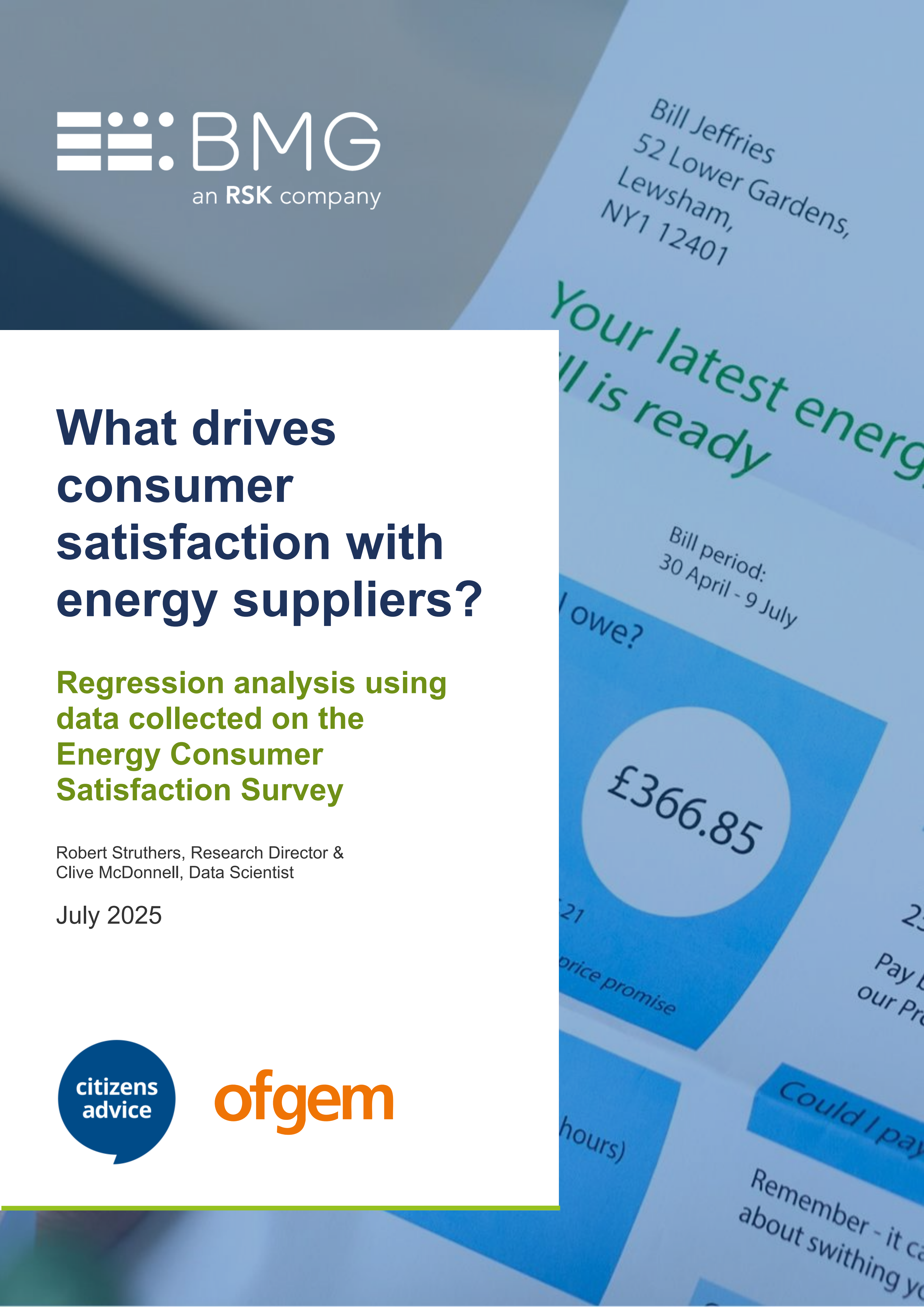

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What drives consumer satisfaction with energy suppliers?

Regression analysis using data collected on the Energy Consumer Satisfaction Survey

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citizens advice

ofgem

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Foreword

BMG have been running the Energy Supplier Customer Satisfaction Survey for Ofgem and Citizens Advice since 2023. In January 2025 we completed wave 20 of the survey, BMG's 4th wave.

Since we inherited the programme, the survey has tracked the perceptions of Great British energy consumers and their suppliers through a time of change. As the energy market has begun to stabilise after the crisis, we have seen overall satisfaction scores steadily rise across the last few waves-reaching a record high of 81% in January 2025.

We have already done significant work to understand what leads to consumers being satisfied with their supplier. This includes asking consumers directly capturing the reasons behind people's views in their own words. We also used standard cross-tabulations to explore patterns across satisfaction, whether demographic (like financial circumstances) or more experience-based (such as recent contact or billing interactions).

While both routes offer valuable insights, they have limits. We are left with the following unresolved and interrelated questions:

1. What is the role of demographic and energy characteristics in driving overall satisfaction?
2. Is rising satisfaction partly down to the cost-of-living pressures easing for some consumers?
3. And finally, what is the role of different aspects of customer service in driving overall satisfaction?

This is where regression modelling can help us. This approach allows us to explore multiple variables at once. It holds other factors constant, so we can pinpoint which ones really matter. In doing so, it helps us move from "what looks like a pattern" to "we can point to the unique contribution of each factor considered in our models."

It also lets us uncover links that consumers might not articulate themselves. For example, if you ask an energy consumer directly what makes them satisfied with their supplier, they might not mention that their age or financial situation has any bearing on their satisfaction – but the model can reveal whether these things are statistically connected to how satisfied they feel.

Likewise, it can show whether recent behaviours – like switching suppliers, getting a smart meter, or having an inaccurate bill – are linked to better or worse satisfaction outcomes.

Using data from four waves of the study and responses from over 15,000 energy customers, this report uses regression to explore the factors driving customer satisfaction.

Robert Struthers
Research Director

Executive summary

Background and approach

To understand what shapes satisfaction with suppliers in the energy market, this report applies regression analysis to pinpoint the distinct contribution of each factor.

This is particularly useful in the context of recent trends. Satisfaction rose to a record 81% in January 2025, recovering sharply from the drop during the 2022 energy crisis. At the same time, the Financial Vulnerability classification used in this survey shows that there has been an improvement in financial circumstances for some consumers.[1] Together, these trends raise an additional question: is rising satisfaction partly down to the cost-of-living pressures easing for some consumers?

Using regression analysis on over 15,000 survey responses collected across four waves (August 2023 to January 2025), this report helps answer this question and many others. It identifies the drivers of overall customer satisfaction with energy suppliers through separate models focused on demographics and energy characteristics, satisfaction metrics, and a combined hybrid approach.

What is the role of demographic and energy characteristics in driving overall satisfaction?

Just under 12% (11.6%) of the variance in overall satisfaction can be explained by demographic and energy characteristics. This level of explained variance is typical in social research models using demographic factors. The rest of the variance may be explained by satisfaction with different dimensions of customer service and other unobservable factors such as higher levels of marketing spend by suppliers or wider consumer sentiment. The results showed:

Consumers' financial circumstances was the most influential factor in the model. Measured by the Financial Vulnerability Classification, this variable accounts for 32% of this variance explained by this model (3.7% of the variance in absolute terms). This classification captures a consumer's ability to save, manage unexpected costs, and avoid borrowing.[2] Consumers classified as "highly financially vulnerable" are significantly less likely to be satisfied than those "doing well."

The customer's energy supplier emerges as the second strongest predictor of satisfaction in this model. Supplier explained 29% of the overall model's variance (or 3.3% of the variance in absolute terms). This demonstrates that even after accounting for demographic and energy-related factors, a clear gap remains between the best and worst-performing suppliers.[3]

Three other variables show moderate influence; others have minimal or no impact. Three demographic and energy characteristic variables play a moderate role in shaping satisfaction.

1. Customers with smart meters tend to report higher satisfaction than those without.
2. Switching is also associated with higher satisfaction, particular those who have done so while staying with the same supplier.

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[1] See: [Energy Consumer Satisfaction Survey: January 2025 | Ofgem]

[2] See appendix for more detail.

[3] Implied Impact Satisfaction Scores (IISS) help translate odds ratios into clearer percentage terms. Based on the average satisfaction rate across four waves (75%), they show how satisfaction would change if everyone shared a specific characteristic: for example, if all customers were with the top- or bottom-rated supplier. This makes differences easier to interpret, especially when overall satisfaction is already high. For a fuller explanation, see page 13.

3. Age also plays a role, following a U-shaped trend similar to that seen in life satisfaction research – with those aged 35 to 64 generally less satisfied, while customers over 75 are the most likely to report high satisfaction with their supplier.[4]

Prepayment customers show higher satisfaction than those on direct debit. While payment type has minimal weight in the model, it reveals a different pattern from that suggested until now by descriptive analysis,once other variables are controlled for. Meanwhile Standard credit payers are the least likely to be satisfied.

The remaining variables in the model have minimal or no impact at all.

Is rising satisfaction partly down to the cost-of-living pressures easing for some consumers?

We were keen to explore how much improving financial circumstances could explain the increase in satisfaction between August / September 2023 and January 2025. A simulation using regression suggests that **perceived improvements in household finances account for 1.3% pts or just over 1/10th of the increase of the rise in satisfaction** from 69% to 81%.

This suggests that improved household finances played a role, but most of the rise in satisfaction likely reflects supplier performance and other unobservable factors.

What is the role of different aspects of customer service in driving overall satisfaction?

We ran a second regression model to understand the specific contribution of customer service metrics to overall satisfaction. This model accounts for 37.5% of the variance in overall satisfaction.

Ease of contacting their supplier and **bill satisfaction** emerge as joint top predictors of overall satisfaction, with relative importance scores of 35% and 34% respectively (or 13% of the variance in absolute terms). Together with smart meter satisfaction, these three factors account for the majority of the model's explanatory power. If suppliers are looking to understand what most effectively improves customer satisfaction, these are the areas to prioritise – ease of contact and billing satisfaction as joint top, followed closely by smart meter experience.

Lower-incidence measures have limited impact but still matter at the individual level. Other variables in the model, such as satisfaction with complaints handling, switching supplier, and engineer visits, rank lower in predictive power. This is largely due to their low incidence in the population, which limits their ability to explain overall satisfaction. These touchpoints still have a big impact on satisfaction for the smaller groups they are relevant to.

Positive interactions deliver more than 'passive satisfaction'. The analysis shows that well-handled customer interactions lead to higher satisfaction than no interaction at all. Whether it's resolving a complaint, seeking support, or switching tariffs, satisfied customers report better outcomes than those who never engaged. Positive engagement adds value beyond passive experience.

The reverse is also true. For example, a bad smart meter experience can harm customer satisfaction more than not having one at all. It's the gap between expectation and delivery that does the damage. This shows why getting engagement right matters: positive experiences can boost satisfaction, but poor ones can undermine it.

[4] Galambos, N. L., Krahn, H. J., Johnson, M. D., & Lachman, M. E. (2020). The U shape of happiness across the life course: Expanding the discussion. *Perspectives on Psychological Science, 15*(4), 898–912. Available here.

Methodology

Research question

Each model is built to answer one central research question: what are the key factors that influence whether customers feel satisfied with their energy supplier?

