Environmental Research 306 (2026) 125126

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Weathering the ride: Associations of heat, smoke, precipitation, and ozone with bus ridership in Colorado

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ARTICLE INFO

Keywords:
Heat
Precipitation
Wildfire smoke
Ozone
Bus ridership
Free fare policies
Front range

ABSTRACT

Weather and climate variability increasingly shape urban travel behavior, yet the short-term temporal dynamics and contextual modifiers of weather-transit relationships remain poorly understood. We analyzed system-wide hourly bus ridership in the Denver metropolitan area from June 2022 through September 2023 using fixed-effects negative binomial distributed lag nonlinear models with lags up to 24 h. Nonlinear exposure-response and lag-response functions were specified for hourly Universal Thermal Climate Index (UTCI) and precipitation, with additional indicators for daily ozone exceedance and wildfire smoke. Models adjust for hour-of-day, day-of-week, and month-year fixed effects, with standard errors clustered by day. Stratified analyses assess heterogeneity by time period, season, fare policy, and shelter availability, with interaction evaluated using Wald tests. Cold thermal stress was associated with the largest, most persistent reductions in ridership, with cumulative declines of −15.7% (95% CI: −26.0%, −4.0%) over 0-24 h. Precipitation was associated with sharp but transient reductions concentrated within 3-6 h (−8.4% to −9.8%), with little evidence of longer-term displacement. Heat associations were weaker and context-dependent, with modest short-run increases, but net same-day declines. Associations varied by time of day and season, were attenuated during the free-fare period, and differed by shelter availability. In contrast, ozone exceedance and wildfire smoke exhibited limited and inconsistent associations, with measurable reductions primarily during morning commute during heavier smoke conditions. Overall, transit ridership is more strongly associated with short-term weather exposure, than with ambient air quality. Fare policy and stop-level infrastructure modify these associations, highlighting actionable strategies to enhance transit resilience under increasing climate variability.

1. Introduction

Climate change is intensifying heat (Dahl et al., 2019), wildfire smoke (Di Virgilio et al., 2019), and air pollution (Volckens, 2024) across the United States, with more frequent and severe events projected in the coming decades (IPCC, 2023). While the adverse health impacts of these exposures are well documented (Kinney, 2018), their implications for daily mobility, particularly public transportation use, remain comparatively underexplored.

Although public transit represents a relatively small share of total travel in the United States (approximately 1.2% of passenger-miles and 1.5% of trips) (BTS Data Inventory, 2025), it remains important for

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https://doi.org/10.1016/j.envres.2026.125126
Received 21 February 2026; Received in revised form 3 June 2026; Accepted 26 June 2026
Available online 2 July 2026

mobility access among transit-dependent populations and lower-income communities, and plays a key role in supporting equitable access to employment, health care, and other essential services (Urban Institute, 2025). It is especially important for the 9.1 million U.S. households without access to a private vehicle (U.S. Census Bureau, 2021). As climate-related environmental hazards increasingly affect urban travel behavior (Martens, 2016), understanding how weather and air quality influence transit use is essential for planning resilient and equitable transportation systems.

A substantial body of research has examined how weather variability and extreme events affect transit ridership (Barnes, 2015; Gössling et al., 2023). Precipitation, temperature extremes, and storms can disrupt operations and reduce demand, with effects reflecting both physical exposure and behavioral adaptation. These impacts are typically more pronounced for bus systems than for rail, as bus riders are more exposed to ambient conditions while waiting and boarding and have fewer opportunities for climate controlled-travel (Ngo, 2019). Importantly, weather-related disruptions are not evenly distributed and may disproportionately affect socioeconomically vulnerable populations (Adkins et al., 2017; Gu et al., 2024; Ngo, 2019).

A smaller but growing literature has examined the effects of air pollution and wildfire smoke on transit use. Evidence suggests that behavioral responses are complex and vary by pollutant type, transit mode, time of day, and information availability (Meena and Goswami, 2024; Soltani Mandolakani et al., 2025). Prior studies have reported modest declines in subway ridership during high pollution events (Wu and Liao, 2020) and stronger responses to air quality alerts than to continuous pollutant concentrations (Kim et al., 2024). In contrast, some evidence suggests wildfire smoke may increase rail ridership, potentially reflecting substitution away from active travel (Han et al., 2024). However, evidence for bus systems, particularly analyses that consider multiple environmental stressors at high temporal resolution, remains limited.

Infrastructure and policy may further shape how riders respond to adverse environmental conditions. Bus shelters can provide some protection from heat and precipitation, although evidence of their effectiveness is mixed, and their distribution is often uneven, raising equity concerns (Lanza and Durand, 2021; Miao et al., 2019). Policy interventions, such as fare reductions, may also influence responses by altering the cost of travel under adverse conditions.

Several additional gaps remain in the literature. First, most studies rely on dry-bulb temperature to characterize heat exposure (Ngo, 2019; Tao et al., 2018), despite evidence that composite indices such as the Universal Thermal Climate Index (UTCI), which incorporate radiation, wind, and humidity, more accurately reflect thermal stress (Li et al., 2024). Second, most analyses focus on same-day effects, even though responses to environmental exposures may unfold over multiple hours or days (Böcker et al., 2013; Liu et al., 2017). Taken together, prior studies suggest that environmental conditions influence transit use, but the evidence remains fragmented across hazards, modes, temporal scales, and contextual factors.

The DMA provides a particularly relevant setting for examining these relationships because it combines substantial climate variability, persistent air-quality challenges, and a large bus-dependent transit population. Located along the Colorado Front Range at high elevation (~1600 m above sea level), the region experiences large diurnal and seasonal temperature variability, intense solar radiation, episodic convective precipitation, winter cold spells, and increasingly frequent wildfire smoke intrusions originating from both in-state and western U. S. fires. The region also faces chronic ozone pollution driven by transportation emissions, oil and gas activity, topographic trapping, and meteorological conditions favorable to photochemical ozone formation (deSouza and Hood, 2024; deSouza et al., 2025a). These overlapping environmental stressors make Denver representative of many rapidly growing western metropolitan regions increasingly exposed to compound climate and air-quality hazards.

The Regional Transportation District (RTD) operates one of the largest transit systems in the Mountain West, serving approximately 3 million residents across eight counties through an extensive network of local, regional, and express bus services. Bus transit plays a particularly important role for lower-income and transit-dependent populations, with approximately 65% of riders reporting dependence on the system for daily travel (RTD, 2025). At the same time, much of the bus network relies on outdoor waiting environments, and shelter availability is spatially uneven across the system. These characteristics make the DMA especially well suited for studying how weather, wildfire smoke, and air pollution shape short-term transit behavior and how infrastructure and fare policy may modify vulnerability to environmental exposures.

In this study, we address the gaps identified in the literature by examining associations between extreme weather, air pollution, wildfire smoke, and hourly bus ridership in the Denver metropolitan area. We pursue three objectives: (1) to estimate the average associations between extreme weather, wildfire smoke, and ozone exceedances and ridership; (2) to assess temporal variation by time of day, season, and fare policy; and (3) to evaluate association modification by bus stop amenities.

2. Data and methods

2.1. Ridership data

We used Automatic Passenger Counter (APC) data provided by the Regional Transportation Division (RTD) in Colorado to measure bus ridership at each stop in the DMA from 1 June 2022 to 30 September 2023. APC systems record passengers boarding and alighting vehicles and are widely used in transit operations and research to quantify ridership patterns (Lee and Miller, 2022). The study period was determined based on data availability.

Zero boardings at stops, particularly near route termini, are not uncommon. Some stops also experienced extended periods of zero boardings due to service changes, road construction, or other operational factors. The dataset excluded atypical travel days as defined by RTD, including federal holidays; days immediately preceding or following holidays; and operational outlier days (defined as days on which more than 30% of bus arrivals between midnight and noon at Union Station or the Civic Center were late).

In addition, we excluded 31 days affected by exogenous factors (e.g., holidays, and severe weather events resulting in system closures). Excluded dates in 2022 were June 30, 2022, July 1st and 4th, September 5, 12, and 13; October 10; November 3, 11, 24, 25, and 29; and December 23-26, 29, 31. Excluded dates in 2023 were January 1, 2, 8, 16, and 31; February 20; April 9; May 28 and 29; June 29; and July 4. The final analytic sample included 456 days of ridership.

Fig. S1 displays a flow chart of the methodology used in this study. Fig. S2 displays a heat map of total boardings by hour of day, our primary outcome, across all stops for the full study period. The dataset contained 44,298,787 stop-hour observations across 7283 bus stops. For our analysis, we aggregated ridership to a system-level hourly time series by summing boardings across all stops within each hour, yielding 10,573 hourly observations. We selected this aggregation strategy because several key environmental exposures, including ERA5/ERA5-Land meteorological fields, wildfire smoke plume classifications, and ozone exceedance indicators, are measured at relatively coarse regional spatial scales and do not resolve hyperlocal stop-level conditions. Aggregation therefore aligns the outcome with the effective spatial resolution of the exposure data and facilitates estimation of overall system-wide ridership responses. In addition, aggregation reduces noise associated with sparse stop-level counts, operational variability, temporary service disruptions, and prolonged zero-boarding periods that are unrelated to environmental conditions. While primary analyses are conducted at the system-hour level, stop-level information is retained for subsequent heterogeneity analyses stratified by shelter availability.

