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The Hidden Lifecycle of Public EV Charging Infrastructure in the United States

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The Hidden Lifecycle of Public EV Charging Infrastructure in the United States

Abstract

Public electric vehicle charging infrastructure is expanding rapidly, but comparatively little is known about how stations perform, deteriorate, and exit after deployment. This evidence gap is consequential given the substantial costs of deploying and maintaining charging infrastructure and the limited documentation of lifecycle transitions at the individual-station level. In this study, we analyzed national port-level public charging-status data collected at 10-minute intervals from July 2023 through September 2026. We classified stations as newly added, active, transient, or exited and compared utilization, data-reporting quality, port availability, and repair performance across lifecycle stages. We then estimated discrete-time hazard models and developed temporally validated machine-learning models to identify stations at elevated risk of exit. We find that newly added stations generally matured from lower utilization toward more stable performance, whereas transient and exited stations exhibited greater volatility, more frequent port unavailability and reporting disruptions, and heavier repair burdens. Station exit was associated more strongly with persistent reporting gaps, repeated maintenance events, port unavailability, and prolonged outage recovery than with low utilization alone. Machine-learning models successfully concentrated subsequent exits among relatively small groups of high-risk stations, demonstrating their potential to support lifecycle-based monitoring and risk-ranked inspection. These findings show that operational and reporting deterioration can provide early warning of station exit, while underscoring that station-level risk scores are more appropriate for prioritizing inspections.

Introduction

Public electric vehicle (EV) charging infrastructure is a cornerstone of the electric mobility transition, as the availability, accessibility, and reliability of charging networks are key determinants of EV adoption by reducing range anxiety and improving the convenience and feasibility of electric vehicle ownership (Greene et al., 2020; Raman et al., 2022). Its importance is especially pronounced in the United States, where personal vehicles dominate daily travel and per-capita vehicle miles traveled are among the highest in the world, making widespread and reliable public charging infrastructure essential for accelerating EV adoption (Gifford and Barbier, 2026; Muratori et al., 2025). Accordingly, the U.S. public charging network is expanding rapidly with substantial public and private investment. Announced investments already exceed $24 billion, while cumulative infrastructure investment needs could approach $100 billion by 2030 (Lou, 2024; Yang et al., 2024).

Despite this rapid expansion, comparatively little is known about the post-deployment lifecycle of charging stations, including how they are maintained, upgraded, replaced, or retired as their performance deteriorates. This knowledge gap is consequential because sustained charging access depends not only on deploying new stations but also on preserving the performance and availability of the existing network (Asensio et al., 2020). Additionally, the financial stakes are substantial: commercial Level 2 chargers cost approximately $4,400 to $10,600 per port to install, whereas 150–350 kW fast chargers cost roughly $105,000 to $166,000 per port, excluding grid upgrades (Lommele et al., 2024; USDOT, 2024). A six-port highway station equipped with 150 kW chargers can approach $900,000 when five years of maintenance are included (Chu et al., 2023; Wood et al., 2023). Recent local-government cases illustrate how post-deployment costs can lead to station exit. In 2026, Pinellas County, Florida, discontinued chargers at seven public locations after assuming approximately $56,600 in annual operating and maintenance costs, while Gill, Massachusetts, suspended a low-use municipal station whose subscription and maintenance costs exceeded its cumulative revenue (Gill County, 2026; Hoffman, 2026; Pinellas County, 2026). Therefore, understanding when and why stations are maintained, upgraded, replaced, or retired is therefore essential to sustaining reliable charging access, targeting maintenance and reinvestment, and protecting substantial infrastructure investments.

A central challenge is that lifecycle transitions are rarely documented at the individual-station level. Longitudinal infrastructure inventories, such as the National Renewable Energy Laboratory's Alternative Fuels Data Center (AFDC) Station Locator (NLR, 2026), are widely used to identify where public charging is available, but they have several limitations. First, a station may be removed from the inventory when its status can no longer be verified, without documentation of the underlying reason. Its disappearance therefore does not necessarily indicate that the physical equipment has been decommissioned; the station may instead have experienced a reporting disruption, changed identifiers, or fallen outside the inventory's verification system. Second, because station information is verified semiannually, stations may remain classified as active after they have ceased operating or reporting through other data sources (Department of Energy, 2026). These discrepancies are compounded by the AFDC's reliance on information supplied by charging-network operators, whose reporting practices and criteria vary, potentially resulting in incomplete, outdated, or misclassified records. Third, the AFDC relies partly on information supplied by charging-network operators, whose reporting practices and criteria vary, potentially

resulting in incomplete, outdated, or misclassified records (Yu et al., 2025). Finally, although the AFDC provides essential information on station locations and configurations, it does not include continuous, high-frequency measures of station- or port-level operating performance.

Figure 1a compares the AFDC with the real-time charging database we obtained and reveals delays in updating station status. Specifically, we identify 2144 (25%) "ghost stations", stations listed as active in the AFDC that had already been decommissioned in practice, whereas only 6473 (75%) retired stations were consistently classified as such in both datasets. The pre-exit trajectories in Figures 1b–d show that both groups experienced sharply increasing reporting failures and port unavailability as they approached exit. Stations absent from both datasets nevertheless exhibited consistently higher utilization than ghost stations, suggesting that disappearance was not driven by low demand alone. Together, these results demonstrate the value of high-frequency operational data for detecting reporting discontinuities and performance deterioration that may not be visible in periodically updated infrastructure inventories.

