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Research Paper

Exploring the Implications of ChatGPT AI for Business: Efficiency and Challenges

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Abstract
Public transportation is vital for addressing urban mobility challenges and reducing traffic congestion. Understanding commuter behaviour, attitudes, and preferences is crucial to improving public transportation systems and encouraging usage. This research aims to identify commuter segments based on demographics, attitudes, and behaviours, and to determine their future intentions towards public transportation. An online survey collected data from 257 respondents residing in the Greater Jakarta area, encompassing Jakarta, Bogor, Depok, Tangerang, and Bekasi. Segmentation was achieved using factor analysis. However, they had significant health concerns, especially during the COVID-19 pandemic. Surprisingly, all three segments demonstrated similar future intentions regarding public transportation use post-pandemic, posing governance challenges for promoting public transportation and integrating transport systems in Jabodetabek. These facets included a positive perception of public transit, an intent to pivot transportation modes influenced by factors such as risk, cost, and comfort, and heightened health apprehensions about using public transportation during the COVID-19 pandemic. While invaluable for policymakers seeking tailored interventions for different commuter segments, these insights come with a caveat: the primary focus on Greater Jakarta might limit the broader applicability of the findings. Therefore, policymakers and researchers should approach the results with discernment, especially when considering their implications in other urban contexts.

Keywords: *public transportation, urban mobility, traffic congestion, commuter behaviour, attitudes, preferences*

INTRODUCTION

Public transportation is a transport system for passengers, using group travel systems available to the general public, unlike private transport. It is typically managed on a schedule, operated on established routes, and charges a posted fee for each trip (Laplume et al., 2008; Bourgonje & Tromp, 2011). Public transportation is a means of independent transportation for individuals such as children too young to drive, the elderly without access to cars, those without a driver's license, and the infirm, such as wheelchair users. Public transportation includes a variety of modes such as buses, light rail, subways, commuter trains, streetcars and trolleys, cable cars, vanpool services, ferries and water taxis, and paratransit services for senior citizens and people with disabilities. Public transportation benefits individuals, families, communities, and businesses by connecting them to people, places, and possibilities. It also builds thriving communities, creates jobs, eases traffic congestion, and promotes a cleaner environment. Public transportation investment spurs local and national economies (Baig et al., 2022; Cserdi & Kenesei, 2021).

As the capital city of Indonesia, Jakarta is one of the country's centres, not only for government activity but also for the economy and social life. Therefore, it is unsurprising that Jakarta has become a magnet for residents, making it the city with the highest population density and urbanization rate in Indonesia. According to the Central Bureau of Statistics of the Republic of

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Indonesia, the total population of DKI Jakarta, as estimated from the 2020 population census, was 10,562,088. With a land area of 664.01 square kilometres, DKI Jakarta has a population density of 15,906 people per square kilometre (Sinaga et al., 2020). It is 118 times compared to Indonesia's population density of only 141 people per square meter. Furthermore, an additional 20 million people live in cities surrounding Jakarta (Bogor, Depok, Bekasi, and Tangerang), bringing the total to 3,259,894 people who commute to Jakarta each day, thereby increasing Jakarta's density.

The city's density becomes a challenge as congestion worsens each year, driven by the increase in private vehicles (cars and motorcycles). There are 24.897.391 vehicles, consisting of 75% private motorcycles, 23% private cars, and 2% public transport. The number of people travelling in Jakarta, Bogor, Tangerang, and Bekasi (Jabodetabek) increases yearly. According to 2018 data, at least 47.5 million people are moving daily. Of that number, as many as 23.4 million people move within Jakarta. At the same time, the other 4 million are Bodetabek residents whose mobility is to Jakarta. At the same time, the other 20 million movements are within the Bodetabek area.

With motorized vehicle growth of about 5% over five years (Finkelstein et al., 2021; Lee et al., 2021), which is much higher than the rate of road growth, which is less than 0.1%, congestion is one of the main problems in Jakarta. Jakarta ranked 10th among the world's most congested cities in 2019, according to the TomTom Traffic Index. The congestion problem worsens each year, resulting in inefficient travel times for road users in Jakarta and surrounding areas (Bogor, Depok, Tangerang, and Bekasi). The National Development Planning Agency (Bappenas) estimates that economic losses from congestion amount to Rp 67.5 trillion annually (US$4.73 billion).