2.2. Weather data

Hourly and daily environmental exposures were assigned to each bus stop using a standardized geospatial extraction workflow implemented in Google Earth Engine (GEE) and R (via the *rgee* package (Aybar et al., 2020)). We constructed a high-resolution, stop-hour panel dataset spanning June 1, 2022, through September 30, 2023, linking each ridership observation to meteorological conditions, thermal stress indices, precipitation, and wildfire smoke at the corresponding stop and hour. Hourly exposures were matched to each ridership observation to ensure alignment with service hours. Daily exposures were merged with all stop-hour observations occurring on the same date, yielding a harmonized hourly system-level dataset containing 10,572 hourly observations.

Meteorological data were obtained from the ERA5 and ERA5-Land reanalysis products developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is a global atmospheric reanalysis that combines observations with numerical weather models to provide hourly estimates of atmospheric variables at ~31 km resolution. ERA5-Land is a complementary dataset derived from ERA5 that provides higher spatial resolution (~9 km) estimates over land surfaces, with improved representation of land-atmosphere processes. We used the ERA5products because they provide data at an hourly-time resolution.

2.2.1. Hourly air temperature and precipitation data

We used ERA5-Land to obtain hourly near-surface (2 m) temperature (°C) and total precipitation (~9 km resolution). Precipitation (m) was converted to millimeters and assigned to each bus stop at the corresponding hour. Variables were extracted at each bus-stop in GEE for all hours within the study period.

2.2.2. Universal Thermal Climate Index (UTCI)

Hourly UTCI was computed at each bus stop using meteorological and radiative inputs from the ERA5-Land and ERA5, following Di Napoli et al. (2018) and Brimicombe et al. (2022). From ERA5-Land, we extracted 2-m air temperature, 2-m dew point temperature, 10-m wind components (u and v), and surface shortwave and longwave radiation terms (downwelling and net). Because ERA5-Land does not provide total-sky direct shortwave radiation, this variable was obtained from ERA5.

Mean radiant temperature was calculated using the thermofeel Python package (Brimicombe et al., 2022), combining radiation components and solar geometry. Wind speed was derived from 10-m wind components and water vapor pressure from dew point temperature. UTCI was then computed using the standard polynomial approximation and expressed in °C.

Although exposures were assigned at bus stop locations, ERA5 and ERA5-Land represent area-averaged conditions at relatively coarse spatial resolution and do not capture microclimate variability at individual stops (e.g., shading, built environment, or localized wind conditions). Accordingly, we interpret exposure-response relationships at the transit system (regional) scale. This aggregation may smooth over localized meteorological variability within the transit network, particularly for convective precipitation and microclimatic heat differences between stops. This spatial alignment motivates specification of the primary models at the system-hour level, while allowing incorporation of stop-level attributes in effect-modification analyses.

2.3. Wildfire smoke exposure

Wildfire smoke exposure at each bus stop was characterized using the NOAA NOAA, 2025 smoke product (NOAA, 2025), which provides daily spatial plume polygons and categorical smoke density classifications (light, medium, heavy) across North America.

For each day in 2022-2023, HMS smoke polygons were intersected with bus-stop point locations in GEE. A bus stop was considered smoke-exposed on a given day if it fell within any HMS plume polygon. When available, plume density was assigned as an ordinal exposure metric (light < medium < heavy) to capture variation in smoke intensity.

Because HMS is based on satellite imagery and analyst interpretation, it provides qualitative rather than quantitative estimates of smoke exposure; accordingly, we interpret these measures as indicators of smoke presence and relative intensity rather than precise concentration levels.

2.4. Ozone exceedance days

Under the 2015 National Ambient Air Quality Standards (NAAQS), the 8-h ozone standard is 0.070 ppm. To identify exceedance days, we used daily 8-h ozone observations from regulatory monitors located in Front Range counties that have been out of compliance (Adams, Arapahoe, Boulder, Broomfield, Denver, Douglas, Jefferson, Larimer, and Weld).

For each monitoring site, we extracted the daily maximum 8-h ozone concentration. A day was classified as an exceedance day if any monitor reported a value greater than 0.070 ppm. Exceedances were then collapsed to unique calendar dates, yielding a binary indicator of whether the region experienced an ozone exceedance on each day of the study period.

To align environmental exposures with the system-level ridership outcome, hourly meteorological variables (e.g., UTCI and precipitation) were aggregated to system-wide means. Wildfire smoke exposure was summarized as the maximum plume density observed across all bus stops on each day. Ozone exceedances were defined at the regional (system-wide) scale and merged directly with the hourly ridership time series, yielding a harmonized system-level dataset.

2.5. Additional covariates

We used RTD data on bus stop amenities to classify stops according to whether a shelter was present (section S3). Information on shelter amenities was unavailable for 322 stops, primarily due to ongoing construction at the time of data collection. These stops were primarily located along Colfax Avenue (currently being converted into a BRT corridor), Wadsworth Avenue, and the 16th Street Mall. In addition, stops at major regional transit hubs (e.g., Union Station and Civic Center Station), which serve intercity routes and park-n-rides, were not included in the amenities survey. We excluded all stops with missing amenity data from shelter-specific analyses.

Section S3 characterizes the distribution of shelter amenities across the transit network, including differences by neighborhood context and vulnerability. These descriptive patterns provide context for interpreting infrastructure-stratified analyses but are not directly incorporated into the main statistical models.

2.6. Statistical methods

We first present descriptive statistics summarizing average environmental exposures and their correlations with system-wide bus boardings.

Hourly system-level boardings were analyzed using a fixed-effects negative binomial distributed lag nonlinear modeling (DLNM) framework to estimate potentially nonlinear and delayed associations with thermal stress (UTCI) and precipitation (Gasparrini, 2011, 2014; Gasparrini et al., 2010). Models were implemented using the *dlnm* package in R.

DLNMs are specifically designed for time-series settings where exposures may have both nonlinear effects and delayed impacts over time. The approach constructs a cross-basis function that simultaneously represents (1) the exposure-response relationship (e.g., nonlinear effects of heat intensity) and (2) the lag-response relationship (e.g., how effects unfold over subsequent hours). By modeling all lags jointly, DLNMs estimate the contribution of each lag while adjusting for other lags, avoiding bias from serially correlated exposures. This framework is widely used in environmental epidemiology to study short-term effects of weather and air pollution on health and behavior.

Let y_{ht} denote total system boardings in hour h on calendar day t. The conditional mean was specified as:

$$log\ (E[y_{ht}|X_{ht}]) = \beta_1 UTCI_{ht} + \beta_2 Prec_{ht} + \beta_3 Smoke_t + \beta_4 OzoneExceeded_t + \delta_h + \omega_d + \mu_m + \varepsilon_{sh} \quad (1)$$

Where $UTCI_{ht}$ and $Prec_{ht}$ represent hourly thermal stress and precipitation, $Smoke_t$ indicates wildfire smoke exposure, and $OzoneExceeded_t$ indicates daily ozone exceedance.

To account for temporal structure in ridership, we included fixed effects for hour of day (γ_h), day-of-week (δ_d), and month-year (μ_m), which capture diurnal cycles, weekly travel patterns, and seasonal variation. This specification absorbs much of the serial dependence in ridership by controlling for systematic temporal patterns, while day-level clustered standard errors account for residual within-day autocorrelation. Standard errors are clustered at the calendar-day level to allow arbitrary correlation among hourly observations within the same day.

UTCI and precipitation were each modeled using DLNM cross-basis functions with a maximum lag of 24 h, allowing exposure effects to vary nonlinearly and evolve over time. The 24-h lag window captures short-term behavioral responses within a day, consistent with prior literature on transit use. Cross-basis functions were parameterized using natural cubic splines for both the exposure-response and lag-response dimensions. Spline complexity was selected via grid searches over degrees of freedom (2-10) for both dimensions, choosing specifications that minimized the Akaike Information Criterion (AIC). The final specification included UTCI (lags 0-24 h; 5 lag-response df; 6 exposure-response df) and precipitation (lags 0-24 h; 4 lag-response df; 10 exposure-response df).

In contrast, ozone exceedance and wildfire smoke were modeled as day-level indicator variables rather than using DLNM cross-basis functions. This reflects their episodic nature, limited within-day temporal variation, and the absence of sufficient information to estimate flexible lag-response relationships at the hourly scale. Because these variables vary primarily between days rather than within days, estimated coefficients should be interpreted as differences in the overall hourly ridership profile on exposed versus non-exposed days after adjustment for systematic temporal patterns, rather than as true intra-day exposure-response effects.

