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Assessing Californians' awareness of their daily electricity use patterns

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The timing of electricity consumption is increasingly important for grid operations. In response, households are being encouraged to alter their daily usage patterns through demand response and time-varying pricing, although it is unknown if they are aware of these patterns. Here we introduce an energy literacy concept, 'load shape awareness', and apply it to a sample of California residents (n = 186) who provided their household's hourly electricity data and completed an energy use questionnaire. Choosing from four prominent load shape designations, half of respondents (51%) correctly identified their dominant load shape before COVID-19 shelter-in-place (SIP) orders while only one-third (31%) did so during SIP orders. Those aware of their load shape were more likely to have chosen evening peak, the most frequent dominant shape in the electricity data. Our work provides proof of principle for the load shape awareness concept, which could prove useful in designing energy conservation interventions and helping consumers adapt to an evolving energy system.

In the transition to a smarter, cleaner and more reliable grid, the alignment of electricity supply and demand will become even more critical[1–3]. While renewables, such as solar and wind, are essential to decarbonizing the energy sector and slowing global climate change, they are variable and intermittent in their production, adding complexity to forecasting and other grid operations[4,5]. At the same time, the tighter coupling of the electrical grid to the transportation sector and the push for more electrification of household appliances will alter consumption patterns and increase society's need for a reliable and resilient power system[6–8]. Expanding deployment of distributed energy resources, such as wind, solar and storage, and technical advances in grid information systems and infrastructure can ease some of these burdens; however, the challenge of meeting demand with clean sources of electricity supply in every hour across every day will probably remain for years to come.

Though the timing and magnitude of many renewable production sources are constrained by factors such as available sunlight and wind, demand for electricity does not have such rigid physical constraints. To take advantage of potential flexibility in electricity demand, utilities are implementing programmes designed to encourage changes in demand patterns that are beneficial to the grid, with increasing focus on residential users as a source of flexibility through Demand Response (DR) programmes[9,10]. These DR programmes operate through various mechanisms, such as variable and critical peak pricing, and are intended to induce changes in residential electricity demand that will lessen the need for non-renewable, dirtier and/or more expensive sources of electricity generation during peak demand periods. As a result, households enrolled in DR programmes, such as time-of-use pricing programmes, face variable electricity prices throughout the day, often higher prices when grid demand is at its peak—for example, on weekdays spanning from late afternoon to evening—and lower prices during off-peak periods. In California, some utilities have already begun to make time-of-use pricing the default option for residential customers[11].

However, it is unknown if household members are aware of their daily electricity use patterns, even though they are now being urged to make financial decisions and change household electricity use behaviours related to their time-based electricity consumption. Examples of these decisions include: opting out of time-of-use pricing altogether,

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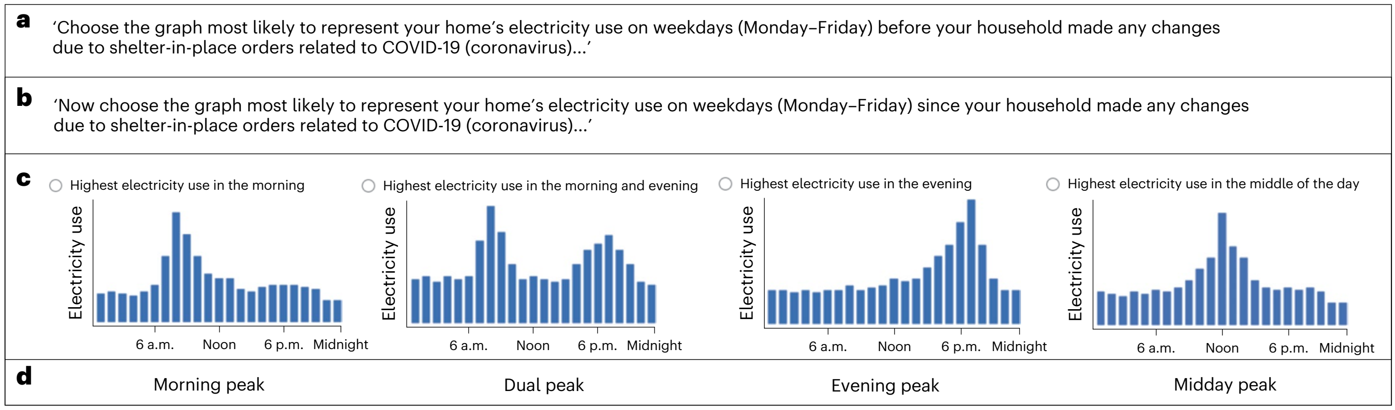

Fig. 1 | Questionnaire with response choices for perceived weekday electricity use patterns. a, The survey question that assesses perceived dominant load shape before SIP. **b**, The survey question that assesses perceived dominant load shape during SIP. **c**, For **a** and **b**, participants chose one of the load shapes from **c** as a question response. For **b**, participants also had the option of choosing 'My household has not made any changes due to shelter-in-place orders related to COVID-19 (coronavirus)'. **d**, The load shape designation assigned to each response choice from **c** for comparison to observed load shapes.

selecting among various time-of-use rate pricing programmes and responding to critical peak hours; taking advantage of incentives for residential solar, storage and electrical vehicle adoption; adopting smart home devices; enrolling in programmes that afford utilities some control over their appliance use; and managing the day-to-day timing of large loads (for example, electric vehicle charging, laundry and so on).

