ROMY: Risk-Optimized Mobility Through Graph-Based Prediction

Sabine Janzen[1,*], Kanav Avasthi[1], Behkam Fallah[1], Hannah Stein[1,2] and Wolfgang Maass[1,2]

[1]German Research Center for Artificial Intelligence (DFKI), Saarbrücken, Germany
[2]Saarland University, Saarbrücken, Germany

Abstract

Reliable routing in multimodal transport networks requires more than minimizing travel time: it demands accounting for the risk of delays and disruptions. This paper presents ROMY (Risk-Optimized Mobility), a decision support system that integrates heterogeneous data sources, advanced feature engineering, and a graph neural network (GNN)–based predictive core to deliver personalized, risk-aware route recommendations. ROMY models the transport network as a directed, attributed graph, combining spatial, temporal, modal, and semantic attributes to capture complex dependencies between network segments. The predictive core employs edge-conditioned message passing to incorporate contextual information such as travel mode, time-of-day, and navigation instructions into segment-level risk estimation. A pilot implementation demonstrates the system's ability to identify high-risk segments, outperform baseline models, and offer alternative routes that reduce risk with minimal impact on travel time. The results highlight ROMY's potential to enhance the reliability of multimodal mobility services and support data-driven transport planning.

Keywords

Risk-aware routing, Graph neural networks, Multimodal transport, Decision support systems

1. Introduction

Mobility is a cornerstone of modern society, yet public transport suffers from limited service frequency, punctuality issues and limited infrastructure coverage, particularly outside metropolitan areas [1, 2, 3, 4, 5]. Fewer than 63% of long-distance trains run on time [6], while rural areas often lack frequent, well-connected service [7, 8]. As a result, the majority of everyday trips are made by car (68%) [7], reinforcing reliance on private transport and limiting the uptake of public travel options. These structural issues pose serious implications for accessibility, economic participation, and environmental sustainability [9, 10]. Digital tools for travel planning, such as Google Maps and public transport apps (e.g., DB Navigator), provide static schedules and real-time disruption alerts, but fail to quantify the overall risk associated with a given journey. Travelers currently lack decision support that accounts for uncertainty, multimodal complexity, and personal constraints. This results in inefficient route selection, increased stress, and reduced adoption of sustainable transport options [8, 11]. These shortcomings highlight a critical gap in mobility planning: the absence of reliable, data-driven risk assessments that empower users to make informed transport decisions. Most current systems inform users of ongoing disruptions but do not quantify the probability of delay or failure across an entire journey, particularly when involving multiple modes of transport like car, train, bus etc. [12]. Additionally, there is little support for personalizing route recommendations based on individual preferences [13, 14].

The ROMY (Risk-optimized Mobility) approach aims to close this gap through an AI-driven framework that fuses open data sources (e.g., weather, infrastructure disruptions) with predictive models to generate risk-aware travel recommendations. Using methods such as Temporal Convolutional Neural Networks

ER2025: Companion Proceedings of the 44th International Conference on Conceptual Modeling: Industrial Track, ER Forum, 8th SCME, Doctoral Consortium, Tutorials, Project Exhibitions, Posters and Demos, October 20-23, 2025, Poitiers, France

*Corresponding author.
sabine.janzen@dfki.de (S. Janzen); kanav.avasthi@dfki.de (K. Avasthi); behkam.fallah@dfki.de (B. Fallah); hannah.stein@iss.uni-saarland.de (H. Stein); Wolfgang.Maass@dfki.de (W. Maass)
0000-0002-7504-4169 (S. Janzen); 0000-0000-0000-0000 (K. Avasthi); 0000-0000-0000-0000 (B. Fallah); 0000-0001-7021-0845 (H. Stein); 0000-0003-4057-0924 (W. Maass)

(TCNNs) and Graph Attention Networks (GATs), ROMY models temporal and spatial risks across transportation networks [15, 16, 17]. This enables both unimodal and multimodal route planning to be evaluated through the lens of reliability and individual relevance. The approach is designed to be extensible and generalizable across different mobility contexts. ROMY defines two primary use cases: rural regions with low transport coverage, and high-frequency corridors with dense demand and infrastructure pressure in Germany.

While the framework is intended to support both, this paper focuses on the rural use case, for which early system components and evaluation results are available. Early analysis in a rural test region indicates that predictive models can successfully identify high-risk routes [18]. These findings demonstrate the potential of ROMY's risk-optimized planning service to enhance confidence in public and shared mobility.

The remainder of this paper is structured as follows: Section 2 discusses related work. Section 3 presents the ROMY system architecture and key components. Section 4 details the data sources and processing strategies. Section 5 outlines the rural use case implementation with initial results given in section 6 before discussing implications in section 7. Finally, Section 8 concludes with an outlook and next steps.

2. Related Work

Mobility planning under uncertainty has become an increasingly important research area, particularly in the context of smart cities and sustainable transport. Numerous approaches intend to improve travel experience by incorporating real-time information, optimizing routes, or modeling travel behavior. However, few integrate multiple data sources to provide personalized, predictive risk assessments across multimodal routes. Classical models of travel behavior, such as Random Utility Maximization (RUM) and Random Regret Minimization (RRM), have been widely used to describe modal choice under static assumptions [19]. These have been extended through frameworks like the Cumulative Prospect Theory, which accounts for behavioral responses to variability in travel time [15]. While these approaches provide valuable theoretical insight, they are less effective in real-time, operational settings with dynamic risk factors.

