Modelling Preference Heterogeneity for Context-Aware Decision Support During Public Transport Disruptions

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Abstract

Public transport disruptions require travellers to make rapid replanning decisions under uncertainty, increasing cognitive burden and negatively affecting the travel experience. Supporting such decisions through personalised, context-aware recommendations requires modelling heterogeneous and context-dependent behaviour. This paper investigates how such behaviour can be modelled for route recommendations during disruptions. Using a discrete choice experiment and latent class modelling, we identify recurring decision strategies—context-adaptive, efficiency-driven rerouting, and waiting-oriented—rather than stable traveller types. Overlap between classes suggests that individuals shift strategies across situations. By framing latent classes as decision strategies, this work provides modelling insights beyond the public transport domain and positions latent class modelling as a structured step toward personalisation in context-dependent decision settings.

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, Decision-Support, User Modelling, Preference Modelling, User Choices, Personalisation, Context-Aware Systems

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1 Introduction

Many personalised decision-support systems rely on user models that approximate how people make decisions across contexts. A central challenge is representing behavioural heterogeneity in a way that captures meaningful individual differences while remaining structured enough to generalise to unseen users and situations [40]. This is particularly difficult in real-world decision-making, where choices involve trade-offs between multiple attributes under uncertainty. In this setting, aligning recommendations with users' reasoning is critical, as transparent representations of preferences and trade-offs foster user trust and acceptance [53, 73].

We investigate this challenge in the context of *route recommendation in public transport (PT) during disruptions*, a setting in which heterogeneity and context dependence are especially pronounced. When services fail, travellers must replan and choose among alternative routes that differ in, for instance, travel time, reliability, transfers, waiting time, or travel mode. These decisions occur under heightened uncertainty and increase cognitive load [5, 20, 69]. Preferences and trade-offs may shift with situational context, such as time pressure or trip purpose [25, 38].

Providing information during disruptions is critical for the overall travel experience [16, 37, 69]. While disruptions can have substantial impacts, timely and actionable support can mitigate their effects [50, 54]. However, disruption support often remains generic and one-size-fits-all [67], failing to account for individual preferences, needs, and situational context [22, 71].

Prior research shows that both personal and contextual factors shape travel experience and decision making [30, 66, 72], motivating user models that can capture structured variation in decision strategies across individuals and contexts. Our goal is to model travellers in a way that enables personalised decision-support for route recommendations during disruptions.

Our contributions are threefold: (i) We formulated users' route choice in PT during disruptions as a user modelling problem, capturing how choice preferences are person-specific and depend on context. (ii) Using Latent Class Model (LCM), we show that latent classes are best interpreted as *overlapping decision strategies* rather than as distinct traveller types, suggesting that individuals may draw on multiple decision strategies depending on context. (iii) We demonstrate that a LCM provides a structured step toward personalisation in settings characterised by behavioural heterogeneity and context dependence, while highlighting the limits of static class-based models.

By shifting the focus from fixed user profiles to interpretable decision strategies, this work points toward a more flexible approach to user modelling that is suitable for dynamic, context-sensitive decision-support settings such as public transport.

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2 Related work

2.1 Public Transport Disruptions and Travel Experience

In public transport (PT), deviations from planned schedules—such as delays, cancellations, and detours—are common and strongly shape travellers' experiences. Disruptions can be categorised as planned (e.g., maintenance or strikes) or unplanned (e.g., accidents or system failures), with unplanned events in particular reducing traveller satisfaction and perceived service quality [76]. Such situations often introduce annoyance and discomfort through waiting, crowding, or exposure to adverse weather [9].

From a user-centred perspective, disruptions represent cognitively demanding situations. Cognitive Load Theory suggests that working-memory capacity is limited [60, 61]. During disruptions, travellers must process uncertain, time-sensitive information while comparing unfamiliar alternatives, often under stress. Poorly structured or overly detailed information can quickly overwhelm this capacity, hindering effective decision making [5, 31, 69]. Decision-support systems therefore play a critical role not only in identifying feasible alternatives, but in structuring information in a way that supports interpretation, comparison, and trade-off reasoning, thereby reducing cognitive burden.

This underscores the importance of timely and actionable information during disruptions [16, 67]. However, such support is rarely personalised. Manual preference configuration places additional demands on users precisely when cognitive resources are scarce [e.g., 3, 59]. Automated personalisation offers a more promising approach [21, 36], as it allows decision-support systems to adapt to heterogeneous preferences and contextual conditions without increasing user effort.

