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Article

Energy, Emissions, and Cost Impacts of Charging Price Strategies for Electric Vehicles

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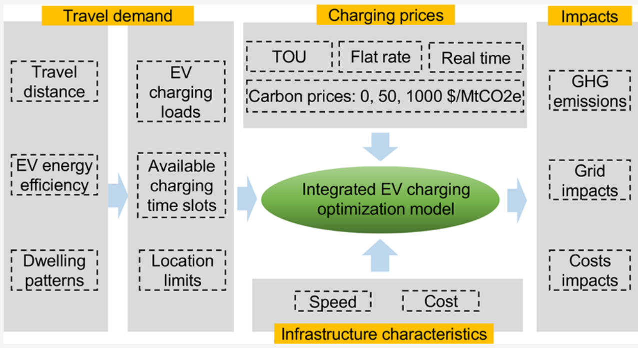

ABSTRACT: While utilizing price signals to affect charging behaviors has been identified as a promising strategy to manage charging loads, few studies discuss their impacts comprehensively. We investigate how different charging price strategies can affect the spatial and temporal distribution of charging activities at the individual level and the required charging infrastructure system. We utilize an integrated optimization platform for electric vehicle (EV) charging management and infrastructure placement in home and nonhome locations in San Diego, CA, that include charging price strategies, infrastructure costs, and mobility demand patterns. We evaluate three pricing scenarios and demonstrate that the time-of-use pricing scheme results in the highest emissions and the real-time one the lowest, which are 20.2% higher and 0.7% lower than the annual emissions under the flat rate scenario, which is about 8,787 $MtCO_2e$. Our results show that the charging load profile is the result of various determinants including the dynamic electricity price, price elasticity of charging demand, travel and dwelling constraints, carbon price, as well as exclusive home and shared nonhome charging patterns. The effectiveness of changing charging behavior through internalizing climate damage to obtain environmental benefits depends largely on charging price strategies, implying that policymakers should consider charging price strategies in conjunction with carbon pricing rather than independently.

KEYWORDS: *charging behavior, price elasticity, optimization, GHG emissions, grid impact*

■ INTRODUCTION

The transportation sector is the largest source of emissions in the United States, accounting for 28.6% of total greenhouse gas (GHG) emissions in the year of 2019.[1] Vehicle electrification has been identified as one of the most important ways to reduce transport-related GHG emissions due to the higher efficiency of electrified powertrains and lower emission rate of electricity.[2,3] Individual travel and charging patterns not only determine how much electricity is used, but the timing of the charging decides whether base or peak electricity will be used to charge the battery. Some studies find that plug-in electric vehicle (PEV) charging will not impact the generation and transmission of the electric grid in the short term but may need to be managed when the vehicles are deployed in greater numbers.[4] However, other studies show uncoordinated PEV charging could significantly change the shape of the aggregate residential demand, with impacts for electricity infrastructure, even at low adoption levels.[5] Proper management is critical because charging strategies may also significantly impact the environmental outcome of charging electric vehicles.[6,7]

Previous research points to the promising prospect of managing EV charging load through price mechanisms to achieve a safe, reliable, and affordable electricity service while advancing system efficiency, enhancing environmental sustainability, and facilitating renewable resources integration.[8,9] Recent studies have discussed the EV driver's response to the charging price in order to shift the charging loads to the off-peak time period[10−14] or to reduce the expenditure of distribution grid operators and/or the charging cost of EV owners.[15−20] However, few studies have been explicitly designed to explore the environmental benefit of shifting consumers' charging loads with various price signals. Some studies examined the GHG emissions of several charging strategies considering the variation in electricity emissions but ignored the impact of electricity prices on charging behaviors.[21,22] Additionally, many EV charging optimization models fail to consider the travel and dwelling constraints of EV drivers.[15,16] It is unrealistic to expect the EV drivers to charge the vehicles during the time when they are not available or at the places where they are not there only to accommodate with the grid needs. Moreover, managing EV charging loads

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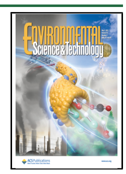

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without considering the availability of electric vehicle charging infrastructure is also inappropriate.

Another research gap in the existing literature is that they take a naive approach in assuming that EV owners are completely rational in changing their charging behaviors in response to price changes.[9,15,19] While some studies have shown that electricity consumption is relatively inelastic,[23−25] there are studies demonstrating that the availability of smart technology can increase price elasticity and grid efficiency.[26,27] A recent empirical study by San Diego Gas & Electric Company (SDG&E) shows that EV consumers are responsive to price signals, especially the on-peak and off-peak prices, and the own-price elasticities were estimated in the range of −0.3 to −0.5.[28]

We develop a unique approach that simulates EV charging behaviors to internalize environmental damages (across diverse sets of electricity rates and GHG intensities) while simultaneously optimizing for electric vehicle charging infrastructure planning and respecting the dynamics of individual mobility demand. The purpose of this study is to understand the energy, economic, and environmental performance of various pricing strategies based on data from San Diego, CA. Our paper is unique in the literature because it (1) utilizes a comprehensive optimization model platform to manage charging activities while identifying optimal EV charger placement and (2) improves upon a large body of literature that treats charging behavior independent from electricity pricing but instead employs price elasticity of charging demand into the optimization model.

■ MATERIALS AND METHODS

We utilize an electric vehicle infrastructure planning and charging management model platform to investigate the implications of charging price strategies when integrating climate damage and price elasticity of charging demand in emission reductions, grid impacts, costs breakdown, as well as infrastructure deployment. The optimization model platform was designed based on a previous study[29] to determine the optimal strategy for electric vehicle charging infrastructure placement at different levels for home and nonhome locations simultaneously, as well as the optimal charging time slots and locations at individual level given a set of constraints including travel demand and dwelling patterns. Our overall modeling framework (Supporting Information Figure S1) consists of four modules: travel demand, infrastructure characteristics, charge pricing, and impacts evaluation. Charge pricing and impacts evaluation are the core modules of this model. The charge pricing is determined by a specific pricing scenario that is related to the electricity price and the carbon price internalized.