Scholars have delineated many different types of energy literacy, including device (that is, knowledge of appliance- or device-level energy consumption), action (that is, knowledge of the energy savings associated with particular actions) and financial (that is, knowledge about monetary savings associated with energy savings investments) energy literacies[12–15]. 'Multi-faceted' energy literacy incorporates broader concepts in addition to these more 'practical' measures—including cognitive or content knowledge (for example, about sources of electricity generation, societal impacts), affective components (for example, attitudes towards energy conservation, efficacy) and behavioural aspects (for example, energy-saving habits, advocacy)[15–19]. Across all types, findings indicate generally low levels of energy literacy, and none measure time-based electricity consumption awareness.

Moreover, few studies have linked energy literacy to actual contextualized energy use within the home[13]. When they have, links between energy literacy and energy use have been inconclusive, except for action energy literacy[15]. Previous literature has rarely considered awareness about household energy consumption patterns and the intensity and timing of usage patterns across the day, although an understanding of these concepts is essential for households to effectively engage in a transitioning energy system that is increasingly focused on *when* energy is used. It could also prove useful in designing effective energy conservation interventions by encouraging connections between the timing of activities in the home and electricity consumption.

To address this gap, we introduce an energy literacy concept, 'load shape awareness', and provide an initial proof of principle or a demonstration of its potential for future research and applications. To do so, we apply data from a sample of Californian residents (242 total participants, 186 with complete data; Methods provide more detail on our sample) who completed a questionnaire about the timing of their household's electricity use and provided access to their household's smart meter data. The load shape—which captures temporal (typically hourly) variation in energy use—is a critical unit of measurement for understanding time-related usage of electricity[20–22]. For example, previous research conducted in California identified that while there is substantial variability in daily load shapes within and across households, the most frequently occurring residential daily load shape is evening peak[21]. This frequent residential load shape coincides with California's system peak period and is a motivation for why utilities have begun charging higher prices to residential customers during the evening (for example, time of use)[23].

To assess our respondents' load shape awareness, we compared survey questionnaire responses about perceived dominant daily load shapes (morning peak, evening peak, midday peak and dual peak; Fig. 1) to observed daily load shapes calculated from their smart meter data. When these shapes align, we consider the participant as having awareness about their load shape. Due to the timing of our survey, we were also able to assess how a disruptive event that had broad impacts on nearly every household in California, shelter-in-place (SIP) orders in response to the COVID-19 pandemic, influenced perceptions of energy use patterns in the home. Past research has highlighted the importance of disruptive life events (for example, moving, birth of a child) in altering daily energy usage patterns[24]. COVID-19 and associated government restrictions on social interactions represent a disruption that affected many people at the same time, and recent research has explored the implications of this disruption on energy consumption more generally[25]. Here we explore how this disruption impacted our respondent's load shape awareness.

Perceived dominant load shapes before and during SIP orders

Exploring respondent perceptions of their daily load shape patterns based on their survey responses (Fig. 1), we see that before SIP, most respondents (61.3%) reported evening peak as their dominant weekday load shape (Fig. 2). However, during the SIP period, respondents chose dual peak (39.8%) as their household's most dominant peak shape, with fewer choosing evening peak (33.9%). Figure 2 shows that many of these respondents who had chosen evening peak to characterize their load shape before the SIP period selected either dual or midday peaks to characterize their load shape during the SIP period.

Observed dominant load shapes before and during SIP orders

Identifying a household's observed dominant daily load shape using electricity data will always be somewhat sensitive to the particular method being applied with no definitive ground truth to compare against. We therefore attempted several different methods for determining a household's observed load shape (Methods). In the approach we present here, which was both feasible with a smaller sample and best aligned with our survey question, we normalized household daily

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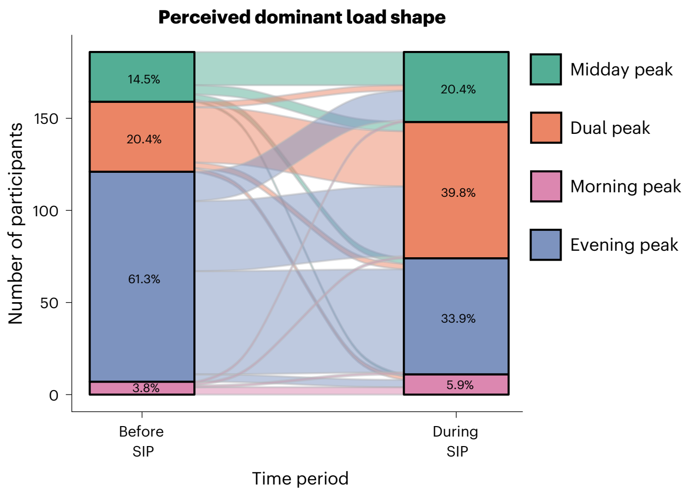

Fig. 2 | Before- and during-SIP comparison using perceived load shapes. Perceived dominant load shapes were self-reported by a participant from each household. The width of the paths corresponds to the proportion of participants with complete load shape perception and household electricity data ($n = 186$).

load profiles and passed them through a peak detection algorithm. This identified common shape characteristics, particularly the timing of peak usage, which was then matched to one of four load shapes described in the questionnaire. The most frequently occurring load shape for each household was then designated as the observed dominant shape (Methods).

A comparison of observed dominant load shapes during the SIP period (Fig. 3) reveals far more temporal stability in dominant load shapes before and during the SIP period than our participants perceived, with the most notable change in load shape categories occurring for the midday peak, which doubled in size among our participants (7.5% before SIP versus 16.7% during SIP).

