A Hierarchical Model for Ascending-Descending Multimodal Itinerary Formation

J. Oh^a, Y. Jung^a, C. Lee^{a,*}, J. Lee^{b,*}

 ^a < Department of Civil and Environmental Engineering, Seoul National University>, <Korea> david9698@snu.ac.kr, yeonwoo@snu.ac.kr, chungwon@snu.ac.kr
^b <Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology>, <Korea> jinwoo@kaist.ac.kr
* Co-Corresponding author

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30) September 02-04, 2024, Crete, Greece

April 29, 2024

Keywords: Multimodal itineraries, Modal hierarchy, Ascending-descending formation, Mobility efficiency, Accessibility

1 INTRODUCTION

In recent years, the emergence of new mobility options, such as shared micromobility, has seen an increase in use. These mobility options play a crucial role in facilitating conventional modes, serving as first/last mile solutions for citizens. The integration of new mobility with conventional modes, known as multimodal mobility, can ensure seamless and efficient door-to-door itineraries for citizens (Lyons, *et al.*, 2020). In this sense, understanding how users make itinerary choices for their multimodal trips has become important for co-optimizing such existing and emerging modes within an ecosystem.

Previous studies have considered algorithms for routing or generating Pareto-optimal itineraries for multimodal trip planning. Studies on multimodal routing have developed network search algorithms to identify multimodal door-to-door itineraries (Bast, *et al*, 2016; Dibbelt, *et al.*, 2018). However, these methods can generate unrealistic trips, such as car usage between two bus rides since they are not fully data-driven but optimization methods built on few assumptions (Barret, *et al.*, 2008). Studies on itinerary choice have progressed toward developing algorithms that consider users' preferences to generate Pareto-optimal itineraries (Delling, *et al.*, 2013; Horstmannshoff, *et al.*, 2022). However, these approaches which distinctly define a limited set of conventional modes, fall short of seamlessly incorporating a variety of new modes into a flexible and integrated framework.

While existing studies analyze multimodal itineraries from various perspectives, their representation of reality and applicability remains limited, especially for a system with a number of modes being newly introduced. In this paper, for systematic understanding and general applicability in terms of multimodal itineraries, we quantitatively define a modal hierarchy in factors which influence the mode's preference and explore how itineraries are formed based on this modal hierarchy. To the best of the authors' knowledge, no prior research has incorporated a hierarchical framework into multimodal itinerary modeling.

2 A HIERARCHICAL MODEL

In this study, transportation modes are generalized as vectors with two types of integrative factors, i.e., mobility efficiency and access sparsity. We define mobility efficiency as the effectiveness of invehicle trips in terms of cost and time, while access sparsity indicates how readily available a mode is in temporal and spatial perspectives. For example, walking exhibits a low sparsity thanks to high accessibility with a low efficiency due to slow speed, whereas flights demonstrate the opposite. Additionally, more diverse factors can be added to mobility efficiency and access sparsity. Even though users generally prioritize high mobility efficiency and low access sparsity, there generally exists a trade-off between them. The basic hypothesis of this model is that users start their trips with modes with low mobility efficiency and access sparsity in an ascending order and end the trip with low mobility efficiency and access sparsity modes in a descending order as depicted in **Figure 1(a)**. We call it ascending-descending itinerary formation rule. In such itineraries, we expect that dominated modes (e.g., mode 3 is dominated by mode 2 in **Figure 1(b)**) are usually not selected and forming itinerary chain that violates the ascending-descending order (as shown in **Figure 1(c)**) is unnatural.



Figure 1 - *Examples of multimodal itinerary formation: (a) ascending-descending formation, (b,c) violations*

We consider a city, where multiple mobility modes coexist. Each mode is indexed by *i*, and its vector p_i includes selected one factor from each of mobility efficiency E_i and access sparsity A_i . In this study, we define the access sparsity as the average distance between separate points of mode *i* can reach, denoted by s_i [km], and the average out-of-vehicle waiting time at the transfer point, t_i [min]. Since people can walk with the highest spatial resolution and at any time, s_i and t_i for walking are almost zero. Moreover, we consider two mobility efficiency factors: per-time efficiency and percost efficiency. The per-time efficiency, denoted as v_i [km/h], is defined as the average Euclidean speed between two points, which can account for the maximum speed, the number of stops during a trip, and how winding routes are (i.e., route circuity (Daganzo, 1978)). The per-cost efficiency c_i [km/\$] is defined as Euclidean distance per unit cost with the consideration of the value of time. In this study, we utilized Revealed Preference (RP) data from Bucheon City Pass dataset from 07/01/2021 to 08/31/2022. This dataset contains actual usage data for four modes: shared e-scooter, shared e-bike, buses, and subways. Additionally, walking has been added to the beginning and end of each multimodal itinerary. After data preprocessing, a total of 51,706 single trips were identified within 17,166 multimodal itinerary chains. From the dataset, we calculate s_i, t_i, v_i , and c_i for each modal trip and each chain.

