WHO'S RIDING THE BUS: AN INVESTIGATION OF BIAS IN TRANSIT MODE CHOICE

Zoey Yandell

Math Modeling Fall 2023

Professor Will Mitchell

Introduction

American cities are incredibly dependent on cars. Highways run through the middle of neighborhoods, carrying commuters to downtown centers with never enough parking and congestion everywhere. In this context, a robust transit system can do a lot to reduce car dependence, easing that congestion as well as reducing transportation emissions and making the city more accessible for those who do not have or cannot afford what for many is one of the largest investments of their lives.

However, public transit has been slow to catch on in America. It's a common truth that public transit is used in America much less intensively than many parts of Europe[1]. With limited ridership, the growth of transit systems is slow, and their impact smaller than it could be. That's why it's important to study the factors influencing transit choice.

There is already a robust literature employing many different methods and models to study transit choice, although the fact that transit systems vary across the world means that many of these studies are specific to their location. Still, some common themes emerge. Riders may be influenced by convenience factors, such as reliability of transit, route speed, amount of transfers, and how frequently the bus comes, comparing these all to a car trip, which is consistently reliable and available, and does not require any transfers. Riders may also take into account cost, whether that be transit fare or the cost of gas and parking. This factor is complicated by the fact that there is a large one-time cost for a car, representing perhaps an adoption barrier, which is made irrelevant once the rider has bought the car (since they will continue to pay it off whether or not they use it). Finally, there is an aspect of personal safety or safety perception that may dissuade riders from choosing public transit if it is perceived as less safe.[2]

Other studies investigate more complex factors or interactions, such as the impact of the route's purpose or different choices that are made by individuals, families with children, and

[1] Committee for an International Comparison of National Policies and Expectations Affecting Public Transit, "Transit Use, Automobility, and Urban Form: Comparative Trends and Patterns."

[2] Catalano, Casto, and Migliore, "Car Sharing Demand Estimation and Urban Transport Demand Modelling Using Stated Preference Techniques"; "Travel Mode Choice Preferences of Urban Commuters in Kuching City, Malaysia Based on Stated Preference Data"; Mullyani et al., "Transportation Mode Choice Model between Private Car and Railway for Responding the Operation of Makassar."

other groups.[3] However, none of the studies I reviewed significantly interfaced with the impact of bias on transit choice.

As mentioned above, perception of safety is a factor for many people when choosing transit routes[4]. Perception of safety can be influenced by actual safety incidents or by conditions of the route, such as darkness, remoteness, or lack of transit staff (for example on a light rail transit line). It can also be influenced by biases about the people who are riding that bus, whether that be racism, anti-homeless sentiment, or other conscious or subconscious biases. People might even have biases about the "type of people" who ride the bus, in the same way that an article from BCG Henderson characterizes sentiment about alternative transit measures: "users of new-mobility options are seen as disruptors too, making them an outgroup set apart from commuters who use traditional modes"[5]. A study conducted in Germany by Liebe and Bayer also showed that prejudices impacted transit choice when choosing between carpooling options with varying factors including the ethnicity of the driver[6].

These biases can be reinforced or weakened by the actual experience of riding public transit. That makes them a factor that, unlike the other factors mentioned above, is responsive in real time to the ridership of the routes. Thus, the impact of bias is well-suited to study using an agent-based model.

This study attempts to use a simple agent-based model of binary transit choice to investigate how larger trends in a transit system might be shaped by the responsive biases of its travelers. It models this interaction on two different simple transportation networks, using simplifying assumptions about other factors. The model shows that in a system where both groups experience bias at equal levels, one group will quickly adopt a higher rate of transit ridership than the other.

Methods

[3] Mullyani et al., "Transportation Mode Choice Model between Private Car and Railway for Responding the Operation of Makassar."

[4] Spears, Houston, and Boarnet, "Illuminating the Unseen in Transit Use"; Delbosc and Currie, "Modelling the Causes and Impacts of Personal Safety Perceptions on Public Transport Ridership."

[5] Hazan et al., "What Drives Drivers?"

[6] Liebe and Beyer, "Examining Discrimination in Everyday Life."

