

A Spatial Approach for the Prioritization of Bicycle Lanes in Metro Manila to Improve Accessibility of Low-income Households

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Abstract: Local studies have found out that low-income earners are the main users of bicycles in Metro Manila. Despite them being the main users, the region's current bike lanes are observed to be highly clustered in cities with low poverty incidence. Therefore, through a spatial approach, this study determined the priority, low-income locations for future bike lane construction and planning to improve the accessibility of the households. Based on the Family Income and Expenditure Survey (FIES) and through a prioritization scheme considering transport expenditure, poverty incidence, bike lane proximity, and bike lane density, the study was able to pinpoint Caloocan District 3, Navotas District 1, and Navotas District 2 as the top three priority, low-income locations. These locations collectively have high poverty incidence but also have the lowest accessibility to constructed bike lanes since on average, their centroids were found to be three kilometers away from the nearest bike lane.

Keywords: bike lane accessibility, prioritization scheme, transport expenditure, FIES, low-income household

1. INTRODUCTION

1.1. Background of the Study

Bicycle users in the Philippines have been expanding in number through the years and even during the pandemic. Following this positive user reception to cycling and as an integral part of the transport-fitting pandemic recovery plan, the bike lane network construction project of the Department of Transportation (DOTr) was funded with Php 1.316 billion under the Bayanihan to Recover as One Act of 2020. This project aimed to support cycling as an effective alternative mode of transportation particularly through development of protected bike lanes and implementation of bike-sharing programs (Ramos, 2020). In June 2021, around 313.12 kilometers, 129.47 kilometers, and 54.74 kilometers of bike lanes were completed in Metro Manila, Metro Cebu, and Metro Davao respectively (Rey, 2021).

Several studies have also been conducted to better understand the cycling population. An example of which is the study conducted by Gaspay *et al.* (2022) that explored the characteristics and behavior of the cycling population. In that study, it was found that cyclists' profile in Metro Manila is 97% composed of low-income earners where 77% of them cycle to work almost six to seven days a week. Majority of them are also male, high school graduates, and below minimum wage earners if not unemployed. In terms of vehicle ownership, the majority of them own a bicycle and do not own either a motorcycle or vehicle car. And despite the lack of bicycle support facilities, the respondents still showed willingness to

continue cycling in the future. In another study, cyclists in Metro Manila are also mostly composed of poor and skilled laborers, who generate relatively longer cycling trip distances (Tolentino and Sigua, 2022).

1.2. Problem Statement

Indeed, low-income earners are the main users of bicycles in Metro Manila. This can be attributed to the affordability of use and its capacity to decently travel longer distances compared to walking. Gaspay *et al.* (2022) even highlighted that ‘travel costs play a significant role in the decision to use a bicycle’. However, when the 2022 bike lane network map of Metro Manila as presented in Figure 1 was combined with the 2021 poverty incidence map of Metro Manila as presented in Figure 2, it showed that the bike lane network was highly dense in areas with low poverty incidence like San Juan, Mandaluyong, and Makati while little to no bike lane network was present in cities with high poverty incidence like Caloocan, Malabon, and Navotas. With this, the combined map in Figure 3 suggests inequity.

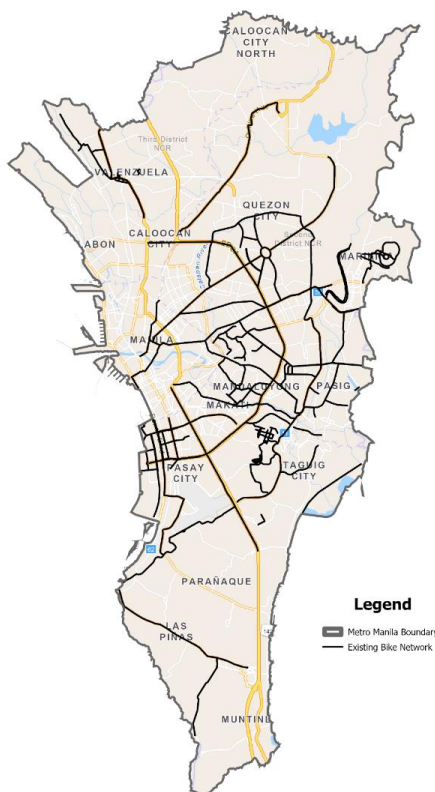


Figure 1. Map of 2022 Bike Lane Network in Metro Manila (DOTr, 2022)

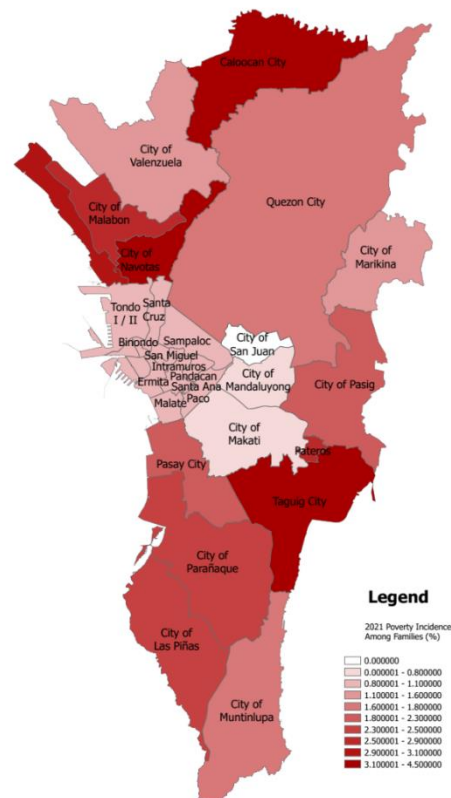


Figure 2. Map of 2021 Poverty Incidence in Metro Manila (PSA, 2022)

The planning of bike lane locations was observed to be inequitable as seen in Figure 3 since the supposed access needs of the target users were not directly considered. Moreover, despite many literatures highlighting the importance of a good cycling infrastructure to promote bicycle use (Cameña and Castro, 2019, Bimbao and Ou, 2022), the bike lane network in Metro Manila, even after completion of the project of the DOTr, still presents insufficiency and lack of interconnectivity to some cities. This problem places the low-income cyclists at risk and inconvenience and provokes an unfair cost of access. The low-income users also

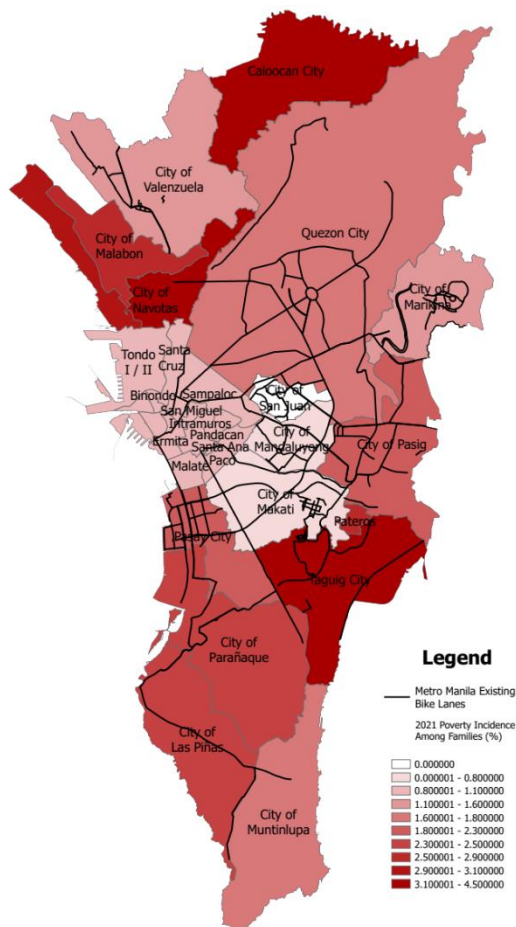


Figure 3. Combined Metro Manila Map of 2021 Poverty Incidence and 2022 Bike Lane Network

become heavily disadvantaged as they spend a proportion of their income on transportation that is greater than the set affordable measures.

With the limited budget from the government for this project, it would be beneficial to conduct a prioritization study on where to put bike lanes in Metro Manila that would greatly serve the low-income users and would result to an equitable, interconnected, and sufficient network.

