Journal of South Asian Logistics and Transport
Volume 5 Issue 1 March 2025
JSALT 5.1.6: pp. 117-135
DOI: https://doi.org/10.4038/jsalt.v5i1.100

PROMOTING SUSTAINABLE MOBILITY BY ADDRESSING INEQUITIES IN ELECTRIC BIKE-SHARING SYSTEMS

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ABSTRACT

Transition to electric bike-sharing systems (EBSS) offers a sustainable and efficient solution for urban mobility, reducing emissions and enhancing accessibility. This study used data from New York City's bike-sharing program, combining socio-demographic factors, built environment indicators, and bike station placement insights to assess EBSS adoption. Using participatory system dynamics modelling, we developed causal loop diagrams to compare the dynamics of cycling adoption in two contrasting contexts: New York, USA, where EBSS is well-integrated as a last-mile and supplementary transportation mode, and Colombo, Sri Lanka, where e-bike adoption remains limited. Key feedback loops identified in New York emphasise the role of infrastructure investments, public transit integration, and safety measures in driving EBSS demand. These insights were adapted to Colombo, revealing potential strategies such as improving cycling infrastructure, integrating EBSS with transit systems, and launching awareness campaigns to overcome cultural and behavioural barriers. The findings provide a systematic framework for policymakers, urban planners, and stakeholders to accelerate EBSS adoption in diverse urban settings. By applying lessons from New York to Colombo, this study highlights actionable pathways to foster e-bike culture and sustainable urban mobility.

Keywords: *Electric bicycle sharing systems, system dynamics, urban mobility, covariate analysis, hypothesis testing*

1. INTRODUCTION

The development of Electric Bike-Sharing Systems (EBSS) marks a transformative approach to sustainable urban transportation. EBSS can potentially reduce emissions, improve mobility, and alleviate congestion. Cycling is often associated with benefits for the environment, society, and the economy. [1], [2]. In the last decade, public bicycle programs or Public Bike Share (PBS) systems have undergone thundering growth, due to the development of better bicycle tracking methods with technological advances. [3]. In recent years, hope for sustainable mobility has been attached to three innovations, which are electric vehicles, shared mobility, and automated vehicles. These options have become very popular in Asian cities, given the population increase and intense traffic congestion. PBS systems have become increasingly popular in transport plans as a strategy for increasing travel decisions, promoting active modes of transport, reducing car needs, and decreasing greenhouse gas emissions, thereby providing a means of sustainable mobility [4].

Previous studies on cycling in cities have yielded diverse information about influence and outcomes. Understanding individual aspects such as age, gender, and socioeconomic position that are linked to cycling has been made possible by the analysis of trip data [5]. Key determinants identified include the provision of infrastructure, like well-planned bike lanes, and docking stations, and the integration of technology, such as GPS and app-based systems that improve accessibility and operational efficiency [6]. The impact of these factors differs between cities based on socio-economic and geographic contexts. For instance, cities with hilly terrain or extreme weather conditions require additional considerations for electric bike support, as seen in studies on electric bike-sharing adoption in various urban environments [7]. Additionally, developing cities face unique adoption challenges related to infrastructure, affordability, and user awareness [8]. Using System Dynamics (SD) modelling, Macmillan and Woodcock's work creates Causal Loop Diagrams (CLDs) that show the dynamics of cycling adoption in three cities, Auckland, London, and Nijmegen, each of which represents a distinct urban cycling context in a high-income nation [5]. The study presents a theoretical framework for the adoption of cycling in various urban or national contexts, indicating that the factors affecting bicycle prominence differ depending on the level of cycling prevalence, ranging from cities with established riding cultures to those with low levels of cycling. The study intends to increase knowledge of the variables influencing urban cycling and provide personalized policy measures that promote sustainable cycling growth according to each city's stage on this trajectory by cooperatively improving an initial model from Auckland. Continuing the same research paradigm, in this study, we have selected two different cities, New York and

Colombo, with unique characteristics that are presented in Macmillan & Woodcock's study [5]. One is a city in a developing country with almost no use of E-bikes, while another utilizes them as a last-mile or supplemental form of transportation. This study's use of CLDs in New York and Colombo highlights various stages of adoption and identifies critical leverage points.

In this paper, we hypothesize that the distribution of electric bike-sharing stations is closely linked to the socio-demographic characteristics of the population. We further hypothesize that features of the local transportation landscape and built environment indicators, such as proximity to major transit stops, may also influence the distribution of e-bike stations. For example, areas with high traffic volumes and concentrations of major employment areas may be more desirable locations for e-bike stations. Therefore, identifying and quantifying these features is crucial. While this paper does not make causal claims, it aims to identify correlations within the data that can inform targeted policy interventions to ensure equitable deployment of e-bike-sharing infrastructure. We emphasize that, although e-bike adoption is currently limited, the uneven accessibility and affordability of this infrastructure across different communities provide a foundation for analysing inequities. These disparities are critical to understanding how they may affect the adoption trends and pace of e-bike usage in various areas.

2. DATA

2.1. Socio-Demographic and 5D Built Environmental Indicators

To determine the socio-demographic and urban mobility factors affecting the distribution of EBSS stations in NYC, we use the publicly available New York City bike data from the NYC Department of Transportation. [9]. This dataset provides a current accounting of the types and locations of all bike stations in NYC from 2013. The dataset includes information such as trip attributes (start and stop time, date, and location), as well as bike IDs. For this analysis, we used bike station opening dates, and each data point in the EBSS station dataset corresponds to one station, regardless of the number of bike docks per station. Similarly, we obtain the demographic data of NYC from the American Community Survey (ACS) [10]. We use ACS 1–year estimates data profiles for 2022, which include features of median household income, poverty rate, and population percentage of different racial groups by Census Block Group (CBG) level.