EV Charging Demand. We simulate individuals' daily travel and dwelling patterns by employing the activity-based travel diary data from the 2010−2012 California Household Travel Survey (CHTS),[30] which provides the start and end times as well as the location of individuals' daily activities taken by a sample of individuals across California, which can then be used to calculate the dwell time of each sampled individual at each stop. We subset sample individuals with trip destinations in San Diego, CA, from CHTS: 2,452 sampled individuals, representing 15,789 BEV drivers with daily travel and dwelling patterns across 614 census tracts of San Diego. Travel distance is calculated as the shortest driving distance between origins and destinations using Google API. We assume the average efficiency as 33.3 kWh per 100 miles for electric vehicles based on fuel economy data from FuelEconomy.gov[31] and EV sales data reported by the Transportation Research Center at Argonne National Laboratory.[32] Daily dwelling locations and travel distance of those BEV drivers within the study area are shown in Supporting Information Figure S2.

Infrastructure Characteristics. Charging equipment is classified by the rate at which the batteries are charged, and three main categories of EV chargers are in the United States: level 1, level 2, and direct current (DC) fast. Level 1 chargers provide charging through a 120 V (V) alternating current (AC) plug, adding 3−4 miles per charging hour. Level 2 offers charging through 208−240 V with a charging speed of 10−20 miles/hour. DC fast chargers (400−1,000 V DC) enable rapid charging of 150−1000 miles per charging hour. Generally, level 2 and DC fast chargers (DCFC) are potentially available at all nonhome locations while home chargers are restricted to level 1 and 2. The equipment and installation costs of charging infrastructures are assumed based on a study estimating electric vehicle charging infrastructure across major U.S. metropolitan areas from the International Council on Clean Transportation[33] and data from the Rocky Mountain Institute.[34] We annualize the charging stations capital costs assuming a lifespan of 10 years and a discount rate of 3% and assume the charging stations have no maintenance cost. The assumptions for each type of charging infrastructures can be found in Supporting Information Table S1. We also conduct a sensitivity analysis on the cost and power of charging infrastructures to ensure the robustness of the model results, and the assumptions can be found in the Supporting Information.

Charging Price Scenarios. We propose three residential charging price scenarios based on the existing charging price strategies in San Diego. The first one refers to the residential EV Time-of-Use (TOU) rates of SDG&E.[35] BEV drivers within the service territory have the option to join in the plan for home charging. The second scenario is the tier two residential flat rate (FR) of electricity from SDG&E Co.[36] The tier two flat price will be charged when the energy in each billing period of the resident hits 130% of the baseline allowance (234 kWh during summer and 343 kWh during winter in San Diego). The last one is constructed as real-time (RT) pricing, which is estimated based on the daily average real-time dispatch locational marginal price (LMP) over the entire year of 2019 in California ISO.[37] Since the LMP does not include upstream electricity distribution and transmission costs, it is an underestimate of retail rates and ultimately real charging costs. As a result, LMP cannot be directly compared with other pricing scenarios which are based on retail rates. Therefore, we estimate the RT price with eqs 1−3 to ensure that the utility would net revenue at whatever the RT price would be compared to the flat rate and that electricity generation accounts for about 56%[38] the price of electricity. In this way, our RT price both captures the dynamics of the electricity generation distribution and transmission in the system while maintaining identical level of revenue for the operating utility under flat rate strategy. Nonhome charging prices are the same across the three scenarios. Charging rates at the public level 2 stations is based on the electricity rates for small business set by SDG&E Company. Direct-current (DC) fast charging rates refers to the "Pay As You Go" rates of EVGo (a charging network provider) for the San Diego area[39]

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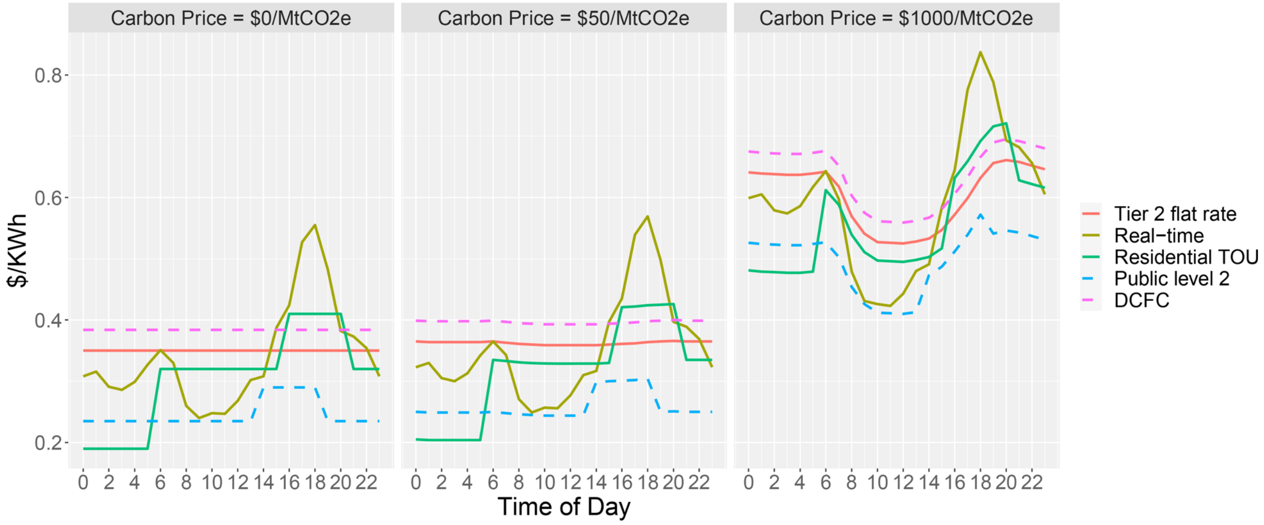

Figure 1. Pricing strategies for charging in the hourly manner.

$$\mathrm{RT}_t = (\mathrm{LMP}_t + d) \times c \tag{1}$$

$$\sum_t^{24} (RT_t \times \mathrm{electricity}_t) = \mathrm{FR} \times \sum_t^{24} \mathrm{electricity}_t \tag{2}$$

$$\sum_t^{24} (\mathrm{LMP}_t \times \mathrm{electricity}_t) \times c = 56\% \times \mathrm{FR} \times \sum_t^{24} \mathrm{electricity}_t \tag{3}$$

where RT_t is the real-time price in time t; $\mathrm{electricity}_t$ is the load of the grid in time t; FR is the flat rate; LMP_t is the locational marginal price in time t; and c and d are fixed coefficients over time.