To address congestion, the public transportation system in the capital city of Jakarta and the surrounding areas (Bodetabek) has been a top government priority for the past four years. Accordingly, the Government is improving the quality of public transportation services and developing Mass Transportation infrastructure. In addition, integration is carried out between modes of public transportation that operate, including integrating physical facilities (including Transit-Oriented Development), payment systems such as Tap on Bus (TOB), and information integration, which is stated in the Working Plan of Jabotabek Transportation Management Agency/ BPTJ.

Over time, public transportation use has increased. It aligns with the improved quality of public transportation services. Therefore, BPTJ targeted that 45% of total people movement in Jakarta would use public transportation in 2025, and 60% in 2029. In 2019, the 32% target was successfully achieved. For instance, in early 2020, Transjakarta averaged 1.000.000 passengers per day. On the other hand, in the same period, MRT reached 88.444 passengers per day, and KRL reached 859.000 passengers per day on average. The increase in public transportation ridership has significantly impacted Jakarta. In early 2020, Jakarta moved out of the world's top 10 most congested cities (TomTom Traffic Index) and is now ranked 31st out of 416 cities (Wang et al., 2022). This fact underscores the strategic role of public transportation in supporting government policies to improve traffic and road conditions (Jakarta Traffic Report | TomTom Traffic Index, n.d.).

This research analyzes the factors that influence individuals' choice of public transportation modes. The choice of transportation mode is a crucial decision with significant implications for traffic congestion, environmental sustainability, and urban planning. Understanding the factors that shape individuals' decisions can provide policymakers and transportation planners with valuable insights for designing effective strategies to promote public transportation. By examining variables such as cost, convenience, accessibility, environmental concerns, social norms, and individual preferences, this study seeks to contribute to the existing knowledge on transportation behaviour and provide evidence-based recommendations for enhancing public transportation usage. Through a comprehensive analysis of these factors, this research intends to shed light on the complex decision-making processes and help guide efforts towards sustainable and efficient transportation systems.

LITERATURE REVIEW

Public Transportation Development

The primary focus of reducing traffic accidents has been addressing the "human factor" through law enforcement, stringent licensing controls, and penalties for violators. However, these measures need to be revised; advancements in non-human factors, such as infrastructure and alternative modes of transportation, are also required. Improving public transportation and infrastructure is essential if travellers are to make decisions that are not solely motivated by a desire to avoid poor transportation conditions (Chen et al., 2021; Soehodho, 2017).

Due to problematic behaviour, motorbike utilization has contributed to traffic congestion and accidents. Jakarta and other Indonesian cities have implemented urban transportation solutions based on three pillars: infrastructure development, expansion of public transportation modalities, and enhanced traffic management measures (Setiawan & Setiyo, 2022). However, due to the country's economic growth, travel demand consistently outpaces supply, resulting in slow road infrastructure development. Motorcycles have become a prominent mode of transportation, particularly in metropolitan areas such as Jakarta. Reducing motorcycle journeys is essential to improving the overall transportation system and mitigating the negative impacts of traffic accidents.

Promoting the use of public transportation is an essential development. All intercity and intracity public transportation modes must be developed to the highest standards to reduce traffic accidents effectively. Road infrastructure development confronts obstacles, including land acquisition and social concerns. National and subnational transportation budget constraints further impede infrastructure development. Although involving the private sector in transportation infrastructure presents challenges, public-private partnerships can be explored as a potential source of strategic financing (Tirachini & Cats, 2020).

Jakarta has assumed the lead in developing public transportation, with Bandung, Surabaya, and Jogjakarta following suit. Bus rapid transit (BRT), mass rapid transit (MRT), and light rapid transit (LRT) projects are funded by national or subnational budgets and partnerships with private entities. Twelve of the fifteen intended BRT corridors have already been established in Jakarta, which has a particularly aggressive BRT system. The MRT, the first in the country, is being constructed with the assistance of the national and subnational administrations. The ongoing development includes the north-south corridor and proposals for an east-west corridor serving multiple provinces (Jumardi et al., 2020).

