"Now What?" Modelling Route Choices for Personalised Context-Aware Decision-Support During Public Transport Disruptions

Anouk van Kasteren
Human-Centred Computing
Utrecht University
Utrecht, Netherlands
a.vankasteren@uu.nl

Marloes Vredenborg
Human-Centred Computing
Utrecht University
Utrecht, Netherlands
m.t.r.vredenborg@uu.nl

Christine Bauer
Department of Artificial Intelligence and Human Interfaces
University of Salzburg
Salzburg, Austria
christine.bauer@plus.ac.at

Judith Masthoff
Human-Centred Computing
Utrecht University
Utrecht, Netherlands
j.f.m.masthoff@uu.nl

Abstract

Public transport disruptions force travellers to replan, increasing cognitive load. We frame this as an HCI problem centred on travellers' needs and decision processes. Using a stated-preference discrete-choice experiment that manipulates weather, disruption certainty, travel direction, nearby amenities, and route attributes, we model route preferences with multinomial and mixed logit models. Results show substantial heterogeneity: travel time and crowdedness deter selection on average, while preferences for waiting, transfers, and mode switching vary between people. Additionally, context systematically shifts preferences; for example, weather, certainty, and commuting direction alter tolerance for transfers, waiting, and crowding. Effective disruption support should adapt to context, communicate uncertainty, and leverage environmental affordances to reduce traveller burden.

CCS Concepts

• **Human-centered computing** → **HCI theory, concepts and models**; **Empirical studies in HCI**; **Human computer interaction (HCI)**; • **Applied computing** → Law, social and behavioral sciences; **Transportation**.

Keywords

Public Transport, Travel Experience, Decision Support, Personalisation, Context-Aware Systems

ACM Reference Format:
Anouk van Kasteren, Marloes Vredenborg, Christine Bauer, and Judith Masthoff. 2026. "Now What?" Modelling Route Choices for Personalised Context-Aware Decision-Support During Public Transport Disruptions. In *Extended Abstracts of the 2026 CHI Conference on Human Factors in Computing Systems (CHI EA '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3772363.3798949

1 Introduction

Public transport provides important societal benefits by enabling accessible mobility and supporting sustainable travel aligned with (inter)national climate goals [e.g. 22, 59]. A positive travel experience is therefore crucial, as it consistently predicts continued public transport use across countries and modes [12, 36]. Although ridership declined during COVID-19 and has not fully recovered, efforts have been made to attract new travellers. However, some of these initiatives resulted in strained capacity, leading to overcrowding and additional disruptions [15, 18, 41]. Such experiences can undermine retention, underscoring the importance of actively managing travel experience through effective information, decision support, and crowding management [e.g. 1, 23, 63].

The Netherlands faces a related challenge, with declining public transport usage despite growth elsewhere in Europe [24, 64]. Frequent planned and unplanned disruptions contribute to dissatisfaction by increasing uncertainty, reducing perceived control, and introducing physical and mental discomfort [11, 14]. While disruptions cannot be entirely prevented, how travellers are supported during them is pivotal [33, 62]. However, disruption support often remains limited and one-size-fits-all, failing to account for individual preferences and situational context [17, 61, 65].

Travel experience and decision-making are shaped by personal, social, and contextual factors [29, 53, 60, 66], and there is little reason to assume this differs during disruptions. While personalised route planners exist for regular travel [e.g. 10, 40], such support is often absent when services fail [61]. This study takes a focused step by examining how selected contextual factors shape route choice during train cancellations in the Netherlands. Using a Discrete Choice Experiment (DCE), we address the research question: *"How does situational context influence route choice behaviour of commuters during train cancellations?"* We contribute (1) empirical and human-centred insights into factors shaping disrupted route choice,

---

CHI EA '26, Barcelona, Spain

ACM ISBN 979-8-4007-2281-3/26/04
https://doi.org/10.1145/3772363.3798949

(2) an understanding of preference heterogeneity, and (3) derive implications for designing context-aware and personalised decision support during disruptions.

2 Related Work

Disruptions and Travel Experience. In public transport, disruptions such as delays, cancellations, and detours are common and strongly affect travellers' experiences. Unplanned disruptions, in particular, reduce satisfaction and perceived service quality [68], often introducing discomfort through waiting, crowdedness, or exposure to adverse weather [6]. Beyond physical inconvenience, disruptions increase cognitive effort: travellers must interpret fragmented information and replan under uncertainty. Cognitive Load Theory [55] highlights that such demands can quickly overwhelm limited working-memory capacity, complicating the comparison of alternatives [4, 62] and reducing travellers' experience [44]. From an Human-Computer Interaction (HCI) perspective, this underscores the need for decision-support systems that actively reduce cognitive load by providing timely, actionable information and highlighting relevant trade-offs [12, 61].

Personalised Route Recommendations. Route planners function as decision-support systems by helping travellers choose between competing routes. During disruptions, this support must operate under time pressure and limited attention, where travellers need help understanding implications of choices such as waiting, rerouting, or switching travel modes. Prior HCI research shows that effective decision support should preserve user agency, support sensemaking, be contextually relevant, and be transparent about trade-offs to enhance trust and adoption [2, 13, 47, 51].

Personalisation offers a way to tailor recommendations to travellers' preferences and situational context [66]. Decision-making theory models choices as comparisons of alternatives based on subjective utility, reflecting travellers' trade-offs in attributes such as time, reliability, and context [e.g. 7, 57]. In public transport, this means that faster but crowded or uncertain routes may be experienced as less favourable than slightly slower, predictable options [60]. Personalised and context-aware route planning for regular travel has been explored using preference learning and multi-criteria routing [e.g. 10, 16, 32, 40]. Here, travel decisions and experiences have been shown to depend on contextual factors such as travel purpose and direction [20, 29], crowdedness [30, 56], weather [9, 21], and nearby amenities [61]. Simultaneously, personalised disruption support typically remains non-actionable [34] or limited to high-level choices (e.g., wait vs. reroute) [e.g. 5, 8, 50], offering little support for evaluating concrete alternatives. This study addresses this gap by analysing how context shapes preferences among available alternative routes during train cancellations, informing the design of context-aware, personalised disruption support that reduces cognitive burden. We position personalised disruption support as an HCI problem centred on understanding travellers' needs, constraints, and decision processes, rather than solely improving prediction accuracy.

3 Method

To study route choice decision-making during train cancellations, we conducted a DCE using a Stated Preference (SP) survey, a widely used method for modelling travel decisions [3, 28, 29]. The experiment used a mixed repeated-measures design with four contextual variables—travel direction, weather, distance to shops, and disruption certainty—yielding 72 possible scenarios. To limit participant burden, each participant evaluated one practice task and two randomly selected scenarios, each containing four choice tasks. Within each choice task, we varied only crowdedness, while holding other route attributes constant, enabling within-subject comparisons and analysis of context–attribute interactions. The study was conducted in accordance with the ethical guidelines of Utrecht University.

Variables. The dependent variable is the route choice, which is modelled as probabilities based on route utility. The independent variables are divided into route-, contextual-, and demographic attributes (see Table 1).

