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Predicting post-COVID-19 commuter transportation choice in greater Jakarta: A logistic regression approach to behavioral analysis and adaptation strategies

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Abstract: This study explores the factors influencing commuter transportation choices in Jakarta during the COVID-19 pandemic through logistic regression analysis, integrating the Theory of Planned Behavior (TPB) with Customer Satisfaction Theory to examine the impact of psychological factors, service-related aspects, and environmental awareness on public transport use. Based on a survey of 254 commuters across Greater Jakarta, the research employs a forward stepwise logistic regression approach to identify key predictors of transportation behavior. The final model demonstrates robust predictive power with a classification accuracy of 69.7% and an ROC score of 0.697, revealing that private vehicle preference and health concerns negatively influence public transport adoption, while environmental awareness and fatigue from driving positively affect modal shift intentions. The findings emphasize the necessity of both push strategies—addressing health and safety concerns—and pull strategies—enhancing public transportation attractiveness through improved reliability, comfort, and environmental messaging. The research highlights the critical need for targeted urban mobility policies that integrate health-focused and environmental messaging to promote sustainable transportation choices, particularly in rapidly urbanizing areas like Jakarta. By addressing multifaceted challenges through comprehensive approaches that combine immediate health concerns with long-term environmental benefits, policymakers can develop more resilient urban mobility systems and reduce reliance on private vehicles in the post-pandemic era.

Keywords: *Commuter behavior, COVID-19 pandemic, Logistic regression, Modal shift, Public transportation, Urban mobility.*

1. Introduction

The rapid urbanization and economic growth in Asia's newly industrialized countries have increased travel demands, resulting in a rise in private vehicle ownership driven by higher incomes and societal perceptions linking cars to status [1-3]. This shift has worsened traffic congestion, environmental pollution, and quality-of-life issues, as many developing countries do not have sufficient public transportation systems to reduce motorization [4]. Unlike developed countries with established mass transit networks, developing cities encounter significant challenges in improving public transport, which is essential for addressing environmental degradation, promoting social equity, and alleviating the pressures of urban expansion [5]. The COVID-19 pandemic has further complicated the urban mobility landscape by significantly altering travel behaviors. According to Sushma and Prusty [6] the pandemic prompted a dramatic reduction in the use and demand for public transportation systems. This shift was driven by strict public transport restrictions aimed at limiting virus transmission and by the public's heightened fear of contracting COVID-19 in crowded, enclosed spaces. Studies reveal a general decline in public transport use due to perceived infection risks, with a concurrent rise in private vehicle use and active transportation modes such as walking and cycling [7]. Public transportation, particularly during

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peak hours, poses a higher risk of virus contamination due to limited space and high passenger density. Consequently, many individuals have turned to private vehicles as a safer alternative, increasing private transport usage [8].

One of the ways of resolving these problems is to increase public transport usage instead of private cars by including certain factors such as comfort, risk reduction, the ticket price, convenience, time and frequency of public buses daily [9]. Governments must prioritize promoting public transport (PT) to counter the negative impacts of excessive car usage. Encouraging commuters to choose buses, trains, and other forms of public transit can help improve traffic conditions, mitigate environmental hazards, and align with Sustainable Development Goals (SDGs) related to sustainable transport [10]. Jakarta, the capital of Indonesia, along with its surrounding cities known as Jabodetabek, represents a notable model of urban development aimed at addressing the challenges of urbanization such as congestion, pollution, and inadequate infrastructure. The city has initiated significant public transportation improvements, including the introduction of Mass Rapid Transit (MRT) and Light Rail Transit (LRT) systems, which set benchmarks for other Indonesian cities facing similar issues [11]. However, despite these advancements, public transportation adoption remains low, with utilization rates between 5%-20% in certain areas and a total penetration of just 26.7% among 3.2 million commuters. Through various initiatives, the Jakarta Transportation Management Agency aims to reach a target of 60% of public transportation usage by 2030. However, it faces obstacles like poor system integration, limited service coverage, and a cultural inclination towards private vehicles [12]. This focus on Jakarta mirrors the challenges faced by other major global cities such as Bangkok [13] Manila [14] Mumbai [15] Cairo [16] and São Paulo [17]. These urban centers are characterized by rapidly increasing vehicle counts, infrastructure that struggles to keep pace with demand, and public transportation systems that need modernization and expansion. These urban centers are characterized by rapidly increasing vehicle counts, infrastructure that struggles to keep pace with demand, and public transportation systems that need modernization and expansion.