In sensitivity analyses, we varied the maximum lag window (12, 24, 36, 48, and 72 h) and estimated alternative models using air temperature in place of UTCI. Results were robust across specifications.

Model outputs are presented as lag-specific and cumulative relative risks (RRs), aggregated over lag windows (0-3, 0-6, 0-12, and 0-24 h). Effects are expressed relative to the median exposure. Coefficients were exponentiated to obtain RRs, and then converted to percent differences in expected boardings using $100\times(e^{\beta k}\text{-}1)$.

2.6.1. *Effect modification*

To assess heterogeneity in weather-ridership associations, we extended the DLNM framework using stratified modeling approaches across key temporal, policy, and infrastructure dimensions.

We first estimated fully stratified DLNMs across temporal and contextual domains: (1) time-of-day and weekday period (AM peak 06:00-08:59; mid-day 09:00-14:59; PM peak 15:00-18:59; early/late 19:00-05:59; weekend), following Denver Regional Council of Governments (DRCOG) definitions; (2) season (winter, spring, summer, fall); and (3) fare policy (free-fare vs. fare-required). The free-fare period corresponds to RTD's *Zero Fare for Better Air* program, which operated system-wide during August 2022 and July-August 2023. Within each stratum, we applied the same model specification, including lag structure, spline functions, covariates, fixed effects, and clustered standard errors. Smoke density and ozone exceedances were omitted in strata with no within-stratum variation.

To evaluate heterogeneity by stop-level infrastructure, we implemented a stratified aggregation approach based on shelter availability. Stop-level observations were first classified according to whether a shelter was present, and separate system-level hourly time series were constructed by summing boardings across stops within each stratum (sheltered vs. unsheltered). DLNMs were then estimated separately within each stratum using identical specifications. Differences in exposure-response relationships across strata were interpreted as evidence of effect modification, and statistical significance was assessed using joint Wald tests comparing cross-basis coefficients across models.

Because shelter availability is not randomly assigned and is correlated with underlying spatial and service characteristics (e.g., stop location, demand, and network design), these analyses do not estimate causal effects of shelter provision. In addition, because outcomes are aggregated within strata, models do not include stop fixed effects and do not isolate within-stop variation. Accordingly, results should be interpreted as system-level differences in weather-ridership associations across groups of stops with different infrastructure characteristics, rather than as causal stop-level effects. Descriptive evidence on the non-random distribution of shelters is provided in section S3.

For time-of-day, season, and fare-policy strata, heterogeneity was assessed through stratified models rather than formal interaction tests, as these strata represent distinct behavioral and temporal regimes where within-context associations are of primary interest. Exposure contrasts were defined using stratum-specific distributions (10th, median, and 90th percentiles), ensuring that estimated associations reflect deviations from typical conditions within each context rather than between-period differences.

All analyses were carried out in R v4.5.0. This study follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for observational research. Statistical significance was assessed as $p < 0.05$.

3. Results

3.1. *Descriptive patterns in ridership and environmental exposures*

Fig. S3 shows temporal variation in average hourly boardings across the study period, stratified by week, day, season, and weekday versus weekend. Ridership followed the expected diurnal pattern, with a morning peak and a larger evening peak. Boardings increased notably during July and August, coinciding with RTD's *Zero Fare for Better Air* program (Webster, 2024).

Fig. S4 and S5 show corresponding temporal patterns for environmental exposures. UTCI and air temperature tracked each other closely, with the highest values occurring in summer and during afternoon hours (Fig. S4). Precipitation was more episodic and was highest in spring (Fig. S5). Ridership patterns were broadly similar at stops with and without shelters (Fig. S6).

Table 1 summarizes system-wide hourly boardings and concurrent environmental conditions. Across the analytic period, hourly boardings ranged from 0 to 19,133, with a mean of 3632 and a median of 3334. There were 171 wildfire smoke days during the study period, including 4 heavy-smoke days, 18 medium-smoke days, and 156 light-smoke days. Ozone exceedances occurred on 60 days across 2022 and 2023.

To aid interpretation of later DLNM results, Table 1 also reports the exposure values used for key contrasts. For UTCI, the 10th percentile (cold) was −14.2 °C and the 90th percentile (hot) was 35.2 °C. For precipitation, the 90th percentile ("wet") was 0.12 mm/h, while the 10th percentile corresponded to dry conditions.

Table 1

Descriptive statistics for system-wide hourly bus boardings and concurrent weather exposures, including Universal Thermal Climate Index (UTCI), 2-m air temperature (°C), and hourly precipitation (mm), aggregated at the hourly level. For each variable, we present the number of hourly observations and number of contributing days, along with the minimum, 5th, mean, median, 75th, 95th percentiles, and maximum. Statistics are shown for the full study period and stratified by time-of-day/weekday period, season, fare policy (free-fare vs non-free fare), and the subset of non-free fare hours during summer. Weather variables represent system-wide hourly averages across stops, and boardings represent total system boardings per hour.

Group	Stratum	N hours	N days	Min	5th percentile	Mean	Median	75th percentile	95th percentile	Max
Boardings										
Overall	**All**	10,572	476	0	37	3632	3334	5644	8473	19133
Period	**AM Weekday**	930	310	83	4167	5886	5760	6655	8174	14835
	MD Weekday	1860	310	88	4421	5973	5873	6713	7875	16635
	PM Weekday	1240	388	69	4189	7505	7601	9158	10415	19133
	EL Weekday	3459	396	0	9	1407	1178	2412	3533	9579
	Weekend	3083	199	0	30	2479	2476	3802	5276	9242
Season	**Spring**	2111	92	0	41	3455	3132	5336	7911	10081
	Summer	4150	184	0	41	3838	3680	5915	8590	19133
	Fall	2524	120	0	36	3645	3225	5723	8930	12683
	Winter	1787	85	0	31	3345	2866	5287	7761	10222
Fare status	**Free-fare**	2130	95	0	44	4339	4408	6627	9332	12799
	Fare Required	8442	384	0	37	3454	3106	5336	7987	19133
	Fare Required (Summer)	2020	90	0	39	3310	3127	4970	7109	19133
UTCI (°C)										
Overall	**All**	10572	476	−34.6	−19.3	11.5	12.3	24.5	38.9	46.0
Period	**AM Weekday**	930	310	−33.1	−24.6	1.5	4.8	12.6	22.3	26.6
	MD Weekday	1860	310	−22.9	−1.6	25.2	28.2	35.6	42.1	46.0
	PM Weekday	1240	388	−22.3	−8.0	22.2	26.6	34.2	41.0	45.5
	EL Weekday	3459	396	−34.6	−21.7	2.9	6.7	13.5	22.2	35.3
	Weekend	3083	199	−29.7	−19.2	11.4	12.6	23.7	38.4	45.0
Season	**Spring**	2111	92	−25.6	−14.7	6.8	5.1	19.1	32.1	38.2
	Summer	4150	184	−1.5	7.2	22.8	20.4	33.6	41.5	46.0
	Fall	2524	120	−29.0	−14.9	10.7	9.5	21.9	35.8	44.2
	Winter	1787	85	−34.6	−27.8	−8.2	−12.6	2.3	19.4	29.5
Fare status	**Free-fare**	2130	95	5.0	8.5	23.4	20.7	34.2	41.7	45.7
	Fare Required	8442	384	−34.6	−20.4	8.4	9.2	21.5	36.5	46.0
	Fare Required (Summer)	2020	90	−1.5	6.0	22.1	20.0	32.6	41.4	46.0
Precipitation (mm)										
Overall	**All**	10572	476	0	0	0.07	0	0.009	0.4	6.0
Period	**AM Weekday**	930	310	0	0	0.03	0	0.001	0.1	2.0
	MD Weekday	1860	310	0	0	0.06	0.001	0.01	0.3	3.9
	PM Weekday	1240	388	0	0	0.1	0.006	0.08	0.7	6.0
	EL Weekday	3459	396	0	0	0.07	0	0.004	0.4	3.3
	Weekend	3083	199	0	0	0.05	0	0.006	0.3	3.7
Season	**Spring**	2111	92	0	0	0.09	0.001	0.03	0.5	3.5
	Summer	4150	184	0	0	0.09	0	0.02	0.5	6.0
	Fall	2524	120	0	0	0.04	0	0.001	0.2	3.7
	Winter	1787	85	0	0	0.04	0	0.004	0.2	2.3
Fare status	**Free-fare**	2130	95	0	0	0.08	0	0.01	0.4	6.0
	Fare Required	8442	384	0	0	0.06	0	0.009	0.4	3.7
	Fare Required(Summer)	2020	90	0	0	0.09	0.001	0.02	0.6	3.0
Air temperature (°C)										
Overall	**All**	10572	476	−27.4	−8.5	11.9	13.7	20.8	29.7	35.1
Period	**AM Weekday**	930	310	−26.7	−12.7	6.5	9.4	15.2	20.1	24.6
	MD Weekday	1860	310	−24.5	−4.5	16.0	18.5	25.1	31.6	35.0
	PM Weekday	1240	388	−18.6	−3.4	17.7	20.3	27.4	32.7	35.0
	EL Weekday	3459	396	−27.4	−10.5	9.2	11.8	18.0	24.7	32.9
	Weekend	3083	199	−23.4	−7.7	11.8	13.2	20.1	29.3	35.1
Season	**Spring**	2111	92	−10.3	−5.0	6.9	7.0	12.4	20.9	25.9
	Summer	4150	184	3.8	11.7	21.3	20.6	26.1	31.9	35.1
	Fall	2524	120	−16.5	−5.2	12.2	12.4	18.9	27.5	34.5
	Winter	1787	85	−27.4	−16.0	−4.2	−4.3	0.1	8.6	14.1
Fare status	**Free-fare**	2130	95	10.8	13.9	22.1	21.3	26.6	31.9	35.0
	Fare Required	8442	384	−27.4	−9.6	9.4	10.2	18.1	28.2	35.1
	Fare Required(Summer)	2020	90	3.8	10.6	20.4	19.8	25.4	31.8	35.1