2.2 Context in Public Transport

Context can be broadly defined as "any information that can be used to characterise the situation of an entity" [1]. Prior work commonly distinguishes between the individual and their context [8, 39, 75], using terms such as internal versus external, intrinsic versus extrinsic, or personal versus environmental. Building on this distinction, we consider the traveller as the entity, while context refers to all factors external to the traveller.

The literature shows that contextual conditions substantially shape PT experiences [37]. Crowdedness has been associated with increased stress, discomfort, and safety concerns in railway travel [19, 35, 63]. Weather affects mood and perceived service quality [14, 26, 49]. Nearby amenities can also improve the waiting experience by reducing the perceived waiting time [27]. Moreover, the influence of context extends beyond experience and directly affects decision-making. For instance, work-bound trips are more time-constrained, increasing the perceived cost of delays compared to home-bound journeys [25, 28], where travellers more often deviate from their usual route [30]. Additionally, perceived efficiency and comfort have been shown to impact route choice [30], while trip purpose and weather influence transportation mode choice [14, 32, 49]. During disruptions, temporal constraints—such as commuting to work—further affect whether travellers choose to wait or reroute [57]. Service reliability also plays a critical role, as unreliable services increase stress and can lead travellers to abandon transport, particularly when service restoration information is lacking [7, 52, 76].

Importantly, contextual effects do not operate in isolation. van Kasteren and Vredenborg [66] show that travellers' experienced context emerges from combinations of contextual factors rather than single variables, and that these combined effects differ across individuals. This supports the view of context as an interactional phenomenon rather than a set of independent factors [24]. Accounting for the contextual situation is essential for effective personalisation of PT decision support, particularly in disrupted and time-critical situations.

2.3 Context-Aware Personalisation for Public Transport Information Systems

Personalisation in PT is increasingly explored as a means to improve traveller experience [e.g., 34, 48, 74], particularly via information provision and route recommendations [72]. While personalised information primarily concerns what content is presented to whom and when, personalised recommendations also require actionable guidance that supports travellers in making concrete choices.

Prior work has demonstrated the potential of contextual information to adapt PT information systems. Examples include context-aware mobile services and displays that adjust information based on vehicle location and speed [70], user location and time of day [42], augmented displays in railway settings [64], and smart mobility services integrating contextual data from multiple external sources [2]. While these systems illustrate how context can tailor information, they often lack the support for detailed route-level decision-making.

Route recommendation systems aim to provide travellers with suitable routes and broadly fall into optimisation-based methods, which compute routes within the network, and classification-based methods, which rank pre-generated alternatives. These approaches are typically driven by attributes such as travel time or cost, optionally weighted by user preferences [36]. Context can be incorporated either as optimisation constraints [17, 23] or as features influencing route ranking [e.g., 4, 51].

Based on prior work on explanations in recommender systems [53, 62], we argue the importance of transparent and interpretable models for recommendation. For systems to be perceived as trustworthy, users must be able to understand recommendations and recognise how these align with their own expectations, reasoning and preferences [73]. In PT route recommendations, making underlying trade-offs explicit is therefore essential for supporting travellers' decisions and managing their travel experience.

In this work, we focus on context-aware route ranking grounded in decision-making theory, which models choices as subjective utility-based trade-offs [e.g., 10, 65]. In PT, this may imply, for instance, that faster but crowded or uncertain routes are less attractive than slightly slower but predictable options [66]. While personalised and context-aware route planning for regular travel has been studied using preference learning and multi-criteria routing [e.g., 15, 21, 36, 45], personalised disruption support remains limited. Existing approaches are often restricted to high-level decisions such as waiting versus rerouting [e.g., 6, 12, 58], offering limited support for evaluating concrete alternatives.

We address this gap by analysing how contextual factors shape preferences among available alternative routes during train cancellations. By doing so, we aim to inform the design of context-aware, personalised disruption support that reduces cognitive burden by aligning recommendations with travellers' decision strategies, rather than solely optimising predictive accuracy.

While models such as Mixed Logit (MXL) can capture substantial heterogeneity in traveller preferences [57, 68], their reliance on continuous random parameters limits their practical applicability for personalised decision support, particularly for unseen users. Traveller preferences are expected to vary across situational contexts, requiring models that balance expressive representations of heterogeneity with interpretability and practical usefulness. To address this, we use a LCM, which represents heterogeneity through a finite number of latent classes, commonly interpreted as user profiles [29, 43]. Each class is characterised by its own set of utility parameters and membership predictors. This approach enables us to capture both observed and unobserved preference heterogeneity relevant for personalised disruption support.