To investigate the environmental, energy, and economic impacts of internalizing the climate damage, we incorporate two carbon prices into the total cost. We utilize a social cost of carbon (SCC) of \$50/MtCO$_2$e[40] (in 2020 dollars) and a carbon price of \$1000/MtCO$_2$e for calculating climate change damages. While such a high pricing level of carbon does not indicate any realistic policy implementation, we demonstrate the effect of the extreme case as well as the trend of potential change of charging behavior. The total social cost, which is the sum of charging cost, infrastructure cost, and environmental damage, indicates the total cost that the whole society needs to pay for the charging system.

Figure 1 compares the pricing strategies for charging in our model. In the base cases (carbon price = 0), joining the residential EV-TOU plan of SDG&E is more economical if avoiding home charging during 16:00 to 20:00, when tier two residential flat rate is lower, for BEV drivers. Real-time pricing reflects the temporal change of electricity with trend aligning with its generation and transmission costs. Compared to the residential strategies, DCFC has the highest pricing most of the day except during 15:00 to 20:00, when residential TOU and RT reach the peak pricing. Public level 2 pricing is cheaper than any other strategies except during the lowest pricing period of residential TOU, which is between midnight and 5:00. In the cases where a carbon price exists, charging during the daytime period when emission factors are lower becomes more attractive, and the relative prices for home vs nonhome charging change accordingly.

EV Charging Optimization. The EV charging optimization platform is based on our IEVCO model,[29] which is formulated as follows: there are n EV drivers (i = {1, 2, 3, ..., n}), each deciding the amount of time to recharge the vehicle in each of their available time slots t among m regions (r = {1, 2, ..., m}), based on their daily activity patterns. The objective is to minimize total costs with respect to the home and nonhome charging time during a specific time slots in certain region for each BEV driver, as well as the number of home and nonhome chargers. The total system cost, which, in the base pricing scenarios, is the sum of costs from fulfilling the charging demand of BEV owners and building the charging stations, reflects the expenditure that we need at least to afford in constructing and running the charging infrastructure system. When internalizing the climate damage, the total cost should also include the associated carbon cost and the total cost becomes the total social cost, which indicates the total cost that the whole society need to pay for the charging system. The objective function for our model is provided in eq 4

$$\begin{aligned}
&\mathrm{Min}_{\mathrm{wrt} x_{\mathrm{irtl}}^{\mathrm{homeTime}}, x_{\mathrm{irtl}}^{\mathrm{nonhomeTime}}, x_{\mathrm{rl}}^{\mathrm{homeCharger}}, x_{\mathrm{rl}}^{\mathrm{nonhomeCharger}}} y^{\mathrm{totalcost}} \\
&\quad = 365 \sum_i \sum_r \sum_t \sum_l w_i [(c_{\mathrm{tl}}^{\mathrm{homeChargingPrice}} + c^{\mathrm{carbonPrice}} g_t) \\
&\qquad x_{\mathrm{itrl}}^{\mathrm{homeTime}} p_l^{\mathrm{homePower}} + (c_{\mathrm{tl}}^{\mathrm{nonhomeChargingPrice}} \\
&\qquad + c^{\mathrm{carbonPrice}} g_t) x_{\mathrm{itrl}}^{\mathrm{nonhomeTime}} p_l^{\mathrm{nonhomePower}}] \\
&\qquad + \sum_r \sum_l (c_l^{\mathrm{homeCharger}} x_{\mathrm{rl}}^{\mathrm{homeCharger}} \\
&\qquad + c_l^{\mathrm{nonhomeCharger}} x_{\mathrm{rl}}^{\mathrm{nonhomeCharger}})
\end{aligned} \tag{4}$$

where $y^{\mathrm{totalCost}}$ is total costs; $x_{\mathrm{irtl}}^{\mathrm{homeTime}}$ and $x_{\mathrm{irtl}}^{\mathrm{nonhomeTime}}$ are the home and nonhome charging time during a specific time slot t in region r with level l charger for BEV driver i; $x_{\mathrm{rl}}^{\mathrm{homeCharger}}$ and $x_{\mathrm{rl}}^{\mathrm{nonhomeCharger}}$ are the number of level l chargers being built in region r; $c_{\mathrm{tl}}^{\mathrm{homeChargingPrice}}$ and $c_{\mathrm{tl}}^{\mathrm{nonhomeChargingPrice}}$ are the price to charge during time t with level l chargers, and $p_l^{\mathrm{homePower}}$ and $p_l^{\mathrm{nonhomePower}}$ are their power; $c_l^{\mathrm{homeChargerPrice}}$ and $c_l^{\mathrm{nonhomeChargerPrice}}$ are the annualized hardware and installation costs for home and nonhome chargers; $c^{\mathrm{carbonPrice}}$ is the carbon