To address these limitations, recent work has focused on integrating reliability and safety risks into route choice models. For instance, Tu et al. [20] and Huang et al. [21] proposed frameworks that integrate travel time variability and crash risk into decision-making processes. Fang et al. [22] introduced a network-level travel risk index to evaluate trip uncertainty. Although valuable, these models often lack real-time adaptability and user-centric design.

From a technical perspective, machine learning methods like Random Forests and Neural Networks have demonstrated utility in predicting delays, optimizing mode choice, or estimating demand [23]. More recently, Graph Neural Networks (GNNs) and their spatio-temporal variants have been applied to shared mobility systems and urban route planning [16, 24, 15]. These methods capture dependencies between spatial locations and temporal dynamics, but their application to risk modeling; especially in personalized, multimodal travel scenarios is still limited. Xiao et al. [16] and Liang et al. [24] show the power of GNNs for demand prediction and trip generation, yet they focus on dense urban environments rather than data-sparse or rural contexts. Existing platforms such as Google Maps, public transport apps like DB Navigator, and motion analytics services like MotionTag [25] or Teralytics [26] provide route suggestions and alerts but do not offer systematic assessments of route reliability. Moreover, most commercial tools fail to accommodate individual preferences or accessibility needs [19, 13]. The gap in existing work lies in the lack of integrated systems that combine historical and real-time data as well as spatial-temporal modeling to deliver user-specific, risk-informed routing advice.

3. System Overview

ROMY (Risk-Optimized Mobility) is an AI-driven decision support system that delivers personalized, risk-aware travel recommendations. In contrast to existing planners that exclusively focus on travel times or isolated disruption alerts, ROMY integrates historical and real-time multimodal data to quantify the probability of delays or failures across an entire journey. Emphasis lies on improving reliability and trust in public transport, particularly in under-served rural regions.

As shown in Fig. 1, ROMY's modular architecture consists of a **data integration** layer, a **preprocessing and feature engineering** stage, a **predictive core**, and a **recommendation layer**. Mobility networks are represented as a directed, attributed graph $G = (V, E, X, Z)$, where V is the set of nodes (e.g., intersections, stations), E the set of directed edges, X the node features, and Z the edge features such as travel time, mode, time-of-day, and travel instructions. The graph-based representation reflects

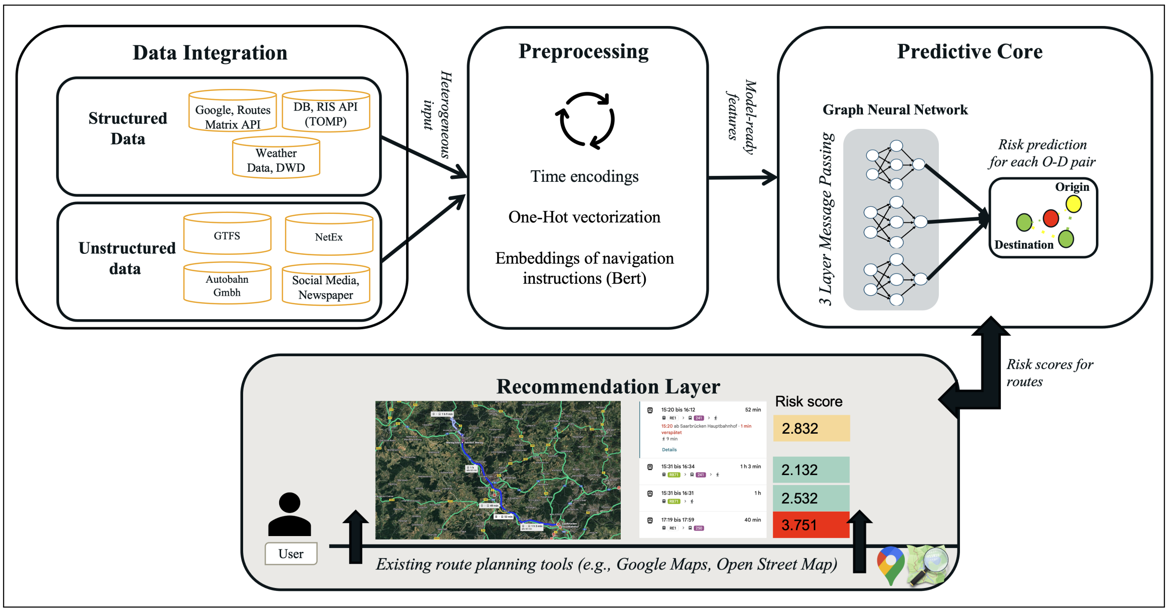

Figure 1: ROMY architecture: The diagram outlines the flow from heterogeneous data ingestion through preprocessing and spatio-temporal GNN-based risk prediction to the recommendation layer that integrates with external route planners. Arrows indicate both real-time and batch update paths showing the systems ability to adapt to new data.

the system's conceptual modeling foundation, where transport entities and relations are explicitly structured to support semantic reasoning and modular analytics (cf. section 7). This structure enables the model to capture spatial relationships and temporal dependencies [27, 15, 16].

