The 13th Symposium of the European Association for Research in Transportation

Predicting Public Transport Resilience to Climate Extremes: A Hybrid Dynamical Systems Thinking Approach

Keren-Or Grinberg-Rosenbaum*[1], Francisco Camara Pereira[2], Bat Hen Nahmias-Biran[3] , and Yoram Shiftan[1]

[1] Civil engineering, Technion, Israel, [2] Technology, Management and Economics, Technical University of Denmark, Denmark, [3] Faculty of Engineering, Tel Aviv University, Israel.

SHORT SUMMARY

This study investigates climate change's impact on travel behavior and provides actionable insights for enhancing public transportation resilience. We employ a novel Hybrid Dynamical Systems Thinking Approach (HDSTA), integrating knowledge graphs with Machine Learning (ML) models, to predict bus ridership, traffic volume and speed. Using data from a major Israeli interstate highway, including weather reports, passenger counts, and traffic sensor inputs, our ML models demonstrated superior predictive accuracy for climate event transportation sensitivity compared to traditional methods like Structural Equation Models (SEM). Empirical analysis revealed rainfall is a more significant factor in reducing bus ridership than heatwaves. Based on these patterns, we propose a Weather Resilience Index (WRI) to quantify weather's impact on ridership at bus stops, highlighting the need for targeted adaptation strategies. These tools empower transportation stakeholders and decision-makers to analyze climate effects on transportation and implement data-driven actions.

Key words (6 words): Big data, Environmental impacts, System Thinking, Ridership, Climate Change Resilience, Data-Driven Actions.

1. INTRODACTION

Climate change significantly impacts transportation, disrupting public transportation due to extreme weather (Gössling et al., 2023). While climate indices exist (Błażejczyk et al., 2013), the climate-transportation relationship remains underexplored (Wang et al., 2020). Existing causality models struggle with real-world network complexities (Pearl, 2009), limiting their use in Transportation Management Centers (TMCs), which often rely on descriptive tools like heat maps (Klein, 2001; FHWA, 2018). These tools, however, often lack system-level insights (Hughes et al., 2020) and are insufficient for engaging non-technical stakeholders, such as TMCs staff, who require more intuitive and accessible representations of system behavior. Projected increases in extreme weather (C3S, 2024) necessitate incorporating climate forecasts into transportation operations, requiring interdisciplinary collaboration (Jacobs et al., 2005). To address this, we leverage systems thinking to formalize causal relationships into a Hybrid Dynamical Systems Thinking Approach (HDSTA) (Grinberg-Rosenbaum et al., 2025), a novel framework for data-driven transportation operations. HDSTA combines causality modeling, Machine Learning (ML), and expert insights for holistic system modeling.

2. METHODOLOGY

This study demonstrates the use of HDSTA through a case study analyzing interurban road (Road 2 in Israel) users' behavior under varying climatic conditions.

Conceptual Modeling

As a foundational step, a knowledge graph representing a conceptual model of the case was constructed using Object-Process Methodology (OPM) (Dori, 1995). OPM was chosen as it can encode assumptions and domain knowledge about a problem, without the need to build and run a full simulation. The OPM outcomes describe the system's structures by:
(1) Object Process Diagram (OPD) - a graphical component we used to design a knowledge graph.
(2) Object-Process Language (OPL) - a text component named we used to define and improve the ML causality modeling.

The knowledge graph in **Figure 1** represents a system-level view of the case study. This step involved experts from transportation, climate science and data science in an iterative process. During these discussions we designed the model including processes required for predicting the target metrics (ridership, transport volume, speed); variables influencing these metrics (e.g., weather conditions, time of day, day of week, events); and other necessary data.