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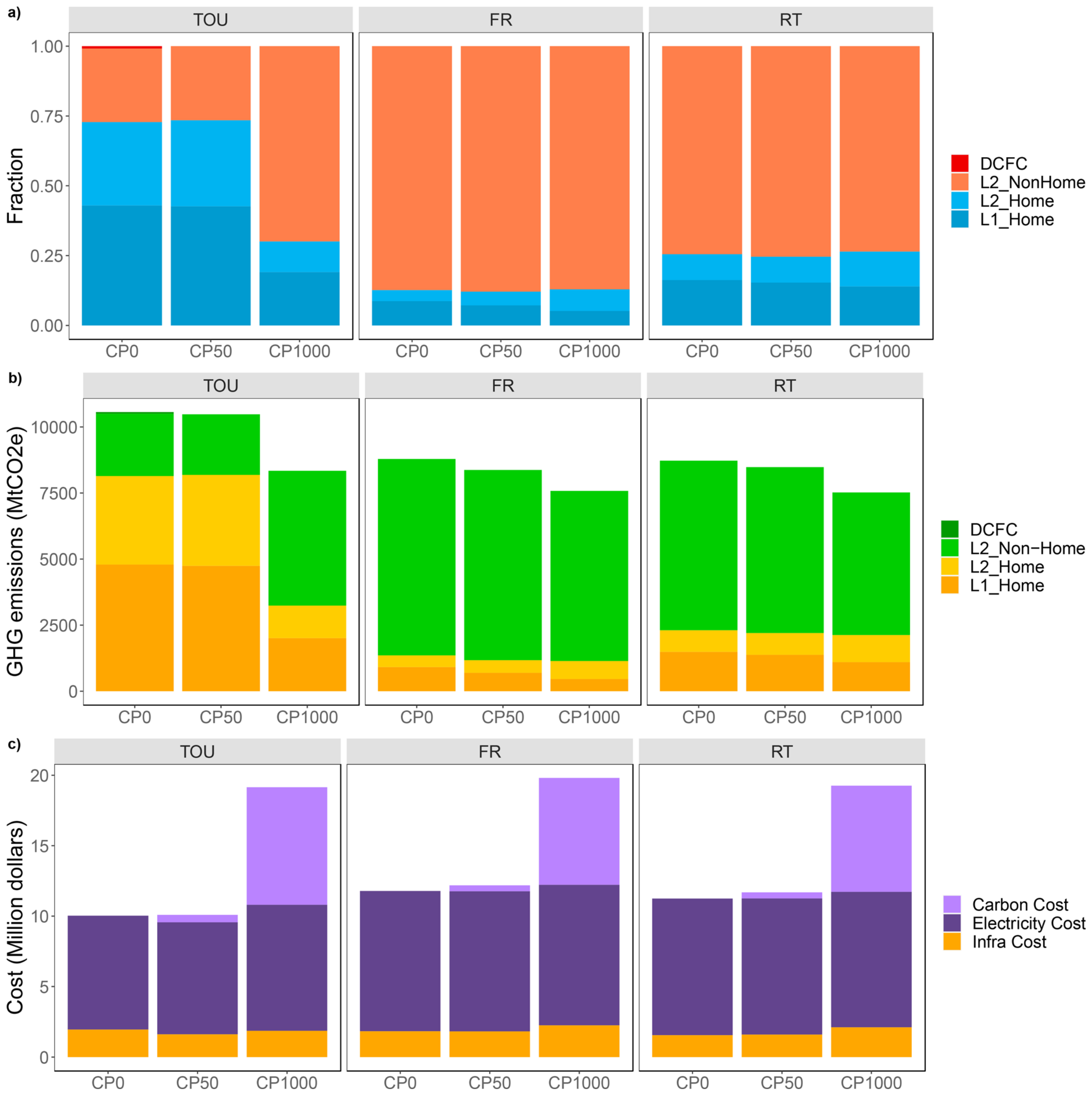

Figure 2. (a) Energy impacts,(b) GHG impacts, and (c) cost breakdown on electricity charging, infrastructure installation, and climate change damage as carbon price increases.

price; g_t is the 2019 average GHG intensity of electricity in CAISO;[41] and w_i is the weight of sample individual i. The total cost is on an annual base to make the three cost components consistent.

To capture the charging behaviors of BEV drivers more precisely, we also consider the price elasticity of charging demand of BEV drivers. Based on a recent study that observes a 3.6% decrease in probability of home charging while a 1.5% increase in the probability of workplace charging when the cost of home charging increases by 10% from a cohort survey of BEV owners in California,[42] our model uses −0.36 and 0.15 as the pricing elasticities of charging demand for home and nonhome charging respectively with the tier two flat rate of SDG&E as the baseline. Then the new charging demand for each BEV driver in each region $x_{\text{ir}}^{\text{chargingDemand}}$ under each alternative pricing scenario could be expressed in eq 5

$$x_{\text{ir}}^{\text{chargingDemand}} = \sum_t \sum_l x_{\text{itl}}^{\text{nonhomeTime,flatRate}} p_l^{\text{nonhomePower}} \left[1 + \frac{\beta^{\text{nonhome}} (c_{\text{tl}}^{\text{homeChargingPrice}} + c^{\text{carbonPrice}} g_t - c_{\text{tl}}^{\text{flatRate}})}{c_{\text{tl}}^{\text{flatRate}}} \right] + \sum_t \sum_l x_{\text{itl}}^{\text{homeTime,flatRate}} p_l^{\text{homePower}} \left[1 + \frac{\beta^{\text{home}} (c_{\text{tl}}^{\text{homeChargingPrice}} + c^{\text{carbonPrice}} g_t - c_{\text{tl}}^{\text{flatRate}})}{c_{\text{tl}}^{\text{flatRate}}} \right], \forall\ ir \quad (5)$$