Jakarta and Palembang in South Sumatra are currently implementing an LRT (light rail transit) project. Compared with mass rapid transit (MRT), light rail transit (LRT) offers practical advantages, particularly in land acquisition. The proposed LRT system in both cities uses the existing road network's airspace and air rights. Its manoeuvrability permits horizontal and vertical alignments, making it a practical mode of conveyance. Seven LRT corridors are planned for Jakarta, with two corridors designated for priority development to ensure smooth transportation services during the 2018 Asian Games. As Palembang will serve as a supporting host city for the Asian Games, a similar scheme has been implemented.

The Jabodetabek region, which includes Jakarta, Bogor, Depok, Tangerang, and Bekasi, is the focus of a second ongoing LRT project that aims to create two corridors to serve inter-city passengers. These LRT initiatives rely on funding from national and subnational budgets for infrastructure development. Private, semi-private, or government-owned businesses finance rolling stock and systems. It is anticipated that involving non-governmental organizations in these initiatives will accelerate the development of public transportation in the country and improve accessibility and mobility for private development projects, such as real estate.

Segmentation in Commuter

Public transportation research has been marked by an evolving understanding of the determinants that shape and guide commuter choices. A common thread running through contemporary research is the emphasis on adopting a multifaceted approach to understanding these determinants. This realization, echoed in various works, is that a singular focus, whether on demographics or behaviour, might yield only a partial picture.

Setiawan and Setiyo (2022) underscored this by suggesting that segmentation in the transportation field should not rely solely on observable metrics but should delve deeper into the nuances of attitudes. Their argument stems from the observation that divergent internal evaluations and reasons might drive similar outward choices. This aligns with the Theory of Planned Behavior, as posited by Ajzen (2020), which holds that our behaviours are often an outward manifestation of a complex interplay among our intentions, subjective norms, attitudes, and perceptions of how much control we have over the behaviour.

Reinforcing this, Shin et al. (2017) unearthed a strong correlation between positive attitudes and perceived behaviour control with an increased intention to adopt public transportation. These positive inclinations were even more pronounced when tangible benefits, such as cost savings and limited alternative transportation options, were present.

Diving deeper into attitudes, some studies have ventured into the domain of market segmentation, mainly to decipher transfer commuting attitudes (Cvelbar et al., 2017; Smith et al., 2021). Their findings painted a picture of a diverse commuting landscape in which different commuter segments exhibited unique behaviours, from their choice of mode to the routes they preferred. This variance among segments underscores the importance of a nuanced understanding of each segment to craft strategies that effectively reduce congestion.

A notable methodological approach gaining traction is psychographic segmentation. By leveraging this, researchers and policymakers can glean insights into commuters' behavioural and attitudinal facets. The granularity of such segmentation enables the identification of distinct commuter segments, thereby enabling the crafting of targeted interventions and services tailored to each segment's unique needs (Ye et al., 2018).

The emerging consensus in the literature is clear: to effectively address and navigate the intricacies of commuter decision-making, a holistic approach that factors in attitudes and employs refined segmentation strategies is imperative. This provides a clearer understanding of commuter choices and offers a robust framework for effective congestion reduction strategies.

RESEARCH METHOD

Case Selection

The research focused on investigating commuter behaviour and preferences in the Jabodetabek (Jakarta, Bogor, Depok, Tangerang, and Bekasi) area, a highly urbanized and densely populated region in Indonesia. Jabodetabek was selected as the study area due to its significance as Indonesia's largest urban agglomeration, comprising the capital city, Jakarta, and its surrounding satellite cities. The region faces numerous transportation challenges, including traffic congestion, inadequate public transportation infrastructure, and a high dependency on private vehicles.

By studying commuter behaviour in Jabodetabek, this research contributes to understanding transportation dynamics in a context that reflects the challenges many urban areas in Indonesia and other developing countries face. The findings have implications for Jabodetabek and urban areas with similar characteristics and transportation issues.

Data Collection and Questionnaire

The data used in this study are primary data, with the population consisting of all residents of Jabodetabek, Indonesia. Purposive sampling was used to determine the method. There is no specific characteristic in behaviour or in transport-mode usage requirements, as this research aims to identify commuters' daily behaviour. The research sample comprised 254 participants, of whom middle- and upper-class individuals dominated. This occurred because the data were collected via an online survey.

