



Full Length Article

Reliability of electric vehicle charging infrastructure: A cross-lingual deep learning approach



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ARTICLE INFO

Keywords:

Electric vehicles
Consumer behavior
Charging infrastructure
Public policy
Machine learning
Natural language processing
Transformer algorithms

ABSTRACT

Vehicle electrification has emerged as a global strategy to address climate change and emissions externalities from the transportation sector. Deployment of charging infrastructure is needed to accelerate technology adoption; however, managers and policymakers have had limited evidence on the use of public charging stations due to poor data sharing and decentralized ownership across regions. In this article, we use machine learning based classifiers to reveal insights about consumer charging behavior in 72 detected languages including Chinese. We investigate 10 years of consumer reviews in East and Southeast Asia from 2011 to 2021 to enable infrastructure evaluation at a larger geographic scale than previously available. We find evidence that charging stations at government locations result in higher failure rates with consumers compared to charging stations at private points of interest. This evidence contrasts with predictions in the U.S. and European markets, where the performance is closer to parity. We also find that networked stations with communication protocols provide a relatively higher quality of charging services, which favors policy support for connectivity, particularly for underserved or remote areas.

1. Introduction

Electric vehicle (EV) mobility has received attention from governments and the private sector as a strategy to reduce greenhouse gas emissions from the transportation sector. Transport electrification has emerged as a global priority to address health-based air quality standards and the associated mobile source emissions, which contribute to ozone, particulate matter air pollution, and climate change (Environmental Protection Agency, 2021; UK Science, 2021). Globally, countries have adopted electrification targets and other policies to promote electric vehicle deployment. These policies have focused on vehicle and manufacturer subsidies at national or local levels. For example, China's

national dual-credit policy aims to increase the share of electric cars to 20% by 2025 through fuel consumption targets and electric vehicle quotas (Ou et al., 2020; International Energy Agency, 2021). However, recent theory and evidence suggest that government policies to accelerate vehicle electrification, such as purchase subsidies, may be twice as cost-effective when they focus on infrastructure deployment as opposed to car sales (Li et al., 2017; Springel, 2021). This is due to indirect network effects because the value of charging services increases adoption exponentially as others join the network (Rohlfs, 1974; Katz and Shapiro, 1994).

The surge in electric vehicles has motivated government-supported spending programs for interconnected EV charging stations. The EV

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charging market is projected to grow by 15.8 billion USD from 2021 to 2026 (Technavio, 2022). However, performance data on the reliability of public charging is largely unstructured and remains distributed due to poor data interoperability (Asensio et al., 2020; 2021). Expanding consumer analysis beyond one country or region presents a fundamental communication challenge related to language inference. Consequently, little is known about the quality of consumer experiences in charging station infrastructure globally across service territories or regions. This article uses machine learning (ML) to classify 20,880 electric vehicle consumer reviews in 72 detected languages from 2022 charging stations and multiple networks in East and Southeast Asia. Our supervised ML classification scheme leverages transformer-based deep learning (Devlin et al., 2018) to identify measures of charging infrastructure reliability and location features.

As EV infrastructure is fast-growing worldwide, there is a need for real-time intelligence about the reliability of public charging. Many papers in the field of intelligent transportation systems have applied machine learning methods to vehicle automatic driving (Fang et al., 2020), EV charge scheduling (Mohanty et al., 2020), and distributed charging management (Zhang et al., 2018), but less is known about the real-time reliability of EV charging infrastructure. Scholars have identified behavioral issues in the quality of charging service provision in the U.S. and European markets, but more needs to be known about charging behavior in East and Southeast Asia. One fundamental challenge is the uncertainty regarding the generalizability of ML-based models for text-based data discovery in both high- and low-resource languages. Low-resource languages for example, are less commonly studied, computerized or have lower densities of training attributes or labeled data (Singh, 2008; Cieri et al., 2016; Tsvetkov, 2017). The processing of low-resource languages typically suffers from data scarcity since expert annotators and translators can be costly and have limited capacity (Magueresse et al., 2020). Therefore, leveraging insights about charging behavior in multiple regions requires cross-lingual language processing and analysis.

Cross-lingual transfer learning typically requires linguistic knowledge and training resources between the source and target language such as parallel corpora (Singh, 2008; Magueresse et al., 2020; Kim et al., 2015; Yarowsky et al., 2001). Such multilingual projection is not always possible, particularly with specialized corpora in transportation-related communications. Pre-trained language models with transformers such as multilingual Bidirectional Encoder Representations from Transformers (BERT) could be very competitive for few-shot cross-lingual transfer learning (Wang et al., 2019; Wu and Dredze, 2019). This is important because, in the future, these models might not require expensive expert annotators in the source language to produce high accuracy classification, which can be cost prohibitive for policy evaluations. We know that supervised knowledge of small tag dictionaries can help guide sentence-level analysis in other target languages even without parallel text (Das and Hasegawa-Johnson, 2015; Chang et al., 2008). For EV consumer reviews, this brings us to a form of zero or few shot-learning in pre-trained large language models, where unlabeled sample reviews from East Asian charging stations could be classified with very few or even zero training examples in the target language. In lieu of language models that can handle the scope of represented languages, we use machine translation to project English training data to its semantic representation across source languages.

