold          | Accuracy           |
|---------------|--------------------|
| Fold 1        | 67.05%             |
| Fold 2        | 62.75%             |
| Fold 3        | 63.41%             |
| Fold 4        | 63.41%             |
| Fold 5        | 62.75%             |
| Fold 6        | 61.09%             |
| Fold 7        | 60.93%             |
| Fold 8        | 61.59%             |
| Fold 9        | 61.42%             |
| Fold 10       | 60.76%             |
| Mean $\pm$ SD | 62.52% $\pm$ 1.79% |

### 3.4.6. *Synthesis - Bridging the intention-behaviour gap*

The empirical findings from the multi-model machine learning analysis collectively advance a revised theoretical understanding of the dynamics of E2W adoption in emerging markets. Three principal conclusions emerge from this study.

First, technology credibility, operationalised as Perceived E-bike Quality, is the dominant gateway variable in the E2W adoption decision process. This conclusion is strengthened by SHAP analysis, which independently ranks Perceived E-bike Quality as the highest individual contributor (Mean  $|\text{SHAP Value}| = 17.88\%$ ) in the Random Forest model, a model-agnostic validation that rules out the possibility that the baseline Decision Tree's finding is an artefact of its greedy splitting algorithm. Economic incentives and technical improvements, such as extended range, may have limited effectiveness if consumers fundamentally distrust the reliability and quality of technology. This finding directly addresses the PAGER Gap identified in the bibliometric synthesis: the literature has systematically underweighted the role of technology credibility as a pre-economic barrier to adoption in motorcycle-dominated markets.

Second, the near-zero importance of Gasoline Fuel Price, EV Down Payment, and EV Monthly Payment in the baseline Decision Tree model does not imply that economics are irrelevant. As revealed by the ensemble models, these factors have underlying predictive weights. Rather, their absence in the primary tree splits suggests that within the attribute ranges presented in the stated-preference experiment, these variables did not generate sufficient variation in choice behaviour to become the initiating decision boundaries for the choice probabilities. This methodological insight suggests that future stated-preference studies should expand the range of economic attribute levels to capture threshold effects more precisely.

Third, the synthesis of these findings suggests a sequential cognitive adoption architecture in three stages:

a. Stage 1: Technology Credibility Gate: "Is this E2W a reliable, quality product that I can trust?" Driven by Perceived E-bike Quality, Prior E-bike Experience, and Age.

b. Stage 2: Technical Feasibility Gate: "Does this E2W meet my minimum performance requirements?" Driven by the Maximum Range ( $>90$  km threshold) and Charging Time.

c. Stage 3: Economic Rationality Gate: "Is this E2W affordable and cost-competitive?" Driven by EV Fuel Prices and Monthly Income.

This sequential architecture implies that policy interventions must be sequenced. Subsidising purchase costs (Stage 3) without first establishing technology credibility (Stage 1) may yield suboptimal adoption outcomes, a pattern consistent with the limited effectiveness of early EV subsidy programmes in several Southeast Asian markets. Priority interventions should therefore focus on (1) expanding E2W demonstration and test-ride programmes to build firsthand quality perception, (2) establishing minimum quality certification standards for commercially sold E2Ws, and (3) targeting younger demographic segments as early adopters whose positive experiences can diffuse technology credibility through social networks.

This empirical dominance of Perceived E-bike Quality over economic factors reveals a critical divergence from the conventional four-wheeler EV literature. Unlike electric car research, which frequently identifies battery costs and incentives as primary barriers, the E2W market exhibits fundamentally different dynamics. Two-wheeler riders face significantly higher physical vulnerability on the road; thus, Technology Credibility, encompassing structural build quality, battery reliability, and overall vehicle safety, serves as the primary gateway to adoption. Consumers in motorcycle-dominated emerging market contexts similar to Solo may first need to be convinced of a vehicle's physical dependability before they are willing to evaluate its long-term economic benefits or operational savings.