Studying the commuting patterns of the middle and upper classes, often referred to as 'middle-up' in Asia's rapidly urbanizing regions, is essential due to the increasing travel demands and a decrease in private car usage. Understanding the travel behaviors of the middle-up demographic is critical for effective sustainable development planning [18]. Examining middle-up commuting patterns can guide strategies to transition to sustainable transport modes such as public transit. This shift can help address issues like traffic congestion, pollution, and global warming, ultimately improving quality of life [19]. Given the unique challenges faced by developing countries like Indonesia, with Jakarta as a prime example, it is essential to examine how commuter behavior and preferences have changed during crises such as the COVID-19 pandemic. This paper aims to address the existing gap in the literature by providing a comprehensive analysis of commuter behavior and adaptation strategies in Jakarta during times of crisis. By offering new insights into sustainable urban mobility strategies, this research seeks to contribute to developing more resilient and adaptable public transport systems in developing countries.

This study employs logistic regression analysis to examine the factors influencing commuters' transportation choices in Jakarta during the COVID-19 pandemic. It identifies critical predictors that shape commuter behavior by analyzing variables such as attitudes toward private vehicles and public transportation, willingness to switch modes of transportation, and familiarity with new mobility technologies. Research also examines additional factors, specifically the impact of COVID-19 experiences, focusing on trust and perceptions of health safety risks. This approach offers valuable insights into the interactions between these factors, which can aid in developing strategies to promote sustainable urban mobility.

2. Literature Review

2.1. Integration of Theory of Planned Behavior and Customer Satisfaction Theory

The Theory of Planned Behavior (TPB), developed by Ajzen (1991), serves as a foundational framework widely utilized to predict public transportation behavior. TPB suggests that behavioral intentions are shaped by attitudes, subjective norms, and perceived behavioral control, all of which have been consistently validated as significant predictors of public transit use [16, 20, 21]. Customer Satisfaction Theory complements TPB by examining how the gap between customer expectations and actual experiences influences satisfaction and subsequent behavior [22]. Satisfaction arises when experiences exceed expectations (positive disconfirmation), while dissatisfaction occurs when they fall short (negative disconfirmation) [23].

Integrating TPB with Customer Satisfaction Theory provides a comprehensive understanding of public transit use. Studies such as those by Fu and Juan [24] and Zhang and Hayashi [25] have demonstrated that combining these theories helps predict transit use intentions by considering attitudes, norms, perceived control, and satisfaction, especially during the COVID-19 pandemic. Extensions of TPB have further enriched its predictive power. Ng and Phung [26] added personal norms and environmental concerns, while Donald, et al. [20] incorporated habit, showing that car use is driven by both intention and habit, whereas public transport use depends more on intention alone.

2.2. Public Transportation Behavior During the Pandemic

The COVID-19 pandemic has significantly transformed public transportation systems around the world, resulting in notable changes in travel behavior, user perceptions, and overall mobility patterns. This transformation is particularly pronounced in developing countries, where the pandemic accelerated existing trends toward private vehicle preference while simultaneously highlighting the vulnerability of public transportation systems during health crises [6]. Indonesia experiencing significant shifts in mobility preferences [27]. Despite the easing of restrictions, significant changes in trip frequency and mode choice have persisted into the endemic phase, with public transportation usage remaining substantially reduced [27]. In Jakarta, Indonesia, the pandemic had a substantial impact on the adoption of public transportation. During this time, passenger behavior was mainly influenced by their perception of the effectiveness of safety measures, their confidence in the public transport system, and the strict enforcement of health protocols [16]. To maintain ridership and uphold public trust, transportation authorities in Jakarta have changed their communication strategies. Instead of just providing routine service updates, they now take a more comprehensive approach. This includes sharing important health information and offering mental health support through social media platforms [28]. This comprehensive communication strategy was crucial for keeping the public informed and engaged during the crisis.

The relationship between mobility patterns and COVID-19 transmission rates has provided important insights into public transportation usage. Studies have shown that an increase in community mobility often correlates with higher COVID-19 case numbers. This highlights the necessity of a balanced approach that maintains essential transportation services while minimizing public health risks [11, 29]. In densely populated urban areas such as Kalianyar in West Jakarta, implementing community-led health protocols and micro-scale movement restrictions significantly influenced public transit use patterns [30]. These findings highlight the importance of localized interventions and the necessity of tailoring public health strategies to specific urban contexts.

3. Methodology

This research employs a quantitative methodology due to its ability for producing reliable and generalizable outcome data [31]. The study's approach comprised three main stages, namely data collection, data analysis by using Logistic Regression Analysis (LRA), and model evaluation, as shown in Figure 1.