The questionnaire included demographic information, behaviour towards public transportation, and attitudes towards transportation modes, with comparisons before and after the COVID-19 pandemic. The perspectives incorporated into the questionnaire were adopted from Beirão and Cabral (2007), who developed those attitudes toward public and private transportation based on a literature review and a previous qualitative study. The 10-point Likert scale was used for all attitudinal statements, ranging from 1 (strongly disagree) to 10 (strongly agree). This ten-point scale was applied to better measure the intensity of the feeling and the likelihood of an action. The attitudinal statement is divided into three sections: attitudes toward public transportation (11 statements), attitudes toward private vehicles (11 statements), and attitudes toward mode choice (16 statements). Lastly, the demographic section of the questionnaire included gender, age, marital status, socioeconomic status, number of children, education level, and monthly household expenditure. The approximate time to complete all sections of the questionnaire is 15-20 minutes.

Statistical Analysis

Factor Analysis

Exploratory Factor Analysis is applied to the third round of quantitative survey data. N=50 observations may be considered the absolute minimum (Jung & Lee, 2011; Mor et al., 2020). Hauben et al. (2017) provide EFA tools and evaluate factorability using various reliability and factor-structure metrics. In this instance, IBM SPSS Statistics 25.0 is used to conduct a robust EFA. Before further analysis, the current research examines various data filtering issues, including how to handle missing data. Tests were conducted to evaluate the suitability of the data for the FA. The Kaiser-Meyer-Olkin (KMO) and Barlett tests evaluate a variable's sampling adequacy and practicability. The KMO index ranges from 0 to 1, with values greater than 0.50 considered acceptable for factor analysis and values greater than 0.80 regarded as outstanding. ($p < 0.05$) The Bartlett's Sphericity Test is significant. In addition, Anti-Image Correlation was employed to establish the high correlation between variables (MSA > 0.5). According to Hair et al. (2010), the loading factor for each item exceeds 0.50, a criterion crucial for establishing the questionnaire's applicability. Eigenvalue and scree diagrams illustrate the proportion of variance accounted for by each component. A factor with an eigenvalue below 1.0 is omitted from the list of factors. They are using iterative analysis to achieve the highest-value outcomes.

FINDINGS AND DISCUSSION

Participants Demographic

Table 1. Participants' Demographic

	Total	**Percentage**
Gender		
Man	137	54%
Woman	117	46%
Location of residence		

	Total	Percentage
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%
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%

This introduction provides an overview of the respondents' characteristics, including gender, residence location, and occupation. Research demographics refer to the demographic attributes of individuals who are subjects of a study. In this context, we will discuss the research demographics by gender, residence location, and occupation.

Factor Analysis Result

Communalities play a crucial role in exploratory factor analysis as they indicate the extent to which each variable contributes to the underlying factors. They represent the proportion of a variable's variance that the factors can explain. By assessing commonalities, researchers can gauge the reliability of factor loadings and determine the suitability of variables for the analysis. To ensure an accurate analysis of dichotomous data, the minimum sample size should be determined by factors such as the level of commonality, the number of factors, the variable-to-factor ratio, and the dichotomization threshold. In this study, the iterated principal axis factor (IPAF) technique was employed for extraction. This technique refines the commonalities iteratively until they converge, enabling a comprehensive analysis of both correlations and covariances. The aim was to determine whether the variables under study could effectively explain the underlying factors. In this case, an Extraction value greater than 0.50 was considered indicative of a variable's ability to explain a factor. The analysis revealed that all variables had Extraction values exceeding 0.50, indicating they could explain the factors. Based on the results, 39 factors were identified for further analysis. This suggests a rich and diverse dataset with numerous factors contributing to the phenomenon under investigation. These findings provide a solid foundation for subsequent analyses, enabling a comprehensive exploration and understanding of the relationships between variables and factors (Table 2).

Table 2. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.688
Bartlett's Test of Sphericity	4000.382	4000.382
	741	741
	.000	.000

The results of the factor analysis presented in this academic writing focus on assessing the relative importance of each variable in the dataset. Two specific analyses, namely Initial Eigenvalues and Extraction Sums of Squared Loadings, are employed to elucidate the dataset's variance. Eigenvalues are utilized to identify the number of components or factors that significantly contribute to the observed variance.