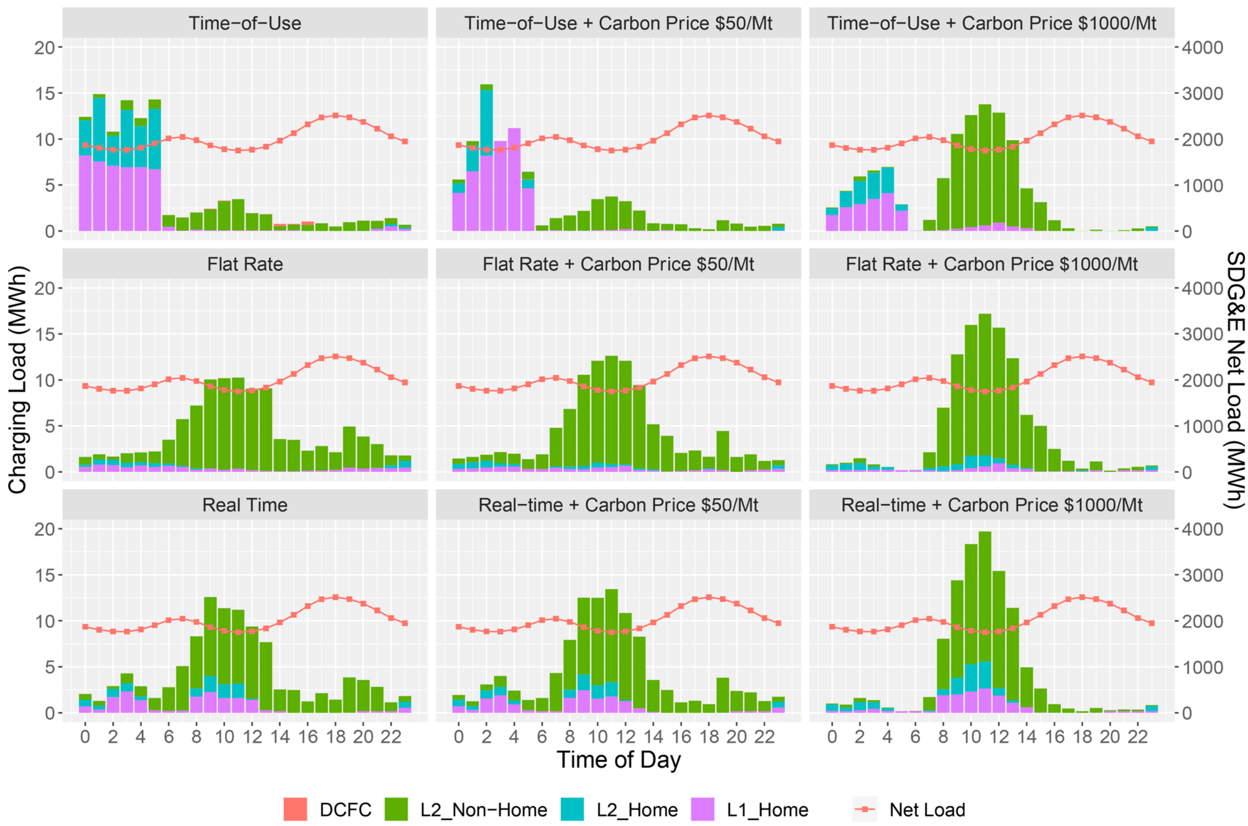

Figure 3. Temporal change in charging loads of the three charge pricing scenarios with carbon price change. Cluster effect of carbon prices is observed in all three base scenarios, but the magnitude of the effect varies.

where $x_{itl}^{\text{nonhomeTime,flatRate}}$ and $x_{itl}^{\text{homeTime,flatRate}}$ are the nonhome and home charging time for individual i during time t at level l charger under the baseline tier two flat rate scenario; β^{home} and β^{nonhome} are the pricing elasticity of charging demand for home and nonhome locations; $c_{tl}^{\text{homeChargingPrice}}$ and c_{tl}^{flatRate} are the customers' alternative home charging price and the tier two flat rate during time t with level l charger, respectively.

The model is subject to major constraints: first, charging activities happening both at home and nonhome locations should meet the average daily energy demand of BEV driver i; second, charging time should be within the available dwelling time slots, which means charging activities should happen only when the drivers are available; finally, nonhome chargers are shared among users while each home charger is exclusive to an individual. Major constraints for the optimization model are shown in Supporting Information Table S2, and more details of the optimization platform can be found in the paper.[29] The optimization model is a Mixed Integer Linear Programming (MILP) problem, which we solve in GAMS with the Cplex solver.

Impact Evaluation. Evaluating the impacts of various charging pricing strategies relies on other information from the grid side. Specifically, the GHG impacts of charging are based on the hour-of-day average emissions factors for CAISO in 2019 (Supporting Information Figure S3). Since the extra charging load is relatively small compared to the overall load of the grid,[43] we do not account for any changes in emission factor due to vehicle electrification. The "green" period from 7:00 to 18:00 with low electricity carbon intensity aligns with the second off-peak period in net load of the grid, indicating a "win−win" for reducing the risk of the grid and GHG impacts of charging together with appropriate charging management strategy through pricing.

RESULTS

Energy and Grid Impact. We investigate how different charging pricing scenarios may change the mix of energy required for different levels of home and nonhome charging, as well as the temporal impacts to the electricity grid. Figure 2a shows the results for the energy requirement from BEV drivers under the three base pricing scenarios with a comparison of carbon price changes in San Diego. The total amount of energy demand is fixed (determined by the total travel distance of all drivers in the study domain), but the distribution of charging load over time across the four categories−level 1 home, level 2 home, level 2 nonhome, and DCFC, are totally different according to pricing scenarios. The dynamic charging price and the price elasticity of charging demand in different locations are two main reasons. The dynamic charging prices affect charging behaviors, and different price elasticities for home and nonhome charging changes the charging demand in different locations disproportionally. In the base TOU scenario (without carbon price), level 1 and level 2 home charging contributes to 72.8% of total energy demand. However, the portion of home charging is only 25.5% in the base RT case, and it becomes even lower in the base FR scenario due to the higher residential charging cost compared to charging with public level 2 chargers. We should note that a massive public charging infrastructure system that provide enough availability is necessary under FR and RT scenarios. The required deployment of charging infrastructures under each price scenario could be found in Supporting Information Figure