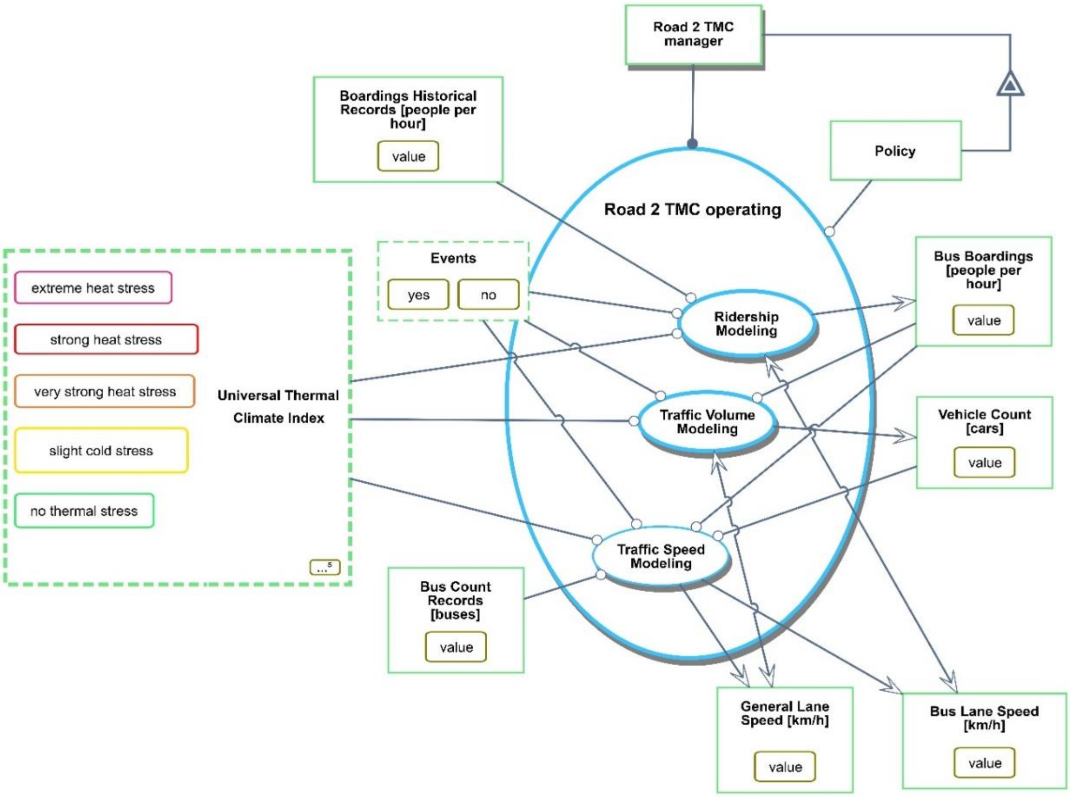
Using OPCloud as a platform to model OPM, we established the links between the identified processes and variables, highlighting their relevance and contribution to each stage of the system analysis, see Figure 1. Processes are blue ellipses and objects are green squares and can have indicators as quantity, states and attributes. Variables with dashed lines (as events) indicate environmental factors external to the system; Variables with solid lines (as vehicle counts) indicate systemic elements within our control. The OPL text was automatically generated in OPCloud with colors defining **processes**, **objects** and other colors related to indexes used. OPL explains the case system dynamics as demonstrated below:

Road 2 TMC manager exhibits **Policy**. **Road 2 TMC manager** handles **Road 2 TMC operating**. **Road 2 TMC operating** requires **Policy** of **Road 2 TMC manger**.
Ridership Modeling requires **Boardings Historical Records**, **Events**, and **Universal Thermal Climate Index**; **Ridership Modeling** yields **Bus Boardings**; **Ridership Modeling** affects **Bus Lane Speed**.

Road 2 TMC operating zooms into 3 predictive processes: **Ridership Modeling**, **Traffic Volume Modeling**, and **Traffic Speed Modeling**.; **Bus Boardings** and **Boardings Historical Records** units are **people per hour**; **Bus Lane Speed** and **General Lane Speed** unit is **km/h**; **Bus Count Records** unit is **buses**; **Vehicle Count** unit is **cars**; **Events** can be **no** or **yes**; **Universal Thermal Climate Index** can be **extreme heat stress**, **strong heat stress**, **very strong heat stress**, **slight cold stress**, **no thermal stress** or at one of five other states.