In each model, the dependent variable is our ‘overall satisfaction’ measure from the Energy Consumer Satisfaction Survey. The metric is the broadest measure of satisfaction in the survey and is used to report how satisfied customers are with their supplier at an overall level.[5] The question wording is:

“Overall, how satisfied or dissatisfied are you with <SUPPLIER> as your supplier of <FUEL TYPE>?” (Variable A5)

With the following response options:

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied
- Unsure
- Prefer not to answer

For dual fuel customers who have different electricity and gas suppliers, a least-fill selection process during the survey was used to determine which supplier to ask the customer about, so they were only asked to rate one supplier.[6]

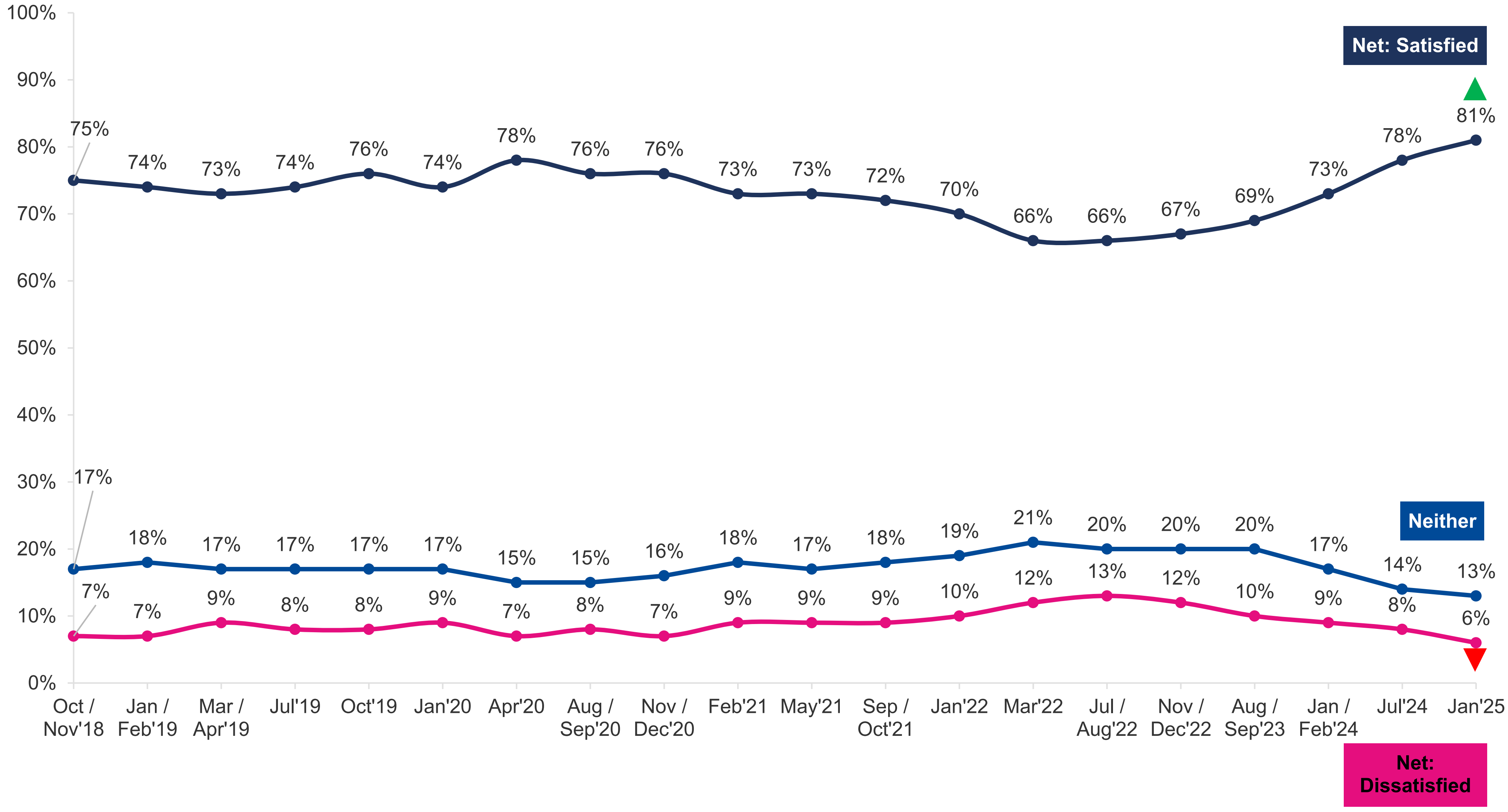
[5] Energy Consumer Satisfaction Survey
[6] For further information on the least fill approach please see our technical report here: Energy Consumer Satisfaction Survey - Technical Report 2025

Context

Since hitting a low in March 2022 during the peak of the energy crisis, energy satisfaction has risen by 15 points. In January 2025 it hit 81%, the highest level since Citizens Advice and Ofgem started tracking this in late 2018.

This improvement coincides with a drop in the share of respondents who said they were neither satisfied nor dissatisfied – down from 21% in March 2022 to 13% in January 2025 – and a fall in dissatisfaction, which declined from a peak of 13% to just 6% in January 2024.

Figure 1: Overall satisfaction trended since October / November 2018



A simple comparison of satisfaction and Energy Price cap levels implies an association between prices and satisfaction. Satisfaction fell to new lows as prices rose during the crisis and began to recover as prices came down. One wrinkle in this pattern is that satisfaction in January 2025 reached a new high, despite a modest increase in the energy price cap and prices still being higher than they were before the crisis in 2020 and early 2021.

Alongside this has been another consistent upward trend. As energy prices alongside inflation more widely have reduced, the share of consumers we categorise as 'doing well' financially using our financial vulnerability classifications has increased from 41% and 52% between August / September 2023 and January 2025, with our 'highly financially vulnerable' group falling from 20% to 14%.

This raises the question of how much recent improvement in satisfaction is driven by falling energy prices and better household finances, compared to improvements suppliers may have made to the service they give to their customers.

Indeed, our analysis using descriptive statistics[7] shows a consistent link between our Financial Vulnerability Classification and overall satisfaction.[8] In the January wave, 89% of people in the most financially secure group (categorised as 'doing well' financially) were satisfied with their supplier, compared to just 66% in our 'highly vulnerable' group.

We have also seen differences in satisfaction across key demographic groups. In January 2024, satisfaction was lower among people aged 50 to 64, those in receipt of benefits, and standard credit payers. The same type of question remains: what is the unique impact of each of these factors on satisfaction?

Similarly, the descriptive statistics show a strong link between satisfaction with the different dimensions of customer service and overall satisfaction. For example, respondents who are satisfied with things like billing or smart meters are much more likely to be satisfied overall. However, it's hard to know from descriptive data alone which factors have the greatest impact.

We also see differences in satisfaction levels when comparing suppliers. In the latest published figures, for example, there is a 21-point gap between the highest and lowest performing suppliers. However, some of this difference may reflect variations in the customer demographics each supplier serves, something that looking at descriptive statistics alone is unable to isolate.

This is where the regression modelling really adds value. The modelling allows us to examine several variables at the same time, holding others constant so we can see which factors "drive" satisfaction and what their unique contribution is.

Modelling approach

To explore what drives energy satisfaction, we ran two main sets of models using logistic regression – a statistical method used to predict the likelihood of a binary outcome. In this case, we simplified the overall satisfaction variable into two categories: customers who said they were "very satisfied" or "satisfied," and everyone else (including those who were dissatisfied, very dissatisfied, or selected "neither").

This choice was driven by both practical and statistical considerations, making the analysis more interpretable and robust.

Satisfaction levels are relatively high, averaging 75% across the last four waves. That leaves only a small proportion of respondents spread across the "neutral," "dissatisfied," and "very dissatisfied" categories. Splitting the outcome into more than two groups would overcomplicate the analysis and risk unstable results due to small sample sizes for some of the categories outside of the satisfied options. A binary outcome gives us a clear and reliable basis for comparing satisfied customers with those dissatisfied or neutral.

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[7] Descriptive statistics provide a summary of the data, highlighting patterns and relationships without identifying causation. Analysis later in this report uses regression analysis to explore the factors driving the patterns.
[8] See page 12 and appendix for more detail on our Financial Vulnerability Classification.

This approach avoids a key limitation of linear regression when applied to survey data with categorical outcomes like satisfaction. Linear regression assumes equal spacing between response options, but in reality, people may see bigger differences between some categories than others. For example, the jump from “fairly satisfied” to “very satisfied” might feel smaller than the shift from “neutral” to “fairly satisfied.” Logistic regression treats the outcome as categorical rather than continuous, allowing us to model the likelihood of being satisfied without making unrealistic assumptions about how these categories are structured.

Two main sets of models were run:

Demographic and Energy Characteristics model

This model included respondent demographics and energy-related characteristics. In total, 18 independent variables were tested.[9] Demographic factors covered variables such as age, region, parent supplier and our Financial Vulnerability Classification. Energy characteristics included variables such as payment type and smart meter uptake.

Satisfaction Metrics model

This model focused solely on the relationship between overall satisfaction and more specific satisfaction questions – such as satisfaction with billing, contact, and smart meters.

A hybrid model was also run, combining variables from both sets above. While it broadly reinforced the findings of the two individual models, it is only referenced briefly where relevant to avoid duplication.

We made deliberate choices about which variables to include from the start. For example, income and the Index of Multiple Deprivation were excluded because they overlap with our Financial Vulnerability Classification, which we use instead as a clearer and more comprehensive way of measuring consumers’ household financial circumstances.

In each model, the variables were selected using a stepwise regression approach, which systematically refines predictors to improve the model’s accuracy. Stepwise selection involves:

- **Forward selection**: Starting with no variables and adding predictors one by one based on their statistical significance based on the greatest statistically significant improvement to model fit.
- **Backward elimination:** Starting with all variables and systematically removing less significant predictors. At each step, the variable whose removal has the smallest negative impact on model fit is eliminated, helping to reduce overfitting and retain only the most meaningful predictors.

This iterative process ensures that only the most meaningful variables are included in the final models. Additionally, tests for multicollinearity were conducted. The results showed no issues, meaning the variables are not too closely related to distort our findings.[10]

[9] All variables were checked and constructed to ensure sufficient sample sizes for detecting statistically significant effects. A full breakdown of variables and sample sizes from the combined model in the Appendix.
[10] Analysis based on Adjusted Generalised Variance Inflation Factor (GVIF) scores. See appendix for further details.

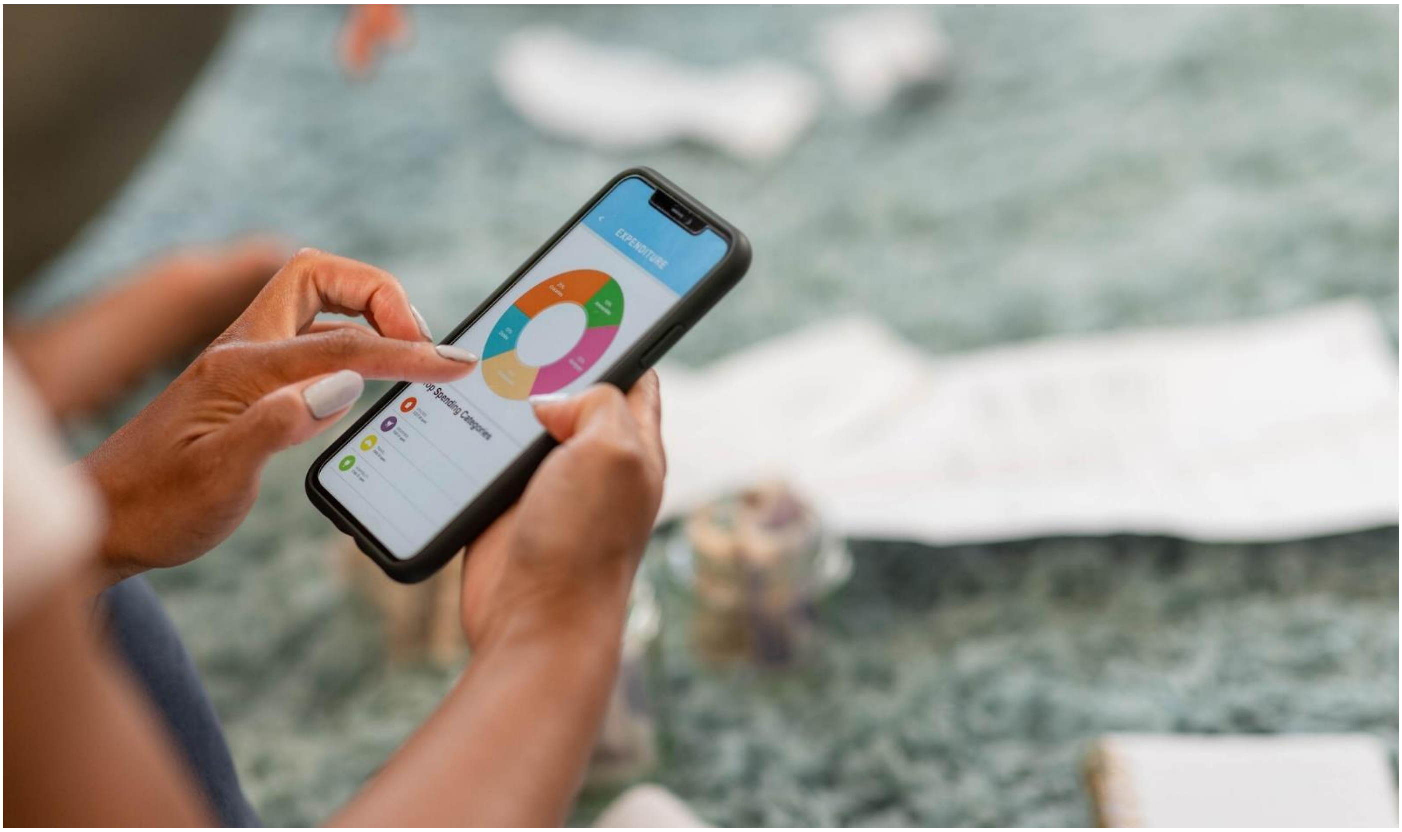
As part of this process, we conducted correlation checks to assess multicollinearity among the independent variables. Apart from strong correlation between value for money and satisfaction with information in our Satisfaction Metrics Models – analysis which led them to be excluded from the final reported models – no other significant issues were identified.[11]

Data

The models featured in this report combine data from four waves of the Energy Satisfaction Survey. BMG began working on the programme in Wave 17 (August / September 2023), with the most recent data coming from Wave 20 (January 2025).[12]

After removing missing cases (see below), the combined Demographic and Energy Characteristics model is based on 14,054 survey responses. The Satisfaction Metrics Model draws on 15,201 responses. By merging data across four waves, we achieve a robust sample size, allowing for confident identification of statistically significant relationships.