The actual built environment (objective measurement) was quantified across five dimensions (5D) – Density, Design, Diversity, Distance, and Destination –detailed in Table 1 with data obtained from the U.S. Environmental Protection Agency's (EPA) and U.S. General Services Administration (GSA) Smart Location Database (SLD) [11]. The database includes indicators of the commonly cited "D" 5 variables shown in the transportation research literature to be related to travel behaviour. The "Ds" include residential and employment density, land use diversity, design of the built environment, access to destinations, and distance to transit [12]. In this study, SLD variables were used as inputs to identify features that impact the distribution of EBSS stations in NYC.

Density factors, such as residential density (D1a), population density (D1b), and employment density (D1c), are fundamental in determining the areas with a higher concentration of potential users. Locations with greater residential and employment density offer a more significant pool of potential riders, making them prime targets for the placement of electric bike stations. These areas also experience higher foot traffic, which increases the likelihood of consistent station usage. **Diversity factors**, such as the regional jobs-population balance (D2r_JobPop), land use diversity (D2c_TripEq), and workforce balance diversity (D2a_WrkEmp), help to understand the mix of land uses and how people interact with the environment. A balanced mix of residential, commercial, and employment spaces, as indicated by land use diversity, creates areas where bike sharing can serve multiple functions—commuting, shopping, and recreation. Additionally, regions with a better jobs-population balance and workforce balance can help ensure that stations are accessible to both workers and residents, fostering increased usage. **Design indicators**, including road network density (D3a), pedestrian-oriented network density (D3apo), and active intersection density (D3b), are key to ensuring that bike stations are in areas with a robust infrastructure conducive to safe and convenient cycling. A denser road network promotes easier access to and from bike stations, while active intersections ensure better connectivity and visibility for cyclists, encouraging more frequent usage. **Distance indicators**, such as distance to the nearest transit stop (D4a), proximity to fixed-guideway transit (D4b025), and evening peak transit service frequency (D4c), are vital for identifying strategic locations for bike stations in proximity to public transportation. Stations placed near transit hubs and fixed-guideway systems, with high service frequencies, ensure seamless multimodal transport options for users, enhancing the overall accessibility and appeal of bike-sharing systems. **Destination indicators** like transit-weighted job accessibility (D5br), regional auto job accessibility index (D5cri), and regional transit worker accessibility index (D5de) highlight the importance of accessibility to key destinations, particularly jobs, by public transportation or car. The proximity to major job centres and transit hubs will ensure that bike stations are placed where they can effectively complement existing transportation options and meet the mobility needs of the population. Thus, an indepth analysis of socio-demographic and 5D built environment data is required to capture features that determine the presence and accessibility of EBSS stations.

Table 1: Quantification of the 5D built environmental indicators

5D Parameter	Indicator	Abbreviation in SDL	Definition
Density	Residential density	D1a	Gross residential density (HU/acre) on unprotected land
	Population density	D1b	Gross population density (people/acre) on unprotected land
	Employment density	D1c	Gross employment density (jobs/acre) on unprotected land
Diversity	Regional jobs-population balance	D2r_JobPop	Regional Diversity. Standard calculation based on population and total employment: Deviation of CBG ratio of jobs/pop from the regional average ratio of jobs/pop
	Land use diversity	D2c_TripEq	Trip productions and trip attractions equilibrium index; the closer to one, the more balanced the trip-making
	Workforce balance diversity	D2a_WrkEmp	Household Workers per Job, by CBG
Design	Road network density	D3a	Total road network density
	Pedestrian-oriented network density	D3apo	Network density in terms of facility miles of pedestrian-oriented links per square mile
	Active intersection density	D3b	Street intersection density (weighted, auto-oriented intersections eliminated)
Distance	Distance to the nearest transit stop	D4a	Distance from the population-weighted centroid to the nearest transit stop
	Proximity to fixed-guideway transit	D4b025	The proportion of CBG employment within ¼ mile of a fixed-guideway transit stop
	Evening peak transit service frequency	D4c	Aggregate frequency of transit service within 0.25 miles of CBG boundary per hour during evening peak period
Destination	Transit-weighted job accessibility	D5br	Accessibility of jobs for residents within a CBG within a reasonable commute time using public transportation.
	Regional auto job accessibility index	D5cri	Job accessibility by automobile for a specific CBG
	Regional transit worker accessibility index	D5de	Proportional accessibility of working-age population via transit for a specific CBG

2.2. Participatory Delphi Interviews

Transport researchers and students from New York University, USA, and the University of Moratuwa, Sri Lanka, were interviewed using the Delphi technique to identify the causal links between the variables. For the New York case, the CLDs were designed using both Macmillan & Woodcock's study and the covariate analysis presented in Section 4.1 [5]. The researchers were first presented with the CLD developed and then asked to add or remove variables based on their experiences. Following the workshops, we used the facilitators' notes, verbal comments, and edited diagrams to refine the set of CLDs. Refinements were made to the preliminary feedback, reflecting the comments and debates from the workshops, as well as triangulating the data from the workshops and discussions with multidisciplinary literature on cycling. [13], [14]. For the Sri Lankan context, Macmillan & Woodcock's study [5], which had already developed a CLD for low cycling contexts, was used as the basis for the design.

3. METHODS

3.1. Analysis of the Distribution of E-Bike Stations Across New York City

We perform covariate analyses, in Section 4.1, to identify features in the socio-demographic and built environment datasets that impact the distribution of e-bike stations in NYC. To this end, we define the following two target features:

1. A binary variable representing the presence of at least one e-bike station in a particular CBG.
2. The total number of e-bike stations in each CBG.