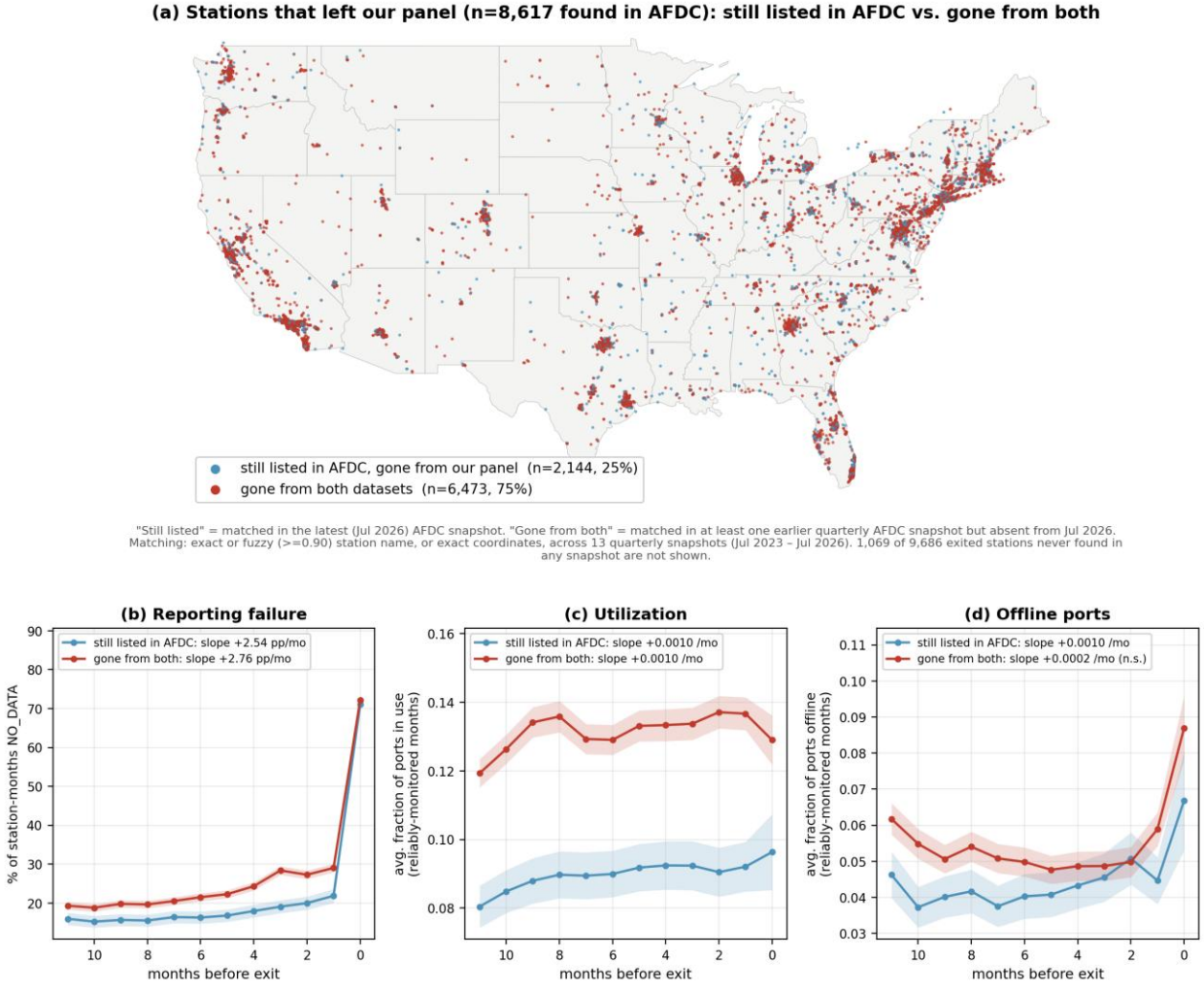


Figure 1. "Ghost stations" in the AFDC: Discrepancies between reported and observed EV charging-station status. a. Identification of "ghost stations". b. Reporting failure between ghost and retired stations. c. Utilization between ghost and retired stations. d. Offline ports between ghost and retired stations. Lines equal to monthly mean, and shaded areas are the 95%

confidence interval. Because the final-month performance measures represent only the minority of stations still reporting, however, the month-zero estimates should be interpreted cautiously. **Note:** Authors' calculations based on AFDC data and independently obtained real-time charging data.

The literature on the performance and evolution of public EV charging infrastructure spans three related themes. First, research on infrastructure deployment and operational performance emphasizes the scale of investment required to support EV adoption and demonstrates that nominal charger availability does not necessarily translate into dependable service (Asensio et al., 2020; Yang et al., 2024). Evidence from field tests, charging-session records and user-generated data reveals substantial variation in charging success and reliability, as well as persistent problems such as equipment failure, interrupted sessions, idle occupancy and "dead piles" (Gamage et al., 2024; Zhao et al., 2025). Second, research on charging equity documents substantial geographic and socioeconomic disparities in both infrastructure access and service quality, with disadvantaged communities often receiving less extensive and less reliable charging coverage (Yu et al., 2025). However, these studies generally assess whether stations are available, accessible or functional at a particular point in time rather than examining how their performance and operational status evolve over time. Third, research on infrastructure investment and exit remains limited. Real-options models examine the timing of charging investment under demand and policy uncertainty but devote less attention to post-deployment withdrawal or abandonment (Dimanchev et al., 2023). Empirical studies of facility closures offer useful methodological insights, but the closest evidence comes from other sectors, including gasoline stations and bank-branch networks (Ormosi et al., 2025; Tranfaglia, 2018). However, none of these studies examines how the performance of individual EV charging stations evolves over their lifecycle, which characteristics precede station exit, or whether disappearance from an operational database represents physical retirement rather than a reporting discontinuity. This study addresses these gaps through a longitudinal, station-level analysis of performance trajectories, exit risk, and the distinction between observed data exit and confirmed retirement.

This paper addresses the following overarching research question: How does the performance of EV charging infrastructure evolve across station lifecycle stages, and which performance and station characteristics are associated with the risk of station exit? To address this question, the analysis establishes a lifecycle-based classification of charging stations, examines systematic differences in performance across lifecycle stages, and evaluates whether these characteristics are associated with subsequent station exit. The study further explores whether these relationships can be used to anticipate retirement risk and inform the long-term planning and durability of public charging infrastructure.

Specifically, the study has three objectives. First, using a lifecycle-based classification and longitudinal descriptive analysis, we examine how reliability, utilization, reporting quality, and charging-event performance differ among newly added, continuously active, transient, and exited stations. We also conduct separate comparisons for L2 and DCFC stations. Second, we estimate discrete-time hazard models to assess how time-varying performance measures, utilization, reliability, and other station characteristics are associated with the likelihood and timing of exit from the observed charging network. Third, using the predictors identified in the lifecycle and hazard analyses, we develop and evaluate out-of-sample prediction models to determine whether

stations at elevated risk of future exit can be identified in advance. We assess these models using temporally separated training and testing samples and measures of discrimination, calibration, and high-risk-station detection. Together, these analyses provide a comprehensive account of charging-station lifecycle dynamics and offer actionable evidence for targeted maintenance, investment prioritization, and long-term charging-network planning.

This study makes three contributions to the literature. First, it introduces a lifecycle perspective to EV charging research by using a national, high-frequency longitudinal dataset containing 10-minute, port-level status observations for 82,185 U.S. charging-station identifiers from July 2023 through June 2026. This structure allows us to move beyond static measures of availability and compare utilization, reliability, reporting quality, and operational performance across newly added, continuously active, transient, and exited stations. Second, the study identifies the performance trajectories and station characteristics associated with the likelihood and timing of exit, providing station-level evidence on how infrastructure vulnerability develops before a station disappears from the observed network. Third, it evaluates whether future exits can be predicted out of sample, establishing the potential for an early-warning framework to guide targeted inspection, maintenance, and reinvestment. Importantly, the study also distinguishes persistent disappearance from the operational dataset from confirmed physical retirement, thereby clarifying a key measurement challenge in longitudinal charging-infrastructure research. Together, these contributions advance understanding of how public charging infrastructure evolves, deteriorates, and exits over time and offer practical evidence for improving the durability and long-term planning of charging networks.

Results

Newly Added Stations Show Stronger Reliability, While Retired and Transient Stations Exhibit Greater Performance Challenges

Figure 2 compares the four lifecycle stages across four monthly performance measures: the share of well-covered station-months with no recorded outage events (“healthy”), the average fraction of ports in use, the average fraction of ports offline, mean outage-level time to fix (TTF), and mean maintenance-level time to fix. Results are reported separately for pure Level 2 (L2) and pure DC fast-charging (DCFC) stations. The figure presents two complementary comparisons because lifecycle stages are not simultaneously observable on a common time axis. In the first two rows, stations are classified dynamically as newly added during their first 12 observed months and as active after exceeding the 12-month threshold. In the final two rows, active stations are compared retrospectively with transient stations, which disappear before accumulating 12 months of tenure, and exited stations, which disappear after becoming established and remain unobserved for at least 12 consecutive months. Because transient and exited stations have no performance records after disappearance, their performance is shown only for the months in which they were still reporting.