Stimuli and Materials. We implemented the survey in Qualtrics [48] and optimised it for laptop or monitor screens, of which participants were notified. Choice tasks consisted of a scenario and route alternatives, refined through a pilot study optimising clarity, realism, complexity, and valence.

Routes were based on real Dutch journeys, with station names altered to avoid bias. Scenarios (Figure 1) described the original route's origin–destination, travel mode, duration, and connection frequency, with costs held constant, followed by randomly assigned contextual factors and a disruption announcement describing cause and certainty. For work-bound trips, time constraints were stated. Alternative routes were presented as images created in Figma, mimicking the Dutch Railways (NS) route planner to ensure a familiar layout. Participants selected their preferred route from waiting, detour, or alternative-mode options (Figure 2).

Sample. Participants were recruited through the Dutch Railways (NS) travellers panel[1]. Sampling aimed for balance across age, gender, and travel frequency; participants younger than 18 or older than 70 were excluded. All participants resided in the Netherlands and were Dutch-speaking.

In total, 681 respondents started the survey and provided informed consent. We excluded 133 incomplete responses and respondents who completed the experiment in under 3 minutes, indicating insufficient engagement. The final sample consisted of 502 participants. The sample covered all adult age groups, with the strongest representation between 46 and 65 years. Gender was balanced (268 men, 220 women; 10 other/prefer not to say). Most participants lived in urban areas (388), with 111 from rural regions. Public transport use ranged from infrequent ($< 1 \times /month$) to frequent ($> 3 \times /week$). Full demographics are reported in Appendix A.

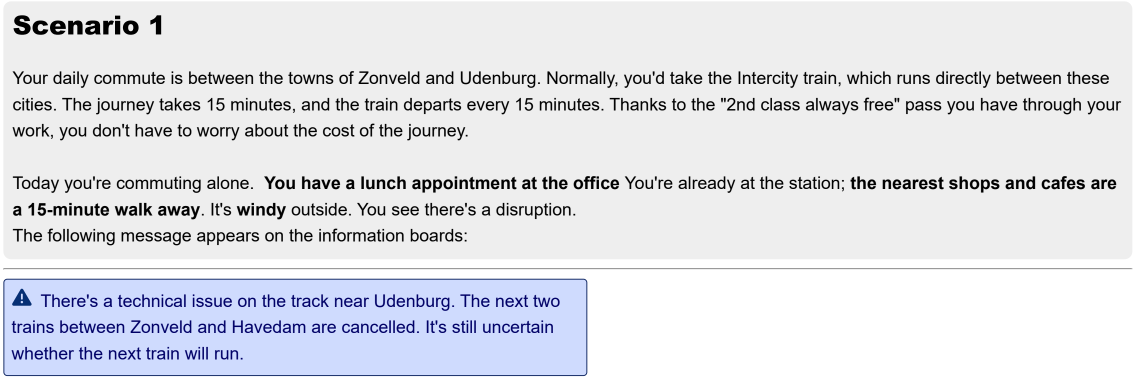
Analysis. Responses were exported and merged with route attributes, categorical variables were one-hot encoded, and travel modes were captured using two dummy variables: `hastrain` and `hasothermode`. We estimated both Multinomial Logit (MNL) [27] and Mixed Logit (MXL) [31] models, common in route choice modelling, using backward elimination. The MNL included route attribute main effects and interactions with contextual and demographic variables, modelling interactions only since context cannot affect utility independently of route attributes. The MXL extended

---

[1] This panel consists of approximately 80000 travellers who voluntarily registered to participate in research.

Table 1: Description of variables used in the experiment. Divided into route attributes, context attributes, and demographic attributes.

Name	Type	Description
Route attributes		
`log.extra_traveltime`	Numerical	The log of the extra travel time in minutes compared to the original route.
`waiting`	Binary	Whether it is the waiting option.
`transfers`	Numerical	Number of transfers.
`crowdedness`	Binary	Not crowded or crowded route.
`hastrain`	Binary	The route includes a train segment.
`hasothermode`	Binary	The route includes segments with other transport modes (bus, tram, bike).
Contextual attributes		
`weather`	Categorical	`Sunny`, `windy`, `rain`.
`direction`	Binary	Going to `work` vs. returning `home`.
disruption certainty	Binary	`Certain` (the following connection will certainly run) vs. `Uncertain` (the connection may not run).
distance to amenities	Categorical	Amenities in walking distance: none (`no_amenities`), within 5 minutes walking (`5min`), within 15 minutes walking (`15min`).
Demographic attributes (self reported)		
age	Categorical	Age grouped per 10-year bins.
travel frequency	Categorical	How often participants travel by public transport: >3/week, 2–3/week, 1/week , 2–3/month, ≤1/month
traveller type	Categorical	`Conscious`, `organised`, `casual`, `confident`, `social`, `venturous`.
region type	Binary	The type of region participants live in: `urban` vs. `rural`.



Scenario 1

Your daily commute is between the towns of Zonveld and Udenburg. Normally, you'd take the Intercity train, which runs directly between these cities. The journey takes 15 minutes, and the train departs every 15 minutes. Thanks to the "2nd class always free" pass you have through your work, you don't have to worry about the cost of the journey.

Today you're commuting alone. **You have a lunch appointment at the office** You're already at the station; **the nearest shops and cafes are a 15-minute walk away**. It's **windy** outside. You see there's a disruption.
The following message appears on the information boards:

⚠ There's a technical issue on the track near Udenburg. The next two trains between Zonveld and Havedam are cancelled. It's still uncertain whether the next train will run.

Figure 1: Example scenario describing the original route, context situation, and disruption. Original scenarios were in Dutch.

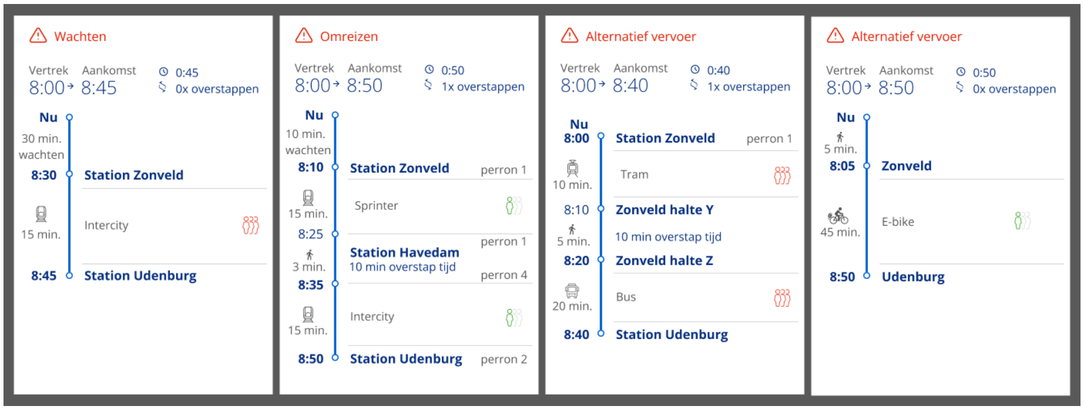


Figure 2: Example choice set displaying the option to wait for the original route and three alternative options.

this by allowing random route-attribute parameters and fixed context interactions, improving robustness to unobserved heterogeneity. Model assumptions were met.