1.3. Objectives

In prioritizing where bike lanes should be located in Metro Manila, the specific objectives are the following:

- Categorize the low-income households based on income level and determine their characteristics with respect to transport expenditure,
- Map out the spatial distribution of low-income households and compare it against the spatial mapping of Metro Manila bike lane network,
- Develop a prioritization scheme using the four criteria: transport expenditure, poverty incidence, average distance to the nearest bike lane network, and bike lane density

1.4. Significance of the Study

The results of this study will provide a map and list of areas in Metro Manila categorized as high, mid, or low priority for bicycle lane construction, to aid transport planners identify key locations where bicycle infrastructure would greatly benefit low-income households. Additionally, this study may offer transport planners valuable insights on the location of low-income households through a map and their corresponding characteristics with respect to transport expenditure, as there has been limited research and representation involving low-income households in bicycle planning, which is a key indicator of urban mobility. The findings could also be used to better understand their travel behavior as well as to better support their quality of life.

1.5. Scope and Limitations

While it is crucial to consider the aspect of travel origins and destinations for bike lane planning, this study could not account for these variables due to the limited literature on the travel behavior of low-income households. As a result, this study introduced the households' characterization and representation by focusing on their transport expenditure through FIES, with the hope that future researchers will further explore and address transport poverty more thoroughly. For clarity, this study also only suggests which locations to prioritize. The

placement of bike lanes within the city will still heavily depend on the current approach of the planners and the DOTr. It also does not advocate merely spreading and expanding routes to achieve accessibility; rather, it takes into consideration that bike lanes would be most helpful if they are within 1000 meters of the centroid of the district’s households.

In measuring the average distance to the nearest bike lane network, other barriers, such as the availability of bicycles within the area and cycling policies, were not considered. Accessibility is defined as the proximity of a district’s centroid to a structured bike lane; therefore, typical roads, even though used by cyclists, are not considered. It was presumed that safety is a fundamental principle of accessibility. The focus was also limited to studying low-income households living in Metro Manila, with data obtained from the Family Income and Expenditure Survey (FIES) provided by the Philippines Statistics Authority—specifically the 2018 version, since only preliminary results were available for 2021. Note that FIES has its own limitations due to inaccuracy of the respondents’ answers and non-sampling errors.

2. REVIEW OF RELATED LITERATURE

2.1. Income Classes

The Philippine Institute for Development Studies divides the income clusters into three broad classes and consequently into seven groups which are all based on a household’s per capita income obtained by dividing the family size from the total household income. This clustering was utilized in the study to categorize the low-income households using 2018 FIES.

Table 1. Income Groups Clustering (Albert et al., 2020)

Clustering	Income Group	Definition
Low income	Poor	Per capita income less than official poverty threshold
	Low income (but not poor)	Per capita incomes between the poverty line and twice the poverty line
Middle income	Lower middle income	Per capita incomes between twice the poverty line and four times the poverty line
	Middle middle class	Per capita incomes between four times the poverty line and seven times the poverty line
	Upper middle income	Per capita incomes between seven times the poverty line and twelve times the poverty line
High income	Upper income (but not rich)	Per capita incomes between twelve times the poverty line and twenty times the poverty line
	Rich	Per capita incomes at least equal to twenty times the poverty line

2.2. Transport Expenditure

Many studies have discussed the impact of transport expenditure related problems on low-income households, emphasizing the significant portion of their income being spent on vehicle ownership, usage, and public transit. Baharun et al. (2021) found that low-income earners allocate a relatively larger percentage of their income to transportation, leaving them with limited budget for other commodities. Additionally, housing and transport expenditures correlate to each other and bear significant trade-offs, with ‘lower housing prices in outlying urban areas often offset by high automobile dependency, longer commuting distances, and the

associated costs of petrol and vehicle maintenance’ (Mattingly & Morrissey, 2014). This proves that the farther a household is located from the central business district, the lower the housing costs and the higher transportation costs.

2.3. Poverty Incidence and Population Density

Poverty is crucial in the realm of transport planning and urban mobility, as it addresses the issues of transport poverty and helps in understanding the travel conditions of the poor. A reformed approach has also debunked misleading studies that apply methodologies from wealthier countries to low-income counterparts. Consideration of poverty incidence in equity analyses using spatial and census data also enables the formation of more effective policies for disadvantaged groups like the low-income, indigenous, and immigrants (Doran et al., 2020).

Similarly, population density is also a vital factor in transport accessibility studies. It was one of the socioeconomic indices in examining the bike lane distribution in Bogota, Colombia (Parra et al., 2018); found to be positively associated with the percentage of workers who cycle or walk to work in 32 cities (Saelens et al., 2003); and deemed as ‘the most important of the three scales’ alongside cycling infrastructure (Nielsen and Skov-Petersen, 2018).

2.4. Bike Lane Accessibility

Bike lane density and proximity to neighborhoods are common variables in assessing bike lane development and accessibility (Houde et al., 2018 & Parra et al., 2018). In their study, Houde et al. (2018) investigated the effects of bike lane network expansion in lessening accessibility inequalities for the low-income communities, immigrants, children, and elderly by measuring bike lane density and proximity through distance of nearest lane to a residential centroid. Apparicio et al. (2008) also identified common accessibility metrics such as distance to the nearest service, the number of services available within an n-meter radius, and the gravity model. Euclidean distance is the most used in evaluating accessibility (Houde et al., 2018 & Firth et al., 2021), with 400 meters frequently cited as an adequate distance (Vale et al., 2015). However, the Transit-oriented Development Standard 3.0 recommends up to a 1000-meter radius for accessing transit lines and public bicycle sharing systems (Institute for Transportation and Development Policy, 2017).

2.5. Multi-Criteria Decision-Making Technique

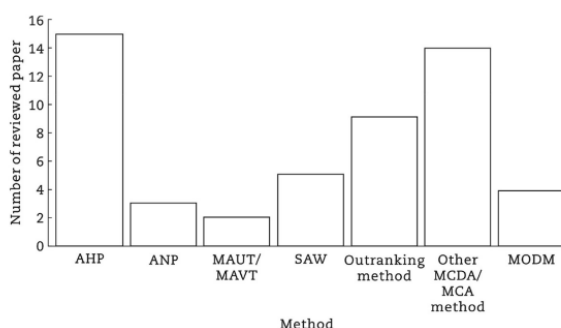


Figure 4. Frequency of AHP Method in Transport Studies (Yannis et al., 2020)

The decision-making process has several techniques however, a ‘more flexible and transparent’ method called the Multi-criteria Decision-making (MCDM) has been increasingly used in studies, offering benefits such as ability to produce ‘better-considered, justifiable, explainable and transparent decisions’, the ability to ‘simplify the immense amount of technical information and data’, and the ability for the researchers to ‘be fully controlled’ over the assignment of scores and weights and any alterations to the model if data is deemed inadequate (Yannis et al., 2020).

The Analytic Hierarchy Process (AHP), developed by Saaty in 1980, is a widely used MDCM method for setting priorities and evaluating alternatives based on quantitative and qualitative measures. It is based on four principles: prioritization, decomposition, sensitivity analysis, and synthesis. Known for its flexibility, the AHP matrix can be adjusted depending on the number of attributes but assumes that each element is independent of the others, which leads researchers to combine it with other decision-making methods. Yannis et al. (2020) illustrate how frequently AHP is used in their examined studies as seen in Figure 4.

3. METHODOLOGY

3.1. Classification and Characterization of Low-income Households

In classifying the low-income households, the bracketing is shown in Table 2. This classification is based on the methodology of Albert et al (2020), which uses per capita income data from FIES. Households with per capita income below the official poverty threshold are initially categorized as poor, while those with income between the poverty line and twice the poverty line are classified as low-income. Both categories were considered the main subjects of this study and were collectively referred to as ‘low-income households.’

Table 2. Bracketing of Low-income Households Using Per Capita Income

Study Clustering	Income Group	Definition	Per Capita
Low-income	Poor	Per capita income less than official poverty threshold	Php 0 – 28,678.5714
	Low-income (but not poor)	Per capita incomes between the poverty line and twice the poverty line	Php 28,678.5714 – 57,357.1428

3.2. Setting the Prioritization Criteria and Study Area

The four criteria used in the study were carefully selected based on their impact, relevance, and frequent application in various bike equity studies and transportation planning research. The selection was further refined considering the availability of data and the feasibility of measuring and assessing each criterion.