The model created for this study is a simple agent-based model over a transportation network. The network is created as a network graph (Fig. 1), where each node, representing a destination, is connected to several other nodes (stored in an adjacency matrix) to represent trips that can be made in a car or through public transit. These connective edges are given a weight corresponding to the "relative appeal" of the route, a variable that is here used as a stand-in for the static choice factors listed above (speed, reliability, transfers, frequency, and those non-bias-responsive factors of perceived safety).

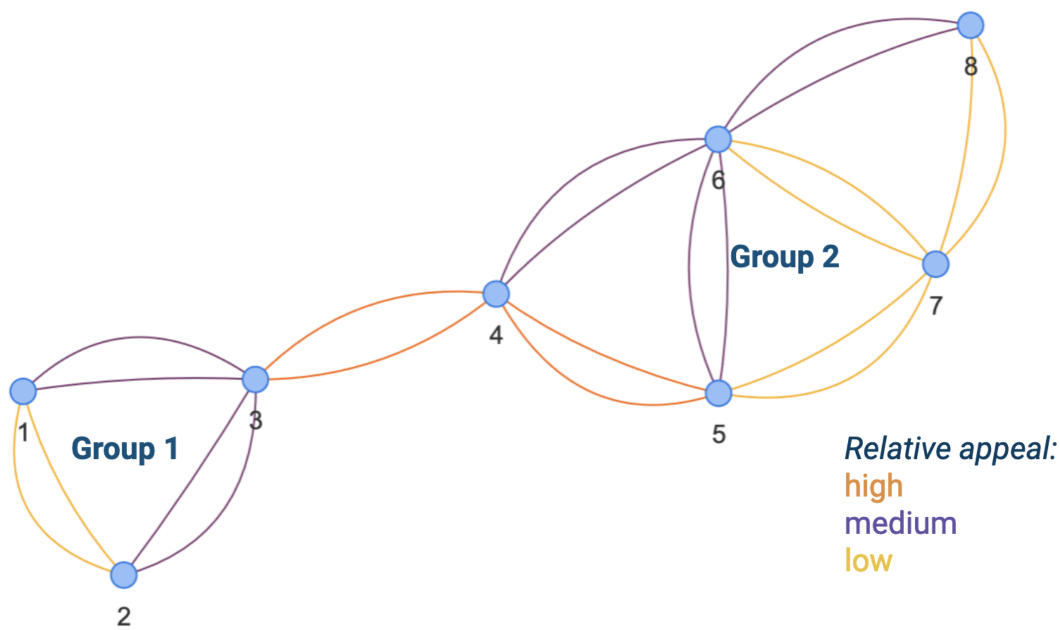


Figure 1. A network graph displaying "Network 1", where relative appeal is designated by route color. Each pair of nodes has two connections, corresponding to routes in both directions.

The initial network created for this model is a network with eight nodes, which are clustered in two "neighborhoods": Neighborhood 1, consisting of nodes 1, 2, and 3, and Neighborhood 2, consisting of nodes 4, 5, 6, 7, and 8. For this study, bias was a function of neighborhood affiliation: riders from Neighborhood 1 would prefer to ride with their own neighbors than riders from Neighborhood 2, and vice versa.

Agents are created with four attributes, location, affiliation, and preference for "comfort" and "appeal" (simply called "agent.comfort" and "agent.appeal"). The location for each agent is randomly picked from the set of nodes, and their neighborhood affiliation assigned based on their starting location. Comfort and appeal are randomly generated percentages that sum to 1. If an agent has a higher "appeal" preference, they will consider the appeal of the route more strongly in deciding whether to drive or take transit. If they have a higher "comfort" preference, they will weight the bias coefficient more strongly.

For each timestep, each of the agents will randomly choose a new destination from the nodes that are connected to their location, including the option to stay in the same place. Then, they will generate a preference for transit, ranging from 0 to 1. This preference is the agent's likelihood of choosing public transit over a car. It is calculated as follows:

$$preference = a \times A + c \times B,$$

Where a is agent.appeal, A is the relative appeal of the route, c is agent.comfort, and B is the bias coefficient of the route.