4 Results

We analysed data from 502 participants, yielding 4016 choice tasks with four alternatives each (16064 observations). On a high level, participants chose waiting 816 times (20.3%; 502 under certain disruptions and 314 under uncertain), while detours were chosen 1883 times (46.9%), and alternative travel modes 1317 times (32.8%).

We estimated both an MNL and MXL model (see Appendix D and E for model specifications). Table 2 summarises their metrics. Both achieved McFadden's pseudo-R^2 values in expected ranges (≈ 0.23 for MNL; ≈ 0.41 for MXL) [42, 43]. While the MXL improved in-sample fit (LL, BIC), differences in accuracy and AUC were marginal, indicating similar ranking performance across models. This suggests that the gains from modelling heterogeneity primarily enhance probabilistic fit rather than substantially altering alternative discrimination. Given this, in this paper, we rely on the MXL model to interpret choice behaviour through its main effects and contextual interactions, as it captures the unobserved preference heterogeneity. To complement this, we interpret the MNL model with demographic interactions to explore observed group-level differences.

Mixed Logit Model. Figure 3 summarises the MXL results. All route attribute main effects were significant except `hasothermode`, although its significant random parameter indicates heterogeneous effects. `crowdedness` had the strongest negative mean effect with a low random *SD*. The log of extra travel time showed diminishing marginal disutility. `Transfers`, `waiting`, and `hastrain` also significantly affected utility, with substantial preference heterogeneity.

Contextual interactions showed systematic effects. Relative to `sunny` weather, adverse weather increased the effect of `transfers`, `waiting`, `hastrain`, and `hasothermode` on route utility. `Crowdedness` had a less negative effect when travelling `to work`. The effect of `waiting` increased when amenities were within a `5-minute` walk, but not at `15 minutes`. Under disruption `uncertainty`, the effect of `waiting` decreased. Full estimation results are shown in Appendix B.

Multinomial Logit Model. Compared to the MXL, the MNL showed limited in-sample fit but similar out-of-sample performance (Table 2). Demographic interactions revealed modest group-level differences. Participants aged 36+ showed lower utility for non-train modes, stronger disutility for transfers, and weaker disutility for crowdedness (except 66+). Crowdedness was more negative for urban travellers and less negative for casual and confident travellers. `hastrain` was positive for organised and confident travellers and negative for social travellers, who also showed a positive interaction with waiting. The full estimation results can be seen in Appendix C. These effects were modest relative to the individual-level heterogeneity captured by the MXL.

5 Discussion

Route attributes and route choice behaviour. Overall, average effects co-exist with substantial individual heterogeneity, particularly for waiting, transfers, and mode choice. Large random standard deviations indicate that preferences vary strongly across travellers. Past travel experiences shape expectations and decisions [45, 49]. This is reflected in opposing evaluations of waiting and non-train segments: some travellers avoid them, while others prefer waiting to avoid transfers or alternative modes. While non-train segments show no significant mean effect, their significant random variation indicates divergent preferences. By contrast, routes including a train segment consistently increase utility. Sensitivity to crowdedness also varies across groups, with a stronger effect for urban travellers and for those aged below 36 or above 65, though substantial within-group variability remains.

Context affects route choice behaviour. Contextual factors—including weather, disruption certainty, travel direction, and nearby amenities— shape route preferences. We found that in disrupted conditions, the typically negative effects [e.g. 19, 46, 58] of transfers, waiting, and alternative modes are attenuated [54], particularly under adverse weather. Rain and wind increase acceptance of transfers and alternative modes, likely because these options reduce exposure to discomfort. Waiting becomes less acceptable under uncertainty, reflecting risk sensitivity when outcomes are unclear [35]. Crowdedness is tolerated more when commuting to work than on the return trip, consistent with higher perceived delay costs [67]. Nearby amenities increase willingness to wait when within a short walking distance, aligning with evidence that nearby amenities reduce the perceived burden of waiting [25]. The study design allowed us to test only a limited number of factors. Numerous contextual factors influence travellers [60, 66], and future research should investigate modelling additional factors to further improve model performance.

Modelling individual preferences. MXL has a better in-sample fit than MNL, indicating that random parameters captured unobserved heterogeneity beyond demographics, context, or route factors. However, cross-validation showed no improvement in the predictive performance, meaning that while MXL offers valuable explanatory insight into decision-making diversity, its predictive power remains limited.

A possible next step is to model heterogeneity in contextual preferences more explicitly. While an MXL with random interaction parameters could capture variation in context effects, it would require a large sample and may remain unsuitable for reliable prediction. In contrast, Latent Class Models (LCMs) cluster travellers with distinct utility functions [39], potentially revealing meaningful differences in how route and context attributes shape decisions while remaining transparent and supporting explainability and trust in decision support [26, 38, 51]. Future work will therefore explore LCMs to improve route-choice prediction during disruptions.

Limitations and considerations. Several limitations apply. One alternative was rarely chosen, limiting the estimate's reliability. Interaction effects were modelled as fixed, despite potential heterogeneity. Some covariance correlations are just below common thresholds. Although alternatives were designed to be independent, independence assumptions can be tricky for route choices. While MXL partially addresses this, future work should explicitly address such dependencies. The study employed a stated preference method; whether the findings persist in real-world behaviour would require further testing.

Table 2: Model performance (MNL vs. MXL). MXL outperforms MNL in-sample; both show limited out-of-sample performance. *LL = Log Likelihood

Model	LL* per obs.	cross validation LL*	AIC	BIC	pseudo-R^2	Accuracy	Micro-AUC	Macro-AUC
MNL	-1.07	-1.11	8704.0	8962.2	0.226	0.53	0.79	0.72
MXL	-0.82	-1.11	6608.3	6727.9	0.410	0.53	0.78	0.69

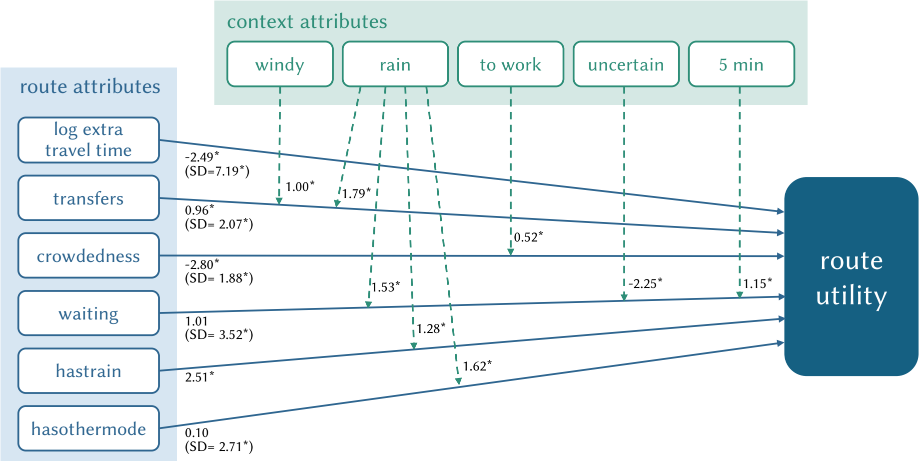


Figure 3: Visual representation of the MXL results, including the attributes (boxes) and effects (arrows). Bold lines represent the main effects of the route attributes, dashed lines represent the context interaction effects. The numbers represent the model estimates and their standard deviations (SD) in parentheses. * indicates statistical significance at $\alpha < 0.05$.
***Interpretation*: Crowdedness has a mean effect of -2.80, which is normally distributed with a standard deviation of 1.88. When travelling to work, the interaction effect increases the coefficient by 0.52.**

