Introduction

This assignment analyzes customer behavior in the Dutch retail energy market using data from Green Power, a retailer promoting solar adoption among long-standing customers. The goal is to uncover insights into the adoption of solar panels, the number of solar panels adopted, the volume of customer service interactions, and the key drivers of follow-up service contacts. We begin with a literature review to develop hypotheses, followed by exploratory data analysis to examine variable distributions, detect anomalies, and ensure data quality for modeling. Special attention is given to outliers and structural irregularities in continuous variables that could affect model reliability.

Literature Review: Factors Influencing Solar Adoption and Customer Contact Outcomes

Timing of Solar Panel Adoption

Prior studies identify customer traits and interventions that influence the timing of household solar panel adoption. Based on this literature, we propose the following hypotheses on variables affecting adoption timing.

H1: Higher household energy use and costs lead to earlier solar adoption, as greater potential savings incentivize quicker uptake (Shakeel et al., 2023). Similarly, regions or households with higher electricity prices show higher adoption rates (Penrod, 2024)

H2: "Larger households adopt solar sooner, as more occupants typically mean higher electricity use and greater incentive to reduce costs through solar (Shakeel et al., 2023). We expect faster adoption among larger households

H3: Urban areas see faster solar adoption due to greater rooftop visibility, which enhances peer influence and social learning (Bollinger et al., 2022). Increased visibility in dense neighborhoods strengthens these effects, accelerating adoption.

H4: Greater satisfaction and trust in the energy provider accelerate solar adoption. Positive customer-provider relationships reduce perceived risks and encourage earlier uptake (Shakeel et al., 2023). We hypothesize that satisfied customers adopt sooner.

H5: Exposure to solar-related information leads to earlier adoption. Personalized or general marketing increases awareness, boosting adoption likelihood (Shakeel et al., 2023). Even modest information efforts have been shown to raise adoption rates by several percentage points.

Number of Solar Panels Adopted

When a household decides to install solar panels, the quantity of panels (or system size) can vary. We identify factors that literature suggests will influence how many panels a customer installs:

H6: Higher electricity demand leads to larger solar installations, as households with greater consumption need more panels. Industry guidance identifies energy use as the key factor in system size decisions (ShopSolar, 2023).

H7: Households with higher energy bills tend to install more solar panels, as larger systems yield greater cost savings (Raghoebarsing et al., 2022; Shakeel et al., 2023). We expect larger households to install more panels due to greater financial benefits.

H8: Targeted promotion of financial and environmental benefits increases both solar adoption and system size (Schulte et al., 2022). Households perceiving greater benefits are more likely to install larger systems, and such perceptions can be shaped by informational strategies like emails or loyalty programs.

Customer Service Contact Frequency

We next examine factors influencing how often customers contact customer service, via phone or chatbot. The dataset includes total service calls (nrservice) and chatbot interactions (nrchatbot). Based on customer service research, we propose:

H9: Proactive information and engagement can lower reactive service contacts. Well-informed customers, via emails like newsletters or energy tips, are less likely to call or chat. Research shows such communication can cut complaint contacts by up to 40% (Riegel, 2025).

H10: Lower customer satisfaction correlates with more service contacts, as dissatisfied customers are likely to seek help or voice complaints. Complaint volume is a key indicator of low satisfaction (CxToday, 2022). Thus, we expect support interactions to rise as satisfaction declines.

Timing of the Second Contact After the First (Calls and Chatbot)

Finally, we examine what influences the time between a customer's first and second service contact, whether via call or chatbot. Our hypotheses draw on concepts of first-contact resolution and customer persistence.

H11: Unresolved chatbot or service interactions often lead to quick follow-ups or escalation. Only 35% of customers feel chatbots resolve their issues, with most seeking human support instead (Zoho, 2025). We hypothesize that failed attempts drive escalation to other channels.

H12: Solar panel adopters tend to contact support again sooner, as installation may raise questions or technical issues. We hypothesize a positive link between adoption and the likelihood of a second contact.

