Speed vs. Sense: The Hidden Logic of Cyclist Routes

Andrii Kolisnyk

Table of Contents

0. Declaration of AI use

I have used AI for initial scoping, documentation research, project development and grammar checking.

Purpose of AI use	**Specific tool**
Initial scoping	ChatGPT, Gemini 2.5 Pro
Python libraries documentation research (loguru, concurrent futures)	Gemini 2.5 Pro, Claude 3.7 Thinking
Creating a README for GitHub repo	Gemini 2.5 Pro
Grammar and spelling checking	Microsoft MS Tool and Grammarly

Although, Gemini and Claude models are not free, I have used their integration into GitHub Copilot, which provides free access to all its features for students.

I declare that this submission is my own original work and that no AI-generated text or images have been used.

1. Introduction

Cities around the world are seeing a shift in agenda. Growing concerns about sustainability, well-being, and urban congestion influence a change in policy: moving away from car-centric planning to promote urban cycling and pedestrian-oriented environments (McClintock, 2002). London reflects this trend (Di & Palmieri, 2016), with cycling overtaking cars as the most common vehicle in Central London (The Economist, 2025). This shift can be accredited to the London Cycle Hire Scheme (LCHS), launched in 2010, which led the effort to normalise cycling citywide (Lovelace et al., 2020).

Research highlights existing debates around the socio-economic characteristics and spatial distribution of LCHS users. According to Goodman and Cheshire (2014), residents of poorer areas remain under-represented. This can be partially explained by the spatial distribution of cycle docking stations (Lovelace et al., 2020). Santander bike stations are primarily focused in central and inner London (Beecham et al., 2023), which can exacerbate inequality (Lovelace et al., 2020). Newer research suggests that with LCHS expansion, rental biking encourages sustainability and well-being in deprived areas while being a cheaper public transport alternative (Dalton et al., 2022). Another study found that rental bike schemes can help mitigate some of the barriers that lower-income residents face, such as bike costs, maintenance, and lack of secure storage and parking (McNeil et al., 2017)[1].

Building on this, it is essential not only to understand who uses the cycle scheme and where but also how they navigate the city. Prior research explored factors impacting cyclists' behavioural patterns regarding route choice (Nacxit et al., 2023), like having a quality bicycle infrastructure, public transport alternatives and individual's perception of the journey (Ma et al., 2014). Most research was done qualitatively or using a small sample. Although this approach offers invaluable insights into the motivation and perception of cyclists, cities are complex organisms where infrastructure interacts with culture in ways that make scalable, straightforward interventions challenging[2] (Colville-Andersen, 2018). Moreover, this study focuses on capturing behavioural patterns, which introduces an additional layer of unpredictability due to human behaviour.

This study will conduct statistical modelling to consider a plurality of infrastructural and contextual factors that may shape the choice between the fastest and ideal routes. Because the nature of the dependent variable (route choice) is binary, logistic regression is the best statistical approach for modelling in this instance (Hosmer et al., 2013). It allows the assessment of the probability of each choice using log-odds. These values give insight into each predictor's influence on choosing a specific route, which provides key intervention points for urban planners.

A mixed-method approach will be used to mitigate a limitation regarding the dataset used, which does not account for qualitative predictors such as streetscape design features, route

[1] This study was done in the United States, so it is not directly about the LCHS.

[2] Urban planning research consists of severe limitations regarding data capturing. Cities develop rapidly, as does our society, and capturing data about those cities can take a long time. Moreover, creating or changing a policy based on that data will require substantial time. New policies are based on historical data and can no longer be relevant when implemented (Raco, Durrant and Livingstone, 2018).

familiarity, safety concerns, etc. The introduction of systems mapping will provide a way to capture and assess this data. Systems mapping is essential for data capturing when dealing with larger scales, such as the city level, where the complexity and interconnection within the data make it difficult to obtain and process it (Bedinger et al., 2020). In a world where it is impossible to address every context and predict every future, systems mapping presents a framework that can cut through multiple scale levels and capture a wide breadth of system dimensions.

2. Quantitative Method: Statistical Modelling

2.1 Data Collection, Sources and Justification

The study will use TFL's Cycling Data Portal and TFL Journey Planner (API) to analyse cyclists' behavioural patterns regarding route choice. The data portal provides individual datasets containing information on all cycling journeys made via LCHS over two weeks. The study analyses two datasets[3]: 15 - 31 January 2025 and 15 - 31 July 2024 (Transport for London, n.d.-a).

