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Behavioral choice analysis of student transit transition towards subsidized school bus services in Ponorogo Regency

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ABSTRACT

This study aims to evaluate the modal shift probability utility toward the fully subsidized Smart School Bus in the integrated educational zone of Ponorogo Regency. A discrete choice experiment using an orthogonal fractional factorial design was conducted, drawing primary data from 346 homogeneous student respondents across SMPN 1, SMPN 5, and SMPN 6 Ponorogo. The purified dataset was analyzed using a binary logit difference model incorporating operational attributes alongside latent socio-demographic covariates. The calibrated utility function indicates that out-of-vehicle wait time ($\beta_T W = -0.045$) and in-vehicle travel time ($\beta_T T = -0.035$) act as significant disutilities, whereas active cabin air conditioning ($KF = 0.826$) serves as a dominant behavioral pull factor. Econometric extraction reveals an empirical travel Value of Time of Rp466.67 per minute, an operational waiting Value of Time of Rp600.00 per minute, and a Value of Comfort of Rp11.013.33 per trip. These findings prove that qualitative cabin upgrades effectively buffer wait time penalties and reduce the need for aggressive parking surcharges. This study delivers a data-driven policy framework to transition underage motorcycle riders toward sustainable transit systems.

1. Introduction

Rapid urbanization triggers severe traffic externalities in integrated educational zones. In Ponorogo Regency, this is empirically demonstrated by a 96.53% underage student motorcycle dependency. Conversely, ridership on the fully subsidized Angkutan Cerdas Sekolah transit system reaches only 3.55%, leaving the public fleet highly underutilized. This severe modal imbalance results in a 59.06% peak load factor, failing to meet the 70.0% economic operational standard established for peak transit services by Vuchic [1]. Although legally classified as captive market riders prohibited from driving under national licensing laws [2], students commute via motorcycles due to transit routing gaps and waiting penalties [3], [4]. To mitigate these spatial externalities, Miro [5] emphasizes that zero-fare transit policies must be coupled with strict fiscal-based push measures to break private vehicle inertia [6].

The spatial agglomeration of SMP Negeri 1, SMP Negeri 5, and SMP Negeri 6 Ponorogo generates intense daily trip attractions, drawing students from rural hinterlands with commutes



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exceeding 4.00 kilometers. While transport choice models focus on adult commuters [7], adolescent mobility investigations remain significantly underdeveloped [8], [9]. Crucially, conventional frameworks neglect cabin comfort in the generalized cost architecture [6]. This study will bridge this research gap by proposing a stated preference discrete choice framework [10]. Adopting the fractional factorial design principles of Ortúzar and Willumsen [11] and the econometric foundations pioneered by Tamin [12] and extended by Amaheka and Ohorella [13], the model will determine the exact indifference thresholds required to disrupt motorcycle dominance.

2. Research Method

2.1 Problem and Research Scope

This research will be conducted in Ponorogo Regency, focusing on underage motorcycle commuting within the urban educational corridor. As reported by the PTDI-STTD Field Practical Team [14], the subsidized school bus operates below capacity due to uncalibrated preferences, mirroring systemic underutilization where zero-fare programs fail against private vehicle dominance [3]. Centered on the school agglomeration of SMP Negeri 1, SMP Negeri 5, and SMP Negeri 6 Ponorogo, the proposed system boundary will capture a spatial cluster with severe bottlenecks. Within this corridor, zoning policies draw rural students across long commutes exceeding active transit thresholds [15]. These spatial frictions are projected to force underage students onto private motorcycles, sustaining unlicensed riding driven by individual utilities [4]. The proposed transit intervention will evaluate these choice factors to encourage sustainable adoption [6].

To capture the behavioral parameters of this captive market, the research will execute a systematic five-phase modeling pipeline.

1. Problem identification and spatial system boundary mapping will be conducted within the educational corridor. This step will gather baseline data from the local database of Ponorogo [14] to analyze traffic delays and localized spatial frictions that constrain student travel [16], [17].
2. Experimental design will construct the stated preference framework. Anchored on the random utility maximization framework of Ortúzar and Willumsen [11], the study will apply the orthogonal fractional factorial design guidelines of Hensher et al. [18] to compress the choice permutations into nine manageable orthogonal scenario cards [19]. This experimental setup will employ four operational attributes across nine unlabeled binary choice tasks with zero blocking, achieving optimized orthogonality and efficiency (comprehensively detailed, visualized, and mathematically verified in Section 2.3).
3. Primary data acquisition will be executed via face-to-face questionnaires at the gates of SMPN 1, SMPN 5, and SMPN 6 Ponorogo during peak commute hours. Applying the Taro Yamane sampling formulation [20], the survey will draw exactly 346 homogeneous student respondents, aligning with regional student transit survey parameters [19]. Dataset purification and instrument validation will employ a strict lexicographic screening filter to eliminate non-trading behaviors [11] (comprehensively detailed, justified, and structurally outlined in Section 2.4).
4. The reliability and validity of the psychometric survey questions will be verified using SPSS-based Pearson correlation and Cronbach's Alpha indicators [21], [22].
5. Econometric data analysis will process the purified dataset using Maximum Likelihood Estimation to calibrate the binary logit parameters. These calibrated coefficients will be utilized to extract the localized Value of Time, Value of Comfort, and marginal effects at the 50.0% equilibrium point [11], [18].

2.2 Stated Preference Experimental Design

The stated preference experiment is systematically structured to capture the trade-offs of student transit adoption under simulated policy scenarios. The primary choice data will be acquired using four distinct travel attributes, which are travel cost difference (ΔTC), travel time difference (ΔTT), waiting time difference (ΔTW), and cabin thermal comfort (KF). To prevent cognitive fatigue among junior high school respondents, the full factorial design of 54 hypothetical profile permutations is compressed into exactly nine orthogonal choice tasks using the SPSS Orthoplan fractional factorial algorithm. The operational definitions and physical levels of these attributes are detailed in Table 1.

