Consumers' Perceptions, Acceptance, and Valuation of Carbon Labeling in Energy Policy

White Paper

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Executive Summary

Electricity generation remains a leading contributor to global greenhouse gas (GHG) emissions, accounting for roughly 40% of global CO_2 emissions from fossil fuel use (EIA, 2024). However, consumers rarely have the information necessary to align their energy use with periods of lower carbon intensity to adjust energy use in ways that support climate goals (Gao et al., 2017; Li, 2019). This study evaluates carbon labeling, the provision of real-time information on the emissions intensity of electricity, as a potential mechanism to enable more sustainable household energy decisions. To assess the feasibility of this intervention, a national survey (N=487) of U.S. adults was conducted, and an extended Theory of Planned Behavior (TPB) framework was estimated using structural equation modeling (SEM) (Yadav & Pathak, 2016). The analysis identified three principal patterns:

- Attitudes (ATT) were the strongest predictor of behavioral intention (BI). A one-point increase in attitudes toward shifting electricity use was associated with nearly a one-point increase in intention, underscoring the central role of attitudinal evaluations in shaping willingness to act.
- Environmental concern (EC) and environmental knowledge (EK) exerted opposite influences on ATT. Concern strongly enhanced pro-environmental attitudes, yet greater awareness may suggest skepticism or perceived barriers.
- Subjective norms (SN), perceived behavioral control (PBC), EC, and EK did not exert significant direct effects on intention once ATT were accounted for.

These findings suggest that shifting attitudes is the most effective lever for promoting carbon-responsive behavior, but concern and knowledge alone do not translate into action, highlighting a value–action gap. Carbon labeling can help only if paired with structural supports

such as automation tools, dynamic pricing, and incentives that reduce friction, expand agency, and build trust. To be effective, carbon transparency must be made socially salient and embedded within supportive infrastructures that make low-carbon choices simple, practical, and compelling.

Background

Electricity generation remains a leading source of global greenhouse gas (GHG) emissions, responsible for nearly 40% of CO_2 emissions from fossil fuel use (EIA, 2024). The carbon intensity of electricity, measured in grams of CO_2 per kilowatt-hour (gCO_2/kWh), varies hourly depending on demand and the energy mix. During peak hours, fossil-fueled plants often ramp up, making consumption significantly more carbon-intensive (Li et al., 2020; Jiang et al., 2023). This temporal variation presents a behavioral opportunity: shifting demand to cleaner periods can reduce emissions without reducing total consumption.

Most consumers, however, lack access to real-time carbon information, limiting their ability to make climate-conscious decisions (Gao et al., 2017; Li, 2019). This study evaluates carbon labeling, the provision of real-time information on the emissions intensity of electricity, as a way to empower households to align energy use with lower-emission hours. While labeling has proven effective in other high-emission domains such as food and consumer goods (Zhao et al., 2018), its application to electricity remains underexplored.

This study addresses that gap by applying an extended Theory of Planned Behavior (TPB) framework (Ajzen, 1991; Yadav & Pathak, 2016) to examine how environmental concern (EC), environmental knowledge (EK), attitudes (ATT), subjective norms (SN), and perceived behavioral control (PBC) relate to behavioral intention (BI), defined here as willingness to shift electricity usage in response to carbon labeling. Using a national U.S. survey (N=487) and structural equation modeling (SEM), the analysis provides new evidence on the psychological drivers of carbon-responsive energy behavior and their implications for policy design.

Survey Design

To evaluate consumer responses to carbon labeling in electricity, this study surveyed (N= 487) U.S. adults recruited through CloudResearch's Connect platform and hosted on Qualtrics. The sample reflected a broad cross-section of U.S. households, with regional, gender, and income variation. Respondents skewed somewhat more educated, higher income, and politically liberal than the national population, with White participants overrepresented relative to other racial and ethnic groups.

Figure 1 : *Theoretical Framework (Yadav & Pathak, 2016)*

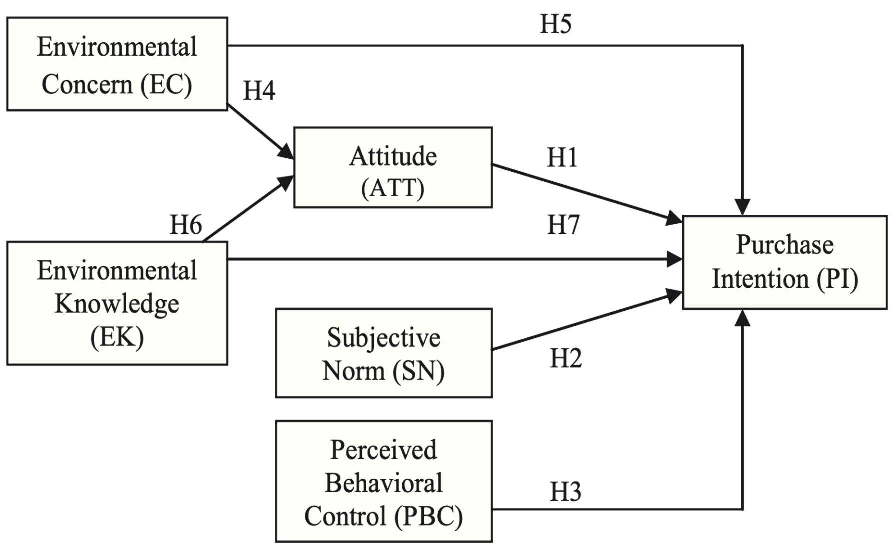

Figure 1 illustrates that concern and knowledge shape people's attitudes, which then drive intention, alongside the added influence of norms and perceived control. The survey measured six latent constructs based on TPB and its extensions: ATT, SN, PBC, EC, EK, and BI. Items were drawn from validated TPB scales and adapted to the energy context (Zhao et al., 2018; Kamalanon et al., 2022). Most items used 5-point Likert scales, recoded such that higher values indicate stronger agreement. Indicators were screened for quality, and missing data were addressed through multiple imputation (MICE).