Table 3. Prioritization Criteria Selection and Rationale

Criteria	Target Attribute	Rationale	Study Area
Transport Expenditure	Affordability	Transport expenditure incurs a relatively high proportion of one’s income (Baharun et al, 2021)	Cities in Metro Manila
Poverty Incidence	Equity	Consideration of poverty incidence is important in understanding accessibility and promoting equity in transportation studies and policies (Houde et al., 2018 & Doran et al., 2020)	Cities in Metro Manila
Average Distance to the Nearest Bike Lane Network	Accessibility	Measuring the proximity of bike lanes to neighborhoods is highly evident and relevant in assessing the development and accessibility of bike lanes in cities (Houde et al., 2018 & Parra et al., 2018)	Districts in Metro Manila

Bike Lane Density	Interconnectivity	Bike lane density measurement of an area is usually used to determine the distribution of bike lanes (Houde et al., 2018)	Districts in Metro Manila
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The first criterion assessed the transport expenditure of each low-income household by calculating it as a percentage of their total income. This approach considered affordability and spending capacity in the decision-making process. A reduction in transport expenditure, potentially driven by increased bike lane accessibility and a shift towards cycling, can have a significant impact. Therefore, the study implied that higher transportation expenditure is positively associated with higher priority for bike lane improvements.

The second criterion assessed the poverty incidence, specifically the percentage of low-income households in a city. This criterion, on the other hand, addressed equity in the distribution of bike lanes. The study used this to guide prioritization, emphasizing that a higher number of low-income households in a city increases the priority for bike lane development as these households are the primary users of bike infrastructure.

The last two criteria focused on the accessibility and interconnectivity of the bike lanes. Accessibility was measured using the Euclidean distance of the centroid of a district to the nearest available bike lane network, whereas interconnectivity was measured by dividing the total bike lane length by the computed area of the district. These two criteria were inseparably considered because high accessibility does not guarantee high density, and vice versa.

As observed, the study area varied across the four criteria depending on data availability and feasibility. Initially, all four criteria were intended to be assessed at the district level. However, due to data source limitations, the FIES data was only sample representative until city level only. Data at smaller levels, such as districts and barangays, proved to be inaccurate. Consequently, for the assessment of transport expenditure and poverty incidence, a city-wide approach was used due to high dependency on FIES data. In contrast, the average distance to the nearest bike lane network and bike lane density were assessed at the district level, as these metrics relied heavily on GIS shapefiles, which permitted analysis at this more detailed level.

3.3. Prioritization Scheme Through Analytic Hierarchy Process

Table 4. Hierarchy of Importance of All Criteria

Rank	Criteria
1	Average Distance to the Nearest Bike Lane Network
2	Bike Lane Density
3	Poverty Incidence
4	Transport Expenditure

The prioritization scheme was based on the total score of each location across the four criteria. However, the total score was not a simple sum because each criterion was assigned a different weight depending on its relative importance to the study. Assuming equal importance for all four criteria would lead to overestimation and potentially misleading rankings and priorities. Therefore, the AHP was used to determine their appropriate weights.

The hierarchy of each criterion based on importance was determined as shown in Table 4. This was evaluated through examination of relevance and frequent use of each criterion in several transportation studies. Moreover, thorough consideration and assessment of related literature were conducted to establish this hierarchy. In summary, average distance to a nearest bike lane network was deemed the most important criterion because ‘accessibility is a measure of proximity and, therefore, farther away implies lower accessibility’ (Saghapour

et al., 2016). Research has also demonstrated that providing the marginalized with greater access by means of a closer distance to several transportation options, such as bicycles, would enhance urban mobility (Firth et al., 2021) and would also increase the likelihood of cycling to others (Houde et al., 2018). The next important factor is the interconnectivity of the bike lane network, which ensures a seamless and uniform riding experience. It also has a positive correlation with the willingness and likelihood to cycle due to its perceived safety (Houde et al., 2018). And it also enhances trip efficiency by reducing route complexity and allowing users to shorten their travel distances (Houde et al., 2018).

Since the goal of this study is to identify priority low-income areas for bike lane distribution, it is obviously crucial to consider the poverty incidence in each area. Bike lanes shall be able to address the transport needs of more low-income households, making the areas with high poverty incidence a higher priority. Inclusion of low-income households in transport planning is a key aspect of bicycle equity since bicycle infrastructure and facilities have historically favored middle- and high-income groups (Mora et al., 2021). Transport expenditure ranked lowest because low-income households still allocate a significant portion of their budget to other essential commodities.

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment strongly favor one activity over another
5	Essential of strong importance	Experience and judgment strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed

After establishing the hierarchy, the data was subjected to AHP. Each criterion was compared against each other, and their importance was quantified using the importance scale shown in Figure 5. In the pair-wise comparison, the importance value is equivalent to the scale of the row element divided by the scale of the column element. The resulting matrix is in Table 5. The values in the matrix were then normalized and the average of each row finally yielded criteria weights in Table 6.

Figure 5. Importance Scale (Saaty, 1980 as cited in Ammarapala et al., 2016)

Table 5. Pair-wise Comparison Matrix of the Criteria

	Average Distance to the Nearest Bike Lane Network	Bike Lane Density	Poverty Incidence	Transport Expenditure
Average Distance to the Nearest Bike Lane Network	1	2	3	4
Bike Lane Density	1/2	1	2	3
Poverty Incidence	1/3	1/2	1	2
Transport Expenditure	1/4	1/3	1/2	1

Table 6. Normalized Pair-wise Comparison Matrix and Criteria Weight

	Average Distance to Nearest Bike Lane Network	Bike Lane Density	Poverty Incidence	Transport Expenditure	Criteria Weight

Average Distance to Nearest Bike Lane Network	0.4800	0.5217	0.4615	0.4000	0.4658
Bike Lane Density	0.2400	0.2609	0.3077	0.3000	0.2771
Poverty Incidence	0.1600	0.1304	0.1538	0.2000	0.1611
Transport Expenditure	0.1200	0.0870	0.0769	0.1000	0.0960

The consistency of the generated criteria weights was verified using the consistency index (CI) as shown in Equation 1. The weighted sum in each row was then divided by the criteria weights. The average of these values represented λ_{max} , which was used to calculate the CI. Consistency ratio was also calculated by dividing CI to the random consistency index (RI) found in Figure 6. If the consistency ratio is less than RI, then the calculated criteria weights are reasonably consistent and can therefore be used as a valid criteria weight for the decision-making process.

Table 3. Random Index (RI) (Saaty, 1980).

Matrix size	Random consistency index(RI)
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

Figure 6. Random Index (Saaty, 1980 as cited in Ammarapala et al., 2016)

$$Consistency\ Index = \frac{\lambda_{max} - n}{n - 1} \quad \text{where, } n \text{ is the no. of attributes} \quad (1)$$

After determining the criteria weights, the total score of each district under the four criteria was determined through a linear combination. However, since the scores from each criterion vary from percentage, distance in meters, and density, the scores were normalized first to deduce discrepancies and large deviation as shown in Equation 2.

$$x_{normalized} = \frac{x - x_{minimum}}{x_{maximum} - x_{minimum}} \quad (2)$$

3.4. Spatial Mapping

3.4.1. Generation of spatial maps

The 2018 FIES data set and prioritization rankings were integrated into the GIS boundary shapefiles to produce spatial maps. These data were merged with the designated boundary layers in ArcGIS while the field, normalization, method, classes, and color were set.

3.4.2. Measuring the average distance to the nearest bike lane network

The average distance from barangays to the nearest bike lane across city districts was calculated using GIS shapefiles from the DOTr, which included barangay boundaries and bike lane networks in Metro Manila. These two layers were overlaid in ArcGIS to create a map showing the barangay boundaries and its centroids, and the existing bike lanes shown in Figure 7. The distances between the barangays to bike lanes were averaged per city district.