Traffic Speed Modeling requires **Bus Boardings**, **Bus Count**, **Events**, **Universal Thermal Climate Index**, and **Vehicle Count**; **Traffic Speed Modeling** yields **Bus Lane Speed** and **General Lane Speed**;

Traffic Volume Modeling requires **Bus Boardings**, **Events**, and **Universal Thermal Climate Index**. **Traffic Volume Modeling** affects **General Lane Speed**. **Traffic Volume Modeling** yields **Vehicle Count**.



Legend for Links

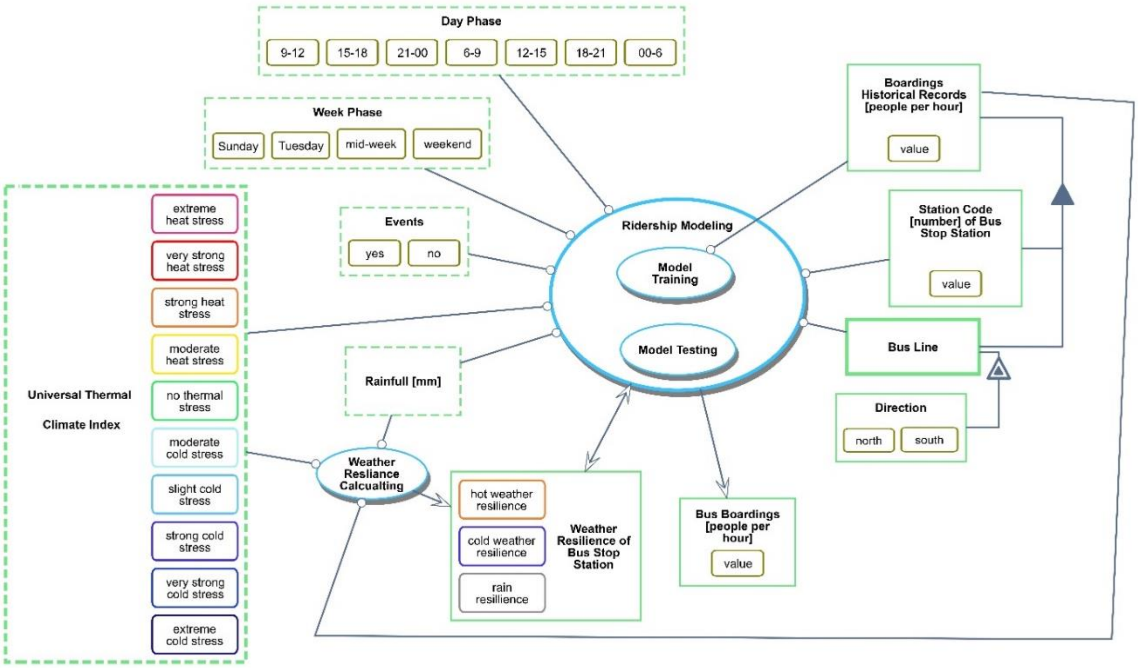
	structural link for exhibition-characterization
	results link for a process that generates an object
	effect link for a process that changes an object
	agent link for a human/group who enable the occurrence of the process
	instrument link for an object that enable the occurrence of the process

Figure 1: HDSTA Conceptual Case Study model using OPM's OPD

In Figure 2 we demonstrate a zoom in to a more detailed ridership modeling process, which is part of the system in Figure 1. The OPL explains:

Ridership Modeling is done by **Model Training**, and **Model Testing**. **Ridership Modeling** requires **Bus Line, Day Phase**, **Events**, **Station Code**, **Universal Thermal Climate Index**, and **Week Phase**; **Ridership Modeling** yields **Bus Boardings**. **Week Phase** can be **Sunday**, **Tuesday**, **mid-week** or **weekend**; **Day Phase** can be **00-6**,**12-15**,**15-18**,**18-21**,**21-00**,**6-9** or **9-12**; **Boardings Historical Records** consists of **Bus Line** and **Station Code of Bus Stop Station**. **Bus Line** exhibits **Direction**. **Direction** of **Bus Line** can be **north** or **south**. **Events** can be **no** or **yes**. **Weather Resilience Calculating** requires **Boardings Historical Records**, **Rain**, and **Universal Thermal Climate Index**. **Weather Resilience Calculating** yields **Weather Resilience of Bus**