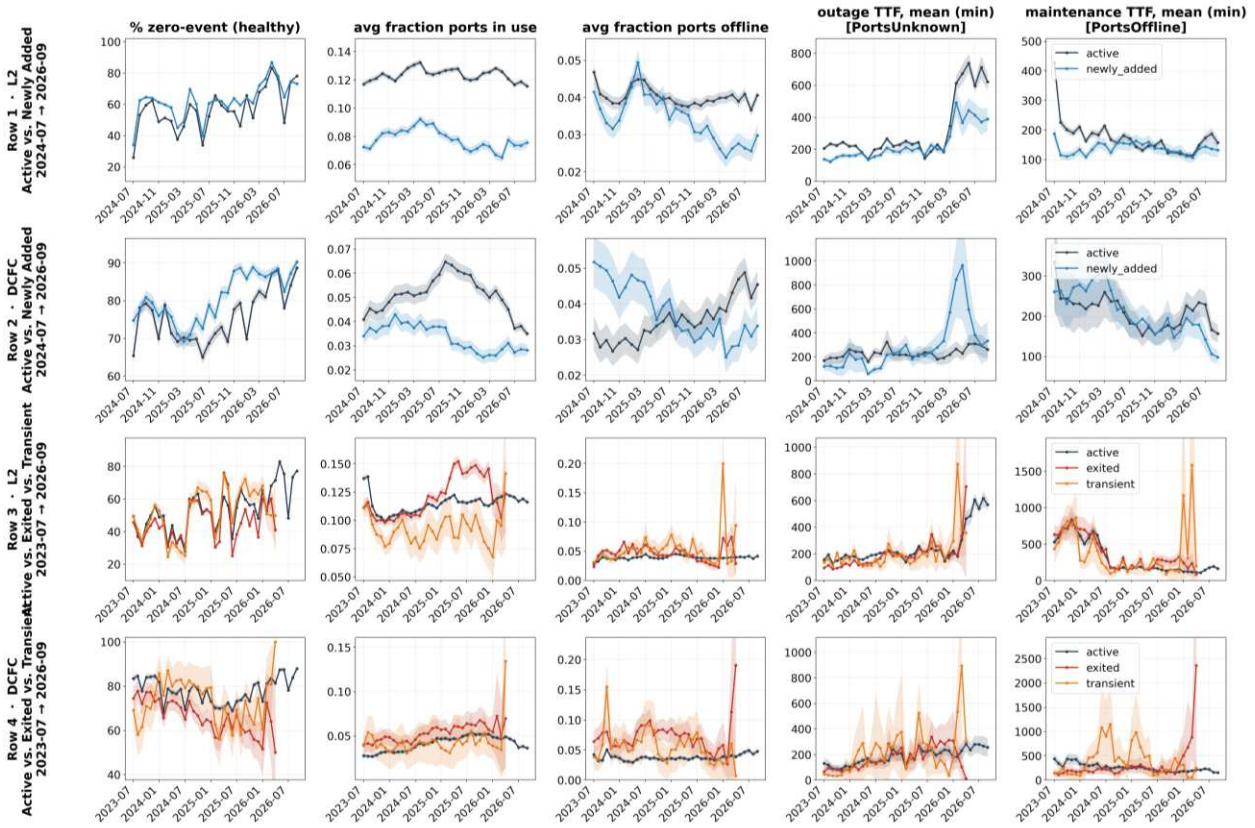


Figure 2: Operational Performance by EV Charging-Station Lifecycle Cohort and Charger Type (12-Month Threshold). Columns report the percentage of zero-event stations classified as healthy, average fraction of ports in use, average fraction of ports offline, mean outage-level time to fix (TTF) in minutes, and mean maintenance-level TTF in minutes. Rows 1–2 compare dynamically classified Active and Newly Added stations from July 2024 to July 2026, following a 12-month warm-up period. Rows 3–4 compare whole-lifetime Active, Exited, and Transient cohorts from July 2023 to July 2026 using a 12-month classification threshold. Note: Tesla stations are excluded because their operational data are not observed. Lines equal to monthly mean, and shaded areas are the 95% confidence interval.

The first key finding is that newly added stations exhibit a distinct maturation pattern, progressing from low initial utilization toward improved reliability over time. Active stations consistently have higher utilization than newly added stations. Among L2 stations, the average fraction of ports in use is approximately 12% for active stations, compared with roughly 7% to 9% for newly added stations; the corresponding difference is smaller but persistent among DCFC stations. As newly added stations mature, their offline-port fractions generally decline and their shares of healthy station-months increase. These improvements are especially visible among newly added DCFC stations, whose healthy share exceeds that of active DCFC stations during much of the later observation period. Nevertheless, newly added stations exhibit greater instability in outage time to fix, including a pronounced late-period spike among DCFC stations. Maintenance time to fix generally declines for both groups, although active stations often experience longer repair durations. Overall, early lifecycle performance is characterized by lower utilization and greater

instability, whereas maturation is associated with rising use and improved, but not uniformly superior, reliability.

Second, station exit is associated more strongly with deteriorating and unstable operational performance than with low utilization. In the retrospective comparison, exited L2 stations frequently have higher port utilization than active stations, while exited DCFC stations also exhibit utilization at or above that of the active cohort. Exit therefore does not appear to result from insufficient use alone. Instead, exited stations, particularly DCFC stations, have higher offline-port fractions, indicating more frequent or persistent maintenance-related unavailability. Although the share of zero-event station-months fluctuates for both active and exited stations, this measure may reflect partly unpredictable station-wide disruptions, such as power or communication outages, and therefore provides a less consistent distinction between the groups. The clearest differences emerge in performance stability and recovery. Active stations maintain relatively stable offline-port shares and TTF trajectories, whereas exited stations exhibit greater volatility and sharp increases in both outage and maintenance repair times near the end of their observed histories. The especially large increase in maintenance TTF among exited DCFC stations suggests that persistent hardware problems or delayed repairs may precede disappearance from the network.

Third, transient stations display the greatest month-to-month volatility. Their utilization is generally lower and less stable than that of established stations, while offline-port prevalence and repair times exhibit occasional extreme spikes. This instability is consistent with short observational histories, heterogeneous reasons for appearing and disappearing, and smaller numbers of stations or events in some months. Similar late-period spikes among exited stations should also be interpreted cautiously because cohort sizes and event counts diminish as stations leave the panel.

Fourth, the alternative 3-, 6-, and 18-month thresholds produce lifecycle patterns consistent with the main 12-month specification, confirming the robustness of our principal findings (see Supplementary Figures 1- 3). The principal differences concern magnitude and volatility rather than direction. The 3- and 6-month thresholds classify more short-lived stations as established, producing noisier transient and exited trajectories and more extreme repair-time spikes. The 18-month threshold imposes a stricter definition of an established station and shortens the dynamic comparison window, resulting in smoother trends for some measures but smaller late-period cohorts.

Reporting Gaps and Maintenance Burden Are Strong Predictors of Station Exit

Table 1 presents linear discrete-time hazard models of monthly station exit using 826,884 station-month observations. The models include year-month and state fixed effects, with standard errors clustered by station, and examine reporting quality, outages, maintenance, station performance, and local socioeconomic characteristics. Performance measures are calculated over the preceding three months. The four specifications differ only in their representation of recent NO_DATA exposure: separate monthly lags (Column 1), three-month mean (Column 2), two-month mean (Column 3), and one-month lag (Column 4). The coefficients represent conditional associations with subsequent exit, not causal effects.