Additionally, we ran the two models above only using data from January 2025, which included new metrics that we wanted to explore. Specifically, electric vehicle (EV) ownership was added to the Demographic and Energy Characteristics model, and a value-for-money satisfaction question was introduced in the Satisfaction Metrics model. These variables are only discussed briefly in this report: EV ownership did not show a statistically significant relationship with overall satisfaction, and the value-for-money measure was ultimately excluded from analysis due to concerns around multicollinearity.[13]



[11] See discussion on page 28

[12] BMG carried out a comprehensive review of the survey and its content when inheriting the programme from the previous supplier. As part of this, we introduced key analytical variables, such as our financial vulnerability classification. This meant we did not combine data from previous waves, as not all variables required for the model could be aligned across datasets.

[13] The variable was too closely aligned with the dependent variable, effectively measuring the same underlying sentiment as overall satisfaction. This can reduce the model's usefulness, as it becomes unclear whether the variable is a true driver of the outcome or simply a reflection of it.

Handling missing cases

Ensuring a large sample size is essential in regression analysis. At times, responses may be incomplete due to survey routing or respondent uncertainty. To handle this, missing cases were either excluded or appropriately recoded:

- **Removal of missing data:** If a respondent did not provide an answer to a critical demographic question such as gender, their response was removed from the model entirely (i.e. entire case), as an "unknown" category does not offer meaningful insights.
- **Recoding for certain variables:** For questions like disability status, if a respondent did not provide an answer, their response was recoded as "No / Unknown." This ensures that analysis actively compares those who stated a disability against those who did not state a disability.

We've set out details of the missing cases alongside the full variable structures in the appendix. Overall, the share removed only accounts for 8% of available cases, meaning impact on the modelling is negligible.

When preparing attitudinal variables for regression, responses were categorised into three groups:

1. **Positive response**: For example, those expressing satisfaction.
2. **Negative response or, at best, neutral responses**: For example, those expressing dissatisfaction and neither dissatisfied nor dissatisfied.
3. **Not asked the question**: Some respondents were not presented with specific attitudinal questions, such as satisfaction with billing if they were on a prepayment meter. In these instances, to retain these respondents in the model (as removing them would significantly reduce the sample and potentially bias the results), we created a separate category for those not asked the question. This ensured consistency across variables while maintaining the full sample size.

Cost of living simulation

Many factors linked to overall satisfaction are closely associated with socio-economic status, particularly indicators of financial comfort. To provide a clearer summary of a respondent's financial situation in the context of rising cost pressures, we combined three measures – savings, debt, and ability to handle unexpected expenses – into a Financial Vulnerability Classification, which identifies levels of financial vulnerability.[14]

To understand how much easing household finances contributed to rising satisfaction scores across Waves 17–20, we used the regression results to build a simulation. This simulation estimated what satisfaction levels in Wave 20 (January 2025) would have been if the distribution across our Financial Vulnerability Classification had remained at the same level as in Wave 17 (August / September 2023), when consumers were generally under greater financial strain.

In the simulation, proportions were reassigned and the expected changes in odds were applied to estimate new satisfaction levels. For example, in Wave 20, 686 respondents were classified as 'highly financially vulnerable' but using Wave 17 proportions, we would expect this number to be 883. As a result, 197 respondents were moved into the 'highly financially vulnerable category'. The same approach was taken across the other categories, so they lined up with the August / September 2023 figures.

[14] For more details, see Appendix.

Key measures

Four measures are used throughout the report to help interpret the regression findings. These are:

Nagelkerke R Square is a measure of the overall explanatory power of each model

The Nagelkerke R Square value is a measure of what percentage of variation in the dependent variable – in this case, customer satisfaction – can be explained by the independent variables in the model. The higher the percentage, the better the model's explanatory power. For example, a Nagelkerke R Square of 30% means that the model accounts for 30% of the variation in satisfaction. The remaining 70% of variation in customer satisfaction reflects the influence of other variables not included in the model.

Relatively low R Square values is common in social science, where models – especially models based solely on demographic-like characteristics – often explain a relatively modest share of variation. Consumer satisfaction is inherently complex and influenced by many unmeasured or intangible factors.

Relative Importance Scores explain the specific predictive power of each independent variable within a model

The relative importance of each independent variable in the logistic regression model was assessed by examining how much each one contributes to explaining the overall explanatory power of the model. This is expressed as a percentage – for instance, a 6% score for age means it accounts for 6% of the model's overall predictive power, having controlled for all other independent variables in the model.

Statistical Significance shows which variables have a meaningful and reliable relationship with satisfaction

In simple terms, statistical significance means that the relationship observed in the data is unlikely to have occurred by chance. In the model, a statistically significant result gives us confidence that the variable genuinely helps to explain differences in overall satisfaction, rather than just being a random pattern. We use a 95% confidence level, meaning we're 95% certain that the observed effect is real and not due to random variation.

Odds ratios show how much a variable changes the odds of being satisfied. If the odds ratio is above 1, it increases the odds; below 1, it lowers them. For example, an odds ratio of 2 means the odds are twice as high – but that doesn't mean the chance of satisfaction doubles.

Odds ratios show how much a variable changes the odds of being satisfied

In logistic regression, they are calculated by taking the exponential of the model's coefficient (exp(b)). This tells us how the odds change when that variable increases by one unit, holding all other variables constant.

If the odds ratio is above 1, the variable increases the odds of satisfaction. If it's below 1, it reduces them. This helps us understand the direction and strength of each variable's impact – not just whether it matters, but how much it shifts the odds.

Implied Impact Satisfaction Scores are used to help quantify the relationship between each sub-category within an independent variable and overall satisfaction

Talking about odds ratios – for example, saying the odds of being satisfied are 1.5, 2, or 2.5 times higher – is often hard to interpret.[15] In our combined model, an average of 75% of respondents across the four waves reported being satisfied. This means the odds of satisfaction are already high, so changes in odds ratios may seem less pronounced and can be harder to interpret for non-technical audiences[16].

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15 See discussion here.

16 Davies, H. T. O., Crombie, I. K., & Tavakoli, M. (1998). When can odds ratios mislead? *BMJ*, 316(7136), 989–991.See: https://doi.org/10.1136/bmj.316.7136.989

For example, in our combined model, an average of 75% of people are satisfied, which means the odds of satisfaction are 3 to 1. If the odds double, they become 6 to 1, but this does not mean the chance of being satisfied doubles too. It only increases from 75% to about 86%. People often mistake “doubling the odds” for “doubling the likelihood,” like going from 30% to 60%. But when most people are already satisfied, there’s less room for improvement, so even big-sounding changes in odds lead to smaller shifts in actual likelihood.

To make this easier, we developed what we call Implied Impact Satisfaction Scores. Take smart meter uptake: in our Demographic and Energy Characteristics model, the odds ratio (Exp(B)) for smart meter ownership is 1.2. This means that, holding other factors constant, consumers with a smart meter are 1.2 times more likely to be satisfied compared to the average – but that is not intuitive.

Using Implied Impact Satisfaction Scores, we can translate this into more meaningful terms: relative to a 75% satisfaction benchmark (the average overall satisfaction across Waves 17-20), if all consumers had a smart meter, satisfaction would be expected to rise to 78%, and if nobody had one, it would fall to 72% – a six-point difference.

Report structure

The report begins by exploring the **Demographic and Energy Characteristics Model.** This shows how customer satisfaction varies across different demographic groups and energy characteristics, such as our Financial Vulnerability Classification, age, region, payment type, and smart meter uptake.

Using our Demographic and Energy Characteristic combined model, we then looked more closely at how parent energy suppliers perform, identifying which ones are most strongly linked to higher customer satisfaction. We also examined how changes in household financial circumstances, particularly improvements in the cost-of-living picture, may have contributed to rising satisfaction scores.

Next, the report sets out findings from our **Satisfaction Metrics Model**, examining how factors such as billing, contact, complaints, and switching shape overall satisfaction and which touchpoints matter most.

The report concludes with a short section outlining the Hybrid model results. As these largely mirror earlier findings, we present them here in a less detailed summary.

Demographic and Energy Characteristic Modelling

Interpreting the model

Our initial regression model focuses on demographic and energy-related characteristics, so excluding direct experience measures such as satisfaction with billing accuracy. The variables included are listed in full below in Table 1 below.[17]

The R-squared value for this model is 11.6%, meaning it explains only a limited share of the overall variation in satisfaction. Accordingly, A 30% relative importance score refers to 30% of that 11.6%, *not* of the total variation.

However, the model still offers valuable insights into which consumers are more or less likely to report a positive experience with their energy supplier. Indeed, an R-squared value of 11.6% in this range are typical in social science when models include only demographic characteristics. This makes sense given that the model is based solely on general characteristics, without including any direct measures of customer experience.

Moreover, as our implied satisfaction scores show, some factors in this model can still noticeably shape how satisfied people are – particularly for certain key variables. For example, when it comes to our Financial Vulnerability Classification, as we will go on to show using our Implied Impact Satisfaction Score, we would expect satisfaction to fall to 66% in a world where everyone was in the ‘highly vulnerable’ category, compared to 84% if everyone were in the ‘doing well’ group. Yes, a clear majority in both groups would be satisfied – but this still represents a notable gap.

The strongest predictor of overall satisfaction is people’s financial circumstances

The regression results show two clear stand-out predictors of satisfaction. The strongest is our Financial Vulnerability Classification, a custom built variable exploring how well respondents are coping financially, incorporating borrowing behaviours and their ability to cover unexpected expenses.[18]

This variable accounts for 32% of the explained variance, which corresponds to 3.7% of the total variance in absolute terms, based on the overall model R-squared. This surpasses even the customer’s supplier (29% of explained variance and 3.3% of total variance). Together, these two variables contribute substantially more than any others in the model. We have marked these as ‘key factors’ in Table 1 below.

[17] Variables included in the final model used to calculate odds ratios and Implied Impact on Satisfaction scores were limited to those that were statistically significant. To calculate these relative importance scores for all variables, a separate version of the model was run with all variables forced in, allowing each one to receive a score.
[18] See appendix for more detail on how this variable is constructed.

Table 1: Energy and demographic characteristics variables ranked by importance (R-square of 11.6%)

Category	Variable	Relative importance score	Nagelkerke R Square	Rank	Statistically significant	Nature of relationship[19]
Key factors	Financial Vulnerability Classification	32%	3.7%	1	Yes	Consumers classified as ‘doing well’ and ‘getting by’ are more likely to be satisfied than average, and ‘vulnerable’ and ‘highly vulnerable’ less likely than average.
	Parent supplier	29%	3.3%	2	Yes	18% point range in Implied Impact Satisfaction Scores between top and bottom parent supplier.
Moderate	Smart meter uptake	8%	1.0%	3	Yes	Consumers with a smart meter are more likely to be satisfied than average, with those without less likely than average.
	Age of respondent	6%	0.7%	4	Yes	Customers aged 35–64 are significantly less satisfied than average, while those aged 75 and over are more satisfied than average.
	Switched supplier / tariff	5%	0.6%	5	Yes	Customers who have switched tariff and stayed with same supplier are more likely to be satisfied than average, with those who have not switched less likely than average.
	Priority Services Register (PSR) membership	4%	0.4%	7	Yes	Customers who are members of the PSR are more likely to be satisfied than average, with customers who a not less satisfied than average.
	Region	3%	0.4%	8	Yes	Consumers in the West Midlands are more likely to be satisfied than average, while those in the East of England and Scotland are less likely than average.

[19] The nature of the relationship between each variable and satisfaction is described in the table, based on how each group’s odds of satisfaction compare to the overall average. This analysis uses effect coding, where each group is compared to the average across all groups, rather than to a single reference category.