To understand whether a cyclist used the optimal (fastest) route or the ideal (scenic) route, I will run the data through the API, which returns the fastest theoretical travel duration. At the same time, the dataset contains a real duration value. If the real duration value is close to the theoretical one, I can safely assume that the cyclist travels using the fastest route. Moreover, the API will return public transport commute time to be used as a control variable. This is done because strong evidence suggests that some users prefer public transport over cycling (Soza-Parra et al., 2019)[4].

2.2 Data Cleaning and Preparation

TFL API has specific input requirements on which parameter formats are acceptable. The datasets provided start and endpoints as bike docking station numbers or street names. Because the API does not recognise these formats, the TFL's "Cycling hiring availability feed" was used to convert these values into coordinates (Transport for London, n.d.-b).

Moreover, API only accepts dates within 7 days prior and 30 days after the request call date[5]. This inability to access historical data can be seen as a severe limitation within this study. Numerous factors historically impacted travel time: strikes, road accidents, different working times for public transport, road repairs, etc. (Noureldin & Diab, 2024). While I cannot address all of them, I can mitigate transport's working hours by preserving historical weekdays[6]. Furthermore, this will also allow me to use the day of the week as a control variable after classifying them as weekdays or weekends.

---

[3] These datasets were chosen to include a variation of weather as a control variable. While this predictor will not include detailed weather conditions, it can predict cycle route choice based on the season temperature. Temperature variation within seasons can be considered an unaccounted factor, but the length of the dataset will help mitigate that.

[4] My dataset is skewed towards cycling, as start and end travel points are at the bike docking stations.

[5] Request call date is the date of making an API request (the date of running the script).

[6] If the original date was a Friday than the converted date will be the following Friday after request call.

After cleaning the data and ensuring the start and end points were not the same[7], the concatenated dataset had more than 850,000 individual data points. Per each data point, two requests are made, resulting in the program running around 60 hours because of TFL's 500 requests per minute restriction. That is why stratified sampling[8] was conducted to run the analysis only on 10% of the data, which is a substantial amount of data for the nature of this study (more than 85,000 data points). This approach created a representative sample based on three variables: 'Bike model' (e-bike or regular), 'season' (winter or summer), and 'type of day' (weekend or weekday). This is essential for preserving the data for future statistical modelling.

2.3 API Processing

This section details an automatic process developed to enrich any journey data set within the Cycling Data Portal with theoretical travel times obtained with TFL Journey API. The script queries the API to return two variables corresponding with cycling and travel time for any origin and destination. This script was made with the aim of reproducibility, as this study found that TFL API lacks concrete documentation. Script can be easily modified and will work with any dataset which has valid API variable formats[9].

Moreover, as the program takes a lot of time to run, implementing an error feedback mechanism and progress update is essential for debugging and optimisation. Therefore, the script includes a logging mechanism (Delgan, 2022) that saves all the necessary information into a separate log file[10].

Given the nature of this study, I prioritised data completeness over runtime optimisation. To combat instances of rate limiting (HTTP 429: Too Many Requests), I introduced a delay strategy (10 seconds) after such a response[11]. Still, the program uses thread processing to run parallel requests for a faster processing speed. This feature prevents the program from getting stuck. If a single process uses the retry logic, other processes can continue sending requests.

Please refer to the code repository for more details (Kolisnyk, 2025).

2.4 Analysis and Preparation for Logistic Modelling

The API processing introduced two new variables: estimated travel times for public transport and cycling. They were transformed into percentages to display two metrics for statistical modelling. The first variable displayed the difference between user-recorded cycling travel times

---

[7] Around 1% of the data points had these values. It can be explained by people using Santander's 24-hour limit to make return journeys. Unfortunately, there is no way to track where they went and which route they took.

[8] When operating on large datasets and taking relatively small samples, random sampling tends to underrepresent smaller groups. In contrast, stratified sampling allows for a more representative sample (Singh & Mangat, 1996).

[9] See full TFL Journey API documentation here.

[10] It would be useful to implement a loading bar feature into my program (TQDM, 2023), but it doesn't integrate well with 'ThreadPoolExecutor.map' function. The program sees '.map' function as a single process, not a loop.