Stop Station which can be **cold weather resilience, hot weather resilience** or **rain resilience**. **Ridership Modeling** affects **Weather Resilience of Bus Stop Station.**



Legend for Links

△	structural link for exhibition-characterization
▲	structural links for aggregation-participation
→	results link for a process that generates an object
↔	effect link for a process that changes an object
—○	instrument link for an object that enable the occurrence of the process

Figure 2: Ridership modeling zoom in using OPM's OPD

Data processing

In collaboration with Ayalon Highways Traffic Control Center and Israel Mobility Living Lab (ISMLL) which is an open data initiative, a section of 54 km long interstate Road no. 2 was investigated from July 2023 until August 2024. Based on the Knowledge graph in **Figure 1** we collected data from various sources, including:

- Speed and vehicles count were provided from AdKnight traffic sensors.
- Bus passenger counts were obtained from Israel Transport Ministry.
- Weather reports, including temperature, precipitation, and other relevant climatic variables, were sourced from Israel Meteorological Data-Canter API.

Several preprocessing steps were undertaken to ensure data quality and suitability for modeling. These included:

- Normalizing the data using MinMaxScaler to scale features to a consistent range.
- Filtering data on holidays and rows with only zeros (indicative of sensor malfunction).
- Adding Features: Universal Thermal Climate Index (UTCI) labels were generated as a feature based on available weather data to represent thermal comfort. Binary variables of “Events” indicator (as sports games) and “Rain” (yes/no) were added.
- Categorizing timestamp to “days of the week” and “time of the day” by similar patterns (such as Sunday morning, Sunday mid-day, mid-week afternoon, Thursday night etc.).

To ensure comprehensive coverage of weather conditions, we analyzed hourly (x-axis) UTCI values (y-axis) by season (Figure 3). We can see "Moderate Heat Stress" was the dominant summer UTCI category, occurring throughout the day and night. In contrast, winter UTCI values reached "Strong Cold Stress" at their lowest, with most of the season exhibiting "No Thermal Stress". These align with Israel's Mediterranean climate.