By leveraging ML models trained with the U.S. data, we demonstrate that cross-lingual transfer learning can automatically detect EV infrastructure failures at a larger geographic scale than previously available. To assess station reliability, we propose an ML-based measure of station service quality from a consumer perspective, represented as the ML-based functionality ratio, which allows us to predict station reliability issues from unstructured consumer data. We find that counter to US-based evidence (Asensio et al., 2020; Kim et al., 2015; Ha et al., 2021), charging stations at government locations (e.g., government and municipal buildings, public libraries, rest areas, public parks, and visitor

centers) are less reliable than those at privately-owned and/or operated locations. We also find that networked charging stations with Internet connectivity are more reliable with consumers than non-connected charging stations. Additionally, charging stations incentivized to offer high-quality charging services such as those at hotels, lodging, and workplace destinations (Asensio et al., 2022) do not necessarily provide a greater degree of reliability beyond the network subscription. In this paper, we demonstrate that ML-based classifiers can be deployed in various resource allocation or infrastructure management decisions (Athey, 2017; Kleinberg et al., 2015). Further, machine classification can be combined with causal inference methods by activating unstructured consumer data to inform government progress on EV infrastructure deployment.

2. Consumer data from mobile apps

There is a growing literature on the use of real-time data from mobile applications for the analysis of sustainability and climate change issues (Asensio et al., 2020; Ford et al., 2016; Asensio et al., 2022). In electric vehicle mobility, a large quantity of unstructured user data requires additional processing efforts to extract and handle information. For example, scholars have recently used unstructured social data from Reddit to uncover public perception issues related to electric vehicle adoption (Ruan and Lv, 2022). These studies reveal important insights from unstructured texts but have not yet incorporated location-based features for analysis. Given the prominent use of smartphones in transportation and mobility services, it is possible to learn about consumer experiences from charging station locator apps in which user networks exchange information. For example, information regarding station location, car model, charger type, network type, and other observable characteristics were collected. We also merged nearby points of interest (POIs) information from Google Places Application Program Interface (API) to identify station amenities. POIs include government, hotel/lodging, retail/supermarket/-shopping center, dealership, education, entertainment, gas station, healthcare, outdoor, parking, place of worship, and residential (see Fig. 1).

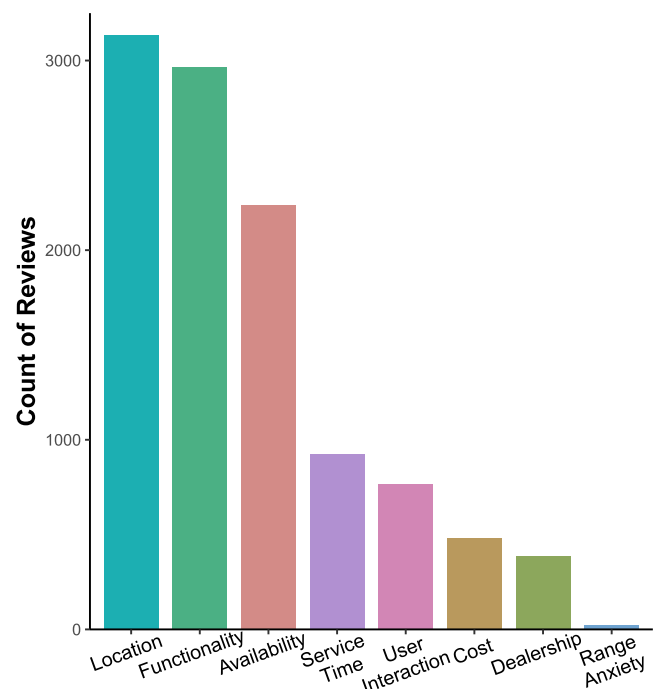


Fig. 1. Distribution of ML-classified topics in EV reviews.

In Table 1, we provide descriptive statistics of consumer reviews data in East and Southeast Asia from 2011 to 2021 by country/region, year, and point of interest. The dataset is comprised of 10,041 publicly-available EV station reviews collected across 2022 charging stations from a popular charging station locator mobile app. Innovations in data collection from digital platforms have uniquely enabled large-scale aggregation of user phenomena in multiple languages from publicly-available data. This includes consumer charging reviews from 10 countries/regions covering Thailand, Japan, Malaysia, Chinese mainland, Taiwan region, Hong Kong/Macao region, Republic of Korea, Philippines, Singapore, and Indonesia. This includes an average of 573 station reviews (S.D. 1041) and 1898 (S.D. 4671) user check-ins per country/region. These locations are generally representative of the existing public non-residential EV charging market to date. We do not have reviews in Brunei, Cambodia, Laos, Vietnam, or Democratic People's Republic of Korea, as these locations are still emerging with respect to publicly-available EV infrastructure data. We also note that stations and reviews in Chinese mainland reflect usage on a U.S. based mobile app and are non-representative of the entire infrastructure in that region. However, EV adoption is large enough in that region to support a domestic market for competing mobile apps in native languages, but with limited data access outside of its geographical borders.

To adjust for factors driving the selection to review, we also captured information about the number of station check-ins with and without written reviews. The total number of check-ins is 20,880 in total, while written reviews represent 49.3% of total station check-ins over a span of 10 years of evidence in the dataset. We find that EV charging infrastructure is already available in 10 out of 16 economies in the region (excluding Vietnam, Laos, Myanmar, Democratic People's Republic of Korea, East Timor, and Brunei). The top 4 distinct languages in this dataset are Chinese, English, Thai, and Japanese, which make up 85.6% of all reviews. Given that Chinese comprises 70.8% of the data, we conducted language validation experiments for machine translation in Chinese. Table 2 provides a detailed list of all the languages detected in our dataset.