First, reporting discontinuities are strong and consistent predictors of station exit. The mean NO_DATA share is positively associated with exit in both the three-month and two-month specifications, with coefficients of 0.696 and 0.602 percentage points, respectively. The one-month lag is similarly positive in Columns 1 and 4. In Column 1, the individual lag coefficients alternate in sign because the three lagged measures are highly collinear; accordingly, their joint significance is more informative than any single coefficient. Collectively, these results indicate that declining or interrupted data availability is an important early signal of subsequent station disappearance.

Second, outage frequency alone is not associated with exit, but the duration of outage recovery is. The number of outage events has a small, statistically insignificant coefficient across all four specifications, whereas longer outage repair times are consistently associated with a higher probability of exit. The indicator for having an outage repair event is positive but is significant only in Models 1 and 2. These findings suggest that exit risk is more closely related to prolonged or difficult-to-resolve outages than to the number of outages itself.

Third, maintenance-related measures show a particularly strong association with exit. A higher fraction of offline ports, more frequent maintenance events, and the presence of maintenance events are all positively and significantly associated with monthly exit probability. For example, a 10-percentage-point increase in the offline-port fraction is associated with a 0.021–0.027-percentage-point increase in monthly exit probability. Conditional on these measures, however, logged maintenance repair time has a negative coefficient. This result should be interpreted cautiously because it reflects the association of repair duration with exit after controlling for maintenance-event occurrence, frequency, and offline-port prevalence; it does not imply that slower maintenance reduces exit risk. Overall, the maintenance results indicate that repeated service interventions and persistent port unavailability are more informative signals of vulnerability than repair duration alone.

Finally, station characteristics and utilization also distinguish stations at risk of exit. Greater port utilization is consistently associated with a lower probability of exit, indicating that station disappearance is not independent of demand. Exit risk initially increases with tenure but subsequently declines, as shown by the positive tenure coefficient and negative quadratic term; in Model 4, the estimated relationship reaches its maximum at approximately 22 months. Stations with more ports are less likely to exit, while DCFC and mixed-technology stations have lower exit probabilities than otherwise comparable L2 stations. Among contextual characteristics, median household income and population density are positively associated with exit, whereas the White population share and EV registrations per 1,000 residents are negatively associated with exit.

Table 1: Estimated Coefficients from Discrete-Time Hazard Models of Public EV Charging-Station Exit

Variable	(1)	(2)	(3)	(4)
Dependent variable: monthly station-exit probability (percentage points)				
Reporting quality				
NO_DATA share, t−1	0.511***			0.589***
	(0.062)			(0.033)
NO_DATA share, t−2	−0.387***			
	(0.076)			
NO_DATA share, t−3	0.577***			
	(0.065)			
Mean NO_DATA share, t−1 to t−3		0.696***		
		(0.036)		
Mean NO_DATA share, t−1 to t−2			0.602***	
			(0.034)	
Power outage				
Outage events per month (hundreds)	−0.005	−0.005	−0.005	−0.005
	(0.043)	(0.043)	(0.043)	(0.043)
Log outage repair time	0.055***	0.054***	0.054***	0.054***
	(0.006)	(0.006)	(0.006)	(0.006)
Has outage repair events	0.038**	0.038**	0.026	0.026
	(0.017)	(0.017)	(0.017)	(0.017)
Maintenance				
Fraction of ports offline, prior 3 months	0.227***	0.214***	0.263***	0.274***
	(0.051)	(0.051)	(0.050)	(0.049)
Maintenance events per month (hundreds)	0.129***	0.131***	0.123***	0.122***
	(0.033)	(0.034)	-0.033	(0.033)
Log maintenance repair time	−0.044***	−0.043***	−0.043***	−0.043***
	(0.006)	(0.006)	(0.006)	(0.006)
Has maintenance repair events	0.127***	0.129***	0.121***	0.120***
	(0.013)	(0.013)	(0.013)	(0.013)
Station performance				
Fraction of ports in use, prior 3 months	−0.165***	−0.168***	−0.186***	−0.187***
	(0.053)	(0.054)	(0.054)	(0.054)
Tenure (months)	0.097***	0.091***	0.088***	0.088***
	(0.003)	(0.002)	(0.002)	(0.002)
Tenure² ÷ 100	−0.223***	−0.211***	−0.202***	−0.201***
Log number of ports	−0.100***	−0.101***	−0.101***	−0.100***
	(0.011)	(0.011)	(0.011)	(0.011)
DCFC (reference: L2)	−0.143***	−0.143***	−0.141***	−0.142***
	(0.018)	(0.018)	(0.018)	(0.018)
Mixed charging level (reference: L2)	−0.104***	−0.104***	−0.102***	−0.102***
	(0.022)	(0.022)	(0.022)	(0.022)
Socioeconomic and demographic characteristics				
	(0.005)	(0.005)	(0.005)	(0.005)
Log median household income	0.102***	0.102***	0.103***	0.103***
	(0.023)	(0.023)	(0.023)	(0.022)
Log population density	0.013***	0.013***	0.014***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)
Bachelor's degree share	−0.001	−0.001	−0.001	−0.001

	(0.001)	(0.001)	(0.001)	(0.001)
White population share	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic population share	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
EV registrations per 1,000 people	−0.051***	−0.051***	−0.049***	−0.048***
	(0.004)	(0.004)	(0.004)	(0.004)
Electricity price	−0.004	−0.005	−0.005	−0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Year-month fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by station	Yes	Yes	Yes	Yes
Observations	826,884	826,884	826,884	826,884
R^2	0.0124	0.0122	0.0120	0.0121

Note: Each observation is a station-month. Shares range from 0 to 1; event counts are measured in hundreds per month; tenure is measured in months. Outages correspond to PortsUnknown, and maintenance corresponds to PortsOffline. All specifications include the same controls; only the NO_DATA encoding differs. In column (1), the three NO_DATA lags are interpreted jointly. Clustered standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Prediction of retirement risk and better infrastructure planning

The machine-learning analysis proceeded in two components. First, we developed and evaluated six models to determine whether impending station exit could be identified from routinely collected monitoring data. This component assessed discrimination, calibration, and predictor contributions (Figure 3). Second, we translated the resulting risk scores into monthly watchlists to evaluate their potential use as an early-warning and inspection-prioritization system (Figure 4). The first component establishes that the models are better suited to ranking stations by relative risk than to forecasting the number of exits; the second evaluates the operational value of that ranking.

The prediction sample contained 248,304 station-months and 1,834 confirmed exits from 27,812 L2 stations; the held-out test period included 50,677 station-months and 335 exits. All six models distinguished stations approaching exit from those remaining in the panel (Figure 3a). XGBoost achieved the highest test AUC (0.77; 95% confidence interval, 0.74–0.79), but logistic regression performed similarly (0.75; 0.72–0.78), and confidence intervals overlapped across models (Supplementary Table 3). Calibration was less stable across periods (Figure 3b). In the highest-risk decile, the observed exit rate was 3.5%, compared with mean predicted rates of approximately 1.2% for XGBoost and 2.7% for logistic regression. The models are therefore suited to ranking stations for inspection, not to forecasting how many stations will exit. Recent reporting failure provided the strongest predictive signal (Figure 3c). The prior-three-month NO-DATA share accounted for 28% of total XGBoost SHAP attribution, followed by the fraction of ports offline (15%). Station-operation and reporting measures together accounted for 55% of attribution, exceeding the combined contribution of tenure, location, and seasonal characteristics.