Table 1. Operational Attributes and Simulated Levels for the Stated Preference Experiment

Attribute Name (Symbol)	Level 1 (Baseline)	Level 2 (Symmetric Middle)	Level 3 (Extreme/ATP Limit)
Travel Cost Difference (ΔTC)	-Rp5,000.00	-Rp10,000.00	-Rp15,000.00
Travel Time Difference (ΔTT)	5 minutes	10 minutes	15 minutes
Waiting Time Difference (ΔTW)	5 minutes	10 minutes	15 minutes
Thermal Comfort Facility (KF)	Non-AC (0)	Full AC (1)	Not Applicable

No blocking will be applied to the questionnaire deployment. Every respondent will evaluate the same sequence of nine choice cards. Each choice task will utilize an unlabeled binary layout, forcing students to select between Option A (Subsidized School Bus) and Option B (Private Motorcycle). The final orthogonal design matrix is presented in Table 2.

Table 2. Orthogonal Fractional Factorial Design Matrix for Questionnaire Deployment

Scenario Number	Travel Cost Difference (ΔTC)	Travel Time Difference (ΔTT)	Waiting Time Difference (ΔTW)	Thermal Comfort Facility (KF)
Scenario 1	-Rp5,000.00	10 minutes	10 minutes	Full AC (1)
Scenario 2	-Rp15,000.00	5 minutes	10 minutes	Non-AC (0)
Scenario 3	-Rp5,000.00	5 minutes	5 minutes	Non-AC (0)
Scenario 4	-Rp10,000.00	5 minutes	15 minutes	Full AC (1)
Scenario 5	-Rp5,000.00	15 minutes	15 minutes	Non-AC (0)
Scenario 6	-Rp10,000.00	10 minutes	5 minutes	Non-AC (0)
Scenario 7	-Rp10,000.00	15 minutes	10 minutes	Non-AC (0)
Scenario 8	-Rp15,000.00	15 minutes	5 minutes	Full AC (1)
Scenario 9	-Rp15,000.00	10 minutes	15 minutes	Non-AC (0)

To guarantee the mathematical validity of the experimental design, an orthogonality check is performed. The pairwise design correlation matrix in Table 3 confirms that all off-diagonal Pearson correlation coefficients are exactly zero, indicating a complete absence of multicollinearity (VIF = 1.00).

Table 3. Pairwise Design Correlation Matrix for Orthogonality Verification

Attribute Columns	Travel Cost Difference (ΔTC)	Travel Time Difference (ΔTT)	Waiting Time Difference (ΔTW)	Thermal Comfort Facility (KF)
Travel Cost Difference (ΔTC)	1	0	0	0
Travel Time Difference (ΔTT)	0	1	0	0
Waiting Time Difference (ΔTW)	0	0	1	0
Thermal Comfort Facility (KF)	0	0	0	1

2.4 Sampling and Primary Data Acquisition

To represent the student population accurately, a multi-criteria sampling approach will be executed. The target population consists of active students enrolled across the three agglomerated schools, totaling 2,542 students. To determine the minimum sample size required for descriptive representation, the formulation developed by Yamane [20] is applied as written in (1):

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

n : Minimum required sample size

N : Total student population across the three target schools

e : Maximum acceptable margin of error set at five percent

Applying this formulation with a 95.0% confidence level yields a minimum threshold of 345.615, which is rounded to exactly 346 proposed respondents. This target comprehensively exceeds the minimum statistical power threshold of 88 respondents required under parametric guidelines [23]. To accommodate non-uniform student densities, a proportionate stratified random sampling technique will be executed, distributing the target sample as 123 respondents from SMP Negeri 1, 122 from SMP Negeri 5, and 101 from SMP Negeri 6 Ponorogo.

To ensure statistical rigor, the survey will deploy a structured participant selection and data-cleaning protocol [18]. Demographically and spatially homogeneous underage motorized commuters will be surveyed face-to-face at school gates. A two-stage purification pipeline will combine missing

data audits with lexicographic filtering to eliminate non-trading respondents, preventing model estimation errors [18].

3. Description and Technical

3.1 Econometric Data Analysis Pipeline

Following data purification, the clean Stated Preference dataset will be processed through a sequential econometric pipeline. The analysis operates as a continuous computational sequence transitioning from parameter calibration to sensitivity evaluation of student travel decisions.

3.1.1 Binary Logit Difference Model

The mathematical framework of the choice model relies on Random Utility Theory, which assumes that student commuters behave as rational agents who select the transport alternative that yields the maximum net utility [11], [18]. For the binary choice set comparing the subsidized school bus against private motorcycles, a binary logit model is calibrated. The transition probability toward the subsidized school transport system is specified in (2):

$$P_{ACS} = \frac{1}{1 + e^{-\Delta U}} \quad (2)$$

P_{ACS} : Probability of transition towards subsidized school transport.

e : Base of natural logarithms.

ΔU : Utility difference between subsidized school bus and private motorcycle.

The utility difference function represents the net satisfaction difference between the competing modes, incorporating simulated operational attributes and socio-demographic covariates to capture student travel behavior. Following the discrete choice modeling structures established by Tamin [12], the utility difference equation is formulated in (3):

$$\Delta U = \alpha + \beta_1 \Delta TC + \beta_2 \Delta TT + \beta_3 \Delta TW + \beta_4 KF + \sum_{i=1}^n (\gamma_i \times Z_i) \quad (3)$$

To control for individual taste heterogeneity and prevent specification bias, the product sum of respondent covariates is decomposed based on their measurement scales as formulated in (4).

$$\sum_{i=1}^n (\gamma_i \times Z_i) = \gamma_{Scale} Z_{Scale} + \sum_{p=1}^{a-1} \gamma_p Z_{Binary,p} + \sum_{q=1}^{b-1} \gamma_q Z_{Ordinal,q} \quad (4)$$

The operational definitions, measurement scales, mathematical coding schemes, and reference categories for all parameters entering Equation 3 and Equation 4 are systematically structured in Table 4.

