ST312: Applied Statistics Project

Are behavioural models a suitable approach to changing attitudes to climate change mitigation?

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Contents

Abstract

Climate change is one of the biggest current global challenges, becoming increasingly relevant year upon year. There is a range of research which shows that people are, over time, becoming more concerned the effects of on the planet by this phenomenon. The purpose of this report is to see whether socio-demographic factors can impact a person's attitudes towards climate change mitigation. The public attitudes towards 'Department for Business, Energy and Industrial Change' (BEIS) policies collected for "Public Attitudes Tracker 2019" survey has been used for this analysis. It is based on a sample of approximately 4200 adults and tests attitudes towards climate change against various variables such as age, gender, tenure, social class, ethnicity, area and employment status. Through the analysis, we will use existing behavioural models to show where shortfalls in climate change mitigation behaviour lie and focus on how socio-demographic factors may influences these undesirable behaviours. Lastly, we will form a proposal for future research to focus on segmentation to achieve higher levels of pro-environmental behaviour in the UK.

Glossary

All definitions here have been extracted directly from the PAT survey report, MetOffice, ClimateXChange and Cambridge Dictionary

Belief-attitude-intention pathway – A dominant approach to behaviour change that suggests an individual's beliefs and attitudes will determine their intentions to enact a specific behaviour.

Climate change - Climate change is the long-term shift in average weather patterns across the world. Since the mid-1800s, humans have contributed to the release of carbon dioxide and other greenhouse gases into the air. This causes global temperatures to rise, resulting in long-term changes to the climate.

Global warming – A gradual increase in the world temperatures caused by gases such as carbon dioxide that are collecting in the air around the earth and stopping heat escaping into space.

Greenhouse effect – An increase in the amount of carbon dioxide and other gases in the atmosphere (mixture of gases around the Earth), that is believed to be the cause of gradual warming of the surface of the Earth.

Greenhouse gas – A gas that causes the greenhouse effect.

Mitigation - Any activity that helps reduce the flow of heat-trapping gases into the atmosphere. Decreasing the amount of these greenhouse gases released into the atmosphere, reduces the overall rate and magnitude of climate change.

Natural gas - Gas, found underground, that is used as a fuel.

Shale gas and fracking - Shale gas is natural gas found in shale, a non-porous rock which does not allow the gas to escape. Hydraulic fracturing or "fracking" is the process of pumping water at high pressure into shale to create narrow fractures which allow the gas to be released and captured. The gas can then be used for electricity and heating.

Statistical Significance - A statistical test to determine whether relationships observed between two survey variables are likely to exist in the population from the sample drawn.

1.1 Introduction

Attitude through a sociological lens is the "disposition of men to view things in a certain way and to act accordingly" (Cohen, 1966). We can explain attitudes using the 'ABC model of attitudes' (Mcleod, 2018). The model refers to three inter-linked elements:

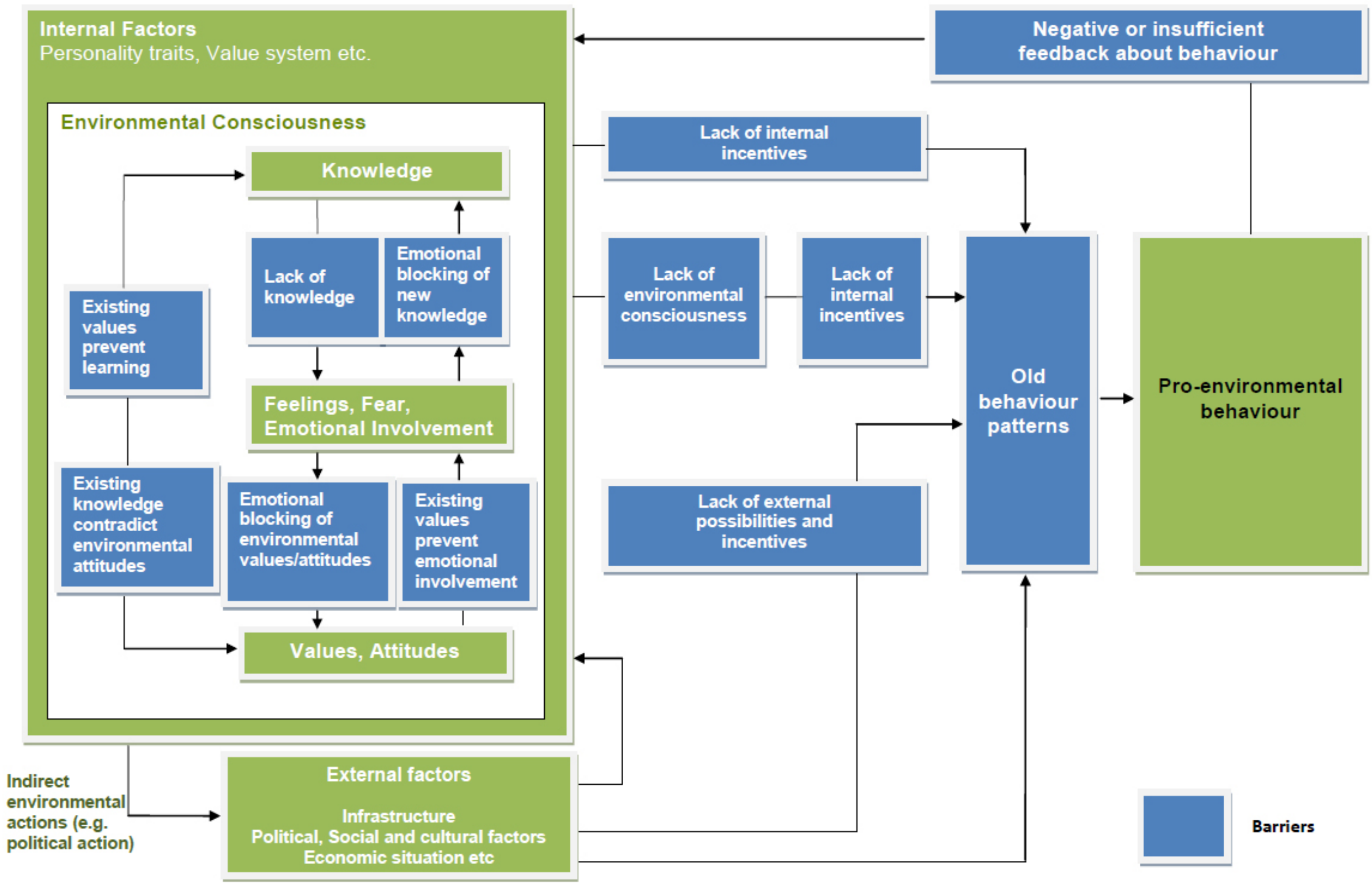
1) Affective component – This involves a person's feelings/ emotions about the attitude object.
2) Behavioural component – This involves the way the attitude we have influences how we act or behave.
3) Cognitive component – This involves a person's belief/ knowledge about an attitude object.

Figure 1.1 - A linear model of pro-environmental behaviour [reproduced from Kolmuss and Agyeman, 2002]

Figure 1.1 shows how the ABC model has been adapted to attitudes towards climate change mitigation. It is worth noting that 'affect' is often used seamlessly in research with the term attitude itself. An underlying assumption of this model is the 'principle of consistency' which claims that the behaviour of a person is consistent with the attitudes they hold – in line with how they feel about the subject. Clearly this can be seen as a reductionist argument, but it still provides a useful basis for an insight into the behavioural psychology behind climate change mitigation.

Figure 1.2 provides a much more comprehensive explanation of behaviours to climate change mitigation. "Although the academic debate between the more individualistic behavioural economics models and social practice models (Shove, 2010; Whitmarsh et al., 2011; Shove, 2011) is ongoing, one approach does not have to be taken at the expense of the other" (Dr Eiseman, 2009). In fact, considering that both the models have been recreated from the same research paper, it would not be far-fetched to say that they could be used alongside one another. The steps preceding pro-environmental behaviour in Figure 1.1 seem to fit well into the 'Internal Factors' section of Figure 1.2.

Figure 1.2 – Model of pro-environmental behaviour [Adapted from Kollmuss & Agyeman, 2002]



Climate change refers to a broad range of changes that are happening on our planet as a result of human and naturally produced warming. These include "rising sea levels; ice loss at Earth's poles and in mountain glaciers; frequency and severity changes in extreme weather such as hurricanes, heatwaves, wildfires, droughts, floods and precipitation; and cloud and vegetation changes" (NASA Website). It is a social issue which has gained traction in recent times as its effects are becoming increasingly prevalent. The UN have stated that we only have "11 years to prevent irreversible damage from climate change" (UN General Assembly 73rd Session, 2019).

