Demographic Factors and Climate Action: Understanding How Age and Education Shape Sustainable Choices*

Older Individuals and Those with Higher Education Show Stronger Commitment to Long-Term Sustainable Actions

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This study investigates how age and education influence people's likelihood to adopt climate-friendly behaviors, such as reducing car use and conserving energy. The analysis shows that younger individuals and those with higher education are more likely to engage in these actions, while older people tend to focus on energy-saving behaviors. However, financial barriers and doubts about the impact of individual actions prevent many people from taking steps to address climate change. These findings suggest that targeted policies are needed to make sustainable choices more accessible to different groups, helping to drive broader participation in climate action.

Table of contents

*Code and data are available at: https://github.com/LexiKnight/toronto_climate/tree/main.

Introduction

Climate change is one of the most pressing issues of our time. Its effects—rising temperatures, extreme weather events, and ecosystem disruptions—are already being felt globally, and the urgency for action has never been higher (Intergovernmental Panel on Climate Change (IPCC) 2023). Despite widespread awareness of the risks associated with climate change, many individuals still struggle to adopt behaviors that could help mitigate its impact. This gap between understanding and action is a major barrier to effective climate solutions, and understanding the underlying reasons for this disconnect is essential for crafting strategies that encourage widespread behavioral change (Gifford 2011).

This paper seeks to explore how certain demographic factors—specifically age and education—affect individuals' likelihood to adopt climate-friendly behaviors. By analyzing data from a 2018 survey (City of Toronto 2024), we aim to understand how these factors influence behaviors such as reducing energy consumption, using greener transportation, and minimizing waste. The estimand of this study is the effect of age and education on the likelihood of adopting these climate-friendly behaviors. We focus on these variables to understand whether younger, more educated individuals are more likely to engage in sustainable actions, and whether targeted strategies could drive greater participation in climate-positive behaviors.

Through our analysis, we found that younger individuals and those with higher levels of education were more likely to adopt behaviors such as reducing car usage and embracing plant-based diets (Fulton 2022). However, older individuals were more inclined to engage in actions like cutting down on household energy use (Lee 2019). This suggests that while age and education are important predictors, the types of climate-friendly behaviors people adopt may differ across these groups. Additionally, we identified key barriers to adoption, including financial cost and doubts about the effectiveness of individual actions, which often prevent people from taking meaningful steps to reduce their environmental impact (Kollmuss and Agyeman 2002). These insights emphasize that a one-size-fits-all approach to climate communication and action will not be effective; instead, strategies must be tailored to address the specific needs and motivations of different demographic groups.

The findings from this study are significant because they provide a clearer understanding of how demographic characteristics shape the adoption of climate-friendly behaviors. By identifying which groups are more likely to act and which face greater barriers, we can design more effective policies and interventions that speak directly to the concerns of these populations. This study not only contributes to the broader understanding of climate change engagement but also offers practical insights for shaping messages and policies that can inspire individuals to take action.

The remainder of this paper is structured as follows: Section describes the data and methodology used for analysis, Section outlines the statistical model used to assess the effects of age and education on behavior adoption, Section presents the key findings, and Section explores the implications of these results, addresses limitations, and suggests directions for future research. Finally, Section summarizes the main takeaways and offers recommendations for enhancing climate action engagement. Additional methodological details and the data cleaning process are provided in Section .

Data

The primary data source for this project is the Climate Perception Study dataset, provided by the City of Toronto via the Open Data Toronto platform (City of Toronto 2024). This dataset offers insights into public perceptions of climate change in Toronto in the years 2018 and 2021. This dataset was accessed from `Open Data Toronto` ("Open Data Toronto" 2024) on 6 November 2024.