3 Methods

3.1 Experimental Setup

To study route choice behaviour during train cancellations, an unlabelled discrete-choice experiment was conducted via a stated-preference survey. This setup allowed controlled manipulation of route attributes and contextual factors to elicit trade-offs under disruption. The study used a mixed repeated-measures design with four contextual variables (i.e., travel direction, weather, distance to shops, and disruption certainty) yielding a total of 72 possible scenarios. To limit participant burden, each participant evaluated two randomly selected scenarios, each comprising four route choice tasks. Within each task, only crowdedness varied, while all other route attributes were held constant at the scenario level, enabling within-subject comparisons and analysis of context–attribute interactions. Ethical approval was received from the Utrecht University Research Institute of Information and Computing Sciences Ethics Review Board, and all participants provided informed consent.

3.2 Data Collection Setting

Data were collected in the Netherlands, where the PT system is dense, multimodal network with frequent departures, enabling flexible rerouting during disruptions. Rail services are primarily operated by Dutch Railways (NS), complemented by regional rail, buses, trams, and metros. Most travellers use a travel card, which allows travel across operators but records only check-in and check-out events rather than exact routes. As a result, rerouting behaviour during disruptions is not directly observable, motivating the use of stated-preference data to study route choice under disruption.

3.3 Stimuli and Materials

We implemented the survey in Qualtrics [55]. Due to the visual elements (choice sets presented as images), the survey was optimised for laptop or monitor screens. Participants were notified of this in the invite and redirected when opening the link on a mobile device.

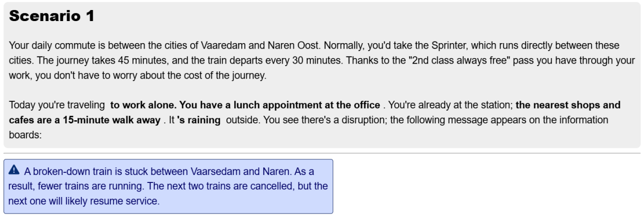
Routes were chosen based on real journeys with station names altered to avoid bias. To help participants imagine the context, scenarios (see Figure 1) described the original route's origin–destination, transportation mode, duration, and connection frequency, with cost held constant. Contextual conditions were randomly selected and described. For scenarios with work-bound trips, time constraints were stated. Each scenario concluded with a disruption announcement describing the cause and certainty. Scenarios were refined through a pilot study assessing clarity, realism, and cognitive demand. Alternative routes were presented as images created in Figma[1], mimicking the Dutch Railways app to ensure a familiar layout (see Figure 2). A pilot study evaluating realism, complexity, and valence guided final adjustments. The route-choice tasks were created using the hotspot question type in Qualtrics.

3.4 Variables

Route choice is the dependent variable, which is modelled as probabilities based on route utility. The independent variables can be grouped as route attributes, context attributes, and demographic attributes. Table 1 provides more elaborate variable descriptions.

3.5 Sample

Participants were recruited via the Dutch Railways travellers panel[2], with sampling aimed at balancing age, gender, and travel frequency; individuals under 18 or over 70 were excluded. Of 681 people who started the survey, 133 did not complete it and were removed. Furthermore, those finishing the survey in under 3 minutes were excluded due to low data quality (threshold informed by pilot medians and minimum reasonable reading time). The final sample comprised 502 participants. Table 2 summarizes the demographic information.



Scenario 1

Your daily commute is between the cities of Vaaredam and Naren Oost. Normally, you'd take the Sprinter, which runs directly between these cities. The journey takes 45 minutes, and the train departs every 30 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 traveling **to work 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 raining** outside. You see there's a disruption; the following message appears on the information boards:

A broken-down train is stuck between Vaarsedam and Naren. As a result, fewer trains are running. The next two trains are cancelled, but the next one will likely resume service.

Figure 1: Translated example of a scenario used.

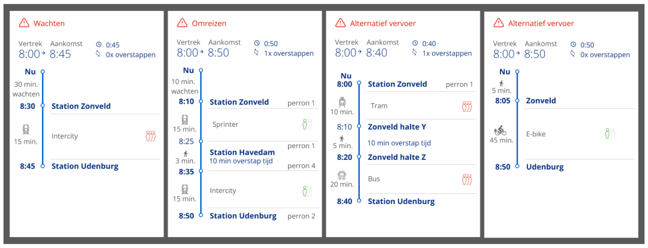


Figure 2: Example choice set displaying the option to wait for the original route and three alternative options.

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[1] https://www.figma.com/

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

Table 1: Description of variables used to model route choice behaviour during disrupted journeys.