6 Conclusions for Personalised Route Alternative Recommendations

We used a stated-preference discrete-choice experiment to examine how travellers choose between route alternatives during train cancellations. While the current models are not yet accurate enough for personalised route prediction, the findings highlight clear design directions for future decision-support systems: (i) Context-awareness: Weather, disruption certainty, travel direction, and nearby amenities systematically influence willingness to wait, transfer, or switch modes. These factors should inform route recommendations to align better with travellers' own reasoning. (ii) Communicating uncertainty: Travellers are less likely to wait under uncertainty. Previous research has shown increased reliance on intelligent systems under uncertainty [52]. Explicitly presenting uncertainty and enabling comparison across options can strengthen perceived control and reduce cognitive burden in decision-making [37]. (iii) Utilising the environment: Proximity to amenities like shops or cafes enhances tolerance for waiting. Systems can become more environment-focused by offering suggestions and navigational support for these amenities when recommending waiting, thereby reducing the perceived burden of delays.

Methodologically, latent class models (LCMs) offer a promising next step by capturing interpretable personas with distinct preference profiles. This potentially enables more reliable and explainable decision support when combined with richer contextual features and participant-wise validation. Overall, this work serves as a stepping stone toward traveller-centred systems that help people navigate disruptions more easily. By reducing cognitive burden and making uncertainty explicit, future designs can mitigate the negative impact of disruptions on the travel experience.

Acknowledgments

This publication was partially funded by the Dutch Railways. This publication was also supported by the Excellence in Digital Sciences and Interdisciplinary Technologies (EXDIGIT) project, funded by Land Salzburg under grant number 20204-WISS/263/6-6022.

References

[1] American Public Transportation Association. 2021. *On the Horizon: Public Transportation in 2021.* Technical Report. American Public Transportation Association. https://www.apta.com/wp-content/uploads/APTA-On-The-Horizon-Nov2021.pdf
[2] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N. Bennett, Kori Inkpen, Jaime Teevan, Ruth Kikin-Gil, and Eric Horvitz. 2019. Guidelines for Human-AI Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 13 pages. doi:10.1145/3290605.3300233
[3] Marie Karen Anderson, Otto Anker Nielsen, and Carlo Giacomo Prato. 2017. Multimodal route choice models of public transport passengers in the Greater Copenhagen Area. *EURO Journal on Transportation and Logistics* 6, 3 (2017), 221–245. doi:10.1007/s13676-014-0063-3
[4] Allan Armougum, Alexandre Gaston-Bellegarde, Chantal Joie-La Marle, and Pascale Piolino. 2020. Physiological investigation of cognitive load in real-life

train travelers during information processing. *Applied Ergonomics* 89, Article 103180 (2020), 10 pages. doi:10.1016/j.apergo.2020.103180

[5] Joshua Auld, Hubert Ley, Omer Verbas, Nima Golshani, Josiane Bechara, and Angela Fontes. 2020. A stated-preference intercept survey of transit-rider response to service disruptions. *Public Transport* 12, 3 (2020), 557–585. doi:10.1007/s12469-020-00243-z

[6] Gabriela Beirão and José António Sarsfield Cabral. 2007. Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy* 14, 6 (2007), 478–489. doi:10.1016/j.tranpol.2007.04.009

[7] Moshe Ben-Akiva and Michel Bierlaire. 1999. Discrete choice methods and their applications to short term travel decisions. In *Handbook of Transportation Science*. Springer, Boston, MA, USA, 5–33. doi:10.1007/978-1-4615-5203-1_2

[8] Julia Bickel, Nejc Geržinič, Niels Van Oort, Menno De Bruyn, and Eric Molin. 2026. Heterogeneity in route choice behaviour during unplanned train disruptions considering the possibility of teleworking. *Transportation Research Part A: Policy and Practice* 203, Article 104708 (2026), 18 pages. doi:10.1016/j.tra.2025.104708

[9] Lars Böcker, Martin Dijst, and Jan Faber. 2016. Weather, transport mode choices and emotional travel experiences. *Transportation Research Part A: Policy and Practice* 94 (2016), 360–373. doi:10.1016/j.tra.2016.09.021

[10] Paolo Campigotto, Christian Rudloff, Maximilian Leodolter, and Dietmar Bauer. 2016. Personalized and situation-aware multimodal route recommendations: The FAVOUR algorithm. *IEEE Transactions on Intelligent Transportation Systems* 18, 1 (Jan. 2016), 92–102. doi:10.1109/TITS.2016.2565643

[11] Mairead Cantwell, Brian Caulfield, and Margaret O'Mahony. 2009. Examining the factors that impact public transport commuting satisfaction. *Journal of Public Transportation* 12, 2 (2009), 1–21. doi:10.5038/2375-0901.12.2.1

[12] Rui Carreira, Lia Patrício, Renato Natal Jorge, and Chris Magee. 2014. Understanding the travel experience and its impact on attitudes, emotions and loyalty towards the transportation provider–A quantitative study with mid-distance bus trips. *Transport Policy* 31 (2014), 35–46. doi:10.1016/j.tranpol.2013.11.006

[13] Yiling Chen, Ian A Kash, Michael Ruberry, and Victor Shnayder. 2014. Eliciting predictions and recommendations for decision making. *ACM Transactions on Economics and Computation* 2, 2, Article 6 (June 2014), 27 pages. doi:10.1145/2556271

[14] Graham Currie and Carlyn Muir. 2017. Understanding passenger perceptions and behaviors during unplanned rail disruptions. *Transportation Research Procedia* 25 (2017), 4392–4402. doi:10.1016/j.trpro.2017.05.322

[15] Jingchen Dai, Zhiyong Liu, and Ruimin Li. 2021. Improving the subway attraction for the post-COVID-19 era: The role of fare-free public transport policy. *Transport Policy* 103 (2021), 21–30. doi:10.1016/j.tranpol.2021.01.007

[16] Madhuri Debnath, Praveen Kumar Tripathi, Ashis Kumer Biswas, and Ramez Elmasri. 2018. Preference aware travel route recommendation with temporal influence. In *Proceedings of the 2nd ACM SIGSPATIAL Workshop on Recommendations for Location-Based Services and Social Networks* (Seattle, WA, USA) *(LocalRec'18)*. Association for Computing Machinery, New York, NY, USA, Article 2, 9 pages. doi:10.1145/3282825.3282829

[17] Edward L Deci and Richard M Ryan. 2014. *Intrinsic motivation and self-determination in human behavior*. Springer Science & Business Media, New York, NY, USA. doi:10.1007/978-1-4899-2271-7

[18] Deutsche Welle. 2022. *Germany's 9-euro travel ticket: Success or failure?* https://www.dw.com/en/germanys-9-euro-travel-ticket-success-or-failure/a-62329405 News article.