The aim of this report is to explore the socio-demographic differences and how these interact with internal factors. Through doing this policy can be implemented which is more applicable and effective in creating pro-environmental behaviour within adults in the UK.

1.2 Research Questions

1) Do socio-demographics influence a person's knowledge of fracking?
2) Do socio-demographics influence a person's attitude towards fracking?

1.3 Literature Review

Fracking is the process of drilling down into the earth before a high-pressure water mixture is directed at the rock to release the gas inside. One of the major effects of hydraulic fracturing is that it releases methane into the air. Methane is "25 times more potent in trapping heat in the atmosphere than carbon dioxide" (Hoffman, 2012). "Scientists estimate that around 25% of current global warming traces to methane" (Roberts, 2019). It is also becoming one of the most popular natural gasses and research suggests that "63% of the total increase in global natural gas production in the 21st century has come from shale gas" (Roberts, 2019). Due to its increasing relevance and significant impact on climate change, our questions will be aimed at fracking in particular.

Socio-demographic differences in attitudes towards climate change have been reported in many studies. With one of the most consistent findings being that young people (16-34) are more concerned about global warming and "more inclined to agree that alternative fuels should be used to reduce greenhouse gas emissions" than older people (55+) (Special Eurobarometer 313, 2009; Curtis et al., 2018). Despite this, one study has found that as much as 84% of young people agreed "that they need more information to prevent climate change" (UN YouthStat, 2015).

These conflicting findings, namely positive attitude without 'sufficient' understanding, supports the school of thought that one of the main determinants of pro-environmental behaviour is social norms (Culiberg & Elgaaied-Gambier, 2015). This is also supported by Figure 1.2 – see 'External Factors'.

Gender differences have been reported in a number of studies with females reporting higher levels of concern but lower levels of understanding and less likely than males to "not have an opinion on the usage of alternative fuels to reduce greenhouse gas emissions" (Eurobarometer 313, 2009). One reason for this is that when it comes to policy, "males are more likely to base their votes on economic outcomes, while women are more influenced by the need for healthcare" (Kelley, 2020).

The disparity between attitudes and behaviours with regards to climate change is also prevalent in many studies. It has been described as one of the greatest barriers to the public climate change agenda. “Reducing the emissions of carbon from the transport sector will require far reaching technological as well as behavioural shifts” (Banister and Hickman 2006; Anable and Boardman 2005; Bristow et al. 2004). There is a growing evidence base highlighting the limitations of focusing on changing beliefs and attitudes the intention of changing behaviour (Dr Eiseman, 2019). Since support for climate change is now common, as many studies are finding the issue is not of feelings, it is knowledge.

Since there are differences between different demographic, geographic and attitudinal factors we can propose the use of segmentation. Segmentation is a marketing technique which targets groups of people - of similar demographics, values, attitudes or beliefs - who have similar needs that can be influenced using targeted messaging strategies. This method encourages “communication efforts to effectively drive engagement” and prioritises “the potential for behaviour change among a specific group” (Cabiness et al. 2020). Through the use of this device

2. Dataset and Methodology

The Public Attitudes Tracker survey covers attitudes to BEIS policies to energy and climate change. This report is based on findings from 'wave 31' where 4201 in-house face-to-face interviews were conducted with UK adults 16+. The survey is designed to be representative of all adults in the UK. The questions have been refined in this survey through cognitive testing.

BEIS reports that they "exclude some categories (e.g. "don't know" and "refused") before analysis" (BEIS Technical Note). We will also remove "refused" and missing values but will keep "don't know" answers as this response relates to our behavioural models (Figures 1.1 and 1.2). In total 73 candidates were removed which only makes ~1.8% of our data. Variables that were considered to have excessive levels were regrouped and recoded for ease of interpretation. Details are presented in the tables below.

Figure 2.1 – Regrouping and Recoding of Independent Variable

Variable	Previous Categories	New Categories
Main Heating	1) Gas 2) Electric 3) Oil 4) Solid Fuel 5) Other 6) Unknown	1) Gas 2) Electric 3,4) Other non-renewable energy source 5,6) Other/ Unknown

Figure 2.2 – Regrouping and Recoding of Dependent Variables

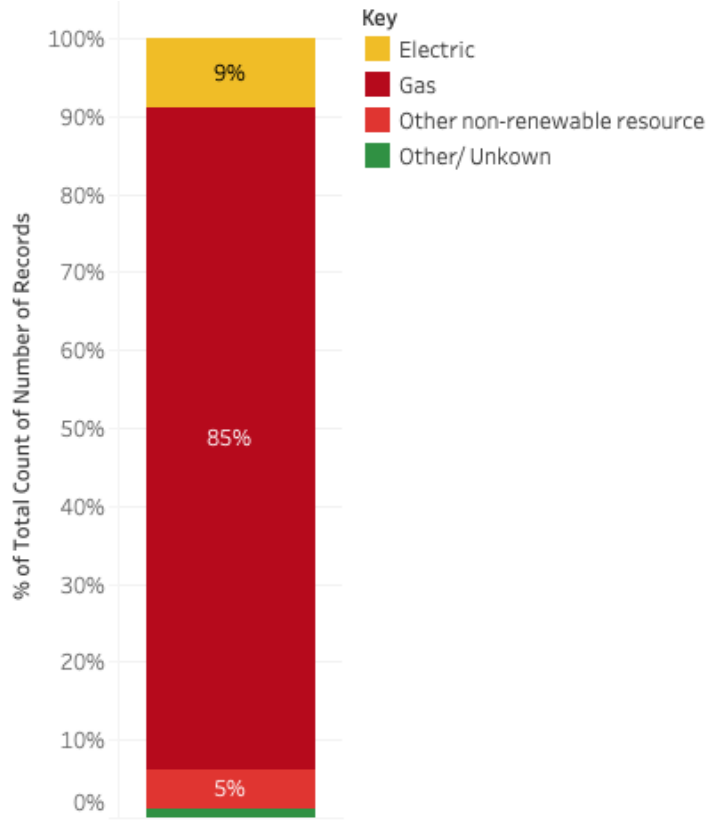
Variable	Previous Categories	New Categories
Employed	1) Full time 2) Part time 3) Not working/ looking 4) Not working' not looking	7) Full time 8) Part time 3,4) Not working
GB Region (gor)	1) North East 2) North West 3) Yorkshire and The Humber 4) East Midlands 5) West Midlands 6) East of England 7) London 8) South East 9) South West 10) Scotland 11) Wales 12) Northern Ireland	1,2,3) North England 4,5,6) The Midlands 7) London 8,9) South England 10) Wales 11) Scotland 12) Northern Ireland

3.1 Analysis of Internal Factors

The graphs and tables presented in this report were created using Tableau and statistical analysis has been done using R.

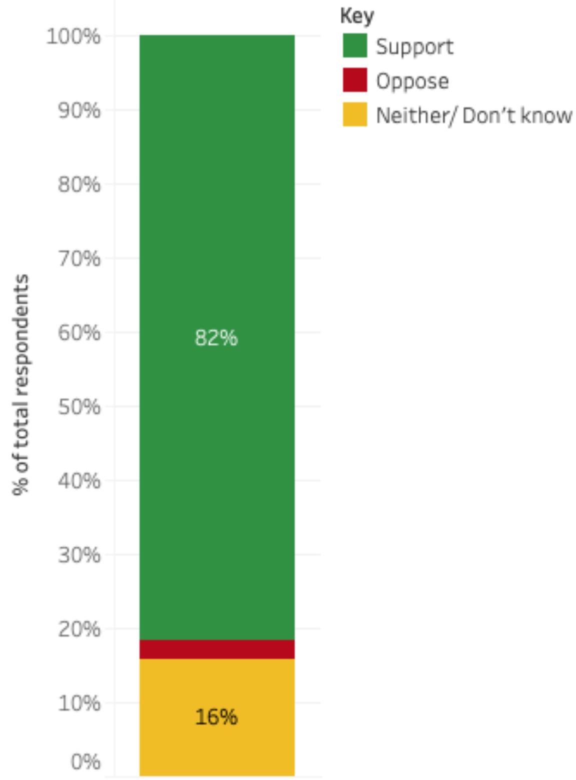
For segmentation to be effective, it is important for us to identify which parts of our data would be the most useful for us to explore in detail. The focus in this report will be more on 'undesirable' behaviours as this will be the main target area for policy makers. Undesirable behaviour consists of those who support fracking, oppose renewable energy sources and those who report "neither/don't know". The latter has been identified as undesirable because under both our behavioural models, it shows a failure in pro-environmental behaviour.