Table 4. Variable Operationalization and Coding Specifications

Variable Class	Variable Name (Symbol)	Data Type and Scale	Operational Definition and Coding Values	Reference Category
Dependent	Mode Choice (Y)	Binary Nominal	Selected commute mode: 1 = ACS, 0 = Private Motorcycle	Private Motorcycle (0)
Independent (Generic SP)	Cost Difference (ΔTC)	Continuous Interval	Simulated travel cost difference in thousands of Rupiah	Not Applicable
Independent (Generic SP)	Travel Time Difference (ΔTT)	Continuous Interval	Simulated travel time difference in minutes	Not Applicable
Independent (Specific SP)	Waiting Time Difference (ΔTW)	Continuous Interval	Simulated waiting time difference in minutes	Not Applicable
Independent (Specific SP)	Thermal Comfort (KF)	Binary Nominal	Cabin conditioning upgrade: 1 = Full AC, 0 = Non-AC	Non-AC (0)
Covariate (Respondent)	Continuous Characteristics (Z_{Scale})	Continuous Ratio	Real-valued numeric parameters representing chronological age and home-to-school travel distance	Not Applicable
Covariate (Respondent)	Binary Characteristics (Z_{Binary})	Binary Nominal	Dichotomous attributes representing riding permission and vehicle availability: 1 = Yes, 0 = No	Parameter-specific baseline (0)

Covariate (Respondent)	Ordinal Characteristics ($Z_{ordinal}$)	Ordinal Nominal	Categorized socio-demographic brackets representing pocket money mapped as (m-1) dummy sets	Parameter- specific baseline (0)
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3.1.2 Value of Time and Value of Comfort Extraction

Once the parameter coefficients are estimated using maximum likelihood in SPSS, the parameters will be subjected to post-estimation extraction to obtain their monetary equivalents. Based on the microeconomic foundations of consumer behavior theory established by [18] and further operationalized for transit systems in [11], these valuations represent the Marginal Rate of Substitution between the travel time or comfort attributes and the travel cost parameter. The Value of Time for travel duration is calculated as the ratio of the travel time coefficient to the travel cost coefficient, specified in (4):

$$VoT_{TT} = \left(\frac{\beta_{\Delta TT}}{\beta_{\Delta TC}} \right) \times 1000 \quad (4)$$

VoT_{TT} : Value of travel time savings in Rupiah per minute.

$\beta_{\Delta TT}$: Parameter coefficient for travel time difference.

$\beta_{\Delta TC}$: Parameter coefficient for travel cost difference.

This formulation translates the subjective utility of travel duration into monetary savings, matching the discrete choice paradigms applied in regional transport studies [13].

Similarly, the Value of Time for waiting duration is extracted by dividing the waiting time coefficient by the travel cost coefficient to represent the transit waiting penalty, as specified in (5).

$$VoT_{TW} = \left(\frac{\beta_{\Delta TW}}{\beta_{\Delta TC}} \right) \times 1000 \quad (5)$$

VoT_{TW} : Value of wait time savings in Rupiah per minute.

$\beta_{\Delta TW}$: Parameter coefficient for wait time difference.

$\beta_{\Delta TC}$: Parameter coefficient for travel cost difference.

This waiting-time evaluation aligns with scheduling delay and terminal friction trade-offs modeled in student transit choice frameworks [24] and regional transport network studies [25].

Furthermore, qualitative service enhancements can be translated into monetary terms to evaluate the willingness to pay for improved transit environments [11]. The monetary equivalent of cabin comfort, representing the Value of Comfort, is derived by dividing the comfort dummy coefficient by the cost parameter, as specified in (6).

$$VOC = \left(\frac{\beta_{KF}}{|\beta_{\Delta TC}|} \right) \times 1000 \quad (6)$$

VOC : Monetary Value of Comfort in Rupiah per travel cycle s

β_{KF} : Parameter coefficient for cabin comfort dummy.

$\beta_{\Delta TC_1}$: Parameter coefficient for travel cost difference.

3.1.3 Marginal Effect on Probability

To measure the direct leverage of individual attributes on transition probability, marginal effects will be estimated. Because logistic functions are non-linear, the parameters do not represent a constant rate of change across the probability spectrum [18]. The marginal effect of an attribute represents the change in choice probability resulting from a one-unit change in that specific independent variable. Following the calculus of discrete choice probabilities formulated in [11], the marginal effect of an attribute represents the change in choice probability resulting from a one-unit change in that specific independent variable, formulated in (7):

$$ME_k = \frac{\partial P_{ACS}}{\partial X_k} = \beta_k \times P_{ACS} \times (1 - P_{ACS}) \quad (7)$$

ME_k : Marginal effect of the k -th operational attribute on transition probability.

β_k : Utility parameter coefficient for the k -th attribute.

P_{ACS} : Transition probability toward subsidized school transport.

To identify the maximum policy leverage, the marginal effect will be evaluated at the highest

elasticity point of the logit curve where P_{ACS} equals 0.50, which serves as the theoretical equilibrium threshold in disaggregate mode choice analysis [12]. This specific threshold represents the point of maximum behavioral indifference. At this point, the mathematical expression simplifies the marginal effect multiplier to exactly 0.25 of the calibrated coefficient parameter [18], thereby establishing a direct, standardized policy leverage metric across different attributes [13].

3.1.4 Extended Generalized Cost Formulation

To analyze travel disutility on a uniform scale, the calibrated parameters will be integrated to construct the Extended Generalized Cost framework based on the paradigms of Ortúzar and Willumsen [11]. This methodology translates physical and qualitative attributes into monetary equivalents [18]. Utilizing the extracted Value of Time and Value of Comfort, modal operational attributes will be converted into a standardized financial metric. The Extended Generalized Cost for private motorcycles is formulated in Equation (8).

$$GC_{Mc} = TC_{Mc} + (VoT_{TT} \times TT_{Mc}) + (VoT_{TW} \times TW_{Mc}) \quad (8)$$

GC_{Mc} : Extended Generalized Cost for private motorcycle in Rupiah.