Category	Variable	Relative importance score	Nagelkerke R Square	Rank	Statistically significant	Nature of relationship[19]
Minimal but statistically significant	Payment type	3%	0.4%	9	Yes	Standard Credit customers are less likely to be satisfied than average, prepayment meter customers more likely to be satisfied than average, and Direct Debit customers in line with the average.
	Disability status	2%	0.2%	10	Yes	Customers with a disability are less likely to be satisfied than average, with those without less likely to be so.
	Fuel type	1%	0.1%	11	Yes	Dual-fuel customers are more likely to be satisfied than average with mains gas only and mains electricity only customers in line with the average.
	Gender	1%	0.1%	12	Yes	Females are more likely to be satisfied than average and males less likely than average.
	Children under 5 or expecting	1%	0.1%	13	Yes	Households with children under 5 or expecting are more likely to be satisfied than average, while those without children are less likely to be satisfied than average.
Not statistically significant	Tenure	4%	0.4%	6	No	Not applicable.
	Whether claiming benefits	0%	0.1%	14	No	
	Ethnicity	0%	0.0%	15	No	
	Carer status	0%	0.0%	16	No	
	Urban / Rural	0%	0.0%	17	No	
	Digitally excluded	0%	0.0%	18	No	

*Nagelkerke R Square: 11.6%. **Green** = Statistically significant. **Red** = Not statistically significant.*

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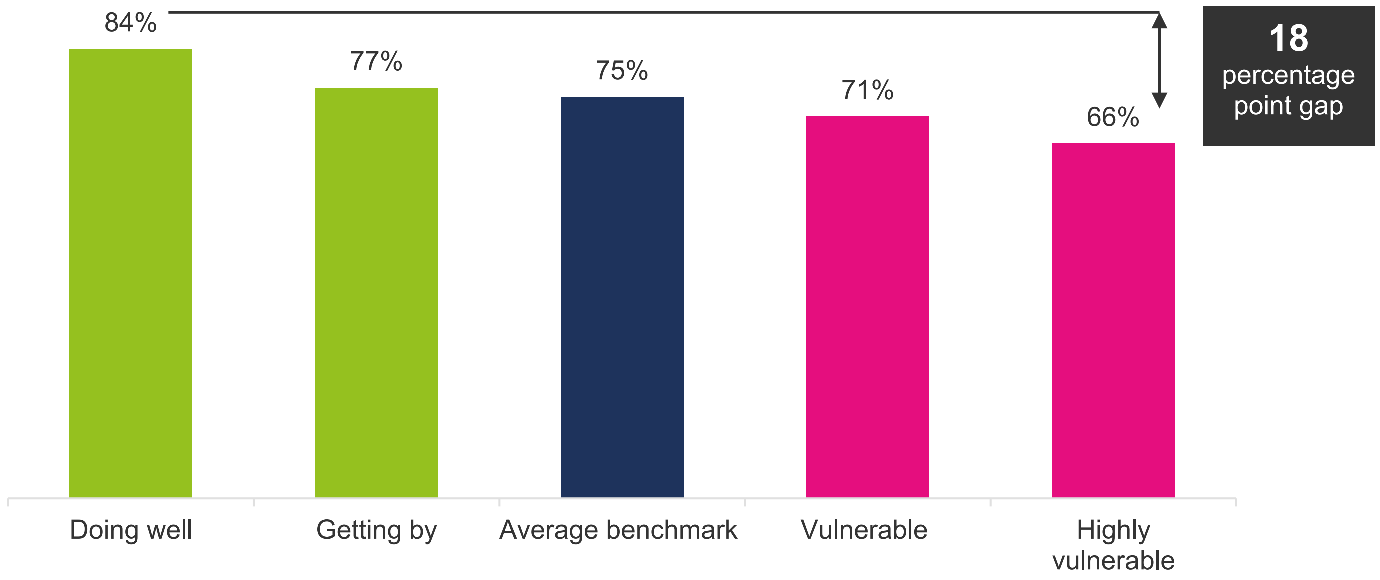
Put simply, people who are struggling financially are much less likely to be satisfied. Using our Implied Impact Satisfaction Scores, relative to our 75% benchmark and controlling for other factors, if the whole sample was just in the 'highly financially vulnerable' category, we would expect a satisfaction score of just 66%, compared to as high as 84% if the whole sample was allocated to the 'doing well' category.

While this aligns with patterns we've consistently seen in satisfaction data, seeing this factor top the regression model underlines how central it is to satisfaction.

Figure 2: Implied Impact Satisfaction Scores by Financial Vulnerability Classification



Statistical significance key

Above average | Below average | Average benchmark

This finding also highlights a broader theme in how domestic energy consumers relate to their suppliers: customers can have a passive relationship with their supplier, where satisfaction often simply means "nothing has gone wrong."[20] This passivity shapes how they judge their experience: affordability and financial strain tend to carry more weight in satisfaction scores, with price often the most obvious reference point consumers have.

That said, the likelihood is that dissatisfaction among financially struggling consumers may not be solely about affordability or financial strain. Our data shows they're slightly more likely to have contacted their supplier – likely for support, given their situation. So, in some cases, lower satisfaction could be reflective of those interactions.

[20] See coded open responses on page 16 of the latest Energy Satisfaction Survey. Available here.

Parent supplier ranks a close second

Ranking very closely behind our Financial Vulnerability Classification, the customer's supplier is the second strongest predictor of satisfaction.[21]

Although all suppliers have a majority of satisfied customers, there is a large gap in satisfaction between the highest and lowest rated providers. Relative to our benchmark satisfaction score of 75%, our Implied Impact Satisfaction Scores system predict that, controlling for other factors, satisfaction would rise to 86% if all consumers were with the top-performing supplier, and fall to just 64% if everyone were with the lowest performer – a gap of 22 percentage points.

The differences shows that suppliers can play an active role in shaping customer satisfaction, it's not simply out of their hands. However, the data also highlights uneven performance, with some customers far more likely to report positive experiences than others.

This also tackles a key question: are some suppliers doing better simply because they serve a different demographic profile of customers, and does this explain the underlying differences? It's a fair challenge – the customer make-up does differ between suppliers. Take our Financial Vulnerability Classification: in the latest January wave some suppliers had a range of 44%-69% of their customers in the doing well group.

However, a key strength of regression modelling is its ability to control for variables such as demographics and financial circumstances. This means the results account for differences in customer profiles. Even after this adjustment, the model still shows that the supplier itself remains one of the top predictors of satisfaction, with a wide variation in supplier performance.

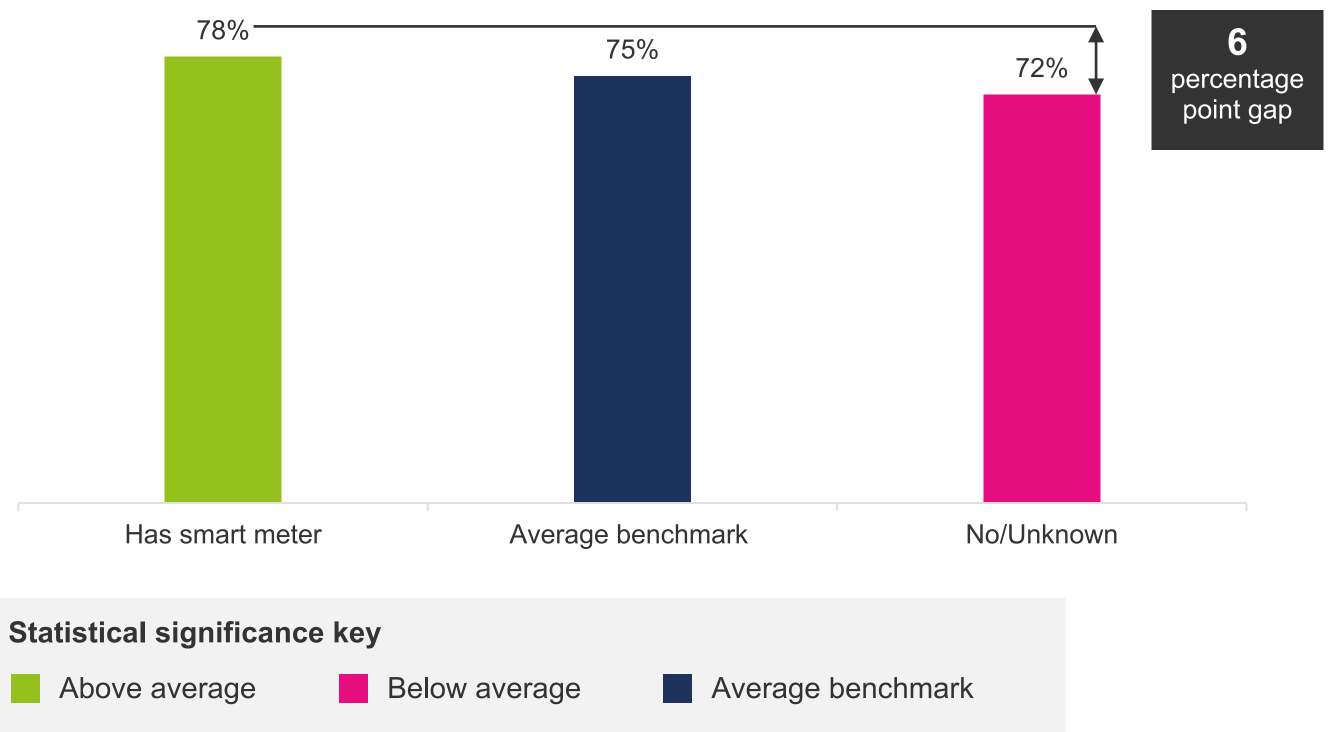
Several other factors also have useful predictive value

While cost of living pressures and parent supplier are the dominant drivers of satisfaction in our Demographics and Energy Characteristics Model, a second tier of moderate factors listed in Table1 above – smart meter uptake, age, and switching behaviour – still deserve attention. Together, these factors account for nearly 20% of the explanatory power in our Demographic and Energy Characteristics Model. We explore the relationship with each and satisfaction in turn:

Smart meter ownership is linked with higher satisfaction: Smart meter ownership emerges as the third most significant energy-related factor in our model. Controlling for other variables, customers with a smart meter tend to report higher satisfaction levels, while those without are less satisfied. The Implied Impact Satisfaction Scores show a range of 6 percentage points between those with and without a smart meter – see Figure 3, below.

[21] Parent supplier was used as the supplier variable. Subsidiary brands such as white label brands are included in the supplier group that is responsible for their customer service operations.

Figure 3: Implied Impact Satisfaction Scores by smart meter uptake

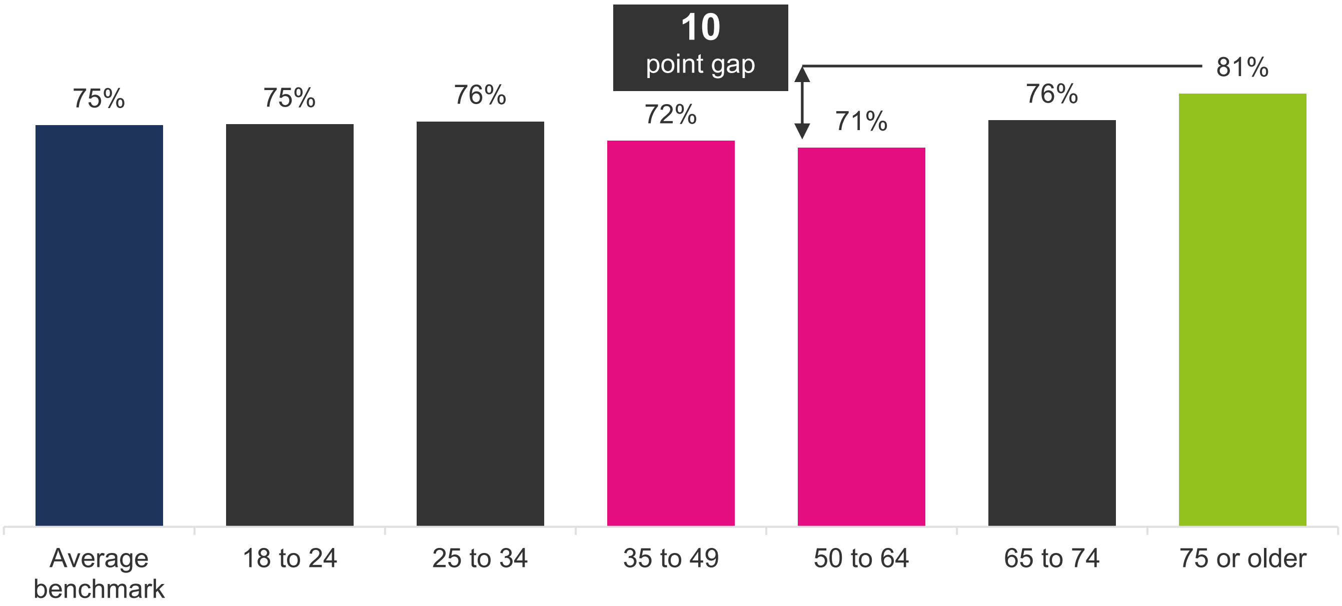


Two implications follow from this. First, the growing rollout of smart meters, from 62% in August / September 2023 to 68% in January 2025, has likely contributed to the overall rise in satisfaction scores observed across the last four waves. Second, it suggests that continuing the rollout could help sustain or even enhance satisfaction, as more customers benefit from the potential advantages smart meters offer (e.g. clearer usage information, fewer estimated bills).

That said, some caution is needed. Smart meter ownership may also act as a proxy for customer mindset – those who adopt smart meters may be more engaged, more trusting of the energy system, and more open to sharing data. In this sense, higher satisfaction may reflect a broader orientation toward confidence in the market or a wider set of attitudes towards the energy sector, rather than the impact of the device alone.

Customers aged between 35 and 64 are less satisfied: Our Implied Impact Satisfaction scores show that once other factors are controlled for, younger groups report satisfaction levels close to the average. Middle-aged customers (35–64) are significantly less satisfied than the average, while those aged 75 and over are much more likely than average to report high satisfaction.

Figure 4: Implied Impact Satisfaction Scores by age group



Statistical significance key

Above average | No different to average | Below average | Average benchmark

This mirrors a broader trend found in wider wellbeing research: numerous studies have shown that life satisfaction often follows a U-shaped curve across the life course.[22] People in midlife-typically between their late 30s and early 60s-tend to report lower overall satisfaction. In contrast, older adults often report greater contentment, possibly due to increased stability, reduced daily demands, or a shift in perspective that comes with age.

The energy satisfaction data may reflect these same underlying dynamics, with middle-aged consumers more likely to scrutinise services critically or feel frustrated by issues, while older customers may approach the experience with more patience or lower expectations.