Moreover, we test the hypotheses in Section 1 by defining two groups in our dataset, such that all CBGs with at least one e-bike station constitute one group (treatment group), whereas the remaining CBGs constitute the other group (control group). Across the four boroughs of NYC (excluding Staten Island, as there are no e-bike stations in its CBGs), there are 6,310 CBGs with accompanying demographic data from the ACS (U.S. Census Bureau, 2022). Of these, 1,553 CBGs have at least one e-bike station, while 4,757 CBGs have none. Hence, group 1 in our dataset comprises 1,553 data points, whereas group 2 contains 4,757 data points. We use the t-test as a hypothesis testing tool, in Section 4.2, to compare the average values of the two groups [15]. Our null hypothesis assumes that the means of the two data groups are equal, i.e., there are no statistical differences between the two groups. The null hypothesis implies that socio-demographic and built environment features do not affect the presence of e-bike stations in CBGs, rendering the two groups statistically identical. We use the p-value and t-value to assess the likelihood of rejecting the null hypothesis. In this case, we consider p-value $\leqslant 0.05$ as statistically significant [16], indicating strong evidence against the null hypothesis. On the contrary, for a significance level (α) = 0.05, the t-value is considered significant if $|t| \geqslant 1.96$.

A three-phase analysis [Phase 1 (2013–2017); Phase 2 (2018–2020); Phase 3 (2021–2024)] was conducted to study the adoption and distribution of e-bike stations in NYC, to identify the socio-demographic and built environment factors influencing their establishment. The analysis was structured into three distinct phases to account for the different stages of e-bike station development and their contextual impacts. This phased approach enabled us to analyse and address factors specific to each stage and draw insights that could be applied to different contexts, including developing countries such as Sri Lanka. The phased approach allowed us to examine the evolving dynamics and barriers at each stage of development. This method also provided a robust framework to draw comparisons with regions in developing countries, where similar phased adoption of new transportation technologies may be observed.

3.2. System Dynamics Methodology

The SD methodology was employed in this study to analyse the socio-demographic and built environment factors influencing the establishment and adoption of e-bike stations in NYC. SD is particularly suited for this analysis because urban cycling trends are shaped by complex, dynamic interactions between factors such as population characteristics, infrastructure, and user behaviour. By constructing CLDs, the study mapped the feedback loops within the system to identify reinforcing and balancing dynamics affecting the growth of e-bike infrastructure. The CLDs adapted from Macmillan & Woodcock's research on Auckland, London, and the Netherlands served as a foundational framework, enriched with local data from NYC to reflect the unique socio-demographic and urban planning context. [5]. These diagrams integrated insights from primary data (stakeholder feedback) and secondary data (demographic statistics, NYC Department of Transportation data) to comprehensively understand the systemic factors driving e-bike station establishment.

The insights from NYC's e-bike data were crucial to constructing meaningful CLDs and applying the SD methodology. These insights were mapped as feedback loops, such as the reinforcing loop in which increased station density leads to greater adoption and demand, or balancing loops in which equity gaps limit adoption in underserved neighbourhoods. By iteratively refining these CLDs, the study offered not only a robust analysis for NYC but also a transferable framework to inform similar efforts in cities like Colombo, where socio-demographic and infrastructure dynamics could differ significantly.

4. CASE STUDY

The case study focuses on NYC, with Figure 1 illustrating the three-phase timeline of e-bike station development across its four boroughs – Manhattan, Bronx, Queens, and Brooklyn, – shown in different colours. Staten Island is excluded from the analysis due to the absence of e-bike stations. In this section, we use demographic and e-bike station data at the CBG level to analyse the socio-demographic and built environment factors influencing the distribution of e-bike stations across NYC during each phase. Hypothesis testing is conducted to compare the set of CBGs with at least one e-bike station and those with no stations in each phase, aiming to identify key factors driving station deployment and adoption. Furthermore, to understand the interdependencies of socio-demographic features, we use covariate analysis to explore how the distribution of e-bike stations evolved over the three phases in different CBGs of NYC.

Using data from the U.S. Census Bureau [10]We visualise the population density across NYC's CBGs in Appendix 1, noting that population density is neither uniform across CBGs nor consistent among the five boroughs. Fig. 1 highlights the three distinct phases of e-bike station development: Phase 1 (2013–2017) represents the early stage with 668 stations, Phase 2 (2018–2020) marks the middle stage with 454 stations, and Phase 3 (2021–2024) illustrates the wide-scale establishment with 1,022 additional stations. By comparing Figure 1 and Figure 2, we observe that Brooklyn has the highest population density in 2022, while parts of Manhattan exhibit much lower densities. Regarding the deployment of e-bike stations, Manhattan, northern Brooklyn, and upper Queens have consistently been at the forefront experiencing substantial growth during Phases 1 and 2, whereas the Bronx and other regions within Queens and Brooklyn exhibit comparatively slower growth. This trend underscores an alignment in station deployment relative to population density, particularly in densely populated areas such as Brooklyn.