[11] 10 seconds was chosen due to running the code on an unstable network. If a reliable network is used it is possible to lower the delay time in half.

and theoretical (API-provided) estimates. The second metric (cycling_public_delta_pct) derives from the difference between the user's cycle time and corresponding public transport alternative duration, which indicates relevant efficiency[12].

Cycling efficiency will be transformed into a Boolean dependent variable (cyclist_class). This study assumes that whenever a cyclist is travelling close (10%) to the theoretical time estimate (API-provided) – this cyclist is taking the fastest route (returns 1). On the other hand, if a cyclist's travel time is more than 10% of the theoretical estimate – this study assumes that the scenic (ideal) route was taken[13] (returns 0).

Additionally, two more categorical control variables were created: 'time_class', which corresponds to a time of day (morning, day, evening, night), and 'distance_class', which shows how long a cyclist travelled.

These categorical predictors were created to transform raw data into meaningful variables that capture different aspects that impact route choice.

2.5 Logistic Regression Model and Assessing the Fit

Logistic regression was selected as a primary analytical method. It is the best statistical approach to analyse Boolean variables (Hosmer et al., 2013). While the logit regression returns log-odds, which are extremely hard to interpret, it is simple to transform them into odds ratios, which are much more intuitive. Furthermore, the model works as a classifier and is easily testable using prediction evaluation. If its accuracy score is not close to 100%, several unaccounted predictors should be found and tested (Steyerberg et al., 2010).

In this study, a logistic model is used to assess a relationship between route choice and having public transport alternatives while using several categorical variables as control. Treatment categories were selected to provide meaningful baselines for comparison: 'workday' represents a typical travel day, 'morning' is a time of commuting, 'summer' represents more favourable cycling conditions, 'medium_distance' represents a standard journey length, and 'CLASSIC' bikes are the standard non-electric bike option. Those control variables are of particular interest due to the exploratory nature of this study.

To see the significance of each predictor within this model, I used odds ratios which correspond to this formula (Hosmer et al., 2013):

$$\mathrm{OR} = \mathrm{e}^{\beta_1}$$

One of the ways to assess the fit of a logistic regression model is through the analysis of the Pseudo R-squared value. Pseudo R-squared functions similarly to regular R-squared when assessing the distribution of residuals (Hu et al., 2006). The Pseudo R-squared value of the model is 0.23. This means that this model fit can explain 23% of the cycling route choices within the data[14].

---

[12] There are some outliers within the dataset which, through this process (division), created a small amount of infinite and NaN values which had to be dropped.
[13] The large data size allows me to make those assumptions.
[14] The Pseudo R-squared value tends to be lower than regular R-squared (Hosmer et al., 2013).

This highlights that a lot of potential predictors were not included. Because of this, it is vital to identify them (see qualitative method section).

The most significant categorical predictor is short distance compared to medium distance (OR = 18). This means that people travelling under 5 minutes are 18 times more likely to take the fastest route (more in Emergent Findings). Moreover, 95% confidence interval values were included to see the range within the higher and lower ceilings. Please refer to the corresponding code section or Figure A (see Appendix) for more details.

As logistic regression functions as a classifier, it is possible to test the model's overall accuracy. This study does not perform an 80/20 test split as the model can be tested on itself. The performance is 72% accuracy. This is relatively low considering the dichotomous status of the dependant variable. Hence, if the model chose the route randomly, the baseline accuracy would be around 50%. Despite this, although 22% uptake signifies that multiple predictors within this model can contribute massively towards route choice, it is still important to identify other predictors that are not included.

3. Qualitative Method: Systems Mapping

As discussed in the statistical modelling section, the logistic regression generated does not fully explain the cyclist' route choice. The behavioural pattern of choosing the fastest or the ideal (scenic) route involves a number of qualitative predictors that are not easily quantifiable. This section aims to assess those predictors through systems mapping.

As mentioned previously (see Introduction) systems mapping is an invaluable framework to be used within urban planning discipline. According to Bedinger et al. (2020) one of the ways to understand urban systems through mapping is by using the Abstraction Hierarchy (AH) approach.

Although Abstraction Hierarchy (AH) is a powerful systems-mapping tool adaptable to urban planning, the time constraints of this research do not allow for its full application. Nevertheless, AH will be adapted as a guiding framework for constructing a causal loop diagram in this study.