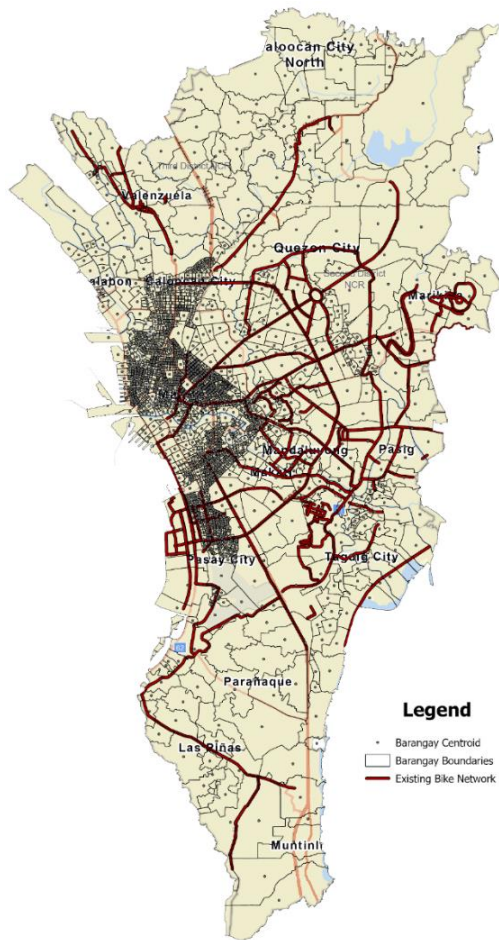


Figure 7. Barangay Boundaries & Centroids, and the Existing Bike Lane Network in Metro Manila

3.4.3. Measuring bike lane density

To measure bike lane density, the shapefiles of barangay boundaries and bike lane network were combined. The lengths of bike lanes and barangay areas were calculated, and the bike lane density per city district was determined by dividing the sum of the bike lane lengths in each barangay within a district by the sum of the barangay areas within that district.

4. RESULTS AND DISCUSSION

4.1. Characterization of Low-income Households

4.1.1. Percentage of low-income households per city

Figure 8 shows varying percentage of low-income households across cities in Metro Manila. Central cities like Makati, San Juan, and Mandaluyong have the lowest percentages at 8.6%, 13.5%, and 15.2% respectively. Meanwhile, Navotas has the highest percentage at 35.9%, followed closely by Malabon at 32.7% and Caloocan at 30.4%.

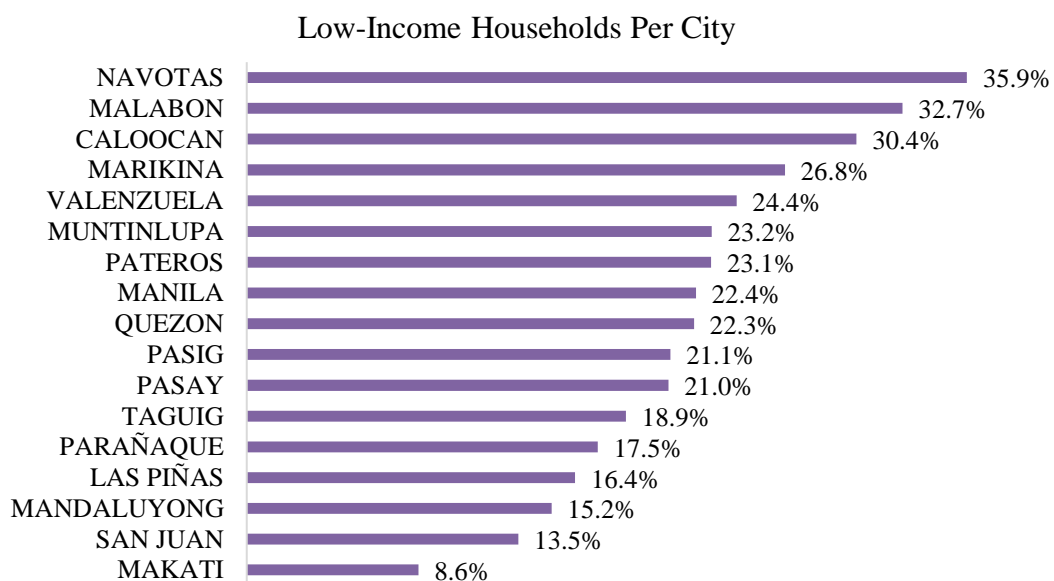


Figure 8. Percentage of Low-income Households Per City

4.1.2. Vehicle ownership of low-income households

Figure 9 reveals that in Metro Manila, most low-income households, approximately 87% (3598 out of 4114 households), do not own a vehicle. While there is still 12% who owns a vehicle, they are primarily motorcycle users (494 out of 4114 households) and only 0.5% (22 out of 4114 households) are car owners.

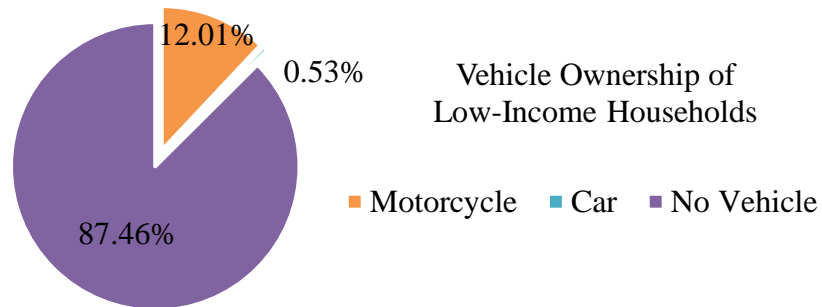


Figure 9. Vehicle Ownership of Low-income Households in Metro Manila

4.1.3. Percentage of low-income households who spend on transportation

Almost all low-income households in Metro Manila, total of 97%, are public transport users. Figure 10 shows that 75.3% of them rely solely on public transportation while 21.7% spends on both private and public. This indicates that even those who own private vehicles still use public transportation, likely due to the type and size of their vehicle and the associated costs of usage and maintenance. For instance, a motorcycle, which typically seats only two people, is inadequate for a household of four, leading to the use of public transport. Moreover, as seen in the figure, only 1.5% of low-income households rely exclusively on private vehicles and 1.6% have no transportation expenditure at all.

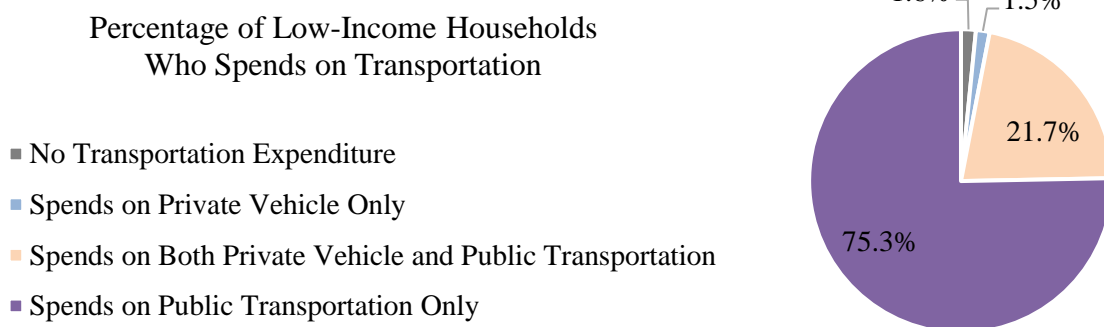


Figure 10. Percentage of Low-income Households Who Spend on Transportation

4.1.4. Public transportation usage of low-income households

The preference of low-income households for different modes of public transportation is illustrated in Figure 11. Jeepneys and Tricycle are the most used modes, with annual spending percentages of 86.9% and 60.4% respectively. This is expected since these are the most accessible and affordable modes available in Metro Manila. In contrast, railways and taxis are less popular options, with annual spending percentages of 5.8% and 3.5% respectively.