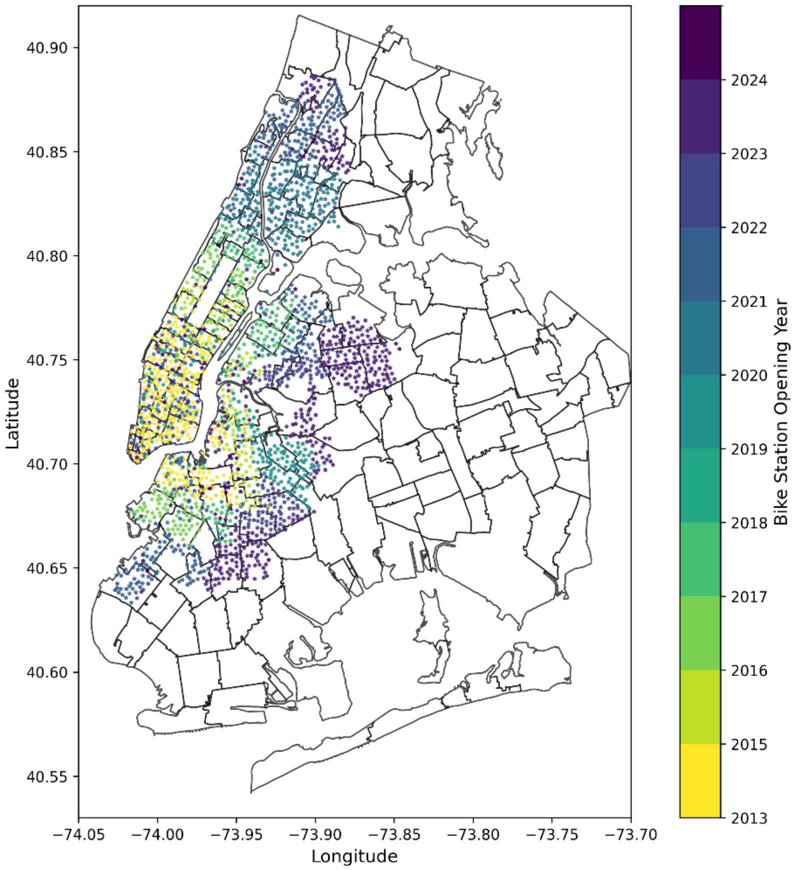

Figure 1: CBG-level distribution of e-bike stations in NYC

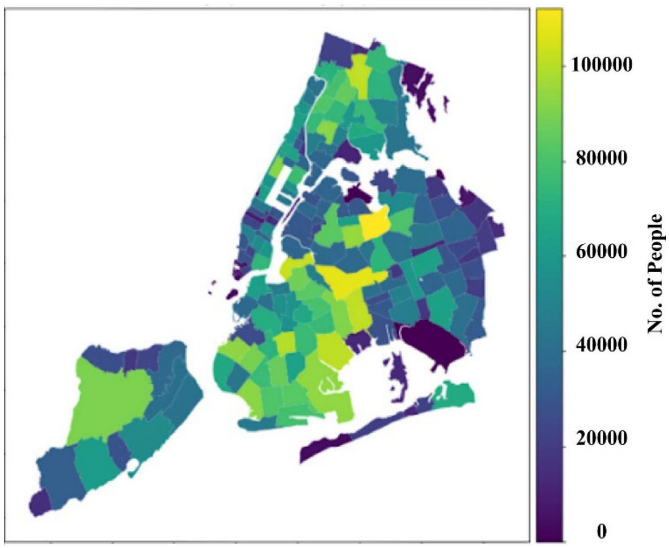

Figure 2: Heat map depicting the population density in NYC, based on data in U.S. Census Bureau (2022)

To test our hypothesis, we analyse whether trends in population density correlate with the phase-wise distribution of e-bike stations. Comparing Figs. 1 and 2, we observe a clear relationship between population density and e-bike station deployment in certain areas, yet there are notable inconsistencies elsewhere. For example, although several densely populated CBGs in Brooklyn received stations during Phases 2 and 3, Manhattan, despite having relatively lower population densities, obtained a disproportionately large number of stations, particularly during Phases 1 and 2. This indicates that factors beyond population density influence the distribution of e-bike stations, highlighting potential inequities in access to e-bike infrastructure. This initial observation leads us to hypothesize that other socio-demographic and built environment factors, such as income levels, transit accessibility, and land use diversity, may play a more significant role. In the following sections, we analyse these features to capture their correlation with the development and allocation of e-bike stations across NYC during each phase of deployment.

4.1. Covariate Analysis

Fig. 3 shows the results of the covariate analysis by implementation stage. It reveals distinct trends in the socio-demographic and built environment factors influencing e-bike station deployment across the three phases. Early deployment (Stage 1) prioritized areas with high residential and employment densities, reflecting an initial strategy aimed at maximising the utilisation of e-bike stations. Interestingly, population density itself did not strongly correlate with station placement, indicating that other factors were more critical during this phase. Furthermore, areas with a higher White population were favoured, suggesting potential socio-demographic biases in the initial deployment strategy. This raises questions about equity in access to e-bike infrastructure during the early stages of development. Additionally, the strong correlation among land use diversity, Regional Transit Worker Accessibility Index (D5de), and Transit-weighted Job Accessibility (D5br) underscore that the initial deployment phase prioritized improving accessibility for the working population, particularly through integration with public transit systems.

As deployment progressed into Stage 2 and Stage 3, the focus shifted significantly towards improving socio-demographic equity, and connectivity and integrating e-bike stations with public transit and active transportation networks. Black population and population density have been influential in the second stage, where it interprets the inclusivity of the population considered in this stage. Variables related to transit accessibility, such as proximity to fixed-guideway transit stops (D4b025) and regional auto job accessibility index (D5cri), became more influential. This indicates a strategic effort to align e-bike stations with existing transportation systems, encouraging multi-modal commuting options. By combining cycling with public transit, and private vehicle usage planners aimed to enhance overall mobility and increase the adoption of both e-bikes and transit services, especially in areas with diverse land use and active transportation infrastructure.