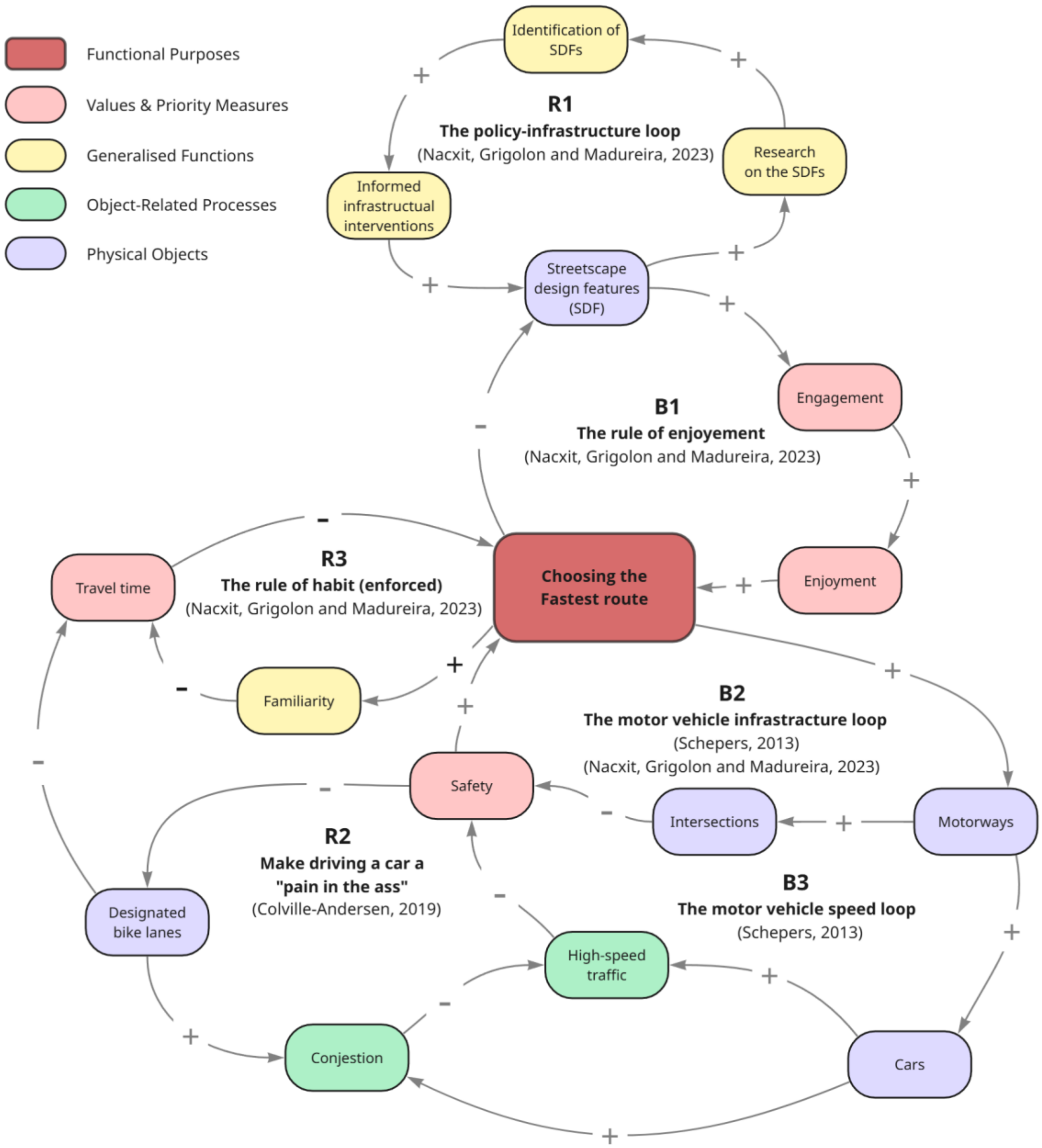
3.1 Sources and Evidence Base

This study did not collect any primary data, so this method will use secondary research data to justify the causal relationships. This data will primarily consist of academic literature and policy reports. This data was chosen to ensure reliability and consistency.