Due to variability in load shape patterns within households and across time, the dominant observed load shape may have a very similar prevalence to another load shape that the respondent perceived as their dominant shape. Thus, we generated a heat map to display the daily percentage of each load shape for each household in the before- and during-SIP periods (Fig. 4). Across all households, we find the percentage of evening peaking load shapes appears the highest both before and during SIP, which is further reinforced by the high percentages of this shape within the evening peak dominant load shape category. Moreover, across all dominate load shape categories, there are few instances where there is a 'close second' to the dominant shape, with 95% of all households having a dominant shape that comprises at least one-third (33.8%) of a household's total daily shapes. For a description of the distributional characteristics of observed load shapes before- and during-SIP periods and dominant load shape distributions, see Supplementary Note 2.

Assessing load shape awareness

We next assess load shape awareness by comparing whether the load shape that the respondent perceived as dominant during weekdays aligned with their observed dominant weekday load shape derived using their household's electricity data (Fig. 5). For the before-SIP period, approximately half of respondents (51.1%) were aware of their dominant weekday load shape. However, during the SIP period, respondent load shape awareness was substantially lower at one-third (30.6%).

Exploring further (Fig. 6a), we find that in the before-SIP period, those who were aware of their load shape tended to have an evening peak as their observed dominant load shape (86%). For a majority of respondents who thought their household had dual peaking load shapes, we observed evening peaks (76%). In contrast, for only a few respondents who thought they had midday peaks did we observe this load shape (19%).

During the SIP period, a much larger mismatch existed in perceived and observed dominant load shapes (Fig. 6b). The majority of respondents perceived a dual peak, followed by evening peak, then midday peak and morning peak. However, in terms of observed load shapes, as in the before-SIP period, our analysis of household electricity data suggested that a majority of dominant load shapes were evening peak during the SIP period. Many respondents in the during-SIP period thus did not have alignment between their perceived and observed dominant load shapes, resulting in lower overall load shape awareness during SIP.

Participant characteristics and load shape awareness

We also consider the relationship between individual-level and household-level characteristics of participants (for example, gender, age, income, education, occupancy, electricity rate plan and home ownership) and their load shape awareness for both before- and during-SIP periods. For the individual- and household-level characteristics that we were able to test, one was statistically significant: respondent gender in the before-SIP period. We found that in the before-SIP period, females were more likely to be aware of their load shape compared with males/prefer to self-describe (female 56.1% correct; male/prefer to self-describe 38.6% correct; odds ratio = 2.0247; 95% CI = (1.0221, 4.0773), $P < 0.0371$). It is important to note that the gender balance in our sample does not represent the population, with two-thirds of respondents identifying as female. The results of these and other alternative tests can be found in Supplementary Note 3. In general, our findings suggest that the demographic and household characteristics we explored were not good predictors of load shape awareness. In addition to bivariate analysis, as a robustness check, we also conducted more complex analysis, including binary logistic regression modelling, and did not observe any appreciable differences in the findings.

Discussion

We compared perceived and observed energy use patterns to provide proof of principle for a proposed energy literacy concept—load shape awareness. Existing measures of energy literacy tend to focus on more general energy concepts related to device consumption, savings from

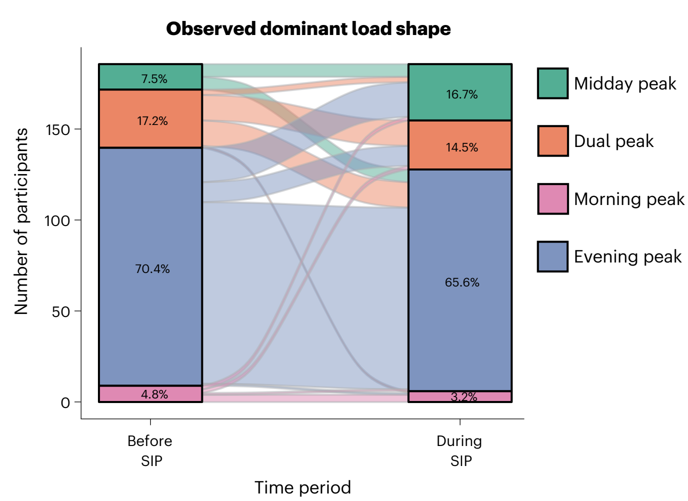

Fig. 3 | Before- and during-SIP comparison using observed dominant load shapes. Observed dominant load shapes were derived using hourly electricity data from households. The width of the paths corresponds to the proportion of participants with complete load shape perception and household electricity data ($n = 186$).