As Britain's population continues to age, and older groups represent a larger share of consumers, this demographic shift could become a subtle yet meaningful factor supporting rising energy satisfaction – provided the observed relationship with age and satisfaction continues.[23]

Switching – particularly those who switched tariff while remaining with the same supplier – is associated with higher satisfaction: Both switching supplier and switching tariff without changing supplier are associated with higher satisfaction compared to customers who did not switch or whose switching status is unknown.

Switching tariff while staying with the same supplier delivers a bigger uplift in satisfaction than moving to a new supplier, suggesting that customers particularly value getting a better deal without the disruption of changing provider – see Figure 5.

This highlights a specific aspect of switching either with a new supplier context of an existing relationship, perhaps reinforcing perceptions of value and service. As our model controls for supplier, this effect is not simply due to these customers moving to or remaining with higher-performing providers.

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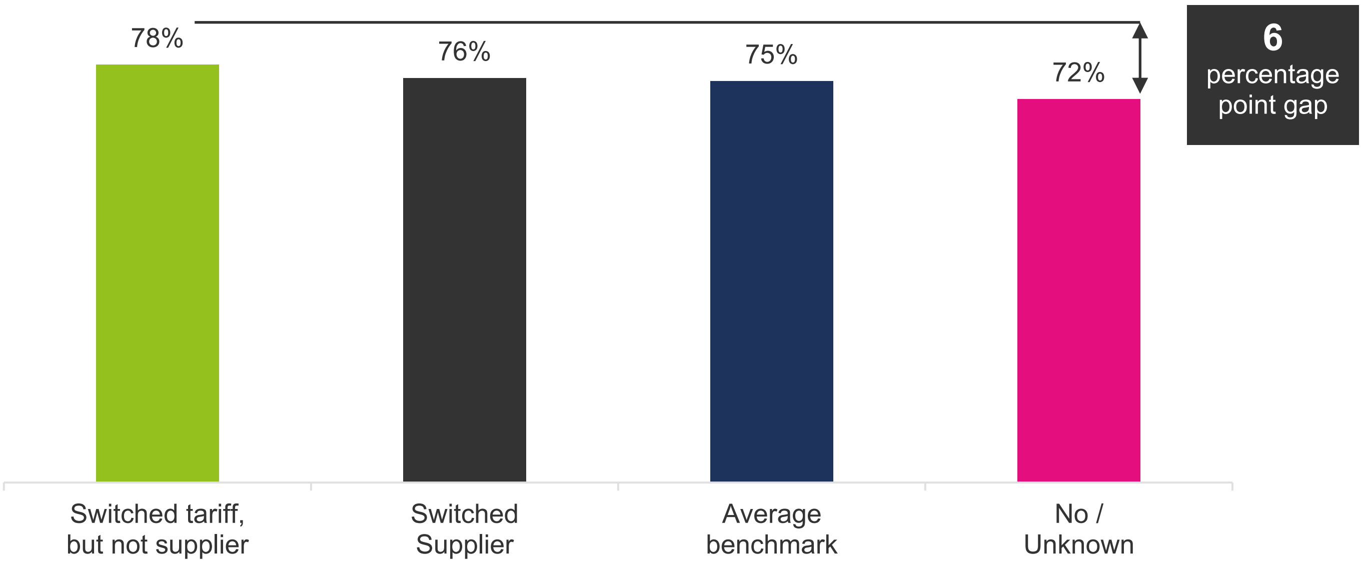
[22] Galambos, N. L., Krahn, H. J., Johnson, M. D., & Lachman, M. E. (2020). The U shape of happiness across the life course: Expanding the discussion. *Perspectives on Psychological Science, 15*(4), 898–912. Available here.
[23] For projections on ageing population, see: National population projections – Office for National Statistics.

However, we acknowledge that customers who switch tariffs within the same supplier may do so because they are already more satisfied. While the model identifies associations, it cannot definitively establish the direction of causality. Moreover, consumers who switch may have a broader tendency toward market engagement, including greater confidence or trust in navigating options, which could contribute to higher satisfaction levels.

Figure 5: Implied Impact Satisfaction Scores by switching behaviour



Statistical significance key

Above average | No different to average | Below average | Average benchmark

Note: While switching supplier does not produce a statistically significant difference from our 75% benchmark, switching tariff is significantly associated with higher satisfaction compared to not switching.

Between July 2024 and January 2025, the proportion of customers in the Energy Consumer Satisfaction Survey who reported switching tariffs with their existing supplier rose from 12% to 17%. This rise is likely one of several factors contributing to the recent uplift in satisfaction scores.

It may also have regulatory relevance. While market engagement is often seen as valuable in its own right, this analysis suggests it can be linked to better customer outcomes. It indicates that customers who switch – even after accounting for other factors – tend to report higher satisfaction with their supplier. In this light, encouraging engagement may not only be a matter of principle, but also a practical route to improving customer experience.

Several other variables are statistically significant drivers – but have a low predictive value

After accounting for age, switching habits, and smart meter usage, a few other variables emerge as statistically significant but have minimal impact on satisfaction. This serves as a reminder that with large sample sizes, statistical significance doesn't always translate to meaningful influence.

Table 2 below summarises the relationship for each of these variables. Payment type is discussed separately later, as it has more notable implications.

Table 2: Summary of relationships with satisfaction for minimal but statistically significant variables

Variable	Relative Importance Score	Nature of relationship[24]
Priority Services Register membership	4%	Customers who are members of the PSR are more likely to be satisfied than average, with customers who are not PSR members less likely to be satisfied than average.
Region	3%	Consumers in the West Midlands are more likely to be satisfied than average, while those in the East of England and Scotland are less likely than average.
Payment type	3%	See discussion below on page 23 and 24.
Disability status	2%	Customers with a disability are less likely to be satisfied than average, with those without less likely to be so.
Fuel type	1%	Dual-fuel customers are more likely to be satisfied than average with mains gas only and mains electricity only customers in line with the average.
Gender	1%	Females are more likely to be satisfied than average and males less likely than average.
Children under 5 or expecting	1%	Households with children under 5 or expecting are more likely to be satisfied than average, while those without children are less likely to be satisfied than average.

Once other factors are controlled for, prepayment meter customers are more likely to be satisfied than consumers paying by other methods

One of the more surprising findings from the model relates to payment type. Firstly, it is notable that payment type – a variable frequently used to analyse energy consumer experiences – has relatively low importance in the model once other factors are controlled for (relative importance score of 3.1%).

Secondly, and more surprisingly, the model shows that prepayment meter (PPM) customers are actually more likely to be satisfied than direct debit customers once other variables are controlled for.

This may seem counterintuitive. Although no longer the case in the latest wave, earlier data – such as January–February 2024 – showed that PPM customers were less satisfied than Direct Debit customers based on simple cross-tabular analysis (68% vs 76%). At no point have PPM customers reported statistically higher satisfaction than those paying by Direct Debit.[25]

The fact that the regression controls for wider factors is especially important in this context. PPM customers are disproportionately represented among our vulnerable and highly vulnerable groups. As set out below, in January 2025, 37% of PPM customers fell into these categories, compared with 29% for Standard Credit consumers, and 22% for Direct Debit customers.

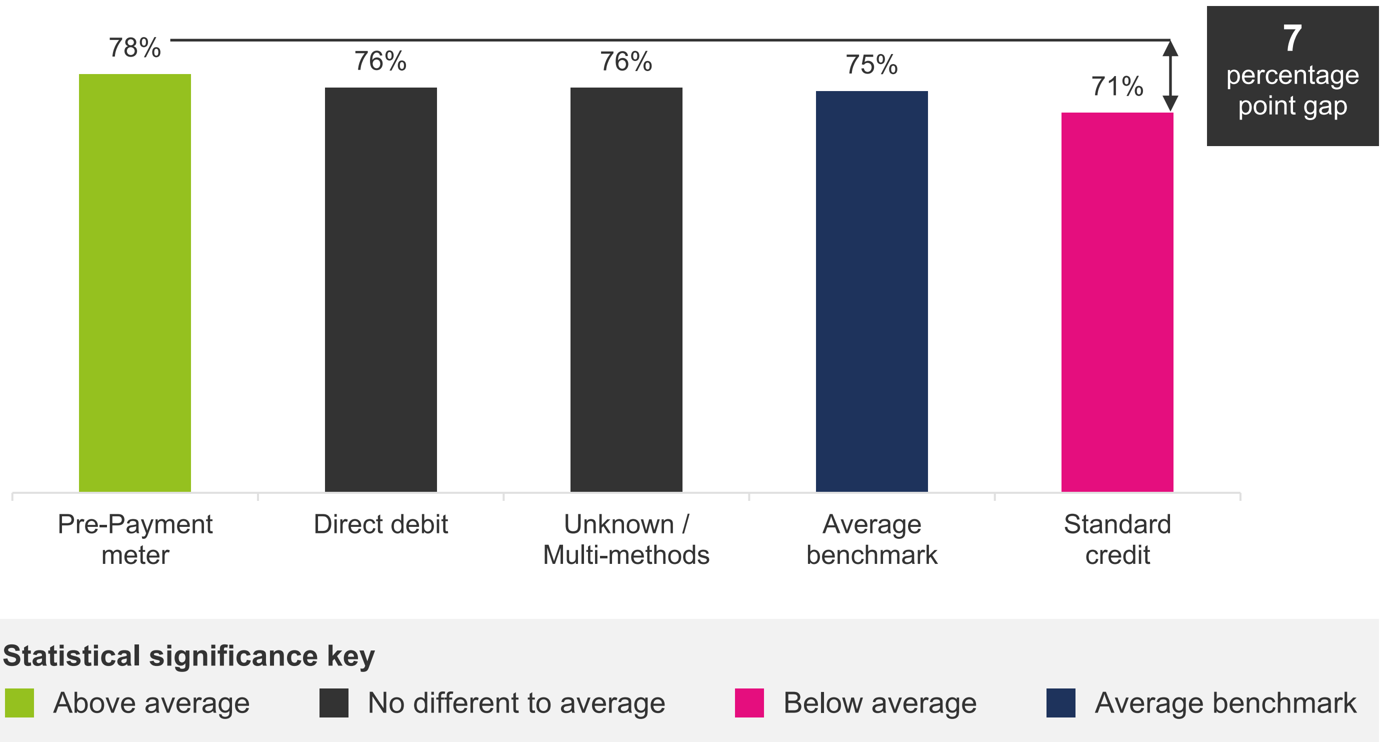
[24] The nature of the relationship between each variable and satisfaction is described in the table, based on how each group's odds of satisfaction compare to the overall average. This analysis uses effect coding, where each group is compared to the average across all groups, rather than to a single reference category.
[25] Since July 2023, prepayment meter (PPM) customers have no longer faced the highest energy costs. This change may have gradually influenced satisfaction levels over time. See: Prepayment meter customers to pay less for energy from today – GOV.UK

Table 3: Financial vulnerability by payment type (January 2025 data)

Financial Vulnerability Classification group	Direct debit	Prepayment meter	Standard credit
Doing well	42%	31%	41%
Getting by	13%	7%	9%
Financially vulnerable	12%	20%	16%
Highly financially vulnerable	9%	18%	13%
Not classified	24%	25%	21%
SUMMARY: Vulnerable	22%	37%	29%

Once the Financial vulnerability Classification and others accounted for, there's no evidence that there's something about paying via prepayment meter itself that lowers satisfaction. In fact, as Figure 6 illustrates, the model suggests doing so is actually linked with higher satisfaction.

Figure 6: Implied Impact Satisfaction Scores by payment type



Meanwhile, the model shows that controlling for other factors, Standard Credit customers are less satisfied than both Direct Debit and PPM customers (Implied Impact Satisfaction score of 71%).

Several variables show no statistically significant impact on the model

Several variables included in the model do not show a statistically significant relationship with overall satisfaction.[26] These are:

[26] An earlier version of the model attempted to test for a seasonal effect (whether satisfaction varied between winter and summer waves). However, with only four waves of data available, there was insufficient variation to detect any seasonal impact. It is likely that many more waves would need to be collected before such an effect could be meaningfully explored.

- Digital exclusion
- Tenure
- Whether receiving benefits
- Ethnicity
- Carer status
- Urban / rural location

While individuals in certain groups may report lower satisfaction, our model indicates that once factors like our Financial Vulnerability Classification are accounted for, variables such as benefits status, ethnicity, and housing tenure do not independently influence satisfaction levels. These characteristics are often linked to financial vulnerability, but they are not direct drivers of satisfaction in our analysis.

No evidence to link EV ownership and supplier satisfaction (yet)

In January 2025, we introduced a survey question on EV ownership, enabling us to run a dedicated model using January data alone. This allowed us to test whether EV drivers – controlling for other factors-are more likely to report higher satisfaction with their energy supplier.[27]

The hypothesis was that EV owners might have a notably different use case for electricity, may be on specialist tariffs, and could be more engaged and potentially more satisfied overall. To test this hypothesis, we ran the Demographic and Energy Characteristics Model using only the Wave 20 data, the only one to include the new question about EV ownership. This model is based on 3,518 cases, a much lower sample size than the 14,054 in the main model using four waves of data.

No statistically significant relationship was found at this stage. A possible cause is the lower sample size of this model, which makes it harder to detect statistically significant relationships. This is an area worth continuing to monitor as we collect more waves of data.