3. Methods

Deep learning models for NLP typically require large data and graphics processing units (GPUs) in order to achieve state-of-the-art performance in classification tasks. Pre-trained, large language models, such as transformer neural networks offer a solution for supervised text classification without a large corpus of annotated data. These language models utilize vast amounts of unannotated web text as a pre-training resource, while learning bidirectional context from unstructured text (Devlin et al., 2018). Transformer-based deep learning models have been applied to a broad range of tasks including sentiment analysis, question answering, entity recognition, and importantly for our analysis, multi-label topic classification and machine translation (Devlin et al., 2018; Vaswani et al., 2017; Lin et al., 2022). These models can be useful in generating insights from datasets spanning across several languages,

Table 1
Descriptive statistics for user reviews from 2011 to 2021.

	Mean	SD	Min	Max
Reviews per				
Country/region	573	1,041	14	3,996
Year	103	1,304	1	3,283
Point of interest	937	2,526	1	8,517
Check-ins per				
Country/region	1,898	4,671	24	15,874
Year	1,899	2,532	1	6,535
Point of interest	1,160	2,184	19	8,575

Note: There are a total of 20,880 user check-ins and 10,041 reviews.

Table 2

List of all languages detected in the dataset.

Language	Number of reviews	Percent
Chinese	7,304	70.85%
English	739	7.17%
Thai	540	5.24%
Japanese	246	2.39%
Luxembourgish	107	1.04%
Marathi	84	0.81%
Hindi	68	0.66%
Nepali	54	0.52%
Serbian	36	0.35%
Frisian	26	0.25%
Galician	23	0.22%
Xhosa	23	0.22%
Czech	22	0.21%
Korean	22	0.21%
Haiti	20	0.19%
Filipino	19	0.18%
Catalan	17	0.16%
Germany	16	0.16%
Norwegian	16	0.16%
Ukrainian	13	0.13%
Spanish	12	0.12%
Indonesian	12	0.12%
Hungarian	11	0.11%
Lithuanian	11	0.11%
Igbo	10	0.10%

Note: Other languages that are less 0.1% representative include Irish, Danish, Polish, Slovenian, Dutch, Vietnamese, French, Malay, Pashto, Syriac, Swedish, Afrikaans, Finnish, Maltese, Portuguese, Somali, Corsican, Basque, Persian, Icelandic, Kyrgyz, Russian, Estonian, Scottish Gaelic, Italian, Romanian, Urdu, Zulu, Bulgarian, Welsh, Kazakh, Central Kurdish, Macedonian, Malayalam, Slovak, Sotho, Tajik, and Tsonga.

including low-resource languages (Das and Hasegawa-Johnson, 2015; Chang et al., 2008). Machine translation systems typically rely on the availability of parallel data to generate multilingual model predictions, usually using English as an assisting language (Pires et al., 2019; Fan et al., 2021; Libovický et al., 2019; Wu et al., 2016; Johnson et al., 2017b; David et al., 2001). In recent advancements, multilingual BERT has been proven effective in 104 languages with zero-shot cross-lingual models (Tsvetkov, 2017; Libovický et al., 2019). In other developments, multiple groups have recently released multilingual translation models (Johnson et al., 2017b; Firat et al., 2017; Bapna et al., 2019; Dabre et al., 2019; Rubino et al., 2020; Haddow et al., 2022), which could enable language processing without relying on English (Radford et al., 2022; Face, 2023). Though well-received and compatible with many low-resource languages, these models are still in development and have yet to reach the quality achieved by machine translation. Therefore, this paper employs a three-stage methodology to analyze unstructured text data by combining machine translation in a ML classification pipeline, followed by econometric analysis for statistical adjustment, see Fig. A1 in the Appendix.

In the first stage, we fine-tune BERT and tailor it to specific classification tasks related to EV consumer reviews data. We use domain-specific and human-expert curated English language training data as described in Asensio et al. (2020) and Ha et al. (2021), to develop BERT for multi-topic classification of EV consumer reviews in other target languages. To assure training data quality standards, the reviews go into a pre-processing step that includes machine translation and validation using Google Cloud's Translation API service. For example, the consumer review detected in Chinese, “總是壞掉” is translated into “Always Broken”. We use the advanced edition of the Google Translate API to perform the translation. The application provides support for over 100 languages and it conforms to the ISO-639 identifiers, which is a set of standards for representing names of languages and language groups (Google Cloud, 2023).

Second, the translated reviews are then embedded and classified with English BERT-uncased model according to a comprehensive multi-label

typology that identifies 8 main discussion topics for each review: service time, station availability, cost, range anxiety, station functionality, dealership issues, location attributes, and user tips and interactions (Ha et al., 2021). The multi-label classifier allows for each review to be assigned to one or more categories as appropriate. The domain-specific machine learning model achieves strong performance. In scientific replications, we report high accuracy (89.1%) and F1 (0.78) scores, both within the published uncertainty in Ha et al. (2021). We expanded the data processing to include support for native languages observed in consumer reviews, other than English.