Software and R-packages

This project was conducted using the statistical software `R` (R Core Team 2023), with several packages facilitating data cleaning, analysis and reporting. The `tidyverse` package (Wickham, Averick, et al. 2024) was central to the project, with `dplyr` (Wickham, François, et al. 2024) used in the cleaning and exploratory data analysis scripts for filtering, summarizing, and joining datasets. `readr` (Wickham, Hester, et al. 2024) handled reading and writing text data, while `tidyr` (Wickham, Henry, et al. 2024) reshaped data. `stringr` (Wickham 2024c) managed character strings, and `forcats` (Wickham 2024a) reordered factor levels for visualizations.

In the download script, `httr`(Wickham 2024b) retrieved files from `Open Data Toronto` ("Open Data Toronto" 2024), while`readxl` (Wickham and Bryan 2024) read Excel files, and `openxlsx` (Walker et al. 2024) created structured Excel workbooks. The `arrow` package (Richardson et al. 2024) optimized data storage and was used in the simulation and cleaning scripts to save datasets as Parquet files.

For modeling, `rpart` (Therneau and Atkinson 2024) and `partykit` (Hothorn and Zeileis 2024) built and visualized decision trees in the model script. The `testthat` package (Wickham et al. 2024b) validated simulated and cleaned datasets in their respective scripts. Visualizations were created using `ggplot2` (Wickham et al. 2024a) in the exploratory data analysis. Reporting relied on `knitr` (Xie 2024) and `kableExtra` (Zhu 2024) to integrate code, outputs, and styled tables. The `tinytable`package (Mikolas 2024) generated compact tables in both the exploratory data analysis script as well as in the paper. These packages ensured efficient and streamlined data management, analysis and reporting throughout the project.

Methodology

Data Collection

To embark on this analysis, we turn to two pivotal surveys commissioned by the City of Toronto to capture residents' perceptions of climate change and their readiness to take action. Our journey begins in 2018, when Environics Research conducted an online survey with 404 Toronto residents aged 18 and older, from October 11 to 18. The sample, drawn from an online panel, was carefully crafted with quotas based on region, age, and gender to mirror the 2016 Census. A touch of minor weighting ensured a more representative reflection of the population. However, it's important to note that this non-random sample introduces some potential bias, an aspect we keep in mind as we move forward.

The path continues in 2021 with Ipsos at the helm, stepping in with a more expansive survey, engaging 1,400 residents from a mix of methods: 1,000 from an online panel, 300 via phone, and 100 through online interviews conducted in Mandarin, Cantonese, and Punjabi. This diverse approach sought to enhance the survey's representativeness across Toronto's varied communities. For our analysis, we used Version 2 of the 2021 dataset, where responses were presented in a clear, numeric format, offering a solid foundation for our exploration.

With this data in hand, we are now ready to delve into the intricacies of the findings, unearthing patterns, and understanding the deeper story they tell about Toronto's residents and their views on climate change and collective action.

Data Analysis

The focus of this analysis was the 2018 dataset, which examined five key variables: age, education, extent informed, likelihood to take action, and preferred methods for delivering information about climate change action. These variables were analyzed at the individual level, allowing for an in-depth exploration of residents' perspectives.

For 2021, summary data was available instead of individual-level data. To compare trends, I created summary data for 2018. Calculating the percentage distribution for each variable in both years helped identify shifts in demographics, public awareness, and engagement, as well as changes in preferred communication methods. Although the absence of individual data for 2021 posed a challenge, this comparison still provided a dynamic view of evolving climate change perspectives in Toronto. The two-step approach—detailing 2018 data and then comparing it with 2021 trends—created a comprehensive narrative of change.