[27] For dual fuel customers with different suppliers for gas and electricity, a small share of respondents with EVs have answered the satisfaction questions with reference to their gas supplier.

Modelling the impact of improving household finances on rising supplier satisfaction scores

Improving household finances explain around 1/10th of the overall increase in energy satisfaction scores between August / September 2023 and January 2025

Satisfaction has been rising steadily across the last four waves of ESAT, from 69% and 81% between August / September 2023 and January 2025. The 81% recorded in January 2025 is a record high since the tracker began.

However, over the same period, consumers' financial situations have also been improving. As the table below shows, the proportion of consumers we classify as "doing well" financially has increased substantially over the same period – see table 4.[28] This prompts a key question: how much of the rise in satisfaction is driven by improvements in the cost of living?

Table 4: Financial Vulnerability Classification shares in weighted sample for Aug / Sep 2023 and Jan 2025

Financial Vulnerability Classification	August / September 2023 (wave 17)	January 2025 (wave 20)
Doing well	36%	46%
Getting by	17%	15%
Vulnerable	20%	17%
Highly financially vulnerable	21%	17%
Unclassified	6%	5%

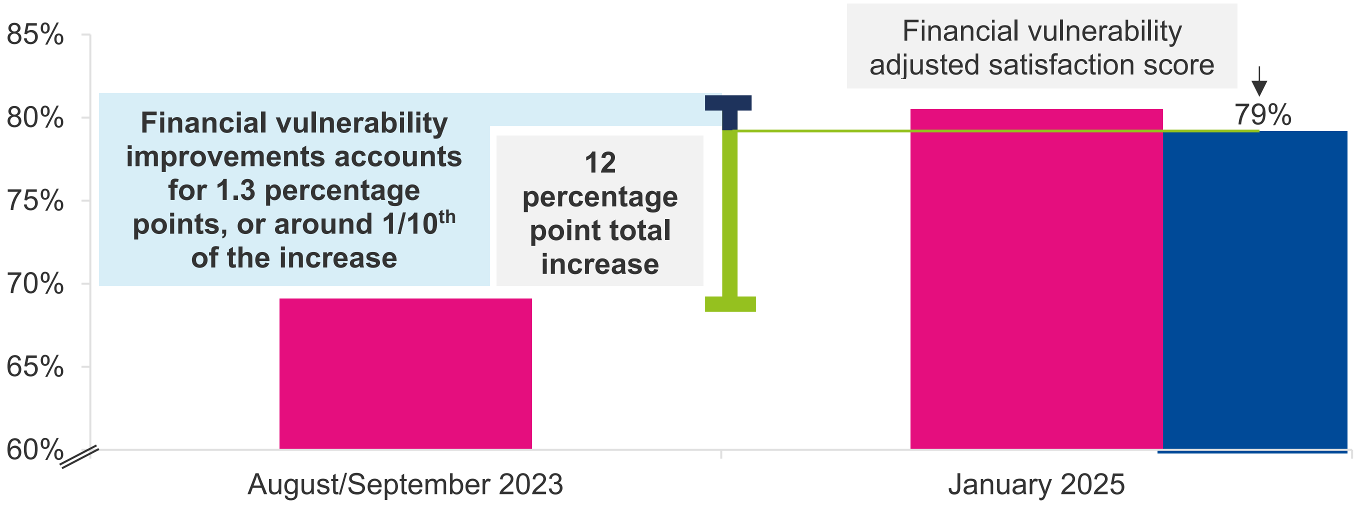
To explore this, we conducted additional modelling using our regression results to isolate the effect of financial wellbeing on satisfaction levels. The simulation estimated what satisfaction levels in Wave 20 (January 2025) would have been if the distribution across our Financial Vulnerability Classification had remained at the same level as in Wave 17 (August / September 2023), when consumers were generally under greater financial strain.[29]

As illustrated in Figure 7, the results show that if we simulate what satisfaction would have looked like in January 2025 had financial circumstances remained at the level seen in August / September 2023, our headline satisfaction drops from 81% (80.5%) to 79% (79.2%), a 1.3% point drop.

[28] BMG conducted additional modelling on unclassified respondents – those who answered "don't know" or "prefer not to say" to the Financial Vulnerability Classification questions – to estimate their likely responses. This reduced the share of unclassified respondents from 24% to 5%. The overall patterns remained consistent across both the remodelled and original versions, though the vulnerable group saw slightly higher figures. The figures presented use these remodelled figures. More detail on the Financial Vulnerability Classification process is in the appendix.
[29] See methodology for more detail.

In other words, changes in people's financial vulnerability account for 1.3% – or about one-tenth – of the total increase in energy satisfaction from 69% to 81% observed between August / September 2023 and January 2025.

Figure 7: Simulated impact on overall satisfaction for January 2025 data



Note: Scale break in axis- increase is not proportionally represented.

How should we interpret the findings?

In some ways, the finding is striking. This one derived variable – a broad measure of financial wellbeing – accounts for around one tenth of the total change in energy satisfaction between Aug / Sep '23 and Jan '25. That's a relatively high figure, especially considering the measure itself is not directly related to energy experiences or supplier interactions.

On the flip side, it's also just over a tenth, meaning that around nine tenths of the change in satisfaction cannot be explained by this financial improvement alone. This adds weight to the idea that much of the change is being driven by other factors.

This could be supplier performance, for example, improvements in satisfaction across multiple customer touchpoints, such as billing, smart meters, and customer contact. However, it is also likely that other non-measured 'external' factors likely contribute too. As is the case in most regression models in social research, the model's explanatory power is modest, with a Nagelkerke R Square of 11.6% for demographics and energy variables, increasing to 37.5% when broader satisfaction measures are added (covered later in the report).[30]

This reflects a broader reality in social research: how consumers think and feel – including about their energy supplier – are influenced by a wide array of factors, many of which are unobservable and difficult to quantify.

From trust in government and confidence in the energy sector, to media narratives, climate concerns, or general economic outlook, many potential influences on satisfaction operate in ways that are complex, and subtle. Some of these can be captured in surveys, but because this survey isn't just about modelling satisfaction, and space is limited, we have taken a practical approach and used what's available.

[30] As set out earlier in the report, Nagelkerke R Square is a version of the R Square statistic adapted for logistic regression models. It provides an indication of how much of the variation in the outcome is explained by the model. Values range between 0% and 100%, but in social research, even relatively low values can still represent meaningful explanatory power, given the complexity of human perceptions.

Satisfaction Metrics Modelling

So far, we have discussed our model based on demographic and energy characteristics. However, regression analysis also allows us to explore which specific satisfaction measures – particular types of good or bad experiences – are most strongly linked to overall satisfaction. That's the focus of this section. But before we do so, we first need to define which variables to include, a more difficult task when working with attitudinal measures.

The measures we have arrived at are: bill satisfaction; complaint satisfaction; support satisfaction; switching process satisfaction; and satisfaction with their smart meter.

Two variables – satisfaction with the information received and satisfaction with value for money – were considered but ultimately excluded from the final models used for analysis because they are strongly associated with overall satisfaction, reflecting how consumers broadly evaluate their experience with their supplier. Including them in our final reported model would blur whether it is these specific areas driving satisfaction, or simply an echo of overall sentiment already captured by overall satisfaction.

This makes intuitive sense. Satisfaction with value for money is a broad measure, reflecting not just price perceptions but also views on service quality and customer support. Similarly, satisfaction with information received could cover letters, emails, texts, contact centre conversations, smart meter displays, or billing accuracy. On balance, we felt including them had little explanatory value.

In earlier modelling, we tested a customer service satisfaction variable carried over from a previous supplier model. While it showed a strong link to overall satisfaction, it suffered from the same multicollinearity issue – strongly predictive but effectively duplicating the outcome we were trying to explain. Again, including it would have undermined the model's interpretive value.

Contact satisfaction, bill satisfaction, and smart meter satisfaction are the three key drivers of overall satisfaction with suppliers

To begin with, it's worth noting that satisfaction metrics provide significantly greater explanatory power. Compared to the Demographics and Energy Characteristics model, which has a Nagelkerke R Square of 11.6%, the Satisfaction Metrics Model jumps to 37.5%. This is not surprising: direct measures of customer experience tend to be far more predictive of overall satisfaction.

When it comes to more specific aspects of satisfaction, our modelling shows that overall customer satisfaction is primarily driven by three key factors: ease of contacting their supplier, satisfaction with billing, and satisfaction with smart meters.

Ease of contacting their supplier and bill satisfaction emerge as joint top predictors of overall satisfaction, with relative importance scores of 35% and 34% respectively. This highlights the critical role that both smooth customer interactions and clear, accurate billing play in shaping customer perceptions. Satisfaction with smart meters is the third strongest factor, with an index score of 21%.

Table 5: Satisfaction metrics ranked by importance (R-square of 37.5%)

Category	Variable	Relative importance score	Nagelkerke R Square	Rank	Statistical significance
Key factors	Ease of contacting supplier /[31]	35%	13%	1	**Yes**
	Bill satisfaction[32]	34%	13%	2	**Yes**
	Satisfaction with smart meter	21%	8%	3	**Yes**
Lower predictive power due to interaction incidence	Support satisfaction	5%	2%	4	**Yes**
	Complaint satisfaction	4%	2%	5	**Yes**
	Switching process satisfaction	2%	1%	6	**Yes**

Nagelkerke R Square: 37.5%. ***Green*** *= statistically significant.* ***Red*** *= Not statistically significant.*

You can see the impact each has on satisfaction using our Implied Impact Satisfaction Scores in Table 6 below. For example, relative to the 75% average satisfaction benchmark (Waves 17–20), if all consumers were satisfied with their bill, overall satisfaction would be expected to rise to 87%. If no one was satisfied, it would fall to 52%, marking a 35-point difference.

Together, each of these areas account for most of the explained variation in satisfaction outcomes. Suppliers focusing their efforts here are likely to see the biggest improvements in their satisfaction scores.

[31] This variable groups respondents based on two questions: ease of contact and satisfaction with the interaction. Easy or satisfied with contact includes anyone who found it fairly/very easy to get in touch **or** was fairly / very satisfied with how it was handled. Not easy AND not satisfied includes those who found it fairly / very difficult **and** were dissatisfied. A separate group includes those who hadn't tried to contact their supplier in the last 3 months.
[32] Respondents are classified as satisfied if they reported being fairly or very satisfied with **either** the ease of understanding **or** the accuracy of their bill. They are classified as **not** satisfied only if they did not report satisfaction both aspects. This question was asked only to those who pay for gas or electricity by direct debit or on receipt of bill (standard credit). Prepayment meter (PPM) customers were excluded, as they pay upfront and do not receive bills in the same way.

Table 6: Implied Impact Satisfaction Scores for Satisfaction Metrics model

Category	Variable	Response[33]	Implied Impact Satisfaction Score
Key factors	Ease of contacting supplier / satisfaction with contact	Easy to contact Or Satisfied with contact	86%
		NOT easy AND NOT satisfied	57%
		Has not tried to contact in prior 3 months	78%
	Bill satisfaction	Satisfied	87%
		NOT satisfied	52%
		Pre-payment meter / other / Unknown	79%
	Satisfaction with smart meter	Satisfied with smart meter	86%
		NOT satisfied with smart meter	64%
		No smart meter	72%
Lower predictive power due to interaction incidence	Support satisfaction	Satisfied with support	82%
		NOT satisfied with support	62%
		Not received support	79%
	Complaint satisfaction	Satisfied with complaint handling	87%
		NOT satisfied with complaint handling	49%
		Not made a complaint	81%
	Switching process satisfaction	Satisfied with switching process	82%
		NOT satisfied with switching process	65%
		Not switched	76%

Every measure counts, but the incidence of interaction shapes overall predictive power

Other measures, while still statistically significant, have a more modest impact on overall satisfaction. Satisfaction with support services (relative importance score of 5%) and complaint handling (4%) both contribute positively but less substantially to the model. Satisfaction with the switching process has the smallest impact, with a relative importance score of 2%.