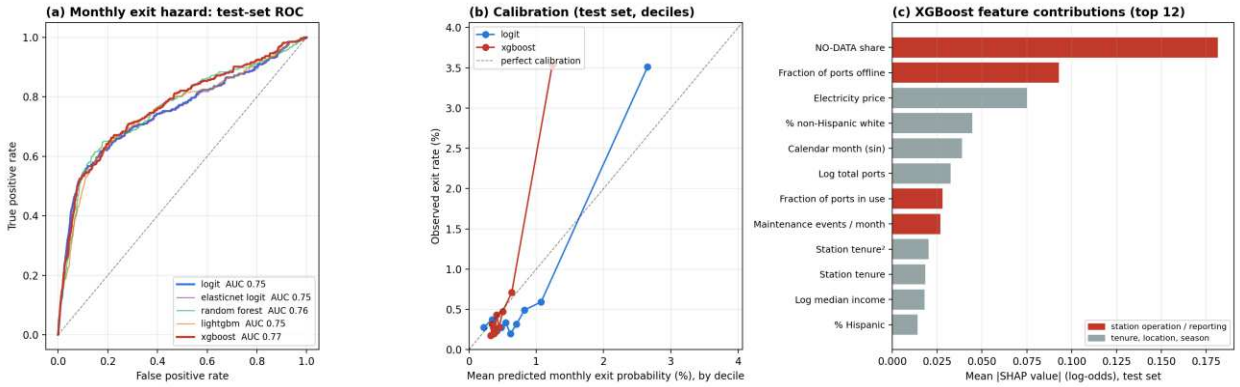


Figure 3. Out-of-sample prediction of L2 charging-station exit, July–September 2025. a. Receiver operating characteristic (ROC) curves for five model families. b. Calibration of predicted exit risk by decile for the logistic regression and XGBoost models. c. XGBoost feature importance, measured by the mean absolute SHAP value across test-set station-month observations. Red bars indicate operational and reporting characteristics; gray bars indicate station tenure, location, and seasonality. Note: Firth logistic regression is omitted because its results are indistinguishable from those of the standard logistic regression model.

Figure 4 further demonstrates how our model can support an early-warning and inspection-prioritization system. Panel a shows a clear risk gradient: the observed exit rate was 11.0% among stations in the highest-risk 5%, compared with 2.1% across all stations, which is a 5.3-fold increase. The observed exit rate declined progressively as the inspection pool expanded, reaching 9.8% for the top 10%, 7.5% for the top 15%, 6.2% for the top 20%, 5.2% for the top 25%, and 4.5% for the top 30%. Thus, the model meaningfully concentrated subsequent exits within relatively small groups of stations, supporting its use for prioritizing inspections rather than predicting the total number of future exits. Panels a and c reveal substantial geographic variation in the distribution of high-risk stations. California had the largest absolute number of high-risk stations (330), followed by Florida (173), Texas (142), and Maryland (103). However, the states with the largest numbers were not necessarily those with the greatest proportional burden. Maryland had the highest share of stations classified as high risk (23.5%), followed by Nevada (20.9%), Georgia (18.2%), Florida (18.0%), New Jersey (17.5%), and Washington (16.7%). These findings indicate that an inspection system based only on counts would direct resources toward large charging markets, whereas a share-based measure identifies states facing a disproportionately high concentration of at-risk infrastructure.

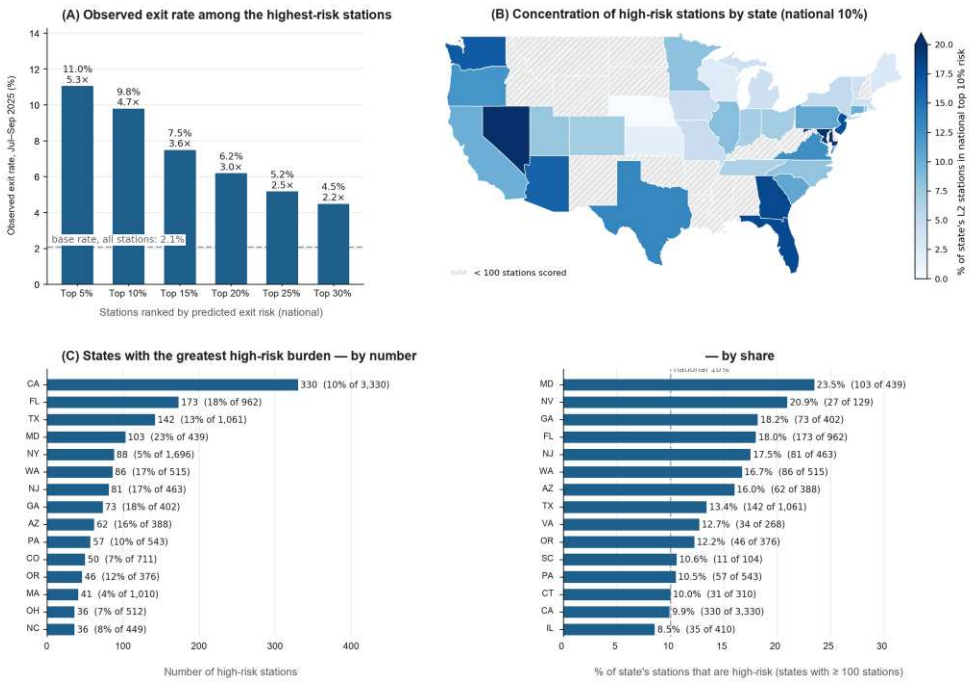


Figure 4. **Translating Machine-Learning Predictions into an Early-Warning and Inspection-Prioritization System**. **a. Observed Exit Rates Among the Highest-Risk Stations. b. Geographic Concentration of High-Risk Stations by State. c. States with the Greatest High-Risk Burden by Number. d. States with the Greatest High-Risk Burden by Share.** Note: Gray, hatched states contain fewer than 100 eligible stations and are therefore excluded from state-level percentage estimates because their high-risk shares would be sensitive to only one or two stations. Please refer to Supplementary Tables 5 and 6 for details.

Discussion and Conclusion

This study provides a lifecycle-based assessment of public EV charging infrastructure by combining descriptive performance comparisons, discrete-time hazard models, and machine-learning prediction. Station performance varies systematically across lifecycle stages: active stations generally have higher utilization and more stable maintenance outcomes than newly added stations, although new stations tend to improve as they mature. Stations that subsequently exit are not necessarily underused; many have utilization comparable to or greater than active stations but exhibit greater port unavailability and increasingly unstable repair times before disappearing from the observed network. The hazard models further show that persistent *NO_DATA* exposure, a larger fraction of offline ports, more frequent maintenance events, and longer outage-repair times are associated with higher exit risk, whereas greater utilization, more ports, and DCFC or mixed configurations are associated with lower risk. Finally, the machine-learning analysis demonstrates that historical performance and station characteristics can help identify stations at elevated risk of future exit, highlighting the potential of high-frequency operational data to support proactive inspection, maintenance, and reinvestment.