3.2. *System-wide associations*

Fig. 1 and Table 2 summarize the main distributed lag nonlinear model results for system-wide hourly ridership. Fig. 1 shows how estimated effects evolve hour by hour after exposure, while Table 2 reports cumulative effects over four lag windows (0-3, 0-6, 0-12, and 0-24 h). We focus on contrasts between cold versus median UTCI, hot versus median UTCI, and wet versus median precipitation.

Cold thermal stress was associated with clear and persistent reductions in ridership. Relative to median conditions, UTCI at the 10th percentile (−14.2 °C) was associated with cumulative declines of 9.2% over 0-3 h (95% CI: −14.4%, −3.7%), 10.9% over 0-6 h (95% CI: −17.0%, −4.2%), 10.5% over 0-12 h (95% CI: −18.3%, −1.8%), and 15.7% over 0-24 h (95% CI: −26.0%, −4.0%). These results indicate that cold suppressed ridership quickly and that the effect accumulated over the course of the day.

Hot thermal conditions showed a different pattern. At the 90th percentile of UTCI (35.2 °C), cumulative effects over 0-3 and 0-6 h were small and not statistically distinguishable from zero, and remained imprecise over 0-12 h. However, over the full 24-h window, hot

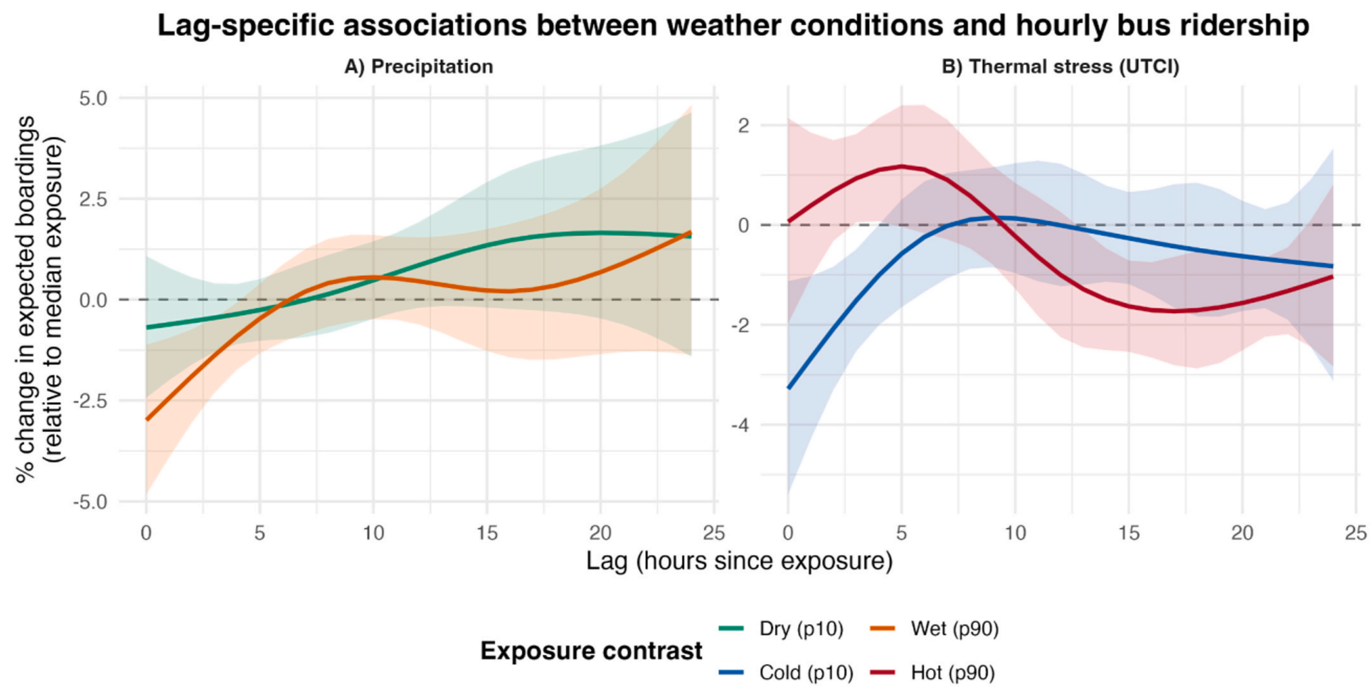

Fig. 1. Lag-response associations between weather conditions and system-wide hourly bus ridership. Panel (A) shows precipitation and Panel (B) shows thermal stress measured by the Universal Thermal Climate Index (UTCI). Curves represent percent changes in expected hourly boardings at each lag (0-24 h) relative to median exposure levels. For each panel, lines compare low (10th percentile) and high (90th percentile) exposure conditions to the median (reference). Solid lines denote point estimates and shaded ribbons indicate 95% confidence intervals. The x-axis represents hours since exposure and the y-axis represents percent change in expected boardings. Negative values indicate reductions in ridership relative to median conditions. Estimates are derived from fixed-effects negative binomial distributed lag nonlinear models (DLNMs), which simultaneously model nonlinear exposure-response relationships and lagged effects. Models include fixed effects for hour of day, day of week, and month-year, with standard errors clustered at the day level.

Table 2
Cumulative percent changes in expected system-wide hourly bus boardings associated with weather conditions, relative to median exposure levels. Estimates are aggregated over lag windows from 0 to 24 h using fixed-effects negative binomial distributed lag nonlinear models (DLNMs), which account for both nonlinear exposure-response relationships and delayed effects over time. Cold and hot thermal conditions are defined as the 10th and 90th percentiles of system-wide hourly UTCI, respectively. Wet and dry conditions correspond to the 90th and 10th percentiles of hourly precipitation. Percent changes represent the total cumulative effect of exposure across the specified lag window, compared to median conditions. Models adjust for hour-of-day, day-of-week, and month-year fixed effects to control for temporal patterns in ridership, with standard errors clustered at the day level. Statistically significant estimates (95% confidence interval excluding zero) are shown in **bold**.

Exposure	Exposure level	Lag window	Percent change (95% CI)
UTCI	Cold (p10, −14.2 °C)	0-3 h	**−9.2% (-14.4%, -3.7%)**
		0-6 h	**−10.9% (-17.0%, -4.2%)**
		0-12 h	**−10.5% (-18.3%, -1.8%)**
		0-24 h	**−15.7% (-26.0%, -4.0%)**
	Hot (p90, 35.2 °C)	0-3 h	2.1% (−2.7%, 7.2%)
		0-6 h	5.6% (−0.4%, 11.9%)
		0-12 h	5.4% (−3.2%, 14.7%)
		0-24 h	**−11.9% (-21.7%, -0.7%)**
Precipitation	Dry (p10, 0 mm)	0-3 h	−2.3% (−7.0%, 2.7%)
		0-6 h	−3.0% (−8.7%, 3.1%)
		0-12 h	−0.6% (−8.2%, 7.6%)
		0-24 h	18.7% (−7.2%, 52.0%)
	Wet (p90, 0.12 mm)	0-3 h	**−8.4% (-13.2%, -3.4%)**
		0-6 h	**−9.8% (-15.6%, -3.5%)**
		0-12 h	−7.3% (−15.5%, 1.6%)
		0-24 h	0.3% (−22.0%, 29.1%)

conditions were associated with an 11.9% decline in cumulative ridership (95% CI: −21.7%, −0.7%). Thus, unlike cold, heat did not produce strong immediate reductions but was associated with lower same-day ridership overall.