[19] Naveen Eluru, Vincent Chakour, and Ahmed M El-Geneidy. 2012. Travel mode choice and transit route choice behavior in Montreal: insights from McGill University members commute patterns. *Public Transport* 4, 2 (2012), 129–149. doi:10.1007/s12469-012-0056-2

[20] Dick Ettema, Margareta Friman, Tommy Gärling, Lars E Olsson, and Satoshi Fujii. 2012. How in-vehicle activities affect work commuters' satisfaction with public transport. *Journal of Transport Geography* 24 (2012), 215–222. doi:10.1016/j.jtrangeo.2012.02.007

[21] Dick Ettema, Margareta Friman, Lars E Olsson, and Tommy Gärling. 2017. Season and weather effects on travel-related mood and travel satisfaction. *Frontiers in Psychology* 8, Article 140 (2017), 9 pages. doi:10.3389/fpsyg.2017.00140

[22] Eurocities and UITP. 2024. European Declaration for Sustainable and Attractive Public Transport in Cities. Declaration adopted in Barcelona on 5 November 2024. https://transition-pathways.europa.eu/system/files/2024-11/Final-version-Public-Transport-Declaration-Barcelona-FINAL-002.pdf

[23] European Commission. 2023. *Planning for Attractive Public Transport*. Technical Report. European Commission, Directorate-General for Mobility and Transport. https://urban-mobility-observatory.transport.ec.europa.eu/system/files/2023-11/planning_for_attractive_public_transport.pdf

[24] Eurostat. 2025. *Rail transport of passengers*. https://ec.europa.eu/eurostat/databrowser/view/ttr00015/default/table?lang=en&category=t_rail Eurostat metadata (ESMS).

[25] Yingling Fan, Andrew Guthrie, and David Levinson. 2016. Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transportation Research Part A: Policy and Practice* 88 (2016), 251–264. doi:10.1016/j.tra.2016.04.012

[26] Anja K. Faulhaber, Ina Ni, and Ludger Schmidt. 2021. The effect of explanations on trust in an assistance system for public transport users and the role of the propensity to trust. In *Proceedings of Mensch und Computer 2021* (Ingolstadt, Germany) *(MuC '21)*. Association for Computing Machinery, New York, NY, USA, 303–310. doi:10.1145/3473856.3473886

[27] William H Greene. 2003. *Econometric Analysis* (5th ed.). Prentice Hall, Upper Saddle River, NJ, USA.

[28] Elise Grison, Jean-Marie Burkhardt, and Valérie Gyselinck. 2017. How do users choose their routes in public transport? The effect of individual profile and contextual factors. *Transportation Research Part F: Traffic Psychology and Behaviour* 51 (2017), 24–37. doi:10.1016/j.trf.2017.08.011

[29] Elise Grison, Valérie Gyselinck, and Jean-Marie Burkhardt. 2016. Exploring factors related to users' experience of public transport route choice: influence of context and users profiles. *Cognition, Technology & Work* 18, 2 (2016), 287–301. doi:10.1007/s10111-015-0359-6

[30] Luke Haywood, Martin Koning, and Guillaume Monchambert. 2017. Crowding in public transport: Who cares and why? *Transportation Research Part A: Policy and Practice* 100 (2017), 215–227. doi:10.1016/j.tra.2017.04.022

[31] David A Hensher and William H Greene. 2003. The mixed logit model: the state of practice. *Transportation* 30, 2 (2003), 133–176. doi:10.1023/A:1022558715350

[32] Daniel Herzog, Hesham Massoud, and Wolfgang Wörndl. 2017. RouteMe: A mobile recommender system for personalized, multi-modal route planning. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization* (Bratislava, Slovakia) *(UMAP '17)*. Association for Computing Machinery, New York, NY, USA, 67–75. doi:10.1145/3079628.3079680

[33] Elina Hildén, Kaisa Väänänen, and Simo Syrman. 2018. Modeling bus travel experience to guide the design of digital services for the bus context. In *Proceedings of the 22nd International Academic Mindtrek Conference* (Tampere, Finland) *(Mindtrek '18)*. Association for Computing Machinery, New York, NY, USA, 143–152. doi:10.1145/3275116.3275120

[34] Åse Jevinger, Emil Johansson, Jan A Persson, and Johan Holmberg. 2023. Context-aware travel support during unplanned public transport disturbances. In *Proceedings of the 9th International Conference on Vehicle Technology and Intelligent Transport Systems* (Prague, Czech Republic) *(VEHITS 2023)*. SciTePress, Setúbal, Portugal, 160–170. doi:10.5220/0011761000003479

[35] Chenming Jiang, Linjun Lu, Junliang He, and Caimao Tan. 2020. A two-class stochastic network equilibrium model under adverse weather conditions. *Journal of Advanced Transportation* 2020, 1, Article 2626084 (2020), 14 pages. doi:10.1155/2020/2626084

[36] Tri Basuki Joewono and Hisashi Kubota. 2007. Exploring negative experiences and user loyalty in paratransit. *Transportation Research Record* 2034, 1 (2007), 134–142. doi:10.3141/2034-15

[37] Matthew Kay, Tara Kola, Jessica R. Hullman, and Sean A. Munson. 2016. When (ish) is My Bus? User-centered Visualizations of Uncertainty in Everyday, Mobile Predictive Systems. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, CA, USA) *(CHI '16)*. ACM, New York, NY, USA, 5092–5103. doi:10.1145/2858036.2858558

[38] Johannes Kunkel, Tim Donkers, Lisa Michael, Catalin-Mihai Barbu, and Jürgen Ziegler. 2019. Let me explain: Impact of personal and impersonal explanations on trust in recommender systems. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 12 pages. doi:10.1145/3290605.3300717

[39] Paul Felix Lazarsfeld. 1968. *Latent structure analysis*. Houghton Mifflin Company, Boston, MA, USA.

[40] Hao Liu, Yongxin Tong, Panpan Zhang, Xinjiang Lu, Jianguo Duan, and Hui Xiong. 2019. Hydra: A personalized and context-aware multi-modal transportation recommendation system. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (Anchorage, AK, USA) *(KDD '19)*. Association for Computing Machinery, New York, NY, USA, 2314–2324. doi:10.1145/3292500.3330660

[41] Allister Loder, Fabienne Cantner, Lennart Adenaw, Nico Nachtigall, David Ziegler, Felix Gotzler, Markus B Siewert, Stefan Wurster, Sebastian Goerg, Markus Lienkamp, et al. 2024. Observing Germany's nationwide public transport fare policy experiment "9-Euro-Ticket"'–Empirical findings from a panel study. *Case Studies on Transport Policy* 15, Article 101148 (2024), 20 pages. doi:10.1016/j.cstp.2024.101148

[42] Daniel McFadden. 1972. Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics* (1972), 105–142.