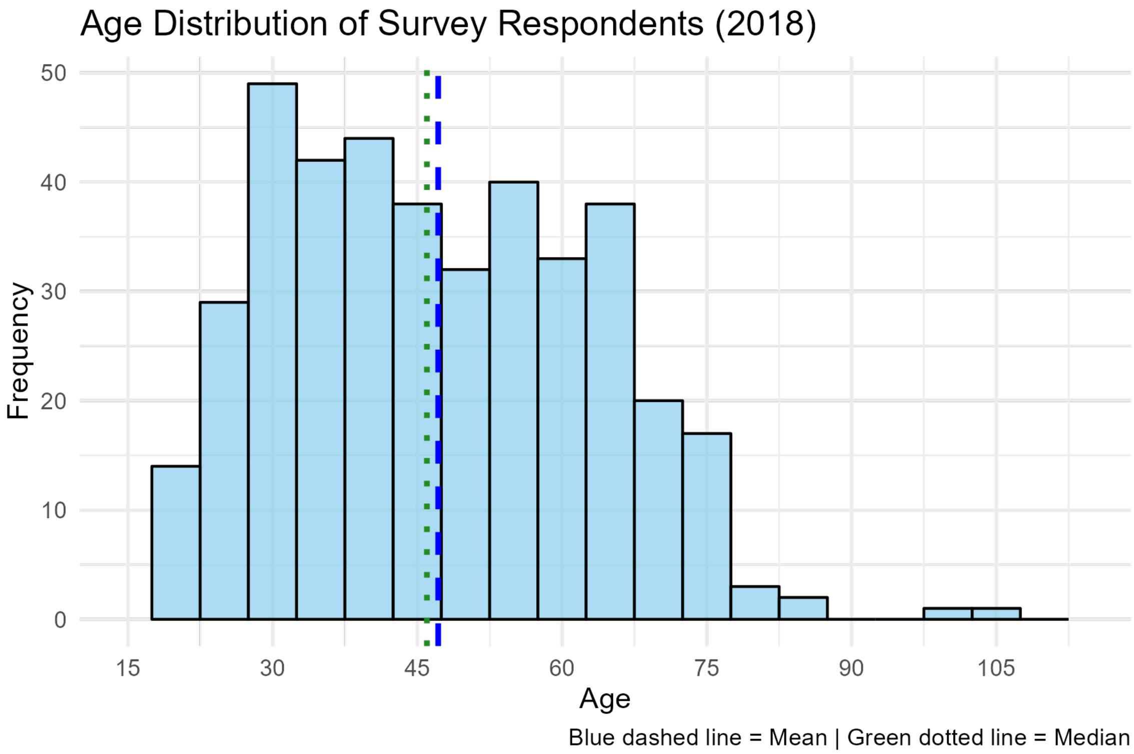
Features

Age

Individual 2018

fig-one presents the age distribution of survey respondents in 2018. The histogram shows the frequency of respondents across age groups, with age intervals on the x-axis and the number of respondents on the y-axis. The distribution is fairly balanced, with peaks around the 30–40 and 50–60 age ranges, indicating that these groups were the most represented in the survey.

The vertical dotted lines highlight the median and mean ages. The green dotted line represents the median age, and the blue dashed line represents the mean age, both located just above 45. This suggests the sample is predominantly middle-aged, with a gradual decline in respondent frequency after the age of 60. Few participants were over 80, indicating a lower representation of older individuals


Age Distribution of Survey Respondents (2018)
Frequency
Age
0
10
20
30
40
50
15
30
45
60
75
90
105
Blue dashed line = Mean | Green dotted line = Median

Age Group	2018 Percentage	2021 Percentage
18-23	4	11
24-39	33	30
40-55	30	26
56+	33	33