Data Preparation and Exploration

Boxplots were constructed for all numerical variables to visually identify outliers. Several variables, such as av_gas, av_bill, av_service_length, nrchatbot, av_chatbot_length, service_year#, chatbot_year#, and email-related metrics, showed unusually high values. In contrast, the satisfaction variable displayed numerous low (and high) outliers, indicating widespread customer dissatisfaction.

We also observed structural patterns in service and chatbot variables. Service_2009 has a mean of zero, suggesting customer service was not yet active. Likewise, chatbot_2009 to chatbot_2012 show no variation, indicating chatbot services were unavailable during that period.

Lastly, we found 745 duplicate entries with identical values across all columns except av_bill. To resolve this, we grouped by all other variables and averaged av_bill for each duplicated user_id, retaining a single unique record per user while preserving key information (av_bill).

Methodology

Duration Model

This study examines consumer behavior in the retail energy market, with a specific focus on the timing of solar panel adoption among long-time customers of the energy retailer Green Power. First, this study wants to evaluate which customer characteristics and marketing exposures influence when customers adopt solar panels. We employed duration analysis using the Cox proportional hazards model. Specifically, we investigate two research questions using the duration analysis:

1. What variables affect the timing of long-time customers adopting solar panels?
2. What variables affect the timing of a customer's second contact with customer service (either through live agents or chatbot) after their first interaction?

The Cox proportional hazards model was selected because it does not assume a specific distribution for the baseline hazard function, making it a flexible tool for examining the timing of events. Its semi-parametric nature allows for robust estimation of the effect of multiple covariates while accommodating right-censored data. This enables us to quantify the contribution of the explanatory variables to the likelihood and timing of adoption or follow-up contact, rather than merely predicting occurrence.

Timing of Solar Panel Adoption

The dependent variable is the number of years between the customer's contract start year and the year they adopted solar panels. Customers who had not adopted by 2022 were treated as right-censored. To avoid invalid zero durations, we reassigned an event time of 1 year to those who adopted in the same year they joined.

Explanatory variables: av_bill, hh_size, urban, satisfaction, email_gen_solar, email_pers_solar, email_sustainability, and email_save.

Timing of the Second Contact After the First (Customer Service / Chatbot)

The second analysis focuses on customer engagement with support channels. We define the duration variable as the number of days (or months, depending on granularity) between a customer's first and second contact with either a live customer service agent or a chatbot. Customers who only made one interaction during the observation period were treated as censored cases. This allows us to account for partial follow-up behavior while still using all available data. Separate models were estimated for:

1. Second customer service call
2. Second chatbot interaction

Both models share the same core structure and covariates. These variables were chosen to reflect relevant financial, behavioral, and engagement-related aspects that might influence a customer’s likelihood of returning for additional support.

Explanatory variables: av_bill, nr_solar_panels, solar_panels, av_service_length, neg_service, av_chatbot_length, neg_chatbot, satisfaction, and email_information.

We estimated the model using the coxph() function in R and tested the proportional hazards (PH) assumption using cox.zph(). To deal with violations of the assumption, we interpret the hazard ratios as weighted averages (Stensrud & Hernán, 2020).

Count Model

In addition to modeling the duration model. This study also examines the frequency of those actions using count models. Specifically, we investigate two key behavioral outcomes in the context of consumer engagement with renewable energy and support services:

1. What variables affect the number of solar panels adopted by a customer?
2. What variables affect the total number of customer service calls and chatbot interactions?

To address these questions, we applied Poisson regression as the baseline model and tested for overdispersion using the dispersiontest() function. Where overdispersion was detected, we estimated negative binomial regression models using the glm.nb() function. These models allow us to account for variability in count outcomes while estimating the influence of explanatory variables, offering actionable insight into how frequently customers adopt and interact.

Number of Solar Panels Adopted

The first count model investigates what factors influence the number of solar panels a customer adopts (DV: nr_solar_panels).

Explanatory variables: av_bill, hh_size, email_pers_solar, email_gen_solar, email_sustainability, email_loyalty, and email_save.

Customer Service Contact Frequency

The second count analysis focuses on the total number of contacts a customer has made with Green Power’s support services, modeled separately for:

1. Live agent calls, DV: nrservice
2. Chatbot interactions, DV: nrchatbot

Explanatory variables: satisfaction, neg_service, neg_chatbot, nr_solar_panels, solar_panels, email_pers_solar, email_sustainability, email_loyalty, and email_save.