The bias coefficient of a route is calculated as the percentage of riders, over the whole history of the route, that share the group affiliation of the agent. This assumes that agents somehow magically have accurate knowledge of past ridership demographics. In this model, the assumption is used to vaguely approximate the impression that the agent may already have of the route, whether from past rides, speaking with other riders, or other biases. It is important to note that this model is only a very general model of biased behavior trends in transit systems, and is not meant to achieve any numeric significance.

Many other broad assumptions are made that have strong impacts on the numerical outputs of the model, such as the actual numbers assigned to relative appeal, the equal distribution of agent.comfort and agent.choice, and the fact that no other weights are incorporated into the equation to account for the fact that bias may be only a small portion of choice factors agents take into consideration. A test run of this model with the bias portion of this equation halved found different numbers but a similar qualitative result, indicating that these assumptions will impact the quantitative results of the model but not the trends seen. Further work on this project could investigate the relative impacts of these assumptions, as discussed in the "Limitations" section.

Randomness is incorporated into this model both in the distribution of attributes, the choice of destinations, and a random choice of transit mode that follows the agent's calculated preference.

Results

The model was investigated using two different networks (Fig. 2 and Fig. 3). The first features two neighborhoods of differing sizes with semi-randomly scattered relative appeals, and the second features two identical neighborhoods with mirroring relative appeals. For both networks and all runs, the model ran for 50 timesteps with 10,000 agents.

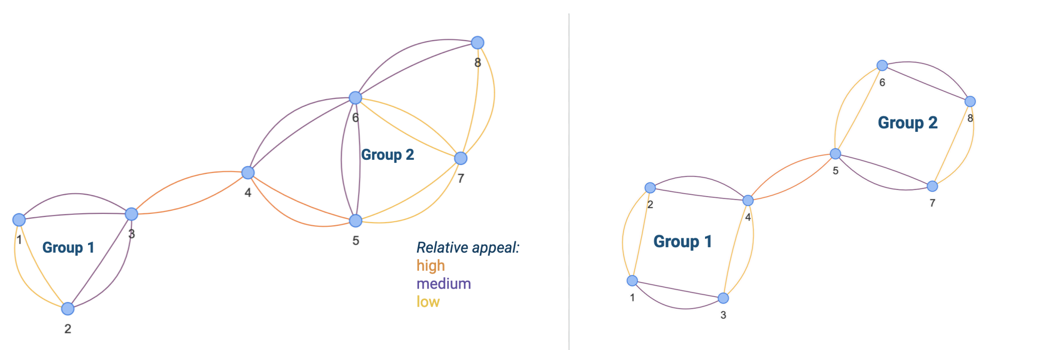


Fig. 2 (left) and 3 (right). Network graphs of "Network 1" and "Network 2" respectively. Both networks have neighborhoods divided between nodes 4 and 5 (that is, Group 1 includes nodes 1-4, while Group 2 includes nodes 5-8).

The model was run for Network 1 with three different bias sensitivities. First, the full, original model was run, incorporating bias as described in the "Methods" section as a percentage of ridership (Fig. 4). The second run was an unbiased run, which replaced the bias coefficient with a percentage of the top route's ridership (Fig. 5). The third run modified the original bias calculations by multiplying it by 0.5, reducing the relative impact of bias (Fig. 6).

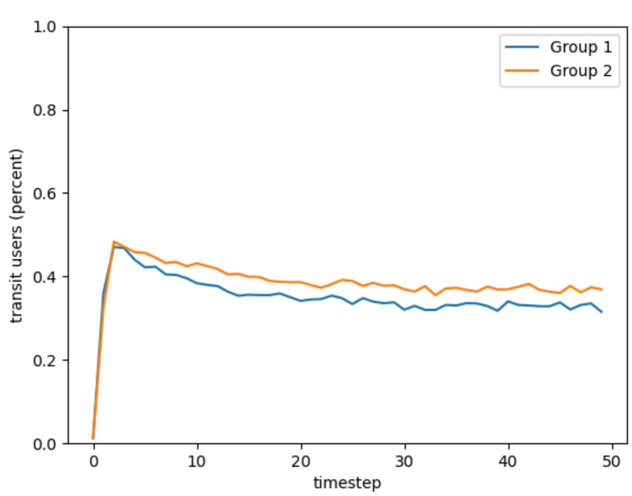


Figure 4. A graph comparing the percentage of each group that chooses to use transit over time in a biased run of the model for Network 1.