TC_{Mc} : Financial operational cost of private motorcycle.

VoT_{TT} : Value of travel time savings in Rupiah per minute.

TT_{Mc} : Travel time of private motorcycle in minutes.

VoT_{TW} : Value of wait time savings in Rupiah per minute.

TW_{Mc} : Wait time of private motorcycle in minutes.

Conversely, evaluating public transit options requires incorporating qualitative variables to capture the non-monetary benefits that influence ridership [26]. Adopting the extended generalized cost principles modeled in Indonesian student transit choice experiments [24], [27], the cost formulation for the subsidized transit system will include a negative cost component representing the psychological premium of cabin comfort. This qualitative pull factor serves to offset the travel and waiting delays inherent in bus services, as validated by previous headway sensitivity evaluations [28]. Consequently, the Extended Generalized Cost equation for the subsidized school bus is formulated in (9):

$$GC_{ACS} = TC_{ACS} + (VoT_{TT} \times TT_{ACS}) + (VoT_{TW} \times TW_{ACS}) - (VoC \times KF_{ACS}) \quad (9)$$

GC_{ACS} : Extended Generalized Cost for subsidized school bus in Rupiah.

TC_{ACS} : Financial fare of subsidized school bus which is zero-rated.

VoT_{TT} : Value of travel time savings in Rupiah per minute.

TT_{ACS} : Travel time of subsidized school bus in minutes.

VoT_{TW} : Value of wait time savings in Rupiah per minute.

TW_{ACS} : Wait time of subsidized school bus in minutes.

VoC : Monetary Value of Comfort in Rupiah.

KF_{ACS} : Dummy variable for cabin air conditioning comfort facility.

The competition between the two modes is modeled using the net difference of their generalized costs, formulated in (10):

$$\Delta GC_{Extended} = GC_{ACS} - GC_{Mc} \quad (10)$$

$\Delta GC_{Extended}$: Net difference in Extended Generalized Cost in Rupiah.

GC_{ACS} : Extended Generalized Cost for subsidized school bus.

GC_{Mc} : Extended Generalized Cost for private motorcycle.

This consolidated metric provides a highly reflective policy testing framework [25], allowing decision-makers to simulate the exact financial disincentives required to disrupt the status quo utility of private vehicles [17].

3.1.5 Partial Sensitivity Analysis and Indifference Point

This evaluation will operate under *ceteris paribus* conditions, systematically varying one specific operational attribute while maintaining all other variables constant to construct logistic diversion curves [11]. This mathematical projection will aim to identify the Indifference Point, which represents the perfect 50.0% probability equilibrium where the utility difference equals exactly zero [18]. Under this disaggregate behavioral framework, the indifference threshold for a specific attribute will be mathematically extracted by forcing the utility difference function to zero, as formulated in equation 11.

$$0 = \alpha_{combined} + \beta_k X_{k,IP} \Rightarrow X_{k,IP} = -\frac{\alpha_{combined}}{\beta_k} \quad (11)$$

$X_{k,IP}$: Value of the k -th operational attribute at the indifference point.
 $\alpha_{combined}$: Combined constant of baseline utility and demographic controls.
 β_k : Sensitivity parameter coefficient for the k -th attribute.

By analyzing this indifferent equilibrium, policymakers can determine the precise boundaries where students become behaviorally neutral toward choosing either the private motorcycle or the subsidized school bus program [12]. This mathematical extraction will serve as the foundation for simulating modal shift sensitivities [13] and determining the exact generalized cost thresholds required to overcome the psychological inertia of private transport modes [24].

3.1.6 Spatial Probability Projection

To capture the geographic variation of student commutes, a spatial analysis will be performed. Travel time will be modeled as a spatial function of distance, reflecting how localized school accessibility dictates motorized commute choices. This spatial relationship is formulated as shown in (12):

$$\Delta TT = f(D) \quad (12)$$

ΔTT : Travel time difference in minutes.
 $f(D)$: Spatial travel time function based on distance D in kilometers.

By substituting this spatial function into the utility model, the distance-based utility difference is formulated in (13):

$$\Delta U(D) = \alpha_{combined} + \beta_1 \Delta TC + \beta_2 f(D) + \beta_3 \Delta TW + \beta_4 KF \quad (13)$$

$\Delta U(D)$: Distance-based utility difference function.
 $\alpha_{combined}$: Combined constant of baseline utility and demographic controls.
 $\beta_1, \beta_2, \beta_3, \beta_4$: Calibrated parameter coefficients for simulated service attributes.
 $\Delta TC, \Delta TW$: Attributes representing differences in travel cost and wait time.
 KF : Dummy variable for cabin air conditioning comfort facility.

This distance-based utility difference will then be transformed into geographic transition probability curves, which model the spatial decay of transit utility as distances exceed active transport thresholds [29]. This spatial probability curve is formulated as shown in (14):

$$P_{ACS}(D) = \frac{1}{1 + e^{-\Delta U(D)}} \quad (14)$$

$P_{ACS}(D)$: Spatial transition probability as a function of distance D .
 e : Base of natural logarithms.
 $\Delta U(D)$: Distance-based utility difference function.

This mathematical transformation maps localized mode choice probabilities along the school corridor [16]. This spatial projection allows researchers to identify the geographic boundaries where motorcycle dependency becomes absolute and where subsidized school bus programs remain competitive [12].

3.1.7 Point Elasticity of Choice Attributes

To measure the immediate responsiveness of student demand to operational improvements, point elasticity is estimated. Point elasticity indicates the percentage change in mode choice probability resulting from a 1.0 percent change in a specific service attribute. The point elasticity of transition probability with respect to attribute X_k is formulated in (15):

$$\eta_k = \frac{\partial P_{ACS}}{\partial X_k} \times \frac{X_k}{P_{ACS}} = \beta_k \times X_k \times (1 - P_{ACS}) \quad (15)$$

η_k : Point elasticity of transition probability with respect to attribute X_k .
 β_k : Calibrated utility parameter coefficient for the k -th attribute.
 X_k : Operational value of the simulated attribute.
 P_{ACS} : Probability of transition towards subsidized school transport.