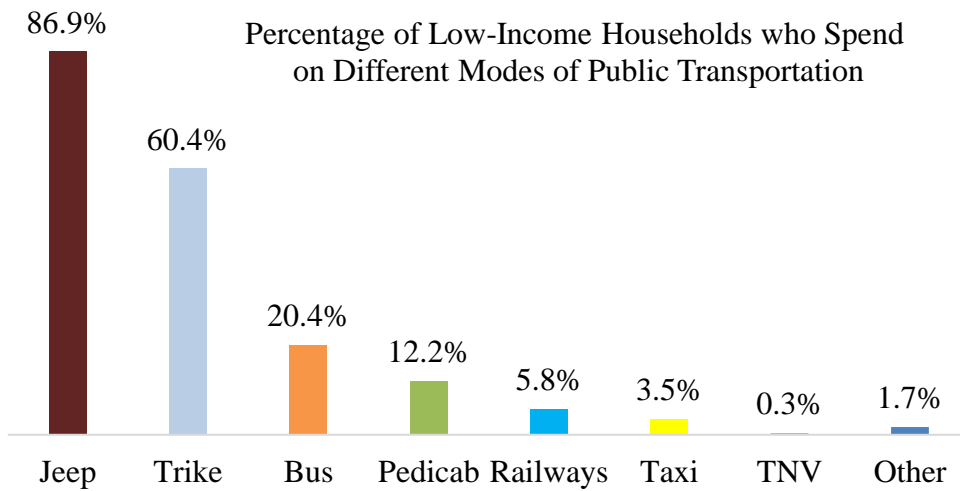


Figure 11. Percentage of Low-income Households Who Spend on Different Modes of Public Transportation

4.2. Bike Lane Prioritization Criteria

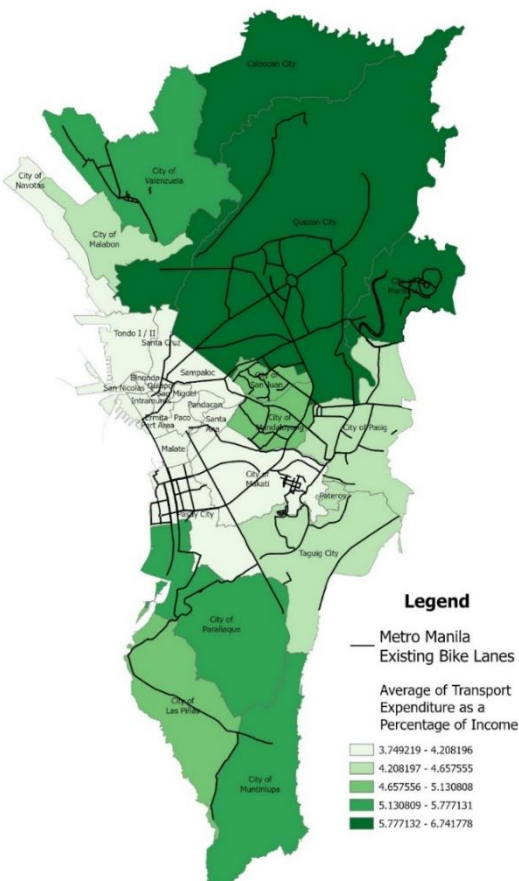


Figure 12. Map of the Average Transport Expenditure as a Percentage of Income Against the Map of 2022 Bike Lane Network

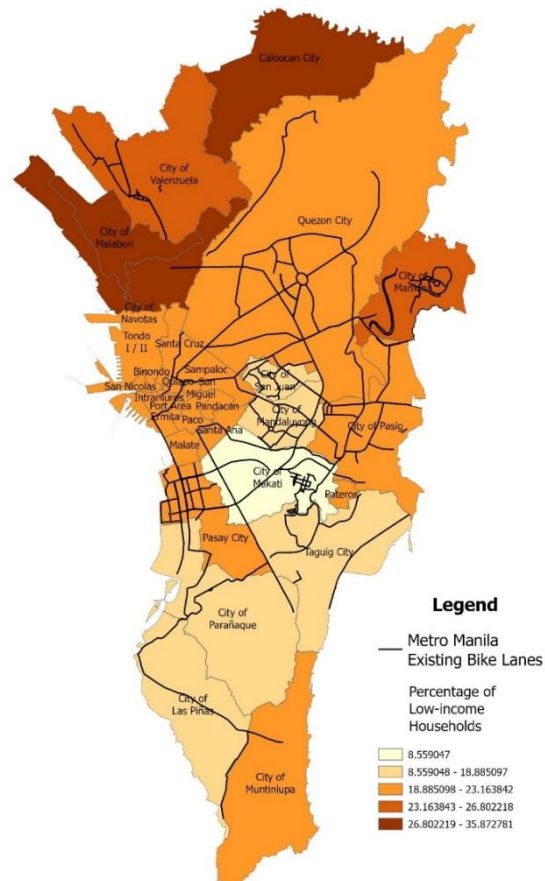


Figure 13. Map of the Percentage of Low-income Households Against the Map of 2022 Bike Lane Network

4.2.1. GIS mapping of average transport expenditure as a percentage of income

A spatial map was produced to evaluate the transportation expenditure of low-income households as observed in Figure 12. This shows that the households spending the smallest percentage of their income on transportation are located in Makati, Manila, Pasay, Navotas, and Pasig. Notably, most of these cities have high bike lane density except Navotas. Conversely, the areas where low-income households spend a larger portion of their income on transportation are located near the boundaries of Metro Manila like Caloocan, Quezon City, Marikina, Valenzuela, Muntinlupa, and Parañaque. The map also indicates that many of these areas, including Caloocan, Malabon, Muntinlupa, Pateros, and Quezon City District 5, have limited or no bike lanes at all.

4.2.2. GIS mapping of percentage of low-income households per city

Similar to the transportation expenditure analysis, a spatial map of the percentage of low-income households per city was also generated. Figure 13 is the result of the FIES data and bike lane data integration which reveals that cities with the highest percentage of low-income households have scarce bike lanes and are located near the upper boundaries of the region. These cities include Caloocan, Valenzuela, Malabon, and Navotas. In contrast, cities with the lowest percentage of low-income households, such as Makati, San Juan, and Mandaluyong, have well-established bike lanes. This reveals a form of bike inequity where the supposed access needs of the target users are not met. Beneficially, Marikina has a significant presence of bike lanes to cater to the needs of the large percentage of low-income households.

4.2.3. Average distance to the nearest bike lane network

The areas with the highest accessibility to bike lanes are Quiapo and San Juan City, with an average distance of 200 meters to a nearest lane. Meanwhile, Caloocan District 3 and Navotas have the lowest accessibility, with an average distance of at least 3000 meters to a nearest lane. Based on Table 7, the districts with highest accessibility are within 500 meters away from the nearest lane, and none of the barangays in the said districts are 1000 meters far from it. The opposite can be observed from those with lowest accessibility—no barangays located in these districts are within a 500-meter radius from the nearest bike lanes, and nearly all of them are more than 1000 meters away.

Table 7. Average Distance of Barangays to Nearest Bike Lanes (High and Low Accessible)

	District	Average Distance of Barangays to Nearest Bike Lane (m)	No. of Brgy	Percentage and no. of brgy within 500 m		Percentage and no. of brgy from 500 m to 1000 m		Percentage and no. of brgy more than 1000 m	
High Accessibility	Manila Quiapo	126.363	16	16	100%	0	0%	0	0%
	San Juan 1	155.89	10	10	100%	0	0%	0	0%
	San Juan 2	157.736	11	11	100%	0	0%	0	0%
Low Accessibility	Caloocan 3	3609.382	11	0	0%	0	0%	11	100%
	Navotas 1	3386.967	9	0	0%	0	0%	9	100%
	Navotas 2	3241.56	5	0	0%	0	0%	5	100%

4.2.4. Bike Lane Density

Areas with the longest bike lanes include Pasay District 1 (32.77 kilometers), Quezon District 4 (30.84 kilometers), and Makati District 2 (25.96 kilometers). Having long lanes, however, does not necessarily imply high density because it is heavily influenced by the size of the district's area. Hence, a district with long bike lanes but has a large area will have a lower density compared to a smaller district with the same length. For instance, Quezon City District 4 has a lower density than Makati District 2 despite having more extensive bike lanes, due to its larger area. As shown in Table 8, even districts with zero density like Pateros and Binondo can still have high accessibility if lanes are present in their surrounding districts.