The latter stages also demonstrated a growing emphasis on road network density (D3a) and active intersection density (D3b), reflecting a commitment to creating safer and more accessible environments for cyclists and pedestrians alike. These findings suggest that while the initial deployment focused on high-usage potential areas, subsequent phases prioritized connectivity and integration within a broader urban mobility framework. However, the persistent underrepresentation of stations in areas with higher Asian populations across all stages highlights the need for more equitable planning to ensure that underserved communities benefit from e-bike infrastructure advancements. Additionally, the co-location of e-bike stations with public transit remains relatively underexplored, representing a significant opportunity to enhance optimal multimodal integration.

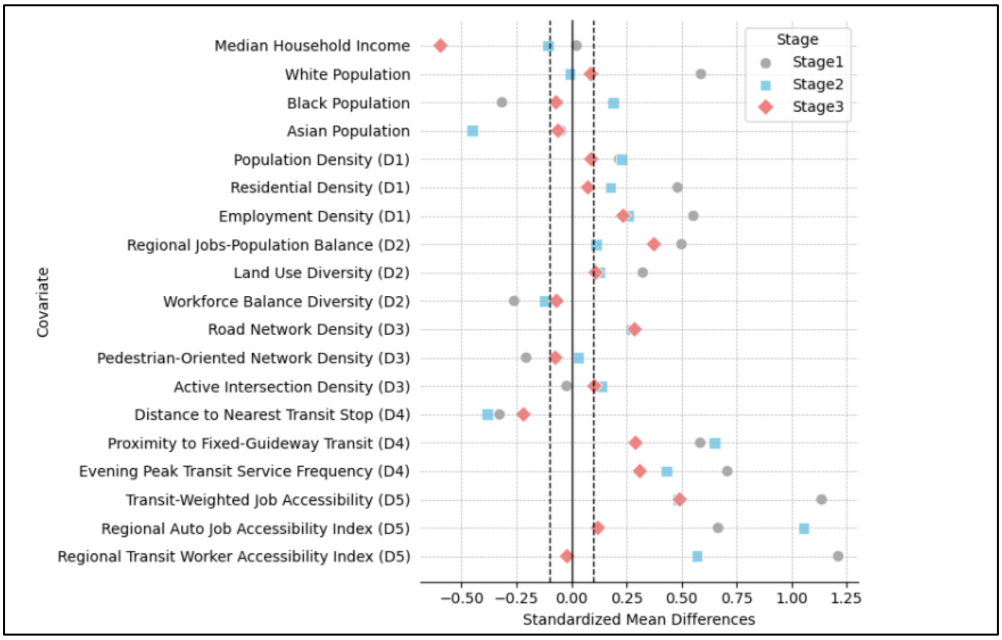

Figure 3: Covariate balance by implementation stage

4.2. Hypothesis Testing

The t-test analysis on e-bike station placement across the three phases reveals a dynamic evolution in the priorities for station deployment, as informed by the 5D built environment factors: Density, Diversity, Design, Distance, and Destination. These factors highlight the interplay between demographic, transportation, and built environment characteristics in shaping e-bike station distribution strategies. Results of the tests during all 3 states are presented in Table 2 below.

Table 2: Results of hypothesis testing between the group of CBGs with and without E-Bike station

Parameter	Phase 1		Phase 2		Phase 3	
	t-statistics	p-value	t-statistics	p-value	t-statistics	p-value
Median household income	0.521	0.603	-1.9	0.058	-11.78	0.000
White population	**11.964****	0.000	-0.153	0.879	**2.193****	0.029
Black population	-8.31	0.000	**3.367****	0.001	-1.867	0.062
Asian population	-1.132	0.258	-11.737	0.000	-1.604	0.109
Residential density	**9.914****	0.000	**3.129****	0.002	1.965	0.05
Population density	**4.722****	0.000	**3.837****	0.000	**2.273****	0.023
Employment density	**8.96****	0.000	**3.354****	0.001	**4.68****	0.000
Regional jobs-population balance	**10.042****	0.000	1.856	0.064	**10.392****	0.000
Land use diversity	**7.323****	0.000	**2.244****	0.025	**3.246****	0.001
Workforce balance diversity	-8.51	0.000	-2.418	0.016	-1.748	0.081
Road network density	**5.367****	0.000	**4.36****	0.000	**6.393****	0.000
Pedestrian-oriented network density	-4.098	0.000	0.537	0.591	-1.705	0.089
Active intersection density	-0.434	0.665	**2.392****	0.017	**2.046****	0.041
Distance to the nearest transit stop	-7.721	0.000	-7.317	0.000	-5.402	0.000
Proximity to fixed-guideway transit	**12.8****	0.000	**11.795****	0.000	**7.43****	0.000
Evening peak transit service frequency	**11.86****	0.000	**6.046****	0.000	**6.543****	0.000
Transit-weighted job accessibility	**21.985****	0.000	**8.78****	0.000	**11.802****	0.000
Regional auto job accessibility index	**16.501****	0.000	**22.464****	0.000	**4.705****	0.000
Regional transit worker accessibility index	**24.546****	0.000	**10.7****	0.000	-0.913	0.361

Note: *p<0.1; **p<0.05

I. Phase 1: Sociodemographic and Work Population Prioritization in High-Density Areas

In the initial deployment phase, station placement was significantly associated with a greater proportion of White-identifying populations, as indicated by t-statistics of 11.964 ($p < 0.001$). These results suggest that early deployment focused on affluent neighbourhoods with predominantly White populations, potentially to ensure high utilization in areas with greater purchasing power and infrastructure readiness. Notably, areas with higher proportions of Black-identifying populations were significantly less likely to host e-bike stations, as reflected by a negative t-statistic of -8.31 ($p < 0.001$). Residential density(D1a) and employment density (D1c) also emerged as important factors. A key interpretation of these results would be that a certain country or a city in the initial phase of EBSS implementation, focusing on attracting the work population and land use diversity is important.