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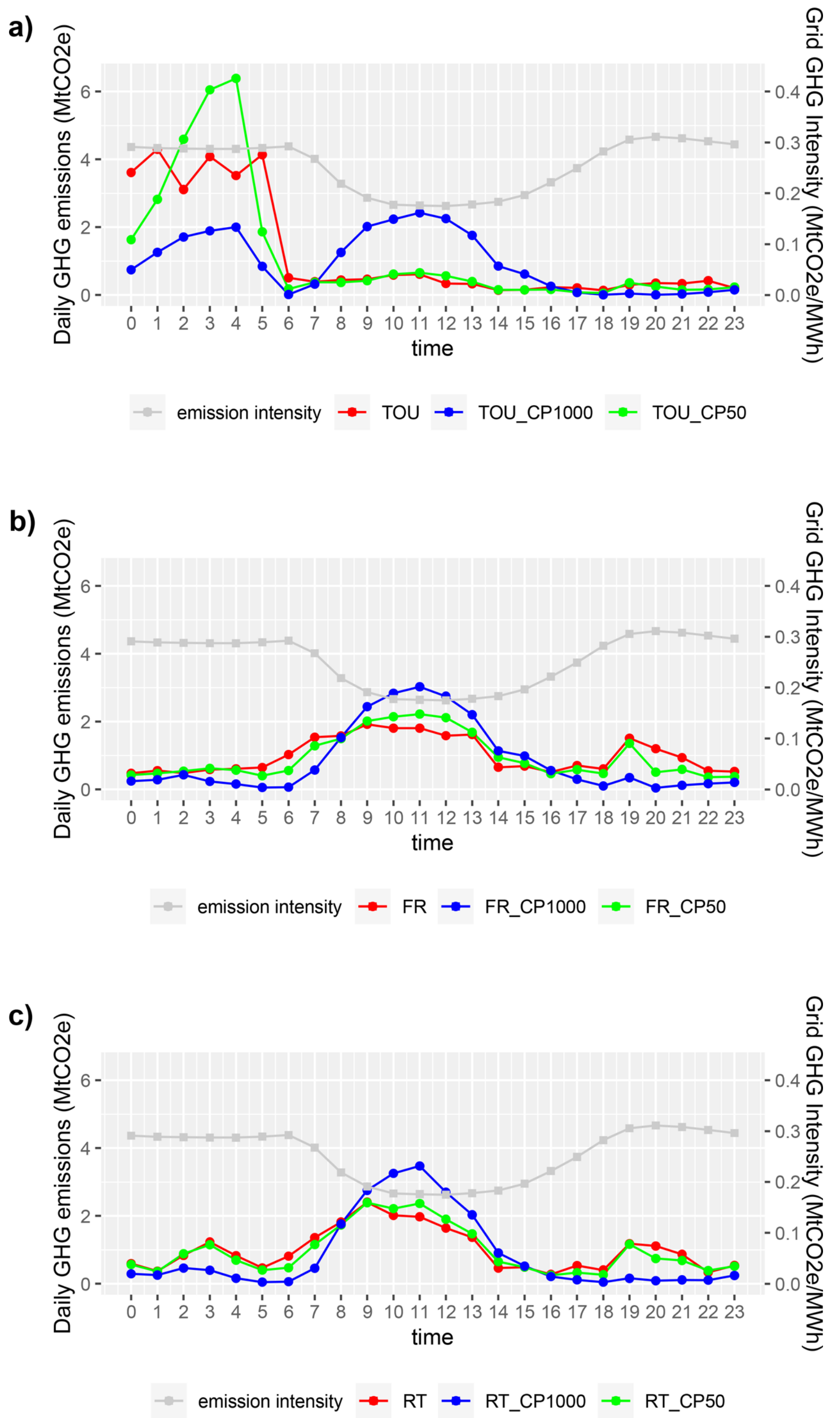

Figure 4. Temporal change in charging emissions with carbon price change for (a) flat rate scenario, (b) real time pricing scenario, and (c) time-of-use scenario.

S4. After internalizing climate change damages by applying carbon rates, the share of nonhome charging in the FR and RT cases has no room to improve even with an extreme high carbon price. An obvious increase from 27.2% to 69.9% in the share of nonhome charging is only witnessed in the case of TOU with a high carbon price of \$1000/$MtCO_2e$, suggesting the maximum potential for shifting overnight home charging (especially level 1 home) to shared public level 2 charging during the day when the GHG intensity of electricity is lower.

We further break down the energy demand by hour-of-day for each of the charging scenarios in Figure 3. In the TOU scenario, level 1 home charging is the major charging strategy, accounting for 48% of the total EV charging demand and dominates the energy requirement from midnight to 5:00 when TOU is always the lowest. However, we still observe a small fraction of nonhome charging during that period. DCFC contributes to charging demand during daytime periods 9:00–11:00 and 13:00–17:00, even when level 2 public charging is always preferable in price, indicating that the empirical travel and dwelling pattern of EV drivers constrains the availability and capacity of pricing management of charging loads. In the case that BEV drivers employ the tier two residential flat rate as home charging price, we are not able to observe a flat home charging load. Instead, the total home charging load from level 1 and level 2 outlets tends to peak in the evening, which emphasizes the importance of considering the staying and travel constraints into the charging strategies optimization again. In the real-time pricing scenario, we see two peaks of home charging: the first one happening during the daytime from 8:00 to 13:00 and a secondary peak during nighttime hours from midnight to 5:00 with level 1 home charging being the main source, aligning with the two off-peak periods of the grid. This indicates the impact of a dynamic electricity rates in managing EV charging loads relative to a flat rate. Among the three base charging scenarios, the local distribution system in San Diego is affected most in the TOU scenario with the extra charging load as high as around 15 MW during 1:00 to 2:00 with the biggest contribution from home charging.

More importantly, we also observe a clustering effect on the charging load profiles by integrating the carbon prices, which makes charging activities more concentrating around daytime hours when the GHG intensity of the grid is lower. We name it as "carbon price clustering effect" in the following paragraphs. We observe the carbon price clustering effects in all the three pricing strategies, but the magnitude of this effects depends heavily on the base pricing strategies. For example, only a carbon price of $50/MtCO2e can shift the home charging load into the daytime hours from 8:00 to 18:00 dramatically in the flat rate scenario, while the increase of home charging load in daytime hours is still limited even under an extreme high carbon price. In the TOU scenario, a carbon price of $50/MtCO2e does not change the share of daytime home charging load, but the extreme high carbon price of $1000/MtCO2e lead to an increase of level 1 home charging during daytime hours from 9:00 to 15:00. Internalizing the climate change damage will not only decrease the environmental impact of EV driving, but also help smooth the grid by shifting EV charging loads toward off-peak hours in the net load profile.