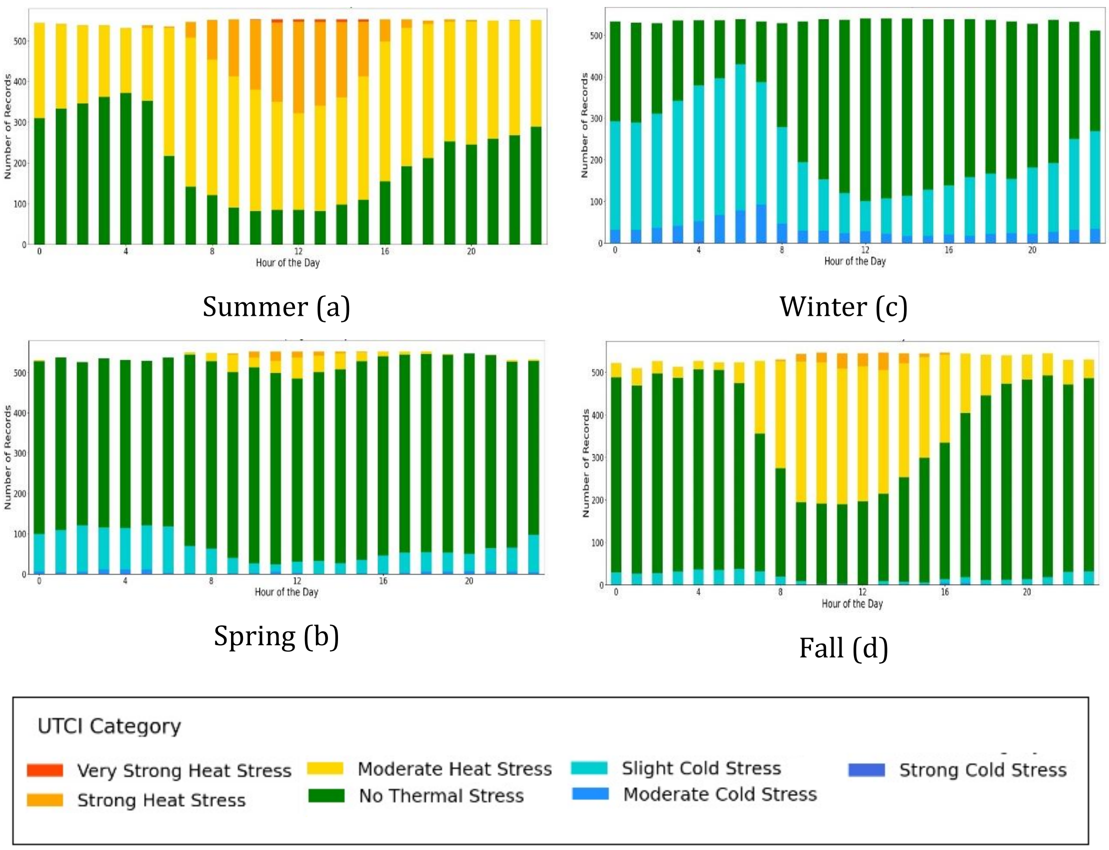


Figure 3: UCTI hourly distribution for July 2023-August 2024 by seasons (a) Summer (b) Spring (c) Winter (d) Fall.

Quantitative modeling

Based on the processes in the knowledge graph (Figure 1**)** we defined mathematical models using Structural Equation Models (SEM) and compared them to ML methods: Neural Networks (NN) and XGBoost. For "**Ridership Modeling**" we used historical records on bus boardings and weather reports to predict boarding per bus station. In some weather conditions we may see changes in users' mode - choosing a car over a bus. Thus, if we have fewer bus passengers, we may see more cars on the road and vice versa. Accordingly, we assumed ridership predictions would affect "**Transport Volume Modeling**" and included it as part of the input. We used bus counts and predicting results of ridership and transport volume to predict "**Traffic Speed modeling**" for the general and the bus lanes assuming these effects the speed as well.

For model development, the following libraries were utilized: semopy and sklearn for the SEM, xgboost and sklearn for the XGBoost model, and tensorflow and sklearn for NN model. The NN architecture consisted of an input layer followed by a dense layer with 128 nodes and a tanh activation function. This was followed by a normalization layer and a dropout layer with a rate of 0.3 to prevent overfitting. A subsequent dense layer with 64 nodes and a tanh activation function, normalization layer, and dropout layer (rate = 0.3) led to the output layer. The dropout layers randomly set input units to 0 at each training step with the specified rate, scaling the remaining inputs by 1/(1-rate). The NN model was trained using an 80/20 train/test split (without a separate validation set), employing the Adam optimizer and Mean Squared Error (MSE) loss function.

3. RESULTS AND DISCUSSION

This case helps identify key relationships between variables obtained from climate and transportation sources for predictions made on ridership, vehicle count, and traffic speed.

Prediction results for traffic measurements

The results presented in Table 1 highlight differences in models' performance across both road directions (north and south). NN outperformed SEMs in terms of R^2 and RMSE across all variables and directions. While XG-Boost showed competitive performance in some cases, there is evidence of overfitting due to high RMSE values. SEMs, on the other hand, underperformed due to their reliance on predefined relationships that lack flexibility to adapt to complex interactions in the data. The ability of NN models to capture nonlinear patterns and integrate diverse data sources provides a significant edge, particularly in dynamic and multifactorial domains like transportation. One limitation of this case is the lack of data on accidents which may explain the NN models medium range values of R^2 (0.5-0.7).