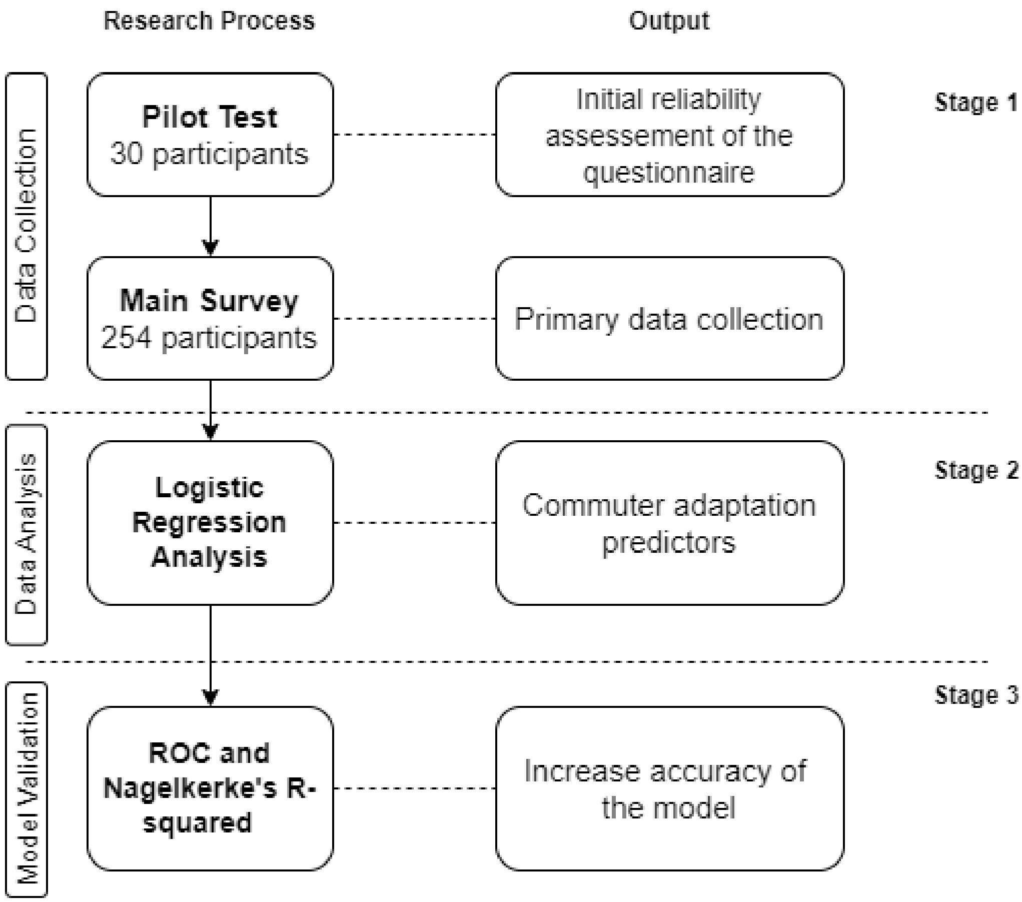

Figure 1.
Research Design.

3.1. Data Collection

The initial phase involved conducting a pilot test with 30 participants to assess the preliminary reliability of the questionnaire. The reliability of the collected data was evaluated using Cronbach's alpha, with a minimum acceptable value set at 0.70 [32]. The second phase consisted an extensive survey conducted to evaluate different facets of commuter conduct and preferences within the framework of urban transportation. This survey was conducted with 254 individuals residing in the Jakarta, Tangerang, Depok, and Bogor. These measures consists of a) Demographic; b) Commuters' attitudes towards private vehicles, including the perceived sense of independence, control, speed, and lifestyle implications connected with owning a private vehicle [15, 33-35]. Commuters' perspectives on public transportation, specifically focusing on its perceived effectiveness, comfort, environmental consequences, and health-related considerations which related to the shifting of COVID-19 [19, 36-38]. Commuters' criteria that increase willingness people to switch into public transport, based on time savings, environmental impact, comfort, cost, and health considerations [12, 17, 39-41]. Type of commuters, including electric automobiles, ride-hailing services, ride-sharing platforms, bike-sharing programs, electric scooters, and high-speed trains [12, 42-45]. Commuters' interest in trying or using these mobility technologies [46-48]. The variable construct used in this research is summarized in Table 1.

Table 1.
Variable's Construct.