3.2 Creating a Causal Loop Diagram

A causal loop diagram (CLD) functions as a tool to map out the structure and the feedback of the system and its behaviour (Haraldsson, 2004). In this study uses CLD to map the different possible predictors that influence cyclists' decision-making regarding route choice. As this research considers two route choices (fastest and ideal), it is difficult to map a causal loop diagram without shifting it into a logical flow diagram[15]. Because of this, fastest route was chosen for mapping, as it is more intuitive and easily identifiable (see Figure 1).

Figure 1. *A cyclist's route choice causal loop diagram*[16]



---

[15] If so, this will create two similar diagrams with the opposite link from the centre. Route choice impacts all connected areas in opposite ways, except route familiarity.

[16] The colour coding was done according to the 5 levels of Abstraction Hierarchy (AH) approach adapted for urban planning (Bedinger et al. 2020).

3.3 Justification of Causal Relationships

To abide by the best practices of systems mapping, each causal link within the diagram needs to be considered a hypothesis, given that it is not intuitive. Therefore, every connection needs to be justified. As previously mentioned (see section 3.1), the primary source of link justification will be a synthesis of academic literature.

Previous research states that the route "aesthetics" have been seen to be a top motivator for the enjoyment of the cycling experience (Nacxit et al., 2023). The study used VR with eye-tracking technology to measure how engaged the cyclist was during a specific route. Because bicycles travel at a "human speed", it is possible to compare cyclists to pedestrians. A study was conducted in China that measured the city's walkability and what variables influence it (Wang & Chen, 2023). Both studies reported an increased engagement when encountering streetscape design elements (SDFs) including greenery, vegetation, water bodies and diversity of land use. This outlines the importance of research and informed infrastructural interventions to improve cyclability[17].

In the city road networks are often structured hierarchically (Schepers, 2013). This hierarchy consists of motorways and distribution roads, both of which are designed to accommodate the high speed of a motor vehicle. Drivers typically use these roads to find the fastest route. The study finds that although cyclists generally avoid large motorways[18], they still interact a lot on the distributor roads. This exposes cyclist to high-speed traffic, which increases a likelihood of bicycle-motor vehicle (BMV) crashes compared to lower-speed access roads. To avoid the risk motor vehicles, pose to cyclists and pedestrians cities impose speed limits and a number of speed barriers (like traffic lights). This increases the risk of congestion but makes cycling and walking more safe.

Moreover, cities around the world are promoting bicycle use. Colville-Andersen (2019) emphasizes the importance of making driving less enjoyable. This can be accomplished by a concept of induced demand (Cervero, 2001). If you build infrastructure for cars – cars will come, if you build for biking – cyclists will[19].

4. Emergent findings

This study's primary focus was data exploration: both quantitative (statistic modelling) and qualitative (systems mapping). The methodological mix worked in tandem to collect and assess the various predictors which impact a cyclist's route choice.

---

[17] When a cyclist is familiar with a route, the travel not only becomes more efficient but also becomes more enjoyable due to cyclists' ability to focus on the SDFs. This highlights the vital importance of SDFs with any route choice.
[18] In London, the existence "cycleways" (separated bike lanes) allows for more of safe road usage for cyclists. Still, the intersections that the vehicles share can lead to a number of BMVs (Aldred, Kapousizis and Goodman, 2021).
[19] This concept is usually mentioned when talking about American "stroads". It describes why creating more traffic lanes brings only temporary congestion relief.

The classification of cyclists' route choice cannot be 100% accurate. As mentioned previously, the statistical model assumes that any cyclists which travels below +10% of the theoretical journey duration is choosing the fastest route. Because of these assumtions the methodology within this study cannot fully evaluate predictors that can impact the route choice. However, due to this study's exploratory nature, it has revealed some emergent findings.

The statistical model reported a substantial likelihood (OR = 4.5) of people taking the scenic route whenever having a good public transport alternative for fast travels. However, as outlined previously, the data used was largely biased towards cycling, as the start and end journey points are LCHS docking stations. For further analysis, it would be beneficial to simulate a number of random coordinates within London and calculate those coefficients afterwards. This will effectively mitigate any bias this study's dataset might have towards cycling travel times.

Furthermore, cyclists are two times more likely to take the fastest route when travelling in the morning. This can be explained by people going to work and prioritising being on time. As evident by the season variable, average temperature impacts cycling route choice, but it is not as drastic as other predictors. This shows that a detailed weather variable might be vital in assessing cyclist's route choice.