II. Phase 2: Integration with Transit and Diverse Land Uses

In the second phase, the emphasis shifted towards integrating e-bike stations with transit infrastructure and promoting accessibility in diverse, mixed-use environments. The Black population showcases a strong positive relationship which interprets the inclusion of different demographic groups ($t=3.367$, $p= 0.001$). Proximity to fixed-guideway transit (D4b025) emerged as a key factor with a t-statistic of 11.795 ($p < 0.001$), emphasizing the integration of e-bike stations with public transportation. Distance to the nearest transit stop (D4a) showed a strong negative association ($t = -7.317$, $p < 0.001$), reinforcing the prioritization of transit-accessible locations. Interestingly, the regional auto job accessibility index (D5cri) showcases the highest significance ($t = 22.464$, $p < 0.001$) indicating the role of integration with private modes for a sustainable approach and promoting modal shift. A key takeaway from this analysis is that enhancing EBSS usage and advancing the system should prioritize multimodal integration, demographic inclusivity, and sustainability strategies.

III. Enhancing Connectivity and Regional Accessibility

In the final phase, the focus shifted towards improving regional connectivity and aligning e-bike stations with active transportation infrastructure. Regional jobs-population balance (D2r_JobPop) and land use diversity (D2c_TripEq) continued to influence placement decisions ($t = 10.392$, $p <0.001$ and $t = 3.246$, $p = 0.001$, respectively), highlighting the role of mixed-use areas in supporting e-bike usage. Design-related factors, such as road network density (D3a) and active intersection density (D3b), gained further significance, with t-statistics of 6.393 ($p < 0.001$) and -2.046 ($p = 0.014$), respectively. These results indicate a continued emphasis on well-designed, pedestrian-friendly environments. Proximity to fixed-guideway transit

(D4b025) and evening peak transit service frequency (D4c) remained highly influential, with t-statistics of 7.43 ($p < 0.001$) and 6.543 ($p < 0.001$), respectively, further emphasizing the importance of transit integration. Additionally, regional transit worker accessibility (D5de) and transit-weighted job accessibility (D5br) were significant, demonstrating a strategic alignment with regional accessibility goals.

Overall, the analysis reveals a progression from targeting affluent, high-employment areas in Phase 1 to promoting integrated transportation solutions and connectivity in Phases 2 and 3. The evolving significance of transit-related variables and land-use diversity underscores the importance of combining e-bikes with public transportation to enhance mobility options.

4.3. System Dynamics Insights

4.3.1 New York City, USA

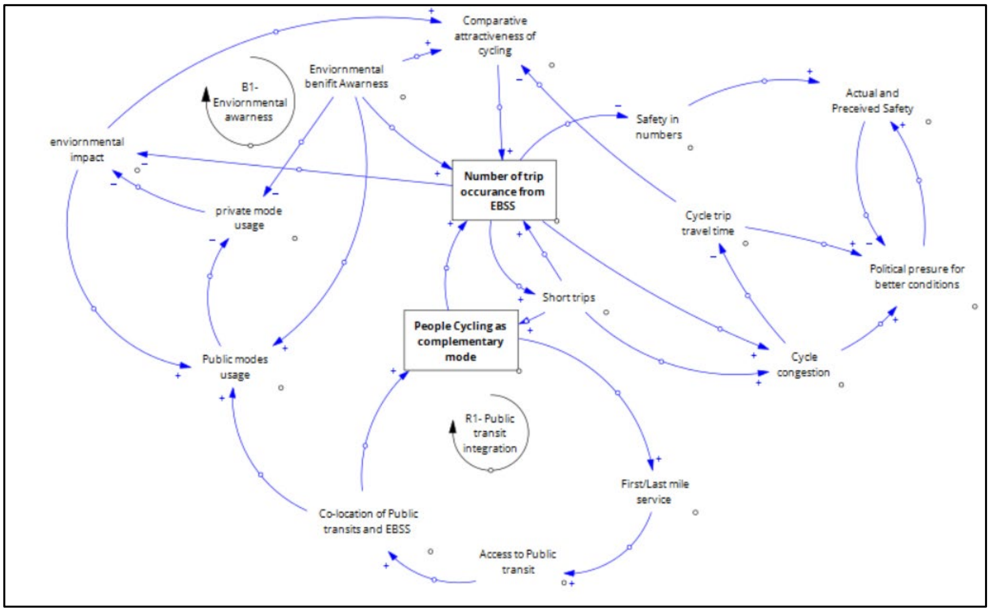

Figure 4: Developed CLD for New York City, USA

Using socio-demographic and built environment factors, we developed a CLD for New York City, combining insights from all three e-bike development phases. This diagram captures the complex dynamics of cycling as a complementary mode within an urban ecosystem. The CLD identifies several key balancing (B) and reinforcing (R) loops that govern the interactions between public transit, environmental awareness, and cycling uptake.

R1: Public Transit Integration

This reinforcing loop highlights the significance of EBSS in enhancing first- and last-mile connectivity to public transit. The strategic co-location of EBSS hubs near public transit stations improves accessibility, making transit a more attractive primary mode of transport. Commuters who use cycles for short trips will be facilitated by access to the transit stations. Integrating EBSS with public transit not only decreases dependence on private vehicles but also supports the development of a multimodal transport network, where different modes work together to improve urban mobility.