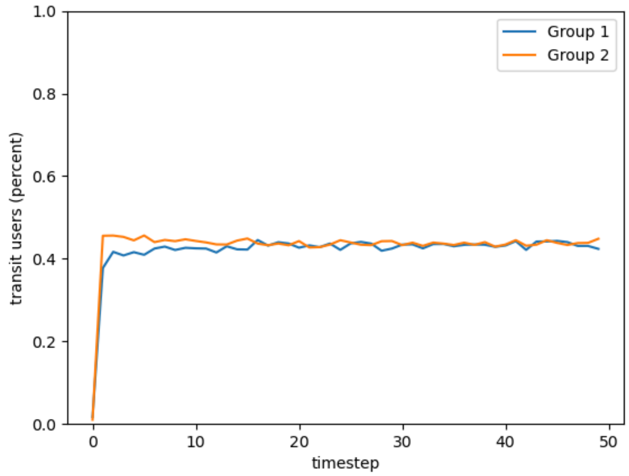


Figure 5. A graph comparing the percentage of each group that chooses to use transit over time in an unbiased run of the model for Network 1.

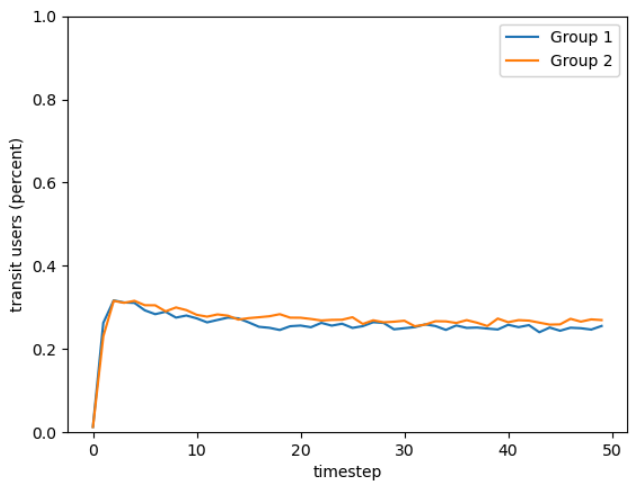
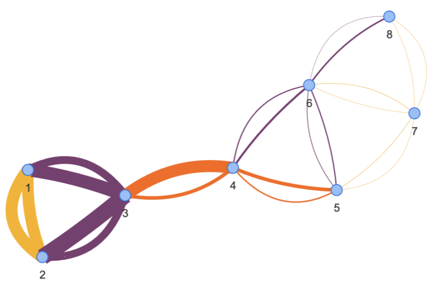


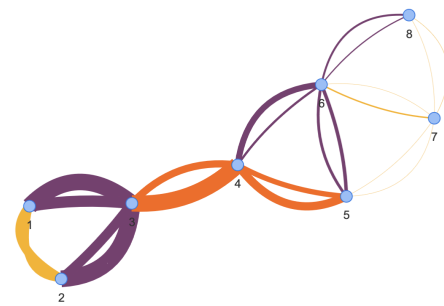
Figure 6. A graph comparing the percentage of each group that chooses to use transit over time in a modified biased run of the model for Network 1.

As these figures show, in both biased runs, one group adopts a higher transit ridership percent. The other shows higher percentages of car use, though that is not show in the figures here. In contrast, though the unbiased runs occasionally begin with one group predominating, they very quickly even out to equal transit ridership among both groups. The patterns displayed here are consistent for many runs of the model.

The trends shown above hold true when the networks are divided as shown in Fig. 2, with equal amounts of destinations, and thus about equal ridership, in both groups. In this case, Group 2 predominates slightly. However, when the division is changed to include nodes 1 through 5 in Group 1, Group 1 will predominate.