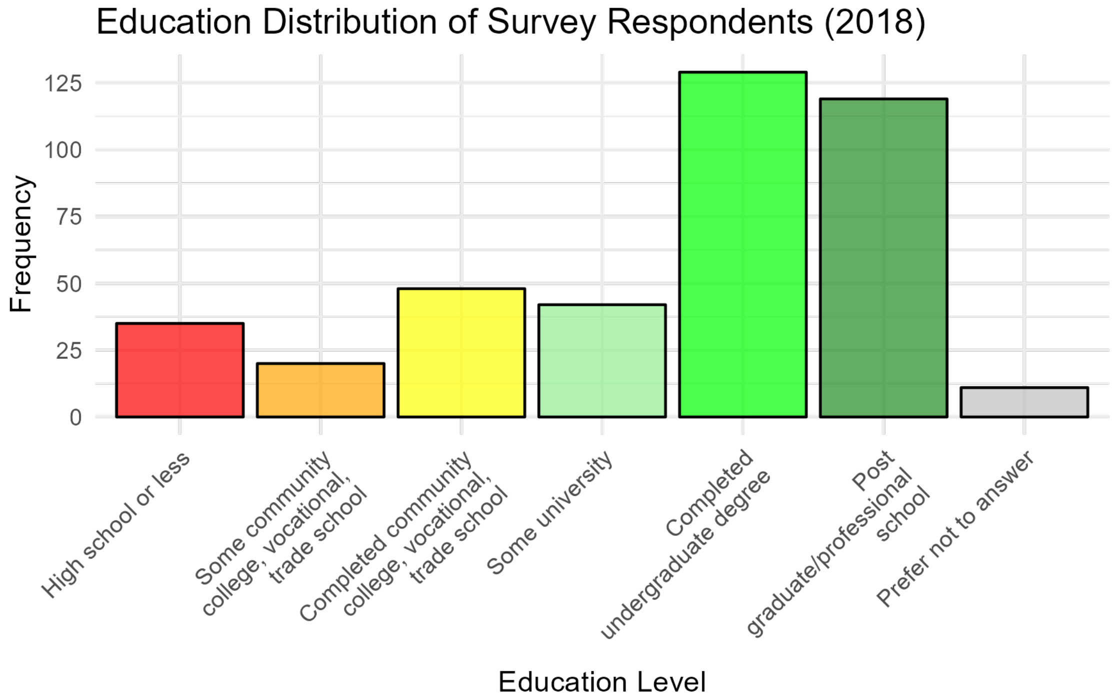
Comparison 2018 to 2021

fig-two compares the age distributions between 2018 and 2021. The main difference is an increase in respondents aged 18-23 in 2021, with other age groups remaining relatively stable. This shift may reflect changing demographic patterns or differences in survey methodologies within the three years.

Education

Individual 2018

fig-three shows the distribution of respondents by their highest level of education attained in 2018. The most common education levels are "Completed undergraduate degree" and "Post-graduate/professional school," indicating a well-educated respondent population. In contrast, fewer respondents reported having attended or completed community college, vocational, or trade school, suggesting lower representation in these categories. A small portion of respondents chose not to disclose their education level. Overall, the distribution reflects a skew toward higher levels of educational attainment.



Comparison 2018 to 2021

fig-four compares the education levels of respondents in 2018 and 2021. The two surveys used different education categories, making direct comparisons challenging. In 2018, 9% of respondents had a high school diploma or less, while in 2021, this figure rose to 38%, due to the addition of the "less than high school" and "high school or equivalent" categories. This shift indicates that the 2021 survey better represented individuals with lower educational attainment.

The 2018 survey provided more detailed categories, including options for community college, trade school, and distinctions between "some" versus "completed" education. In contrast, the 2021 survey used broader categories, which likely reduced the specificity of educational data. Notably, the 2021 survey appears to have offered a more balanced sample, with a wider spread across various education levels, while the 2018 sample was noticeably skewed toward respondents with higher educational attainment. This suggests that the 2021 survey may have captured a broader range of educational backgrounds, providing a more well-rounded representation of Toronto's population.