Finally, in the third stage, we use the outputs of the machine classified reviews as inputs for statistical analysis. For a given station location and year, we regress the conditional probability of a review being tagged as a given topic (i.e., station functionality, cost, and range anxiety) as a function of observable station characteristics. The dependent variables are two empirical measures of reliability: the ML-based functionality ratio and the system-reported error rate. The functionality ratio, indexed between 0 and 1, refers to the share of reviews that mention whether particular attributes are working properly at a given station per year. Values close to 1 are less desirable as they indicate a prevalence of station functionality issues. To validate our ML-based measure of reliability, we consider the system-reported error rate, which is an indicator variable that systematically identifies an error or failed transaction.

Our independent variables include station characteristics such as the number and type of station connectors and network types, common points of interest around the stations, geography (country/region), and time (year) fixed effects resolved to the nearest station. We also include a dummy for machine-translated reviews to mitigate the potential effect of translation errors. The unit of analysis is at the station review level, and we cluster standard errors by location ID. As a robustness check, we include higher-order terms and interactions for sub-group analysis.

To estimate factors influencing the functionality ratio and the error rate, we employ a fractional response model (FRM) using a quasi-maximum likelihood estimator (QMLE) (Ramalho et al., 2011). For each station i , and year t , we regress our outcomes of interest $y_{i,t}$ on a location $x_i E(y_{i,t} | x_i) = G(x_i; \theta)$, where G is a data-driven transfer function such as the cumulative distribution function or logistic function, which is $\in \mathbb{R}$. The station characteristics include an indicator for public versus private stations, the number of plug connectors, the networked station dummy, and points of interest dummies. To investigate the effect of station characteristics on the functionality ratio, we estimate the fractional dependent variable directly using the Bernoulli log-likelihood function, given by

$$\ell_{i,t}(\theta) \equiv y_{i,t} \log[G(x_i; \theta)] + (1 - y_{i,t}) \log[1 - G(x_i; \theta)] \quad (1)$$

where θ is a parameter vector of interest and $y_{i,t}$ is the fractional dependent variable for the AI-based functionality ratio or the system-reported error rate. For fractional data, the Bernoulli QMLE estimator of θ does not require dichotomization of the dependent variable and is computed as

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^N \ell_{i,t}(\theta) \quad (2)$$

We are able to statistically adjust for the factors that influence the likelihood of functionality-related reviews or errors. In a greater context, these “human-in-the-loop” machine learning systems provide the additional benefits of greater model performance through interventional model training (Wu et al., 2022). For an overview of the methodology workflow, see Fig. A1 in the Appendix.

This approach allows us to uniquely: (1) activate citizen generated data (unstructured, hard-to-reach consumer data); (2) offer scalable insights spanning multiple regions and geographies (not limited to cities or states); (3) allow for cross-lingual analysis in at least 72 target languages; and (4) offer the potential for near-real-time updating/station management. In the context of public infrastructure, this approach can pave the

way for operational enhancements, resource allocation and optimization, impact evaluation, and long-term support for EV adoption. The methodology also allows us to overcome the data interoperability challenges resulting from decentralized ownership and the lack of mandatory disclosure policies for EV data sharing. Citizen-generated data from digital platforms can better capture people's real-time behaviors. Additionally, ML-based predictions are highly scalable which allows us to analyze phenomena at larger spatial scales. Furthermore, given the high accuracy of machine translation and transfer-based classifiers, the methodology covers many low-resourced languages in a cross-lingual context, overcoming language barriers.

The proposed methodology provides benefits for proactive operational management strategies in which behavior plays an important role in decision-making. These approaches include real-time control and optimization for charging performance (Zhang et al., 2020; Pandit and Coogan, 2018; Santoyo et al., 2023), reduced grid impacts with increased EV adoption (Powell et al., 2022), and carbon and emissions scenario forecasting (Lei et al., 2022). For example, scholars have argued that to achieve decarbonization, it may be necessary to change utility rates and infrastructure deployment to promote the shift from home to daytime charging. Such real-time updates can better identify day-time barriers to public charging to design targeted policies for efficient resource use. Another potential benefit is in support for public decision-making related to effective investments in infrastructure provision.

To evaluate the accuracy of our machine translations, we conducted human annotator experiments on a representative sample of Chinese reviews. For this task, we recruited 10 independent annotators with native or high proficiency in traditional Chinese and with technical backgrounds. From 7,304 written Chinese language reviews, which encompassed 70.9% of our dataset, we selected a 10% random sample for hand-validation. Every review was labeled by two separate annotators. Annotators were asked to complete two tasks. First, annotators were instructed to validate whether or not the translation was accurate with a binary “yes” or “no” and a short justification. Next, they rated translation quality on a Likert scale from 1 to 5 (see details in Table A1 in the Appendix), where 1 indicated a low-quality translation and 5 indicated a high-quality translation. Based on the experiments, we confirmed that in 38% of cases, the machine translations achieved a perfect rating, according to human experts. In another 42% of cases, the translation is imperfect, but there is no semantic shift that would affect the appropriate tagging of the label for topic classification. Thus, for traditional Chinese, our experiments reveal a machine-translation accuracy for the corpus of EV reviews of about 80%, which is consistent with other reports (Wu et al., 2016; Johnson et al., 2017b). Importantly, we found that machine translation inaccuracy affects the label classification for functionality and other topics in less than 5% of cases.

4. Results and discussion

In this paper, we evaluate the dominant discussion topics at EV charging stations across countries/regions in the dataset. We find that the top 3 concerns relate to: (1) location features or amenities related to the station (38.0%); (2) functionality, such as whether particular features are working properly (28.1%); and (3) availability, whether the station is unoccupied and available for use (15.6%). These 3 topics of discussion account for 76.5% of the total reviews in the multi-label classification dataset, which allows for a review to be simultaneously classified into one or more labels. We also find that charging station service quality in the existing Level 2 and Level 3 public infrastructure is a principal concern. This stands in contrast with the popular narrative that range anxiety is a major barrier to EV owners (Ha et al., 2021).