Figure 3.1 – Primary Heating Source



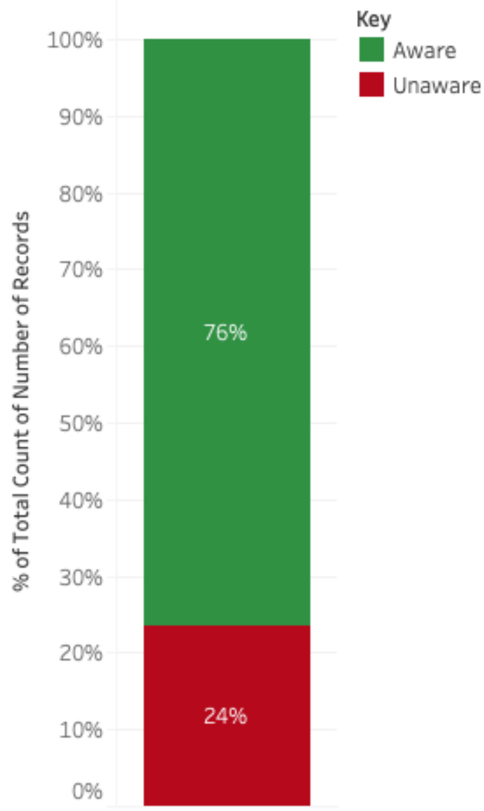
90% of all respondents reported that they use either (shale) gas or some other sort of non-renewable resource to heat their homes. Only 9% of respondents reported to using electricity to heat their homes. The dataset does not give details of the origin of this so it is worth noting electric energy can be created through both renewable and non-renewable energy.

Figure 3.2 – Level of support for renewable energy for providing electricity, fuel and heat



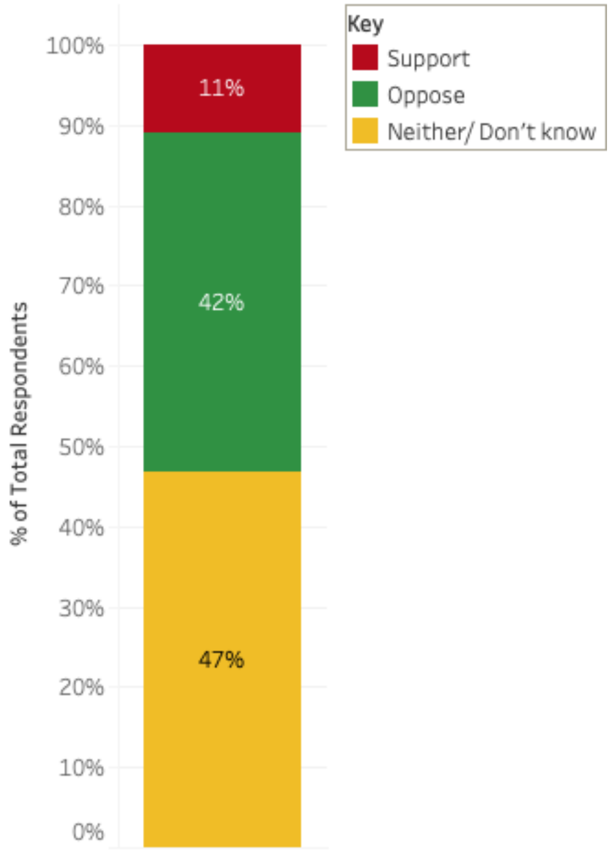
As Figure 3.2 shows that as much as 82% of people do support renewable energy for providing energy. This is no surprise to us as our literature suggested that pro-environmental attitudes are increasingly common. Nonetheless, 16% of our sample had no opinion or did not know about renewable energy. Here we only observe a total of 18% of undesirable behaviour from respondents.

Figure 3.3 – Knowledge of Fracking



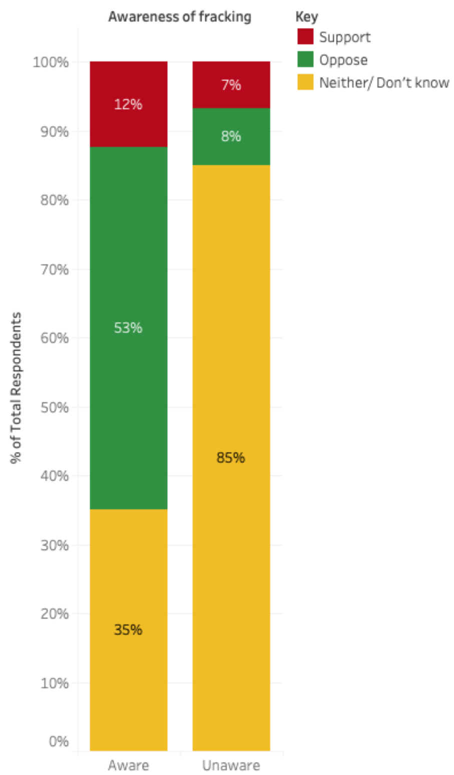
We can see an 6% increase in the undesirable behaviour when the question has changed from renewable energy to fracking. 85% of respondents had reported that they used gas to heat their homes (Figure 3.1) yet only 76% of all people reported they knew anything about fracking. It shows a lack of knowledge: failure at the first step of the approach in Figure 1.1; and a shortfall within 'internal factors' presented in Figure 1.2.

Figure 3.4 – Attitude to fracking



Considering the significant negative impact that fracking has upon the environment, we might except Figure 3.4 to look similar to Figure 3.2. However, this table presents findings that are more in line with our behavioural models in Figures 1.1 and 1.2. Almost half of all respondents were indifferent or did not know what fracking was, up 31% for the same option when asked about their levels of support for renewable energy sources. Only 2% of people opposed the use of renewable energy in Figure 3.2 but as much as 11% support the use of hydraulic fracturing for shale gas – a non-renewable energy source.

Figure 3.5 – Attitude to fracking



These findings are very interesting and support a lot of what our literature had suggested. 85% of people who were unaware of fracking were also indifferent about it compared to only 35% of those who had awareness. Those who were aware were a massive 45% more likely to oppose fracking than those who were unaware.

At this stage we can see that Figure 1.1 appears to be applicable at face value. Subsequently, this can also be said about the 'internal factors' in Figure 1.2. Now we will take a closer look at the 'external factors' and how these interact with our internal factors of feelings/attitudes and cognition.

3.2 Analysis of External Factors

In order to understand the interaction between the different socio-demographic factors and these internal factors, the chi-squared test was used to test the univariate relationships for nominal variables and Cochran-Armitage test for ordinal variables. All values were tested at the significance level 5% as literature suggested was the most appropriate for this topic.

Gender

In terms of gender differences, the BEIS is in line with past studies, females were 8% less likely to have an opinion on the use of alternative fuels (Eurobarometer 313, 2009) than their male counterparts. Males were almost twice as likely to support the use of fracking for energy. Both these results were statistically significant with the difference of 'Neither/ Don't know' yielding $\chi^2(1, N = 4124) = 28.096$, $p = 0.0010167$. The difference between the two genders in terms of supporting fracking was also statistically significant with the the chi-squared values of $\chi^2(1, N = 4124) = 14.61294$, $p = 1.199e^{-14}$.

This same difference in genders extends into the differences in cognition where women are 13% more likely to report being unaware of fracking. This result is also statistically significant $\chi^2(1, N = 4124) =98.773$, $p = 2.2e^{-16}$.

Figure 3.6 – Attitude to fracking

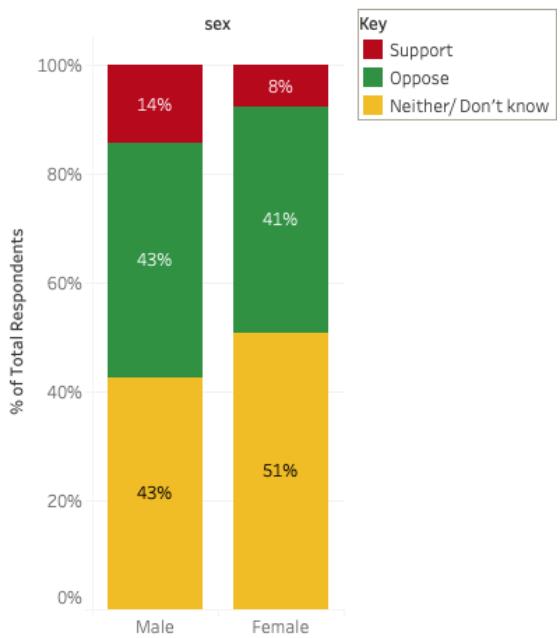
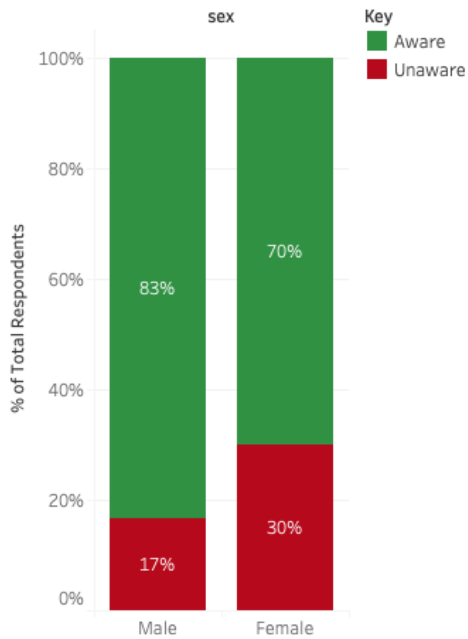


Figure 3.7 – Knowledge of fracking



Age

As suggested by literature, when some level of knowledge is required more than half of all 16-34 year olds responded with ‘Neither/Don’t know’ when asked if ‘they support or oppose hydraulic fracturing for shale gas’. The result being 9% higher than that of 34-54 year olds and a massive 15% higher than those 55 or older. The Cochran Armitage test showed this was a statistically significant result, χ^2(df =2) =63.877, $p = 1.347e^{-14}$.