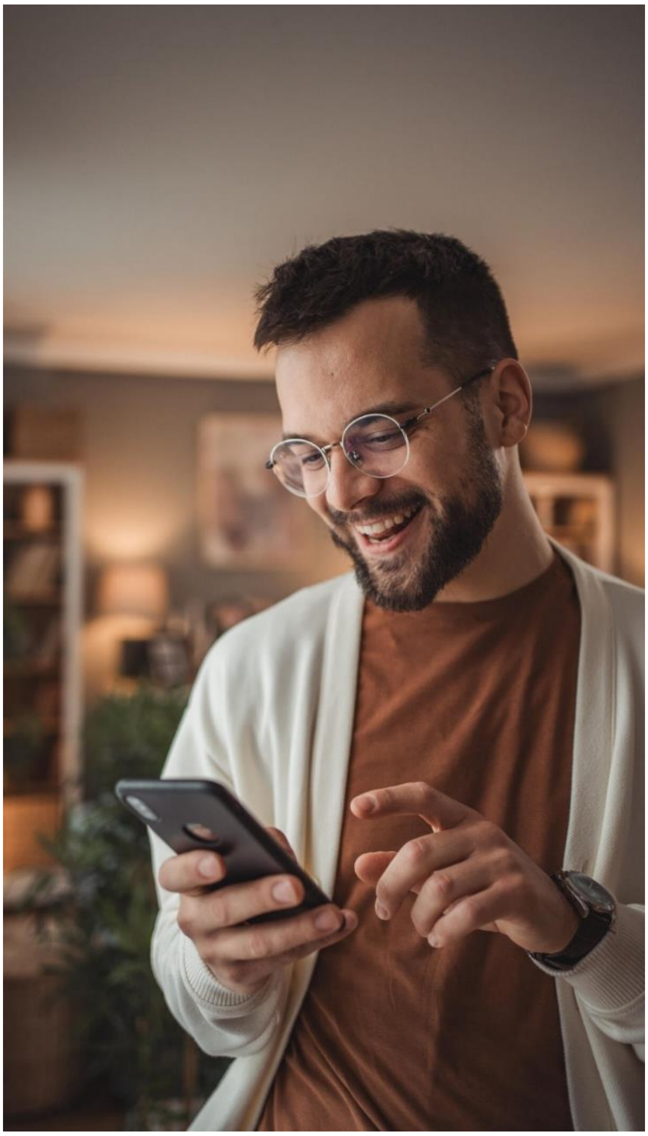
[33] "Not" satisfied categories include both explicitly negative responses (such as "dissatisfied") and neutral responses (such as "neither satisfied nor dissatisfied").

The lower scores for each in part reflect the smaller share of customers who experience these events – not necessarily weaker effects. Indeed, as Table 6 above shows, our Implied Impact Satisfaction Scores show strong shifts within these groups: for example, satisfaction with complaint handling increases overall satisfaction from 49% to 87%.

However, because only 2% of customers reported making a complaint in January 2025, its contribution to explaining overall satisfaction remains limited. The structure of the complaint satisfaction variable means most variation comes from the small number of customers who have made a complaint. Those who haven't complained are grouped together, so satisfaction differences only show within this smaller group. This is why we see big differences between those satisfied and dissatisfied with complaint handling – but overall, complaint satisfaction has limited impact across the full customer base.

The same is true, though to a lesser extent, for satisfaction with support and satisfaction with switching. Relatively few customers have sought help with bill payments or likely to be more limited.

Positive interactions deliver more than 'passive satisfaction'



The results consistently show that positive interactions drive significantly higher satisfaction than no interaction at all – a pattern clearly illustrated by the Implied Impact Satisfaction Scores.

This is most starkly seen in the case of complaints: you might expect that even a customer satisfied with complaint handling would still feel less satisfied overall than one who never had to complain. However, the opposite is true – customers satisfied with complaint handling report have and Implied Impact Satisfaction Score of 87%, compared to 81% among those who never made a complaint. By contrast, dissatisfied complainants' satisfaction falls dramatically to just 49%.

A similar pattern appears across other areas: satisfied support seekers (82%) score higher than those who never sought support (79%), and customers satisfied with their switching experience (82%) outpace those who did not switch at all (76%).

This is supported by findings in other studies that highlight the phenomenon known as the "service recovery paradox," where a well-handled service failure can lead to higher customer satisfaction than if no problem had occurred.[34] Academics suggest this happens because effective complaint resolution shows responsiveness, fairness, and care, building trust and emotional connection. When customers feel heard and valued, the recovery can outweigh the original issue.

However, this does work both ways: a bad smart meter experience is actually worse for customer satisfaction than not having one at all. It's the failure to deliver on expectations that damages satisfaction more than the absence of the technology. To contradict the Shakespeare-inspired phrase, in the case of smart meters, it is *not* better to have had and lost than never to have had at all!

[34] See, for example: McCollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An empirical investigation of customer satisfaction after service failure and recovery. Journal of Service Research, 3(2), 121–137. Available here.

Nevertheless, this highlights a crucial point for suppliers: successful engagement even in tricky circumstances is an opportunity. When handled well, customer interactions can lift satisfaction beyond what passive experiences alone can achieve – meaning suppliers should actively welcome opportunities to engage, provided they deliver them well.

Hybrid Modelling

The hybrid model reveals a similar pattern of key drivers as the satisfaction metrics model

We now turn briefly to the hybrid model, which combines variables from both the Satisfaction Metrics Model and the Demographic and Energy Characteristics Model. Only statistically significant variables from these models were retained in the hybrid model.

Two findings are of note. First, satisfaction metrics continue to play a dominant role. Satisfaction with ease of contacting the supplier, billing, and smart meters together account for 76% of the model's total explanatory value and remain the strongest predictors of overall satisfaction.

Second, as expected, demographic and energy characteristics play a secondary role once satisfaction metrics are controlled for. The Nagelkerke R^2 rises only modestly – from 37.5% to 40.8% – when these variables are added.

This pattern is well-established across modelling exercises of this nature. Specific attributes of the customer-supplier relationship – such contact, billing and smart meter experiences – are direct reflections of the experiences shaping satisfaction. In contrast, structural characteristics (e.g. age, financial vulnerability) influence the *likelihood* of certain experiences but are not experiences themselves so will in most circumstances be less predictive in regression exercises.

That said, the demographic and energy characteristics model is still really key as it tells us who is more likely to have these experiences, both overall, but also by implication, the specific experiences that drive this.

A helpful analogy is to think about healthcare. In a regression model predicting patient satisfaction, the strongest predictors are likely to be whether patients felt listened to, respected, and found it easy to get an appointment or treatment. By contrast, factors like their financial circumstance or whether they used an app to book the appointment might matter but are likely less predictive on their own

But if patients from lower-income areas consistently report worse outcomes, that signals a sperate issue. The demographic model may be less predictive *statistically*, but it's crucial for identifying which groups are experiencing worse outcomes and where action could be needed most.

Table 7: Hybrid model metrics ranked by importance, all statistically significant (R-square of 40.8%)

Variable	Relative importance score	Nagelkerke R Square	Rank
Ease of contacting supplier / satisfaction with contact	30%	12%	1
Bill satisfaction	28%	12%	2
Satisfaction with smart meter	17%	7%	3
Parent supplier	6%	2%	4
Financial Vulnerability Classification	5%	2%	5
Support satisfaction	4%	2%	6
Complaint Satisfaction	4%	2%	7

Variable	Relative importance score	Nagelkerke R Square	Rank
Age of respondent	1%	1%	8
Switching process satisfaction	1%	1%	9
Smart meter uptake	1%	0%	10
Priority Services Register (PSR) membership	1%	0%	11
Payment type	1%	0%	12
Gender	0%	0%	13

Nagelkerke R Square: 40.8%. Grey shading represent those variables from Satisfaction Metrics model. Non-shaded is variables from Demographic and Energy Characteristics Model.

Financial vulnerability and parent supplier remain in the model as the fourth and fifth most influential variables

As outlined, demographic and energy variables tend to play a secondary role. Nonetheless, our Financial Vulnerability Classification and parent supplier remain notable contributors in the hybrid model, ranking fourth and fifth with relative importance scores of 6% and 5% respectively.

The continued contribution of the Financial Vulnerability Classification in predicting retention and satisfaction is notable. Given that financial vulnerability is associated with lower satisfaction across multiple metrics, including some of the core drivers like billing satisfaction, we might expect its effect to diminish completely once these factors are controlled for.

The fact that it doesn't drop out highlights the lasting, independent influence of broader financial circumstances. Satisfaction can't be fully understood in isolation of specific aspects of experience; rather, it must be viewed in the context of consumers' wider financial realities, which shape their experiences.

The fact that parent supplier remains in the model is also interesting and perhaps more surprising. Even after adding more detailed satisfaction metrics, parent supplier remains statistically significant with a relative importance score of 6%.

As to be expected, some of its predictive power reduces since factors like billing, contact, and smart meter experience now capture much of what people think about their supplier. But the fact that it still plays a role in the hybrid model suggests there is something broader or more emotional at play that is not fully captured by those specific questions.

For example, there may be aspects of satisfaction not fully captured in our model. such as bundle offers or unmeasured touchpoints. Second, its staying power could reflect brand affinity, where some consumers have developed loyalty or attachment to their supplier that persists beyond specific service factors (a factor that is a little harder to measure and control for in a model like this).

Appendix

BMG's Financial Vulnerability Classification

Overview

Many of the factors linked to overall satisfaction also relate to socio-economic status – especially indicators of household financial comfort. To provide a clear summary of each respondent's financial situation in the context of rising financial pressures, we have combined three measures – savings, debt, and ability to handle unexpected expenses – into a set of financial vulnerability classifications. This build on analysis questions used by the ONS using data from the Opinions and Lifestyle survey.[35]

These categories are defined as follows:

- **Highly financially vulnerable –** not able to save, and who cannot afford an unexpected but necessary expense of £850 and who are borrowing more than usual.
- **Financially vulnerable –** not able to save, who either cannot afford an unexpected expense of £850 or are borrowing more than usual.
- **Getting by –** expect to save or can afford unexpected expense of £850, who are not borrowing more than usual.
- **Doing well –** expect to save in the next 12 months, can afford an unexpected £850 expense, and who are not borrowing more than usual.

For those who answered "don't know" or "prefer not to say" to one of the three input questions, we used modelling to assign them to the groups they most closely resembled. This significantly reduced the proportion of unclassified cases – now just 5% in the latest wave. Figures below for are the latest figures from January 2025. This version of the variable was used in the regressions as it significantly recued the number of missing cases in the model.

Financial Vulnerability Classification category	Share of consumers in January 2025
Doing well	46%
Getting by	15%
Vulnerable	17%
Highly financially vulnerable	17%
Unclassified	5%

[35] Impact of increased cost of living on adults across Great Britain I ONS

Classification questions

Base: All respondents

SINGLE RESPONSE

CL1. In view of the general economic situation, do you think you will be able to save any money in the next 12 months?

Please select one only

Fixed code	Answer list	Scripting notes	Routing
1	Yes		
2	No		
97	Don’t know		
98	Prefer not to say		

Base: All respondents

SINGLE RESPONSE

CL2. Could your household afford to pay an unexpected, but necessary, expense of £850?

Please select one only

Fixed code	Answer list	Scripting notes	Routing
1	Yes		
2	No		
97	Don’t know		
98	Prefer not to say		

Base: All respondents

SINGLE RESPONSE

CL3. Have you had to borrow more money or use more credit than usual in the last month, compared to a year ago?

Borrowing or using credit includes credit cards, overdrafts, or taking out loans, borrowing from friends, family, neighbours or other personal connections.

Please select one only

Fixed code	Answer list	Scripting notes	Routing
1	Yes		
2	No		
97	Don’t know		

98	Prefer not to say

Variable summary

Variable	Category	Questionnaire logic	Numbers	Missing cases excluded
n/a	Total	All	15,201	n/a
Dependent: Overall satisfaction with supplier	Satisfied	A5="Very satisfied" OR A5="Satisfied"	3,834	n/a
	NOT Satisfied	A5="Very dissatisfied" OR A5="Dissatisfied" OR A5="Unsure" OR ~A5="Prefer not to answer"	11,367	n/a
Financial Vulnerability Classification	Doing well	CLR=1 (see appendix for full definition of CLR variable)	5,820	n/a
	Getting by	CLR=2 (see appendix for full definition of CLR variable)	2,344	n/a
	At risk	CLR=3 (see appendix for full definition of CLR variable)	3,091	n/a
	At high risk	CLR=4 (see appendix for full definition of CLR variable)	3,123	n/a
	Not classified	CLR = Missing (see appendix for full definition of CLR variable)	823	Removed as unable to classify.
Gender	Male	S10=Male	6,964	n/a
	Female	S10=Female	8,204	n/a
	Missing	S10="Non-binary" OR "Other" OR "Prefer not to say"	33	Too small to use.
Age	18 to 24	S9A="18 to 24" OR (S9>17 & S9<25)	648	n/a
	25 to 34	S9A="25 to 34" OR (S9>24 & S9<35)	2,128	n/a
	35 to 49	S9A="35 to 49" OR (S9>34 & S9<50)	4,251	n/a
	50 to 64	S9A="‘50 to 64" OR (S9>49 & S9<65)	4,627	n/a
	65 to 74	S9A="65 to 74" OR (S9>64 & S9<75)	2,449	n/a
	75 or older	S9A="75 or older" OR (S9>74)	1,098	n/a
	North East	dregion = "North East"	688	n/a
	North West	dregion = "North West"	1,787	n/a
	Yorkshire and the Humber	dregion = "Yorkshire and the Humber"	1,322	n/a
	East Midlands	dregion = "East Midlands"	1,120	n/a