In this analysis, 11 components with eigenvalues greater than one are observed, indicating substantial contributions to explaining the dataset's variance. The researchers selected these eleven components as they represent the most influential factors in the analysis. The Eigenvalues measure the relative significance and explanatory capability of each component, allowing researchers to identify the most prominent factors driving the dataset's variations.

In the first round of the analysis, 14 factors were initially considered, collectively explaining 63.206% of the total variance. However, to refine the analysis and focus on the most relevant factors, several variables, namely Q27F_INV, Q27I_INV, Q29A_INV, Q29E_INV, Q29J_INV, Q33A_INV, 128D_INV, Q29P_INV, Q33J_INV, and Q33F_INV, were removed (Table 3). These variables were discarded because their loadings were less than 0.5 or comprised only one variable per factor, suggesting limited contribution to the overall analysis.

In the second analysis round, 12 factors were derived, explaining 68.505% of the variance. However, even in this round, some variables still needed to meet the desired criteria and were removed from consideration. These variables included Q27J_INV and Q29H_INV due to their low loadings or single-variable associations with a factor. Finally, in the third round of analysis, 10 factors were obtained, accounting for a total variance of 69.101%. This round further refined the analysis by identifying the most relevant and significant factors that best explained the dataset's variations.

The analysis of Extraction Sums of Squared Loadings (APPENDIX 1) sheds additional light on the presence and significance of ten factor components. These components represent the dataset's underlying structures or patterns. The Extraction Sums of Squared Loadings reveal the degree to which each variable contributes to each factor component, indicating the strength of its relationship. By analyzing these loadings, considering both Initial Eigenvalues and Extraction Sums of Squared Loadings, it is possible to understand the dataset's structure and the variables' contribution to the observed variance. This analysis enables researchers to identify the primary factors behind observed patterns and variations. These insights are valuable for future analysis, decision-making, and research endeavours.

Table 3. Extraction squared loading

	1	2	3	4	5	6	7	8	9	10
Q28E_INV	.796									
Q28F_INV	.769									
Q28G_INV	.761									
Q28H_INV	.693									
Q28I_INV	.628									
Q29M_INV		.869								
Q29N_INV		.842								
Q29K_INV		.720								
Q29L_INV		.691								
Q27A_INV			.939							
Q27B_INV			.930							
Q27C_INV			.565							

	1	2	3	4	5	6	7	8	9	10
Q34H_INV				.808						
Q34G_INV				.772						
Q34I_INV				.728						
Q34F_INV				.700						
Q27D_INV					.771					
Q27E_INV					.715					
Q27H_INV					.625					
Q27G_INV					.507					
Q29C_INV						.841				
Q29B_INV						.753				
Q29D_INV						.669				
Q29F_INV							.775			
Q29G_INV							.702			
Q30C_INV							.601			
Q28A_INV								.807		
Q28B_INV								.772		
Q33G_INV									.714	
Q33H_INV									.662	
Q28K_INV										.902
Q27K_INV										.649

Responses to online surveys are entered into the SPSS database and evaluated. No data was deleted due to incompleteness based on the 254 answers received. We computed the Bartlett's test of sphericity (χ^2 = 7527,35; p = 0.000) and the Kaiser-Meyer-Olkin sampling adequacy (0.732; limit> 0.50) before performing exploratory analyses. The determinant value is 0.001, suggesting that the analytics factor solution is possible (cutoff> 0.0001). To analyze the correlation matrix of the data, Bartlett's test of sphericity was used to assess the significance of the analytical variables examined (Hair et al., 2005). Anti-image-correlation findings for all items have a value of 0.5, allowing data processing to proceed. Our findings indicate that our samples satisfy the criteria for various generations and trustworthy variables. EFA is carried out using SPSS software using Principal Component Analysis (PCA) with Kaiser Normalization (eigenvalue>1) and Varimax rotation. The research was iterated three times throughout data processing to get acceptable findings. Cronbach's Alpha is used to determine the internal dependability of such claims. Therefore, it ranges from 0.90 to 0.95 and is acceptable (Bagozzi & Yi, 1988; Nunnally, 1978).

Table 4. Measurement Constructs and Questionnaire Items

Construct		**Item Code**	**Measurement Items**
FAC1_1	Positive Perception Toward Public Transportation	Q28e	I feel happy when I use public transportation
		Q28f	I have a positive opinion about public transportation.
		Q28g	I feel relaxed and enjoy my time when using public transportation instead of private vehicles.
		Q28h	Many times, I feel tired of using a car and choose to use public transportation.