The **data integration layer** fuses structured and unstructured sources, including GTFS and NeTEx datasets from DELFI and Deutsche Bahn [28, 29, 30, 31], real-time feeds from Autobahn GmbH and DB's RIS API [31, 32], weather forecasts, planned construction activities [32, 31], and event data (cf. Fig. 1). Social media and news APIs are also monitored for emerging disruptions [33]. **Preprocessing** transforms heterogeneous inputs into model-ready features, including cyclic time encodings that preserve the periodic nature of hours and days [34], one-hot vectors for travel modes like DRIVE or TRANSIT, and 384-dimensional embeddings of navigation instructions derived from a pre-trained BERT-based SentenceTransformer model [35] to capture their semantic meaning.

The **predictive core** is implemented as a Graph Neural Network (GNN) that incorporates both the topology of the transport network and rich edge attributes. The model uses edge-conditioned message passing via NNConv layers [36], where the transformation of a node's embedding depends directly on the attributes of the connecting edge. This allows the model to adapt its message passing according to variations in travel mode (e.g., car, bus, walking), temporal context (e.g., weekday vs. weekend, rush hour vs. off-peak), and semantic content derived from navigation instructions (e.g., "merge onto highway" vs. "turn onto side street"). For an edge (i, j) with attribute vector z_{ij}, the message passed is

$$m_{ij} = \phi(z_{ij}) \cdot x_i,$$

with x_i the source node embedding and ϕ a learnable Multi-Layer Perceptron (MLP) generating an edge-specific weight matrix. This design allows ROMY to adapt message passing to differences in travel mode, time encoding, and semantic context. Cyclic temporal features are embedded directly in z_{ij} enabling time-aware transformations. The network stacks three NNConv layers, each followed by batch normalization [37] and ReLU activation [38], with residual connections [39] to preserve earlier representations:

$$h^{(l)} = h^{(l-1)} + \text{ReLU}(\text{BN}(\text{NNConv}(h^{(l-1)}, z))).$$

Finally, the MLP with dropout [40] predicts a scalar risk score for each edge from the concatenation of the two node embeddings and the edge attributes:

$$\hat{y}_{ij} = \text{MLP}([h_i, h_j, z_{ij}])$$

This architecture ensures that both structural and segment-level context contribute to the risk estimate. Output of the predictive core is a set of risk scores that quantify the likelihood of disruption or delay for each route segment.

These scores are passed to the **recommendation layer** and can be incorporated as additional cost functions into routing algorithms used by platforms such as Google Maps, alongside traditional metrics like travel time or distance. This enables ROMY to recommend not just the fastest route but the one that best balances efficiency and reliability. Furthermore, the system accounts for personal constraints, such as limited time flexibility, mobility impairments, or preferences regarding the number of transfers [15]. For example, a user with strict arrival requirements may be guided towards a slightly longer route with a lower probability of delay, while a user with reduced mobility may receive options that minimize transfers even if this increases nominal travel time. ROMY supports continuous retraining and near real-time updates, and can be deployed as a standalone service or integrated via APIs.

4. Data Sources and Processing

In its current implementation, ROMY is deployed in a rural pilot, applying historical data streams for risk-optimized routing. To enable this, we compiled a dataset by combining anonymized human mobility traces with publicly available route data, ensuring that it captures both structural and temporal variability relevant to rural transport risk modeling. The mobility traces originate from a MotionTag dataset collected in a field study on rural mobility decision support systems in the German region of Saarland [41]. This dataset comprises approximately 433,849 anonymized datapoints, each containing latitude–longitude coordinates and trip metadata from 521 participants who tracked all their journeys using the MotionTag app between October 2023 and April 2024. To protect privacy, coordinates were mapped to the nearest publicly available Point of Interest via reverse geocoding, consistent with established rural mobility DSS practices [42, 41].

From these records, a geographically balanced set of origin–destination (OD) pairs was derived. We identified the 1000 most frequent origins and destinations based on trip frequency, then applied spatial K-Means clustering to group them into 500 clusters, ensuring coverage across the region. One representative OD pair was selected from each cluster. One pair was later removed due to excessive proximity of origin and destination, leaving 499 OD pairs. This selection strategy reflects findings from rural mobility research that emphasize both spatial diversity and representative coverage of actual travel patterns [43, 44, 41].

To capture inter-day and intra-day variation in travel conditions, we queried the Google Maps Routes API for each OD pair at hourly intervals between 08:00 am and 10:00 pm over a continuous period of 21 days. The time intervals were selected according to time and trip frequency in MotionTag data. This produced a temporally rich dataset encompassing differences in travel times, route options, and mode

Figure 2: Data processing pipeline for the ROMY rural pilot. Anonymized mobility traces from the Saarland MotionTag dataset (420k points) are privacy-preserved via mapping to public Points of Interest. The 1000 most frequent locations are clustered into 500 groups, yielding 499 representative origin-destination (OD) pairs. For each pair, the Google Maps API is queried hourly (08:00–22:00) over 21 days. Retrieved routes are converted into a directed, attributed graph retaining all spatial, temporal, modal, and semantic features for GNN-based risk estimation.