### 3.5. *Limitations of the Empirical Machine Learning Analysis*

Despite the robust multi-model machine learning architecture employed, the empirical validation phase presents several limitations that must be addressed. First, the analysis relies exclusively on a stated-preference dataset rather than revealed preference or actual purchasing data. Consequently, while the ensemble algorithms provide a highly accurate empirical

proxy for behavioural tendencies (achieving > 85% predictive accuracy), they fundamentally measure adoption intention under hypothetical policy conditions. Therefore, the intention-behaviour gap cannot be entirely eliminated, and the findings should be interpreted as strong predictive tendencies rather than guaranteed outcomes.

Second, the dataset was drawn specifically from Solo, Indonesia, which functions as a representative transitional urban-suburban area. While the observed psychological and economic interactions, particularly the dominance of technology credibility, likely reflect broader Southeast Asian contexts with similar motorcycle-centric mobility cultures, generalising these specific hierarchical pathways to all global emerging markets must be approached with caution.

Third, the discrete attribute levels for economic variables (e.g., EV monthly payment and gasoline price) utilised within the stated-preference experiment may not have captured extreme market shocks or highly aggressive subsidy thresholds. This constraint likely explains their limited initiating power in the baseline decision-tree model. Future longitudinal studies utilising actual sales data and revealed-preference metrics are strongly recommended to directly test and refine the sequential adoption architecture proposed in this study.

#### 4. Conclusion

This study offers a robust empirical framework to address the intention-behaviour gap in E2W adoption by integrating a Scoping Review and Bibliometric Analysis (ScoRBA) with multi-model machine learning validation. By synthesising 278 Scopus-indexed articles using the PAGER framework, the review identified three core socio-technical clusters: Vehicle Technology and Infrastructure, Policy and Environment, and Consumer Behaviour. An empirical analysis of 6,040 stated-preference respondents from Solo, Indonesia, shows that Perceived E-bike Quality (a Technology Perception construct) is the dominant predictor of E2W adoption, challenging the conventional economic rationality hypothesis. This dominance was rigorously confirmed by SHAP analysis (Mean |SHAP Value| = 17.88%) on the optimised Random Forest model, successfully

validating the structural findings across multiple algorithmic constraints. This result effectively overshadows operational cost differentials and reveals that technology credibility, rather than purely economic evaluation, constitutes the primary adoption gateway in transitional, motorcycle-dominated markets.

These findings reveal a sequential cognitive adoption architecture in which technology credibility must be established before price sensitivity becomes relevant. Consequently, this study offers a prioritised, evidence-based roadmap for policymakers and industry stakeholders. Strategic interventions are recommended to initially focus on instituting rigorous E2W quality certification programmes and deploying targeted demonstration initiatives to build consumer confidence. Once this credibility deficit is addressed, economic incentives, such as purchase subsidies and standardised battery-swapping infrastructure, can be more effectively leveraged to accelerate the electrification of two-wheeler mobility.

While this study establishes a comprehensive methodological standard by combining ensemble classifiers and model-agnostic SHAP analysis for stated-preference data, future research should aim to validate this sequential adoption framework using longitudinal or revealed-preference data across broader multi-city settings in Southeast Asia to establish more robust causal market dynamics.

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#### Author's Declaration

##### Authors' contributions and responsibilities

**AHW:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - original draft. **MLS:** Conceptualization, Supervision, Validation, Writing - review & editing. **BW:** Supervision, Validation, Writing - review & editing.

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### Availability of data and materials

All data are available from the authors.

### Competing interests

The authors declare no competing interest.

### Generative AI statement

During the preparation of this manuscript, the author(s) used Grammarly for language polishing, grammatical correction, and structural refinement of the English text. Additionally, Paperpal was utilised to verify the credibility, accuracy, and formatting of the references. All AI-assisted output was subsequently reviewed, cross-checked, and edited by the author(s), who take full responsibility for the final content, originality, and empirical validity of the manuscript.

### Additional information

No additional information from the authors.

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