Construct		Item Code	Measurement Items
FAC2_1	Intention to change transportation mode due to risk, cost, duration, and comfort	Q29k	I will keep the mode of transportation that I frequently use even though it is riskier.
		Q29l	I will keep the mode of transportation that I frequently use, even if it is more expensive.
		Q29m	I will keep the mode of transportation that I frequently use, even if it is more tiring.
		Q29n	I will keep the mode of transportation that I use occasionally, even if it takes longer.
FAC3_1	Private Vehicle, Lifestyle, and Social Status	Q27d	It won't be easy to adapt if I live without a personal vehicle every day.
		Q27e	Only private vehicles that suit my lifestyle
		Q27g	I love to drive and love my vehicle.
		Q27h	The type of private vehicle a person drives describes their lifestyle and social status.
FAC4_1	Intention to change transportation mode due to environmental concern	Q29d	I am willing to pay more when travelling to protect the environment
		Q29b	I will change the mode of transportation if it saves time.
		Q29c	I will change the mode of transportation to protect the environment
FAC5_1	New Transportation Mode Trial Intention	Q34f	Desire to try Ride Hailing
		Q34g	Desire to try Ride Sharing
		Q34h	Desire to try Bike Sharing
		Q34i	Desire to try Electric Scooters
FAC6_1	Difficulty in using public transportation	Q28a	Public transportation is only for the less fortunate
		Q28b	Using public transportation wastes my time
FAC7_1	Less Cost Consideration	Q29f	I use the vehicle that provides the most comfort regardless of cost.
		Q29g	I always go with the fastest type of vehicle, even if I have a cheaper alternative.
FAC8_1	Intention to use a shared vehicle	Q33G	Ride Sharing (contoh: Nebengers)
		Q33H	Bike Sharing (contoh: Gowes, Boseh)
FAC9_1	Healthy Concern in using public transportation	Q28K	I'm worried that I could be affected by my health (for example, contracting a disease from other people) when using public transportation.
		Q27K	I use a private vehicle because I feel safer from a health point of view (for example, it is not easy to catch a disease from other people)
FAC10_1	leaning	Q27a	A personal vehicle gives freedom to go wherever I want

Construct	Item Code	Measurement Items
towards private vehicles	Q27b	With a personal vehicle, I am in control of my trip
	Q27c	Usually, private vehicles are the fastest means of reaching my destination.

Factor Analysis Result

The factor analysis results provide valuable insights into the transportation personas and their associated factors. The identified factors help us understand commuters' underlying attitudes, preferences, and perceptions regarding various aspects of transportation. Below is a discussion of the extracted factors and their implications:

The results of the factor analysis can be connected to and further elaborated upon in the context of prior research, thereby providing a more comprehensive understanding of the factors that influence commuter behaviour and transportation mode choices.

Factor 1: Positive Perception Toward Public Transportation

The positive sentiment towards public transportation in Factor 1 emphasizes the importance of enhancing commuters' perceptions and experiences of public transport. Positive emotions and comfort while using public transport contribute to its adoption. This factor supports the notion that a favourable opinion of public transport services and reduced stress and greater enjoyment associated with their use can lead to a preference for public transport.

Factor 2: Intention to Change Transportation Mode due to Risk, Cost, Duration, and Comfort

Factor 2's focus on the influence of risk, cost, duration, and comfort echoes findings by Levinson and Kumar (1994). Levinson and Kumar (1994) highlighted commuters' trade-offs between these factors when choosing transportation modes. This factor underscores the challenge of persuading individuals to switch modes, even when potential benefits are present. Addressing these concerns that comfort, cost, and travel time are essential considerations for promoting mode shift.

Factor 3: Private Vehicle, Lifestyle, and Social Status

The psychological connection between private vehicles, lifestyle, and social status found in Factor 3 aligns with the research of Bamberg and Schmidt (2003) and Kuhnimhof et al. (2012). Bamberg and Schmidt (2003) explored the influence of social identity on transportation choices and found that car ownership can symbolize status and self-identity. Kuhnimhof et al. (2012) emphasized the role of lifestyles in shaping mobility preferences. This factor reinforces the notion that private vehicles represent not just a mode of transportation but also a statement of identity and social status for specific commuter segments.