Current U.S. policies governing public EV-charger performance remain closely tied to infrastructure funding. At the federal level, the National Electric Vehicle Infrastructure (NEVI)

Formula Program and other Title 23–funded projects require each charging port to maintain annual uptime above 97%, support remote monitoring and diagnostics, report outages and maintenance costs, provide mechanisms for reporting malfunctions, and remain compliant with federal standards for at least five years after entering service (Federal Highway Administration, 2023). State policies generally follow two approaches. First, several states extend similar requirements to chargers receiving state, ratepayer, or other public support. California requires eligible publicly or ratepayer-funded DC fast chargers to maintain 97% uptime and report reliability and availability data (California Energy Commission, 2026) , while New Jersey requires state agencies offering charger incentives to impose a 97% site-wide uptime standard and establish procedures for monitoring and enforcement (New Jersey, 2024). Second, comprehensive performance requirements for privately financed public chargers remain uncommon. Although California requires inventory reporting for most chargers irrespective of funding source, its binding uptime standard remains limited to publicly or ratepayer-funded DC fast chargers (California Energy Commission, 2026). Narrower exceptions include Maryland, which applies NEVI-equivalent uptime and reporting requirements to public charging networks operated by electric utilities (Maryland General Assembly, 2023), and Portland, Oregon, which requires private companies installing chargers in the public right-of-way to accept enforceable uptime, maintenance, and data-sharing obligations (City of Portland, 2023). These measures regulate particular funding arrangements, operators, or locations rather than the entire privately financed charging network, leaving many public chargers subject to pricing, payment, metering, and accessibility rules but not enforceable standards for uptime, repair time, maintenance, or operational reporting.

The limited scope of existing performance requirements highlights an important opportunity to close the regulatory gap for public charging stations not supported by federal funding and therefore not covered by Title 23, including state- and locally supported infrastructure and privately financed stations. Our findings show that station exit is not primarily associated with low utilization, as exiting stations may be used as much as, or more than, stations that remain active. Instead, persistent reporting gaps, greater offline-port prevalence, repeated maintenance events, and prolonged outage-recovery times provide stronger warning signals of subsequent exit. First, policymakers should establish standardized, port-level reporting requirements for operating status, outages, repairs, and maintenance across all publicly accessible chargers, regardless of funding source. Second, performance standards should extend beyond annual uptime to incorporate reporting continuity, recurring failures, repair duration, and the share of ports simultaneously unavailable. Third, agencies should use these indicators to create early-warning and corrective-action systems that direct inspections, technical assistance, maintenance funding, or replacement investment toward deteriorating stations before they exit the network. Applying these requirements through state regulations, utility programs, local permits, and public right-of-way agreements would complement existing federal standards and shift policy from simply deploying chargers toward sustaining reliable charging access throughout the infrastructure lifecycle.

An important limitation is the exclusion of Tesla charging stations because the data feed does not provide comparable port-level operating-status information for Tesla's network. Therefore, an important opportunity for future research is to extend this lifecycle framework to Tesla's charging network, for which comparable port-level operating-status data were unavailable. Tesla represents a substantial share of U.S. charging infrastructure, accounting for approximately 60.4% of public DC fast-charging ports and 7.6% of public Level 2 ports recorded by the AFDC in the first quarter

of 2024 (Brown et al., 2024). Evidence also suggests that Tesla's network may follow different performance patterns: approximately 7% of Tesla users identified nonfunctional chargers as a major problem in 2023, compared with 46% of non-Tesla drivers using public DC fast chargers (Powell and Johnson, 2024). Incorporating comparable Tesla data would therefore broaden the coverage of this analysis and enable valuable comparisons of lifecycle dynamics, maintenance practices, and exit risk across different charging-network models.

Methods

Data

Charging station data: Port-level charging-status data were obtained from ChargeHub, a national charging-station aggregator, at 10-minute intervals from July 2023 through July 2026 (37 months). Each record represented a station-level snapshot and included the station's location, charger type, total number of ports, and the contemporaneous status of each port—available, in use, offline, or unknown. Across the study period, 87,001 unique stations appeared in the dataset. Of these, 67,246 remained active as of July 2026, while 11,582 met our definition of a retired station. Overall, 75.9% of stations contained only Level 2 (L2) ports, 16.3% contained only direct-current fast-charging (DCFC) ports, and 6.0% contained both L2 and DCFC ports. Supplementary Table 4 provides a detailed breakdown of the charging-station data. To facilitate analysis of these high-frequency data, we aggregated the 10-minute observations to the station-month level, summarizing port counts, port states, and status-reporting coverage. This aggregation produced an unbalanced station-month panel comprising 898,385 observations over the 37-month study period.

Demographic and economic data. We obtained county-level socioeconomic and demographic measures from the American Community Survey (ACS) five-year estimates, including population and population density, educational attainment, median household income, race, residential electricity price, EV registration and vehicle ownership. We spatially assigned each charging station to its corresponding county and linked it to the county's socioeconomic characteristics. Supplementary Table 1 presents the summary statistics for these variables.

Data Inclusion, Aggregation, and Exclusion. The original data consist of charging-status observations recorded at 10-minute intervals for individual station identifiers. To construct the analytical panel, we aggregate these observations to the station-month level, calculating monthly measures of utilization, reliability, reporting quality, and charging-event performance. We apply two principal exclusions. First, we identify 9,997 Tesla-network station identifiers using the union of the network indicator and station names containing "Tesla" or "Supercharger." These stations report structurally zero utilization throughout the panel and exhibit no meaningful temporal variation. This pattern indicates that the data feed does not capture Tesla port status, rather than that these stations are continuously unused. Second, we exclude 10,329 identifiers, which is about 11.4% of the initially geocoded sample, affected by a systematic cross-border geocoding error. In these cases, stations physically located in Canada near the international border were incorrectly assigned to the nearest U.S. state. We identify these records using a point-in-polygon test based on authoritative U.S. state boundaries, with a 3-km buffer to accommodate ordinary GPS imprecision. The correction is limited to the 12 states bordering Canada to avoid inadvertently excluding legitimate coastal or island stations elsewhere. After geographic cleaning, 87,001 distinct station identifiers remain. Of these, roughly 17% are associated with the Tesla network. Removing the remaining Tesla records produces a final analytical sample of 72,358 non-Tesla station identifiers for the lifecycle classification and subsequent station-month analyses. We use the term *station identifiers* rather than physical locations because a small number of sites appear under multiple identifiers, while some identifiers are replaced or reissued following equipment changes.

Lifecycle classification. Because many stations were already operating when the dataset began, their true commissioning dates are not observed. We therefore require a 12-month observation

period before assigning a mature lifecycle status. The 12-month cutoff corresponds to a local minimum in the kernel-density distribution of tenure among stations no longer observed and is applied symmetrically to station entry and exit (Supplementary Figure 4). Using this rule, we classify stations each month into four mutually exclusive categories: newly added, active, transient, and exited. Stations present when data collection began in July 2024 are classified as active beginning in July 2025 if they remain observed throughout the initial 12-month period. Stations entering later are initially classified as newly added and transition to active status after completing 12 consecutive months in the dataset. A station that disappears before reaching 12 months of observed tenure is classified as transient. By contrast, an established station is classified as exited only after it has remained absent from the dataset for 12 consecutive months. We use *exited* rather than *retired* because disappearance from the dataset does not necessarily indicate physical decommissioning The dataset spans July 2024 through July 2027, providing 37 monthly observations. We use July 2024 through June 2025 as the initial observation period and begin classifying established stations as active or exited in July 2025. Performance outcomes for active stations are analyzed from July 2025 onward, after they have satisfied the minimum observation requirement. For exited stations, however, we retain all available historical performance observations preceding their disappearance to characterize pre-exit trajectories and estimate the discrete-time hazard model. Newly added and transient stations are followed from their first appearance, and each station's status is reevaluated monthly, allowing newly added stations to transition to active status after 12 months. Although this approach shortens the effective analytical window for some lifecycle categories, it reduces the risk of assigning lifecycle status based on short or incomplete observation histories. As a robustness check, we repeat the classification using 3-, 6-, and 18-month thresholds. The qualitative patterns reported in Supplementary Figure 1 to Supplementary Figure 3 remain consistent across these alternative specifications.