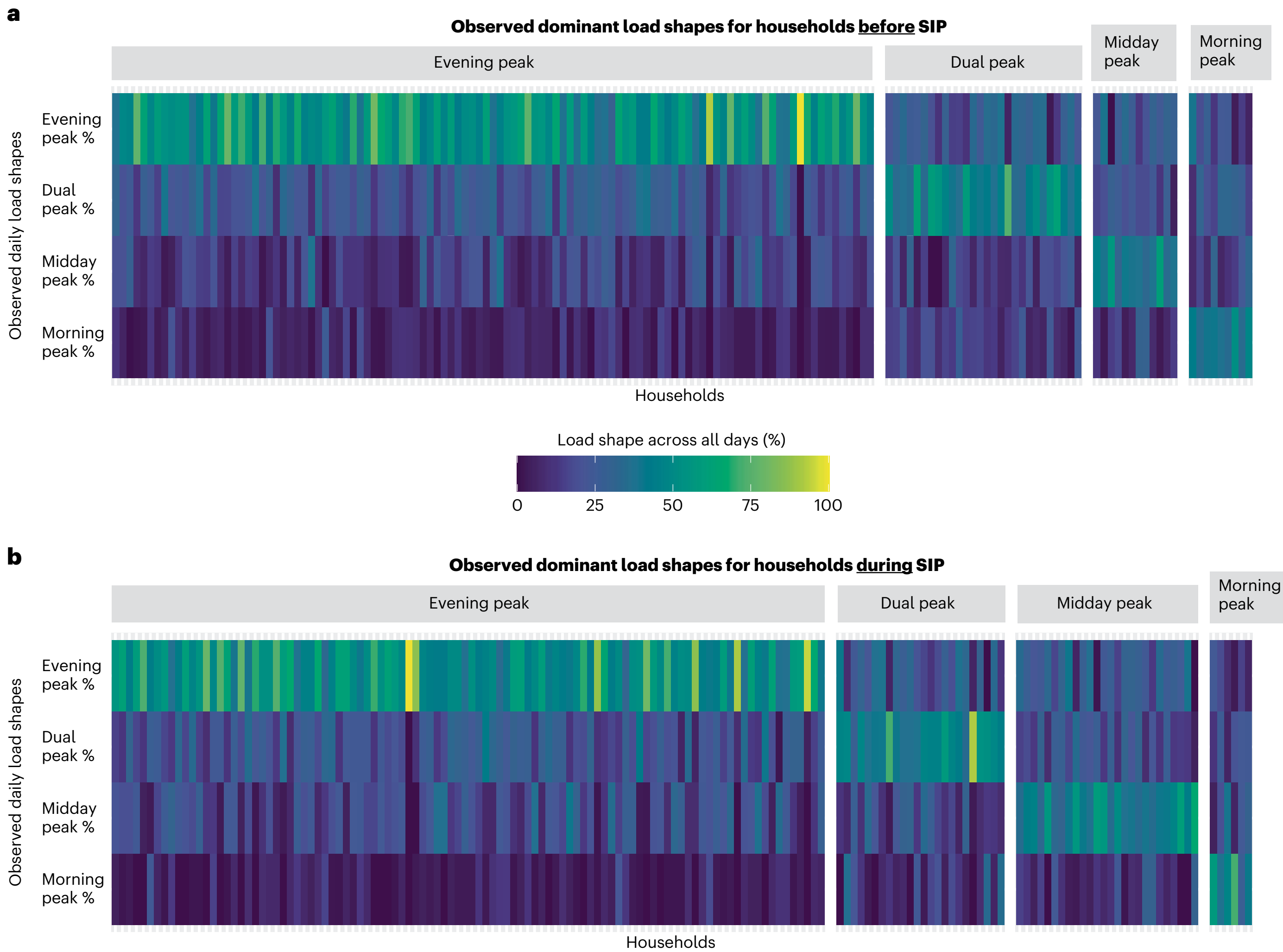

Fig. 4 | Summaries of daily household load shapes before and during SIP. Heat map displays the percentage of morning peak, dual peak, evening peak and midday peak load shapes observed for each household. Each column in the heat map represents a household with complete load shape perception and electricity data ($n = 186$) and each row a load shape designation. Lighter colours correspond to higher percentages of daily load shapes for the weekdays during that period, darker colours correspond to lower percentages of weekday load shapes. **a**,**b**, The household's observed dominant load shape in the period before SIP (**a**) and during SIP (**b**).

particular actions, financial considerations, behavioural choices, attitudes towards conservation and system-level understandings about energy generation. Few studies of energy literacy connect to actual contextualized household energy usage data[13,26]. None of these conceptualizations account for a temporal understanding of electricity use patterns, which would allow consumers to more effectively engage with a rapidly evolving electricity system. This is important for understanding pricing initiatives by utilities, in particular, the selection of a favourable time-varying pricing plan from available options. Load shape awareness could also prove useful in energy conservation interventions, as it incorporates several important aspects of consumption, including both peak and base load, which, when connected to knowledge about household activities, can provide a clear pathway to energy savings. We were also able to compare awareness levels before and during a period of intense disruption in daily lives due to the COVID-19 pandemic and associated restrictions.

For the before-SIP period, approximately half of respondents were able to correctly identify their dominant energy use pattern; however, this was mostly the case for respondents who chose evening peak—which was also the dominant load shape in our respondents' smart meter data, both before and during the SIP period. However, for the during-SIP period, respondents had more difficulty correctly identifying their dominant load shapes, with approximately one-third identifying their dominant use pattern.

Energy literacy studies have generally found low levels of energy literacy across many different conceptualizations[12,13,15–17,26]. As a comparison, when asked about their monthly energy expenditures, 44% of Dutch respondents in a representative survey had 'no idea' about how much they paid, and only 60% correctly answered an energy-related financial literacy question[26]. Across an 11-item energy knowledge index, most respondents from a representative sample of Americans answered less than 60% of the items correctly, and, for three items focused on energy bill interpretations, only 27% answered all correctly[19]. Thus, our findings are on par with other measures of energy literacy. Moreover, given the relative recency of data availability to consumers about their daily electricity usage patterns via smart meters, high levels of load shape awareness should not necessarily be expected. It is worth noting that our participants had to know their online utility account login information to participate in the study, which may not be the case for many utility customers. Our participants may then have more exposure to their household's usage data than the average customer, and thus, we might expect them to be more aware of their