Factor 4: Intention to Change Transportation Mode due to Environmental Concern

Factor 4's emphasis on environmental consciousness aligns with studies by Bamberg and Möser (2007) and Axhausen and Gärling (1992). Bamberg and Möser (2007) explored the role of environmental concern in influencing sustainable travel behaviour. Axhausen and Gärling (1992) highlighted the importance of environmental attitudes in travel mode choices. This factor supports the idea that increasing environmental awareness can drive shifts towards more sustainable modes.

Factor 5: New Transportation Mode Trial Intention

Factor 5's focus on the willingness to try new transportation modes is consistent with Shaheen (2018). Shaheen (2018) studied the intention to use shared mobility services. This factor underscores the potential to introduce innovative transportation options that cater to commuters' evolving preferences.

Factor 6: Difficulty in Using Public Transportation

The insights derived from Factor 6 align with prior research on barriers to public transportation use. Inconveniences associated with public transport, such as longer travel times or complex routes, can discourage its use. The current factor's identification of the perception that public transportation is inconvenient resonates with these findings. Addressing these barriers by improving accessibility, optimizing routes, and enhancing user experiences becomes paramount for broadening public transportation's appeal.

Factor 7: Less Cost Consideration

Factor 7's findings echo research explores the intricate interplay between cost, comfort, and mode choice. The challenge of reconciling affordability with convenience has been well documented in the transportation literature. Insights from this factor align with the notion that a balance between cost-saving and comfort influences commuters' decisions. Policies encouraging sustainable transportation choices must navigate this delicate balance to promote alternative modes effectively.

Factor 8: Intention to Use a Shared Vehicle

The emergence of shared mobility solutions, as highlighted in Factor 8, aligns with broader transportation trends. The current factor's identification of an intention to embrace shared options underscores the growing acceptance of these alternatives and their potential to transform urban mobility patterns.

Factor 9: Health Concerns in Using Public Transportation

The emphasis on health-related considerations in transportation decisions, as indicated by Factor 9, aligns with the heightened awareness of health and safety concerns in the wake of the COVID-19 pandemic. The current findings underscore the importance of addressing these concerns through measures that enhance cleanliness, provide personal space, and ensure health and safety during public transportation use.

Factor 10: Leaning towards Private Vehicles

Factor 10's observations reinforce research on the allure of private vehicles, driven by perceived autonomy and efficiency. The current factor's identification of commuters' valuation of the control and speed associated with personal vehicles underscores the enduring appeal of private transport modes and the need to develop strategies that balance individual preferences with sustainability goals.

In conclusion, the factor analysis outcomes provide valuable insights into commuters' diverse perspectives and motivations. Understanding these factors can help policymakers, urban planners, and transportation providers tailor strategies to different commuter preferences and promote sustainable, efficient transportation systems.

CONCLUSION

In conclusion, this research provides valuable insights into commuter behaviour, attitudes, and preferences towards transportation modes in Jabodetabek, Indonesia. The study used a primary data collection method, with a sample of 254 respondents selected through purposive sampling. The questionnaire included sections on demography, behaviour towards public transportation, and attitudes towards transportation modes. This research yields in-depth insights into preferences and the factors that influence mode choice. The findings reveal a diversity of user preferences, with some showing a positive view of public transport services.

In contrast, others tend to be reluctant to change habits despite the potential benefits. Psychological links between private vehicles, lifestyle, and social status were also identified, while environmental awareness and interest in exploring new modes of transport emerged as essential factors in users' decisions. Factors such as comfort, cost, and health also influence fashion choices. These findings contribute to planning more inclusive and sustainable transport policies.

LIMITATION AND FURTHER RESEARCH

Despite the valuable insights gained from this research, some limitations should be acknowledged. The sample size of 254 respondents may not fully represent the diverse commuter population of Jabodetabek. While this approach allows flexibility and nuanced classification, it may introduce subjectivity and bias into the grouping process. Researchers may interpret the data differently, which could affect the final groupings. Future research could employ cluster analysis to group the findings and overcome this limitation objectively. Cluster analysis is a statistical method that identifies patterns and groups similar items together based on specific criteria or similarities. By applying cluster analysis, researchers can obtain more objective, data-driven groupings that may provide a more robust, consistent framework for understanding commuter behaviour and preferences.