Code	Construct
Q1	Private vehicles provide the freedom to go wherever I want.
Q2	With a private vehicle, I have control over my journeys.
Q3	Typically, private vehicles are the fastest means of reaching my destination.
Q4	It would be challenging for me to adapt if I had to live without a private vehicle every day.
Q5	Only private vehicles align with my lifestyle.
Q6	I used to use PT for years, but not anymore since I got my private vehicle.
Q7	I enjoy driving and love my private vehicle.
Q8	The type of private vehicle someone drives often reflects their lifestyle and social status.
Q9	I don't like driving with people I don't know.
Q10	People I know find it strange if I don't have a private vehicle.
Q11	I use a private vehicle because I feel safer in terms of health (e.g., less susceptible to diseases from others).
Q12	PT is only intended for those less fortunate.
Q13	Using PT wastes my time.
Q14	I only use PT if I have no other choice.
Q15	There are many problems and difficulties in using PT.
Q16	I feel happy when using PT.
Q17	I have a positive opinion about PT.
Q18	I feel relaxed and enjoy my time when using PT compared to private vehicles.
Q19	I often experience fatigue from using a car repeatedly and choose to use PT.
Q20	Using PT helps improve the quality of the environment.
Q21	If PT is crowded, I will wait for the next one.
Q22	I am concerned about potential health issues (e.g., getting sick from others) when using PT.
Q23	I have considered changing my mode of transportation during my travels.
Q24	I will change my mode of transportation if it can save time.
Q25	I will switch my mode of transportation to protect the environment.
Q26	I am willing to pay more when traveling to help the environment.
Q27	I rarely use private vehicles to be environmentally conscious.
Q28	I choose the type of vehicle that offers the most comfort without considering the cost.
Q29	I always use the fastest type of vehicle even if I have a cheaper alternative.
Q30	I avoid traveling at certain times because it makes me very tired.
Q31	If the distance is short, I prefer to walk during the daytime.
Q32	Having a relaxed and stress-free journey is more important than arriving quickly.
Q33	I am committed to sticking with the mode of transportation I frequently use, even if it's perceived as riskier.
Q34	I am dedicated to using the mode of transportation I frequently use, even if it comes at a higher cost.
Q35	I am determined to continue using the mode of transportation I frequently use, even if it requires more physical effort.
Q36	I am inclined to maintain my usual mode of transportation, even if it results in a longer journey.
Q37	Usually, I feel accomplished and content when I reach my destination.
Q38	I prefer a mode of transportation that can guarantee health and safety inside the vehicle.
Q39	I have a good understanding of the developments in mobility technology related to Electric Cars.
Q40	I am well-informed about the advancements in mobility technology related to Ride Hailing (e.g., Online Motorcycle Taxis and Ride-Sharing Services).
Q41	I have a good grasp of the developments in mobility technology related to Ride Sharing (e.g., Carpooling services like Nebengers).
Q42	I am knowledgeable about the advancements in mobility technology related to Bike Sharing (e.g., Services like Gowes and Boseh).
Q43	I am well-versed in the developments in mobility technology related to Electric Scooters (E-Scooters).
Q44	I am well-informed about the advancements in mobility technology related to High-Speed Trains.
Q45	I am highly interested in trying or using Electric Cars.
Q46	I am highly interested in trying or using Ride Hailing services, such as Online Motorcycle Taxis and Ride-Sharing Services.
Q47	I am highly interested in trying or using Ride Sharing services, such as Carpooling services like Nebengers.
Q48	I am highly interested in trying or using Bike Sharing services, including services like Gowes and Boseh.
Q49	I am highly interested in trying or using Electric Scooters (E-Scooters).
Q50	I am highly interested in trying or using High-Speed Trains.

3.2. Data Analysis

The third phase of the study utilized Logistic Regression Analysis (LRA) to further analyze the data, focusing on binary categorical outcomes of commuter behaviors. LRA is a statistical technique employed when the dependent variable is categorical, specifically binary (e.g., success/failure or presence/absence), and the objective is to estimate the probability of an event occurring based on a set of independent variables.

The logistic regression model for binary outcomes is represented by the equation:

$$\log\left(\frac{p}{(1-p)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where:

1. P represents the probability of choosing a particular transport mode
2. β_0 is the intercept
3. $\beta_1, \beta_2, .., \beta_n$ are the coefficients
4. $X_1, X_2, .., X_n$ are the independent variables

Previous studies have demonstrated the application of LRA in analyzing shifts in public transport usage. For example, Mazanec, et al. [49] utilized multinomial logistic regression to estimate the probability of choosing different transport modes during the pandemic. Similarly, Tan and Ma [50] employed a logistic model to analyze commuters' choice of rail transit, considering factors such as occupation, pre-pandemic commuting habits, and perceived infection risk. Javid, et al. [51] integrated logistic regression within a structural equation modeling framework to examine public transport use under COVID-19 precautions, while Shelat, et al. [18] applied logistic regression to assess the impact of COVID-19 risk perceptions on route choice behavior in train networks. Furthermore, Akuh et al [52] used logistic regression to study transport mode shifts among international students in Wuhan, China, during the pandemic.