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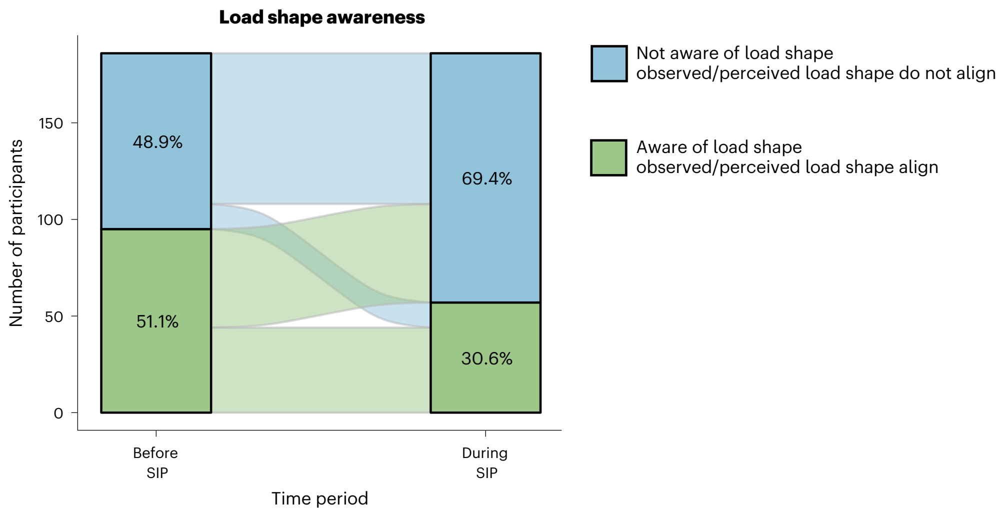

Fig. 5 | Load shape awareness among participants. Load shape awareness is generated by comparing the participant's survey responses with their household's hourly electricity data. The width of the paths corresponds to the proportion of participants with complete load shape perception and household electricity data ($n = 186$).

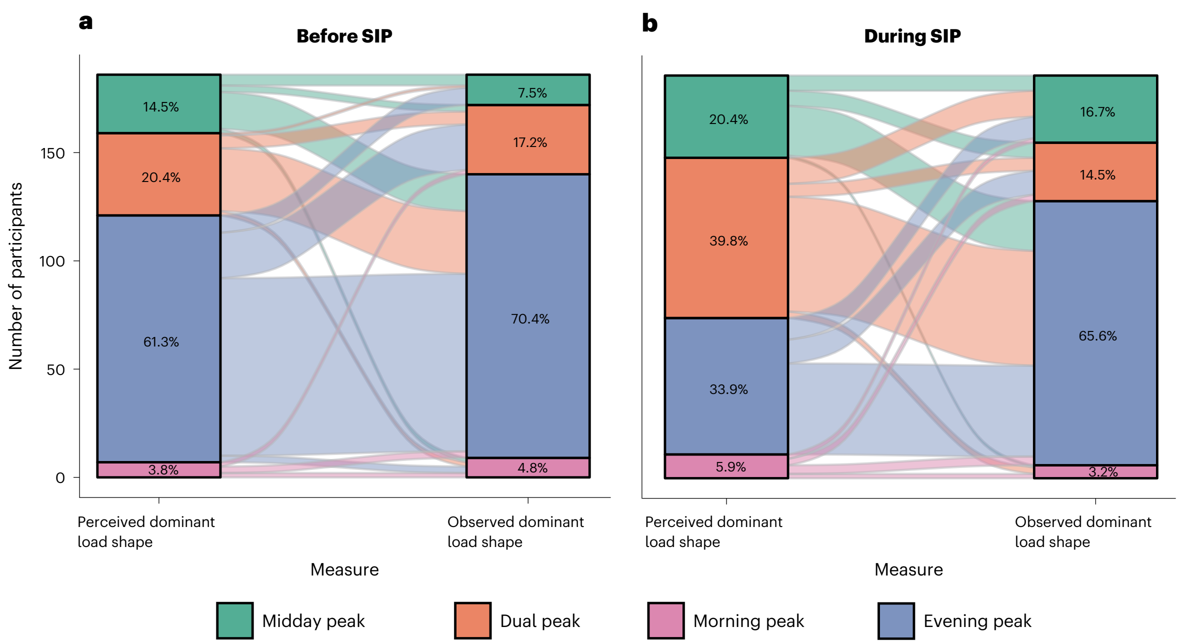

Fig. 6 | Perceived and observed dominant load shape comparison before and during SIP. a, Observed dominant load shapes that were derived using hourly electricity data from participant households. **b**, Perceived dominant load shapes that were self-reported by a participant from each household. The width of the paths corresponds to the proportion of participants with complete load shape perception and household electricity data ($n = 186$).

load shapes. Additional research using a representative sample of participants would prove enlightening in this respect.

As time-of-use pricing becomes more widespread, consumers may be forced to become more aware of their load shapes to avoid higher bills, though we did not find a link between participants who reported being charged time-of-use rates and load shape awareness. Because such variable pricing schemes may have disproportionate impacts on already vulnerable populations[10], building load shape awareness should be a priority as utilities move to implement such policies.

In many ways, our conceptualization of load shape awareness responds to calls from scholars to create more practical measures of energy literacy that do not require people to become 'human calculators…accurately estimating how much energy every activity uses' but instead understand general consumption patterns and actions that are most effective for reducing carbon emissions and facilitating system-level changes[27]. Additional research aimed at understanding the relationship between our load shape-awareness measure and other energy literacy concepts, in particular, action energy literacy, will be critical to establish evidence of discriminant validity (that is, distinctness of our concept). What is clear is that, for both practical and theoretical reasons, energy literacy researchers need to consider and possibly adjust major concepts to incorporate time-based energy use considerations and determine if, how and why these may align or differ from existing energy literacy concepts.