Passenger data serves as a proxy for demand which is crucial for understanding traffic dynamics. Their inclusion enriches the input features, allowing the model to better capture interactions between ridership, traffic volume, and speed. The results suggest that passenger predictions connects system-level interactions, thereby enabling more accurate predictions and robust model generalization

Table 1: Results for traffic measurements predictions

(a) Ridership

Model	Lane Direction	Test RMSE	R^2
SEM	North	3.417	0.232
XG-Boost	North	2.895	0.437
NN	North	0.032	0.406

Model	Lane Direction	Test RMSE	R^2
SEM	South	3.391	0.201
XG-Boost	South	2.621	0.479
NN	South	0.031	0.474

(b) Vehicle counts in general lane

Model	Lane Direction	Test RMSE	R^2
SEM	North	830.478	<0.000
XG-Boost	North	63.620	0.955*
NN	North	0.125	0.651

Model	Lane Direction	Test RMSE	R^2
SEM	South	252.779	0.333
XG-Boost	South	80.225	0.932*
NN	South	0.104	0.738

* Overfitting

(c) **Speed in general lane**

Model	Lane Direction	Test RMSE	R^2
SEM	North	87.480	<0.000
XG-Boost	North	2.222	0.992
NN	North	0.031	0.616

Model	Lane Direction	Test RMSE	R^2
SEM	South	57.811	<0.000
XG-Boost	South	2.197	0.989
NN	South	0.031	0.690

(d) **Speed in bus lane**

Model	Lane Direction	Test RMSE	R^2
SEM	North	86.188	<0.000
XG-Boost	North	9.333	0.956
NN	North	0.114	0.571

Model	Lane Direction	Test RMSE	R^2
SEM	South	50.020	<0.000
XG-Boost	South	8.359	0.951
NN	South	0.071	0.552

Bus stations' weather resilience index

Another outcome of this research is the creation of a Weather Resilience Index (WRI) to assess bus station vulnerability to extreme weather: hot, cold, or rainy weather. WRI was modeled as a feature of the bus stop station (Figure 2). Using ridership and climate data, we calculated the probability of ridership decline under extreme conditions (Heat, Cold, Rain) compared to normal weather. High positive WRI values show weather-sensitive stations, while lower values suggest resilience. Figure 4 presents a distinct series for each weather type. The x-axis shows the bus stations, with their positions reflecting their geographical locations from north to south. We can note rain as the dominant factor, affecting nearly all stations most significantly. Varied heat and cold impacts have less impact than rain. While rain is consistently dominant, some stations (e.g., 20118, 30000, 30007) show notable heat effects, and stations 20118, 20142, and 27145 display significantly higher rain sensitivity than to heat or cold. These differences between bus stations can be due to factors such as lack of adequate shelter or the demographics of the passengers who use these stations.

This approach helps identify which stations may benefit most from weather-related adaptations and prioritize improvements according to the stations' specific weather-related sensitivities, enhancing the commuting experience across all conditions. These improvements can include adding shelter, heating, or cooling measures to improve comfort and retain passenger numbers across different weather conditions.