Recent studies have pointed to the conceptualization of range anxiety as primarily a psychological or rhetorical barrier (Noel et al., 2019). Other studies have also reported that range anxiety may be a perception problem mainly for inexperienced EV drivers and, therefore, this issue might decrease with practical experience (Rauh et al., 2014). Many have

suggested that this disparity comes from a disproportionately large number of scalable interventions focused on reducing situational range anxiety through means of first-hand EV experiences (Herberz et al., 2022). Conversely, interventions targeting anticipatory range anxiety – a unique barrier to those who have not considered driving or purchasing an EV – have been largely neglected (Herberz et al., 2022). The compatibility bias, the difference between perceived and actual EV compatibility with a potential driver's needs, is cited as a major roadblock for potential buyers (Noel et al., 2019). Fundamentally, this bias subsides when an individual acquires an EV because over 90% of individual mobility needs are consistent with increasingly affordable EV battery ranges (Herberz et al., 2022). A longitudinal study of range anxiety found users to be considerably satisfied after 3 months of EV usage (Franke and Krems, 2013). Consistent with this, we find that range anxiety is a minor issue for existing EV owners. For review of additional factors on mitigating range anxiety, we point readers elsewhere (Neubauer and Wood, 2014; Guo et al., 2018; Xu et al., 2020).

We define the ML-based functionality ratio as the probability that a written review mentions functionality at a given station location and year. When we use the functionality ratio as the dependent variable, we find that stations at government locations (e.g., public buildings, transit, visitor centers, and public parks) are 18.6% more likely to mention functionality issues in consumer reviews than charging stations at private locations or points of interest (Table 3, Model II). This result is statistically significant at the 1% level and net of all statistical controls. Although there is some heterogeneity in the charging service quality at various POIs, we find limited evidence of differences in the functionality ratio across POIs (Table 3, Model II). We hypothesize that this could be due to common maintenance, operation, and subscription services at a network level. Further, we evaluate the performance of networked stations versus non-networked stations. We find that networked chargers are 5.1% more reliable than non-networked charging stations (Table 3,

Model II), which favors centralized as opposed to individually managed operations and maintenance subscription services. To validate these estimates, we also evaluated performance using the system-reported error rates as the dependent variable, which provides a systematic reliability measure. The results suggest that networked chargers have 7.8% fewer errors than non-networked charging stations (Table 3 Model IV) and that government-provided charging stations are 5.6% less reliable than privately provided charging stations (Table 3, Model IV). These results are significant at the 5% level. These estimates are consistent with the ML-powered findings. However, we note a larger effect size for government stations from the consumer perspective than the system-reported error rates.

4.1. Public provision is worse

There has been an active debate on the public versus private provision of public goods and services as a means to investigate environmental externalities (Andreoni, 1990; Andreoni, 1989; Bergstrom et al., 1986; Kotchen, 2006; Warner and Hefetz, 2008; Grant and Langpap, 2018). There has been mixed empirical evidence on whether private provision is preferred in a wide range of domains, such as water quality and sanitation (Braadbaart, 2002; Baisa et al., 2010), air quality (Davis, 2005; Li et al., 2019), renewable energy (Kotchen and Moore, 2007; Khan et al., 2020), and climate change adaptation (Tompkins and Eakin, 2012). In the context of EVs, we can conceptualize EV charging infrastructure as an impure public good that has two components – a public environmental good of reduced emissions and a private attribute of energy consumption (Kotchen, 2006; Andreoni, 1989, 1990; Cornes and Sandler, 1984; Ribar and Wilhelm, 2002). As more countries announced zero-emission vehicle targets with plans to install charging stations with public funds, it is unclear who will provide a better quality of charging service. From the standpoint of policymakers and business leaders, relevant strategies are focused on establishing more flexible pricing mechanisms for private stations (De Alessi, 1977), stimulating entrepreneurship (Wiederer and Philip, 2010), supporting customer-based quick response (Jimenez et al., 1991), and developing profit-maximizing strategies (Besley and Ghatak, 2007). These efforts could contribute to higher customer satisfaction of privately provided stations. From a public choice perspective, it is still unclear whether consumers might prefer private over public provided EV charging stations.

Government investment in charging infrastructure often includes funding or subsidies to achieve a targeted number of electric vehicle charging installations. For example, as of January 2022, China has built approximately 810,000 public charging piles, according to the National Development and Reform Commission (NDRC) (Xinhua News, 2022). Similarly, in 2021, Japan earmarked JPY 6.5 billion to expand its charging station network to 150,000 chargers by 2030 (NIKKEI Asia, 2021). Another important policy mechanism is the use of subsidies to encourage joint investment with the private sector. In Thailand, the government has utilized subsidies to encourage the PTT Plc, a state-owned oil and gas company, and the Electricity Generating Authority of Thailand to build charging stations in the country/region (IHS Markit, 2020). The Thai government also offered soft loans to small and medium-sized enterprises (SMEs) and startups for charging station investment (Paultan, 2022; Lei et al., 2022). Although governments in Asia vary in their approach to promoting electrification efforts, they are all rapidly investing in EV infrastructure development. Long-term commitments, including bans and restrictions on internal combustion, are also reinforcing these actions to promote transport electrification engine (ICE) vehicles, official EV targets, and consumer subsidies (McKinsey, 2022).