In terms of the differences in respondent accuracy before and during SIP orders, such findings could have several explanations. First, in assessing the changes that their household experienced during SIP orders, respondents may have felt these changes would be more evident in their electricity use patterns. A second explanation relates to the structure of the survey instrument, which could have made respondents more likely to select a response in the during-SIP period that was different from the before-SIP period, as these questions were asked in the same sequence and not randomized. Randomization of the load shape choices, which we did not implement in this study, could help reduce the potential for response order bias. We also provided respondents with only four options for load shapes. More load shape options, such as a flat shape or even the option to 'draw' their own load shape, could be considered in future research. Relatedly, first assessing whether respondents were aware of their load shape (that is, self-reported load shape awareness) before asking about load shape perceptions could be used to help disentangle some of the variation in respondent accuracy. While it is difficult to unpack which explanation is most prominent, such findings suggest that assessing differences in energy use patterns during times of disruption—whether they be SIP orders, new household members (such as infants) or a change in employment schedules (such as retirement)—could be particularly challenging.

The primary limitation of our study is the sample due to its size and construction using purposive, rather than probability-based, elicitation methods. Our findings should thus be interpreted as exploratory and are not generalizable or representative of the California population. With respect to the few studies that have linked residential electricity use with surveys[28–31], however, our sample is commensurate with, or exceeds, extant datasets. Indeed, collecting smart meter data that is linked to individual survey respondents is an on-going challenge but may become easier as advanced metering infrastructure becomes more commonplace. Apart from obtaining access to the energy data, which in and of itself can be difficult, there are also issues with electricity data quality and scale, varying from incomplete or missing data to households living at their address for only a short time period and lacking a longer record of historical data. Some of these sample size limitations may have contributed to our challenges in linking other respondent characteristics to load shape awareness. Another limitation and direction for future research is to not only consider electricity usage but other energy sources, such as natural gas, and even other resources, such as water. While deployment of smart meters for these other consumptive resources are behind that of electricity usage, it could nonetheless be an important direction for future research to develop an even more comprehensive understanding of temporal consumption patterns in the home.

When we tried to relate load shape awareness to household or sociodemographic characteristics, we found statistically significant relationships only with gender. Women were more likely to be aware of their load shape in the before-SIP period. Why we did not find more statistically significant relationships to demographic or household characteristics could be due to our small size or that these relationships do not exist. Our finding of higher load shape awareness among women is interesting given past research. Women have typically been found to have lower levels of energy literacy, particularly financial energy literacy, than men. Yet they also tend to report more willingness to engage in energy-saving behaviour, involvement in more energy-using activities in the home and are more likely to pay bills[32–36]. It could be that women are more aware of their electricity consumption patterns—which are more directly tied to actual behaviours in the home—because they are, on average, more likely to be engaged in these activities[32,33,37].

Other factors that we did not measure (for example, numeracy, environmental attitudes, values, cognitive traits) but have proven important for energy literacy in previous studies[15] could be relevant for load shape awareness and should be considered in future studies. Such factors could be used to help design future interventions aimed at improving load shape awareness, as has been done with other energy literacy concepts[38,39]. Future research should also explore the link between load shape awareness and behavioural outcomes (for example, choices about time-varying rate plans, peak energy consumption) to better delineate its policy relevance, especially in comparison to other more established energy literacy concepts.

For energy providers considering the widespread automatic enrolment of customers into time-of-use rate plans across the United States and elsewhere, our research raises some important issues. We found that only half of our respondents were aware of their dominant load shapes, suggesting that a large proportion of household members may not be aware of their household energy use patterns and may struggle to determine whether to opt out of such programmes or adjust their usage patterns. This lack of understanding could also present challenges for households as they attempt to identify which electricity-related activities to shift, and when to shift them, to avoid usage during times of higher electricity rates, a challenge potentially exacerbated during large-scale lifestyle disruptions. It could be that the technology to apply variable time-use electricity pricing is a step ahead of our understanding of residential time-based electricity use, and more effort needs to be made to educate the public about concepts such as load shapes and daily energy use patterns to bring them into lock step. We offer a way of assessing energy literacy that is both practical and relevant in this new energy era of advanced metering infrastructure and increasingly data-driven, time-based consumer electricity markets.

Methods

Survey and energy data collection

We fielded a survey to a sample of California residents over the course of two months from 22 April 2020 to 15 June 2020. To be eligible to participate in this study, participants had to be 18 years or older and meet multiple criteria. First, participants had to be a customer of a utility company in California that partners with UtilityAPI, a platform that facilitates third-party access to energy data from residential customers. At the time of the survey, five utility partners provided access to smart meter data: Pacific Gas and Electric Company, Southern California Edison, San Diego Gas and Electric, Los Angeles Department of Water and Power and Sacramento Municipal Utility District. Next, the participant had to be able to login to the online account of their households' utility company and consent to sharing their energy data through the UtilityAPI platform. After these initial criteria were met, participants then had to complete an online questionnaire that asked about energy use behaviours and demographic characteristics. Only one participant per household completed the questionnaire.