edge_id	src_id	tgt_id	trip_id	distance_s	duration_s	hour_sin	hour_cos	day_sin	day_cos	month_sin	month_co	weekday_	weekday_	mode_DRI	mode_TR	mode_WA	instr_emb_
0	7914	4130	T61386	-0.32065	-0.46869	0.707107	-0.70711	0.897805	-0.44039	1	6.12E-17	0	1	1	0	0	-0.13622
1	4130	4994	T61386	-0.32235	-0.44651	0.707107	-0.70711	0.897805	-0.44039	1	6.12E-17	0	1	1	0	0	-0.45922
2	4994	3248	T61386	-0.31775	-0.4382	0.707107	-0.70711	0.897805	-0.44039	1	6.12E-17	0	1	1	0	0	-0.31173
3	3248	7606	T61386	-0.23691	-0.33285	0.707107	-0.70711	0.897805	-0.44039	1	6.12E-17	0	1	1	0	0	-0.19936
4	7606	1382	T61386	2.533683	1.311089	0.707107	-0.70711	0.897805	-0.44039	1	6.12E-17	0	1	1	0	0	-0.59684

Figure 3: Sample feature set for trip ID: T61386 after preprocessing. The raw features were transformed into model-compatible vectors. Each row represents an edge with its transformed features.

combinations under varying demand and network states. Fig. 3 shows a data snippet of a route after preprocessing (cf. Section 3). The retrieved route records (104.857 datapoints) were then transformed into a directed graph suitable for GNN-based modeling. Nodes represent stops or intersections, while edges correspond to travel segments between them. All available attributes, i.e., spatial attributes (e.g., GPS coordinates of bus stop), temporal attributes (e.g., scheduled departure time), modal attributes (e.g., DRIVE), and semantic attributes (e.g., "Board bus line X") were retained to allow downstream models to leverage the full contextual richness of the data. An overview of the pipeline from MotionTag data collection through OD pair selection, route retrieval, and graph construction is shown in Fig. 2.

5. Rural Use Case: Implementation

The rural pilot is focused on the Saarland region of Germany, which combines small towns, dispersed villages, and limited public transport coverage. Travel patterns in this setting differ substantially from dense urban areas: service frequencies are lower, transfer opportunities fewer, and mode combinations (e.g., walking to a bus stop, then taking a regional train) more common. Road networks are also more heterogeneous, ranging from highways to narrow rural roads, and are affected by seasonal and event-driven fluctuations in demand. These characteristics create unique challenges for mobility planning, as delays or disruptions on a single segment can disproportionately impact overall journey reliability. The ROMY predictive core is adapted here to account for such sparsity, multimodality, and temporal variability, enabling risk-aware routing in an environment where resilience and reliability are as important as travel time.

In the rural pilot, the ROMY predictive core described in Section 3 was trained on the graph constructed from the MotionTag dataset and Google Maps route retrieval process outlined in Section 4. The retained spatial, temporal, modal, and semantic attributes were directly used as node and edge features. Due to the absence of ground-truth disruption labels, we defined a regret-based proxy risk score [45] that reflects how atypical an edge's features are compared to the overall network. This is calculated as:

$$R_{ij} = \sum_k \log\left(1 + \exp\left(\beta_k (z_{ij}^{(k)} - \bar{z}^{(k)})\right)\right),$$

with feature-specific sensitivities $\beta_{\texttt{distance}} = 1.0$, $\beta_{\texttt{duration}} = 1.5$, $\beta_{\texttt{hour\_sin}} = 0.5$, and $\beta_{\texttt{day\_cos}} = 0.5$. These hyperparameters were selected based on domain knowledge about factors that disproportionately affect perceived and actual travel risk in mobility, with emphasis on temporal irregularities, modal transfers, and semantic disruptions. For instance, duration deviations are more impactful than small shifts in distance or late-night trips are known to increase perceived and real travel risk. Some features like time-of-day or day-of-week were scaled to reflect user-reported pain points in mobility based on insights of the MotionTag data set [41] and related studies [46]. The feature-specific sensitivities weight how strongly deviations in each attribute (e.g., distance, duration, time-of-day) contribute to the overall regret score, allowing the proxy risk to emphasize factors more indicative of potential delays. Segments with durations, times, or distances far from the mean incur higher regret, reflecting increased likelihood of delay or user dissatisfaction.

Training the GNN on these regret scores enables the model to learn structural and contextual patterns that correlate with risk in a rural context. These include longer travel segments with fewer transfer points, service irregularity during off-peak hours, and semantic indicators of complexity in navigation instructions. By capturing such patterns, ROMY produces risk estimates that are sensitive to the unique operational and infrastructural characteristics of rural mobility networks.

6. Results and Discussion

We evaluated the ROMY predictive core (cf. section 3) on the rural pilot dataset described in section 4, using the regret-based risk scores from section 5 as proxy labels. The model was trained for 50 epochs with a mean squared error (MSE) loss between predicted and proxy risk values on both the training and the test set (75%/25% split), and performance was assessed using the coefficient of determination (R^2) on the test set. Tab. 1 summarizes results at 10-epoch intervals. The model converged around epoch 50, with a final test loss of 0.6160 and R^2 of 0.8132. Learning curves show steady improvement and minimal overfitting, as indicated by the small gap between training and test loss (cf. Fig. 4). To assess the added value of the GNN, we trained two baselines: (i) a linear regression using only edge features, and (ii) a feed-forward MLP without message passing. The GNN substantially outperformed both baselines, achieving an R^2 of 0.8132 vs. 0.7723 for the best baseline, and reducing MSE from 0.7509 to 0.6160 (cf. Tab. 2). This demonstrates that incorporating graph structure and edge-conditioned message passing improves risk estimation in sparse rural networks. To interpret model predictions, we computed average risk scores by mode and time-of-day. On average, TRANSIT segments exhibited the highest predicted risk (6.779), followed by DRIVE (2.682) and WALK (2.556). Temporal analysis showed