Initially, Poisson regression was used as the baseline modeling framework for the count model. We then tested for overdispersion to assess whether the variance exceeded the mean. In cases where overdispersion was present, we employed Negative Binomial regression to accommodate the greater variability and yield more reliable estimates of the effects.

To avoid multicollinearity issues, we examined Variance Inflation Factors (VIFs) using vif(), where necessary, variables were excluded. To evaluate and compare model fit, we used the following test: Likelihood Ratio (LR) test, to assess the overall significance of the model relative to a null model, and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), to compare models with different specifications and determine the most parsimonious fit. Lower AIC/BIC values indicate better-fitting models, penalized for complexity.

Results and Discussion

Timing of Solar Panel Adoption

A Cox proportional hazards model was estimated to examine the timing of solar panel adoption among long-time Green Power customers, using time-to-adoption (in years) as the dependent variable. Explanatory variables included household energy usage, demographic factors, customer satisfaction, and exposure to solar-related marketing emails. A total of 1,255 observations were included, with 360 observed adoption events.

Initial model diagnostics revealed that the proportional hazards assumption was violated for key variables, including average bill, household size, and sustainability email exposure, based on the global and individual tests.

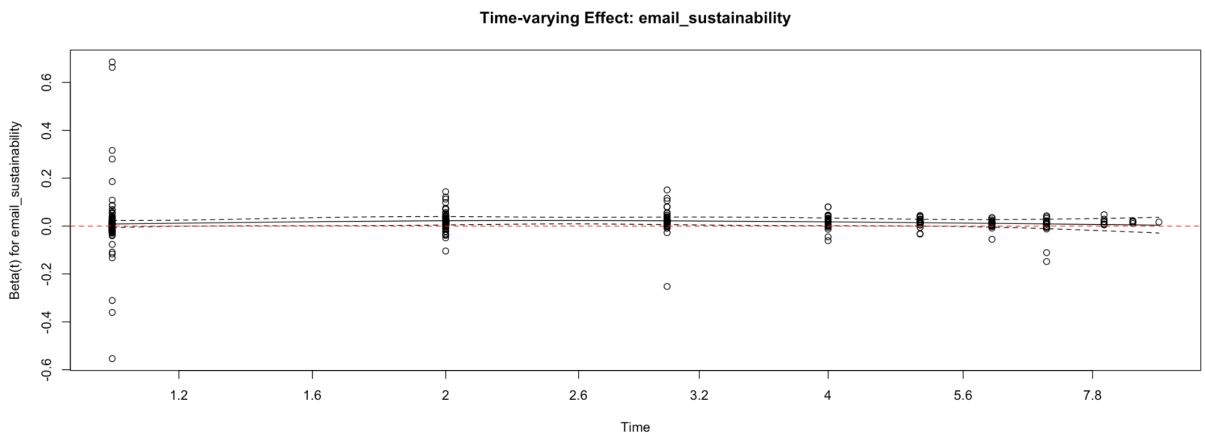

Figure 1 - Schoenfeld Residuals for email_sustainability

Visual inspection of the Schoenfeld residual plot for email_sustainability (Figure 1) shows no substantial deviation from a horizontal line. The trend remains approximately linear and centered around zero, with confidence bands staying narrow and symmetric. This supports the interpretation that the time-varying effect is mild. Following Stensrud & Hernán (2020), we therefore treat the estimated coefficient as a reasonable weighted-average hazard ratio.

Hypothesis Testing

Results support H1, higher energy bills are significantly positively associated with faster solar adoption (HR = 1.0006, $p < 0.001$). Furthermore, H2, stating that larger households are significantly positively associated with faster solar adoption is largely supported. Larger households adopt solar panels significantly faster than single-person households likely due to higher energy demand. For household sizes 2 - 5 the hazard ratios are 11.02, 29.44, 44.50 and 49.98, respectively. However, the increase in hazard seems to flatten beyond 5 members, indicated by a lower hazard ratio of 40.37, which may suggest diminishing marginal effects of additional household members.