B1: Environmental Benefit Awareness

Environmental awareness remains a critical driver for the adoption of EBSS, as demonstrated by New York City's bike-sharing program. This balancing loop highlights how increased awareness of the environmental benefits of cycling fosters a shift from private vehicle use to more sustainable transportation modes, such as cycling and public transit. New York's success underscores the importance of public education campaigns, media outreach, and partnerships with community organizations to emphasize the eco-friendly nature of EBSS.

4.3.2 Colombo, Sri Lanka

Colombo's urban environment presents unique challenges and opportunities for implementing an EBSS. The insights from New York City's phased e-bike station deployment provide a valuable framework for analysing Colombo's dynamics under the 5D aspects. Below are the designed feedback loops contextualized for Colombo:

R1: Built Environment – Enhancing Urban Design through Cycling Infrastructure.

As user demand for EBSS increases in Colombo, investments in cycling infrastructure follow. These investments improve the built environment, such as creating dedicated bike lanes, reducing vehicle congestion, and enhancing pedestrian areas. Improved urban design makes cycling safer and more appealing, thereby stimulating further uptake of EBSS. This loop fosters a positive cycle of urban regeneration and increased adoption of cycling, particularly in areas with high population density and mixed land use. Integrating cycling infrastructure into the city's design aligns with Colombo's growing focus on sustainable urban development.

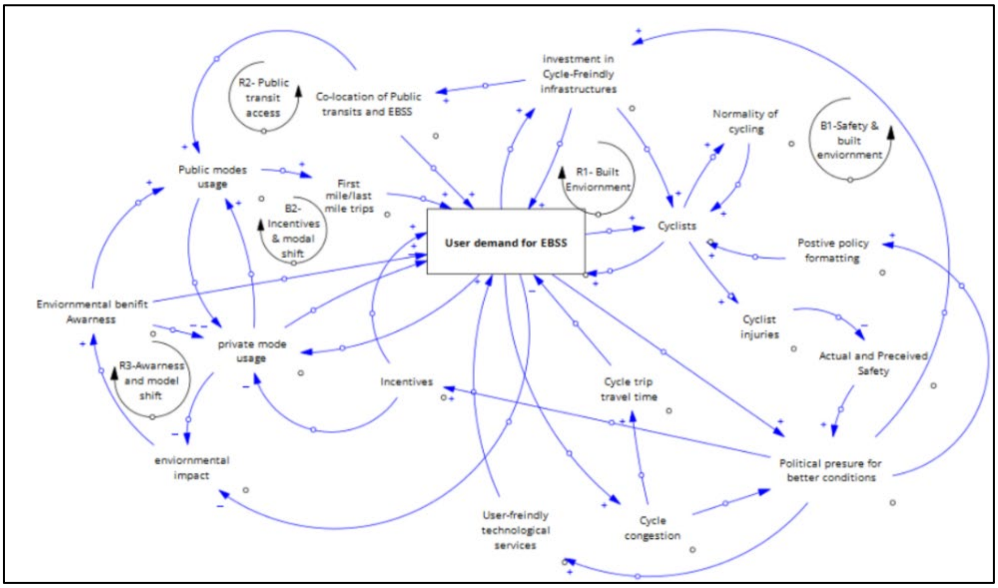

Figure 5: Developed CLD for Colombo, Sri Lanka

R2: Public Transit Access – Bridging Gaps in Accessibility

Positioning EBSS stations near Colombo's public transit hubs significantly improves first- and last-mile connectivity. By aligning EBSS with the "Distance to Transit" aspect, more users find it convenient to combine cycling with public transit. This integration boosts public transit utilization while reducing dependence on private vehicles. The loop encourages a modal shift towards shared and sustainable transportation, creating a reinforcing cycle of improved accessibility and growing EBSS demand. Colombo's high urban density and reliance on public transport make this loop especially relevant in reducing urban traffic congestion.

R3: Awareness and Modal Shift – Promoting Sustainable Behaviour.

Environmental and mobility awareness campaigns in Colombo can drive a shift from private vehicle use to EBSS and public transport. By emphasizing the environmental benefits of cycling and the convenience of EBSS, users are given incentives to adopt more sustainable transport modes. As awareness grows, private vehicle usage decreases, resulting in lower emissions and reduced traffic congestion. This loop highlights the importance of education and community engagement in fostering a culture of cycling, particularly in Colombo's high-density neighbourhoods.

B1: Safety and Built Environment – Addressing Perceived and Actual Safety.

With increasing cycling activity in Colombo, the need for improved safety infrastructure and policies becomes evident. Dedicated bike lanes, traffic calming measures, and lighting improvements are critical to enhancing perceived and actual safety. However, as cycling volumes grow, the risk of injuries may also rise, leading to concerns that could slow adoption. This balancing loop highlights the tension between user demand and safety concerns, necessitating continuous investments in infrastructure and awareness campaigns to sustain growth.

B2: Incentives and Modal Shift – Balancing Demand with Infrastructure Capacity

As EBSS demand grows, incentives such as subsidies, discounts, and promotional campaigns encourage more users to shift from private to shared/public modes of transport. This shift reduces private vehicle usage, contributing to lower congestion and emissions. However, Colombo's infrastructure capacity may limit further growth, creating a balancing effect as private mode usage stabilizes. This loop underscores the need for long-term planning and investment to accommodate growing demand without overburdening existing systems.