Table 1: Training and test losses with R^2 scores over training epochs

Epoch	Train Loss	Test Loss	R^2 Score
1	14.0054	297.0139	-89.0556
10	2.4278	5.3984	-0.6368
20	1.2298	1.7444	0.4711
30	0.8067	0.7897	0.7606
40	0.6557	0.6637	0.7988
50	0.5723	0.6160	0.8132

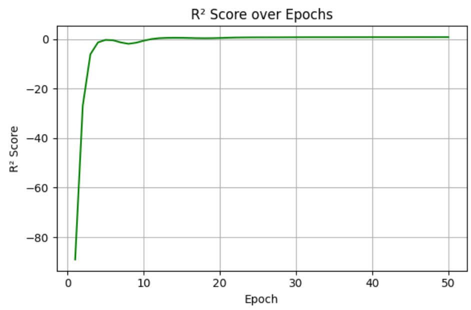

Figure 4: R^2 score vs. training epochs

Table 2
Baseline comparison of risk prediction models

Model	MSE	R^2
Linear Regression	0.7509	0.7723
MLP (no message passing)	0.7846	0.7104
ROMY Predictive Core	0.6160	0.8132

peaks in predicted risk during the morning rush (08:00–09:00am) and early evening (05:00–06:00pm), consistent with expected congestion and transfer pressure in rural contexts (cf. Tab. 3).

Table 3
Average predicted risk by transport mode and time-of-day

Mode	Avg. Risk	Morning Peak (08:00–09:00)	Midday (12:00–13:00)	Evening Peak (17:00–18:00)
DRIVE	2.723	2.762	2.650	2.757
TRANSIT	7.026	7.287	6.583	7.209
WALK	2.566	2.566	2.551	2.581

To estimate potential real-world effects, we simulated risk-aware routing for a sample of 3 high-risk OD pairs (cf. Tab. 4). Compared to the fastest route, selecting the lowest-risk route reduced average risk by 39.14%, while on average increasing the time only by 1.62 minutes. In some cases, both travel time and risk were reduced, indicating opportunities for "win-win" optimizations. The riskiest edge in the test set (cf. Fig. 5) is the longest in the dataset, includes a modal transfer, occurs at 09:00am, and falls on a Monday; yielding a predicted risk of 19.7. This matches the intuition that such segments are prone to delays or disruptions.

Table 4
Simulated changes in travel time and risk when using risk-aware routing

OD pair	Fastest Route: Risk	Lowest-Risk Route: Risk	Risk Reduction (%)	Travel Time Δ (min)
7914-4994	7.641	2.851	62.68	0.25
10045-12467	3.359	2.471	26.43	3.33
4246-1884	4.706	3.374	28.31	1.28

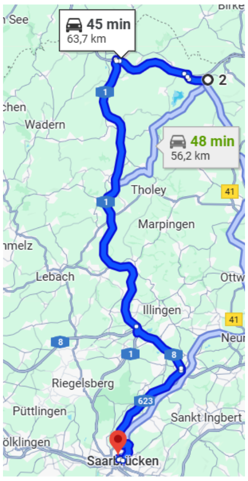

Figure 5: Riskiest edge in the test dataset with predicted risk of 19.7

We examined edges with the highest absolute prediction errors (cf. Tab. 5). Most involved infrequently used segments combining unusual modes (e.g., WALK and DRIVE), routes at atypical hours (e.g., after 09:00pm), or incomplete semantic data from the Google Maps API. These findings suggest that expanding the temporal coverage and improving semantic parsing could further enhance accuracy. Overall, these results show that ROMY's predictive core can learn context-sensitive risk patterns from proxy labels, outperform simpler models, and offer actionable routing alternatives that balance efficiency and reliability in rural transport networks.

Table 5
Examples of edges with highest absolute prediction error

Edge ID	Mode(s)	Time	True Risk	Pred. Risk	Error	Notes
75268	Transit	13:00	14.548	7.81	6.738	Incomplete instructions
50379	Transit	12:00	6.513	11.539	5.026	Infrequently traversed
1005	Drive	09:37	10.113	6.175	3.938	Incomplete instructions

7. Implications

The results of the rural pilot suggest that integrating risk estimation into route planning can significantly improve the reliability of mobility services in sparsely connected transport networks. By quantifying the likelihood of delay or disruption at the segment level, ROMY enables decision support systems to balance travel time with resilience, offering routes that reduce user uncertainty without imposing substantial time penalties. For transport operators and planners, predicted risk patterns can inform targeted interventions, for instance, adjusting schedules for consistently high-risk segments, improving infrastructure at vulnerable transfer points, or deploying on-demand services during periods of elevated risk. For travelers, risk-aware recommendations can increase confidence in public transport, potentially improving modal share in regions where car dependency is high.

While the case study focuses on the Saarland region, the approach is transferable to other rural and semi-urban contexts where service frequency is low, network topology is heterogeneous, and disruptions can have disproportionate impacts. In the longer term, combining ROMY's predictions with user feedback could support adaptive, data-driven transport policy that prioritizes not only efficiency but also reliability and inclusivity.