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Variable	Category	Questionnaire logic	Numbers	Missing cases excluded
Region	West Midlands	dregion = “West Midlands”	1,550	n/a
	East of England	dregion = “East of England”	1,458	n/a
	London	dregion = “London”	2,004	n/a
	South East	dregion = “South East”	1,984	n/a
	South West	dregion = “South West”	1,246	n/a
	Wales	dregion = “Wales”	780	n/a
	Scotland	dregion = “Scotland”	1,262	n/a
Urban/ Rural	Rural	UR_Code=“Rural”	2,232	n/a
	Urban	UR_Code=“Urban”	12,642	n/a
	Missing data	UR_Code is BLANK	327	No logical code to recode into.
Disability status	No/Unknown	H4=“No” OR H5=“No” OR H5=“Don’t know” OR H5=“Prefer not to say”	10,313	n/a
	Yes	H5=“Yes”	4,888	n/a
	Total	All	15,201	n/a
Digitally excluded	Yes	digitallyexcluded=“DIGITALLY EXCLUDED” (no access to the internet; OR access to the internet but not confident using; OR only use the internet for email, browsing, accessing news, social media or none of these)	1,832	n/a
	No	digitallyexcluded=“NOT DIGITALLY EXCLUDED” (all else)	13,369	n/a
Tenure	Being bought on a mortgage	H10 = “Being bought on a mortgage”	3,475	n/a
	Owned outright by household	H10 = “Owned outright by household”	5,237	n/a
	Shared ownership	H10 = “Shared ownership”	186	n/a
	Rented from Local Authority	H10 = “Rented from Local Authority”	1,549	n/a
	Rented from Housing Association / Trust	H10 = “Rented from Housing Association / Trust”	1,673	n/a
	Rented from private landlord	H10 = “Rented from private landlord”	2,710	n/a
	Living rent free	H10 = “Living rent free”	138	n/a

Variable	Category	Questionnaire logic	Numbers	Missing cases excluded
	Other / Uknown	H10 = "Other" OR H10 = "Don't know" OR H10 = "Prefer not to say"	233	n/a
In Receipt of benefits	No / Unknown	H2="None" OR H2="Don't know" OR H2="Prefer not to say"	9,570	n/a
	Yes	H2 = Any code (1 to 12)	5,631	n/a
Someone expecting/ children under 5	No / Unknown	NOT(H12="Someone who is expecting" OR H12="Children aged under 5 ")	13,378	n/a
	Yes	H12="Someone who is expecting" OR H12="Children aged under 5 "	1,823	n/a
Ethnicity	White / Unknown	Missing DEthncity OR DEthncity="White categories"	12,693	n/a
	Ethnic minority group	DEthncity="Mixed / Multiple ethnic categories" OR "Asian / Asian British categories" OR "Black / African / Caribbean / Black British categories" OR "Other ethnic group" categories.	2,508	n/a
Full time carer	No / Unknown	H7="No" OR H7="Prefer not to answer" OR "Don't know"	13,346	n/a
	Yes	H7="Yes"	1,855	n/a
Electric vehicle ownership	No / Unknown	NOT(H13="A plug-in hybrid car or van" OR H13="A fully electric car or van")	3,431	n/a
	Yes	H13="A plug-in hybrid car or van" OR H13="A fully electric car or van"	423	n/a
Priority Services Register (PSR) membership	No / Unknown	S15="No" OR S15="Don't know" OR S15="Prefer not to say"	9,824	n/a
	Yes	S15+"yes"	5,377	n/a
Smart meter uptake	No / Unsure	C1="No, but I would consider getting one in the future" OR C1="No, and I would not consider getting one in the future" OR C1="Don't know"	5,374	n/a
	Yes	C1="Yes – I have a smart meter for mains electricity" OR C1="Yes – I have a smart meter for mains gas" OR C1="Yes – I have a smart meter for mains gas and electricity"	9,827	n/a

Variable	Category	Questionnaire logic	Numbers	Missing cases excluded
Switched	Switched Supplier	F1="Yes – I have switched my energy supplier"	1,184	n/a
	Switched tariff, but not supplier	F1="Yes – I have switched my energy tariff but stayed with the same supplier"	1,729	n/a
	No / Unknown	NOT (F1="Yes – I have switched my energy supplier") & NOT(F1="Yes – I have switched my energy tariff but stayed with the same supplier")	12,288	n/a
Payment type	Direct debit only	(paymenttyperecode_1="Direct debit") AND NOT(paymenttyperecode_2="Standard credit" AND NOT(paymenttyperecode_4="Pre-Payment meter")	9,937	n/a
	Standard credit	NOT (paymenttyperecode_1="Direct debit") AND (paymenttyperecode_2="Standard credit" AND NOT(paymenttyperecode_4="Pre-Payment meter")	2,096	n/a
	Pre-Payment meter	NOT (paymenttyperecode_1="Direct debit") AND NOT(paymenttyperecode_2="Standard credit" AND (paymenttyperecode_4="Pre-Payment meter")	2,499	n/a
	Unknown / Multi-methods	Remainder	669	n/a
Bill satisfaction	Satisfied	MAX(b8_1,b8_2)="Very Satisfied" OR MAX(b8_1,b8_2)="Satisfied"	10,101	n/a
	NOT satisfied	MAX(b8_1,b8_2)="Very dissatisfied" OR MAX(b8_1,b8_2)="Dissatisfied" OR MAX(b8_1,b8_2)="Neither satisfied nor dissatisfied" OR MAX(b8_1,b8_2)="Unsure" OR MAX(b8_1,b8_2)="Prefer not to answer"	1,972	n/a
	Pre-payment meter / other / Unknown	Not Asked B8_1 OR B8_2	3,128	n/a
Complaint satisfaction	Satisfied with complaint handling	E10="Very Satisfied" OR E10="Satisfied"	202	n/a
	NOT satisfied with complaint handling	E10="Very dissatisfied" OR E10="Dissatisfied" OR E10="Neither satisfied nor dissatisfied" E10="Unsure" OR E10="Prefer not to answer"	261	n/a
	Not made a complaint	Not Asked E10	14,738	n/a

Variable	Category	Questionnaire logic	Numbers	Missing cases excluded
Ease of contacting supplier/ satisfaction with contact	Easy to contact Or Satisfied	MAX(e2,e16)="Very Satisfied" OR MAX(e2,e16)="Satisfied"	9,081	n/a
	NOT easy AND NOT satisfied	MAX(e2,e16)="Very dissatisfied" OR MAX(e2,e16)="Dissatisfied" OR MAX(e2,e16)="Neither satisfied nor dissatisfied" OR MAX(be2,e16)="Unsure" OR MAX(e2,e16)="Prefer not to answer"	3,680	n/a
	Has not tried to contact	Not Asked e2 AND e16	2,440	n/a

Model outputs

The tables below set out in full the model outputs for the Demographic and Energy Characteristics model and Satisfaction Metrics model for the model (waves 17-20 combined).

Exp(B) (commonly referred to as an odds ratio) shows how the odds for each group differ from the overall average across all categories. For example, an Exp(B) of 1.09 means the odds are 9% higher than the average. This value is used as basis to calculate our Implied Impact Satisfaction Scores (see page 13).

The **P-value** indicates whether this difference is statistically significant. A p-value of 0.04 means there's a 4% probability the result occurred by chance, which meets the 95% confidence level for significance.

Demographic and Energy Characteristics model (waves 17-20 combined)

Variable	Exp(B)	P-value	Implied Impact Satisfaction Score
Financial Vulnerability Classification			
Getting by	1.09	0.04	77%
At risk	0.82	0.00	71%
At high risk	0.65	0.00	66%
Doing well	1.73	0.00	84%

Variable	Exp(B)	P-value	Implied Impact Satisfaction Score
Smart meter uptake			
Yes	1.20	0.00	78%
No / Unknown	0.84	0.00	72%
Age			
18 to 24	1.00	0.96	75%
25 to 34	1.03	0.65	76%
35 to 49	0.85	0.00	72%
50 to 64	0.80	0.00	71%
65 to 74	1.04	0.49	76%
75 or older	1.40	0.00	81%
Priority Services Register (PSR) membership			
Yes	1.14	0.00	78%
No / Unknown	0.90	0.00	73%
Payment type			
Standard credit	0.81	0.00	71%
Pre-Payment meter	1.18	0.00	78%
Unknown / Multi-methods	1.03	0.74	76%
Direct debit	1.03	0.50	76%
Switched supplier / tariff			
Switched Supplier	1.021	0.72	76%
Switched tariff, but not supplier	1.17	0.00	78%
No / Unknown	0.83	0.00	72%
Gender			
Female	1.09	0.00	77%
Male	0.92	0.00	74%
Disability status			
Yes	0.91	0.00	73%
No / Unknown	1.11	0.00	77%
Region			
North West	1.05	0.37	76%
Yorkshire and the Humber	0.98	0.71	75%
East Midlands	1.03	0.65	76%
West Midlands	1.29	0.00	80%

Variable	Exp(B)	P-value	Implied Impact Satisfaction Score
East of England	0.88	0.03	73%
London	0.92	0.11	74%
South East	0.96	0.48	74%
South West	1.04	0.62	76%
Wales	1.08	0.34	77%
Scotland	0.83	0.00	71%
North East	1.02	0.82	76%
Fuel type			
Mains gas only	0.84	0.18	72%
Mains electricity only	1.00	0.96	75%
Mains gas and electricity	1.18	0.01	78%
Children under 5 or expecting			
Yes	1.08	0.04	77%
No / Unknown	0.93	0.04	74%

Nagelkerke R Square	11.6%
Number of cases	14,348 (94.4%)

Satisfaction Metrics model (waves 17-20 combined)

Variable	Exp(B)	P-value	Implied Impact Satisfaction Score
Bill satisfaction			
Satisfied	2.222	0.00	87%
NOT satisfied	0.364	0.00	52%
Pre-payment meter / other / Unknown	1.236	0.00	79%
Complaint satisfaction			
Satisfied with complaint handling	2.230	0.00	87%
NOT satisfied with complaint handling	0.319	0.00	49%
Not made a complaint	1.407	0.00	81%
Support satisfaction			
Satisfied with support	1.543	0.00	82%
NOT satisfied with support	0.532	0.00	62%
Not received support	1.218	0.00	79%

Switching process satisfaction			
Satisfied with switching process	1.548	0.00	82%
NOT satisfied with switching process	0.615	0.00	65%
Not switched	1.050	0.51	76%
Satisfaction with smart meter			
Satisfied with smart meter	1.988	0.00	86%
NOT satisfied with smart meter	0.579	0.00	64%
No smart meter	0.869	0.00	72%
Ease of contacting supplier / satisfaction with contact			
Easy Or Satisfied	2.000	0.00	86%
NOT easy AND NOT satisfied	0.430	0.00	57%
Has not tried to contact	1.162	0.00	78%

Nagelkerke R Square	37.5%
Number of cases	15,201 (100%)

Multicollinearity tests

When assessing multicollinearity in regression models, the Generalised Variance Inflation Factor (GVIF) is a useful diagnostic tool, especially when dealing with categorical variables with multiple levels.

GVIF is an extension of the standard Variance Inflation Factor (VIF) used to detect multicollinearity in regression models. While VIF is suited for single-parameter (scalar) predictors, GVIF is designed to handle predictors with multiple degrees of freedom, such as categorical variables with multiple levels or factor variables such the case in our models

GVIF quantifies how much the variance of a regression coefficient is inflated due to correlations with other predictors. A high GVIF value suggests that a predictor is highly collinear with others, which can undermine the stability and interpretability of the regression model. The table below quantifies the thresholds.

We use the **Adjusted GVIF** value to the number of levels in a categorical variable, making multicollinearity easier to interpret.[36] It puts GVIF values on the same scale as standard GVIFs, so we can fairly compare variables. This helps us spot potential collinearity problems more accurately and make better decisions about which variables to keep.

Adjusted GVIF	Interpretation
≈ 1	No multicollinearity
1–2	Low multicollinearity
2–5	Moderate multicollinearity
>5	High multicollinearity

As set out in the table below, all Adjusted GVIF values across both the Demographic and energy Characteristics and Satisfaction Metrics Models are well below the common threshold of concern (typically

[36] Formula: GVIF^(1/(2*Df))

between 2 and 5), indicating no concerning multicollinearity issues.This suggests the predictors included in both models are sufficiently independent, allowing for reliable interpretation of the regression results.

Table 8: Demographic and Energy Characteristic Model variables

Variable	GVIF	Degrees of freedom	Adjusted GVIF
Financial Vulnerability Classification	1.4	3	1.1
Gender	1.0	1	1.0
Age	1.9	5	1.1
Region	1.4	10	1.0
Urban / Rural	1.1	1	1.1
Disability	1.4	1	1.2
Digital	1.2	1	1.1
Tenure	2.0	7	1.1
Whether claiming benefits	1.5	1	1.2
Children under 5 or expecting	1.2	1	1.1
Ethnicity	1.2	1	1.1
Carer	1.2	1	1.1
Priority Services Register (PSR) membership	1.2	1	1.1
Fuel Type	1.2	2	1.0
Smart meter uptake	1.1	1	1.0
Switched supplier / Tariff	1.1	2	1.0
Payment type	1.4	3	1.1
Parent supplier	1.4	10	1.0

Table 9: Satisfaction Metrics Model variables

Variable	GVIF	Degrees of freedom	Adjusted GVIF
Bill satisfaction	1.0	2	1.0
Complaint satisfaction	1.0	2	1.0
Support satisfaction	1.1	2	1.0
Switching process satisfaction	1.0	2	1.0
Satisfaction with smart meter	1.1	2	1.0
Ease of contacting supplier / satisfaction with contact	1.1	2	1.0

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