Younger people also reported on much lower levels of awareness that their older counterparts with a staggering difference of 26%. Since younger people are more inclined to support climate change, according to literature, Figure 1.1 would explain our findings as the lack of knowledge has led to a higher level of indifference. The difference in the awareness of fracking was statistically significant, χ^2(df=2, N = 4124) =266.6, $p = 2.2e^{-16}$.

Figure 3.8 – Attitude to fracking

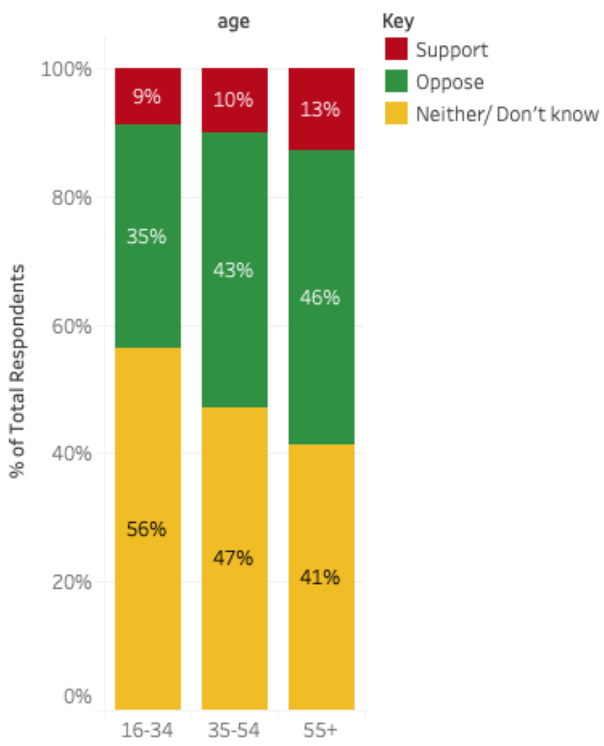
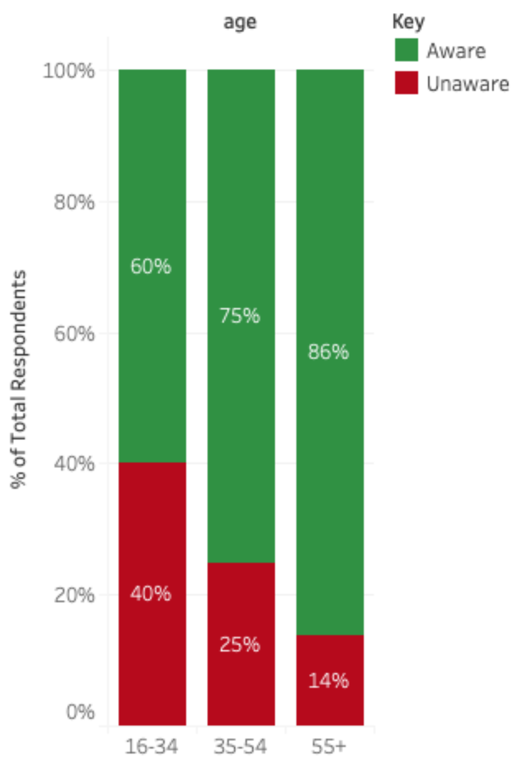


Figure 3.9 - Knowledge of fracking



GB Region

Our results found that differences in regional support for the use of hydraulic fracturing for shale gas was statistically significant, χ^2(df=6, N = 4124) =16.221, p = 0.01262. Londoners reported the highest level of support for fracking, 9% higher than the lowest reported percentage by Northern Ireland.

Despite their high levels of support, those residing in London also reported the lowest levels of knowledge about fracking with 43% of all Londoners reporting a lack of awareness of what fracking was. Scotland and Southern England reported the highest levels of awareness at 84%, a whopping 27% higher than those from London. Our chi squared test found these differences were statistically significant, χ^2(df=6, N = 4124) =173.13, p = 2.2e^{-16}.

Figure 3.10 – Attitude to fracking

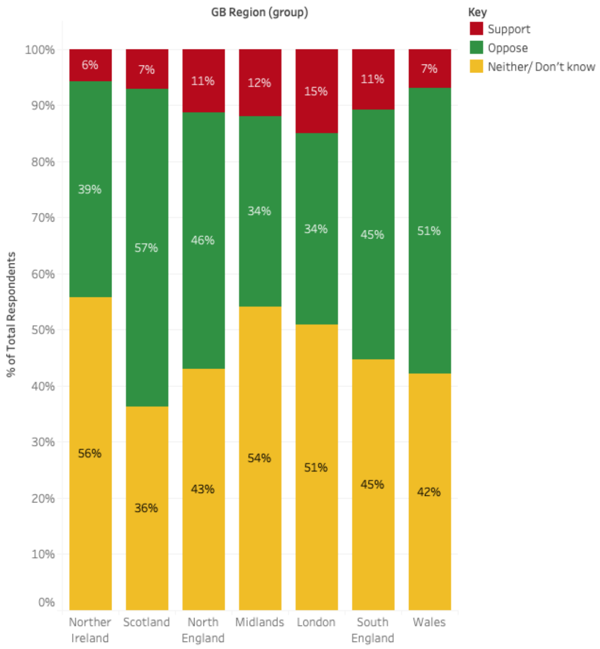
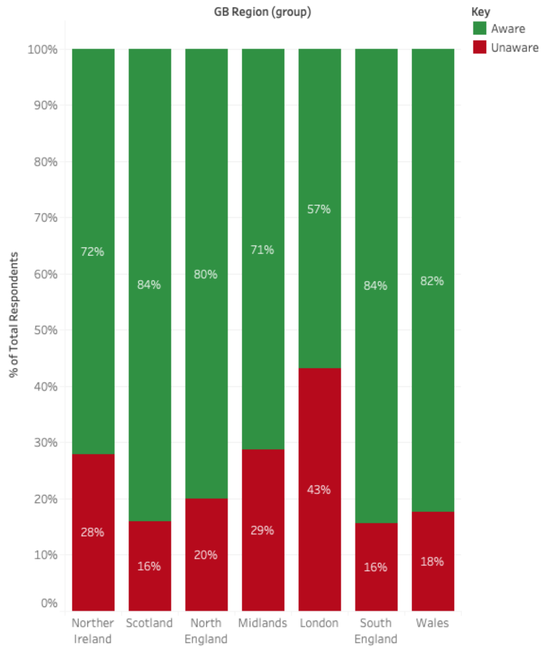


Figure 3.11 - Knowledge of fracking



Rather than the 12 official government regions, we have grouped our data into 7 for ease of presentation.
North England consists of North East, North West and Yorkshire and The Humber
Midlands consists of East Midlands, West Midlands and the East of England
South England consists of South East and South West

Social Grade

Although support for hydraulic fracturing between social classes shows only a 4% difference between the highest and lowest level, this was a significant result, χ^2(df=3, N = 4124) =9.7838, *p = 0.0205*. The more apparent difference in our graphs is clearly in those responding 'Neither/ Don't know'. Those in social grade DE were 18% more likely to report this response. The result is statistically significant, χ^2(df=3, N = 4124) =78.075, $p = 2.2e^{-16}$.

Similarly, we can see a disparity between social grade and awareness of fracking. Respondents who reported belonging to class AB were up to 27% more likely to report an awareness of fracking than any other social class. Clearly this was a statistically significant result, χ^2(df=3, N = 4124) =220.72, $p = 2.2e^{-16}$.