Name	Type (Range)	Description
Route attributes		
`log. extra_traveltime`	Continuous (25–60)	Centred variable of the log of the extra travel time in minutes compared to the original route.
`waiting`	Binary	ASC for the waiting alternative
`transfers`	Continuous (0–2)	Number of transfers.
`crowdedness`	Binary	Not crowded or crowded route.
`hastrain`	Binary	The route includes a train segment.
`hasothermode`	Binary	the route included segments with other modes of transport (bus, tram, bike).
Context attributes		
weather	Categorical (3 levels)	Weather type: `sunny`, `windy`, `rain`.
direction	Binary	Travelling to `work` vs. returning `home`.
disruption certainty	Binary	`Certain` (the next connection will run) vs. `uncertain` (the connection may not run).
distance to amenities	Categorical (3 levels)	Amenities within `no`, `5-minute`, or `15-minute` walking distance.
Demographic attributes		
age	Ordinal (6 levels)	Grouping age per 10-year bins.
travel frequency	Ordinal (3 levels)	Frequency in which participants travel by PT: weekly, monthly, less than once a month.
traveller type	Categorical (6 levels)	Conscious, organised, casual, confident, social, venturous.
region type	Binary	The type of region participants live in: urban vs. rural.

Table 2: Sample demographics ($N = 502$).

Age	Count	Travel frequency	Count
18–25	53	>3/week	111
26–35	52	2–3/week	130
36–45	71	1/week	71
46–55	97	2–3/month	124
55–65	144	≤1/month	64
>65	84	Unknown	2
Unknown	1		
Gender	**Count**	**Environment**	**Count**
Male	268	Urban	388
Female	220	Rural	111
Other	12	Unknown	4

3.6 Procedure

Participants received an invitation email with a study description and survey link. Mobile users were warned about limited optimisation and could continue or reopen the survey on a larger device. After providing informed consent, participants received instructions, completed a practice choice set, and then evaluated two scenarios with four choice tasks each, followed by demographic questions.

3.7 Data Preparation and Analysis

Survey data were exported from Qualtrics, reshaped from wide to long format (one row per route alternative), and merged with route attributes. Categorical variables were one-hot encoded, including transport modes via indicators for train (`hastrain`) and non-train modes (`hasothermode`). Extra travel time was centred.

We model route choice using a latent-class discrete-choice framework to capture unobserved preference heterogeneity relevant for personalised disruption support by grouping individuals into a finite number of latent preference profiles [29, 43]. Each class is characterised by its own set of utility parameters. Person-level covariates were included in the class membership model; those insignificant across all classes were removed to improve model efficiency and stability. To account for variability in decision making, contextual factors were specified as interactions with route attributes. Crowdedness, defined at the alternative level, was included as a main effect, while other factors (e.g., weather, disruption uncertainty), defined at the choice situation level, were only included through interactions. As route alternatives (except waiting) lack inherent meaning, a status-quo Alternative Specific Constant (ASC) was specified only for the waiting option to maintain generalizability to unseen routes.

The model was estimated using maximum likelihood in Biogeme (v3.3) [13], accounting for repeated choices per individual. The final specification was obtained through backward elimination. The number of classes was selected based on model fit (log-likelihood, BIC) and interpretability, resulting in a three-class model. The LCM was compared to an MXL model in terms of predictive performance and interpretability. While we complementarily report accuracy and $F1$-scores with a descriptive purpose, these metrics are sensitive to class imbalance and do not reflect the probabilistic nature of route choice. We therefore treat log-likelihood as the primary evaluation metric, with accuracy-based measures as complementary.

4 Results

We analysed data of 502 participants, yielding 4016 choice tasks with four alternatives each (16064 observations). On a high-level, participants chose to wait 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%).

4.1 Model Selection

First, a MXL model was estimated as a baseline, capturing preference heterogeneity through normally distributed random parameters. While it achieves superior in-sample fit, indicating substantial heterogeneity, predictions for unseen users rely on population-level distributions, leading to lower out-of-sample performance and uncertainty at the individual level.

A LCM represents heterogeneity through distinct classes, resulting in improved out-of-sample performance. Although less flexible, it offers greater transparency and interpretability, as recommendations can be linked to explicit preference profiles. This highlights a trade-off between expressive power and practical applicability: continuous models capture richer variation, whereas profile-based models provide more stable and actionable predictions.

Two-, three-, and four-class LCM models were estimated. Although the four-class model shows a better fit, it yields less distinctive classes, with some reflecting residual patterns rather than meaningful strategies. We therefore focus on the three-class model, which balances fit and interpretability, without losing predictive accuracy. Table 4 reports the model comparison metrics.

Variance inflation factors (VIF) and a correlation matrix were used to assess multicollinearity in the main effects. Given the inclusion of interaction terms, a threshold of 10 was applied; all VIF scores remained below this level. The correlation matrix for the main effects is shown in Table 3.