The largest relative impact on route choice (as described in Figure A) is the 'class_distance' variable. Compared to medium distances short distance journeys (under 5 minutes) are 16 times more likely to take the fastest route, while long distance (over 15 minutes) are almost 7 times less likely. This is an interesting phenomenon that can reflect the qualitative findings. While this finding is not a conclusive, this could mean that cyclists are less likely to choose routes that are unsafe and do not have streetscape design features (SDFs) when travelling across bigger time periods. Moreover, as highlighted by systems mapping there are a number of predictors that SDFs include. It includes quality of bike-lanes, congestion, number intersections. This exposes an interesting area for future research. A combination of GIS mapping with logistic regression modelling can be an interesting way to quantitatively capture this type of data.

Several smaller-scale studies are needed to collect each predictor identified through systems mapping and integrate them to assess if a cyclist's route choice behaviour can be predicted at all.

5. Appendix

Figure A. *Odds ratios of the logistic regression*.

	Lower CI	Upper CI	OR
Intercept	19.307057	21.864932	20.546228
C(type_of_day, Treatment(reference='workday'))[T.weekend]	0.564737	0.615255	0.589455
C(time_class, Treatment(reference='morning'))[T.evening]	0.561578	0.613790	0.587104
C(time_class, Treatment(reference='morning'))[T.midday]	0.500876	0.549013	0.524392
C(time_class, Treatment(reference='morning'))[T.night]	0.437106	0.492065	0.463772
C(season, Treatment(reference='summer'))[T.winter]	1.332287	1.423276	1.377030
C(distance_class, Treatment(reference='medium_distance'))[T.long_distance]	0.159320	0.172844	0.165944
C(distance_class, Treatment(reference='medium_distance'))[T.short_distance]	16.830372	19.622717	18.172992
C(bike_model)[T.PBSC_EBIKE]	2.666843	2.936050	2.798211
cycling_public_delta_pct	4.389387	4.642155	4.514002

(Kolisnyk, 2025)

6. Bibliography

Aldred, R., Kapousizis, G., & Goodman, A. (2021). Association of Infrastructure and Route Environment Factors with Cycling Injury Risk at Intersection and Non-Intersection Locations: A Case-Crossover Study of Britain. *International Journal of Environmental Research and Public Health*, *18*(6), 3060. https://doi.org/10.3390/ijerph18063060

Bedinger, M., Beevers, L., Walker, G. H., Visser-Quinn, A., & McClymont, K. (2020). Urban Systems: Mapping Interdependencies and Outcomes to Support Systems Thinking. *Earth's Future*, *8*(3). https://doi.org/10.1029/2019ef001389

Beecham, R., Yang, Y., Tait, C., & Lovelace, R. (2023). Connected bikeability in London: Which localities are better connected by bike and does this matter? *Environment and Planning. B, Urban Analytics and City Science/Environment & Planning. B, Urban Analytics and City Science*, *50*(8), 2103–2117. https://doi.org/10.1177/23998083231165122

Cervero, R. (2001). Induced Demand: An Urban Metropolitan Perspective. *Escholarship.org*. https://escholarship.org/uc/item/5pj337gw

Colville-Andersen, M. (2018). *Copenhagenize*. https://doi.org/10.5822/978-1-61091-939-5

Colville-Andersen, M. (2019). *Hour of Truth for Copenhagen's Great Urban Experiment*. Medium. https://colvilleandersen.medium.com/hour-of-truth-for-copenhagens-great-urban-experiment-3e196842e55b

Dalton, A. M., Burke, A., & Jones, A. (2022). Free-to-use cycle provision schemes have potential to encourage cycling and reduce inequalities. *Journal of Transport & Health*, *26*, 101391. https://doi.org/10.1016/j.jth.2022.101391

Delgan. (2022). *Delgan/loguru*. GitHub. https://github.com/Delgan/loguru

Di, G., & Palmieri, S. (2016). *CYCLING IN A MEGACITY: THE CASE OF LONDON*. ResearchGate. https://www.researchgate.net/publication/308419064

Goodman, A., & Cheshire, J. (2014). Inequalities in the London bicycle sharing system revisited: impacts of extending the scheme to poorer areas but then doubling prices. *Journal of Transport Geography*, *41*, 272–279. https://doi.org/10.1016/j.jtrangeo.2014.04.004

Haraldsson, H. V. (2004). *Introduction to system thinking and causal loop diagrams*. ResearchGate; Department of Chemical Engineering, Lund University. https://www.researchgate.net/publication/258261003_Introduction_to_system_thinking_and_causal_loop_diagrams

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied Logistic Regression* (3rd ed.). John Wiley & Sons.