Figure 3.12 – Attitude to fracking

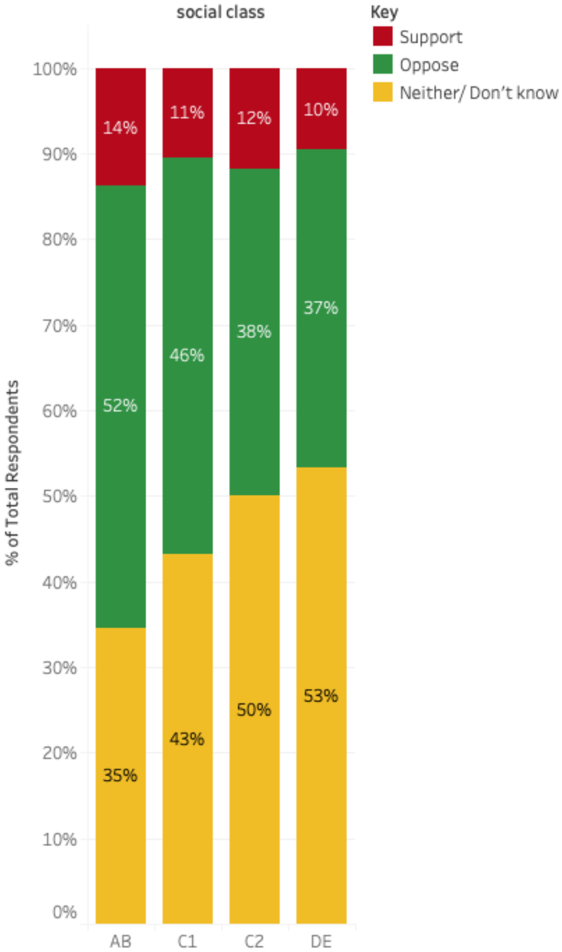
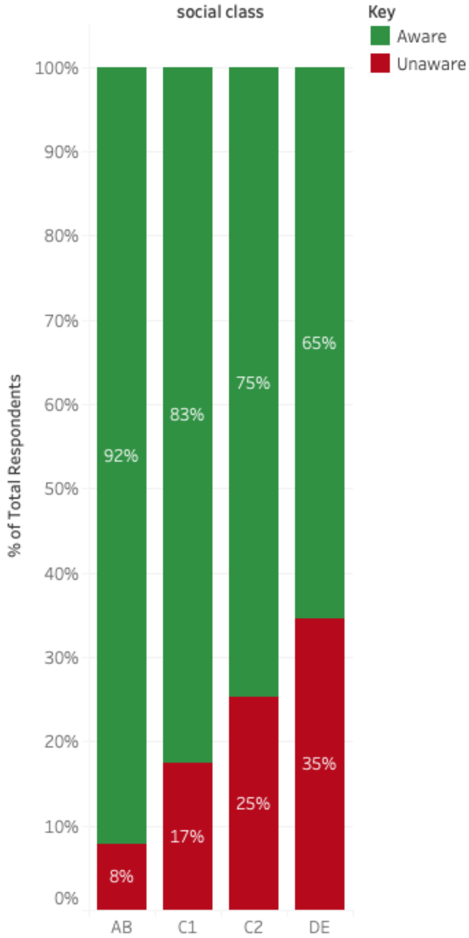


Figure 3.13 - Knowledge of fracking



Social Grade – Social grade is an occupation-based classification system.
AB: Higher/ Intermediate managerial, administrative and professional. E.g. Doctors, university lecturers and heads of local governments.
C1: Supervisory, clerical and junior managerial. E.g. Nurses, pharmacists, store managers, salesmen.
C2: Skilled manual workers. E.g. Qualified apprentices, carpenters, brick layers, technicians.
DE: Semi-skilled and unskilled manual workers, state pensioners, casual and lowest grade workers, unemployed with state benefits only. E.g. Those in apprenticeships and others on minimum levels of income.

Employment

The BEIS survey shows levels between supporting fracking among different employment status only varies by 4%, this result is not statistically significant, χ^2(df=2, N = 4124) =1.6462, p = 0.4391. The number of respondents who reported 'Neither/ Don't know' when asked about fracking between different employment statuses was also quite even, with a difference of only 3% between the highest and lowest group. The chi squared test revealed this was also statistically insignificant, χ^2(df=2, N = 4124) =3.3785, *p = 0.1847*.

Knowledge about fracking was the same between those who worked full time and those who did not work, the number being 5% higher than those who worked part time. Surprisingly our chi squared test found that this was a statistically significant result, χ^2(df=2, N = 4124) =6.65567, *p =0.03769*.

Figure 3.14 – Attitude to fracking

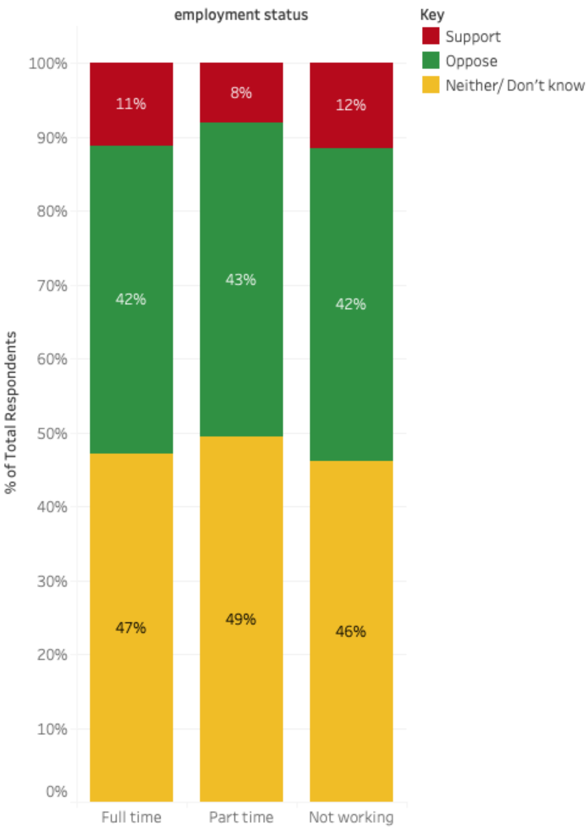
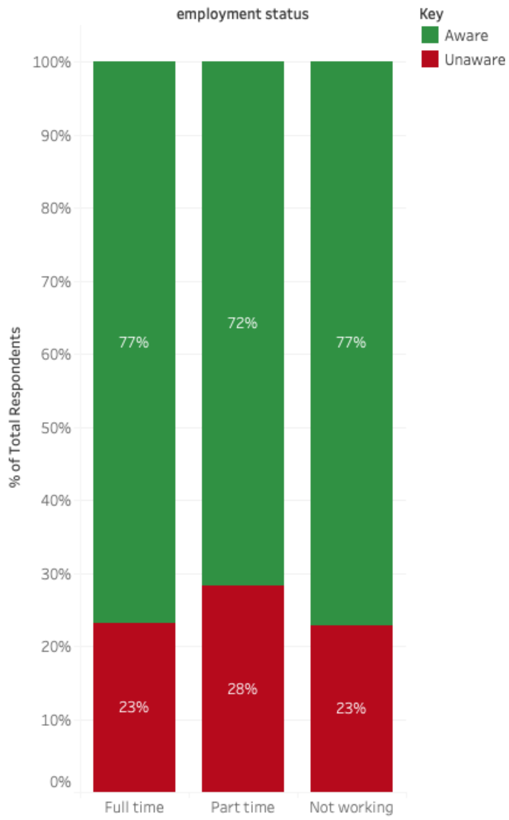


Figure 3.15 - Knowledge of fracking



3.3 Analysis of Models

For the next part of our analysis we will categorise our data into 'desirable' and 'undesirable' attitudes. The 'desirable' attitudes will consist of being aware and being opposed to fracking. Whereas the 'undesirable' will indicate unawareness and supporting or being indifferent to fracking as these behaviours will, according to our models in the introduction, restrict a change in climate change mitigating behaviours.

For the purpose of segmentation we will trial a number of different methods for testing if our data is appropriate for segmentation.

Decision Tree Modelling
This is a common widely used classification system. Here we attempt to use it for approximating both attitude and cognition which would be represented by a decision tree. A decision tree classifies factors of the tree from root by some leaf 'node' which provides a classification. Here the 'nodes' are different socio-demographic factors and each branch was a different response for each demographic.

Dependent Variable	Estimate of Accuracy
Awareness of fracking	0.7744845
Support or oppose fracking	0.3943299

Random Forest Modelling
The random forest model proposes the use of a large number of relatively uncorrelated models which together becomes a much better predictor than any one tree itself. Each tree will predict an outcome and the most predicted outcome will be selected by this model.