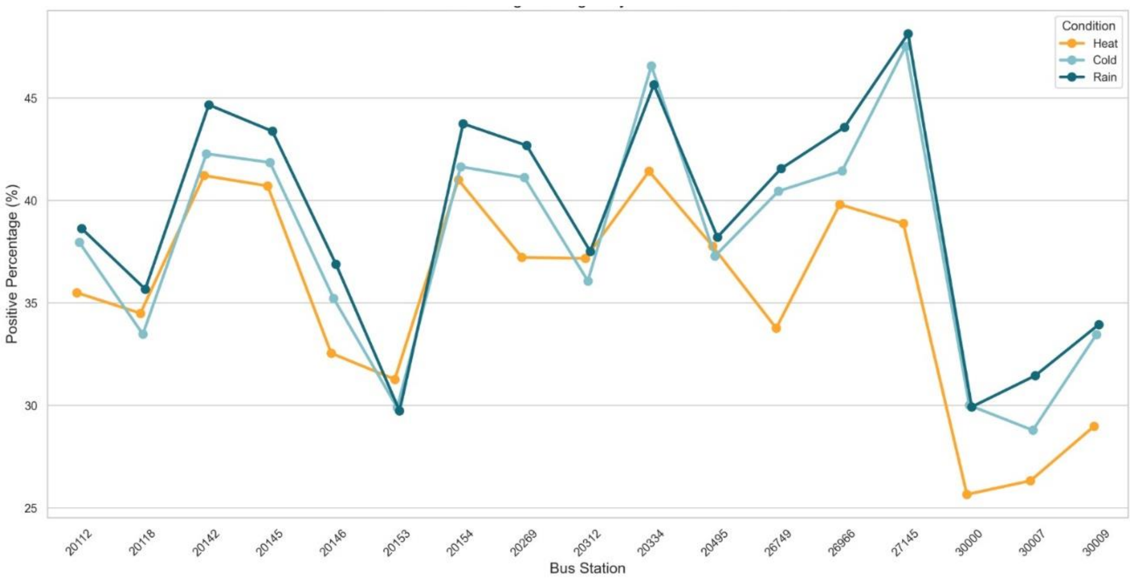


Figure 4: Probabilities of ridership decline under hot, cold, and rainy weather

Table 2 presents the probabilities shown in Figure 4, along with bus station direction (north/south road) and landmark proximity. Statistical significance was visualized using a color gradient based on the following scale: dark red (above 45%), red (40-45%), orange (30-40%), yellow (below 30%). Table 2 provide further insights:

Cold: High WRI values suggest cold sensitivity. P-values are mixed, with some stations (e.g., 20334) showing significant effects, warranting heating/shelter solutions.

Hot: High WRI values show heat sensitivity. Shade/cooling measures are recommended. Many stations show non-significant heat effects (high p-values, close to 1.0), with exceptions at stations 26966, 20269, and 20118.

Rain: Rain consistently and significantly ($p < 0.05$) impacts ridership across nearly all stations (high WRI values), especially 20334 and 27145, suggesting shelter improvements.

Table 2: Probabilities for a change in ridership under different weather conditions

Stop Nu.	Direction	Proximity	Cold	Heat	Rain
20112	South	Bridge Junction	37.97% P-value: 6.00e-19	35.51% **P-value: 0.966**	38.64% P-value: 2.42e-06
20118	North	Wingate Bridge Junction	33.48% P-value: 4.55e-14	34.50% P-value: 5.03e-31	35.68% P-value: 9.90e-20
20142	South	Junction Industrial area	42.28% P-value: 6.37e-05	41.22% **P-value: 1**	44.67% P-value: 6.03e-64
20145	North	Bridge	41.86% P-value: 2.41e-38	40.72% **P-value: 1**	43.38% P-value: 1.61e-38
20146	South	Bridge	35.23% P-value: 1.81e-48	32.55% **P-value: 1**	36.89% P-value: 1.08e-50
20153	North	Bridge	29.91% P-value: 2.23e-19	31.28% **P-value: 0.944**	29.74% P-value: 3.44e-03
20154	South	Junction	41.65% P-value: 3.35e-60	41.01% **P-value: 1**	43.75% P-value: 1.34e-88
20269	South	Industrial area Bridge	41.12% P-value: 1.19e-27	37.23% P-value: 0.044	42.69% P-value: 2.00e-38
20312	North	Junction	36.08% **P-value: 0.428**	37.18% **P-value: 1**	37.52% P-value: 8.52e-05
20334	North	Junction	46.58% P-value: 4.33e-110	41.43% **P-value: 1**	45.65% P-value: 1.62e-44
20495	South	Bridge	37.29% **P-value: 0.952**	37.78% **P-value: 1**	38.21% P-value: 6.99e-14
26749	North	Cinema Bridge	40.46% P-value: 7.38e-197	33.77% **P-value: 1**	41.56% P-value: 9.85e-108
26966	South	Cinema Bridge	41.45% P-value: 3.61e-51	39.81% P-value: 3.50e-14	43.58% P-value: 6.98e-55
27145	North	Bridge Junction	47.52% P-value: 8.16e-55	38.88% **P-value: 1**	48.14% P-value: 6.86e-31