Patterns of where this ridership appears are, as may be expected, shaped heavily by the home base of each neighborhood. Here is the ridership distribution of Group 1 in a biased and unbiased run at time t=9, when Group 1 is defined to include only nodes 1-3:

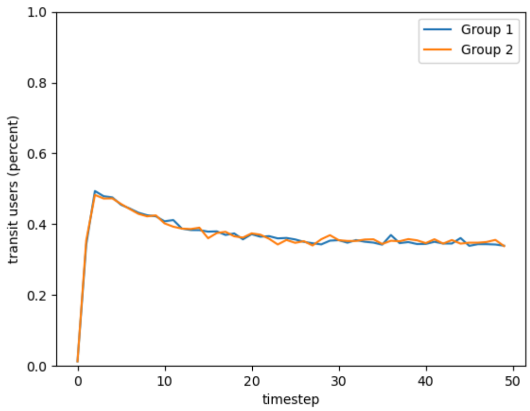


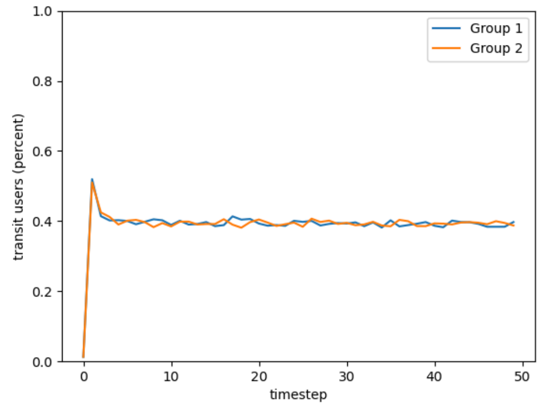


Figures 7 and 8. Network graphs showing the distribution of Group 1 riders in a biased (left) and unbiased (right) run of the model at time t=9. Stroke weights denote ridership density, while color corresponds to route relative appeal.

In the unbiased run, Group 1 adopts transit in neighborhood 2 more quickly than in a biased run, although because riders still have to distribute themselves to that neighborhood there are many more riders still in neighborhood 1. Over time, that uneven distribution will equalize for the unbiased run, and ridership will be evenly spread through the system. For the biased run, ridership will equalize to an extent, but at t=49 Group 1 still prefers routes in their own neighborhood.

For Network 2, the results look slightly different. Here are the relative riderships for both a biased and unbiased run, where the groups are divided exactly evenly:





Figures 9 and 10. Graphs comparing the percentage of each group that chooses to use transit over time in a biased run (left) and unbiased run (right) of Network 2.

Even in a biased run, ridership is even between the groups. In an unbiased run, for both groups, ridership consistently spikes and then drops to around 42%, while in a biased run ridership gradually lowers from its spike to somewhere around 37%. It is possible that the inclusion of bias negatively impacts total transit ridership by making each group less likely to ride in each other's neighborhood, but given the robust assumptions made in this model, the difference between the two runs is too small to make strong inferences.

Discussion

The various trends in ridership in the first network strongly suggest that when combined with geographic differences between the groups, mutual bias does result in different patterns of transit use. Generally, this presents as higher ridership in the group of higher population, but when populations are relatively similar, one group is still consistently favored. This may be the result of geography, although a deeper exploration of this phenomenon is beyond the scope of this study.

The results of Network 2 also indicate that this disparity in results does not come only from the inclusion of bias in the model, but depends upon some difference in circumstance giving preference to one group over the other. While this version of the model incorporates geographic difference, further research might look into the impacts of difference of preference on a population level. In reality, bias rarely exists on the same level between two different groups.

An extension of this study might investigate the results of one-sided bias. Likewise, given more time, this study could more deeply investigate the factors – both geographic and population-based – that prefer one group over another.

Even on the basic level that a simple model provides, this study opens up new insights about the working of a transit system with important implications for transit design, policy and education. It introduces a potentially complicating variable not considered in other models. Although individual preferences are commonly included in transit models, many do not consider riders' feelings not only about public transit or the route itself, but about their fellow passengers. Bias and prejudice are an important part of human behavior. We see it play out in many transit systems around the world, especially in America, where many perceive the bus as unsafe or used predominantly by "other"s: poor people, the unhoused, African Americans. This bias can have a real impact on who takes public transit, and where. When one group avoids public transit because of their preconceptions about who else is riding, we remain trapped in a system that is dependent on cars and incapable of significant change. And even if the measurable impact of bias in a transit system is relatively small, it only takes a small amount of effort to make inroads on this issue.