The effectiveness of an LRA model can be assessed using various metrics, including classification accuracy (the percentage of correctly predicted cases), the area under the receiver operating characteristic (ROC) curve (which illustrates the true positive rate versus the false positive rate), and pseudo-R-squared measures (such as Nagelkerke's R-squared, which quantifies the proportion of variance explained by the model). A model is generally considered robust if it achieves a classification accuracy of 70% or higher, an area under the ROC curve of 0.7 or greater, and a Nagelkerke's R-squared value of 0.2 or higher. These metrics are essential for evaluating the model's predictive capabilities and overall fit.

3.3. Validation Testing

The model validation process focused on ensuring the reliability and robustness of the logistic regression model through a series of well-structured steps, beginning with data preparation and advancing through model refinement and evaluation. Initially, the dataset consisted of 228 cases, with 221 cases retained for final analysis after excluding those with missing data. The dependent variable, representing commuter behavior, was encoded as a binary outcome, while categorical variables were transformed into dummy variables to allow proper inclusion in the model. A forward stepwise logistic regression approach was employed, where predictor variables were added incrementally, enhancing the model's explanatory power with each step. The Omnibus Tests of Model Coefficients confirmed the statistical significance of these predictors, evidenced by consistent decreases in the -2 Log Likelihood values. The model's goodness of fit was evaluated using the Hosmer-Lemeshow test, which showed improved calibration across the analysis, culminating in a well-fitting final model. Additionally, the predictive power of the model was assessed through a Receiver Operating Characteristic (ROC) Curve analysis, which demonstrated the model's increasing ability to distinguish between outcomes, as reflected in the satisfactory area under the curve (AUC) achieved in the final model.

3.4. Ethics Statement

This research was conducted following ethical guidelines that prioritize participant safety, confidentiality, and informed consent. All participants were fully informed of the study's purpose and voluntarily provided consent to participate. The research adhered to the ethical principles outlined in the Helsinki Declaration, ensuring that no participants were exposed to harm or risk. Data privacy and confidentiality were rigorously maintained throughout the study, and ethical approval was obtained prior to commencing the research.

4. Result

4.1. Research Demography

A survey of 254 commuters across the Greater Jakarta area provides detailed insights into these dynamics. The gender distribution (54% male, 46% female) reflects a balanced view of commuter behavior, while the geographic diversity, including areas like Depok City, South Tangerang, and South Jakarta, reveals regional differences in transportation preferences and challenges. The age and occupational diversity of respondents further enrich the analysis. Younger commuters (aged 20-25), who constitute 30% of the sample, may be more open to adopting PT if modern technology and improved services are integrated. In contrast, older commuters, particularly those over 40, tend to prefer private vehicles due to established habits and a focus on convenience. Occupationally, private employees (48% of the sample) may prioritize PT options with reliable schedules and connectivity to business districts, while students might value affordability and accessibility. These findings highlight the need for targeted PT policies that cater to the specific needs of different commuter segments, rather than a one-size-fits-all approach. The research demography data can be seen in Table 2.

4.2. Incremental Model Enhancement and Fit Evaluation

The analysis was conducted on a dataset comprising 228 cases, with 221 cases included in the final analysis after excluding 7 cases due to missing data. The dependent variable was encoded as a binary outcome, facilitating the logistic regression model's prediction of transportation choices. Categorical variables such as Q12, Q11, and Q3 were encoded using dummy variables to capture the effects of different groups on the dependent variable.

Table 2.
Research Demography.

	Total	Percentage
Gender		
Man	137	54%
Woman	117	46%
Work		
Private employees	123	48%
Student / Student	48	19%
Government employees	28	11%
BUMN/BUMD employees	22	9%
Entrepreneur / Entrepreneur	19	7%
Unemployed	14	6%
Socioeconomic Status (SES)		
A	150	59%
B	37	15%
C	68	27%
Age		
<20	4	2%
20-25	77	30%
26-30	45	17%
36-40	50	20%
>40	47	18%
Marital Status		
Married	128	50%
Single	126	50%
Location of residence		
South Jakarta City	53	21%
East Jakarta City	42	16%
Central Jakarta City	5	2%
West Jakarta City	19	7%
City and Regency of South Tangerang	46	18%
City and District of Depok	68	27%
Bogor City and Regency	21	9%

4.3. Model Improvement

Model improvement was achieved using a forward stepwise selection method based on the Likelihood Ratio, where variables were added incrementally to enhance the model's explanatory power. The process began with an initial model (Block 0) that included only the constant term, serving as a baseline for comparison. The initial model had limited explanatory power, with a classification accuracy of 54.8%. As variables were introduced in subsequent steps, the model's fit significantly improved, as indicated by the decreasing -2 Log Likelihood values and increasing Cox & Snell R Square and Nagelkerke R Square values.