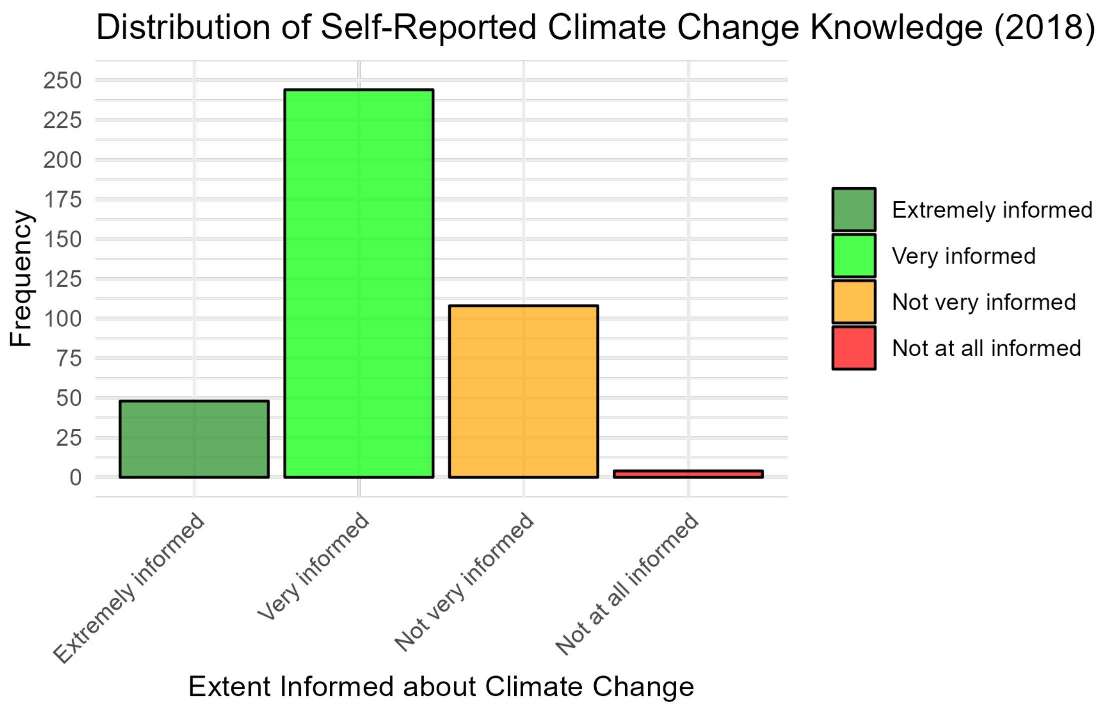
Education Level	2018 Percentage	Education Level
High school or less	9	Less than high school
Some community college, vocational, trade school	5	High School or equivalent
Completed community college, vocational, trade school	12	Degree or diploma from a college
Some university	10	Graduate or professional degree (
Completed undergraduate degree	32	Prefer not to answer
Post graduate/professional school	29	DK/NS
Prefer not to answer	3	

Extent Feel Informed

Individual 2018

fig-five depicts the distribution of self-reported climate change knowledge among survey respondents in 2018. The majority of participants identified as “Very informed,” making this the most prevalent category by a significant margin. A moderate number of respondents reported being “Not very informed,” while a smaller yet noticeable group described themselves as “Extremely informed.” In contrast, the categories “Not at all informed” and “Not very informed” have the lowest frequencies, with “Not at all informed” being particularly rare. This distribution suggests that most respondents possess a relatively high level of awareness about climate change, with very few indicating a lack of knowledge on the topic.

Extent Informed	2018 Percentage	Extent Informed	2021 Percentage
Extremely informed	12	Extremely informed	13
Very informed	60	Very informed	48
Not very informed	27	Only a little informed	37
Not at all informed	1	Not at all informed	2