Simply considering the interaction of bias with other aspects of the transit system when designing messaging, geography and policy can have big results. Intentional messaging or education can change riders' perception of who rides the bus and who is welcome, challenging those preconceived stereotypes. Transit providers who consider how their routes are designed and who might ride them can work with drivers and communications departments to break down those perception barriers and ensure that everyone feels comfortable on the bus and that the bus is for them. And policy, such as reduced fare programs, can be designed to support current riders as well as welcome new riders. It's hard to fight biases that have been prevalent in our society for a long time. But recognizing that they exist, and have an impact on the behavior of a transit system, can be a first step towards cognizant design and a healthier, more universal transit system.

<u>Limitations</u>

It's important to remember that this is only a model, and a transit system is very complicated. On top of the workings of thousands of agents, with preferences and behaviors much more complex than those modeled here, there is also a complex system where the differences between routes are much more than a simple gradient in relative appeal. The attributes that make a route appealing to one traveler might disincentivize another. One important aspect of a transit system is transfers between routes, which are not considered in this model at all. Neither is the connectivity of a whole trip (an agent might take the bus to their first location then drive to the next, when their car shouldn't be available to them at all). The factors that go into a transit system are much more complex than this model accounts for, and the emergent behavior much different than displayed here.

There are models that consider the many different levels and interactions that might paint a fuller picture of a transit network. This model does not do that. This model investigates a very simplified system in terms of one specific behavior. It cannot say anything about either the specifics of the behavior displayed, or the way that behavior might present itself in reality, because there are far too many simplifying assumptions made.

What this model can do is demonstrate that, given that the phenomenon of bias exists, it may have an impact on the emergent behavior of transit systems. Despite its simplicity, that is a significant finding that should be taken into account in working with these systems.

Given more time, this study might examine the factors that privilege one group over another, including geography, the distribution of relative appeal, and the characteristics of each group. As mentioned above, it would be interesting to investigate the trends that emerge when only one group exhibits bias, or when one group has a stronger preference for transit over cars. It would also be worth attempting to account for a more complex transit system, including different ways to travel between nodes and routes with transfers. An ideal model would be able to incorporate multiple different aspects of a transit choice, from route frequency to associated costs. However, an ideal model would be difficult to design and even more difficult to analyze.

Conclusion

Though simple, this transit model takes into account an aspect of transit choice behavior not considered by previous works on the topic. By focusing in on the bias-driven interactions between agents, the study demonstrates how an agent-based model can add value to the field of transit system modeling. It proves that bias can have an impact on the behaviors of a transit system, and result in disparities in adoption of public transit. The implications of this are relevant throughout the transit field.

It can be difficult to model a system characterized by human behavior, just as it can be difficult to design such a system. Both require careful consideration of how these designs will interact with reality. The truth is, bias is not the most important factor to consider in a transit system. Even if some potential riders are made uncomfortable by the existence of unhoused people riding the bus, those buses are far more essential to their unhoused riders than they are to ridership that has the privilege to choose between transit and their own personal vehicle. And making the bus attractive to a broader audience requires consideration of much more than personal biases. Still, we live in a world where various types of biases are widespread, and it will impact the way that people interact with their transit system – not just the routes they choose to ride, but the complaints they make, the way they vote, the transit lines they don't want extended into their communities because it will bring the "wrong people" there.

Likewise, bias may not have a statistically relevant impact on the broader workings of a transit system. Since this study is so abstract, it cannot quantify the size of disparities related to bias. However, it interacts with the system as a whole differently than many other factors. A variable that is responsive to ridership might complicate the behavior of a system that depends on static variables. The idea of bias as an input into transit models introduces a different way of looking at this phenomenon that might yield startling results.

References

Bastarianto, Faza Fawzan, Thomas O. Hancock, Charisma Farheen Choudhury, and Ed Manley. "Agent-Based Models in Urban Transportation: Review, Challenges, and Opportunities." *European Transport Research Review* 15, no. 1 (June 15, 2023): 19. https://doi.org/10.1186/s12544-023-00590-5.