5. CONCLUSIONS

This study leveraged data from NYC's bike-sharing program, incorporating socio-demographic factors, built environment indicators, and bike station placement analysis, to assess the impact of these variables on user demand and adoption. A structured, three-phase trial approach in New York provided critical insights that informed strategies to address the low adoption of e-bike-sharing systems (EBSS) in Sri Lanka. The first phase demonstrated the importance of strategically placing bike stations near high-demand zones, such as residential areas, business districts, and transit hubs, to maximize ridership and facilitate seamless first- and last-mile connections. This integration strengthened public transit systems by improving accessibility, fostering a shift toward shared and sustainable modes of transportation.

The second phase highlighted the significance of built environment enhancements, including investments in cycling infrastructure, such as protected bike lanes, and safety measures to improve perceived and actual safety. These improvements encouraged a larger and more diverse group of users, creating a positive feedback loop that fueled further infrastructure investments and user demand. The third phase focused on policy interventions, such as incentive programs and awareness campaigns, which further amplified the modal shift from private vehicles to shared mobility options. By emphasizing the environmental and economic benefits of cycling, these interventions successfully addressed behavioral and cultural barriers to adoption, enabling long-term growth in the bike-sharing system.

The insights from NYC case study, combined with CLDs developed through SD modeling, offer a comprehensive framework for understanding the interactions and feedback loops critical to EBSS success. Key recommendations include identifying high-demand zones for station placement, improving cycling infrastructure, and launching awareness campaigns to highlight the environmental and health benefits of e-bikes. Additionally, co-locating bike stations with public transit hubs and creating incentive schemes, such as reduced fares and membership discounts, can encourage a shift from private vehicles to shared mobility solutions.

6. ACKNOWLEDGEMENTS

This study was financially supported by the SRC grant (# SRC/ST/2024/43) from the University of Moratuwa, Sri Lanka.

REFERENCES

[1] Q. Li, D. Luca, F. Fuerst, and Z. Wei, “Success in tandem? The impact of the introduction of e-bike sharing on bike sharing usage,” *Research in Transportation Economics*, vol. 107, p. 101476, Oct. 2024, doi: 10.1016/J.RETREC.2024.101476.

[2] H. Mohiuddin, D. T. Fitch-Polse, and S. L. Handy, “Does bike-share enhance transport equity? Evidence from the Sacramento, California region,” *J Transp Geogr*, vol. 109, p. 103588, May 2023, doi: 10.1016/J.JTRANGEO.2023.103588.

[3] P. DeMaio, “Bike-sharing: History, Impacts, Models of Provision, and Future,” *J Public Trans*, vol. 12, no. 4, 2009, doi: 10.5038/2375-0901.12.4.3.

[4] C. Contardo, C. Morency, and L.-M. Rousseau, “Balancing a dynamic public bike-sharing system,” 2012, Accessed: Jan. 14, 2025. [Online]. Available: https://www.cirrelt.ca/documentstravail/cirrelt-2012-09.pdf

[5] A. Macmillan and J. Woodcock, “Understanding bicycling in cities using system dynamics modelling,” *J Transp Health*, vol. 7, 2017, doi: 10.1016/j.jth.2017.08.002.

[6] D. Chondrogianni, Y. J. Stephanedes, and P. Fatourou, “Assessing Cycling Accessibility in Urban Areas through the Implementation of a New Cycling Scheme,” *Sustainability (Switzerland)*, vol. 15, no. 19, 2023, doi: 10.3390/su151914472.

[7] J. de Kruijf *et al.*, “Integrated weather effects on e-cycling in daily commuting: A longitudinal evaluation of weather effects on e-cycling in the Netherlands,” *Transp Res Part A Policy Pract*, vol. 148, 2021, doi: 10.1016/j.tra.2021.04.003.

[8] P. K. Machavarapu, S. Ram, and P. Kant, “Factors influencing bike share intentions of users in Indian cities: a structural equation modelling approach,” *Urban Plan Transp Res*, vol. 11, no. 1, 2023, doi: 10.1080/21650020.2023.2276405.

[9] NY Department of Transportation, “New York Citibike Data.”

[10] American Community Survey, “U.S. Census Bureau.”

[11] US Environmental Protection Agency, “Smart Location Database.”

[12] S. Wang *et al.*, “Reducing the social inequity of neighborhood visual environment in Los Angeles through computer vision and multi-model machine learning,” *Sustain Cities Soc*, vol. 119, p. 106062, Feb. 2025, doi: 10.1016/J.SCS.2024.106062.

[13] M. M. De Silva, O. K. Herath, T. Nakayama, and A. S. Kumarage, “A system dynamics model for vehicle fleet transformation towards energy efficiency and low-carbon development: A case study of Sri Lanka and its strategies,” *Transp Policy (Oxf)*, vol. 147, pp. 244–258, Mar. 2024, doi: 10.1016/J.TRANPOL.2024.01.004.

[14] K. Eswaranathan, T. Sivakumar, M. M. De Silva, and A. S. Kumarage, “Modelling the factors influencing carbon efficiency of consumer choice to promote energy-efficient vehicles,” *Transport Economics and Management*, vol. 2, pp. 130–142, Dec. 2024, doi: 10.1016/J.TEAM.2024.05.002.

[15] H. A. U. Khan, S. Price, C. Avraam, and Y. Dvorkin, “Inequitable access to EV charging infrastructure,” *The Electricity Journal*, vol. 35, no. 3, p. 107096, Apr. 2022, doi: 10.1016/J.TEJ.2022.107096.

[16] E. W. Gibson, “The Role of p-Values in Judging the Strength of Evidence and Realistic Replication Expectations,” *Stat Biopharm Res*, vol. 13, no. 1, pp. 6–18, 2021, doi: 10.1080/19466315.2020.1724560.