Dependent Variable	Estimate of Accuracy
Awareness of fracking	0.9906542
Support or oppose fracking	0. 953271

For Cognition, one of the main social demographics that affect cognition were someone's race: White people were more likely to be cognisant of fracking than their minorities' counterparts were. Other variables of equal importance are the whether the respondent has children, their housing situation, as well as the gender and age. What is particularly surprisingly is that internet access had little effect on a person's knowledge of fracking.

On the other hand, for the attitude towards fracking, gender played the most important role. The area that someone lives in also proved to be important with those in urban settings being more likely to have an undesirable attitude towards fracking. Family characteristics such as children and whether someone was married also played a role. Further, the employment characteristic was also crucial. Social grade again proved to be an important characteristic showing to be responsible for variance within attitudes.

An index of abbreviations used in Figures 3.16 and 3.17 can be found in Appendix E

Figure 3.16 – Random Tree 1: Testing against cognition of fracking

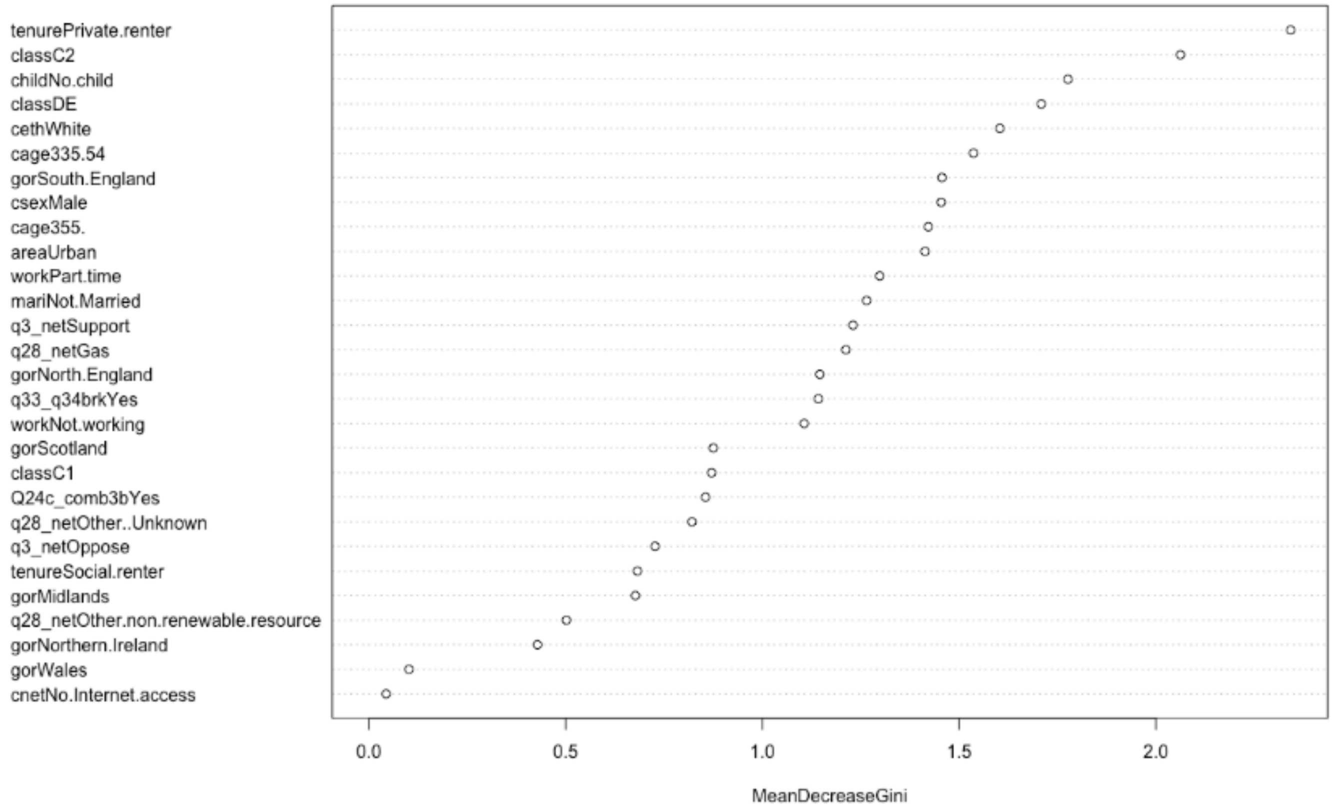
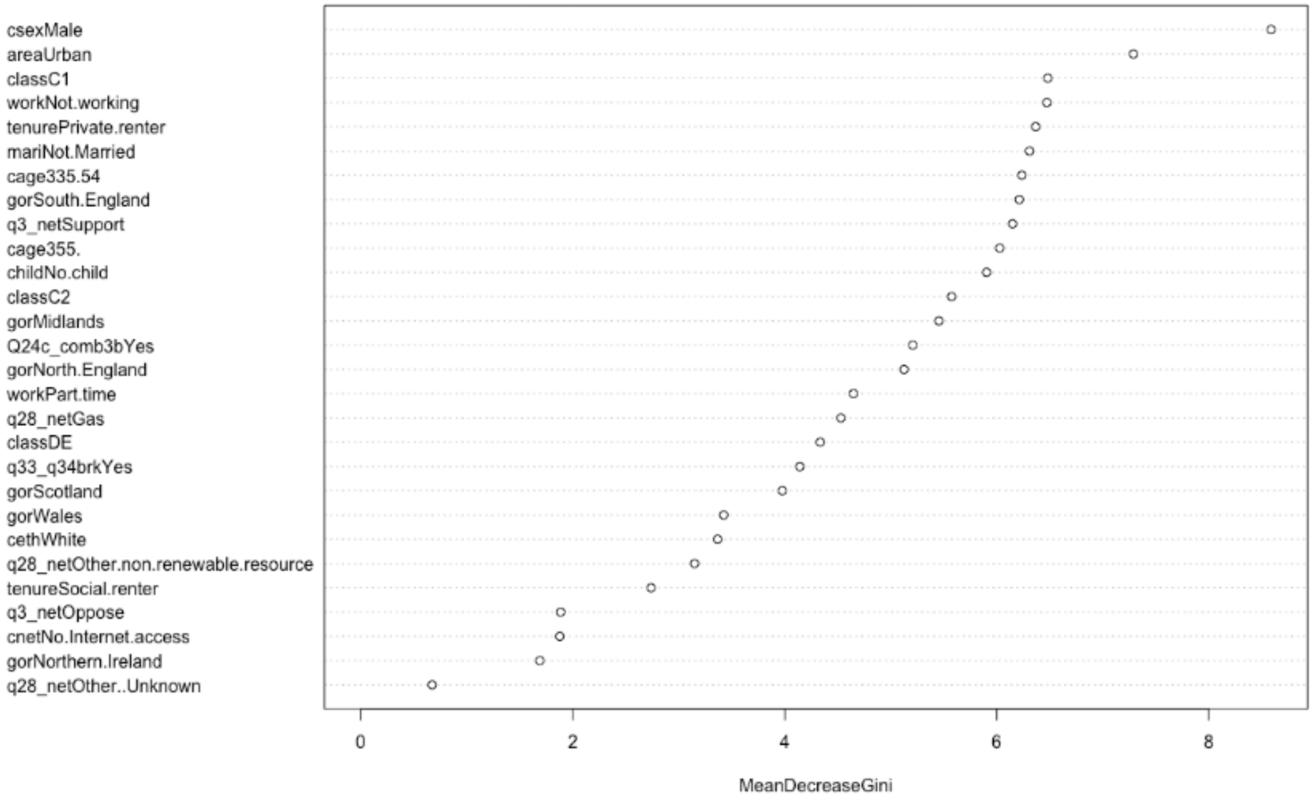