Our finding that stations in government locations provide a lower degree of reliability could be attributed to the additional cost of upkeep and maintenance to support long-term use (Alternative Fuels Data Center, 2022). Government points of interest in our analysis include libraries, courthouses, fire stations, city halls, post offices, police stations,

Table 3
Summary of FRM results.

Variable	Dependent variable: AI-generated functionality discussion ratio (0–1)		Dependent variable: System-reported error rate (0–1)	
	I	II	III	IV
Service provision				
Government provision	18.84%*** (5.81)	19.11% *** (5.70)	5.16%* (2.93)	5.40% * (2.90)
Station characteristics				
Networked station	−4.90% *** (1.55)	−5.01% *** (1.55)	−7.32% *** (1.24)	−7.45% *** (1.24)
No. of connectors	5.28% *** (0.92)	5.38% *** (0.93)	−2.00% ** (0.74)	−1.80% ** (0.74)
Location features				
POI – retail/dining/ shopping centers/ supermarkets	−1.38% (2.70)	−1.28% (2.70)	−1.26% (1.35)	−1.09% (1.35)
POI – lodging	−3.10% (2.92)	−3.05% (2.92)	−1.32% (1.46)	−1.23% (1.45)
POI – services	0.69% (4.46)	1.04% (4.41)	0.90% (2.44)	1.58% (2.35)
POI – entertainment	1.00% (3.55)	1.08% (3.55)	−0.36% (2.03)	−0.19% (2.03)
POI – gas station	−0.79% (4.58)	−0.60% (4.54)	−7.17%* (4.01)	−7.08%* (3.93)
Translation dummy	—	−8.61% ** (4.32)	—	−19.64% *** (2.19)
Location FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes
No. of observations	10,041	10,041	20,880	20,880

Note: Coefficients reported are average partial effects. Standard errors are clustered by location ID. Significant to * $p < 0.5$, ** $p < 0.1$, *** $p < 0.01$. Other POIs include dealership, education, healthcare, outdoor, parking, place of worship, and residential.

government offices, and visitor centers. As governments often seek to increase access to EV charging rather than to generate revenue for station owners, the charging stations may not be cost-recovering and could lead to differential quality in charging experiences for users. To exemplify the automated process, a user writes in Thai: “เจ้าหน้าที่แจ้งว่าเครื่องเสียชั่วคราว” which the Google API translates to “The officials reported that the device was broken. Can't charge”. Similarly for another case, the user writes in Chinese: “第一次去停車充電,設備竟然損壞待修中,不知這情況已經多久了”, which the Google API translates to “The first time I went to charge my car, the equipment was damaged and awaiting repair. I do not know how long it has been”. Given that these infrastructure failures are mentioned frequently within the reviews, government support for EV infrastructure is critical to enabling reliable and equitable access to charging especially in otherwise underserved areas. Electric vehicle charging infrastructure is a form of quasi-public goods, where the initial investment is large but not sufficient. In this sense, the government's mitigating role could have important equity implications for infrastructure growth, as the private providers of charging services are profit-maximizing and may not sufficiently develop infrastructure in areas with weaker demand.

4.2. Networked stations deliver better service

As countries continue to set ambitious vehicle electrification targets (UK Science, 2021), the lack of sub-metering of EV infrastructure and poor data interoperability makes it increasingly difficult to have real-time performance tracking and management of charging infrastructure. With this in mind, our consumer-based performance measure (e.g., the functionality ratio) allows us to unique circumvent data challenges and determine whether networked stations have differential performance as compared to non-networked stations. After controlling for observable station-characteristics, our results indicate that networked chargers are 5.1% more reliable than non-networked charging stations (Table 3, Model II), which demonstrates that consumers have better experiences in networked charging infrastructure. To validate, we utilize the technology-based measure (e.g., the system-reported error rate) and find networked stations were indeed 7.5% more likely to have system-reported errors. Both measures indicate that networked chargers are more reliable with consumers.

Although there could be many reasons for differences in performance between networked and non-networked stations, the main drivers are: (1) dedicated customer support: networked stations could have more responsive operations and maintenance services. For example, one user comments in Chinese: “反應後修好了。感謝本站服務人員” which the Google API translates to: “Fixed after response. Thanks to the service staff of this site!”; (2) remote access and connectivity: networked stations typically include mobile applications, allowing the networked stations to offer actionable information through open-sourced communication standards. For example, another user comments in Chinese: “設備完善空間寬敞,有聯網雲端控管,厲害了” which the Google API translates to: “The equipment is well-equipped and the space is spacious with networked cloud control. Great!”; iii) real-time response: networked stations provide real-time updates such as availability and station amenities for users to easily access and benefit from. Another user comments in Thai: “วันนี้ชาร์จได้ครบ และทานข้าวชาไปพอด แต่ชาร์จครึ่งชม.ตัดนะครม”, which the Google API translates to “You can charge today. I just stopped by to have some tea but the charge is half an hour and I cut it off.”