The robustness check with all ASCs shows that including alternative-level effects alters some parameter estimates. In particular for Class 2, core attributes such as travel time become insignificant, while several ASCs are large and significant. This suggests that the ASCs absorb systematic variation that may otherwise be attributed to route attributes, potentially acting as a categorical representation of these attributes. Given the experimental design, in which alternatives differ in their attribute composition but lack inherent semantic meaning, these constants likely capture design-specific or correlated attribute effects rather than stable behavioural preferences and do not generalise beyond the experimental setting. This interpretation is supported by the fact that the full ASC model does not improve model fit and performs worse in terms of BIC (See table 4. Overall, the main specification yields more interpretable, generalisable, and theoretically consistent parameter estimates, supporting its use for modelling disruption decision-making.

The final three-class model is specified below. Route choice behaviour is modelled using a latent class discrete choice framework [33]. For individual n, alternative i, choice task t, and latent class c, utility is defined as

$$U_{nit|c} = V_{nit|c} + \varepsilon_{nit} \tag{1}$$

Preference heterogeneity is represented by a finite set of C latent classes, each associated with a class-specific parameter vector.

The systematic utility is specified as a linear function $V_{nit|c}$ of route attributes and context-dependent interaction terms:

$$V_{nit|c} = \alpha^{(c)}_{\text{wait}} \cdot 1(i = \text{wait}) + \boldsymbol{\beta}_c^\top \mathbf{x}_{nit} + \boldsymbol{\theta}_c^\top \mathbf{z}_{nit} \tag{2}$$

where $\alpha^{(c)}_{\text{wait}}$ is a class-specific status-quo constant for the waiting alternative, $\mathbf{x}_{nit}$ contains route attributes (e.g., extra travel time, transfers, waiting, crowdedness, and mode indicators) and $\mathbf{z}_{nit}$ contains interactions between contextual factors (e.g., weather, disruption certainty, trip purpose) and route attributes. Corresponding coefficient vectors $\beta_c^\top$ and $\theta_c^\top$ are class-specific, allowing trade-offs between route attributes and contextual effects to differ across decision strategies.

Class membership model. The probability that individual n belongs to class c is modelled using a multinomial logit:

$$P_{nc} = \frac{\exp\left(\alpha_c + \boldsymbol{\gamma}_c^\top \mathbf{s}_n\right)}{\sum_{m=1}^{C} \exp\left(\alpha_m + \boldsymbol{\gamma}_m^\top \mathbf{s}_n\right)} \tag{3}$$

where α_c denotes class-specific intercepts and $\mathbf{s}_n$ denotes person-level covariates (e.g., age) with $\gamma_c^\top$ as the corresponding, class-specific, coefficient vector. One class serves as the base class for identification.

Choice probability and mixture. Conditional on class c, route choice follows a multinomial logit model:

$$P_{nit|c} = \frac{\exp\left(V_{nit|c}\right)}{\sum_{j \in \mathcal{J}_{nt}} \exp\left(V_{njt|c}\right)} \tag{4}$$

where $\mathcal{J}_{nt}$ denotes the set of route alternatives j available to traveller n in at choice task t. The unconditional choice probability is obtained as a mixture over classes, reflecting soft class membership:

$$P_{nit} = \sum_{c=1}^{C} P_{nc}\, P_{nit|c}. \tag{5}$$

Panel likelihood. With repeated choice tasks per respondent, the individual likelihood is defined as

$$\mathcal{L}_n = \sum_{c=1}^{C} P_{nc} \prod_{t} P_{ni_t t|c} \tag{6}$$

and model parameters are estimated by maximum likelihood.

4.2 Estimation Results

Our final three-class LCM has a McFadden's pseudo-R^2 of 0.32 and a final log-likelihood per observation of −0.93, considered a good in-sample fit for route choice modelling standards [46, 47]. An 8-fold cross-validation indicates stable out-of-sample performance across folds with a mean log-likelihood per observation of −0.96. A low $F1$ score (0.38) indicates difficulty with minority alternatives.

Table 5 displays the full estimation results, which reveal three distinct decision-making profiles characterised by different trade-offs between waiting, rerouting, and mode switching during disruptions. While these profiles reflect systematic differences in decision logic, posterior class membership probabilities exhibit overlap. Based on the available data on user characteristics, the model cannot successfully assign travellers to classes.

4.3 Class Descriptions

The final model consists of three latent classes. Soft shares based on mean class probabilities indicate a balanced distribution (Class 1: 51%, Class 2: 23%, Class 3: 26%), whereas hard shares based on assigning individuals to the class with the highest posterior probability yield a more uneven split (96% of participants in Class 1, 4% in Class 2, none in Class 3). This discrepancy reflects overlap in class membership probabilities and supports the interpretation of the classes as decision-making strategies rather than distinct traveller profiles. Below, these strategies are described.