ROMY's architecture is grounded in an explicit, graph-based conceptual model of the transport domain. By structuring the multimodal network as a directed, attributed graph $G = (V, E, X, Z)$, the system formalizes domain knowledge into a machine-readable structure that supports reasoning and modularity. This abstraction aligns with core conceptual modeling principles, separating structural entities (nodes and edges) from contextual attributes (e.g., time, mode, semantics), and enabling scalable integration of heterogeneous data sources [47, 48, 49]. It also reflects traditional conceptual modeling concerns such as attribute typing, relationship directionality, and cardinality, adapted for dynamic, real-time environments [50]. This modeling layer underpins the predictive core demonstrating how conceptual modeling can inform the development of trustworthy decision support systems in complex domains [51, 52].

8. Limitations

In the absence of reliable, labeled disruption or delay data for rural multimodal segments, we adopted a regret-based proxy risk function to approximate perceived and operational uncertainty. This choice is grounded in empirical evidence that deviations from typical patterns, especially in travel duration, time-of-day, and semantic route complexity, correlate with user dissatisfaction and increased disruption likelihood [20, 14]. While this approach does not capture all facets of risk, it offers a pragmatic yet meaningful approximation in data-scarce contexts. Preliminary analyses (cf. section 6) further confirm that high proxy risk scores align with empirically observed bottlenecks, such as early morning transfers, infrequent services, and segments with semantic ambiguity. Future work will incorporate labeled data from real-time disruption feeds (e.g., GTFS-RT, RIS API), and user feedback to refine the risk estimation.

Furthermore, although the pilot study focused on the German Saarland region, ROMY's architecture is explicitly designed to generalize across geographic and modal contexts. The modular graph representation and feature encoding support seamless adaptation to both dense urban settings (e.g., with high-frequency transit and short transfer windows) and inter-regional transport corridors. Key modifications for scaling include incorporating denser topologies, fine-tuning semantic encodings for diverse routing instructions, and adjusting the regret-based risk formulation to account for different congestion or reliability baselines. A logical next step is a dual-site deployment comparing rural and urban model behavior. This would validate ROMY's adaptability and enable cross-regional risk transfer learning.

To illustrate transferability, consider a hypothetical urban deployment of ROMY in a medium-density city with multiple transit lines, shared micromobility services, and dynamic traffic flows. In such a context, ROMY's ability to embed semantic navigation steps (e.g., "exit metro, cross plaza") and real-time feeds (e.g., traffic camera alerts, micro-events) would allow it to identify latent risk clusters, such as unreliable last-mile transfers (e.g., walking from a metro to a destination) or construction-affected segments. By retraining on urban-specific data, the GNN core could prioritize different edge features, e.g., congestion patterns over temporal sparsity, while maintaining personalization capabilities.

9. Ethics and Privacy Considerations

All personal mobility traces used in this study were collected under informed consent through the MotionTag app, in line with GDPR and institutional research ethics guidelines. To preserve privacy, GPS coordinates were anonymized and mapped to the nearest public Points of Interest via reverse geocoding. No raw identifiers or behavioral profiling techniques were used. Additionally, we adopted a minimal data retention policy and ensured that model training used only abstracted, de-identified features. Future iterations of ROMY will include ethics review checkpoints, especially as real-time user preferences, feedback, or accessibility constraints are integrated into the recommendation layer.

10. Conclusion

This paper presented ROMY, a graph-based decision support system for personalized, risk-aware route planning in multimodal transport networks. By integrating heterogeneous data sources and leveraging edge-conditioned Graph Neural Networks, ROMY estimates segment-level disruption risks and provides reliability-optimized routing alternatives. A rural pilot implementation in Germany demonstrated the feasibility and effectiveness of the approach, with the predictive model outperforming baseline methods and revealing actionable mobility patterns.

Future work will extend ROMY beyond the rural context, integrating real-time user feedback, broader geographic coverage, and stronger coupling with existing transport planning tools. In addition, we plan to refine the risk proxy with labeled disruption events and conduct user studies to evaluate ROMY's real-world impact on travel behavior. Beyond the technical contributions, ROMY also exemplifies how graph-based conceptual modeling can support interpretable, modular, and scalable AI systems providing a pathway for integrating semantic modeling principles into data-driven mobility applications.

Declaration on Generative AI

During the preparation of this work, the author(s) used Grammarly in order to perform grammar and spelling checks. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

References

[1] M. Kiss, Understanding Transport Poverty, At a Glance – Policy Brief PE 738.181, European Parliamentary Research Service (EPRS), Brussels, 2022. URL: https://www.europarl.europa.eu/RegData/etudes/ATAG/2022/738181/EPRS_ATA(2022)738181_EN.pdf, transport poverty refers to a lack of adequate transport services necessary to access general services and work, or to the inability to pay for these transport services.