H3 is supported. Results show that urban households adopt solar significantly sooner than rural ones (HR = 1.52, $p < 0.001$). This aligns with Bollinger et al. (2022), who found that higher visibility in dense neighborhoods enhances peer influence, accelerating adoption through social learning.

H4 is rejected, the effect of satisfaction on solar adoption timing is not significant ($p = 0.12$).

Findings partially support H5. Personalized solar emails significantly increase the hazard of adoption ($HR = 1.03$, $p < 0.05$), together with emails about sustainability ($HR = 1.015$, $p < 0.001$). While general solar emails ($HR = 0.997$, $p < 0.01$), and energy saving tips ($HR = 0.998$, $p < 0.001$) show negative effects. This suggests that the specificity and relevance of outreach matter more than volume.

Model Fit

The baseline Cox model showed excellent predictive performance, with a concordance of 0.908. The model fit was highly significant, as indicated by the likelihood ratio test ($\chi^2 = 907.2$, $p < 0.001$, $df = 12$), and both the Wald and score tests confirmed the overall significance of the covariates. The standard Cox proportional hazards model provides the best overall fit, with the lowest AIC (4129.13) and BIC (4175.76) values compared to the null model (AIC = 5012.29; BIC = 5012.29) and the time-varying model (AIC = 4726.99; BIC = 4758.08). Variance Inflation Factor (VIF) values for all predictors remained below 5, indicating no problematic multicollinearity. The highest VIF was observed for email_gen_solar (≈ 5.04), which was monitored but retained.

Number of Solar Panels Adopted

To examine what drives the number of solar panels installed, we estimated Poisson and Negative Binomial regression models, with the latter preferred due to significant overdispersion ($\alpha = 0.12$, $p < 0.001$). For interpretation, we call the exponentiated coefficient the incidence rate ratio (IRR).

Hypothesis Testing

Higher average energy bills are strongly associated with a greater number of solar panels adopted ($IRR = 1.0007$, $p < 0.001$), consistent with the idea that higher consumption leads to larger system size (H6). However, the effect is relatively small.

Household size (H7) also shows a strong positive relationship, with larger households installing significantly more panels ($p < 0.001$ across all hh_size categories). However, just like the timing of solar panel adoption, there seems to be a non-linear effect here. Compared to single-person households, IRRs for household sizes 2 -5 are 11.13, 30.00, 49.42, 49.47 respectively. Household sizes larger than five have an IRR of 39.11, showing this non-linear relationship with the quantity of solar panels adopted.

H8 is partially supported: while personalized solar emails show no significant effect, general solar emails are negatively associated with panel count ($IRR = 0.999$, $p < 0.05$), and sustainability-focused emails have a weak positive association ($IRR = 1.006$, $p = 0.052$). Emails containing energy saving tips have a significant negative effect on expected adopted solar panels ($IRR = 0.999$, $p < 0.001$).

Model Fit
The baseline Cox model showed excellent predictive performance, with a concordance of 0.908. The model fit was highly significant, as indicated by the likelihood ratio test ($\chi^2 = 907.2$, $p < 0.001$, $df = 12$), and both the Wald and score tests confirmed the overall significance of the covariates. Model fit was evaluated using AIC, BIC, and a likelihood ratio test against a null model, all favoring the Negative Binomial model (AIC = 2269.3; LR test: $\chi^2 = 3431.9$, $p < 0.001$). VIF values for all predictors remained below 5, indicating no problematic multicollinearity. The highest VIF was observed for email_gen_solar (≈ 5.04), which was monitored but retained.

Customer Service Contact Frequency

To analyze what drives the frequency of customer service contacts, we estimated Negative Binomial regression models for two dependent variables: the total number of customer service calls and the total number of chatbot interactions. Overdispersion was confirmed in both Poisson models (Service Calls: $\alpha = 0.78$, $p < 0.001$; Chatbot: $\alpha = 0.43$, $p < 0.001$), indicating that the Negative Binomial specification is more appropriate. Interpretation is based on the exponentiated coefficients, or incidence rate ratios (IRRs).