Hu, B., Shao, J., & Palta, M. (2006). PSEUDOR. *Statistica Sinica*, *16*(3), 847–860. JSTOR. https://doi.org/10.2307/24307577

Kolisnyk, A. (2025). *Doctor2007/tfl-analysis*. GitHub. https://github.com/Doctor2007/tfl-analysis

Lovelace, R., Beecham, R., Heinen, E., Vidal Tortosa, E., Yang, Y., Slade, C., & Roberts, A. (2020). Is the London Cycle Hire Scheme becoming more inclusive? An evaluation of the shifting spatial distribution of uptake based on 70 million trips. *Transportation Research Part A: Policy and Practice*, *140*, 1–15. https://doi.org/10.1016/j.tra.2020.07.017

Ma, L., Dill, J., & Mohr, C. (2014). The objective versus the perceived environment: what matters for bicycling? *Transportation*, *41*(6), 1135–1152. https://doi.org/10.1007/s11116-014-9520-y

McClintock, H. (2002). *Planning for Cycling*. Elsevier.

McNeil, N., Dill, J., MacArthur, J., Broach, J., & Howland, S. (2017). Breaking Barriers to Bike Share: Insights from Residents of Traditionally Underserved Neighborhoods. *TREC Final Reports*. https://doi.org/10.15760/trec.176

Nacxit, R., Grigolon, A. B., & Madureira, A. M. (2023). Cyclists' perception of streetscape and its influence on route choice: A pilot study with a mixed-methods approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, *99*, 374–388. https://doi.org/10.1016/j.trf.2023.10.029

Noureldin, M. G., & Diab, E. (2024). Impacts of long-term transit system disruptions and transitional periods on travelers: a systematic review. *Deleted Journal*, *1*(1). https://doi.org/10.1007/s44327-024-00015-5

Raco, M., Durrant, D., & Livingstone, N. (2018). Slow cities, urban politics and the temporalities of planning: Lessons from London. *Environment and Planning C: Politics and Space*, *36*(7), 1176–1194. https://doi.org/10.1177/2399654418775105

Schepers, P. (2013, December 6). *A safer road environment for cyclists*. ResearchGate. https://www.researchgate.net/publication/259280723_A_safer_road_environment_for_cyclists

Singh, R., & Mangat, N. S. (1996). Stratified Sampling. *Kluwer Texts in the Mathematical Sciences*, *15*, 102–144. https://doi.org/10.1007/978-94-017-1404-4_5

Soza-Parra, J., Raveau, S., Muñoz, J. C., & Cats, O. (2019). The underlying effect of public transport reliability on users' satisfaction. *Transportation Research Part A: Policy and Practice*, *126*, 83–93. https://doi.org/10.1016/j.tra.2019.06.004

Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., Pencina, M. J., & Kattan, M. W. (2010). Assessing the Performance of Prediction Models. *Epidemiology*, *21*(1), 128–138. https://doi.org/10.1097/ede.0b013e3181c30fb2

The Economist. (2025, May 22). *London has become a cycling city*. The Economist. https://www.economist.com/britain/2025/05/22/london-has-become-a-cycling-city

TQDM. (2023, May 1). *tqdm/tqdm*. GitHub. https://github.com/tqdm/tqdm

Transport for London. (n.d.-a). *Cycle data portal*. Cycling.data.tfl.gov.uk. https://cycling.data.tfl.gov.uk/ 412JourneyDataExtract15Jan2025-31Jan2025.csv, 400JourneyDataExtract15Jul2024-31Jul2024.csv

Transport for London. (n.d.-b). *Cycle Hire availability – London Datastore*. Retrieved June 6, 2025, from https://data.london.gov.uk/dataset/cycle-hire-availability

Wang, F., & Chen, F. (2023). Factors Affecting Neighborhood Walkability: A Pilot Empirical Study in Qingdao, China. *Journal of Urban Planning and Development*, *149*(1). https://doi.org/10.1061/jupddm.upeng-4138