Class 1: Context-adaptive (51%)**:** This class represents an adaptive decision-making strategy. Extra travel time is moderately penalised, more so under uncertain disruptions. Travellers show a

Table 3: Correlation matrix of the main effects included in the Latent Class Model. Moderate correlations are highlighted.

	`log.extra_traveltime`	`transfers`	`waiting`	`crowdedness`	`hastrain`	`hasothermode`
`log.extra_traveltime`	1	0.28	0.29	0.12	0.12	0.12
`transfers`	0.28	1	-0.65	0.04	-0.11	0.45
`waiting`	0.08	-0.65	1	0.45	0.45	-0.45
`crowdedness`	0.29	0.04	0.45	1	0.20	0.07
`hastrain`	0.12	-0.12	0.45	0.20	1	-0.47
`hasothermode`	0.12	0.45	-0.45	0.07	-0.47	1

Table 4: Model performance comparison. MXL vs. two-, three- and four-class LCM including the three-class full ASC set robustness check. Log-likelihood (LL) is presented both in and out of sample. Accuracy and Macro-$F1$ are presented out-of-sample.

Model	LL per obs.	Out of sample LL	BIC	pseudo-R^2	Accuracy	Macro-$F1$
MXL	-0.82	-1.11	6728	0.41	0.53	0.38
2-class LCM	-0.99	-1.01	8226	0.28	0.53	0,37
3-class LCM	-0.93	-0,96	7724	0.33	0.53	0.38
4-class LCM	-0.91	-0.93	7628	0.34	0.52	0.38
3-class all ASCs	-0.93	-0.96	7751	0.33	0.53	0.38

Table 5: Full estimation results for each class of the LCM model including p-values. Statistical significance is set at $\alpha = 0.05$.

	Class 1 (51%)		Class 2 (23%)		Class 3 26%)	
	Estimate	$P > \|z\|$	**Estimate**	$P > \|z\|$	**Estimate**	$P > \|z\|$
`ASC_waiting`	0.18	0.461	2.09	0.165	2.87	<0.001
Route attributes						
`extra_traveltime`	-1.75	<0.001	-5.15	0.019	-4.78	<0.001
`crowdedness`	-1.41	<0.001	-2.16	<0.001	-0.84	<0.001
`transfers`	0.10	0.547	3.44	0.003	1.09	0.005
`hasothermode`	0.70	<0.001	0.81	0.481	0.01	0.990
`hastrain`	0.99	<0.001	6.20	<0.001	3.09	<0.001
Context interactions						
`crowdedness` × `extra_traveltime`	0.85	0.006	5.84	0.029	2.46	0.018
`work` × `extra_traveltime`	-	-	4.00	0.029	0.19	0.012
`uncertain` × `waiting`	–	–	–	–	-0.69	0.012
`uncertain` × `extra_traveltime`	-0.99	0.086	–	–	–	–
`windy` × `transfers`	0.62	0.001	–	–	–	–
`rain` × `transfers`	1.05	<0.001	–	-	–	–
`rain` × `hasothermode`	0.50	0.005	1.30	0.003	–	–
Class membership						
Constant	Base class		-1.39	<0.001	-1.27	0.002
Travel frequency			0.08	0.629	-0.31	0.030
Age 35–65			0.48	0.159	1.17	0.001
Age >65			1.25	0.004	1.26	0.006

moderately positive attitude towards both train and alternative transport modes. Decisions are influenced by situational context, with increased willingness to transfer or switch modes under adverse weather conditions. Crowded routes are penalised, more so for alternatives with little extra travel time. This strategy optimally balances the trade-offs, seeking not only efficient but also comfortable alternatives. This strategy is most likely to be adopted, yet more likely for frequent and young travellers.

Class 2: Proactive efficiency-driven rerouting (23%)**:** This strategy is time-sensitive but remains flexible. Extra travel time is penalised, however, less so when travelling towards work. Travellers are willing to accept transfers when this reduces overall travel time. There is a strong preference for train segments and a moderate acceptance of other modes in rainy weather. Crowdedness is mainly penalised when there is little extra travel time. Travellers above 65 are more likely to adopt this strategy.

Class 3: Risk averse & waiting-oriented (26%)**:** This strategy reflects a tendency to "wait it out". Travellers are more risk-averse and prefer to remain within the rail system, favouring waiting until the original connection resumes. This group may also reflect inertia or aversion to action. Although uncertain disruptions reduce the willingness to wait, waiting remains a substantial preference. Crowdedness is penalised stronger for alternatives with less extra travel time. Extra travel time is strongly penalised, however a little less when travelling towards work. People that travel less frequently are more likely to adopt this strategy.