Precipitation produced sharp but short-lived decreases in ridership. At the 90th percentile of hourly precipitation (0.12 mm), boardings declined by 8.4% over 0-3 h (95% CI: −13.2%, −3.4%) and 9.8% over 0-6 h (95% CI: −15.6%, −3.5%). These associations weakened by 0-12 h and were no longer detectable by 0-24 h. This pattern suggests that rain mainly discourages travel in the near term rather than generating persistent same-day suppression.

Overall, environmental exposures exhibited distinct temporal signatures: cold was associated with immediate and persistent suppression, precipitation with immediate but transient reductions, and heat with

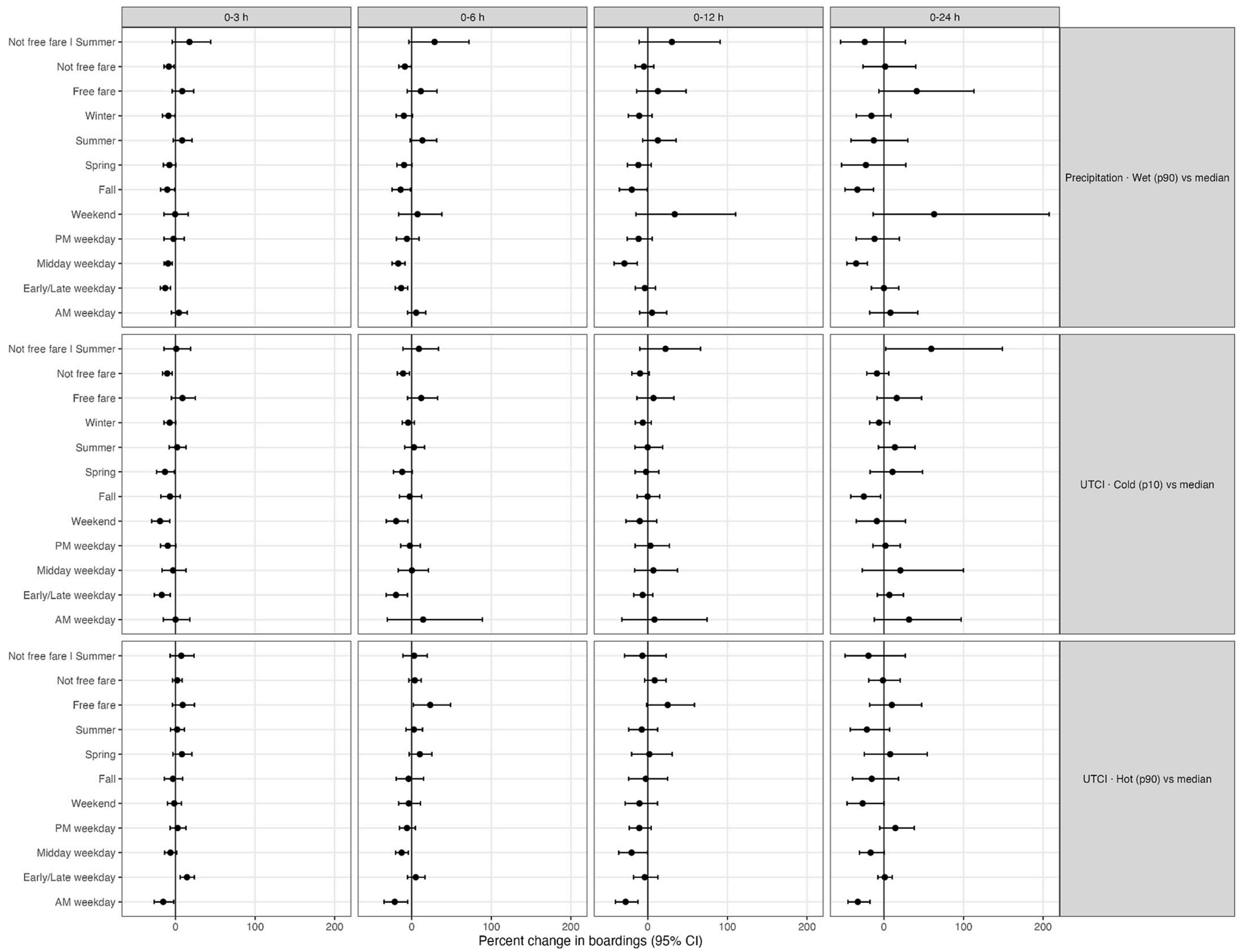

Fig. 2. Stratified cumulative effects of weather conditions on system-wide hourly bus ridership across time-of-day, season, and fare policy. Points represent cumulative percent changes in expected hourly boardings relative to median exposure, and horizontal bars denote 95% confidence intervals. Columns correspond to cumulative lag windows (0-3 h, 0-6 h, 0-12 h, and 0-24 h), representing the total effect of exposure over increasing time horizons. Rows show results stratified by (i) time-of-day and weekday period (AM peak, midday, PM peak, early/late, weekend), (ii) season (spring, summer, fall, winter), and (iii) fare policy (free fare, fare-required, and summer fare-required). Panels display contrasts for wet precipitation (90th percentile vs median), cold thermal stress (UTCI 10th percentile vs median), and hot thermal stress (UTCI 90th percentile vs median). The vertical reference line at 0 indicates no change in ridership; values to the left indicate reductions, and values to the right indicate increases relative to median conditions. Estimates are derived from fixed-effects negative DLNMs, which capture nonlinear exposure-response relationships and cumulative lagged effects. All models adjust for hour-of-day, day-of-week, and month-year fixed effects, with standard errors clustered at the day level.

weaker short-term associations that emerged cumulatively over longer windows.

Ambient air quality indicators showed limited associations with system-wide ridership. Wildfire smoke and ozone exceedance were not consistently associated with hourly boardings after adjustment for weather and temporal patterns (Table S1). Point estimates for smoke exposure were small and imprecise across categories, and ozone exceedance days were not associated with statistically detectable changes in ridership. These results suggest that, within the current hourly modeling framework, short-term variation in ridership was more strongly associated with weather conditions than with the day-level ambient air quality indicators examined here.

3.3. Associations by time of day and day type

Fig. 2 and Table S2 show that weather-ridership associations differed substantially across time-of-day and weekday/weekend periods. In Fig. 2, each point represents the cumulative percent change in ridership for a given exposure contrast and lag window, and the horizontal bars show the corresponding 95% confidence intervals.

During AM peak weekday hours, heat was most salient. Hot UTCI (90th percentile versus median) was associated with progressively larger cumulative reductions in ridership, ranging from −15.5% over 0-3 h (95% CI: −26.9%, −2.3%) to −32.9% over 0-24 h (95% CI: −45.3%, −17.6%). In contrast, cold and precipitation were not significantly associated with AM peak ridership.

During midday weekday hours, precipitation showed the strongest effects. Wet conditions were associated with increasingly large cumulative declines as the lag window lengthened, from −9.4% over 0-3 h (95% CI: −14.3%, −4.2%) to −35.0% over 0-24 h (95% CI: −46.6%, −20.9%). Midday heat was also associated with reduced ridership at short and intermediate lags, while cold effects were close to null.

During PM peak weekday hours, both weather (Fig. 2) and air quality associations (Table S2) were generally weak and imprecise. In the early/late weekday period, however, both cold and wet conditions were associated with significant short-run reductions in ridership. Heat, by contrast, was associated with a short-run increase over 0-3 h, although this did not persist at longer lags.

Weekend ridership showed a different pattern. Cold conditions were associated with clear short-run declines, including −19.5% over 0-3 h (95% CI: −30.1%, −7.3%) and −19.5% over 0-6 h (95% CI: −31.9%, −4.7%), whereas associations with heat and precipitation were generally unstable and statistically insignificant.

Taken together, these results indicate that heat mainly reduced weekday daytime ridership, especially during the morning and midday periods; cold mattered more for off-peak and weekend travel; and associations with precipitation were largest during midday and early/late periods rather than during peak commute hours.

Air quality associations were weaker than weather associations in all time strata. Ozone exceedance was generally not associated with ridership, with the exception of one positive AM weekday association estimate of 7.3% (95% CI: 1.2%, 13.7%). Wildfire smoke effects were concentrated in the morning commute: medium smoke was associated with a 6.8% decline in ridership (95% CI: −13.0%, −0.1%), and heavy smoke with a 16.6% decline (95% CI: −30.2%, −0.3%). Detectable smoke associations were otherwise limited (Table S2).

3.4. Associations by season

Season-stratified models revealed substantial variation in weather-ridership associations over the calendar year (Fig. 2; Table S2). Associations with precipitation were strongest in cooler seasons, especially fall.