Table 8. Bike Lane Density Per District Ranking

Rank	District	Area <i>km²</i>	Bike Lane Length <i>km</i>	Bike Lane Density <i>km/km²</i>	Rank	District	Area <i>km²</i>	Bike Lane Length <i>km</i>	Bike Lane Density <i>km/km²</i>
1	Caloocan 3	12.28	0	0	28	Manila Intramuros	1.23	0.617	0.502
2	Navotas 1	3.19	0	0	29	Valenzuela 1	29.03	15.013	0.517
3	Navotas 2	7.76	0	0	30	Manila Sta Ana	1.79	0.950	0.531
4	Malabon 1	10.15	0	0	31	Manila San Andres	1.73	1.052	0.610
5	Muntinlupa 1	21.02	0	0	32	Manila Sta Mesa	2.71	1.655	0.610
6	Manila Tondo	11.45	0	0	33	Las Piñas 1	14.98	9.551	0.637
7	Malabon 2	6.25	0	0	34	Quezon City 3	23.05	16.432	0.713
8	Manila San Nicolas	0.97	0	0	35	Manila Malate	2.88	2.084	0.723
9	Caloocan 1	35.17	0	0	36	Pasig 2	19.10	14.542	0.761
10	Manila Binondo	0.69	0	0	37	Makati 1	17.68	15.558	0.880
11	Pateros 1	0.42	0	0	38	Marikina 2	14.41	13.809	0.958
12	Pateros 2	1.26	0	0	39	Quezon City 1	20.35	19.741	0.970
13	Manila Port Area	1.84	0.026	0.014	40	Manila Ermita	2.59	2.561	0.988
14	Muntinlupa 2	19.66	1.922	0.098	41	Parañaque 1	17.85	18.114	1.015
15	Manila Pandacan	1.71	0.181	0.106	42	Quezon City 4	24.09	30.837	1.280
16	Quezon City 5	55.31	6.901	0.125	43	Manila Sampaloc	5.35	7.302	1.366
17	Parañaque 2	28.72	4.137	0.144	44	Mandaluyong 2	4.14	7.035	1.700
18	Quezon City 2	23.52	4.020	0.171	45	Marikina 1	9.43	16.690	1.770
19	Caloocan 2	7.91	1.585	0.200	46	Pasig 1	13.44	24.004	1.786
20	Manila Paco	2.94	0.638	0.217	47	Manila Quiapo	0.92	1.688	1.840
21	Manila Sta Cruz	3.88	1.362	0.351	48	Pasay 2	3.04	5.754	1.893
22	Valenzuela 2	19.38	7.309	0.377	49	Pasay 1	15.55	32.772	2.108
23	Manila San Miguel	0.94	0.369	0.392	50	Mandaluyong 1	7.62	16.980	2.228
24	Las Piñas 2	19.03	7.820	0.411	51	Makati 2	11.56	25.960	2.246
25	Quezon City 6	22.58	9.762	0.432	52	San Juan 1	1.94	4.974	2.569
26	Taguig 2	12.98	6.185	0.477	53	San Juan 2	4.07	11.290	2.774
27	Taguig 1	20.75	10.046	0.484					

4.3. Prioritization Scheme Through Analytic Hierarchy Process

As observed in Table 9, there is a significant disparity in poverty incidence between wealthier (8.56%) and poorer cities (35.87%) in Metro Manila. Specifically, Makati, San Juan, and Mandaluyong are identified as wealthier cities, while Navotas, Malabon, and Caloocan are classified as poorer. Being a wealthy city, however, does not directly connote having low transport expenditure as a percentage of income, and vice versa. For example, despite Navotas

being considered a ‘poor’ city, its transport expenditure is relatively low, similar to that of a ‘rich’ city like Makati. On the other hand, there is a notable gap between the highest and lowest ranks, indicating an inequitable distribution of the bike lane network.

Table 9. Raw Scores of Each District Under All Criteria

District	Percentage of Low-Income Households	Average Transport Expenditure as Percentage of Income	Average Distance to the Nearest Bike Lane Network (m)	Bike Lane Density
Caloocan 1	30.366%	6.279%	1031.342	0
Caloocan 2	30.366%	6.279%	1156.429	0.200
Caloocan 3	30.366%	6.279%	3609.382	0
Las Piñas 1	16.356%	5.131%	527.033	0.637
Las Piñas 2	16.356%	5.131%	696.538	0.411
Makati 1	8.559%	3.910%	310.400	0.880
Makati 2	8.559%	3.910%	194.885	2.246
Malabon 1	32.665%	4.658%	2308.060	0
Malabon 2	32.665%	4.658%	1557.700	0
Mandaluyong 1	15.189%	4.899%	166.179	2.228
Mandaluyong 2	15.189%	4.899%	239.569	1.700
Manila Binondo	22.371%	4.180%	761.910	0
Manila Ermita	22.371%	4.180%	255.515	0.988
Manila Intramuros	22.371%	4.180%	506.620	0.502
Manila Malate	22.371%	4.180%	464.970	0.723
Manila Paco	22.371%	4.180%	415.077	0.217
Manila Pandacan	22.371%	4.180%	716.037	0.106
Manila Port Area	22.371%	4.180%	729.460	0.014
Manila Quiapo	22.371%	4.180%	126.363	1.840
Manila Sampaloc	22.371%	4.180%	317.681	1.366
Manila San Andres	22.371%	4.180%	248.705	0.610
Manila San Miguel	22.371%	4.180%	272.908	0.392
Manila San Nicolas	22.371%	4.180%	1270.007	0
Manila Santa Ana	22.371%	4.180%	482.117	0.531
Manila Santa Mesa	22.371%	4.180%	209.978	0.610
Manila Sta Cruz	22.371%	4.180%	451.176	0.351
Manila Tondo	22.371%	4.180%	1725.589	0
Marikina 1	26.802%	6.063%	308.033	1.770
Marikina 2	26.802%	6.063%	518.257	0.958
Muntinlupa 1	23.164%	5.777%	2287.125	0
Muntinlupa 2	23.164%	5.777%	1584.800	0.098
Navotas 1	35.873%	4.208%	3386.967	0
Navotas 2	35.873%	4.208%	3241.560	0
Parañaque 1	17.487%	5.377%	417.900	1.015
Parañaque 2	17.487%	5.377%	1322.288	0.144
Pasay 1	21.010%	3.749%	160.393	2.108
Pasay 2	21.010%	3.749%	288.617	1.893
Pasig 1	21.098%	4.586%	288.191	1.786
Pasig 2	21.098%	4.586%	484.488	0.761
Pateros 1	23.126%	4.591%	755.233	0
Pateros 2	23.126%	4.591%	512.529	0
Quezon City 1	22.277%	6.742%	522.614	0.970
Quezon City 2	22.277%	6.742%	1520.880	0.171
Quezon City 3	22.277%	6.742%	322.281	0.713
Quezon City 4	22.277%	6.742%	354.129	1.280
Quezon City 5	22.277%	6.742%	809.879	0.238
Quezon City 6	22.277%	6.742%	505.336	0.432
San Juan 1	13.527%	4.913%	155.890	2.569

San Juan 2	13.527%	4.913%	157.736	2.774
Taguig 1	18.885%	4.593%	431.867	0.484
Taguig 2	18.885%	4.593%	660.854	0.477
Valenzuela 1	24.400%	5.275%	922.929	0.517
Valenzuela 2	24.400%	5.275%	1325.444	0.377