The results show that the identified decision-making strategies differ in sensitivity to route attributes and contextual factors. Not all attributes are significant across classes, indicating strategy-specific trade-offs. For example, segments involving other transport modes positively affect preferences in the context-adaptive class, but not in the waiting-oriented or efficiency-driven strategies. Extra travel time is consistently negative, with stronger effects in the efficiency-driven and waiting-oriented classes. Crowdedness is also disliked across all classes, although its effect varies and is most pronounced in the efficiency-driven strategy. Interestingly, the interaction between crowdedness and extra travel time is positive, particularly for the efficiency-driven and waiting-oriented strategies. Uncertainty manifests differently across strategies: in the context-adaptive class, it moderates tolerance for extra travel time, whereas in the waiting-oriented class, it affects willingness to wait. Overall, differences between strategies are subtle but systematic, reflecting overlapping and context-dependent decision-making rather than sharply separable traveller types. Table 6 compares attribute sensitivities across classes.

5 Discussion

Latent class models are typically used to segment users into distinct profiles [11]. In contrast, our LCM shows substantial class overlap and weak individual-level assignment, suggesting that latent classes are better interpreted as *decision-making strategies* rather than stable traveller types. This framing acknowledges that individuals may draw on multiple strategies depending on the situation, aligning with findings by Kroesen [41].

In our model, context is incorporated via interaction effects, implying it modulates preferences within strategies. However, context may also influence which strategy is used. This highlights a limitation of static latent class models and points to the complexity of modelling route choice behaviour under disruption. This calls for approaches that capture both preference variation and shifts in strategies or logic under disruptions.

The identified strategies broadly align with established trade-offs between comfort, reliability, and travel time [12, 30, 44], but also manifest differently under disruption and varying contexts. Notably, transfers show a positive effect, suggesting this trade-off differs under disruptions. Travellers may accept additional transfers to maintain progress or reliability. The negative correlation with the waiting ASC (−0.65) reflects this: a positive valuation of additional transfers when rerouting may relate to an aversion to waiting. Travellers are more lenient towards transfers if it means that waiting for the service to resume can be avoided. Transfers represent an active strategy, whereas waiting reflects a passive one.

Crowdedness is consistently disliked, yet its interaction with extra travel time is counterintuitively positive, indicating greater tolerance for delay under crowded conditions. This may reflect expectation adjustment or a requirement that alternative routes offer a clear comfort improvement to be considered. If an alternative route provides little time benefit, it may still be rejected unless it is less crowded. This aligns in particular with the efficiency-driven and waiting-oriented strategies. Similarly, travelling to work reduces sensitivity to additional delays, suggesting that goal-oriented trips for less flexible activities increase tolerance for longer travel times. Conversely, when travelling home, travellers may be more sensitive to additional delays and prefer faster routes.

Finally, contextual factors further shape behaviour. Although the waiting-oriented strategy shows a strong baseline preference for waiting, this preference reduces under uncertainty, reflecting the risk it entails. Adverse weather increases acceptance of transfers and alternative modes for the adaptive strategy. Normally, these might not optimise comfort or efficiency, but trade-offs can be made to reduce exposure to the weather conditions. Together, these findings illustrate how travellers flexibly adapt their decision-making under disruption.

5.1 Implications for User Modelling and Personalisation

Our results highlight the inherent complexity of PT route decision-making during disruptions. Such situations with uncertainty and time pressure require travellers to make rapid decisions based on incomplete and evolving information. We observe substantial heterogeneity in preferences across individuals, as well as systematic shifts in preferences depending on situational context. The class structure aligns with the expectation that context does not affect everyone equally [66]. Together, this makes disrupted route choice particularly challenging to model and predict.

Despite this, our findings reveal structured patterns in how travellers trade off route attributes under different conditions. These strategies enable personalised disruption support and crowd balancing. The modest predictive accuracy of our models does not indicate a lack of behavioural structure, but rather reflects the limits of cold-start personalisation in highly dynamic settings. Even so, the model can already rank or filter alternative routes to better align with different decision strategies, offering a meaningful improvement over one-size-fits-all recommendations.

Importantly, our results suggest that decision strategies are not equivalent to stable user profiles. Travellers may rely on different strategies depending on the situation, for example prioritising reliability when travelling to an important appointment and comfort when travelling home. While the latent class framework provides a useful approximation of this heterogeneity, it assumes stable class membership and therefore cannot fully capture strategy switching across situations. More dynamic user modelling approaches, such as latent state models, may better represent how strategies are activated in response to contextual cues, but require careful theoretical grounding to distinguish factors that influence strategy selection from those that modulate preferences within a strategy.