The Omnibus Tests of Model Coefficients confirmed that each step significantly enhanced the model's performance, with chi-square values consistently demonstrating improvements in fit. By Step 5, the model accounted for approximately 32.1% of the variance in the dependent variable, as reflected by the Nagelkerke R Square value. Key variables such as Q27E_inv, Q28H_inv, Q27K_inv, Q29C_inv, and

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Q29K_inv were included based on their significant contributions, resulting in a robust model with improved predictive power.

Table 3 summarizes the progression of key model fit indicators, highlighting the effectiveness of the stepwise approach in refining the logistic regression model and enhancing its accuracy.

Table 3.
Summary of Model Improvement.

Step	-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square
1	281.586	0.132	0.177
2	269.914	0.176	0.235
3	261.658	0.205	0.274
4	256.124	0.224	0.3
5	251.304	0.24	0.321

4.4. Goodness of Fit Evaluation

The Hosmer-Lemeshow test is used to evaluate how well the logistic regression model fits the data. A non-significant p-value (greater than 0.05) indicates a good fit, meaning the model's predicted probabilities are well-calibrated with the observed outcomes. This test divides the data into deciles based on the predicted probabilities and compares the observed and expected frequencies of the outcome within each decile. In this analysis, the Hosmer-Lemeshow test results across the five steps are as shown in Table 4.

Table 4.
Hosmer-Lemeshow test results.

Step	Chi-square	df	Sig.
1	18.634	8	0.017
2	13.038	8	0.111
3	9.784	8	0.28
4	11.894	8	0.156
5	6.127	8	0.633

In Step 1, the Hosmer-Lemeshow test indicated a misfit ($p = 0.017$) between predicted and observed values, but by Step 5, the test showed a significant improvement with a chi-square of 6.127 and a p-value of 0.633, confirming an excellent fit. This progression indicates that the model's predicted probabilities align closely with observed outcomes, validating its predictive performance. Contingency analysis further demonstrated that as more variables were added, the alignment between observed and expected frequencies of the dependent variable improved, enhancing the model's calibration. Correspondingly, classification accuracy increased, reaching 69.7% in Step 5, reflecting the model's growing ability to correctly classify outcomes as more predictors were incorporated (Table 5).

Table 5.
Classification accuracy.

p	Q18 = 0 Accuracy	Q18=1 Accuracy	Overall Accuracy
1	70.40%	54.40%	63.20%
2	72.80%	56.30%	65.40%
3	74.40%	59.20%	67.50%
4	73.60%	58.30%	66.70%
5	75.20%	63.10%	69.70%

4.5. Logistic Regression Equation

The logistic regression analysis identifies key predictors influencing transportation choices (Q18_inv). Variables such as Q27E_inv (Private Vehicle Preference) and Q27K_inv (Health and Safety Concerns) showed negative coefficients, indicating that higher values decrease the likelihood of Q18_inv being 1, aligning with push policy strategies. Conversely, Q28H_inv (Fatigue from Driving), Q29C_inv (Environmental Awareness), and Q29K_inv (Risk Acceptance and Transportation Habits) displayed positive coefficients, increasing the likelihood of the outcome, which supports the implementation of pull policies. The final logistic regression model for binary outcomes is represented by the equation:

$$\log\left(\frac{p(x)}{(1-p(x))}\right) = 0.471 - 2.77\,Q27E - 2.92\,Q27K + 0.161\,Q28H + 0.216\,Q29C + 0.152\,Q29K$$

Where $p(x)$ represents the probability of choosing a particular transport mode, $Q27E$ is Private Vehicle Preference, $Q27K$ is Health and Safety Concerns, $Q28H$ is Fatigue from Driving, $Q29C$ is Environmental Awareness, $Q29K$ is Risk Acceptance and Transportation Habits.

4.6. Wald Statistics and Odds Ratios Analysis

The Wald statistic tests whether a variable's coefficient significantly differs from zero, indicating its importance in the model. For instance, Q27E_inv consistently showed high Wald statistics, confirming its role as a significant predictor with a negative impact on the outcome (Q18_inv = 1), which aligns with push policies aimed at reducing private vehicle use. Similarly, Q27K_inv displayed a negative relationship, further supporting the need for push strategies focused on health and safety concerns.