This mathematical formulation captures how incremental adjustments in transport supply parameters trigger active behavioral shifts, matching disaggregate elasticity concepts applied in student transit studies [30]. By calculating these elasticities, researchers can evaluate which service policy—such as fare adjustments or travel time savings—exhibits the highest leverage on student choice probability [31]. The resulting elasticities reflect localized behavioral sensitivities, providing an empirical basis to forecast ridership responses to service variations within school corridors **Research Method**

4.1 Descriptive Profile and Spatial Homogeneity

Geographic origins are aggregated relative to the Kelurahan Bangunsari centroid. The spatial distribution of student commuters across the target schools is presented in Table 5.

Table 5. Spatial Distribution of Accessibility Distance Rings Across Target Schools

Accessibility Rings	Total Generation (Students)	Percentage (%)
Ring 1 (< 1.0 km)	54	15.61%
Ring 2 (1.0 - 2.0 km)	103	29.77%
Ring 3 (2.1 - 3.0 km)	77	22.25%
Ring 4 (3.1 - 4.0 km)	23	6.65%
Ring 5 (> 4.0 km)	89	25.72%
Totaled aggregate	346	100.00%

The uniform grouping of 74.28% of student commuters within Rings 1 to 4 validates the baseline spatial consistency of the urban core, satisfying the discrete modeling prerequisites to avoid structural bias [11]. Conversely, the 25.72% suburban cohort clustered in Ring 5 highlights the severe travel impedance and spatial friction typical of rural-urban fringes, matching the travel delay trends observed in similar school commute corridors and zoning-induced travel patterns under private vehicle dominance [3]. This dual spatial structure provides the quantitative baseline for subsequent ring-based probability forecasting and targeted micro-feeder routing policies validated in other regional educational zones [16].

4.2 Model Diagnostics and Lexicographic Screening

Before calibrating the utility models, Ordinary Least Squares regression diagnostics will be executed on the covariates to ensure the Variance Inflation Factor remains below 10.00 and Tolerance exceeds 0.10 [22]. To satisfy Random Utility Theory assumptions [11], a two-stage screening protocol will be applied to prune the raw sample of 346 respondents to a purified matrix of 338 active traders [18]. This purification procedure systematically excludes 1 absolute non-trading lexicographic respondent to prevent singular Hessian matrices and 7 non-motorized transport commuters who face zero out-of-pocket costs to avoid travel-cost coefficient distortions [11], [18].

4.3 Binary Logit Difference Model Calibration

The initial unpruned utility difference model incorporating all attributes and covariates is formulated in Equation (70).

$$\begin{aligned} \Delta U = & -1.292 - 0.075\Delta TC - 0.035\Delta TT - 0.045\Delta TW + 0.826KF + 0.439Z_{Nym} - 0.447Z_{Amn} \\ & - 0.301Z_{Sak1} - 0.537Z_{Sak2} - 0.512Z_{Usi1} - 0.978Z_{Usi2} - 1.312Z_{Usi3} - 0.776Z_{Mot1} \\ & - 1.452Z_{Mot2} + 0.049Z_{WTE} + 0.134Z_{WAK} \end{aligned} \quad (16)$$

To satisfy the verification of individual parameter significance, the complete maximum likelihood estimation results containing the parameter coefficients (Tabel Wald) are tabulated in Table 6.

Table 6. Maximum Likelihood Estimates and Individual Significance (n = 338)

Variable	Coefficient (B)	Standard Error (S.E.)	Wald Statistic	df	Significance (p-value)	Odds Ratio (Exp(B))	95.0% C.I. Lower	95.0% C.I. Upper
Policy Attributes								
Travel Cost Difference (ΔTC)	-0.075	0.012	41.582	1	0	0.927	0.907	0.949
Travel Time Difference (ΔTT)	-0.035	0.012	8.803	1	0.003	0.965	0.943	0.988
Wait Time Difference (ΔTW)	-0.045	0.012	14.552	1	0	0.956	0.935	0.978
Cabin AC Facility (KF)	0.826	0.097	72.645	1	0	2.284	1.889	2.762
Socio-Demographics & Perception								

Variable	Coefficient (B)	Standard Error (S.E.)	Wald Statistic	df	Significance (p-value)	Odds Ratio (Exp(B))	95.0% C.I. Lower	95.0% C.I. Upper
Comfort Perception (Z_{Nym})	0.439	0.093	22.253	1	0	1.551	1.292	1.861
Safety Perception (Z_{Amn})	-0.447	0.102	19.101	1	0	0.639	0.523	0.781
Punctuality Perception	0.067	0.098	0.473	1	0.491	1.07	0.883	1.296
Daily Pocket Money			10.059	2	0.007			
Daily Pocket Money(1) (Z_{Sak1})	-0.301	0.122	6.092	1	0.014	0.74	0.583	0.94
Daily Pocket Money(2) (Z_{Sak2})	-0.537	0.178	9.121	1	0.003	0.585	0.413	0.828
Gender(1)	0.006	0.104	0.004	1	0.953	1.006	0.821	1.233
Student Age Group			32.986	3	0			
Student Age Group(1) (Z_{Usi1})	-0.512	0.141	13.224	1	0	0.6	0.455	0.79
Student Age Group(2) (Z_{Usi2})	-0.978	0.19	26.476	1	0	0.376	0.259	0.546
Student Age Group(3) (Z_{Usi3})	-1.312	0.316	17.201	1	0	0.269	0.145	0.501
Motorcycle Riding Capability			106.611	2	0			
Riding Capability(1) (Z_{Mot1})	-0.776	0.119	42.502	1	0	0.46	0.364	0.581
Riding Capability(2) (Z_{Mot2})	-1.452	1.452	101.507	1	0	0.234	0.176	0.31
Existing Travel Duration (Z_{WTE})	0.049	0.008	40.051	1	0	1.051	1.035	1.067
Existing Travel Cost	-0.006	0.019	0.097	1	0.755	0.994	0.957	1.032
Access Walk Time (Z_{WAK})	0.134	0.055	5.97	1	0.015	1.144	1.027	1.274
Constant	-1.292	0.492	6.908	1	0.009	0.275		