Finally, advancing personalisation in disrupted travel contexts will require richer data, including more detailed contextual information and longitudinal observations of real-world decision-making under disruption. Additional traveller information, such as personality traits [18], personal characteristics [56], or attitudes [12], may

Table 6: Overview of latent decision-making profiles identified in the latent class model. The table abstracts from individual parameter estimates and summarizes dominant decision logic and contextual sensitivities.

Aspect	Class 1: Context-adaptive	Class 2: Proactive efficiency-driven rerouting	Class 3: Risk-averse & waiting-oriented
Primary decision focus	Adapting to situational conditions	Optimize travel time	Waiting and staying within train travel
Sensitivity to travel time	Moderate	High	Strong
Sensitivity to crowding	Conditional on travel time	Conditional on travel time	Conditional on travel time
Attitude toward waiting	Indifferent	Indifferent	Preferred
Attitude toward transfers	Accepting in adverse weather	Positive	Accepting
Using other transport modes	More accepting when it rains	Accepting when it rains	Indifferent
Train preference	Moderate	Very strong	Strong
Effect of uncertainty	Increases sensitivity to travel time	–	Reduces waiting preference
Effect of travel to work	–	More tolerent of travel time	More tolerant of travel time

further support adaptive personalisation. At the same time, practical and ethical constraints related to data availability, privacy, and cognitive burden must be carefully balanced. Future work should therefore pursue minimally intrusive data collection strategies, potentially informed by qualitative methods, to better understand when and why travellers shift between decision strategies.

5.2 Limitations and Future Considerations

Our findings highlight the potential of personalised disruption support, but also several limitations. First, effective personalisation cannot rely on static user profiles alone. While the latent class model identifies decision-making strategies, it does not reliably predict which strategy an individual will adopt in a given situation, particularly under cold-start conditions. Identifying observable signals to dynamically infer strategies and performing warm-start or few-shot personalisation experiments remains an important direction for future work.

Second, the model relies on standard discrete choice assumptions, such as independence of unobserved errors and correct class specification, which may not fully hold in complex real-world settings. In addition, one route alternative was rarely chosen (~6%), potentially affecting parameter estimation and predictive performance.

Third, although a specification with all ASCs did not improve fit, it suggests that unobserved alternative-specific or order effects cannot be fully ruled out. This may also indicate that route choice is influenced by additional factors not captured in the current model. As disruption decision-making is complex, future work should incorporate richer behavioural and contextual variables.

Fourth, the use of stated-preference data enables controlled experimentation but may not capture all real-world influences. Longitudinal revealed-preference data with larger samples would improve ecological validity and allow modelling of strategy adaptation over time. Results are also grounded in the Dutch railway context, which should be considered when generalising.

Finally, although more complex models may improve predictive accuracy, we prioritise interpretability to support transparency and user trust. Future work should examine how personalised recommendations are presented and used in practice, including their effects on decision-making and travel experience.

6 Conclusion

In this paper, we explored how heterogeneous, context-dependent choice behaviour can be represented through a structured modelling approach that is both interpretable and operational for personalised decision-support systems. We studied this challenge in the context of *route recommendation in PT during disruptions*, a setting where behavioural heterogeneity and context dependence are particularly pronounced. We aimed to capture decision-making patterns rather than merely predict choices.

Our contributions are three-fold: (i) We formulate route choice as a user modelling problem, where preferences are both person--specific and context-dependent. This captures how travellers trade off route attributes under varying conditions, supported by recurring patterns in sensitivities to travel time, transfers, transport modes, and contextual factors such as crowdedness and weather. (ii) We show that latent classes are better interpreted as *decision strategies* (context-adaptive, efficiency-driven rerouting, and waiting-oriented) rather than stable traveller types. Their overlap and weak individual-level assignment suggest that route choice is structured but not well captured by fixed profiles, motivating models that allow strategies to vary across situations. (iii) We demonstrate that LCM offers a practical balance between expressiveness and interpretability for modelling behavioural heterogeneity in disrupted route choice. While not fully resolving individual-level prediction, it enables meaningful ranking of alternatives and provides a structured step beyond one-size-fits-all disruption support.

Overall, this work highlights the role of modelling latent behavioural structure for personalised decision-support systems in complex environments. By framing latent classes as decision strategies, we provide modelling insights that extend beyond the PT domain to other settings characterised by heterogeneous and context-dependent choice behaviour.

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