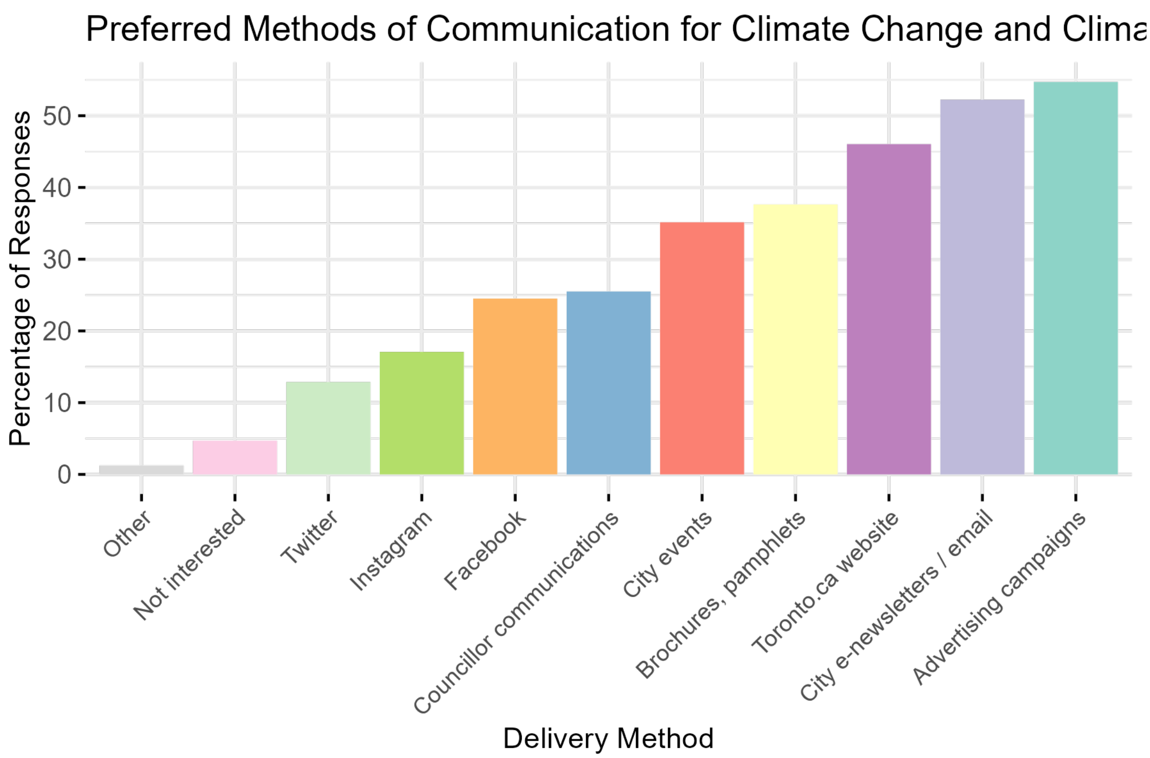
Comparison 2018 to 2021

fig-six illustrates the self-reported level of extent inviduals feel informed about climate change and climate action for 2018 and 2021. In 2018, the large marjority of individuals say they are very informed with 60 percent and the follwoign category is not very informed with 27 percent. In 2021, The majority of inividuals also say they are very informed but to a lesser degree with 48 percent and this is closely followed by only a little informed with 37 percent. There is a trend that invidiusls in 2018 reported greater levels of knowldege about climate change whereas 2021 illstrates a more even split between very informed and only little informed, portraying that fewer individuals have adequate knowledge about climate change.

Best Method of Delivery

Individual 2018

fig-seven, shows 2018 survey results for the preferred method for receiving climate change information. Advertising campaigns emerged as the most popular choice, selected by approximately 55 percent of respondents, followed closely by newsletters with 52 percent and the Toronto.ca website with 46 percent. On the other hand, social media platforms such as Facebook, Instagram, and Twitter were less popular overall, with Twitter 12 percent and Instagram 17 percent garnering the fewer votes. Notably, only 5 percent of respondents reported being uninterested in receiving information about climate action. These findings suggest that more traditional communication methods, such as advertising and newsletters, resonated better with respondents compared to social media.