Station performance measures, outage and maintenance events. We measure monthly station performance using three complementary indicators. The first is the average fraction of ports reported as offline, which captures the unavailability of individual ports because of conditions such as maintenance or equipment malfunction. The second is the average fraction of ports in use, which measures station utilization. Both measures are calculated directly from the 10-minute port-status observations and aggregated to the station-month level. Because port-level offline and utilization measures may not fully capture disruptions affecting an entire site, such as electricity outages, communication failures, or station-wide maintenance, we construct an additional performance indicator termed an event. Whereas the offline fraction measures the prevalence of unavailable individual ports, an event captures a discrete increase in the number of ports simultaneously reporting an unknown or otherwise unobservable status. Supplementary Figure 5 confirms that these measures exhibit distinct empirical patterns, supporting their treatment as separate dimensions of station performance. An event is defined as a closed excursion in the number of unknown-status ports: it begins when this count rises between consecutive 10-minute observations and ends at the next subsequent decline for the same station within the same month. *Time to fix* is the elapsed time between the initial increase and its closing decline. Excursions that do not close by the end of the month are treated as right-censored. Each station-month is then classified into one of three mutually exclusive reporting categories: zero-event, indicating adequate coverage but no observed events; has-events, indicating adequate coverage and at least one event; or NO_DATA, indicating insufficient or unreliable information. A station-month is classified as NO_DATA if status observations cover less than 50% of the month's expected timestamps, ports remain offline

for at least 90% of the month, or port-configuration information is missing. The 50% coverage threshold ensures that monthly averages reflect a majority of the expected observations.

Empirical strategy

Discrete-time hazard model. We used a discrete-time hazard model to examine the timing of charging-station retirement. This approach is appropriate because station status was observed at monthly intervals and the precise date of retirement was not observed. Discrete-time hazard models accommodate interval-censored event times, right-censoring, time-varying covariates, and tied events within the same month (Allison, 1982; Prentice and Gloeckler, 1978; Singer and Willett, 1993).

The station-month was the unit of analysis. Station i entered the risk set in the month in which it was first observed and remained at risk until it was classified as retired or reached the end of the study period in July 2026. Consistent with our lifecycle definition, a station was classified as retired after it disappeared from the data for at least 12 consecutive months. Stations that did not meet this criterion by the end of the observation period were treated as right-censored.

Let T_i denote the month in which station i was retired. The discrete-time hazard is defined as

$$h_{it} = \Pr(T_i = t \mid T_i \geq t,\ X_{i,t-1}) \quad (1)$$

where h_{it} is the conditional probability that station i is retired in month t, given that it remained active through the preceding month. The vector $X_{i,t-1}$ contains lagged station characteristics and operating conditions, including the number and type of charging ports, the fractions of ports in use and offline, zero-event status, status-reporting coverage, and relevant county-level demographic and economic characteristics. Time-varying station measures were lagged by **one month** to ensure that predictors preceded the observed transition and to reduce simultaneity between operating conditions and retirement classification.

We estimated the hazard using a complementary log-log specification:

$$log\ [-\ log\ (1 - h_{it})] = \alpha_d + \gamma_t + X_{i,t-1}\beta, \quad (2)$$

where α_d represents the baseline hazard as a flexible function of the station's observed duration in the panel, and γ_t denotes calendar-month fixed effects that account for common temporal shocks and changes in market or reporting conditions. The complementary log-log link provides a discrete-time representation of an underlying proportional-hazards process when event times are grouped into intervals (Prentice and Gloeckler, 1978). Exponentiated coefficients, $exp\ (\beta_k)$, are therefore reported as hazard ratios. A hazard ratio greater than one indicates a higher conditional rate of retirement, whereas a value below one indicates a lower conditional rate, holding the other covariates constant.

Because each station contributed multiple monthly observations, standard errors were clustered at the station level. Models were estimated separately by charger type where appropriate, particularly for Level 2 and direct-current fast-charging stations. Stations already present at the beginning of

the panel were treated as left-truncated with respect to their true installation histories; consequently, estimated duration effects refer to time observed in the panel rather than the station's complete operating age. The estimates are interpreted as conditional associations with station retirement rather than causal effects.

Machine learning

Model Development and Evaluation. We recast the discrete-time hazard model as an out-of-sample prediction task for pure Level 2 (L2) stations; stations that ever reported DC fast-charging ports were excluded because too few DCFC exits were available for separate model development and evaluation. To avoid conditioning on future information, a station-month entered the analysis only when the station met the dynamic 12-month established-station rule using information available through that month. Because exit required 12 subsequent months of absence for confirmation, the prediction analysis used the panel extended through September 2026 and included eligible station-months from July 2024 through September 2025.

Predictors included the prior-three-month averages of the time-varying measures in Table 1: the share of observations with no usable status, fractions of ports in use and offline, outage and maintenance events, and outage and maintenance repair times and their observation indicators. Additional predictors were station tenure and its square, area-level covariates, log port count, and calendar month represented by sine and cosine terms. Data were divided chronologically into training (July 2024–March 2025), validation (April–June 2025), and test (July–September 2025) periods. Standardization, imputation, and tenure limits were estimated from the training period only; model hyperparameters were selected using validation AUC; and the test period was evaluated once.

We compared unpenalized logistic regression, Firth bias-reduced logistic regression (Firth, 1993), elastic-net logistic regression, random forest, XGBoost (Chen and Guestrin, 2016), and LightGBM (Ke et al., 2017). Discrimination was assessed using the areas under the receiver operating characteristic and precision–recall curves. Practical ranking performance was measured as the share of observed exits captured among the 10% and 20% of station-months with the highest predicted risk. Calibration was evaluated using decile reliability plots and the Brier score. Ninety-five percent confidence intervals were obtained from 500 bootstrap replicates that resampled whole stations. Feature contributions for XGBoost were calculated using TreeSHAP (Lundberg et al., 2020). A secondary model predicted exit within the following three months using an earlier chronological split so that all outcomes remained observable. Full model specifications and performance statistics are reported in Supplementary Table 2.

Early Warning and Inspection Prioritization. To translate the prediction models into an operational decision tool, we ranked eligible stations within each held-out test month from highest to lowest predicted exit risk. We then constructed hypothetical watchlists containing the highest-risk 10% and 20% of station-months. Operational performance was evaluated using capture, defined as the share of all subsequent exits occurring among stations on each watchlist; precision; and lift relative to the test-period exit rate. Because absolute calibration varied across periods, the application used predicted risk as a relative priority score rather than as a forecast of the number of stations expected to exit.

Reference

Asensio, O.I., Alvarez, K., Dror, A., Wenzel, E., Hollauer, C., Ha, S., 2020. Real-time data from mobile platforms to evaluate sustainable transportation infrastructure. Nat Sustain 3, 463–471. https://doi.org/10.1038/s41893-020-0533-6

Brown, A., Cappellucci, J., Heinrich, A., Gaus, M., Cost, E., 2024. Electric Vehicle Charging Infrastructure Trends from the Alternative Fueling Station Locator: First Quarter 2024. National Renewable Energy Laboratory (NREL).

California Energy Commission, 2026. EV Charger Data and Reliability Standards.