Stop Nu.	Direction	Proximity	Cold	Heat	Rain
30000	South	Bridge Bus area	30.01% P-value: 6.43e-13	25.66% **P-value: 1**	29.93% P-value: 2.30e-09
30007	North	Under a bridge	28.80% P-value: 9.19e-03	26.33% **P-value: 1**	31.46% P-value: 1.15e-23
30009	South	Bridge	33.47% P-value: 8.56e-03	28.99% **P-value: 1**	33.95% P-value: 5.49e-26

4. CONCLUSIONS

This study utilizes HDSTA, a method we previously developed and demonstrated, for data-driven transportation decision-making. This interdisciplinary approach enhances ML models, incorporating diverse measures (e.g., UTCI) for more accurate predictions and identification of actionable strategies to optimize transportation outcomes under varying environmental conditions. This is crucial due to projected increases in the frequency and severity of future climate events. Consequently, vulnerability to extreme events, such as heavy rain, may also rise.

The results highlight the importance of considering not only the severity of weather events but also their frequency and population acclimatization when assessing transportation impacts. A key contribution is the WRI, quantifying weather's impact on bus station ridership to support targeted, station-level adaptation strategies such as improved shelters, bus climate control, and schedule adjustments.

HDSTA’s system-level modeling, demonstrated in a case study on Road 2, offers actionable insights (graphical, textual, and numerical) applicable to other datasets and cases through its knowledge graph framework. By combining ML, expert knowledge, and systems thinking, HDSTA establishes a shared framework for data-driven action, enabling transportation stakeholders to address climate-related challenges. Future research could investigate the socio-economic factors influencing station-specific weather sensitivity and explore the transferability of HDSTA to other transportation modes (e.g., rail, cycling).

ACKNOWLEDGEMENTS

This work was partially supported by the Technion, EuroTech alliance, Ph.D. fellowship from the Israel Scholarship Education Foundation (ISEF), Israel Smart Transportation Research Center and Israel Mobility Living Lab (ISMLL).

REFERENCES

Błażejczyk, K., Jendritzky, G., Bröde, P., Fiala, D., Havenith, G., Epstein, Y., ... & Kampmann, B. (2013). An introduction to the universal thermal climate index (UTCI). Geographia Polonica, 86(1), 5-10.

Copernicus Climate Change Service (C3S). (2024). Copernicus: 2024 virtually certain to be the warmest year and first year above 1.5°C. https://climate.copernicus.eu/copernicus-2024-virtually-certain-be-warmest-year-and-first-year-above-15degc

Dori, D. (1995). "Object-Process Analysis: Maintaining the Balance between System Structure and Behavior". Journal of Logic and Computation. 5 (2): 227–249Dori D. (2002), Object-Process Methodology: A Holistic Systems Paradigm. Berlin Heidelberg: Springer-Verlag.

Federal Highway Administration (FHWA). (2018). Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software. FHWA-HRT-18-070. Federal Highway Administration.

Gössling, S., Neger, C., Steiger, R., & Bell, R. (2023). Weather, climate change, and transport: a review. Natural Hazards, 118(2), 1341-1360.

Grinberg-Rosenbaum, K. O., Shiftan, Y., Pereira, F. C., & Nahmias-Biran, B. H. (2025). Best Of Both Worlds: System Thinking Approach for Transportation Data-Driven Decision-Making. Transportation Research Procedia, 82, 3943-3959.

Hughes, S., Giest, S., & Tozer, L. (2020). Accountability and data-driven urban climate governance. Nature Climate Change, 10(12), 1085-1090.

Jacobs, K., Garfin, G., & Lenart, M. (2005). More than just talk: Connecting science and decisionmaking. Environment: Science and Policy for Sustainable Development, 47(9), 6-21.

Klein, L. A. (2001). Sensor technologies and data requirements for ITS. Artech House.

Pearl, J. (2009). Causality: Models, reasoning and inference. Cambridge university press.
Spirtes, P., Glymour, C., & Scheines, R. (2000). Causation, prediction, and search. MIT press.

Wang, T., Qu, Z., Yang, Z., Nichol, T., Clarke, G., & Ge, Y. E. (2020). Climate change research on transportation systems: Climate risks, adaptation and planning. Transportation Research Part D: Transport and Environment, 88, 102553.