In fall, wet conditions were associated with increasingly large cumulative declines as the lag window lengthened, from −10.4% over 0-3 h (95% CI: −18.8%, −1.0%) to −33.4% over 0-24 h (95% CI: −48.9%, −13.2%). In winter, precipitation was associated with a significant short-run reduction over 0-3 h, but estimates became weaker and more imprecise at longer lags. In spring, associations with precipitation were modest and not statistically distinguishable from zero. In summer, precipitation estimates were directionally positive at short lags but remained imprecise throughout.

Cold thermal stress also varied by season. In spring, cold was associated with a significant short-run decline in ridership over 0-3 h, while in fall the effect emerged more gradually and was strongest in cumulative 0-24-h estimates. In winter, cold effects were consistently negative but modest and imprecise, and in summer they were minimal.

Associations with heat also differed seasonally. In winter, warmer-than-usual conditions were associated with increased ridership at intermediate lags, consistent with relative relief from cold conditions. By contrast, associations with spring and summer heat were generally small and statistically indistinguishable from zero, and fall heat estimates were also imprecise.

Air quality indicators were not significantly associated with ridership in any individual season. Overall, these results suggest that precipitation had the clearest seasonal pattern, with the strongest effects in fall and winter, while cold mattered most in spring and fall and warmer winter conditions were associated with higher ridership.

3.5. Associations by fare-policy

Because RTD's free-fare program operated only during summer months, we compared the free-fare period to two reference conditions: the full fare-required period and the subset of summer fare-required days (Fig. 2; Table S2).

Associations with precipitation were strongest when fares were required. Across all fare-required periods, wet conditions were associated with reductions in ridership of −10.2% over 0-3 h (95% CI: −18.3%, −1.4%) and −11.9% over 0-6 h (95% CI: −21.9%, −0.6%). In contrast, during the free-fare period, associations with precipitation were imprecise and not statistically distinguishable from zero across all lag windows. Similar null findings were observed in the summer fare-required comparison, suggesting that the weaker precipitation response during free fare may reflect both fare context and summer travel behavior.

Cold thermal stress also differed by fare policy. During fare-required periods, cold was associated with short-run declines in ridership over 0-3 and 0-6 h. During the free-fare period, these cold effects were not statistically distinguishable from zero. In the summer fare-required stratum, cooler-than-typical summer conditions were associated with a large cumulative increase over 0-24 h, indicating that relative cooling during summer may encourage transit use when fares remain in place.

Associations with heat also varied by fare status. During the free-fare period, hot conditions were associated with higher short-run ridership, including a 23.3% increase over 0-6 h (95% CI: 2.1%, 48.8%). By contrast, associations with heat during fare-required periods were generally small and imprecise.

Air quality indicators were not significantly associated with ridership in either fare stratum. Overall, rain and cold were associated with short-lag reductions in ridership across most strata, although this pattern did not hold in the summer fare-required comparison, where cooler-than-typical conditions were associated with neutral or positive cumulative responses. These results indicate that weather-ridership relationships depend not only on absolute exposure levels but also on seasonal context and fare conditions.

Table 3

Percent changes represent cumulative effects relative to median exposure, estimated from fixed-effects negative binomial distributed lag non-linear models with lag 0-24 h. Models include fixed effects for hour of day, day of week, and month-year and standard errors clustered by day. Cold and hot UTCI correspond to the 10th and 90th percentiles of system-wide hourly UTCI; wet precipitation corresponds to the 90th percentile of hourly precipitation. Statistically significant results are **bolded**.

Shelter	Exposure	Contrast	Lag window	% change in boardings (95% CI)
No	Precipitation	Wet (p90)	0-3 h	**−10.4% (-15.4%, -5.0%)**
No	Precipitation	Wet (p90)	0-6 h	**−11.8% (-18.0%, -5.1%)**
No	Precipitation	Wet (p90)	0-24 h	2.2% (−26.0%, 41.0%)
Yes	Precipitation	Wet (p90)	0-3 h	**−8.6% (-13.7%, -3.2%)**
Yes	Precipitation	Wet (p90)	0-6 h	**−10.8% (-16.9%, -4.3%)**
Yes	Precipitation	Wet (p90)	0-24 h	−7.0% (−25.5%, 16.1%)
No	UTCI	Cold (p10)	0-3 h	**−11.7% (-16.9%, -6.2%)**
No	UTCI	Cold (p10)	0-6 h	**−13.2% (-19.6%, -6.3%)**
No	UTCI	Cold (p10)	0-24 h	**−18.4% (-29.0%, -6.4%)**
Yes	UTCI	Cold (p10)	0-3 h	**−10.5% (-15.3%, -5.4%)**
Yes	UTCI	Cold (p10)	0-6 h	**−12.0% (-18.0%, -5.6%)**
Yes	UTCI	Cold (p10)	0-24 h	**−18.6% (-28.9%, -7.0%)**
No	UTCI	Hot (p90)	0-3 h	3.3% (−1.9%, 8.7%)
No	UTCI	Hot (p90)	0-6 h	**6.4% (0.1%, 13.0%)**
No	UTCI	Hot (p90)	0-24 h	−11.6% (−22.3%, 0.5%)
Yes	UTCI	Hot (p90)	0-3 h	0.8% (−3.8%, 5.7%)
Yes	UTCI	Hot (p90)	0-6 h	2.5% (−3.1%, 8.5%)
Yes	UTCI	Hot (p90)	0-24 h	**−14.2% (-24.2%, -2.8%)**

3.6. Effect modification by shelter availability

Shelter-stratified analyses revealed differences in weather-ridership associations across groups of stops defined by infrastructure (Table 3; Fig. 2). These analyses were conducted by aggregating ridership separately for sheltered and unsheltered stops and estimating DLNMs within each stratum.

Associations with precipitation were similar across shelter strata. Among unsheltered stops, wet conditions (p90 vs median) were associated with reductions of −10.4% (95% CI: −15.4%, −5.0%) over 0-3 h and −11.8% (95% CI: −18.0%, −5.1%) over 0-6 h. Comparable short-run reductions were observed among sheltered stops (−8.6% (95% CI: −13.7%, −3.2%) over 0-3 h; −10.8% (95% CI: −16.9%, −4.3%) over 0-6 h), with attenuation at longer lags. Although formal interaction tests indicated statistical differences between strata ($p < 0.001$), the magnitude and temporal pattern of precipitation associations were broadly similar, indicating limited practical modification by shelter availability.

Cold thermal stress was associated with strong and consistent reductions in ridership in both strata. Among unsheltered stops, cold conditions were associated with −11.7% (95% CI: −16.9%, −6.2%) over 0-3 h and −18.4% (95% CI: −29.0%, −6.4%) over 0-24 h. Nearly identical reductions were observed among sheltered stops (−10.5% (95% CI: −15.3%, −5.4%) over 0-3 h; −18.6% (95% CI: −28.9%, −7.0%) over 0-24 h), indicating minimal modification of cold-related suppression by shelter availability.

In contrast, heat associations differed more substantially by shelter status. Among unsheltered stops, hot conditions were associated with a short-run increase in ridership (6.4% (95% CI: 0.1%, 13.0%) over 0-6 h), followed by attenuation and a shift toward cumulative reductions over 24 h (−11.6% (95% CI: −22.3%, 0.5%)). Among sheltered stops, no short-term increase was observed; instead, hot conditions were associated with cumulative declines (−14.2% (95% CI: −24.2%, −2.8%) over 0-24 h). These differences indicate that shelter availability is associated with distinct temporal response patterns to heat exposure.

Taken together, shelter availability was associated with clear differences in heat-ridership relationships, but only modest differences in precipitation and cold associations. Because these analyses are based on stratified aggregation rather than stop-level models, these patterns reflect differences in system-level responses across groups of stops rather than causal effects of shelter provision.

3.7. Sensitivity analyses

Sensitivity analyses varying the maximum lag length from 12 to 72 h showed that the main conclusions were driven by short-lag responses (Table S3). As the lag window lengthened, cumulative estimates became more attenuated and less precise, particularly for heat and precipitation. This pattern is expected in high-frequency time-series analyses because weather exposures are strongly autocorrelated across adjacent hours and days, which increases collinearity among lagged terms and reduces precision at longer horizons.

Associations with precipitation were robust at short lags across all lag specifications. Cold thermal stress also showed consistently negative short-run associations, although longer-horizon cumulative estimates were more sensitive to the chosen lag structure. Associations with heat were more sensitive to lag length: short-run positive associations strengthened somewhat in longer-lag models, whereas negative cumulative 0-24-h estimates became attenuated and statistically indistinguishable from zero once the maximum lag exceeded 24 h.

Model fit modestly favored longer lag structures, but substantive conclusions were stable for short cumulative windows. Across all specifications, the clearest and most robust findings were short-run reductions in ridership associated with wet precipitation and cold stress.

Replacing UTCI with air temperature yielded similar short-run results (Table S4), although overall model fit modestly favored UTCI. Both metrics captured reduced ridership under cold conditions and small short-run increases under hot conditions. However, only UTCI produced a statistically significant negative 0-24-h cumulative heat association, suggesting that UTCI may better capture the physiologically relevant dimensions of thermal stress.