By substituting this consolidated constant, the finalized mathematical formulation of the utility difference (ΔU) is simplified into a parsimonious linear equation written in (17).

$$\Delta U = -2.1929 - 0.075\Delta TC - 0.035\Delta TT - 0.045\Delta TW + 0.826KF \quad (17)$$

Based on the individual significance tests in Table 8, the four policy variables (ΔTC , ΔTT , ΔTW , and KF) are highly significant at the 95.0% confidence level ($p < 0.01$) [18]. Next, the overall model significance is verified through the Omnibus Tests of Model Coefficients shown in Table 6.

Table 7. Omnibus Tests of Model Coefficients

Test Phase	Chi-square	df	Significance (p-value)
Step	563.61	19	0
Block	563.61	19	0
Model	563.61	19	0

The model chi-square of 563.610 ($df = 19$, $p < 0.001$) in Table 7 rejects the null hypothesis, confirming that the operational attributes and covariates collectively exert a highly significant influence on student mode choice. Next, the explanatory power of the estimated model is summarized in Table 8.

Table 8. Model Summary

Step	-2 Log Likelihood	Cox and Snell R Square	Nagelkerke R Square
1	2818.646	0.169	0.252

The Nagelkerke R Square of 0.252 in Table 10 indicates a strong goodness of fit, satisfying the 0.20 to 0.40 range established for disaggregate discrete choice models by Hensher et al. [18] and Ortúzar and Willumsen [11]. To verify that the model predictions replicate empirical observations without systematic bias, the Hosmer and Lemeshow goodness of fit test is displayed in Table 9 and Table 10

Table 9. Hosmer and Lemeshow Test

Step	Chi-square	df	Significance (p-value)
1	4.75	8	0.784

Table 10. Contingency Table for Hosmer and Lemeshow Test

Decile	Observed Private Motorcycle	Expected Private Motorcycle	Observed School Bus	Expected School Bus	Total
1	294	292.239	10	11.761	304
2	290	282.956	14	21.044	304
3	273	274.779	31	29.221	304
4	259	265.483	45	38.517	304
5	252	253.695	52	50.305	304

Decile	Observed Private Motorcycle	Expected Private Motorcycle	Observed School Bus	Expected School Bus	Total
6	237	239.563	67	64.437	304
7	220	220.813	84	83.187	304
8	194	195.535	110	108.465	304
9	165	163.566	139	140.434	304
10	115	110.372	191	195.628	306

The Hosmer and Lemeshow test value of 4.750 ($p = 0.784$) in Table and the close decile alignment in Table 10 confirm that the model predictions do not systematically deviate from empirical observations, matching the classification standards discussed by Hair et al. [22]. Finally, the classification matrix of the model is tabulated in Table 11.

Table 11. Classification Table (Cut Value 0.500)

Observed Decision	Predicted Private Motorcycle	Predicted School Bus	Percentage Correct
Private Motorcycle	2162	137	94.00%
School Bus	519	224	30.10%
Overall Percentage			78.40%

Table 13 demonstrates a high overall classification accuracy of 78.4%, with an exceptional precision rate of 94.0% for predicting status quo private motorcycle decisions.

4.4 Value of Time and Value of Comfort Extraction

The consolidated results of these post-estimation extractions are summarized in Table 12.

Table 12. Extracted Value of Time and Value of Comfort for Student Commuters

Travel Attribute	Parameter Coefficient (β)	Value of Attribute (Rupiah / Minute)	Hourly Equivalency (Rupiah / Hour)	Trip Equivalency (Rupiah / Trip)
In-Vehicle Travel Time (ΔTT)	-0.035	Rp466.67	Rp28,000.00	-
Out-of-Vehicle Wait Time (ΔTW)	-0.045	Rp600.00	Rp36,000.00	-
Cabin Thermal Comfort Dummy (KF)	0.826	-	-	Rp11,013.33

Table 6 reveals a waiting-to-travel time ratio of 1.29, indicating that student commuters perceive out-of-vehicle waiting as significantly more burdensome than in-vehicle travel duration [11]. Conversely, the extracted Value of Comfort of Rp11.013.33 per trip enables a direct microeconomic trade-off where the travel cost parameter cancels out [18]. This allows a direct evaluation of the additional travel delay students will rationally tolerate in exchange for a climate-controlled cabin facility [11].

4.5 Marginal Effect on Choice Probability

The estimated marginal effects are presented in Table 13.

Table 13. Marginal Effects of Service Attributes and Covariates on Choice Probability

Evaluated Attribute	Parameter Coefficient (β)	Marginal Effect Value (ME)	Impact on Mode Transition Probability
Cabin Air Conditioning (KF)	0.826	0.2065	+20.65% change in transition probability
Latent Comfort Perception ($ZNym$)	0.439	0.1098	+10.98% change per unit increase in perception
Latent Safety Perception ($ZAmn$)	-0.447	-0.1118	-11.18% change per unit increase in perception
Access Time to Stop ($ZWAK$)	0.134	0.0335	+3.35% change per minute increase in access time

The marginal leverage of -11.18% derived in Table 13 indicates that students who perceive private motorcycles as highly safe are heavily resistant to shifting toward public transit. This behavioral friction highlights the urgent necessity of implementing educational safety campaigns to dismantle the psychological illusion of motorcycle safety among underage students [32]. Underage riders in rural-urban fringes often overlook the extreme crash risks of unlicensed motorcycle operation, a behavior widely documented in regional transport safety analyses [25] and student travel risk assessments [3].