Catalano, Mario, Barbara Lo Casto, and Marco Migliore. "Car Sharing Demand Estimation and Urban Transport Demand Modelling Using Stated Preference Techniques," no. 40 (2008).

Committee for an International Comparison of National Policies and Expectations Affecting Public Transit. "Transit Use, Automobility, and Urban Form: Comparative Trends and Patterns." In *Making Transit Work: Insight from Western Europe, Canada, and the United States -- Special Report 257*. Washington, D.C.: National Academy Press, 2001. https://doi.org/10.17226/10110.

Delbosc, Alexa, and Graham Currie. "Modelling the Causes and Impacts of Personal Safety

Perceptions on Public Transport Ridership." *Transport Policy* 24 (November 1, 2012): 302–9. https://doi.org/10.1016/j.tranpol.2012.09.009.

Hazan, Joel, Benjamin Fassenot, Ammar A. Malik, and Joanna Moody. "What Drives Drivers? How to Influence Mobility Behaviors." BCG Global, July 21, 2020. https://www.bcg.com/publications/2020/influencing-mobility-behaviors-what-drives-drivers.

Innocenti, Alessandro, Patrizia Lattarulo, and Maria Grazia Pazienza. "Car Stickiness: Heuristics and Biases in Travel Choice." *Transport Policy* 25 (January 1, 2013): 158–68. https://doi.org/10.1016/j.tranpol.2012.11.004.

Liebe, Ulf, and Heiko Beyer. "Examining Discrimination in Everyday Life: A Stated Choice Experiment on Racism in the Sharing Economy." *Journal of Ethnic and Migration Studies* 47, no. 9 (July 4, 2021): 2065–88. https://doi.org/10.1080/1369183X.2019.1710118.

Mullyani, Savitri Prasandi, Muhammad Islan Ramli, Sakti Adji Adisasmita, Muhammad Asad Abdurrahman, and Hajriyanti Yatmar. "Transportation Mode Choice Model between Private Car and Railway for Responding the Operation of Makassar." In *E3S Web of Conferences*, Vol. 429. EDP Sciences, 2023. https://doi.org/10.1051/e3sconf/202342903016.

Nurhasan, Hadhori, and Utomo Sarjono Putro. "An Analysis of Consumer Behaviors in Choosing Public Transportation." *Journal of Indonesian Applied Economics* 9, no. 2 (August 31, 2021): 17–26. https://doi.org/10.21776/ub.jiae.009.02.3.

Perevozova, Iryna, Svitlana Minakova, Khrystyna Obelnytska, Liliya Mykhailyshyn, and Olena Morozova. "Mathematical Modeling of Multimodal Transportation in Ukraine Using Methods of the Graph Theory." Edited by A. Generowicz, B. Burkinskyi, and V. Koval. *E3S Web of Conferences* 255 (2021): 01030. https://doi.org/10.1051/e3sconf/202125501030.

Resdiansya. "Travel Mode Choice Preferences of Urban Commuters in Kuching City, Malaysia Based on Stated Preference Data." In *MATEC Web of Conferences*. EDP Sciences, 2018. https://doi.org/10.1051/matecconf/201818102007.

Spears, Steven, Douglas Houston, and Marlon G. Boarnet. "Illuminating the Unseen in Transit Use: A Framework for Examining the Effect of Attitudes and Perceptions on Travel Behavior." *Transportation Research Part A: Policy and Practice* 58 (December 1, 2013): 40–53. https://doi.org/10.1016/j.tra.2013.10.011.

Yang, Yong, Ana Diez Roux, Amy Auchincloss, Daniel Rodriguez, and Daniel Brown. "A Spatial Agent-Based Model for the Simulation of Adults' Daily Walking Within a City." *American Journal of Preventative Medicine* 40, no. 3 (March 2011): 353–61. https://doi.org/10.1016/j.amepre.2010.11.017.

Zhang, Guangzhi, Han Zhang, Lefei Li, and Chenxu Dai. "Agent-Based Simulation and Optimization of Urban Transit System." *IEEE Transactions on Intelligent Transportation Systems* 15, no. 2 (April 2014): 589–96. https://doi.org/10.1109/TITS.2013.2285228.