Hypothesis Testing
For customer service calls, satisfaction does not have a significant relationship with service contacts (IRR = 1.05, $p = 0.34$), rejecting H10. However, complaints, measured by negative chatbot and service experiences, strongly increase the expected number of calls (neg_service IRR = 1.81, $p < 0.001$; neg_chatbot IRR = 1.06, $p < 0.001$), supporting H10 in the context of complaint-driven contact escalation. On the other hand, for chatbot interactions, satisfaction increases contact frequency (IRR = 1.22, $p < 0.001$), contrary to service calls. However, this may reflect that satisfied users return to digital channels more comfortably. Strong support exists for the escalation effect: neg_chatbot significantly increased chatbot use (IRRs = 1.37 and 1.09, respectively; both $p < 0.001$), confirming that failed resolutions prompt further digital contact.

H9 is not supported, as proactive email communication does not significantly reduce call volume across most categories. Additionally, personalized solar emails show no effect (IRR = 1.00, $p = 0.90$), and email_loyalty and email_sustainability are not significant.

Model Fit
Both models demonstrated good fit. Model fit was evaluated using likelihood ratio tests as well as AIC and BIC. The Negative Binomial model significantly outperforms the null model. For instance, in the service call model, the deviance reduction was $\chi^2(10) = 7{,}476.5$, $p < 0.001$, indicating a substantially better fit. For customer service calls, the Negative Binomial model achieved the best performance (AIC = 5679.8; BIC = 5736.3), significantly outperforming both the Poisson model (AIC = 8010.1; BIC = 8061.5) and the null model (AIC = 12058.4; BIC = 12063.5). For chatbot interactions, the Negative Binomial model also outperformed the alternatives (AIC = 7083.3; BIC = 7139.8), compared to the Poisson model (AIC = 21951.0; BIC = 22002.4) and null model (AIC = 37561.6; BIC = 37566.7). VIF values for all predictors remained under the acceptable threshold of 5, with most below 3, indicating no problematic multicollinearity.

Timing of the Second Contact After the First (Calls and Chatbot)

We analysed the interval between a customer's first and second support interaction using Cox proportional‑hazards (PH) models, one for a follow‑up service call and one for a follow‑up chatbot session. The service‑call model contains 1 255 customers with 716 observed second calls; the chatbot model covers the same customers with 819 second bot sessions.

Hypothesis Testing

Unresolved interactions lead to quicker follow-up (H11), indicated by neg_chatbot or neg_service, evidence strongly supports this hypothesis. For instance, a one unit increase in negative service call experiences increases the hazard of a second call by roughly 32 % (HR = 1.32, $p < 0.001$). Likewise, a one unit increase in negative chatbot experiences increases the hazard of a second call by about 1.6% (HR = 1.016, p = 0.055).

Furthermore, a one unit increase in negative chatbot sessions increases the hazard of a second chatbot session by about 3% (HR = 1.028, $p < 0.001$). These patterns confirm that unresolved issues in the initial contact prompt quick re‑engagement, often within the same or an escalated channel.

For H12, customers who have installed solar panels are 82% more likely to phone again sooner (HR = 1.82, $p < 0.001$), suggesting post‑installation questions drive additional live support. In the chatbot model, however, the solar‑panel indicator is not significant (HR = 1.11 $p = 0.42$), implying that technical queries after adoption are resolved primarily through human agents rather than digital self‑service.

Other covariates provide additional insight. Longer initial chatbot sessions reduce the likelihood of another bot interaction (HR = 0.996, $p < 0.001$), hinting that more extensive first‑session help lowers immediate need for a repeat visit. Satisfaction mildly raises the hazard of returning to the chatbot (HR = 1.12, $p = 0.074$) but has no clear impact on a second call. Average bill shows a significant positive impact on chatbot hazard, while marginal (HR = 1.0001, p < 0.005). Service length and proactive e‑mail exposure show no meaningful influence on timing in either channel.