In total, we received 242 survey responses that were associated with valid utility accounts through the UtilityAPI platform. The average length of hourly interval smart meter data collected per participant household was approximately one year (347 days). Data from participants were excluded from the study if their households did not have hourly electricity use data with coverage in pre-SIP and post-SIP periods and/or had rooftop solar or battery storage systems, which obfuscate hourly electricity demand patterns, resulting in 198 participants. Out of the 198 participants that met these criteria, 186 had complete survey data for our key measure of interest, self-assessment of household energy use patterns. We did not find evidence that missing data were strongly related to participant characteristics. Supplementary Note 1 provides a detailed description of the sample, including sources of excluded data, and some robustness tests for excluded households with solar systems. Supplementary Table 2 describes the demographic and household characteristics of all participants in our sample compared with the summaries provided by the American Community Survey[40]. This sample is purposive and not representative as it required participants to be California residents who had a smart meter and had access to their utility account, were willing to share this data and completed a survey.

Respondent assessment of dominant electricity use patterns

The core measure generated from our survey is the respondents' self-assessment of their households' energy use patterns during weekdays. We chose to focus on weekdays in this research for two primary reasons: (1) load shapes have been found to be more varied (that is, higher entropy) during weekends[21], making recall of dominant electricity use patterns more challenging as weekday and weekend activities can be quite different for some households; (2) variable rate pricing plans (for example, time of use) are typically implemented on weekdays and not on weekends, reducing some of the salience of understanding weekend electricity use. In the survey, respondents were first asked to 'Choose the graph most likely to represent your home's electricity use on weekdays (Monday–Friday) before your household made any changes due to SIP orders related to COVID-19 (coronavirus)' with images (displayed in Fig. 1) with response categories corresponding to 'Highest electricity use in the morning', 'Highest electricity use in the morning and evening', 'Highest electricity use in the evening' and 'Highest electricity use in the middle of the day'. We then asked the follow-up question, 'Now choose the graph most likely to represent your home's electricity use on weekdays (Monday–Friday) since your household made any changes due to SIP orders related to COVID-19 (coronavirus)' with the same options listed as in the previous question with the additional response choice of 'My household has not made any changes due to SIP orders related to COVID-19 (coronavirus)'. To align these response categories from the survey with daily patterns in hourly energy use, or load shape, we assign the following (Fig. 1): 'Highest electricity use in the morning' to 'Morning peak', 'Highest electricity in the morning and evening' to 'Dual Peak', 'Highest electricity use in the evening' to 'Evening peak' and 'Highest electricity use in the middle of the day' to 'Midday peak'.

Identifying dominant electricity use patterns

We next developed a method for mapping daily electricity use patterns into one of the four weekday load shape designations described in the survey: morning peak, dual peak, evening peak and midday peak. The process of generating one observed dominant load shape is an approximation and is primarily used for the purposes of matching a household's daily electricity use patterns to the closest load shape described in the survey questionnaire. We tested several alternative methods, including a dictionary-based approach, a direct ranking procedure and the peak detection method we ultimately selected.

Our peak detection method was accomplished in four steps: (1) obtaining daily load shapes, (2) smoothing daily load shapes, (3) peak detection, (4) mapping the four load shape designations. The first step for identifying energy use patterns is to normalize the daily household electricity load profile. Let $l(t)$, $t = 1, 2, \ldots, 24$ be a daily load profile; the normalized daily profile, or the load shape $s(t)$ is defined as

$$s(t) = \frac{l(t)}{a},$$

where a is the daily total load denoted by $a = \sum_{t=1}^{24} l(t)$. We then smooth the load shapes and detect the timing of peaks. Smoothing is done before peak detection because applying peak detection to raw load shapes could yield many peaks due to potential high-frequency fluctuation in raw load shapes. The smoothing of daily load shapes is achieved by passing the load shape $s(t)$ through a Savitzky–Golay filter[41], which is a method used in the field of signal processing to increase precision without distorting signal tendency. Specifically, the filter fits successive subsets of adjacent normalized hourly load with a low-degree polynomial by the method of linear least squares. We next find all local maxima by a simple comparison of neighbouring values to detect the peaks in filtered load shapes. A subset of these local maxima is chosen to ensure that locations are prominent peaks by specifying the following peak properties (obtained after some tuning and observation): (1) the peak is higher than 0.042 (the value if the load shape is flat) by 1.1 times the standard deviation of the normalized hourly load and (2) there exist at least six hours between two peaks. An example of smoothed load shapes and detected peaks of the sampled load shapes is displayed in Supplementary Fig. 3.

Finally, we map these load shapes to one of four load shape designations, described previously (Fig. 1). We specify three time periods: morning (3 a.m.–11 a.m.), midday (11 a.m.–5 p.m.) and evening (5 p.m.–3 a.m.). If a load shape has all peaks in one of these three time periods, it is mapped to that corresponding time period. For example, if the only two peaks are at 12 p.m. and 4 p.m., the load shape is designated as midday peak. If peaks are detected in at least two separate time periods, the load shape is designated as dual peak. We purposely chose to be more inclusive of dual peaking shapes, rather than limit ourselves to the stricter definition of the dual peak occurring in the morning and evening, as the perceptions of time windows for these designations may vary by respondent. We refer to these load shape designations mapped from respondent's hourly energy use as observed load shapes. We use this mapping to then explore the distribution of observed load shapes across respondents, the frequency of observed dominant load shapes across respondents and the alignment of perceived and observed dominant load shapes across before- and during-SIP periods. When perceived and observed dominant load shapes align, we identify these respondents as having awareness of their load shape.

When compared to the alternative methods for identifying dominant electricity use patterns, we found general agreement across comparable approaches. Yet, we acknowledge the inherent subjectivity in assigning a single load shape to represent a household's dominant electricity use patterns. As an example, in a direct ranking strategy used to assess the sensitivity of our load shape classifications to alternative identification strategies, we calculated the total amount of energy used in three of our identified potential peak time periods (morning, evening and midday) and classified load shapes by the time period that ranked highest by overall usage. Identification of a dual peak load shape was more ambiguous with the direct ranking method. A comparison of this alternative direct ranking strategy with the peak detection method employed in this study resulted in 77% agreement in observed dominant load shape designations for the shapes (morning, evening and midday) that could be identified by both methods.