Figure 3.17 – Random Tree 2: Testing against attitudes fracking



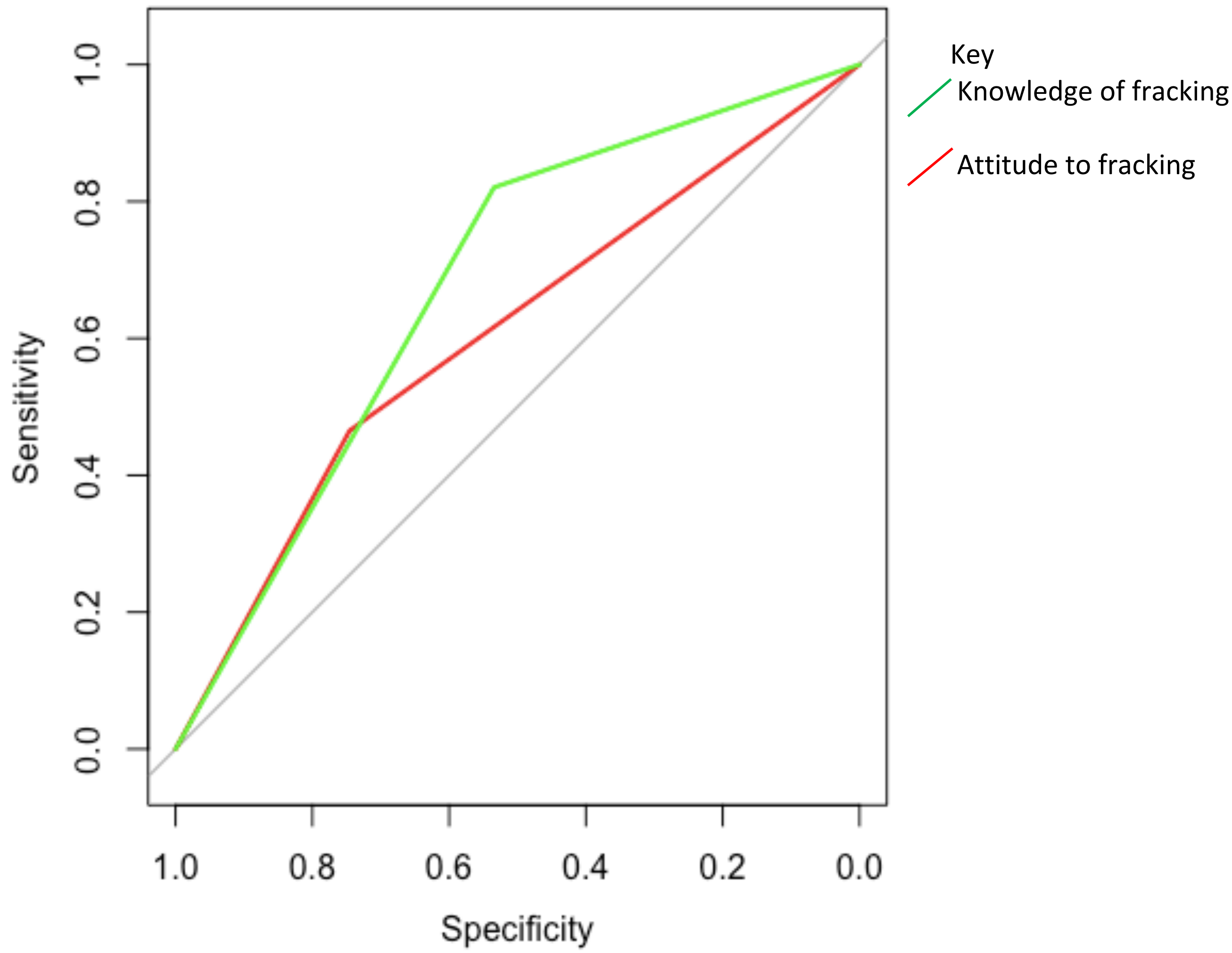
Logistic Regression

The logistic model falls under the generalised linear models. Since our response variable has two levels – desirable/ undesirable - the logistic regression will have a binomial distribution. To identify the best model for this particular dataset, a step regression searches for the best model iteratively and identifies the model that has the lowest AIC.

The process of automated forward selection was used in this model. The procedure begins with no covariates and variables are added to the model base if they pass a p-value threshold, chosen here as <0.05. This process is repeated until no more additions are possible – i.e. all variables selected have a p-value <0.05. Appendix C includes the variables included in this model. The results yielded the same results as backwards regression.

Dependent Variable	AIC	Area under Curve
Awareness of fracking	169.0629	0.6774
Support or oppose fracking	178.4264	0.6053

Figure 3.16 – ROC curves of models found using forward stepwise regression



The area under the cognition curve is the amount of learning that the model has learned, which means that the first model has learned significantly more than the model on attitude below on the second curve. The closer the ROC curve is to mimicking the positive gradient 1, the less accurate the predictor. The forward stepwise regression model is also more appropriate for testing cognition as oppose to attitudes which is indicated by the lower AIC, higher area under the curve and the shape of the graphs.

4.1 Summary of findings

The analysis of internal factors found lower support for mitigation behaviour when the question was switched from the common one of renewable energy to the one of fracking which required some knowledge. The analysis of external factors found that age, gender, GB region and social grade all have significant association with whether a person supports or opposes fracking. These factors, as well as employment status, were significant when testing the association with cognition – the results showed this relationship was statistically more significant for almost all variables (details can be found in Appendix D).

The modelling stage suggested that 'Random Forest' machine learning would provide the best method for segmentation of different groups with an estimated accuracy of ~99% for cognition, and ~95% for attitudes, to fracking. Cognition seems to have a stronger relationship with socio-demographic factors as both our models suggest a higher predictability accuracy with this variable as opposed to attitude. Our ROC curves also suggested that cognition showed a stronger interaction with socio-demographics than attitudes and included a lower AIC indicating a better fit for the data.

All models indicated a poor performance for testing attitude with socio-demographics suggesting that this data alone cannot explain how attitudes to fracking change. Even if socio-demographic variables are important, other variables would be useful in improving the model performance and hence other characteristics would explain attitude even better.

4.2 Conclusion

The behavioural models recreated from Kollmuss and Agyeman (2002) – Figures 1.1 and 1.2 – are reproducible. In line with these models, the analysis showed a significant decrease in pro-environmental attitudes when some level of knowledge was known. This suggests that while literature argues for a behavioural-attitude gap (Banister and Hickman 2006; Anable and Boardman 2005; Bristow et al. 2004), this is still due to a lack of cognition. Even though attitudes towards mitigation are improving, the barrier 'knowledge' (Figure 1.2) is yet to be overcome on a large scale.

Literature suggested that younger people would be more likely to hold pro-environmental attitudes (Special Eurobarometer 313, 2009; Curtis et al., 2018) but less likely to be knowledgeable about climate change (UN YouthStat, 2015). The BEIS dataset supported the latter of these statements showing that younger people were much less likely to know about fracking. The dataset however disagreed with the idea that 16-34 year olds are more pro-environmental as they showed higher levels of undesirable attitudes towards fracking. Again, this supports our behavioural models which suggested a lack of cognition would lead to this.

Similar conclusions can be drawn from the analysis by gender, with females showing the lower levels of cognition and pro-environmental attitudes as predicted by the Eurobarometer (2009). There is not much literature around social grade and mitigation behaviour, but our dataset suggested this would be an interesting area for further research. The data provided a great real-world application of the behavioural models generated from Kollmuss' and Agyeman's (2002) study showing that there were clear differences in cognition and attitudes between the different social grades.

Assessing the interaction of socio-demographic factors with attitudes, and seeing the reproducibility of the behavioural models within dataset, segmentation seems a fitting approach. According to our analysis the target area should still be cognition as the 'first hurdle' of the ABC has still not been overcome. Analysis also suggested cognition was the most appropriate for segmentation by socio-demographics, providing a 99% prediction accuracy for the dataset using random tree machine learning. The most important segments according to the random forest model are ethnicity, social grade housing tenure and age.

4.3 Limitations

It was not possible to tackle all barriers within our behavioural model in Figure 1.2 given the word restriction, this may limit our understanding of the topic overall. Such is the case when studying behaviour, there may exist even further behavioural barriers on a personal level in practice. Secondly since our study focuses quite heavily on fracking, the attitudes might not have been representative of the target population due to the lack of knowledge. Thirdly we were also unable to measure behaviour explicitly as each of these variables had significant numbers of respondents missing, since this is a pivotal part of our models, we cannot be certain behaviour will change.

End.