4.6 Extended Generalized Cost Formulation

The calibrated EGC formulation for private motorcycles is expressed in (19):

$$GC_{Mc} = TC_{Mc} + (466.67 \times TT_{Mc}) + (600.00 \times TW_{Mc}) \quad (19)$$

The calibrated Extended Generalized Cost equation for the subsidized school bus is formulated in (20):

$$GC_{ACS} = TC_{ACS} + (466.67 \times TT_{ACS}) + (600.00 \times TW_{ACS}) - (11013.33 \times KF_{ACS}) \quad (20)$$

The negative sign of the comfort parameter ($-11013.33 \times KF$) represents a psychological subsidy, reducing the total travel disutility felt by students. This application of a negative coefficient to represent a qualitative benefit is supported by Shiddiqi [6] in their evaluation of fiscal-based push-and-pull policies. The net competition between the two modes is expressed as the difference in their extended generalized costs.

4.7 Partial Sensitivity Analysis and Indifference Point

4.7.1 Sensitivity Analysis of Travel Cost Difference (ΔTC)

When the travel cost difference stands at Rp15000.00 per trip, the transition probability is a negligible 3.50%. If local authorities successfully reduce this cost gap to parity ($\Delta TC = 0.00$), the transition rate rises to 10.04% under baseline conditions. However, when this parity is paired with active cabin air conditioning, the shift probability immediately doubles to 20.31%. Figure 1 visualizes this continuous probability transition across varying cost differences.

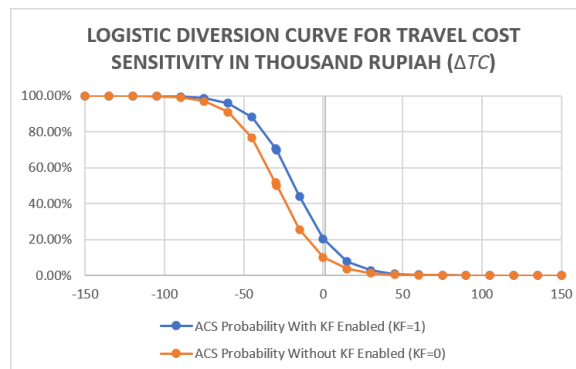


Figure 1. Logistic Diversion Curve for Travel Cost Sensitivity

Conversely, enforcing a Rp30000.00 motorcycle operating penalty (such as through a parking surcharge) pushes the shift probability to a baseline equilibrium of 51.43%. When this identical surcharge is integrated with active cabin AC, student transition skyrockets to a commanding 70.75% [6]. This dramatic leap proves that premium comfort flattens student sensitivity to financial disincentives, allowing local authorities to secure high modal shift targets using politically viable surcharges without overburdening low-income households [13].

4.7.2 Sensitivity Analysis of Out of Vehicle Wait Time Difference (ΔTW)

At wait time parity ($\Delta TW = 0.00$), the baseline shift probability is a meager 10.04% due to student impatience. Reducing transit wait time by 15.00 minutes ($\Delta TW = -15.00$) only nudges this probability to 17.98%. However, active cabin AC surges the choice probability to 49.58% even at a 30.00-minute wait time disadvantage ($\Delta TW = -30.00$). Figure 2 visualizes this probability decay across varying wait time differences.

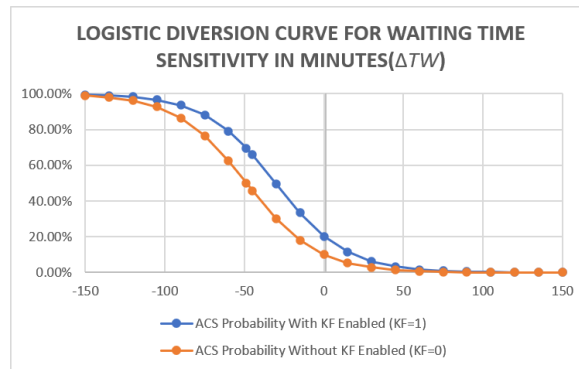


Figure 2. Logistic Diversion Curve for Waiting Time Sensitivity

This steep probability decay confirms the high marginal disutility of out-of-vehicle waiting time under standard fleet parameters [11]. To achieve a 50.00% choice equilibrium without service improvements, local authorities must enforce an unrealistic waiting time deficit of -48.73 minutes, proving that headway reduction alone cannot compete with private motorcycles. Conversely, introducing active cabin comfort shifts this mathematical indifference point to -30.38 minutes [9]. This 37.66% reduction in wait time resistance confirms that premium amenities successfully buffer student impatience, allowing transit agencies to operate with wider, more cost-effective headways while retaining system competitiveness [18].

4.7.3 Sensitivity Analysis of In Vehicle Travel Time Difference (ΔTT)

When the school bus route is unoptimized and runs 30 minutes slower than private motorcycles ($\Delta TT = 30.00$), the transition probability is a negligible 3.76%. If transit planners successfully optimize the routing to reduce this delay to 15 minutes ($\Delta TT = 15.00$), the baseline probability rises slightly to 6.19%, but immediately doubles to 13.10% once active cabin air conditioning is provided. Achieving direct route parity ($\Delta TT = 0.00$) only secures a 10.04% transition under baseline conditions, which instantly surges to 20.31% with active thermal comfort. Figure 3 visualizes this continuous probability transition across varying travel time differences.