[2] A. Nichols, J. Ryan, C.-W. Palmqvist, The importance of recurring public transport delays for accessibility and mode choice, Journal of Transport Geography 115 (2024) 103796. URL: https://www.sciencedirect.com/science/article/pii/S096669232400005X. doi:https://doi.org/10.1016/j.jtrangeo.2024.103796.
[3] A. Minelgaitė, R. Dagiliūtė, G. Liobikienė, The usage of public transport and impact of satisfaction in the european union, Sustainability 12 (2020) 9154.
[4] Eurostat, Urban-rural europe – quality of life in rural areas, https://ec.europa.eu/eurostat/statistics-explained/index.php/Urban-rural_Europe_-_quality_of_life_in_rural_areas, 2024. Connected rural areas: public transport services should be maintained or improved.
[5] European Commission, EU Urban Mobility Observatory, Planning for Attractive Public Transport: Topic Guide, Topic Guide, European Commission, 2022. URL: https://urban-mobility-observatory.transport.ec.europa.eu/system/files/2023-11/planning_for_attractive_public_transport.pdf, guidance on making public transport more attractive through Sustainable Urban Mobility Planning (SUMP).
[6] Deutsche Bahn AG, Explanation of punctuality figures for november 2024, https://www.deutschebahn.com/de/konzern/konzernprofil/zahlen_fakten/puenktlichkeitswerte-6878476, 2024. Accessed: 5 August 2025.
[7] VdTÜV – Association of Technical Inspection Agencies, TÜv mobility study 2024, https://www.tuev-verband.de/studien/tuev-mobility-studie-2024, 2024. Accessed: 5 August 2025.
[8] Statista GmbH, Reasons for not using public transport more often in germany 2019, https://de.statista.com/prognosen/1035632/umfrage-zu-gruenden-den-oepnv-nicht-oefter-zu-nutzen-in-deutschland, 2019. Accessed: 5 August 2025.
[9] J. Hupfeld, Arbeitsbedingte räumliche mobilität und gesundheit (2013).
[10] FasterCapital, Overcoming obstacles to a sustainable approach, https://fastercapital.com/de/thema/hinder-nisse-fur-einen-nachhaltigen-ansatz-uberwinden.html, n.d. Accessed: 5 August 2025.
[11] Andrea Wieland, Werner Eckert, Thomas Reutter, SWR, Expectations for public transport: Reliability and service frequency matter, https://www.tagesschau.de/wirtschaft/verbraucher/bahn-zuverlaessigkeit-verkehr-deutschlandticket-100.html, 2023. Accessed: 5 August 2025.
[12] Y. Liao, J. Gil, R. H. Pereira, S. Yeh, V. Verendel, Disparities in travel times between car and transit: Spatiotemporal patterns in cities, Scientific reports 10 (2020) 4056.
[13] Statista GmbH, Survey on transport mode usage on weekdays in germany 2024, https://de.statista.com/statistik/daten/studie/1245424/umfrage/nutzung-von-verkehrsmitteln-an-werktagen, 2024. Accessed: 5 August 2025.
[14] Y. Tyrinopoulos, C. Antoniou, Factors affecting modal choice in urban mobility, European Transport Research Review 5 (2013) 27–39.
[15] Y. Wang, T. Zheng, S. Liu, Z. Feng, K. Chen, Y. Hao, M. Song, Spatiotemporal-augmented graph neural networks for human mobility simulation, IEEE Transactions on Knowledge and Data Engineering 36 (2024) 7074–7086.
[16] Y. Xiao, F. Ahmed, Z. Sha, Graph neural network-based design decision support for shared mobility systems, Journal of Mechanical Design 145 (2023) 091703.
[17] Y. Huang, D. Li, B. Han, E. Xu, G. Medeossi, Multimodal transportation recommendation: Embedding travel intention and transit reliability by heterogeneous graph attention network, Expert Systems with Applications 255 (2024) 124579.
[18] G. Hinton, O. Vinyals, J. Dean, Distilling the knowledge in a neural network, arXiv preprint arXiv:1503.02531 (2015).
[19] P. Jing, M. Zhao, M. He, L. Chen, Travel mode and travel route choice behavior based on random regret minimization: A systematic review, Sustainability 10 (2018) 1185.
[20] H. Tu, H. Li, H. Van Lint, H. van Zuylen, Modeling travel time reliability of freeways using risk assessment techniques, Transportation Research Part A: Policy and Practice 46 (2012) 1528–1540.
[21] H. Huang, C. Han, G. Xu, M. Jiang, S. Wong, M. M. Haque, Incorporating safety reliability into route choice model: Heterogeneous crash risk aversions, Analytic methods in accident research