Conversely, Q28H_inv, Q29C_inv, and Q29K_inv emerged as positive predictors in the model's later steps, indicating that enhancing these factors through pull policies could increase the likelihood of commuters choosing alternative transport modes. The model's predictive power, as indicated by the ROC curve score of 0.697, suggests it effectively distinguishes between different commuter choices, supporting the development of robust policy recommendations that integrate both push and pull strategies (Table 6).

The model's predictive power, as measured by the Receiver Operating Characteristic (ROC) curve, yields a score of 0.697. An ROC score closer to 1 indicates better discriminatory power of the model, while a score of 0.5 would indicate no better than random chance. In this case, a score of 0.697 suggests that the model has good predictive power. This level of accuracy shows that the model effectively differentiates between commuters who choose different transport modes during the COVID-19 pandemic, allowing for robust policy recommendations to be drawn from the results.

Table 6.
Wald Statistics and Odds Ratios Analysis Results.

Variable	Step	Wald	Sig.	Exp(B)	95% CI for Exp(B)
Q27E_inv	1	28.078	0	0.746	0.669 - 0.831
	2	21.88	0	0.765	0.684 - 0.856
	3	19.762	0	0.772	0.688 - 0.865
	4	15.882	0	0.789	0.703 - 0.887
	5	18.846	0	0.758	0.668 - 0.859
Q28H_inv	2	11.03	0.001	1.23	1.088 - 1.389
	3	8.517	0.004	1.206	1.063 - 1.367
	4	5.738	0.017	1.173	1.029 - 1.336
	5	5.646	0.017	1.175	1.029 - 1.342
Q27K_inv	3	7.48	0.006	0.767	0.635 - 0.928
	4	9.454	0.002	0.732	0.600 - 0.893
	5	8.445	0.004	0.746	0.613 - 0.909
Q29C_inv	4	5.184	0.023	1.217	1.028 - 1.441
	5	5.887	0.015	1.241	1.042 - 1.477
Q29K_inv	5	4.579	0.032	1.164	1.013 - 1.338

4.7. Implications for Urban Mobility Policy

4.7.1. Push and Pull Strategies

The analysis underscores the need for a comprehensive approach that integrates both push and pull strategies to influence commuter behavior effectively. Pull policies should focus on enhancing the attractiveness of public transportation by improving comfort, convenience, and environmental benefits [51]. The strong preference for private vehicles [53] highlights the necessity of making public transport a more appealing option through increased reliability, reduced travel times, and modern amenities. Moreover, the positive impact of environmental awareness [54] suggests that policies promoting the ecological benefits of public transport can effectively encourage a shift away from private vehicles. Public campaigns and incentives that emphasize the environmental advantages of using public transportation, coupled with education on sustainable practices, can significantly influence commuter choices.

Push policies, on the other hand, are essential for overcoming the barriers that discourage the use of public transportation. The significant negative effect of health and safety concerns [55] reveals the need for policies that build trust in the safety of public transport. This can be achieved by implementing stringent health measures such as regular sanitization, reducing overcrowding through increased service frequency, and ensuring visible enforcement of safety protocols. These measures not only address the immediate concerns raised by the pandemic but also establish long-term safety standards that can sustain ridership and foster a culture of trust and reliability in public transportation.

4.7.2. Promoting Safe and Reliable Public Transportation

The findings from the research demography highlight the significant challenges faced by Indonesia's public transportation (PT) system, where user adoption rates remain alarmingly low, typically between 5% and 20%. This underutilization is particularly concerning in rapidly growing urban areas like Greater Jakarta, where the strain on transportation networks is most acute. The demographic insights from the survey, which involved 254 commuters, reveal a complex landscape of transportation preferences influenced by age, occupation, and socioeconomic status. Younger commuters, who are generally more open to adopting public transportation, could be pivotal in driving a shift towards greater PT usage. However, older commuters, especially those over 40, exhibit a strong preference for private vehicles, highlighting the need for targeted strategies that address the specific concerns of different commuter segments.

To bridge this gap and improve PT adoption, enhancing safety and reliability in public transportation is essential. As the study's logistic regression analysis shows, factors like health and safety concerns (Q27K_inv) significantly deter commuters from choosing public transportation, echoing the importance of safety emphasized by Matsumoto, et al. [13] and Gutiérrez, et al. [56]. The incorporation of ICT technologies, such as real-time management systems, can address these concerns by improving the reliability and safety of public transportation, thus making it a more attractive option for commuters. The model improvement process, which significantly enhanced the predictive power of the logistic regression model, underscores the importance of these factors in influencing transportation choices.