Networked EV charging infrastructure is part of a larger move towards information sharing in social Internet of Things (IOT) platforms and smart mobility across cities. These IoT platforms allow for better service management, data and information sharing while enabling social IOT applications for users (Noura et al., 2018; Karpenko et al., 2018). However, many stations are non-networked and do not have Internet access to have real-time information on neither availability or usage. Therefore, technology standards, such as the Open Charge Point Protocol

(OCP) and the Open Smart Charging Protocol (OSCP), can foster a number of benefits for interoperability and innovation diffusion through the means of collaboration, education, testing, and certification (Open charge alliance, 2020). Such strategies, which are being deployed globally, will allow a greater number of firms and entrepreneurs to appropriate gains from innovation (Noura et al., 2018; Karpenko et al., 2018; Tassey, 2000; Teece, 2018). We note that it is unclear whether the use of open standards will in fact provide a greater degree of infrastructure reliability, as opposed to closed, proprietary networks. In future work, we suggest exploration of the impact of open standards on reliability.

Following our discovery of differences in performance between networked and non-networked stations, we also evaluate the differences by point of interest. Charging station locations are primarily centered around user destinations as opposed to proximity along the route. This infrastructure growth model differs somewhat from gas refueling stations. We provide the distribution of station POIs across all locations in Fig. 2, which show dining and lodging as the top 2 most popular locations for charging stations. This is not surprising because having charging at destinations where there is an expectation of an extended stay and at the end of the journey (versus along the route) is more desirable (Dong et al., 2014). For example, hotels and lodging destinations have a greater incentive to provide reliable charging infrastructure in order to attract EV owners to their properties, and can use the EV chargers as an additional stream of revenue similar to paid parking. The addition of EV chargers increases the hotel's visibility in search engines and the provision of reliable services is integral to receiving positive visitor reviews. This aligns well with the finding by Rathnayake et al. (2020) that hotels are the most suitable to establish charging stations since they create additional value and provide additional guest services. Considering both the AI-generated functionality ratio and system-reported error rates as outcome measures for performance, however, we found weak evidence that POIs such as hotels and lodging destinations significantly influence the quality of charging service delivery (Table 3) net of all statistical controls. This is because our dummies for networked stations capture the main heterogeneity. Therefore, we conclude that the quality of

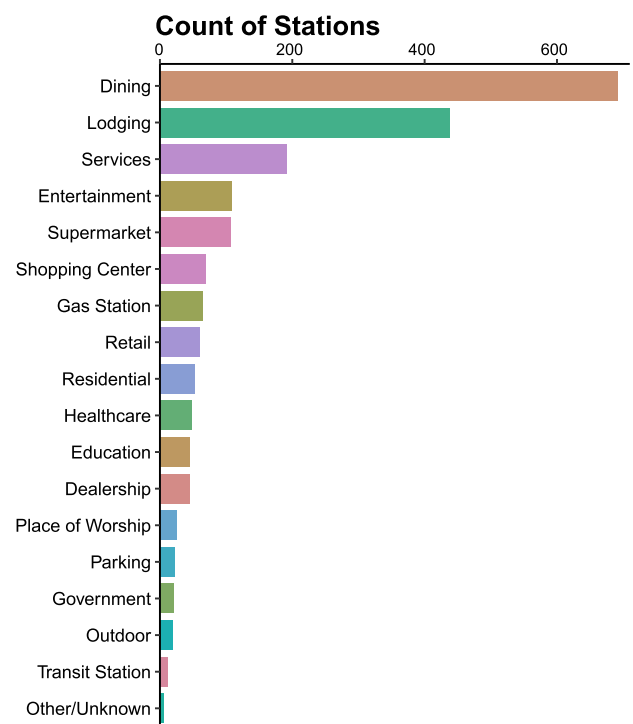


Fig. 2. Distribution of EV charging stations by point of interest.

networked charging, maintenance, and subscription services may be more important than the station point of interest.

4.3. Gaps in infrastructure provision

Based on the publicly available data, we find that 37.5% (6 out of 16) of economies in East and Southeast Asia do not yet have widely-available public fast-charging infrastructure. This includes Vietnam, Laos, Myanmar, Democratic People's Republic of Korea, East Timor, and Brunei. However, based on commitments from the Glasgow Climate Pact, we expect there to be growing momentum and interest in electrification of the transportation sector and associated infrastructure investment, even among countries with significant oil and gas reserves (UK Science, 2021). For example, Brunei, the third largest oil producer in Southeast Asia, has announced in their Wawasan 2035, and in their National Climate Change Policy Strategy 3, to increase the total share of EVs to 60% of the total annual vehicle sales by 2035 (Government of Brunei Darussalam National Council on Climate Change, 2021). Among the remaining 62.5% (10 out of 16) economies, station coverage is primarily situated in the densely populated urban centers. Globally, the International Energy Agency has established proposed population density as an input to predict the optimal EV infrastructure development (International Energy Agency, 2022). Given that many areas in East and Southeast Asia are densely populated, and most countries within the region are still at the early stages of EV adoption, we predict large-scale deployment of EV supply equipment in future years.

Although there remains widespread adoption barriers (Brückmann et al., 2021), our data reveals that consumer information can be beneficial in strategic decision making on infrastructure development. We highlight 3 approaches needed to help governments accelerate the transition. First, better data sharing and interoperability is critical to overcome barriers of distributed and siloed data by encouraging greater collaboration (Ha et al., 2021). This could involve reporting standards and data-sharing agreements between station providers and municipal governments. Second, infrastructure deployments generate increased local visibility, resulting in positive network externalities for consumer intent-to-purchase (Ou et al., 2020; International Energy Agency, 2021). This suggests the further use of subsidies for station deployment to incentivize regional investment and entrepreneurial activity. Third, given the persistence of distributive equity issues in less populated and underserved regions, we expect to see policies targeted in both national corridors and under resourced communities with latent demand. Such targeted policies are needed to catalyze private investment in underserved areas (Ha et al., 2021).