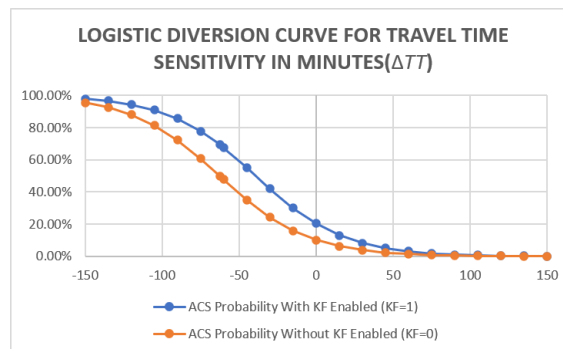


Figure 3. Logistic Diversion Curve for Travel Time Sensitivity

This persistent resistance highlights the high marginal disutility of transit travel duration, confirming that routing optimization alone cannot overcome motorcycle convenience [18]. Achieving a 50.00% choice equilibrium under baseline conditions requires an unfeasible transit travel time advantage of -62.65 minutes. However, active cabin AC introduces an independent, additive utility shift of +0.826, shifting this mathematical indifference point to a more realistic delay of -39.05 minutes. Rather than moderating travel time sensitivity—which remains strictly constant across comfort states—this shift represents a parallel utility expansion [18]. This proves that qualitative comfort upgrades can effectively offset quantitative travel time penalties through compensatory utility accumulation [11].

4.8 Spatial Probability Projection

The spatial projection of transition probabilities across five concentric distance rings is presented in Table 14.

Table 14. Geographic Projection of Mode Transition Probabilities Across Distance Rings

Spatial Boundary Ring	Commute Distance (km)	Projected Bus Probability (PACS)	Projected Motorcycle Probability (PMc)	Competitive Market Status
Ring 1 (Inner Core)	< 1.0 km	14.36%	85.64%	Motorcycle Dominant (High Access)
Ring 2 (Urban Zone)	1.0 - 2.0 km	15.13%	84.87%	Motorcycle Dominant
Ring 3 (Transition)	2.1 - 3.0 km	15.94%	84.06%	Motorcycle Dominant
Ring 4 (Boundary)	3.1 - 4.0 km	16.78%	83.22%	Motorcycle Dominant (High Disutility)
Ring 5 (Hinterland)	> 4.0 km	23.14%	76.86%	Motorcycle Dominant (Long-Distance)

Table 14 reveals a spatial paradox where school bus transition probability rises from 14.36% in Ring 1 to 23.14% in Ring 5. Long-distance commuters tolerate routing delays to secure absolute monetary savings over high motorcycle operating costs. Conversely, urban core students remain motorcycle-captive due to low marginal savings [4]. This polarization justifies targeted routing, matching the optimization frameworks of Alfiah et al. [34] and Ridwan [33].

4.9 Point Elasticity of Choice Attributes

To measure the immediate responsiveness of student demand to operational adjustments, point elasticities were estimated at the sample mean values [18]. The calibrated point elasticities for the primary quantitative attributes are presented in Table 15.

Table 15. Calibrated Point Elasticities for Quantitative Service Attributes

Service Attribute	Parameter Coefficient (β)	Mean Value	Projected Elasticity (η)	Elasticity Classification
Travel Cost Difference (ΔTC)	-0.075	-5.234	0.353	Inelastic
Wait Time Difference (ΔTW)	-0.045	6.31	-0.255	Inelastic
Travel Time Difference (ΔTT)	-0.035	0.76	-0.024	Inelastic

The empirical results in Table 15 confirm that all quantitative attributes are strictly inelastic, with travel cost difference exhibiting the highest relative sensitivity at 0.353. This positive elasticity, despite a negative parameter of -0.075, arises because the mean cost difference is negative (-5.234), representing the school bus subsidy advantage. Multiplying the negative marginal utility by this negative mean yields a positive value [18]. Econometrically, this indicates that a 10.00% increase in private motorcycle costs will drive a 3.53% increase in school bus transition probability [11]. These inelastic values confirm that isolated operational changes cannot dismantle private vehicle bias [3], requiring integrated push-and-pull policy packages [11].

5. Conclusion and Suggestion

5.1 Conclusion

Student mode choice within the educational corridor is simultaneously governed by four primary operational attributes, which are travel cost difference, travel time difference, waiting time difference, and cabin comfort. These main factors co-act and jointly contribute with various minor demographic and latent covariates, including unlicensed motorcycle riding capability, student age categories, daily pocket money limits, stop access duration, and subjective perceptions of travel safety and comfort. Together, this integrated set of variables dictates the final modal transition, as verified by joint model significance tests. The microeconomic extraction of the utility parameters indicates a high non-linear sensitivity toward out-of-vehicle wait times relative to in-vehicle travel duration, suggesting a substantial waiting penalty. Conversely, the high economic equivalent of cabin thermal comfort indicates that qualitative service upgrades function as a significant additive utility contributor. This comfort premium does not alter the underlying marginal disutility of travel duration, but the results imply that students will rationally accept travel time extensions in exchange for an air-conditioned cabin facility through compensatory utility accumulation. A distinct spatial polarization characterizes student commute patterns, where the transition probability toward public transport rises consistently in the outer suburban rings. Students residing in hinterland zones rationally trade off routing delays for physical relief and economic savings, whereas urban core students remain highly captive to private motorcycles due to negligible cost margins. This spatial friction confirms that single-attribute interventions are ineffective without a coordinated push-and-pull policy framework.

5.1 Suggestion

1. Local planners should leverage the identified qualitative-quantitative trade-off mechanisms to design balanced, non-coercive school travel management policies. Rather than relying solely on aggressive fiscal penalties, integrating quality-driven pull incentives such as premium cabin amenities can effectively offset commuter resistance and lower the operational thresholds required to trigger successful modal shifts
2. Future empirical designs should transition from the orthogonal configurations used in this study to Bayesian D-efficient experimental designs. While the current orthogonal setup assumes zero priors and can generate statistically inefficient profiles with dominant options, utilizing the calibrated utility parameters of this study as priors in the D-efficiency algorithm will allow subsequent research to systematically minimize parameter standard errors. This operational prior integration optimizes the Fisher Information Matrix, enabling future models to isolate unobserved preference errors and hidden cognitive biases with smaller sample thresholds.
3. Methodological expansions are recommended to upgrade the current binary logit difference framework into multivariate discrete choice models such as multinomial or nested logit. This expansion will successfully capture competitive interactions between subsidized transit, private motorcycles, public minibuses, and active non-motorized modes across a broader school zoning network.

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