Table 10. Overall Ranking of Each District Based on the Total Score

Rank	District	Percentage of Low-Income Households	Average Transport Expenditure as Percentage of Income	Average Distance to Nearest Bike Lane Network	Bike Lane Density	Total
1	Caloocan 3	0.129	0.081	0.466	0.277	0.953
2	Navotas 1	0.161	0.015	0.436	0.277	0.889
3	Navotas 2	0.161	0.015	0.417	0.277	0.870
4	Malabon 1	0.142	0.029	0.292	0.277	0.740
5	Muntinlupa 1	0.086	0.065	0.289	0.277	0.717
6	Malabon 2	0.142	0.029	0.191	0.277	0.640
7	Quezon City 2	0.081	0.096	0.187	0.260	0.623
8	Muntinlupa 2	0.086	0.065	0.195	0.267	0.614
9	Caloocan 1	0.129	0.081	0.121	0.277	0.608
10	Caloocan 2	0.129	0.081	0.138	0.257	0.605
11	Manila Tondo	0.081	0.014	0.214	0.277	0.586
12	Valenzuela 2	0.093	0.049	0.160	0.239	0.542
13	Parañaque 2	0.053	0.052	0.160	0.263	0.528
14	Manila San Nicolas	0.081	0.014	0.153	0.277	0.525
15	Quezon City 5	0.081	0.096	0.091	0.253	0.522
16	Valenzuela 1	0.093	0.049	0.107	0.225	0.474
17	Pateros 1	0.086	0.027	0.084	0.277	0.474
18	Quezon City 6	0.081	0.096	0.051	0.234	0.462
19	Manila Binondo	0.081	0.014	0.085	0.277	0.457
20	Manila Port Area	0.081	0.014	0.081	0.276	0.452
21	Pateros 2	0.086	0.027	0.052	0.277	0.442
22	Manila Pandacan	0.081	0.014	0.079	0.267	0.441
23	Marikina 2	0.108	0.074	0.052	0.181	0.416
24	Quezon City 1	0.081	0.096	0.053	0.180	0.410
25	Quezon City 3	0.081	0.096	0.026	0.206	0.409
26	Las Piñas 2	0.046	0.044	0.076	0.236	0.403
27	Manila Paco	0.081	0.014	0.039	0.255	0.389
28	Taguig 2	0.061	0.027	0.071	0.230	0.389
29	Manila Sta Cruz	0.081	0.014	0.043	0.242	0.381
30	Manila Intramuros	0.081	0.014	0.051	0.227	0.373
31	Manila Sta Ana	0.081	0.014	0.048	0.224	0.367
32	Taguig 1	0.061	0.027	0.041	0.229	0.358
33	Las Piñas 1	0.046	0.044	0.054	0.213	0.357
34	Quezon City 4	0.081	0.096	0.030	0.149	0.357
35	Manila San Miguel	0.081	0.014	0.020	0.238	0.353
36	Pasig 2	0.074	0.027	0.048	0.201	0.350
37	Manila Malate	0.081	0.014	0.045	0.205	0.345
38	Manila San Andres	0.081	0.014	0.016	0.216	0.328
39	Manila Sta Mesa	0.081	0.014	0.011	0.216	0.323
40	Parañaque 1	0.053	0.052	0.039	0.176	0.320
41	Marikina 1	0.108	0.074	0.024	0.100	0.306
42	Manila Ermita	0.081	0.014	0.017	0.178	0.291
43	Manila Sampaloc	0.081	0.014	0.026	0.141	0.262
44	Pasig 1	0.074	0.027	0.022	0.099	0.221
45	Makati 1	0	0.005	0.025	0.189	0.219

46	Mandaluyong 2	0.039	0.037	0.015	0.107	0.198
47	Manila Quiapo	0.081	0.014	0	0.093	0.189
48	Pasay 2	0.073	0	0.022	0.088	0.183
49	Pasay 1	0.073	0	0.005	0.067	0.145
50	Mandaluyong 1	0.039	0.037	0.005	0.055	0.136
51	San Juan 1	0.029	0.037	0.004	0.020	0.091
52	San Juan 2	0.029	0.037	0.004	0	0.071
53	Makati 2	0	0.005	0.009	0.053	0.067

Although a district may rank relatively low in a particular criterion, it can still achieve a higher overall ranking due to the corresponding weights assigned to each criterion, as shown in Table 10. For instance, Caloocan 3 scores lower than Navotas 1 in poverty incidence and lower than Quezon City 2 in transport expenditure. However, Caloocan 3 still ranks first overall. Therefore, assigning a specific weight to each criterion using AHP is crucial for determining the priority levels of cities, whether high, mid, or low.

4.4. GIS Map of the Priority Areas for Bike Lane Network

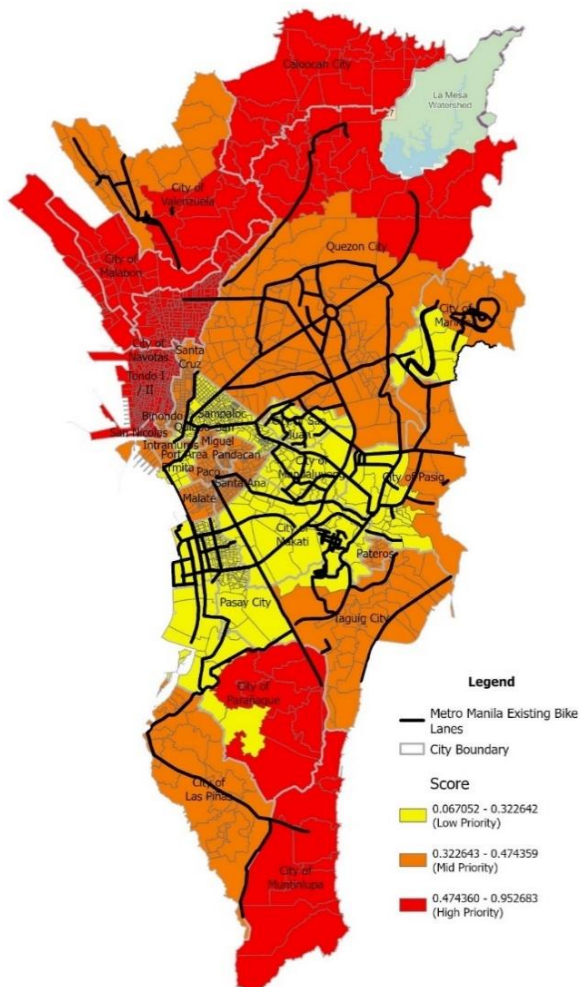


Figure 14. Map of Priority Areas (High Priority, Mid Priority, and Low Priority) Plotted Against the Map of the 2022 Bike Lane Network

The ranking of priority areas was categorized into high-priority, mid-priority, and low-priority groups. This was implemented to identify areas in direct need of bike lane construction in consideration of the needs of the low-income households and to focus on the high-priority areas first in policy-making and in addressing transport poverty in the region. Figure 14 illustrates the spatial distribution of high-, mid-, and low-priority areas in Metro Manila. As shown in the map, the high-priority areas are situated at the boundaries of the region, which are relatively distant from the central business districts like Makati, Mandaluyong, and Pasig. On the other hand, low-priority areas are clustered around the center of the region and near the central business districts. When plotted against the existing bike lane network, the map also reveals that high-priority areas have little to no bike lanes within their districts while low-priority areas have a high concentration of bike lanes, suggesting an inequitable distribution. Additionally, bike lanes are primarily concentrated in the central parts of the region which leaves the boundary areas with limited access. Besides, bike lanes are notably dense in smaller cities like San Juan and Mandaluyong whereas larger cities such as Quezon City only have an average number of bike lanes and an average distance from them.

5. CONCLUSION

For the prioritization of bicycle lanes in Metro Manila to improve the accessibility of low-income households, four criteria were used namely: transport expenditure, poverty incidence, average distance to the nearest bike lane network, and bike lane density. Through 2018 FIES, there were 22.9% households in Metro Manila (4,114 out of 17,977) who belonged to the low-income bracket, where most of them live in Navotas (35.9%) and Malabon (32.7%). While most of them (87.46%) do not own a private vehicle, the few who do are predominantly motorcycle owners (12.01%). Meanwhile, 97% of the low-income households rely on public transportation, with jeepneys and tricycles being the most popular option.

Spatial maps were generated to better represent the criteria. The combined map of the percentage of low-income households across cities and the existing bike lane showed that cities with the lowest percentage, such as Makati, San Juan, and Mandaluyong, have long and more accessible bike lanes while most cities with the highest percentage, like Navotas, Caloocan, and Malabon, have minimal presence of bike lanes, which indicates an inequitable distribution of the network. In the combined map of transport expenditure and existing bike lane network, several cities like Caloocan and Muntinlupa lack the presence of bike lanes despite being home to many low-income households who spend significant share of their income on transportation. The accessibility and density measures revealed that districts with lowest accessibility, such as Caloocan District 3 and Navotas City (Districts 1 and 2), are on average, 3000 meters away from the nearest bike lane whereas the districts with highest accessibility namely, Quiapo, and San Juan City (District 1 and 2) are less than 200 m away from nearest available bike lane. There are also 12 districts that have zero bike lane density.

Based on the bike lane prioritization scheme, the areas where bike lane construction should be highly prioritized are Caloocan City, Navotas City, Malabon City, Muntinlupa City, Quezon City Districts 2 and 5, Tondo, Valenzuela District 2, Parañaque District 2, and San Nicolas. The city district with the highest priority is Caloocan District 3, which demonstrates extreme levels of the four set criteria. Meanwhile, Makati District 2 falls in the lowest priority on the bike lane prioritization ranking since it already has accessible and interconnected bike lanes while being part of a city with the lowest percentage of low-income households and where low-income families spend the smallest share of their income on transportation.