[43] Daniel McFadden and Kenneth Train. 2000. Mixed MNL models for discrete response. *Journal of Applied Econometrics* 15, 5 (2000), 447–470. doi:10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

[44] Serena Midha, Max L Wilson, and Sarah Sharples. 2022. Lived experiences of mental workload in everyday life. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 282, 16 pages. doi:10.1145/3491102.3517690

[45] Pamela Murray-Tuite, Kris Wernstedt, and Weihao Yin. 2014. Behavioral shifts after a fatal rapid transit accident: A multinomial logit model. *Transportation research part F: traffic psychology and behaviour* 24 (2014), 218–230. doi:10.1016/j.trf.2014.04.014

[46] Otto Anker Nielsen, Morten Eltved, Marie Karen Anderson, and Carlo Giacomo Prato. 2021. Relevance of detailed transfer attributes in large-scale multimodal route choice models for metropolitan public transport passengers. *Transportation Research Part A: Policy and Practice* 147 (2021), 76–92. doi:10.1016/j.tra.2021.02.010

[47] Eleftherios Papachristos, Patrick Skov Johansen, Rune Møberg Jacobsen, Lukas Bjørn Leer Bysted, and Mikael B Skov. 2021. How do people perceive the role of AI in Human-AI collaboration to solve everyday tasks?. In *CHI Greece 2021: 1st International Conference of the ACM Greek SIGCHI Chapter* (Online (Athens, Greece), Greece) *(CHI Greece 2021)*. Association for Computing Machinery, New York, NY, USA, Article 10, 6 pages. doi:10.1145/3489410.3489420

[48] Qualtrics. 2024. Qualtrics Survey Software. https://www.qualtrics.com. Provo, Utah, USA.

[49] Ehsan Rahimi, Ali Shamshiripour, Ramin Shabanpour, Abolfazl Mohammadian, and Joshua Auld. 2019. Analysis of transit users' waiting tolerance in response to unplanned service disruptions. *Transportation Research Part D: Transport and Environment* 77 (2019), 639–653. doi:10.1016/j.trd.2019.10.011

[50] Ehsan Rahimi, Ali Shamshiripour, Ramin Shabanpour, Abolfazl Mohammadian, and Joshua Auld. 2020. Analysis of transit users' response behavior in case of unplanned service disruptions. *Transportation Research Record* 2674, 3 (2020), 258–271. doi:10.1177/036119812091192

[51] Leon Reicherts, Zelun Tony Zhang, Elisabeth von Oswald, Yuanting Liu, Yvonne Rogers, and Mariam Hassib. 2025. AI, Help Me Think—but for Myself: Assisting People in Complex Decision-Making by Providing Different Kinds of Cognitive Support. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 255, 19 pages. doi:10.1145/3706598.3713295

[52] Sara Salimzadeh, Gaole He, and Ujwal Gadiraju. 2024. Dealing with Uncertainty: Understanding the Impact of Prognostic Versus Diagnostic Tasks on Trust and Reliance in Human-AI Decision Making. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. ACM, New York, NY, USA, Article 25, 17 pages. doi:10.1145/3613904.3641905

[53] Kevin Sanders and David Geerts. 2019. You Can't Go Your Own Way: Social Influences on Travelling Behavior. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland UK) *(CHI EA '19)*. ACM, New York, NY, USA, 1–6. doi:10.1145/3290607.3313079

[54] Neeraj Saxena, Taha Hossein Rashidi, and Joshua Auld. 2019. Studying the tastes effecting mode choice behavior of travelers under transit service disruptions. *Travel Behaviour and Society* 17 (2019), 86–95. doi:10.1016/j.tbs.2019.07.004

[55] John Sweller. 2010. Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational Psychology Review* 22 (2010), 123–138. doi:10.1007/s10648-010-9128-5

[56] Alejandro Tirachini, Ricardo Hurtubia, Thijs Dekker, and Ricardo A Daziano. 2017. Estimation of crowding discomfort in public transport: Results from Santiago de Chile. *Transportation Research Part A: Policy and Practice* 103 (2017), 311–326. doi:10.1016/j.tra.2017.06.008

[57] Kenneth E Train. 2009. *Discrete choice methods with simulation.* Cambridge University Press, Cambridge, UK.

[58] Arun Ulahannan and Stewart Birrell. 2022. Designing better public transport: understanding mode choice preferences following the COVID-19 pandemic. *Sustainability* 14, 10 (2022), 5952.

[59] United Nations. 2021. *Sustainable Transport, Sustainable Development: Interagency Report for the Second Global Sustainable Transport Conference.* Technical Report. United Nations.

[60] Anouk Van Kasteren and Marloes Vredenborg. 2023. Let's talk about the experienced context: An example regarding public transport information systems. In *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization* (Limassol, Cyprus) *(UMAP '23 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 187–190. doi:10.1145/3563359.3596979

[61] Anouk van Kasteren, Marloes Vredenborg, and Judith Masthoff. 2024. Understanding commuter information needs and desires in public transport: A comparative analysis of stated and revealed preferences. In *HCI in Mobility, Transport, and Automotive Systems.* Springer Nature Switzerland, Cham, Switzerland, 83–103. doi:10.1007/978-3-031-60480-5_5

[62] Christoffel Jacobus Venter, I Fourie, Lesedi Mokoma, S Harvett, N Grant, P Mukwaya, and L Ribet. 2023. Towards the empowered commuter: Exploring information behaviour of informal public transport users. In *Proceedings of the 41st Annual Southern African Transport Conference 2023.* Southern African Transport Conference, 12 pages. https://hdl.handle.net/2263/92461

[63] Vishwajeet Kishore Verma and Rajat Rastogi. 2025. Post COVID-19 behavioural changes in first-last mile travel and perception on service quality of public transport. In *Proceedings of the Eastern Asia Society for Transportation Studies*, Vol. 15. Eastern Asia Society for Transportation Studies, Tokyo, Japan, Article 26, 24 pages. http://www.easts.info/on-line/proceedings/vol.15/pdf/E_PP4050.pdf

[64] Centraal Bureau voor de Statistiek. 2025. *Doordeweeks minder ingecheckt in openbaar vervoer, in weekend juist meer.* https://www.cbs.nl/nl-nl/nieuws/2025/37/doordeweeks-minder-ingecheckt-in-openbaar-vervoer-in-weekend-juist-meer CBS Nieuwbericht.

[65] Marloes Vredenborg, Marit Bentvelzen, Anouk van Kasteren, Christine Bauer, and Judith Masthoff. 2026. EXID: Development and validation of the experienced impact of disruptions scale. *Transportation Research Part F: Traffic Psychology and Behaviour* 116, Article 103418 (2026), 18 pages. doi:10.1016/j.trf.2025.103418

[66] Marloes Vredenborg, Anouk van Kasteren, and Judith Masthoff. 2025. Personalization in public transport passenger information systems: A systematic review and framework. *Comput. Surveys* 57, 9, Article 226 (April 2025), 38 pages. doi:10.1145/3721478

[67] Mark Wardman. 2004. Public transport values of time. *Transport Policy* 11, 4 (2004), 363–377. doi:10.1016/j.tranpol.2004.05.001

[68] Jinhua Zhao, Valerie Webb, and Punit Shah. 2014. Customer loyalty differences between captive and choice transit riders. *Transportation Research Record* 2415, 1 (2014), 80–88. doi:10.3141/2415-09

Appendix

A Demographics

Table 3 displays the demographic composition of the sample of in the discrete choice experiment. The total sample consisted of 502 participants.