4. Discussion and policy implications

Using high-frequency ridership and environmental data, we find that short-term weather exposures exert strong, asymmetric, and time-dependent effects on urban bus use. Cold stress and precipitation produce immediate reductions in ridership, whereas associations with heat are weaker, more heterogeneous, and emerge primarily through cumulative same-day responses. These associations vary by time of day, season, fare policy, and stop-level infrastructure.

Cold stress was associated with the largest and most consistent ridership declines. Exposure to cold conditions reduced boardings by ∼9-11% within 3-6 h and by ∼16% over 24 h, indicating both immediate and sustained suppression. This pattern aligns with prior work showing that cold disproportionately constrains transit use in systems reliant on outdoor waiting and transfers (Arana et al., 2014; Barnes, 2015; Guo et al., 2007). Associations with precipitation were similarly large but short-lived, with reductions of ∼8-10% within 3-6 h and little evidence of cumulative impacts beyond the same day, consistent with short-term trip deferral (Böcker et al., 2013; Guo et al., 2007).

Heat responses were smaller and less consistent. At the system level, hot conditions produced modest short-run increases but net cumulative declines over 24 h. Stratified analyses indicate that associations with heat were concentrated during weekday daytime periods, particularly the morning and mid-day, while off-peak responses were weaker. These findings are consistent with a combination of behavioral adaptation, schedule rigidity, and short-run substitution toward transit under moderate heat (Böcker et al., 2013; Singhal et al., 2014). The asymmetry between cold and heat responses suggests that, in the Denver Metropolitan Area, cold remains the primary thermal constraint, while heat possibly accumulate over longer exposure windows.

Weather sensitivity varied with trip context. Off-peak and discretionary travel were generally more responsive to precipitation and cold, whereas peak commuting was comparatively less sensitive to these exposures. However, heat exhibited measurable suppressive associations even during peak periods, particularly in the AM commute, indicating that thermal stress can influence travel behavior even when schedule flexibility is limited. Fare policy further modified these relationships: cold and precipitation associations were attenuated during free-fare periods, and heat was associated with short-run increases in ridership when fares were removed. These patterns suggest that cost reductions can partially offset environmental deterrence.

Stop-level infrastructure conditioned responses to environmental exposures, with the most substantively meaningful modification observed for heat. Although the precipitation × shelter interaction was statistically significant, precipitation associations were similar in magnitude and temporal pattern across sheltered and unsheltered stops, indicating limited practical modification. Cold-related suppression was likewise comparable across shelter strata. In contrast, heat responses differed qualitatively by shelter availability: unsheltered stops exhibited short-run increases followed by cumulative declines, consistent with short-term mode substitution (walking/biking to using air conditioned buses) and longer-term avoidance, whereas sheltered stops showed sustained cumulative suppression without short-run increases. These findings suggest that shelter availability plays a more important role in shaping behavioral responses to sustained thermal stress than to precipitation or cold.

These results are particularly relevant in light of documented disparities in shelter distribution across the transit network (section S3), which indicate lower shelter availability in more vulnerable communities. While our analysis does not estimate causal effects of shelter provision, this spatial pattern implies that riders in these areas may experience greater exposure to adverse weather conditions, highlighting infrastructure as a key mediator of climate-related vulnerability.

In contrast, day-level air quality indicators showed limited associations with ridership within the hourly modeling framework used here. Aside from reduced morning commuting during medium and heavy wildfire smoke, ozone exceedances and smoke were not consistently associated with same-day ridership after adjustment for weather and temporal patterns. Overall, short-term ridership responses appear to be driven primarily by weather rather than ambient air quality.

Sensitivity analyses indicate that effects are concentrated within 3-6 h of exposure, with longer-lag estimates becoming unstable due to strong temporal autocorrelation. This supports focusing inference on short-term behavioral responses.

Several limitations warrant consideration. First, long-horizon cumulative effects are difficult to identify in high-frequency time series due to autocorrelation among lagged exposures, which reduces precision as lag windows expand. Accordingly, inference is strongest for short-run responses within approximately 3-6 h of exposure. Second, the study period spans approximately 16 months, such that some seasons are observed only once; accordingly, seasonal analyses should be interpreted as descriptive of within-period differences rather than as estimates of stable, long-term seasonal patterns. Third, exposures were assigned at a regional scale and may not capture microclimate or hyperlocal variability (deSouza et al., 2025; Ibsen et al., 2026; Steinharter et al., 2025, 2026). ERA5 and ERA5-Land represent area-averaged meteorological conditions at relatively coarse spatial resolution, and wildfire smoke and ozone exceedance indicators were measured at the daily regional scale. Consequently, system-level aggregation may smooth over localized meteorological variability and stop-level behavioral responses, particularly during convective precipitation events or under heterogeneous urban heat conditions. In addition, because wildfire smoke and ozone exceedance varied primarily between days rather than within days, these variables are identified through day-level contrasts in ridership and should not be interpreted as estimates of fine-scale intra-day air quality responses. Fourth, ridership reflects realized boardings rather than underlying travel demand, limiting inference on behavioral mechanisms such as trip substitution or deferral. Fifth, shelter availability is not randomly distributed and is correlated with underlying spatial and network characteristics. In addition, shelter-stratified analyses were based on aggregation of stops within strata rather than stop-level models with fixed effects; therefore, estimated differences may partly reflect underlying differences between sheltered and unsheltered stops. Accordingly, these findings should be interpreted as differences in system-level weather-ridership associations across stop types rather than causal infrastructure effects. Finally, results are based on a single metropolitan system and may not generalize to other contexts.

Policy implications. These findings have several implications for climate-resilient transit planning. First, because ridership responses are driven by short-term exposures, real-time interventions, such as service adjustments, rider alerts, and operational flexibility, may be more effective than long-term scheduling changes. Second, the attenuation of weather sensitivity under free-fare periods suggests that fare policy may help buffer climate-related disruptions, particularly for vulnerable riders. Third, the strong modification of heat responses by shelter availability highlights stop-level infrastructure, especially shaded and thermally protective shelters, as a critical and actionable adaptation strategy. Finally, the concentration of associations outside peak commuting hours suggests that climate impacts may disproportionately affect discretionary and off-peak travel, with implications for equity and access to essential services.

CRediT authorship contribution statement

Priyanka deSouza: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Elizabeth A. Dzwonczyk:** Writing – review & editing. **Peter C Ibsen:** Conceptualization, Writing – review & editing. **Adam M. Lippert:** Writing – review & editing. **Carl Green:** Data curation, Writing – review & editing. **TC Chakraborty:** Writing – review & editing. **Melissa R. McHale:** Writing – review & editing. **Peter Anthamatten:** Writing – review & editing. **Ebru Altintas:** Writing – review & editing. **Carrie Makarewicz:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This project was supported by NASA's Research Opportunities in Space and Earth Science (ROSES) grant 21- EEJ21-0064. T.C. 's contribution was supported by the Biological and Environmental Research program of the U.S. Department of Energy (DOE) Office of Science through a DOE Early Career Award. Pacific Northwest National Laboratory is operated for the DOE by the Battelle Memorial Institute under contract DE-AC05-76RL01830.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2026.125126.

Data availability

The authors do not have permission to share data.

References

Adkins, A., Makarewicz, C., Scanze, M., Ingram, M., Luhr, G., 2017. Contextualizing walkability: do relationships between built environments and walking vary by socioeconomic context? J. Am. Plann. Assoc. 83, 296–314. https://doi.org/10.1080/01944363.2017.1322527.

Arana, P., Cabezudo, S., Peñalba, M., 2014. Influence of weather conditions on transit ridership: a statistical study using data from smartcards. Transport. Res. Pol. Pract. 59, 1–12. https://doi.org/10.1016/j.tra.2013.10.019.

Aybar, C., Wu, Q., Bautista, L., Yali, R., Barja, A., 2020. Rgee: an R package for interacting with Google Earth engine. J. Open Source Softw. 5, 2272.

Barnes, M., 2015. Transit systems and ridership under extreme weather and climate change stress: an urban transportation agenda for hazards geography. Geogr. Compass 9, 604–616. https://doi.org/10.1111/gec3.12246.

Böcker, L., Dijst, M., Prillwitz, J., 2013. Impact of everyday weather on individual daily travel behaviours in perspective: a literature review. Transp. Rev. 33, 71–91. https://doi.org/10.1080/01441647.2012.747114.

Brimicombe, C., Di Napoli, C., Quintino, T., Pappenberger, F., Cornforth, R., Cloke, H.L., 2022. Thermofeel: a python thermal comfort indices library. SoftwareX 18, 101005. https://doi.org/10.1016/j.softx.2022.101005.