Load shape awareness and participant characteristics

In our last set of analysis, we explored how sociodemographic and household characteristics related to respondent awareness of their household's dominant load shapes in both the before- and during-SIP periods using bivariate analysis. For binary measures, we use a Fisher's exact test, and for continuous measures, we apply difference in means (t-test), using two sided tests for null hypothesis testing. We first considered the relationship between load shape awareness and the respondent characteristics of education, age and gender. We next tested how the household characteristics of electricity rate plan (that is, time-varying rate structure), household income, living in an owner-occupied home and number of household occupants were related to load shape awareness. In alternative analysis, we used binary logistic regression to model load shape awareness using sociodemographic and household characteristics as covariates and did not observe any differences in statistical significance compared to the bivariate analysis approach.

Ethics statement

This research was reviewed and approved by the Oregon State University Institutional Review Board (IRB number 8101). Participation in our study was voluntary, and all study participants provided informed consent. Participant recruitment and compensation was managed by Qualtrics, a survey research firm.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The complete data analysed in the current study are not publicly available due to ethical restrictions and privacy of participant information. However, de-identified versions of the data are made available through the Open Science Framework at https://osf.io/4jxcm/ and https://doi.org/10.17605/OSF.IO/4JXCM.

Code availability

The code that supports analysis using de-identified versions of the data are made available through the Open Science Framework at https://osf.io/4jxcm/ and https://doi.org/10.17605/OSF.IO/4JXCM.

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Author contributions

C.Z., H.B., J.F. and R.R. conceptualized and designed the research; C.Z., T.S. and G.S. performed the research and analysed data; C.Z., H.B. and T.S. wrote the initial paper draft; C.Z., H.B., T.S., J.F., G.S. and R.R. reviewed and edited the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	The Qualtrics platform was used to collect survey data from study participants. The UtilityAPI platform was used to collect electricity usage data from study participants.
Data analysis	Analysis and visualization were conducted in R (version 4.0.4) and Python (version 3.5). R packages included ggplot2 and ggalluvial. Python packages included SciPy, NumPy, and pandas.

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The complete dataset analyzed in the current study are not publicly available due to ethical restrictions and privacy of participant information. However, de-identified versions of the data are made available through the Open Science Framework at https://osf.io/4jxcm/ with DOI 10.17605/OSF.IO/4JXCM.

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Study description	This study analyzes quantitative data from two sources: household survey data and household electricity use data. The survey data is cross-sectional and captures participant responses from one point in time. Electricity data is longitudinal and captures hourly household electricity across multiple points in time.
Research sample	This research sample includes California residents that live within the service territory of five utilities (Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), San Diego Gas and Electric (SDG&E), Los Angeles Department of Water and Power (LADWP), and Sacramento Municipal Utility District (SMUD)) and have access to their household's utility account. This study sample was chosen to enable access to hourly smart meter electricity data, with California having the highest number of smart meter installations in the U.S. This sample is convenience-based and is not representative of the California population.
Sampling strategy	We fielded an internet survey to a sample of California residents. All participants provided informed consent, with participant recruitment and compensation managed by Qualtrics, an internet survey research firm. To be eligible to participate in this study, participants had to be 18 years or older and meet multiple criteria. First, participants had to be a customer of a utility company in California that partners with UtilityAPI, a platform that facilitates third party access to energy data from residential customers. At the time of the survey, five utility partners provided access to smart meter data: Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), San Diego Gas and Electric (SDG&E), Los Angeles Department of Water and Power (LADWP), and Sacramento Municipal Utility District (SMUD). Next, the participant had to be able to login to the online account of their households' utility company and consent to sharing their energy data through the UtilityAPI platform. After these initial criteria were met, participants then had to complete an online questionnaire that asked about energy use behaviors and demographic characteristics. Qualtrics provided us with a sample of 242 study participants that met these criteria.
Data collection	Survey data was collected through the Qualtrics platform. Electricity data was collected through UtilityAPI, a platform that facilitates third party access to energy data from residential customers.
Timing	The survey was administered to study participants from April 22, 2020 to June 15, 2020.
Data exclusions	We received 242 survey responses from participants that were associated with valid utility accounts through the UtilityAPI platform. Participants' data were excluded from analysis if households did not have hourly electricity use data with coverage in pre-SIP and post-SIP periods and/or had rooftop solar or battery storage systems, which obfuscate hourly electricity demand patterns. These exclusions resulted in 198 participants. Of these 198 that met these criteria, 186 participants had complete survey data for our key measures of interest.
Non-participation	All participant recruitment was handled by Qualtrics. As participant recruitment was convenience based, we do not have a way to calculate response rate or other metrics associated with non-participation.
Randomization	No randomization was used in this study.

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Population characteristics	Study participants were 65% female and had a mean age category of 25-34 years old. See the "Research Sample" section for more information.
Recruitment	Participants were recruited via convenience sampling by the survey research firm Qualtrics. Participants received compensation for completing surveys according to previously agreed upon terms as part of a survey panel. All participants were 18 years or older and provided informed consent. See above "Sampling Strategy" section for more information.
Ethics oversight	This research was approved by the Oregon State University Institutional Review Board (IRB #8101).

Note that full information on the approval of the study protocol must also be provided in the manuscript.