Moreover, the research indicates that while safety and reliability are crucial, they must be complemented by a broader strategy that includes both push and pull factors. The model's findings, particularly the positive influence of environmental awareness (Q29C_inv) and the fatigue from driving (Q28H_inv), suggest that policies promoting public transportation should not only focus on mitigating risks but also on highlighting the environmental and health benefits of PT. This dual approach, combining the push strategy of stricter safety regulations with pull strategies that make PT more attractive, aligns with the recommendations of Borhan, et al. [57] and Soza-Parra, et al. [58]. Such an integrated policy framework is likely to foster a culture of safety and reliability in public transportation, ultimately leading to increased ridership and reduced reliance on private vehicles. By addressing both the immediate and long-term needs of commuters, policymakers can enhance the overall effectiveness and sustainability of Indonesia's public transportation system.

4.7.3. Encouraging Modal Shift Through Environmental and Health Messaging

Given the complex dynamics of public transportation usage in Indonesia, especially in the Greater Jakarta area, it becomes clear that a multi-faceted approach is necessary to encourage a modal shift towards public transportation. The demographic analysis reveals significant variations in commuter behavior based on factors such as age, occupation, and socioeconomic status. For instance, younger commuters, particularly those aged 20-25, show a greater openness to adopting public transportation, especially when modern technology and improved services are involved. This aligns with the findings from Poudenx [54] who suggests that environmental awareness can be a powerful motivator for changing transportation behaviors. In this context, targeting younger, environmentally conscious commuters with strong ecological messaging can resonate well, prompting them to choose public transportation over private vehicles [59].

However, the data also indicates that environmental messaging alone may not suffice, particularly for older commuters and those with entrenched habits of private vehicle use. As the logistic regression analysis shows, health and safety concerns (Q27K_inv) significantly influence transportation choices, often deterring the adoption of public transportation. This insight aligns with the work of Bigsby, et al. [60] who emphasize the impact of health-focused campaigns in shaping public attitudes and behaviors. Similarly, Liu et al [61] stress that modal shifts, such as from truck to sea transportation, can significantly reduce health risks from pollution, highlighting the importance of incorporating health benefits into public transport promotion strategies. Therefore, combining environmental messages with health-focused campaigns that highlight the safety benefits of public transportation is crucial. Such dual messaging can address both the immediate health concerns and the long-term environmental impacts, creating a compelling case for public transportation among different commuter segments.

The integration of these messages into a comprehensive policy framework is essential for encouraging a broader modal shift. As Crawshaw [62] notes, social marketing plays a crucial role in promoting healthy lifestyles by shifting focus from social to individual targets, making it an effective tool for influencing transportation behaviors. Additionally, White, et al. [12] propose the SHIFT framework, which suggests leveraging psychological factors like social influence and habit formation to encourage sustainable consumer behaviors, including transportation choices. This approach is further supported by Ogilvie et al [63] who found that targeted behavior change programs show the best evidence for promoting a modal shift towards more sustainable modes of transport. By incorporating these insights into policy design, particularly in rapidly urbanizing areas like Jakarta, policymakers can foster a more sustainable and health-conscious urban mobility system, ultimately reducing the reliance on private vehicles and addressing the current underutilization of public transportation infrastructure.

5. Conclusion

This study provides valuable insights into the factors that influence commuter transportation choices in Jakarta during the COVID-19 pandemic, utilizing logistic regression analysis as a primary tool. By integrating the Theory of Planned Behavior (TPB) with Customer Satisfaction Theory, the research highlighted the complex interplay of psychological factors, such as attitudes and perceived behavioral control, alongside service-related factors like satisfaction and environmental awareness. The findings underscored the critical need for both push and pull strategies to promote a modal shift towards public transportation. Push strategies, including measures to alleviate health and safety concerns, are vital for overcoming barriers to public transport use, especially in the context of a global pandemic. On the other hand, pull strategies should focus on enhancing the attractiveness of public transport through improved reliability, comfort, and the promotion of environmental benefits, particularly targeting younger, environmentally conscious commuters.

Moreover, the study's logistic regression model effectively identified key predictors of transportation choices, such as private vehicle preference, health and safety concerns, and environmental awareness. The robustness of the model, validated through various statistical metrics, provides a solid foundation for developing targeted urban mobility policies. The research suggests that a comprehensive approach, combining health-focused and environmental messaging, is essential for encouraging a broader modal shift, particularly in rapidly urbanizing areas like Jakarta. By addressing both the immediate health concerns and long-term environmental benefits of public transportation, policymakers can foster a more sustainable and resilient urban mobility system, ultimately reducing reliance on private vehicles and enhancing public transportation adoption in the post-pandemic era.

Institutional Review Board Statement:

Ethical clearance for this research was obtained from the relevant institutional review board at the School of Business and Management, Institut Teknologi Bandung (ITB), prior to the commencement of the study.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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