Chapter 2. Passenger travel | BTS data inventory [WWW Document], n.d. URL https://data.bts.gov/stories/s/Copy-of-Copy-of-Chapter-2-Passenger-Travel_v2/3t3v-vpmv#how-we-travel (accessed 2.14.26).

Dahl, K., Licker, R., Abatzoglou, J.T., Declet-Barreto, J., 2019. Increased frequency of and population exposure to extreme heat index days in the United States during the 21st century. Environ. Res. Commun. 1, 075002. https://doi.org/10.1088/2515-7620/ab27cf.

deSouza, P., Crawford, B., Durant, J.L., Hudda, N., Ibsen, P., L'Orange, C., Jimenez, J., Graeber, B., Cicione, B., Mekonnen, R., Purushothama, S., Kahn, R., Kinney, P.L., Volckens, J., 2025a. High-resolution multi-pollutant mapping in Denver, Colorado. Atmos. Environ. X 27, 100364. https://doi.org/10.1016/j.aeaoa.2025.100364.

deSouza, P., Hopke, P., L'Orange, C., Ibsen, P.C., Green, C., Graeber, B., Cicione, B., Mekonnen, R., Purushothama, S., Kinney, P.L., Volckens, J., 2025. Contribution of traffic emissions to PM2.5 concentrations at bus stops in Denver, Colorado. Sustainability 17, 7707. https://doi.org/10.3390/su17177707.

deSouza, P., Hood, G., 2024. Ozone management in Colorado: why aren't we there yet? https://doi.org/10.31235/osf.io/tq4jf.

Di Napoli, C., Pappenberger, F., Cloke, H.L., 2018. Assessing heat-related health risk in Europe via the Universal Thermal Climate Index (UTCI). Int. J. Biometeorol. 62, 1155–1165. https://doi.org/10.1007/s00484-018-1518-2.

Di Virgilio, G., Evans, J.P., Blake, S.A.P., Armstrong, M., Dowdy, A.J., Sharples, J., McRae, R., 2019. Climate change increases the potential for extreme wildfires. Geophys. Res. Lett. 46, 8517–8526. https://doi.org/10.1029/2019GL083699.

Gasparrini, A., 2011. Distributed lag linear and non-linear models in R: the package dlnm. J. Stat. Software 43, 1–20.

Gasparrini, A., 2014. Modeling exposure–lag–response associations with distributed lag non-linear models. Stat. Med. 33, 881–899. https://doi.org/10.1002/sim.5963.
Gasparrini, A., Armstrong, B., Kenward, M.G., 2010. Distributed lag non-linear models. Stat. Med. 29, 2224–2234. https://doi.org/10.1002/sim.3940.
Gössling, S., Neger, C., Steiger, R., Bell, R., 2023. Weather, climate change, and transport: a review. Nat. Hazards 118, 1341–1360. https://doi.org/10.1007/s11069-023-06054-2.
Gu, X., Chen, P., Fan, C., 2024. Socio-demographic inequalities in the impacts of extreme temperatures on population mobility1. J. Transport Geogr. 114, 103755. https://doi.org/10.1016/j.jtrangeo.2023.103755.
Guo, Z., Wilson, N.H.M., Rahbee, A., 2007. Impact of weather on transit ridership in Chicago, Illinois. Transp. Res. Rec. 3–10. https://doi.org/10.3141/2034-01, 2034.
Han, X., Wang, H., Yu, J., 2024. Navigate through the haze: wildfire smoke exposure and Metrorail ridership. Transport. Res. Transport Environ. 133, 104309. https://doi.org/10.1016/j.trd.2024.104309.
Ibsen, P.C., McHale, M.R., deSouza, P.N., Steinharter, L., Green Jr., C., Diffendorfer, J.E., Warziniack, T., 2026. Moving toward a more human-oriented analysis of urban heat: examining differences of heat exposure intensity at busy commuting locations. Environ. Res.: Health. https://doi.org/10.1088/2752-5309/ae4bfc.
Intergovernmental Panel on Climate Change (IPCC), 2023. Climate Change 2021 – the Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge. https://doi.org/10.1017/9781009157896.
Kim, S.-N., Jung, S., Joo, Y., Kim, H., 2024. Air pollution hindering a transit-oriented city: examining the association of particulate matter concentration with public transit ridership and road traffic in Seoul, South Korea. Journal of Public Transportation 26, 100111. https://doi.org/10.1016/j.jpubtr.2024.100111.
Kinney, P.L., 2018. Interactions of climate change, air pollution, and human health. Curr. Environ. Health Rep. 5, 179–186. https://doi.org/10.1007/s40572-018-0188-x.
Lanza, K., Durand, C.P., 2021. Heat-moderating effects of bus stop shelters and tree shade on public transport ridership. Int. J. Environ. Res. Publ. Health 18, 463. https://doi.org/10.3390/ijerph18020463.
Lee, J., Miller, H.J., 2022. Simple pre-post analysis overestimates the impacts of new public transit services on ridership: evidence from a quasi-experimental study of new bus rapid transit in Columbus, Ohio, USA. J. Public Transp. 24, 100035. https://doi.org/10.1016/j.jpubtr.2022.100035.
Li, X., Wang, G., Zaitchik, B., Hsu, A., Chakraborty, T., 2024. Sensitivity and vulnerability to summer heat extremes in major cities of the United States. Environ. Res. Lett. 19, 094039. https://doi.org/10.1088/1748-9326/ad6c64.
Liu, C., Susilo, Y.O., Karlström, A., 2017. Weather variability and travel behaviour – what we know and what we do not know. Transp. Rev. 37, 715–741. https://doi.org/10.1080/01441647.2017.1293188.
Martens, K., 2016. Transport Justice: Designing Fair Transportation Systems. Routledge, New York. https://doi.org/10.4324/9781315746852.
Meena, K.K., Goswami, A.K., 2024. A review of air pollution exposure impacts on travel behaviour and way forward. Transp. Policy 154, 48–60. https://doi.org/10.1016/j.tranpol.2024.05.024.
Miao, Q., Welch, E.W., Sriraj, P.S., 2019. Extreme weather, public transport ridership and moderating effect of bus stop shelters. J. Transport Geogr. 74, 125–133. https://doi.org/10.1016/j.jtrangeo.2018.11.007.
Ngo, N.S., 2019. Urban bus ridership, income, and extreme weather events. Transport. Res. Transport Environ. 77, 464–475. https://doi.org/10.1016/j.trd.2019.03.009.
Hazard Mapping System | OSPO [WWW Document], n.d. URL https://www.ospo.noaa.gov/products/land/hms.html (accessed 2.1.26).
Customer and Community Survey [WWW Document], n.d. URL https://www.rtd-denver.com/2025survey (accessed 2.14.26).
Singhal, A., Kamga, C., Yazici, A., 2014. Impact of weather on urban transit ridership. Transport. Res. Pol. Pract. 69, 379–391. https://doi.org/10.1016/j.tra.2014.09.008.
Soltani Mandolakani, F., Vahedi Saheli, M., Singleton, P.A., 2025. Exploring the impacts of air quality on travel behavior and activity participation: evidence from travel diary surveys in Northern Utah. Transp. Res. Rec. https://doi.org/10.1177/03611981251378497.
Steinharter, L., Ibsen, P.C., deSouza, P., McHale, M.R., 2026. The surface is not superficial: utilizing hyper-local thermal photogrammetry for pedestrian thermal comfort inquiry. Remote Sens. https://doi.org/10.3390/rs18020348.
Steinharter, L., Ibsen, P.C., Lam, T.Y., Nesbitt, L., Park, K., McHale, M.R., 2025. Hot stops, cool looks: aesthetic solutions for thermal comfort at transit stops. Urban Clim. 64, 102606. https://doi.org/10.1016/j.uclim.2025.102606.
Tao, S., Corcoran, J., Rowe, F., Hickman, M., 2018. To travel or not to travel: 'weather' is the question. Modelling the effect of local weather conditions on bus ridership. Transport. Res. C Emerg. Technol. 86, 147–167. https://doi.org/10.1016/j.trc.2017.11.005.
U.S. Census Bureau, 2021. American Community Survey (ACS) 5-Year Estimates: Selected Housing Characteristics.
Volckens, J., 2024. Summertime trends in U.S. population exposure to fine particulate air pollution (PM2.5) from wildfire smoke. Environ. Sci. Technol. Lett. 11, 1182–1186. https://doi.org/10.1021/acs.estlett.4c00770.
Webster, G., 2024. Free fare for better air? Evaluating the impacts of free fare public transit on air pollution. Transport. Res. Pol. Pract. 184, 104076. https://doi.org/10.1016/j.tra.2024.104076.
Wu, J., Liao, H., 2020. Weather, travel mode choice, and impacts on subway ridership in Beijing. Transport. Res. Pol. Pract. 135, 264–279. https://doi.org/10.1016/j.tra.2020.03.020.