Model Fit

Both models showed strong model fit. The likelihood ratio tests were highly significant (service call model: $\chi^2 = 141.2$, $p < 0.001$; chatbot model: $\chi^2 = 105.1$, $p < 0.001$), indicating that the covariates meaningfully improve prediction over a null model. Concordance values were 0.636 and 0.623, respectively, for the service and chatbot models, suggesting adequate ability to discriminate between customers who follow up sooner versus later. For second service calls, the standard Cox model showed superior fit (AIC = 9,387.93; BIC = 9,429.09) relative to the null model (AIC = 9,508.11; BIC = 9,508.11). Although the proportional hazards assumption was violated globally (p < 0.001), the Schoenfeld residual plots indicated most violations were mild, similar to the plot in Figure 1. A time-varying Cox model was tested as an alternative but resulted in higher AIC (9,426.38) and BIC (9,467.55), suggesting inferior fit. Therefore, the standard Cox model is retained as the most parsimonious and interpretable choice for modeling second phone contacts. Multicollinearity was not a concern, as all VIFs were comfortably below the conservative threshold of 4. The highest VIFs were seen for nr_solar_panels and solar_panels (≈ 3.4), due to conceptual overlap, but remained within acceptable bounds.

Conclusion

For this report we researched 12 different hypotheses focusing on factors influencing solar panel adoption. Using a combination of Cox proportional hazards models and Negative Binomial regressions, we found evidence to suggest that energy consumption and household size are both key drivers of not only the timings of solar panel adaptation but also and the amount of solar panels installed. Meaning, larger households with high energy consumption are more likely to adapt to solar panels.

Urban residency and personal sustainability-focused promotions have a significant effect on the acceleration of solar panel adoption. However more general promotions and energy saving tips tend to have a negative impact on the solar panel adoption. Additionally, no form of promotion, whether personal or sustainable, had an impact on the amount of solar panels installed.

When it comes to solar adaptation there is no evidence to suggest that customer satisfaction will increase the adoption of solar.

This report also focuses on the interaction between customers and the customer service. We found that there is no evidence to suggest that proactive information and engagement will reduce the amount of contact with customer service. We also found that customer satisfaction is not important for determining frequency of customer service contacts, unlike complaints measured by negative chatbot or customer service experiences. What was really important for the number of contacts with customer service is the amount of complaints. Additionally we found a pattern that showed an increase in re-engagement in both the customer service and the chatbot channel when issues are unresolved by these channels. Finally we also found that people who have installed are more likely to contact customer service but not use chatbots.

Limitations

The report and subsequent results rely on observational data. This means it is difficult to establish causal relationships. While a lot of the results of various models can tell you whether an increase or decrease of a certain predator variable results in a higher likelihood of the outcome variable being higher or lower, these types of models using observational data cannot directly make causal inferences.

Furthermore, some of the hypotheses derived from the literature review were not supported by the data and results, indicating that there is a key difference in the literature or what is expected to happen and what is really happening in this dataset, warranting further exploration and discussion.

Additionally, there might be some omitted variables that are not accounted for in this report. The models do not account for unobserved variables such as solar installer availability or government subsidies, which could influence both solar adoption and customer behaviors.

Finally, the analysis is limited to long-time customers of a single Dutch energy provider (Green Power), which may not generalize to newer customers, other countries, or different types of utilities.

Recommendations

Based on the report we came up with 3 recommendations for the energy provider Green Power:

Target high-usage, larger households with personalized solar outreach:
Since higher energy bills and larger household size are highly correlated with faster adoption and a higher number of installed solar panels, Green power should prioritize these segments. Personalized and sustainable email advertisements are more effective than generic messages, and therefore tailoring the content to this specific audience could enhance conversion. However, care should be taken to avoid over-communicating with general or low impact emails (e.g. generic solar promotions) as results show these may have no effect, or even a diluting effect, on adoption and system size.

Improve first-contact resolution in customer support:
Unresolved customer service experiences strongly drive repeat contact and escalation. By investing in training, diagnosing and giving adequate support to customers for first-call or first-chat resolutions can reduce repeated contacts and possibly improve efficiency.

Provide support after solar installation and investigate solar installation:
Solar adopters are significantly more likely to contact customer support through phone, suggesting a gap in post installation guidance or even problems that occur with installation. Establishing a structured post-installation support program (e.g., onboarding calls, FAQs, or live support availability) could improve the user experience, reduce confusion, and preempt unnecessary support calls. But in addition to this Green Power should also look into the installation process of the solar panels to check if there are mistakes made or reoccurring issues with the solar panels themselves.

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