Chen, T., Guestrin, C., 2016. XGBoost: A Scalable Tree Boosting System, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16. Association for Computing Machinery, New York, NY, USA, pp. 785–794. https://doi.org/10.1145/2939672.2939785

Chu, J., Gilmore, B., Hassol, J., Jenn, A., Lommele, S., Myers, L., Richardson, H., Schroeder, A., Shah, M., 2023. National Electric Vehicle Infrastructure Formula Program Annual Report: Plan Year 2022-2023 (Technical Report No. NREL/TP-5400-86157; MainId:86930; UUID:29af85b1-943f-4403-a88a-b83d78100f33; MainAdminID:69945). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/https://doi.org/10.2172/1989803

City of Portland, 2023. Amend Vehicles and Traffic Code and direct the Portland Bureau of Transportation to adopt Administrative Rules to create a process for the installation of electric vehicle chargers in the public right-of-way (add Code Sections 16.20.290 and 16.90.111).

Department of Energy, 2026. Alternative Fuels Data Center: Electric Vehicle Charging Networks [WWW Document]. URL https://afdc.energy.gov/stations/charging-networks (accessed 9.26.26).

Dimanchev, E., Fleten, S.-E., MacKenzie, D., Korpås, M., 2023. Accelerating electric vehicle charging investments: A real options approach to policy design. Energy Policy 181, 113703. https://doi.org/10.1016/j.enpol.2023.113703

Federal Highway Administration, 2023. 23 CFR Part 680 -- National Electric Vehicle Infrastructure Standards and Requirements.

Firth, D., 1993. Bias Reduction of Maximum Likelihood Estimates. Biometrika 80, 27–38. https://doi.org/10.2307/2336755

Gamage, T.D., Jenn, A.T., Tal, G., 2024. Novel Methodology to Measure the Reliability of Public DC Fast Charging Stations. Transportation Research Record: Journal of the Transportation Research Board 2678, 1440–1453. https://doi.org/10.1177/03611981241244798

Gifford, T., Barbier, E., 2026. The role of charging infrastructure and income on electric vehicle adoption. Energy Policy 211, 115098. https://doi.org/10.1016/j.enpol.2026.115098

Gill County, 2026. Gill County Meeting Notes.

Greene, D.L., Kontou, E., Borlaug, B., Brooker, A., Muratori, M., 2020. Public charging infrastructure for plug-in electric vehicles: What is it worth? Transportation Research Part D: Transport and Environment 78, 102182. https://doi.org/10.1016/j.trd.2019.11.011

Hoffman, E.-L., 2026. Gill's EV charging station shuts down after earning only $626 in five years. Greenfield Recorder. URL https://recorder.com/2026/04/24/gill-town-suspends-ev-charging/ (accessed 9.26.26).

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., Liu, T.-Y., 2017. LightGBM: A Highly Efficient Gradient Boosting Decision Tree, in: Advances in Neural Information Processing Systems. Curran Associates, Inc.

Lommele, S., Desai, R., Johnson, C., Snelling, A., Brown, A., Singer, M., Bennett, J., Cappellucci, J., Levene, J., Hoehne, C., 2024. Assessment of Alternative Fueling Infrastructure in the United States (No. MainId:89292, UUID:01304729-3c84-4c98-bd44-98b, MainAdminId:73856). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/2447838

Lou, J., 2024. Income and racial disparity in household publicly available electric vehicle infrastructure accessibility. Nature Communications 15. https://doi.org/https://doi.org/10.1038/s41467-024-49481-w

Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.-I., 2020. From local explanations to global understanding with explainable AI for trees. Nat Mach Intell 2, 56–67. https://doi.org/10.1038/s42256-019-0138-9

Maryland General Assembly, 2023. Article - Public Utilities.

Muratori, M., Arent, D., Bazilian, M.D., Bistline, J., Borlaug, B., Brown, A., Cazzola, P., Dede, E.M., Gearhart, C., Greene, D., Jenn, A., Kendall, A., Ledna, C., Liu, Y., Lipman, T., Narumanchi, S., Pesaran, A., Sioshansi, R., Timbario, T., Walkowicz, K., Yip, A., 2025. Trends and 2025 insights on the rise of electric vehicles in the USA. Nat. Rev. Clean Technol. 1, 827–845. https://doi.org/10.1038/s44359-025-00108-3

New Jersey, 2024. 48:25-12, 48:25-2 Establishes uptime requirement for electric vehicle charging station incentive programs.

NLR, 2026. Alternative Fuel Stations API | NLR: Developer Network [WWW Document]. URL https://developer.nlr.gov/docs/transportation/alt-fuel-stations-v1/ (accessed 9.26.26).

Ormosi, P.L., Bokhari, F.A.S., Ennis, S., Mariuzzo, F., 2025. Does Increasing Concentration Hit Poorer Areas More? A Study of Retail Petroleum Markets. The Journal of Industrial Economics 73, 70–123. https://doi.org/10.1111/joie.12403

Pinellas County, 2026. Public EV charging stations to be decommissioned June 1 to save on operational costs. Pinellas County. URL https://pinellas.gov/story/public-ev-charging-stations-to-be-decommissioned-june-1-to-save-on-operational-costs/ (accessed 9.26.26).

Powell, B., Johnson, C., 2024. Impact of Electric Vehicle Charging Station Reliability, Resilience, and Location on Electric Vehicle Adoption (No. MainAdminId:73373, UUID:4ca8c014-e688-47a1-a9a0-043, MainId:90675). National Renewable Energy Laboratory (NREL). https://doi.org/10.2172/2432350

Raman, Gururaghav, Raman, Gurupraanesh, Peng, J.C.-H., 2022. Resilience of urban public electric vehicle charging infrastructure to flooding. Nat Commun 13, 3213. https://doi.org/10.1038/s41467-022-30848-w

Tranfaglia, A., 2018. Shrinking Networks: A Spatial Analysis of Bank Branch Closures (Working paper (Federal Reserve Bank of Philadelphia) No. 18–12), Working paper (Federal Reserve Bank of Philadelphia). Federal Reserve Bank of Philadelphia. https://doi.org/10.21799/frbp.wp.2018.12

USDOT, 2024. EV Charging Infrastructure. United States Department of Transportation.

Wood, E., Borlaug, B., Moniot, M., Lee, D.-Y., Ge, Y., Yang, F., Liu, Z., 2023. The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle

Charging Infrastructure (No. NREL/TP-5400-85654). National Renewable Energy Laboratory (NREL), Golden, CO (United States).
Yang, H., Fulton, L., Kendall, A., 2024. A Review of charging infrastructure requirements for US electric light-duty vehicles. Renewable and Sustainable Energy Reviews 200, 114608. https://doi.org/10.1016/j.rser.2024.114608
Yu, Q., Que, T., Cushing, L.J., Pierce, G., Shen, K., Kejriwal, M., Yao, Y., Zhu, Y., 2025. Equity and reliability of public electric vehicle charging stations in the United States. Nat Commun 16, 5291. https://doi.org/10.1038/s41467-025-60091-y
Zhao, M., Wang, D., Li, W., 2025. Idle occupancy and dead piles: new challenges in public charging station promotion. Annals of GIS 31, 251–271. https://doi.org/10.1080/19475683.2025.2472781

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Author contributions

J.L. is responsible for designing the original study and write the paper. J.S. conducted the entire analysis.

Data availability

This paper employs public EV infrastructure data. All the other data used for this analysis is available at the GitHub: https://github.com/Jiehonglou/EV-Lifecycle.

Code availability

All data and models are processed in R and Python. All relevant code is available on GitHub: https://github.com/Jiehonglou/EV-Lifecycle.

Competing Interests

The authors declare that there are no competing interests.

Supplementary Files

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