It seems there is a concern that minimizing costs will simply cause individuals to charge their vehicles during times corresponding to the cheapest electricity prices. However, there are multiple signals in the model that may lead to different outcomes. If individuals were to charge over short periods of time (if they do not dwell at a particular location for a long period), this would require substantially more charging infrastructure to be available at multiple locations which would increase costs to the system. It is often more efficient for the model to build infrastructure in locations with long dwell times despite higher charging prices since the costs incurred by installing additional infrastructure often outweigh the increased costs from charging price differentials. In sum, the charging load profile with our optimized charging platform is the result of various determinants including the dynamic electricity price, travel and dwelling constraints, carbon price clustering effect, as well as the relative prices for charging through the exclusive home versus shared nonhome charging.

Climate Change Impact. Figure 2b shows the effect of applying different carbon prices on the environmental outcome for EV charging load. Overall, the environmental impact of EV charging load in San Diego under the base time-of-use scenario is the highest and the real-time pricing scenario is the lowest. They are 20.2% higher and −0.7% lower compared with the annual GHG emissions under the flat rate scenario, which is about 8,787 $MtCO_2e$. Charging behavior of EV drivers is changed when the climate change damage is internalized. The climate change impact from EV charging under TOU scenario with extreme high carbon price of $1000/MtCO2e is similar to that under FR or RT scenario with only a carbon price of $50/MtCO2e. We define GHG mitigation from applying carbon prices as the decrease in GHG emissions under the carbon price scenarios compared to their respective base pricing scenario. We find that the effectiveness of carbon price in mitigating GHG emissions depends on the base pricing strategy largely. When a carbon price of $50/MtCO2e is applied, the total GHG emissions decreases by 0.8%, 4.7% and 2.8% for TOU, FR and RT scenarios respectively, and GHG mitigation expands to 21.0%, 13.7% and 13.8% as carbon price increases to $1000/MtCO2e.

In Figure 4a, the red line, which shows the hourly GHG emissions under the base time-of-use scenario, generally follows the trend of its charging load profile. We do not see an obvious "carbon price cluster effect" in the daytime hours when applying a carbon price of $50/$MtCO_2$e. As the carbon price increases to an extreme value of $1000/$MtCO_2$e, the carbon price cluster effect becomes obvious. The reason is that there is a dramatic shift from overnight home charging toward daytime nonhome charging since the benefit of charging during the low emissions daytime hours offsetting the loss from a relative higher level 2 public charging price. The shapes of hourly emission profile of the base flat rate and real-time scenarios (Figure 4b,c, red lines) are similar in a way that they are generally consistent with the hourly GHG intensity of the grid—daytime charging peak aligning with the off-peak period in GHG intensity. Therefore, the shape of the emission profile in these two scenarios does not change too much after introduction of carbon prices, and an extremely high carbon price of $1000/$MtCO_2$e lowers the secondary peaks of carbon emissions during the nighttime hours and enhances the primary peak in the late morning.

Cost Impact. Figure 2c compares the cost impact among charge pricing scenarios. The flat rate scenario has the highest total costs, which is 11.79 million dollars annually. Real time pricing and time-of-use scenario are 4.5% and 17.5% lower. The higher total cost in the flat rate scenario comes from a higher average charging cost (total charging cost divided by total charging demand), which is $0.26/kWh in the flat rate scenario while about $0.25/kWh and $0.21/kWh in the real-time and time-of-use scenarios. This result implies that the volatility of charging price structure and the flexibility of charging locations provide opportunities for BEV drivers to change their charging behaviors and find the optimal time and locations to charge.

We also see a balance among charging cost, infrastructure cost, and carbon cost under the optimization for all scenarios. Without carbon price, the infrastructure cost in the TOU case is the highest among the three pricing strategies but becomes the lowest after introducing a carbon price of $1000/$MtCO_2$e. This is because nighttime home charging loads shift toward daytime hours with level 2 chargers, resulting in an increase of shared level 2 public chargers and a large decrease of less exclusive home charger. But in the scenario of flat rate with a carbon price of $1000/$MtCO_2$e, the extremely high carbon cost makes charging in the daytime, when the grid GHG intensity is lower, more preferable. As a result, the share of the level 2 home and nonhome chargers increase, and the total infrastructure becomes the highest. Generally, the total carbon cost of the charging system is 0.42 to 0.52 million dollars by

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Table 1. Model Outputs with and without Inclusion of Price Elasticity

		flat rate	FR +CP50	FR +CP1000	RT	RT +CP50	RT +CP1000	TOU	TOU +CP50	TOU +CP1000
Modeling Outputs with Price Elasticity										
energy	home %	12.6%	12.1%	12.9%	**25.5%**	**24.6%**	26.4%	72.8%	**73.5%**	30.1%
	nonhome %	87.4%	87.9%	87.1%	**74.5%**	**75.4%**	73.6%	27.2%	**26.5%**	69.9%
annual GHG (MtCO2e)		8,787	8,372	**7,579**	**8,725**	**8,481**	**7,521**	**10,562**	**10,476**	8,344
total cost (million dollars)		$11.79	$12.19	$19.81	$11.25	$11.69	$19.26	$10.03	**$10.07**	$19.15
Modeling Outputs without Price Elasticity										
energy	home %	12.6%	12.1%	12.9%	**25.6%**	**24.7%**	26.4%	72.8%	**73.7%**	30.1%
	nonhome %	87.4%	87.9%	87.1%	**74.4%**	**75.3%**	73.6%	27.2%	**26.3%**	69.9%
annual GHG (MtCO2e)		8,787	8,372	**7,580**	**8,707**	**8,495**	**7,522**	**10,561**	**10,483**	8,344
total cost (million dollars)		$11.79	$12.19	$19.81	$11.25	$11.69	$19.26	$10.03	**$10.09**	$19.15

implementing a carbon price of \$50/MtCO$_2$e, and 7.52 to 8.34 million dollars with a carbon price of \$1000/MtCO$_2$e.