Comparison 2018 to 2021

fig-eight compares the preferred methods of delivering climate change information between the 2018 and 2021 surveys. While the top three methods namely advertising campaigns, newsletters, and the Toronto.ca website remained consistent across both years, there were notable shifts in preferences. Traditional methods such as newsletters, advertising campaigns, brochures, and pamphlets saw a decline in 2021. In contrast, social media platforms including

Communication Method	2018 Percentage	Communication Method	2021 Percentage
Toronto.ca website	46	Toronto.ca website	44
Events	35	City of Toronto events	31
Twitter	13	Twitter	17
Facebook	25	Facebook	26
Instagram	17	Instagram	25
Enewsletter / email	52	City of Toronto e-newsletters / email	43
Councillor communication	25	Councillor e-newsletters	24
Advertising campaigns	55	Advertising campaigns	42
Brochures / Pamphlets	38	Printed or online brochures, pamphlets	31
Other	1	BetterHomesTO.ca website	15
Not interested	5	Not interested in receiving information	8
		Mail/ letter	1
		Nothing	1
		Other	0
		Don't know	0

Twitter, Facebook, and Instagram gained traction, reflecting a growing reliance on digital communication channels.

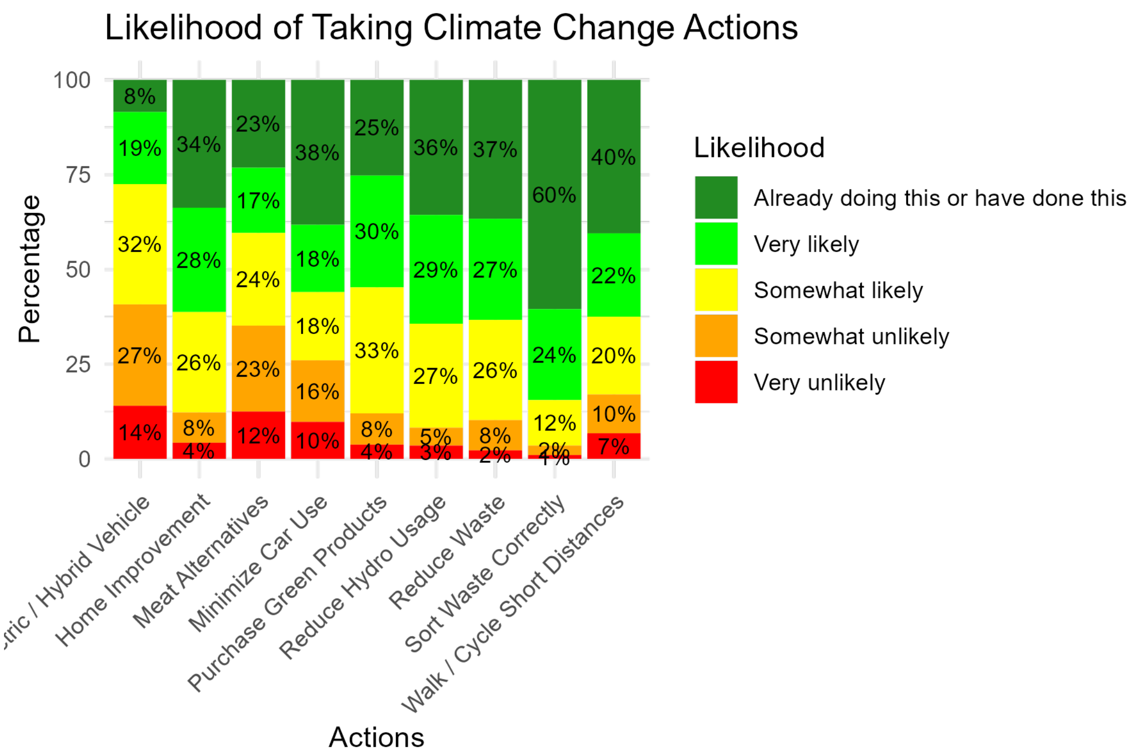
Additionally, the 2021 survey introduced new categories, including the BetterHomesTO.ca website, which accounted for 15 percent of responses. This addition underscores the increasing importance of specialized online platforms in engaging the public on climate action. These changes highlight a shift toward more diverse and digitally focused communication strategies over time.

Likelihood Taking Action

fig-nine illustrates the self-reported likelihood of individuals taking various actions to minimize environmental impacts. The x-axis displays nine different climate actions, while the y-axis represents the percentage of individuals corresponding to each likelihood level. A stacked bar chart is used to visualize the distribution of responses, with a color-coded legend ranging from green (high likelihood of action) to red (low likelihood of action).