3 RESULTS

We analyzed whether a hierarchy exists among the modes in terms of mobility efficiency and access sparsity. We assume that the hierarchy of mobility efficiency and access sparsity among the modes varies according to both the timing and origins of individual itineraries. The values of all four variables $(s_i, v_i, c_i, \text{ and } t_i)$ for each mode are determined based on the precise time and location of the start of each multimodal itinerary. In Figure 2, the small dots represent the access sparsity (x-axis) and mobility efficiency (y-axis) of every single-modal trip included in multimodal itinerary chains.

We first analyzed the presence of the modal hierarchy in mobility efficiency and access sparsity from a macroscopic perspective. The analysis revealed that for s_i , v_i , and c_i , a hierarchy does exist between the modes (i.e., $(s_i > s_{i'}, v_i > v_{i'})$, or $(s_i > s_{i'}, c_i > c_{i'})$ for i > i'). As shown in **Figures 2(a-b)**, a macroscopic hierarchy was observed for all three factors in the order of walk (*i*=1), shared e-bike (*i*=2), shared e-scooter (*i*=3), bus (*i*=4), and subway (*i*=5) in Bucheon, South Korea. This modal hierarchy is collectively illustrated with large dots representing the mean values of access sparsity and mobility efficiency for each mode. This hierarchy of the modes indicates that mobility efficiency improves along this sequence, while access sparsity worsens. However, if we include t_i , no statistically significant hierarchy was found among the modes (see **Figures 2(c-d)**).



Figure 2 – Hierarchy in mobility efficiency and access sparsity among modes

We further conducted hypothesis tests to verify whether each multimodal itinerary chain follows the ascending-descending rule from the microscopic perspective based on the user-specific experienced modal hierarchy. In other words, the modal hierarchy can vary among users due to differences in the timing, origin, and route at the start of their itineraries. For example, in areas where bus stops are sparser than subway stations, users who plan subway-bus-subway itineraries support our hypothesis regarding spatial sparsity, while it violates the macroscopic hierarchy. Four null hypotheses are formulated to encompass all possible combinations of mobility efficiency and access sparsity pairs. **Table 1** demonstrates that the null hypotheses are not rejected when the hierarchy is built based on

 s_i and v_i or s_i and c_i . This implies that users plan multimodal itinerary chains accounting for these modal hierarchical structures. However, for the combinations of t_i and v_i , as well as t_i and c_i , the corresponding null hypotheses are rejected. It means that a mode's temporal sparsity does not contribute to modal hierarchy in both macroscopic and microscopic perspectives.

Tuble 1 Hypothesis lest results for the useenang descending interary formation rate			
Null Hypothesis:	Statistical test		Dojost
Itineraries follow the ascending-descending rule	Test statistic	P-value	Reject
H_0 : considering s_i and v_i	$x^2 = 3.544$	0.170	Х
H_0 : considering s_i and c_i	$x^2 = 4.170$	0.124	Х
H_0 : considering t_i and v_i	$x^2 = 505.5$	0.000	0
H_0 : considering t_i and c_i	$x^2 = 463.1$	0.000	0

Table 1 – Hypothesis test results for the ascending-descending itinerary formation rule

4 DISCUSSIONS

This study validated the existence of a modal hierarchy for multimodal itinerary formation considering mode-specific mobility efficiency and access sparsity, in both macroscopic and microscopic perspectives. Using Bucheon City's multimodal trip RP data, we found that v_i and c_i for mobility efficiency and s_i for access sparsity contribute to the modal hierarchy, and users' multimodal itinerary formation follows the proposed ascending-descending rule based on the modal hierarchy. However, in terms of t_i , there is no modal hierarchy, meaning that the waiting time of each mode does not contribute to the formation of multimodal itineraries. This model has general applicability and is capable of policy-making when introducing new modes of transport and further co-optimizing them with the vector-based hierarchy in a quantitative way.

5 REFERENCES

Barrett, C., Bisset, K., Holzer, M., Konjevod, G., Marathe, M. & Wagner, D. (2008). Engineering label-constrained shortest-path algorithms. *In Algorithmic Aspects in Information and Management: 4th International Conference, AAIM 2008, Shanghai, China, June 23-25, 2008. Proceedings*, **4** pp.27-37.

Bast, H., Delling, D., Goldberg, A., Müller-Hannemann, M., Pajor, T., Sanders, P., Wagner, D. & Werneck, R.F. (2016). Route planning in transportation networks. *Algorithm Engineering: Selected Results and Surveys*, pp.19-80.

Daganzo, C.F. (1978). An approximate analytic model of many-to-many demand responsive transportation systems. *Transportation Research*, **12** (5) pp.325-333.

Delling, D., Dibbelt, J., Pajor, T., Wagner, D., & Werneck, R. F. (2013). Computing multimodal journeys in practice. *In International Symposium on Experimental Algorithms, Berlin, Heidelberg* pp. 260-271.

Dibbelt, J., Pajor, T., Strasser, B. & Wagner, D. (2018). Connection scan algorithm. Journal of Experimental Algorithmics, **23** pp.1-56.

Horstmannshoff, T. & Ehmke, J.F. (2022). Traveler-oriented multi-criteria decision support for multimodal itineraries. *Transportation Research Part C: Emerging Technologies*, **141**, 103741.

Lyons, G., Hammond, P. & Mackay, K. (2020). Reprint of: The importance of user perspective in the evolution of MaaS. *Transportation Research Part A: Policy and Practice*, **131** pp.20-34.