25 (2020) 100112.
[22] K. Fang, J. Fan, B. Yu, A trip-based network travel risk: Definition and prediction, Annals of Operations Research 343 (2024) 1069–1094.
[23] L. Cheng, X. Chen, J. De Vos, X. Lai, F. Witlox, Applying a random forest method approach to model travel mode choice behavior, Travel behaviour and society 14 (2019) 1–10.
[24] Y. Liang, F. Ding, G. Huang, Z. Zhao, Deep trip generation with graph neural networks for bike sharing system expansion, Transportation Research Part C: Emerging Technologies 154 (2023) 104241.
[25] MOTIONTAG GmbH, Making mobility matter – smart mobility, https://motion-tag.com/de, 2025. Accessed: 5 August 2025.
[26] Teralytics Inc., Teralytics (corporate website), https://www.teralytics.net/de, 2025. Accessed: 5 August 2025.
[27] J. Göransson, H. Andersson, Factors that make public transport systems attractive: a review of travel preferences and travel mode choices, European Transport Research Review 15 (2023) 32.
[28] DELFI e.V., Data & services – delfi products and services, https://www.delfi.de/de/leistungen-produkte/daten-dienste/, 2025. Accessed: 5 August 2025.
[29] Deutsche Bahn AG, Db api marketplace – apis for mobility solutions, https://developers.deutschebahn.com/db-api-marketplace/apis/, 2025. Accessed: 5 August 2025.
[30] ADAC e.V., Adac traffic jam report 2023: Germany-ticket did not reduce traffic congestion, https://www.adac.de/verkehr/verkehrsinformationen/staubilanz, 2024. Accessed: 5 August 2025.
[31] Die Autobahn GmbH del Bundes, Roadworks map of the autobahn (baustellenkarte), https://www.autobahn.de/betrieb-verkehr/baustellenkarte, 2025. Accessed: 5 August 2025.
[32] Die Autobahn GmbH des Bundes, Current traffic conditions – autobahn traffic status, https://www.autobahn.de/betrieb-verkehr/aktuelle-verkehrslage, 2025. Accessed: 5 August 2025.
[33] M. R. Alam, A. M. Sadri, X. Jin, Identifying public perceptions toward emerging transportation trends through social media-based interactions, Future Transportation 1 (2021) 794–813.
[34] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin, Attention is all you need, 2023. URL: https://arxiv.org/abs/1706.03762. arXiv:1706.03762.
[35] N. M. Gardazi, A. Daud, M. K. Malik, A. Bukhari, T. Alsahfi, B. Alshemaimri, Bert applications in natural language processing: a review, Artificial Intelligence Review 58 (2025) 1–49.
[36] P. Coupeau, J.-B. Fasquel, M. Dinomais, On the relevance of edge-conditioned convolution for gnn-based semantic image segmentation using spatial relationships, in: 2022 Eleventh International Conference on Image Processing Theory, Tools and Applications (IPTA), 2022, pp. 1–6. doi:10.1109/IPTA54936.2022.9784143.
[37] S. Ioffe, C. Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, 2015. URL: https://arxiv.org/abs/1502.03167. arXiv:1502.03167.
[38] C. Banerjee, T. Mukherjee, E. Pasiliao, An empirical study on generalizations of the relu activation function, in: Proceedings of the 2019 ACM Southeast Conference, ACMSE ’19, Association for Computing Machinery, New York, NY, USA, 2019, p. 164–167. URL: https://doi.org/10.1145/3299815.3314450. doi:10.1145/3299815.3314450.
[39] O. K. Oyedotun, K. A. Ismaeil, D. Aouada, Why is everyone training very deep neural network with skip connections?, IEEE Transactions on Neural Networks and Learning Systems 34 (2023) 5961–5975. doi:10.1109/TNNLS.2021.3131813.
[40] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, Dropout: a simple way to prevent neural networks from overfitting, J. Mach. Learn. Res. 15 (2014) 1929–1958.
[41] S. Janzen, H. Stein, L. A. Khaliq, F. Hergert, W. Maass, Designing decision support systems for rural mobility enhancement, in: R. Guizzardi, L. Pufahl, A. Sturm, H. van der Aa (Eds.), Enterprise, Business-Process and Information Systems Modeling, Springer Nature Switzerland, Cham, 2025, pp. 448–463.
[42] G. Andrienko, N. Andrienko, W. Chen, R. Maciejewski, Y. Zhao, Visual analytics of mobility and transportation: State of the art and further research directions, IEEE Transactions on Intelligent Transportation Systems 18 (2017) 2232–2249. doi:10.1109/TITS.2017.2683539.

[43] H. Poltimae, M. Rehema, J. Raun, A. Poom, In search of sustainable and inclusive mobility solutions for rural areas, European Transport Research Review 14 (2022) 13. doi:10.1186/s12544-022-00536-3.
[44] M. Schoenau, M. M√°ller, What affects our urban travel behavior? a gps-based evaluation of internal and external determinants of sustainable mobility in stuttgart (germany), Transportation Research Part F: Traffic Psychology and Behaviour 48 (2017) 61–73. URL: https://www.sciencedirect.com/science/article/pii/S1369847817303492. doi:https://doi.org/10.1016/j.trf.2017.05.004.
[45] P. Jing, M. Zhao, M. He, L. Chen, Travel mode and travel route choice behavior based on random regret minimization: A systematic review, Sustainability 10 (2018). URL: https://www.mdpi.com/2071-1050/10/4/1185. doi:10.3390/su10041185.
[46] R. Follmer, Mobilität in deutschland – mid kurzbericht studie von infas, dlr, ivt und infas 360 im auftrag des bundesministers für digitales und verkehr (fe-nr. vb600001), https://www.mobilitaet-in-deutschland.de/pdf/MiD2023_Kurzbericht.pdf, 2025.
[47] S. J. Ali, Knowledge graph-based conceptual models search., in: ER Forum/PhD Symposium, 2022.
[48] S. Tuteja, R. Kumar, A unification of heterogeneous data sources into a graph model in e-commerce, Data Science and Engineering 7 (2022) 57–70.
[49] S. Al-Fedaghi, Conceptual data modeling: Entity-relationship models as thinging machines, International journal of computer science and network security: IJCSNS 21 (2021) 247–260.
[50] M. Gogolla, R. Clarisó, B. Selic, J. Cabot, Towards facilitating the exploration of informal concepts in formal modeling tools, in: 2021 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C), 2021, pp. 244–248. doi:10.1109/MODELS-C53483.2021.00044.
[51] A. Jabbari, M. Rosemann, Modeling 4.0: conceptual modeling in a digital era, Communications of the Association for Information Systems 53 (2023) 1028–1051.
[52] D. Prokop, Š. Stenchlák, P. Škoda, J. Klímek, M. Nečaskỳ, Enhancing domain modeling with pre-trained large language models: an automated assistant for domain modelers, in: International Conference on Conceptual Modeling, Springer, 2024, pp. 235–253.