Effect of Price Elasticity. Price elasticities are unique to the locations, and charging preferences will differ between home and nonhome locations. To better understand the impact of including price elasticity of charging demand, we also run the model without price elasticity of charging demand (in which elasticity equals one in both home and nonhome cases) and compare the model outputs with and without price elasticity in Table 1 below. Although its contribution in shaping the charging load profile is subtle (since the absolute value of price elasticities are low and the charging demand is also constrained by many other factors), we still cannot remove its impact completely since the model outputs are different in some cases which are marked in bold.

DISCUSSION

In this study, we utilize an integrated optimization platform for EV charging infrastructure planning and charging management to investigate the energy, cost, and climate change impacts of three charge pricing scenarios in San Diego: EV time-of-use residential rate, tier two residential flat rate, and real-time price. Additionally, we introduce the climate change damage by applying carbon prices of \$50/MtCO$_2$e and \$1000/MtCO$_2$e in each of the base pricing scenarios.

The results show that the charging load profile with our optimized charging platform is determined by various factors including the dynamic electricity price, price elasticity of charging demand, travel and dwelling constraints, carbon price clustering effect as well as the exclusive home and shared nonhome charging. Price elasticities are unique to the locations—even in the case of a flat rate, charging preferences differ between home and nonhome locations. The model also considers some dynamics of locations since EV owners will spend different amounts of time at different locations. This leads to unique infrastructure deployment decisions which in turn influence the charging behavior of EV drivers.

Level 1 home and level 2 nonhome charging are the two major contributors to EV charging loads in the time-of-use scenario. Level 2 public charging accounts for the largest share in total charging load under flat rate and real-time scenarios with the support of a massive public charging infrastructure system. After internalizing the climate change damage by applying various carbon prices, we observe a carbon price clustering effect, which means charging activities more cluster around daytime hours when the GHG intensity of the grid is lower. Therefore, internalizing the climate change damage will not only decrease the environmental impact of EV driving but also help smooth the grid by shifting EV charging loads toward off-peak hours during the day.

Our research also shows that the GHG impacts of EV charging depends largely on charging price strategies. The total GHG emissions of the charging system in San Diego under the base time-of-use scenario is the highest and the flat rate one and the real time pricing one is 16.8% and 17.4% lower, respectively. We also find that the effectiveness of changing charging behavior by internalizing climate damages depends largely on the base charging price strategy, implying the importance of considering charging price strategies in conjunction with carbon pricing rather than independently in the policymaking process. This result demonstrates that the EV time-of-use pricing scheme in San Diego is problematic in terms of GHG mitigation since it favors overnight home charging too much and only an extremely high carbon price can make a significant improvement. The effectiveness of changing charging behavior through internalizing climate change damage to obtain environmental benefits is a combination of carbon price and base charging price strategy, and the optimization platform will balance among charging price, carbon price, and infrastructure costs. The implications of flexibility of charging behaviors, the relative magnitudes in response to carbon price changes, and the relative potentials for carbon reductions across different pricing strategies are results that would extend across analyses of different EV volumes in the near term.

The model results underestimate the number of DCFC and the associated impacts because we only subsample the EV drivers who have home address within the area of San Diego, failing to consider the charging demand from drivers passing through the study domain. They often have long distance trips, but short dwell times in San Diego and pass-through trips may be a main contributor to extra demand for fast charging. Another limitation of our model is that we assume that individuals within the system have perfect information on the charging behavior of other electric vehicle drivers. This, in turn, will lead to an underestimate of required charging infrastructure since no queueing is required and individuals can guarantee availability of charging to satisfy their charging requirements. Nevertheless, this study still reveals the minimum impacts of the local charging infrastructure system under various charging price strategies. Moreover, the charging strategies under certain pricing scenarios from our model provide a way to manage all the charging activates and install the required charging infrastructures from a social system point of view. The management could be possible through a centralized system that sends signals to electric vehicles to

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notify the right time and place to charge once the technology is available. In this study, we regard the EV drivers as price takers since the extra charging load from existing EV fleet are too small to affect generator dispatching. However, California has set a state target of having 5 million ZEVs on California roads by 2030 and deploying 250,000 charging stations, including 10,000 fast-charging stations, by 2025.[44] The next step in our research is to investigate the potential impacts of charge pricing mechanism in future scenarios in which the EV fleet is large.

This paper provides new insights to both policymakers and researchers on how to evaluate the impacts of various charge pricing strategies with an integrated optimization model which assesses the charging behaviors and planning for the required charging infrastructure system simultaneously. Results of this research not only provide policy guidance for charging management and infrastructure planning in San Diego, CA, but may be applicable to other regions for which similar data are available. However, we recommend that future studies with different study domains, especially those without empirical data on the price elasticity, should take the uncertainties on the elasticity into consideration.

Compared to previous studies, this study is the first of this kind to combine both individual mobility dynamics and charging pricing mechanism and consider charging activities management and infrastructure planning together in a comprehensive optimization to explore the economic, energy, and environmental impacts. Considering the price elasticity of EV charging demand into the price strategy impacts analysis is another innovation aspect of our study. This study is based on the mobility of current light-duty vehicle drivers, but it can be easily converted to new mobility with changing vehicle occupation rates under different scenarios such as shared mobility.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c06231.

> Modeling framework for the integrated pricing strategy analysis (Figure S1); daily dwelling locations and travel distance of BEV drivers in San Diego (Figure S2); assumptions on the costs and power for chargers (Table S1); major constraints and parameters for the optimization model (Table S2); GHG emission intensities and load profile of the grid in the hourly manner (Figure S3); charging infrastructure deployment (Figures S4 and S5); sensitivity analysis (Table S3, Figures S6–S9) (PDF)

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Xinwei Li, Alan Jenn; data collection: Xinwei Li; analysis and interpretation of results: Xinwei Li, Alan Jenn; draft manuscript preparation: Xinwei Li, Alan Jenn. All authors reviewed the results and approved the final version of the manuscript.

Notes

The authors declare no competing financial interest.

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