6. RECOMMENDATION

This study can be improved by using the 2021 FIES to account for income and expenditure changes that occurred during the pandemic and to further deepen the results by comparing it against the current situation. Adding or considering other AHP criteria can also enhance the result of the study. Moreover, future research may consider the route origin and destination of the low-income households as well as their place of employment to better understand their travel and cycling behavior given that data would be available. Lastly, the researchers also recommended the Philippine Statistics Authority to expand their survey's reach to further sample representation until the barangay level and to reflect all survey answers completely and accurately in the public use files.

REFERENCES

- Albert, J. R., Abrigo, M., Quimba, F. M., & Vizmanos, J. F. (2020, August 4). *Poverty, the Middle Class, and Income Distribution amid COVID-19*. Pids.gov.ph. <https://pids.gov.ph/publication/discussion-papers/poverty-the-middle-class-and-income-distribution-amid-covid-19>
- Ammarapala, V., Chinda, T., Pongsayaporn, P., & Ratanachot, W. (2018, March). *Cross-border shipment route selection utilizing analytic hierarchy process (AHP) method*. https://www.researchgate.net/publication/323905554_Cross-border_shipment_route_selection_utilizing_analytic_hierarchy_process_AHP_method
- Apparicio, P., Abdelmajid, M., Riva, M., & Shearmur, R. (2008). Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics*, 7(1), 7. <https://doi.org/10.1186/1476-072x-7-7>
- Baharun, N., Masrom, S., & Roshidi, A. (2021). Factors Affecting the Housing Affordability of Homebuyers in Perak: Measuring Transport Expenditure. *Journal of Southeast Asian Research*, 1–11. <https://doi.org/10.5171/2021.676983>
- Benevenuto, R., & Caulfield, B. (2019). Poverty and transport in the global south: An overview. *Transport Policy*, 79, 115–124. <https://doi.org/10.1016/j.tranpol.2019.04.018>
- Bimbao, J. A., & Ou, S. J. (2022). A tale of two cyclists: a cross-cultural comparison between Taiwanese and Filipino perceptions on cycling infrastructure landscapes. *Landscape and Ecological Engineering*. <https://doi.org/10.1007/s11355-022-00516-8>
- Cameña, J. P., & Castro, J. (2019, December). *Cycling Odds: Factors Affecting the Propensity to Use Bicycles in a Highly Urbanized City in the Philippines*. https://www.researchgate.net/profile/Jun-Castro/publication/350134433_Cycling_Odds_Factors_Affecting_the_Propensity_to_Use_Bicycles_in_a_Highly_Urbanized_City_in_the_Philippines/links/60531d2d299bf173674e8b5d/Cycling-Odds-Factors-Affecting-the-Propensity-to-Use-Bicycles-in-a-Highly-Urbanized-City-in-the-Philippines.pdf
- Department of Transportation. (2022). *NETWORK PLANNING FOR THE ESTABLISHMENT OF BIKE LANES IN METRO MANILA, METRO CEBU & METRO DAVAO*.
- Doran, A., El-Geneidy, A., & Manaugh, K. (2021). The pursuit of cycling equity: A review of Canadian transport plans. *Journal of Transport Geography*, 90, 102927. <https://doi.org/10.1016/j.jtrangeo.2020.102927>
- Firth, C.L., Hosford, K., and Winters, M., (2021, June). Who were these bike lanes built for? Social-spatial inequities in Vancouver's bikeways, 2001-2016. <https://doi.org/10.1016/j.jtrangeo.2021.103122>
- Gaspay, S. M., Tolentino, N. J. Y., Tiglao, N. C. C., Ng, A. C., & Tacderas, M. A. Y. (2022, December). *Towards Better Understanding of Metro Manila's Cyclists: Insights From Two Cycling Surveys in Metro Manila*. Research Gate. https://www.researchgate.net/publication/370004469_Towards_Better_Understanding_of_Metro_Manila%27s_Cyclists_Insights_From_Two_Cycling_Surveys_in_Metro_Manila
- Houde, M., Apparicio, P., & Séguin, A.-M. (2018). A ride for whom: Has cycling network expansion reduced inequities in accessibility in Montreal, Canada? *Journal of Transport Geography*, 68, 9–21. <https://doi.org/10.1016/j.jtrangeo.2018.02.005>
- Institute for Transportation and Development Policy. (2017, October 17). *Transit Oriented Development Standard 3.0*. <https://www.eltis.org/Resources/Tools/Transit-Oriented-Development-Standard-30>. <https://www.eltis.org/resources/tools/transit-oriented-development-standard-30>
- Kabak, M., Erbaş, M., Çetinkaya, C., & Özceylan, E. (2018). A GIS-based MCDM approach for the evaluation of bike-share stations. *Journal of Cleaner Production*, 201, 49–60. <https://doi.org/10.1016/j.jclepro.2018.08.033>
- Mattingly, K., & Morrissey, J. (2014). Housing and transport expenditure: Socio-spatial indicators of affordability in Auckland. *Cities*, 38, 69–83. <https://doi.org/10.1016/j.cities.2014.01.004>

- Mora, R., Truffello, R., & Oyarzun, G., (2021, February). Equity and accessibility of cycling infrastructure: An analysis of Santiago de Chile. <https://doi.org/10.1016/j.jtrangeo.2021.102964>
- Nielsen, T. A. S., & Skov-Petersen, H. (2018). Bikeability – Urban structures supporting cycling. Effects of local, urban and regional scale urban form factors on cycling from home and workplace locations in Denmark. *Journal of Transport Geography*, 69, 36–44. <https://doi.org/10.1016/j.jtrangeo.2018.04.015>
- Parra, D. C., Gomez, L. F., Pinzon, J. D., Brownson, R. C., & Millett, C. (2018). Equity in cycle lane networks: examination of the distribution of the cycle lane network by socioeconomic index in Bogotá, Colombia. *Cities & Health*, 2(1), 60–68. <https://doi.org/10.1080/23748834.2018.1507068>
- Philippine Statistics Authority. (2020a). *2018 Family Income and Expenditure Survey*.
- Philippine Statistics Authority. (2020b). *2018 Family Income and Expenditure Survey Report*. <https://psa.gov.ph/sites/default/files/FIES%202018%20Final%20Report.pdf>
- Ramos, M. (2020, November 5). *DOTr secures P1.3B funds for bike lanes*. INQUIRER.net. <https://newsinfo.inquirer.net/1356640/dotr-secures-p1-3b-funds-for-bike-lanes>
- Rey, A. (2021, June 30). *DOTr's 500-km bike lane network completed*. RAPPLER. <https://www.rappler.com/business/dotr-bike-lane-network-completed-june-2021/>
- Saghapour, T., Moridpour, S., & Thompson, R. G. (2016). Measuring cycling accessibility in metropolitan areas. *International Journal of Sustainable Transportation*, 11(5), 381–394. <https://doi.org/10.1080/15568318.2016.1262927>
- Saelens, B., Sallis, J., & Frank, L. (2003). *Environmental Correlates of Walking and Cycling: Findings From the Transportation, Urban Design, and Planning Literatures*. <https://academic.oup.com/abm/article/25/2/80/4631527?login=false>
- Tolentino, N. J., & Sigua, R. (2022). Characteristics of Walking and Cycling in Metro Manila, Philippines. *Philippine Transportation Journal*, 5(1). https://ncts.upd.edu.ph/tssp/wp-content/uploads/2022/12/TSSP2022_Vol5-No1_02-Tolentino-and-Sigua.pdf
- Vale, D. S., Saraiva, M., & Pereira, M. (2015). Active accessibility: A review of operational measures of walking and cycling accessibility. *Journal of Transport and Land Use*, 9(1). <https://doi.org/10.5198/jtlu.2015.593>
- Yannis, G., Kopsacheili, A., Dragomanovits, A., & Petraki, V. (2020). State-of-the-art review on multi-criteria decision-making in the transport sector. *Journal of Traffic and Transportation Engineering (English Edition)*, 7(4), 413–431. <https://doi.org/10.1016/j.jtte.2020.05.005>