Bibliography

1. Anable, J., Lane, B., and Kelay, T. (2006) An evidence base review of public attitudes to climate change and transport behaviour [Internet], The Department of Transport. Available from: <https://www.fcrn.org.uk/sites/default/files/Evidence_of_public_attitudes_and_behaviour.pdf> [Accessed 07 April 2020].
2. Cabiness, J., Malster, J., and Vandermark, J. (2020) Advanced Audience Segmentation for Social and Behaviour Change [Internet], Compass. Available from: <https://www.thecompassforsbc.org/how-to-guides/advanced-audience-segmentation-social-and-behavior-change> [Accessed 21 April 2020].
3. Cambridge Dictionary [Internet]. Available from: <https://dictionary.cambridge.org> [Accessed 07 April 2020].
4. Culiberg, B., Elgaaid-Gambier, L. (2015) Going green to fit in- Understanding the impact of social norms on pro-environmental behaviour, a cross-cultural approach. International Journal of Consumer Studies, 40(2).
5. Department for Business, Energy & Industrial Strategy (2019) BEIS Public Attitudes Tracker [Internet], Department for Business, Energy & Industrial Strategy. Available from: < https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/844940/BEIS_Public_Attitudes_Tracker_Wave_31_key_findings.pdf> [Accessed 07 April 2020].
6. Dr Eiseman, D., and Prof. Black, I. (2019) Climate Change Behaviours - Segmentation Study [Internet], ClimateXChange. Available from: <https://www.climatexchange.org.uk/media/3664/climate-change-behaviours-segmentation-study.pdf> [Accessed 07 April 2020].
7. Hoffman, J. (2012) Introductory-level Geology and Human Health course in the Department of Earth Sciences [Internet], Montana State University. Available from: <https://serc.carleton.edu/NAGTWorkshops/health/case_studies/hydrofracking_w.html> [Accessed 07 April 2020].
8. Kelly, A. Young voters are increasingly concerned with climate change, survey shows [Internet], Changing America. Available from: <https://thehill.com/changing-america/sustainability/climate-change/479783-young-voters-are-increasingly-concerned-with> [Accessed 07 April 2020].
9. Kollmuss, A., and Agyeman, J. (2002) Mind the Gap: Why do people act environmentally and what are the barriers to pro-environmental behaviour?. Environmental Education Research, 8(3), pp239-260.

10. McLeod, S. (2018) Attitudes and Behaviour [Internet], Simply Psychology. Available from: <https://www.simplypsychology.org/attitudes.html> [Accessed 07 April 2020].
11. Met Office, What is climate change? [Internet], Met Office. Available from: <https://www.metoffice.gov.uk/weather/climate-change/what-is-climate-change> [Accessed 07 April 2020].
12. Phillips, D., Curtice, J., Phillips, M., and Perry, J. (eds.) (2018) British Social Attitudes: The 35th Report [Internet], The National Centre for Social Research. Available from: <https://www.bsa.natcen.ac.uk/media/39284/bsa35_full-report.pdf> [Accessed 07 April 2020].
13. Prof. Black, I., Dr. Eiserman, D. (2019) Climate Change Behaviours-Segmentation Study [Internet], ClimateXChange. Available from: <https://www.climatexchange.org.uk/media/3664/climate-change-behaviours-segmentation-study.pdf> [Accessed 07 April 2020].
14. Roberts, D. (2019) Fracking may be a bigger climate problem than we thought {Internet], Vox. Available from: <https://www.vox.com/energy-and-environment/2019/8/15/20805136/climate-change-fracking-methane-emissions> [Accessed 07 April 2020].
15. Shove, E. (2010) Beyond the ABC: climate change policy and theories of social change. Environment and Planning A, 42, pp1273-1285.
16. Shove, E. (2011) On the difference between chalk and cheese - a response to Whitmarsh et al’s comments on “Beyond the ABC: climate change policy and theories of social change’. Environment and Planning A, 43, pp258-261.
17. Special Eurobarometer 313 (2009) Europeans’ attitudes towards climate change [Internet], Eurobarometer. Available from: <https://ec.europa.eu/commfrontoffice/publicopinion/archives/ebs/ebs_313_en.pdf> [Accessed 07 April 2020].
18. UN General Assembly 73rd Session (2019) Only 11 Years Left to Prevent Irreversible Damage from Climate Change, Speakers Warn during General Assembly High-Level Meeting [Internet], United Nations. Available from: <https://www.un.org/press/en/2019/ga12131.doc.htm> [Accessed 07 April 2020].
19. Whitmarsh, L., O’Neil, S., and Lorenzoni, I. (2011) Climate change or social change? Debate within, amongst, and beyond disciplines: Commentary on ‘Beyond the ABS: climate change policy and theories of social change’. Environmental and Planning A, 43, pp258-261.
20. YouthStats, Environment and Climate Change [Internet], Office of the Secretary-General’s Envoy on Youth. Available from: <https://www.un.org/youthenvoy/wp-

content/uploads/2015/06/YouthStatsEnvironmentandClimateChangepdf2.pdf> [Accessed 07 April 2020].

Appendix

Appendix A – Exact wording of dependent variables

1 - Before today, how much, if anything, did you know about hydraulic fracturing for shale gas, otherwise known as 'fracking'?
Responses grouped by BEIS as: aware; unaware.

2 - From what you know, or have heard about, extracting shale gas to generate the UK's heat and electricity, do you support or oppose its use?
Responses grouped by BEIS as: support; oppose; neither or don't know.

3 - Do you support or oppose the use of renewable energy for providing our electricity, fuel and heat?
Responses grouped by BEIS as: support; oppose; neither or don't know.

4 - What is the main way you heat this property during the winter?
Responses in the questionnaire were more detailed than the figures revealed in the dataset which were already grouped by BEIS as: gas; electric; oil; solid fuel; other; don't know.

Appendix B – List of variables and frequencies

Category	Variable	Frequency
Sex	Male	1988
	Female	2136
Social Class	AB	723
	C1	1037
	C2	872
	DE	1492
Marriage Status	Married\Living as Married	2242
	Not Married	1882
Employment Status	Full time	1272
	Part time	470
	Not working	2382
Child	Child	965
	No child	3159

Internet	Any Internet access	3539
	No Internet access	585
Age	16-34	1080
	35-54	1123
	55+	1921
Area	Urban	3280
	Rural	844
Ethnicity	White	3634
	Minority Ethnic	490
Tenure	Owner occupier	2351
	Private renter	776
	Social renter	997
GB Region	North England	984
	The Midlands	1032
	London	478
	South England	928
	Wales	216
	Scotland	364
	Northern Ireland	122
Low income/ vulnerable group	Yes	628
	No	3496

Appendix C – Variables included in the forward selection and stepwise regression

Age + Class + Sex + Ethnicity + Tenure + GB Region + Area + Work Status + Low Income/ Vulnerable group + Social Grade + Marriage + Child

Appendix D – Overview of significance for different variables using variables in Appendix A

Variable	Affect - Renewables	Affect - Fracking	Cognitive - Fracking	Behaviour - Fracking
Social Grade	Yes***	Yes***	Yes***	Yes**
Sex	Yes**	Yes***	Yes***	Yes
Marriage	Yes**	No	Yes**	Yes**
Internet	Yes***	Yes**	Yes***	No
Age	No	Yes***	Yes***	No
Child	No	Yes***	Yes***	No
Area	Yes*	No	Yes**	Yes***
Low income/ Vulnerable group	Yes**	No	Yes***	No
Ethnicity	Yes**	Yes***	Yes***	Yes**
Tenure	Yes***	Yes***	Yes***	Yes***
Employment	Yes***	Yes	Yes	No
Gov. Region	Yes**	Yes***	Yes***	Yes***
	Yes @ 5% siginificance	* @ 2.5%	** @ 1%	*** @ 0.01%

Appendix E – Abbreviations used in Random Trees (followed by the variable)

Variable	Abbreviation
Social Grade	class
Sex	csex
Internet	cnet
Marriage	mari
Age	cage3
Child	child

Low income/ vulnerable group	Q33_q34brk
GB Region	gor
Tenure	tenure
Employment	work
Area	area
Primary Heating Method	Q28_net
Support or oppose renewable energy	Q3_net
Use mains gas	Q24c_comb3b

Appendix F – Output for Random Trees

```
```{r,fig.height = 8}

pacman::p_load(randomForest)
model_rf1 <- randomForest(formula = q15a_net1~.,
              data =na.omit(train1))
model_rf2 <- randomForest(formula = q15b_net~.,
              data = na.omit(train2))
predictions <- predict(model_rf1,test1,method = "class")
x <- confusionMatrix(predictions,test1$q15a_net1) %>% tidy()
x[1,1:3] %>% kable()

predictions <- predict(model_rf2,test2,method = "class")
x<- confusionMatrix(predictions,test2$q15b_net) %>% tidy()
x[1,1:3] %>% kable()


varImpPlot(model_rf1)
varImpPlot(model_rf2)
```
```

term	class	estimate
accuracy	NA	0.9906542

```
```{r,fig.height = 8}

pacman::p_load(randomForest)
model_rf1 <- randomForest(formula = q15a_net1~.,
             data =na.omit(train1))
model_rf2 <- randomForest(formula = q15b_net~.,
             data = na.omit(train2))
predictions <- predict(model_rf1,test1,method = "class")
x <- confusionMatrix(predictions,test1$q15a_net1) %>% tidy()
x[1,1:3] %>% kable()

predictions <- predict(model_rf2,test2,method = "class")
x<- confusionMatrix(predictions,test2$q15b_net) %>% tidy()
x[1,1:3] %>% kable()


varImpPlot(model_rf1)
varImpPlot(model_rf2)
```
```

term	class	estimate
accuracy	NA	0.953271