To test the hypothesized relationships, a SEM was estimated using the diagonally weighted least squares (DWLS) estimator, appropriate for ordinal survey data. SEM was chosen because it allows simultaneous estimation of latent constructs, indirect effects, and model fit, providing greater rigor than multiple regression in testing behavioral frameworks. Latent constructs were defined by their observed indicators, with EC and EK specified to influence both ATT and BI. ATT were modeled as a mediator between these extensions and intention. BI was operationalized as a composite index of three items: willingness to pay more for lower-pollution electricity, willingness to shift appliance use to cleaner hours, and willingness to make lifestyle adjustments to reduce emissions.

Results

Internal consistency was strong, with all constructs demonstrating Cronbach's alpha values above .70 (Hair et al., 1998) and composite reliability values exceeding the .70 threshold (Bagozzi and Yi, 1988). Convergent validity was supported, with most constructs achieving AVE values above .50 (Fornell & Larcker, 1981). The exception was EK (AVE = .49), which fell just below the criterion but was retained given its acceptable composite reliability (.79) and factor loadings above .60 (Chin et al., 1997). Discriminant validity was also supported, indicating that the latent factors were empirically distinct (Brown, 2006). Because of the very high correlation between ATT and BI, the three intention items were averaged into a composite indicator (α = .84), simplifying estimation while retaining reliability.

The structural equation model indicated that ATT were strongly and positively predicted by EC ($\beta = 1.54$, $p < .001$), such that a one-point increase in concern corresponded to nearly a two-point increase in attitudes toward shifting electricity use. EK, in contrast, had a modest but negative effect on attitudes ($\beta = -.25$, $p < .001$), suggesting that greater knowledge was associated with slightly less favorable ATT. When predicting BI, ATT emerged as the dominant determinant: a one-point increase in attitudes was associated with nearly a one-point increase in BI ($\beta = 1.31$, $p = .003$). None of the other predictors - PBC ($\beta = -.03$, $p = .86$), subjective norms ($\beta = -.10$, $p = .51$), EC ($\beta = -.13$, $p = .38$), or EK ($\beta = -.03$, $p = .63$) - were significant once ATT were accounted for.

The model demonstrated excellent fit overall ($\chi^2(77) = 224.16$, $p < .001$; CFI = .995; TLI = .993; SRMR = .051), with RMSEA (.059) indicating a reasonable error of approximation. Overall, the findings reinforce that attitudes are the most robust predictor of intention, while direct effects of EC, EK, PBC, and SN are negligible once ATT are included. This pattern highlights a potential value-action gap, in which concern and knowledge shape pro-environmental attitudes but do not directly translate into reported willingness to act.

Limitations and Future Directions

This study is limited by its U.S.-only, one-time convenience sample, which may not fully represent national or international populations. As with most self-report surveys, risks of social desirability bias, panel fatigue, and limited construct refinement remain. Behavioral intent was measured with a composite index, reducing nuance and obscuring potential measurement error.

Future research should test real-time carbon labeling in field settings, incorporate longitudinal or regional comparisons, and integrate actual usage data to validate self-reported intent. Refining constructs and expanding samples will strengthen generalizability and clarify the mechanisms linking concern, knowledge, and attitudes to low-carbon behavior.

Conclusion

This study demonstrates that carbon labeling has the potential to influence residential electricity use, but its effectiveness depends on the psychological mechanisms driving consumer behavior. The extended Theory of Planned Behavior model confirmed that attitudes are the strongest correlate of behavioral intention, while perceived behavioral control exerts a secondary but meaningful role. In contrast, subjective norms showed little association with intent, suggesting that private, infrastructure-mediated energy decisions are less sensitive to social pressure than other pro-environmental behaviors. The dual effects of environmental concern and knowledge highlight a persistent value–action gap: both constructs strengthen pro-environmental attitudes, yet are negatively associated with reported willingness to act. This paradox indicates that awareness and concern alone are insufficient to drive behavior and may, in some cases, heighten perceptions of barriers or futility.

These findings suggest that policies targeting attitudinal change, when paired with structural supports, may yield the greatest returns. To be effective, information disclosure must be coupled with structural support such as automation tools, dynamic pricing, and financial incentives that reduce behavioral friction. For policymakers and utilities, effective carbon labeling must be integrated with broader measures that expand consumer agency, reduce barriers, and build trust. Carbon transparency should be made socially salient through tools like comparison dashboards and community challenges. Above all, interventions must empower consumers by simplifying choices and ensuring institutional accountability. In short, success depends not on information alone, but on embedding it within supportive infrastructures that make low-carbon behavior both practical and compelling.

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