Additionally, future studies can expand the scope of the research by considering a larger sample size and diverse populations to enhance the generalizability of the findings. Investigating the relationships between the identified groups and other variables such as demographic factors, geographical location, and cultural influences would also be valuable. This would provide a more comprehensive understanding of the factors influencing commuter behaviour, enabling targeted interventions and policy recommendations.

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APPENDIX 1. Total variance explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.579	13.999	13.999	6.480	14.401	14.401	4.733	10.071	10.071
2	4.458	9.485	23.484	3.957	8.793	23.194	3.516	7.480	17.551
3	3.393	7.218	30.703	3.366	7.479	30.673	2.976	6.331	23.882
4	2.923	6.219	36.921	1.945	4.322	46.978	2.782	5.919	29.801
5	2.754	5.860	42.782	1.665	3.699	50.677	2.490	5.299	35.100
6	2.002	4.259	47.040	1.571	3.491	54.168	2.411	5.131	40.230
7	1.640	3.490	50.530	1.455	3.234	57.402	2.332	4.961	45.192
8	1.563	3.325	53.856	1.226	2.725	66.024	1.958	4.165	49.357
9	1.390	2.956	56.812	1.117	2.482	69.101	1.896	4.033	53.390
10	1.355	2.884	59.696						
11	1.247	2.653	62.349						
12	1.114	2.370	64.718						
13	1.055	2.246	66.964						
14	.953	2.029	68.993						
15	.882	1.877	70.870						
16	.825	1.755	72.625						
17	.790	1.680	74.305						
18	.758	1.613	75.917						
19	.717	1.526	77.443						
20	.697	1.484	78.927						
21	.661	1.406	80.333						
22	.645	1.372	81.705						
23	.606	1.290	82.995						
24	.592	1.259	84.253						
25	.558	1.188	85.441						
26	.535	1.138	86.579						
27	.517	1.100	87.679						
28	.476	1.012	88.692						
29	.447	.951	89.642						
30	.444	.944	90.586						
31	.407	.866	91.452						
32	.389	.827	92.279						
33	.367	.782	93.061						
34	.354	.753	93.814						
35	.322	.685	94.499						
36	.295	.627	95.127						
37	.277	.590	95.717						
38	.271	.577	96.293						
39	.263	.559	96.852						
40	.244	.520	97.372						
41	.238	.507	97.879						

42	.199	.423	98.302
43	.187	.398	98.700
44	.174	.370	99.070
45	.163	.347	99.417
46	.150	.319	99.736
47	.124	.264	100.000

Extraction Method: Principal Component Analysis.

APPENDIX 2. Factor analysis result

	Initial	Extraction
Q27A_INV	1.000	.908
Q27B_INV	1.000	.882
Q27C_INV	1.000	.568
Q27D_INV	1.000	.770
Q27E_INV	1.000	.790
Q27G_INV	1.000	.582
Q27H_INV	1.000	.597
Q27J_INV	1.000	.609
Q27K_INV	1.000	.768
Q28A_INV	1.000	.697
Q28B_INV	1.000	.724
Q28E_INV	1.000	.753
Q28F_INV	1.000	.742
Q28G_INV	1.000	.725
Q28H_INV	1.000	.639
Q28I_INV	1.000	.659
Q29B_INV	1.000	.643
Q29C_INV	1.000	.787
Q29D_INV	1.000	.696
Q29F_INV	1.000	.671
Q29G_INV	1.000	.692
Q29H_INV	1.000	.663
Q29K_INV	1.000	.656
Q29L_INV	1.000	.661
Q29M_INV	1.000	.802
Q29N_INV	1.000	.757
Q30A_INV	1.000	.742
Q30B_INV	1.000	.730
Q30C_INV	1.000	.642
Q33A_INV	1.000	.576
Q33G_INV	1.000	.645
Q33H_INV	1.000	.614
Q33I_INV	1.000	.652
Q33J_INV	1.000	.598
Q34F_INV	1.000	.594
Q34G_INV	1.000	.773
Q34H_INV	1.000	.786

	Initial	Extraction
Q34I_INV	1.000	.634
Q28K_INV	1.000	.837