5. Closing

More than 35 countries, along with 43 cities, states, regions, and 6 major vehicle manufacturers, have already committed to all zero-emission vehicle sales by 2040 globally (UK Science, 2021). The electric vehicle supply equipment (EVSE) industry was valued at 3.7 billion USD in 2020 and is projected to grow to 73.3 billion USD by 2031

(Technavio, 2022). Given the scale of both public and private investment, countries are currently lacking evidence-based measures to evaluate the quality of EV infrastructure provision. Here we show that using unstructured consumer data from mobile apps, it is possible to develop new sustainability performance measures that can update in near real-time. Given the decentralized growth models of EV charging infrastructure globally, we demonstrate a unique use case for automated data discovery. Given that EV drivers experience significant differences in reliability and performance between government and non-government stations, as well as networked and non-networked stations, we argue that electrification policies in the region should prioritize quality of service provision and access to EV infrastructure among under-served communities.

Replication and data sharing

The code and anonymized data files for replication can be found at <https://doi.org/10.5281/zenodo.7130962>.

Human subject protection

Protocols for our human subjects annotator experiments were conducted under Institutional Review Board (IRB) Protocol number H18250.

Author contributions

Conceptualization: O.I.A.; Data curation: M.C.L., Y.L., A.C.; Formal Analysis: C.H., Y.L., M.L.; Funding acquisition: O.I.A.; Investigation: O.I.A., A.F., C.H., Y.L., M.C.L., A.C., M.L., O.S., A.B., A.W.; K.B.; Methodology: O.I.A., C.H., Y.L., M.L., M.C.L.; Project administration: A.F., A.B.; Resources: O.I.A.; Software: C.H., O.S., Y.L.; Supervision: O.I.A.; Validation: C.H., Y.L.; Visualization: Y.L., A.F., M.C.L., A.C.; Writing – original draft: O.I.A., C.H., A.F., Y.L.; Writing – review and editing: O.I.A., C.H., A.F., Y.L., A.B., K.B., A.C.

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.

Acknowledgements

This work was supported by funding from the National Science Foundation (Nos. 1931980 and 1945332); Microsoft Azure for research; and the U.S. State Department Diplomacy Lab. For valuable discussions, we thank Jeff Austin and Siree Allers from the U.S. Embassy in Brunei. We also thank Jay Forrest at the Georgia Tech Library. This research was supported in part through research cyber infrastructure resources and services provided by the Partnership for an Advanced Computing Environment (PACE) at the Georgia Institute of Technology, Atlanta, Georgia, USA.

Appendix

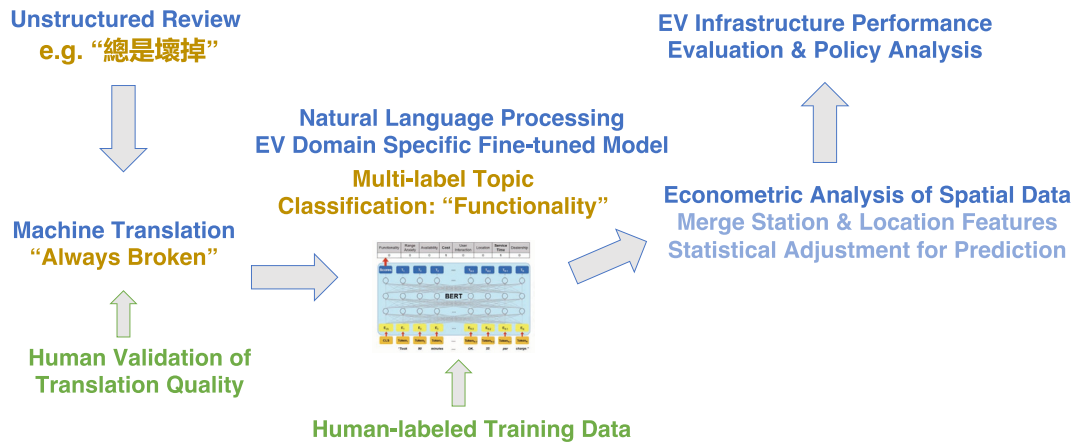


Fig. A1. Human-in-the-loop methodology workflow.

Table A1

Sample reviews and human ratings of translation quality.

Original reviews	Translation	Translation quality
左邊那支怪怪的 試好幾次都沒能充電 右邊倒是正常使用	The weird one on the left has failed to charge after several attempts but the right is in normal use.	Perfect translation
空位很多,但也停很多不是電動車的車	There are a lot of vacancies but there are also many cars that are not electric cars.	Perfect translation
管理良好	Good Management	Perfect translation
左邊維修中	Maintenance on the left	Imperfect translation with minor semantic mistakes that do not affect the delivery of main meanings and the labelling
壞掉,修理中	Broken repaired	Wrong translation which delivers a confusing meaning

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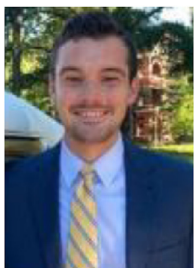
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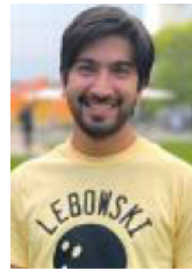
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