Table 3: Demographics of the descrete choice experiment participant sample ($N = 502$). Data is acquired through self report in the survey.

Age	**Count**	**Percentage**
18–25	53	11%
26–35	52	10%
36–45	71	14%
46–55	97	19%
55–65	144	29%
66+	84	17%
Unknown	1	<1%
Gender	**Count**	**Percentage**
Male	268	53%
Female	220	44%
Other	4	1%
Prefer not to say	8	2%
Travel frequency	**Count**	**Percentage**
>3/week	111	22%
2–3/week	130	26%
1/week	71	14%
2–3/month	124	25%
≤1/month	64	13%
Unknown	2	<1%
Residential environment	**Count**	**Percentage**
Urban	388	77%
Rural	111	22%
Unknown	4	1%

B Mixed Logit Estimation Results

Table 4 shows the full estimation results of the MXL model after backwards elimination.

Table 4: Full estimation results of the MXL model, including standard errors, p-values and confidence intervals. Statistical significance is set at $\alpha = 0.05$.

Variable	Est.	Std.Err.	z-val	$P > \lvert z \rvert$	95% CI	
log.extra_traveltime	-2.49	0.74	-3.37	0.001	-3.94	-1.04
transfers	0.96	0.31	3.15	0.002	0.35	1.57
waiting	1.01	0.54	1.86	0.063	-0.05	2.07
crowdedness	-2.80	0.22	-12.86	<0.001	-3.23	-2.37
hastrain	2.51	0.15	16.76	<0.001	2.22	2.80
hasothermode	0.10	0.33	0.32	0.751	-0.55	0.75
windy_transfers	1.00	0.27	3.66	<0.001	0.47	1.53
rain_transfers	1.79	0.41	4.34	<0.001	0.99	2.59
rain_waiting	1.53	0.65	2.34	0.019	0.26	2.80
rain_hastrain	1.28	0.34	3.70	<0.001	0.61	1.95
rain_hasothermode	1.62	0.49	3.27	0.001	0.65	2.58
work_crowdedness	0.52	0.22	2.36	0.018	0.09	0.95
uncertain_waiting	-1.25	0.39	-3.20	0.001	-2.01	-0.49
5min_waiting	1.15	0.43	2.71	0.007	0.31	1.99
sd.extra_traveltime	7.19	0.58	12.44	<0.001	6.05	8.33
sd.transfers	2.07	0.21	9.68	<0.001	1.66	2.48
sd.waiting	3.52	0.49	7.16	<0.001	2.55	4.48
sd.crowdedness	1.88	0.17	10.98	<0.001	1.55	2.21
sd.hasothermode	2.71	0.23	11.65	<0.001	2.26	3.16

C Multinomial Logit Estimation Results

Table 5 shows the full estimation results of the MNL model after backwards elimination.

Table 5: Full stimation results of the MNL model, including standard errors, p-values and confidence intervals. Statistical significance is set at $\alpha = 0.05$.

Variable	Est.	Std.Err.	z-val	P>|z|	95% CI	
log.extra_traveltime	-2.79	0.33	-8.52	<0.001	-3,43	-2,15
transfers	0.81	0.10	8.04	<0.001	0,61	1,00
waiting	1.14	0.14	8.27	<0.001	0,87	1,41
crowdedness	-1.34	0.12	-11.65	<0.001	-1,57	-1,12
hastrain	0.90	0.13	6.89	<0.001	0,64	1,15
hasothermode	0.53	0.11	4.76	<0.001	0,31	0,75
windy_extra_traveltime	0.83	0.36	2.28	0.022	0,12	1,55
windy_transfers	0.50	0.08	6.523	<0.001	0,35	0,65
windy_hastrain	0.48	0.14	3.44	<0.001	0,21	0,76
windy_hasothermode	0.49	0.12	4.22	<0.001	0,26	0,72
rain_extra_traveltiime	1.11	0.37	3.01	0.003	0,39	1,84
rain_transfers	0.86	0.13	6.67	<0.001	0,61	1,11
rain_waiting	0.74	0.18	4.17	<0.001	0,39	1,09
rain_hastrain	0.61	0.15	4.12	<0.001	0,32	0,90
rain_hasothermode	0.94	0.14	6.92	<0.001	0,68	1,21
work_extra_traveltime	0.88	0.28	3.14	0.002*	0,33	1,43
work_transfers	-0.20	0.06	-3.26	0.001	-0,32	-0,08
work_hastrain	0.25	0.09	2.66	0.008	0,06	0,43
uncertain_waiting	-0.65	0.08	-7.56	<0.001	-0,82	-0,48
5min_waiting	0.21	0.09	2.34	0.019	0,03	0,38
organised_hastrain	0.47	0.14	3.49	<0.001	0,21	0,74
casual_crowdedness	0.78	0.17	4.68	<0.001	0,45	1,11
social_waiting	0.93	0.28	3.36	0.001	0,39	1,48
social_hastrain	-0.61	0.30	-2.02	0.043	-1,21	-0,02
confident_crowdedness	0.32	0.09	3.74	<0.001	0,15	0,50
confident_hastrain	0.32	0.10	3.20	0.001	0,12	0,52
36-45_transfers	-0.43	0.09	-4.69	<0.001	-0,61	-0,25
36-45_crowdednes	0.44	0.13	3.29	0.001	0,18	0,70
36-45_hastrain	-0.38	0.17	-2.28	0.023	-0,71	-0,05
36-45_hasothermode	-0.88	0.15	-5.76	<0.001	-1,18	-0,58
46-55_transfers	-0.26	0.09	-3.08	0.002	-0,43	-0,10
46-55_crowdednes	0.38	0.12	3.19	0.001	0,15	0,61
46-55_hastrain	-0.51	0.15	-3.51	<0.001	-0,80	-0,23
46-55_hasothermode	-0.71	0.14	-5.14	<0.001	-0,97	-0,44
55-65_transfers	-0.55	0.12	-4.69	<0.001	-0,77	-0,32
55-65_waiting	-0.54	0.19	-2.79	0.005	-0,92	-0,16
55-65_crowdednes	0.37	0.12	2.95	0.003	0,12	0,61
55-65_hasothermode	-0.87	0.12	-7.41	<0.001	-1,10	-0,64
66+_extra_traveltime	1.37	0.37	3.72	<0.001	0,65	2,09
66+_hasothermode	-0.86	0.13	-6.60	<0.001	-1,07	-0,58
urban_crowdednedness	-0.31	0.10	-3.23	0.001	-0,50	-0,12

D Multinomial logit (MNL) specification

Let respondent n choose route alternative i in task t. Utility is defined as

$$U_{nit} = V_{nit} + \varepsilon_{nit}, \qquad \varepsilon_{nit} \sim \text{i.i.d. type-I extreme value.} \tag{1}$$

The systematic utility is decomposed into route attributes, context interactions, and person-level interactions:

$$V_{nit} = V_{nit}^{\text{attr}} + V_{nit}^{\text{ctx}} + V_{nit}^{\text{pers}} \tag{2}$$

Route attributes.

$$V_{nit}^{\text{attr}} = \beta_{\log tt} \log(\mathit{extraTraveltime}_{nit}) + \beta_{tr}\, \mathit{transfers}_{nit} + \beta_{wt}\, \mathit{waiting}_{nit} + \beta_{cr}\, \mathit{crowdedness}_{nit} + \beta_{ht}\, \mathit{hastrain}_{nit} + \beta_{hm}\, \mathit{hasothermode}_{nit} \tag{3}$$

Context interactions. Let $\mathbb{I}(\cdot)$ denote task-level context indicators.

$$\begin{aligned} V_{nit}^{\text{ctx}} = {} & \mathbb{I}(\text{windy})_{nt} \Big(\beta_{\log tt}^{w} \log(\mathit{extraTraveltime}_{nit}) + \beta_{tr}^{w} \mathit{transfers}_{nit} + \beta_{ht}^{w} \mathit{hastrain}_{nit} + \beta_{hm}^{w} \mathit{hasothermode}_{nit} \Big) \\ & + \mathbb{I}(\text{rain})_{nt} \Big(\beta_{\log tt}^{r} \log(\mathit{extraTraveltime}_{nit}) + \beta_{tr}^{r} \mathit{transfers}_{nit} + \beta_{wt}^{r} \mathit{waiting}_{nit} + \beta_{ht}^{r} \mathit{hastrain}_{nit} + \beta_{hm}^{r} \mathit{hasothermode}_{nit} \Big) \\ & + \mathbb{I}(\text{work})_{nt} \Big(\beta_{\log tt}^{wk} \log(\mathit{extraTraveltime}_{nit}) + \beta_{tr}^{wk} \mathit{transfers}_{nit} + \beta_{ht}^{wk} \mathit{hastrain}_{nit} \Big) + \mathbb{I}(\text{uncertain})_{nt}\, \beta_{wt}^{u} \mathit{waiting}_{nit} \\ & + \mathbb{I}(\text{5min})_{nt}\, \beta_{wt}^{5m} \mathit{waiting}_{nit} \end{aligned} \tag{4}$$

Person-level interactions.

$$\begin{aligned} V_{nit}^{\text{pers}} = {} & \gamma_{\text{org}\times ht}\, \mathit{organised}_n\, \mathit{hastrain}_{nit} + \gamma_{\text{cas}\times cr}\, \mathit{casual}_n\, \mathit{crowdedness}_{nit} + \gamma_{\text{soc}\times wt}\, \mathit{social}_n\, \mathit{waiting}_{nit} + \gamma_{\text{soc}\times ht}\, \mathit{social}_n\, \mathit{hastrain}_{nit} \\ & + \gamma_{\text{conf}\times cr}\, \mathit{confident}_n\, \mathit{crowdedness}_{nit} + \gamma_{\text{conf}\times ht}\, \mathit{confident}_n\, \mathit{hastrain}_{nit} + \gamma_{\text{urb}\times cr}\, \mathit{urban}_n\, \mathit{crowdedness}_{nit} \\ & + \mathbb{I}(36\text{–}45)_n \Big(\gamma_{36\text{–}45\times tr}\, \mathit{transfers}_{nit} + \gamma_{36\text{–}45\times cr}\, \mathit{crowdedness}_{nit} + \gamma_{36\text{–}45\times ht}\, \mathit{hastrain}_{nit} + \gamma_{36\text{–}45\times hm}\, \mathit{hasothermode}_{nit} \Big) \\ & + \mathbb{I}(46\text{–}55)_n \Big(\gamma_{46\text{–}55\times tr}\, \mathit{transfers}_{nit} + \gamma_{46\text{–}55\times cr}\, \mathit{crowdedness}_{nit} + \gamma_{46\text{–}55\times ht}\, \mathit{hastrain}_{nit} + \gamma_{46\text{–}55\times hm}\, \mathit{hasothermode}_{nit} \Big) \\ & + \mathbb{I}(55\text{–}65)_n \Big(\gamma_{55\text{–}65\times tr}\, \mathit{transfers}_{nit} + \gamma_{55\text{–}65\times wt}\, \mathit{waiting}_{nit} + \gamma_{55\text{–}65\times cr}\, \mathit{crowdedness}_{nit} + \gamma_{55\text{–}65\times hm}\, \mathit{hasothermode}_{nit} \Big) \\ & + \mathbb{I}(66+)_n \Big(\gamma_{66+\times \log tt}\, \log(\mathit{extraTraveltime}_{nit}) + \gamma_{66+\times hm}\, \mathit{hasothermode}_{nit} \Big) \end{aligned} \tag{5}$$

Choice probability.

$$P_{nit} = \frac{\exp(V_{nit})}{\sum_{j \in \mathcal{J}_{nt}} \exp(V_{njt})} \tag{6}$$

E Mixed logit (MXL) specification

Utility is defined analogously to the MNL model:

$$U_{nit} = V_{nit} + \varepsilon_{nit}, \qquad \varepsilon_{nit} \sim \text{i.i.d. EV} \tag{7}$$

The systematic utility has the same structure:

$$V_{nit} = V_{nit}^{\text{attr}} + V_{nit}^{\text{ctx}} \tag{8}$$

Route attributes.

$$V_{nit}^{\text{attr}} = \beta_{\log tt,n} \log(\mathit{extraTraveltime}_{nit}) + \beta_{tr,n}\,\mathit{transfers}_{nit} + \beta_{wt,n}\,\mathit{waiting}_{nit} + \beta_{cr,n}\,\mathit{crowdedness}_{nit} + \beta_{ht}\,\mathit{hastrain}_{nit} + \beta_{hm,n}\,\mathit{hasothermode}_{nit} \tag{9}$$

Context interactions.

$$\begin{aligned} V_{nit}^{\text{ctx}} = {} & \beta_{tr}^{w}\,\mathit{windy\_transfers}_{nit} + \beta_{tr}^{r}\,\mathit{rain\_transfers}_{nit} + \beta_{wt}^{r}\,\mathit{rain\_waiting}_{nit} + \beta_{ht}^{r}\,\mathit{rain\_hastrain}_{nit} + \beta_{hm}^{r}\,\mathit{rain\_hasothermode}_{nit} \\ & + \beta_{cr}^{wk}\,\mathit{work\_crowdedness}_{nit} + \beta_{wt}^{u}\,\mathit{uncertain\_waiting}_{nit} + \beta_{wt}^{5m}\,\mathit{5min\_waiting}_{nit} \end{aligned} \tag{10}$$

Random parameters. A subset of route-attribute coefficients is modelled as random:

$$\begin{aligned} \beta_{k,n} = \bar{\beta}_k + \sigma_k \eta_{k,n}, \qquad & \eta_{k,n} \sim \mathcal{N}(0,1), \\ \text{for } k \in \{\log tt,\ tr,\ wt,\ cr,\ hm\} & \end{aligned} \tag{11}$$

Choice probability.

$$P_{nit} = \int \frac{\exp(V_{nit}(\boldsymbol{\beta}_n))}{\sum_{j \in \mathcal{J}_{nt}} \exp(V_{njt}(\boldsymbol{\beta}_n))} f(\boldsymbol{\beta}_n)\, d\boldsymbol{\beta}_n, \tag{12}$$

approximated by simulated maximum likelihood.