Sorting waste into the correct bins is the most frequently reported action that individuals are currently undertaking, accounting for 60 percent of responses. Other common actions individuals are already participating in include walking or cycling short distances with 40 percent, reducing waste by contributing to the repurposing of used products with 37 percent and reducing hydro usage with 36 percent

In contrast, the least popular actions include switching to electric or hybrid vehicles, with 14 percent of respondents reporting they are very unlikely to take this action and 27 percent stating they are somewhat unlikely. Similarly, consuming less meat by incorporating more plant-based foods is unpopular, with 12 percent reporting they are very unlikely and 23 percent somewhat unlikely to adopt this change. Minimizing car use is another action with low reported likelihood, with 10 percent of respondents very unlikely and 16 percent somewhat unlikely to reduce their car usage.



Model

The goal of our modeling strategy is twofold: first, to predict how demographic factors influence individuals' likelihood of engaging in climate-friendly behaviors, and second, to uncover the role of age and education in shaping these actions. The actions considered include investing in electric vehicles, reducing hydro usage, adopting meat alternatives, and walking or cycling shorter distances. We use a decision tree model to provide a clear, interpretable framework for analyzing these relationships.

Model set-up

Our model predicts the likelihood of engaging in specific climate-positive actions, with age and education level serving as predictors. Likelihood is measured on a five-point scale, ranging from

"Already doing this or have done this" to "Very unlikely."

Model Specifications

We employ separate decision tree models for each action. Age (continuous) and education (categorical) are the key predictors driving predictions. Each tree splits the data at nodes based on these variables, revealing demographic conditions associated with greater or lesser likelihoods of climate-positive behaviors.

Model Justification

This approach provides insights into how demographic factors influence climate-friendly actions, including energy reduction, sustainable practices, and green technology adoption. By identifying demographic groups more likely to take these actions, the model can inform targeted interventions.

Response Variable

The response variable measures the likelihood of engaging in specific climate-friendly behaviors, represented on a five-point scale: "Already doing this or have done this," "Very likely," "Somewhat likely," "Somewhat unlikely," and "Very unlikely." This scale reflects an individual's readiness to adopt sustainable practices.

Input Variables

Our predictors are:

- **Age**: Research shows that younger individuals often demonstrate greater environmental awareness and a stronger inclination toward sustainable actions (Leiserowitz et al., 2010; Gifford, 2013).
- **Education**: Previous studies illustrate that higher education correlates with increased environmental awareness and sustainable behavior adoption (Kollmuss & Agyeman, 2002).

Model Structure

The decision tree splits data based on age and education, uncovering demographic patterns in climate-positive behaviors. Unlike linear models, decision trees do not assume direct relationships but instead identify conditions under which certain behaviors are more likely to occur. This assumption of independence allows clear interpretation of each factor's influence.

Understanding Decision Trees

Decision trees predict outcomes by recursively splitting data based on predictor variables. Starting at the root node (entire dataset), the tree branches into nodes based on decision rules, ultimately reaching terminal nodes that represent specific predictions, such as the likelihood of adopting sustainable behaviors. Each split aims to maximize prediction accuracy, and error rates indicate the reliability of classifications.

Decision Trees for Climate-Friendly Actions

We fit nine decision tree models to predict the likelihood of the following climate-friendly actions, using age and education as predictors:

1. Likelihood of switching in an electric or hybrid vehicle
2. Likelihood of minimizing car use
3. Likelihood of walking or cycling shorter distances
4. Likelihood of purchasing green products
5. Likelihood of reducing waste by repurposing used product
6. Likelihood of sorting waste correctly
7. Likelihood of making home improvements
8. Likelihood of adopting meat alternatives
9. Likelihood of reducing hydro usage

Each model follows a consistent structure, highlighting how age and education influence these behaviors.

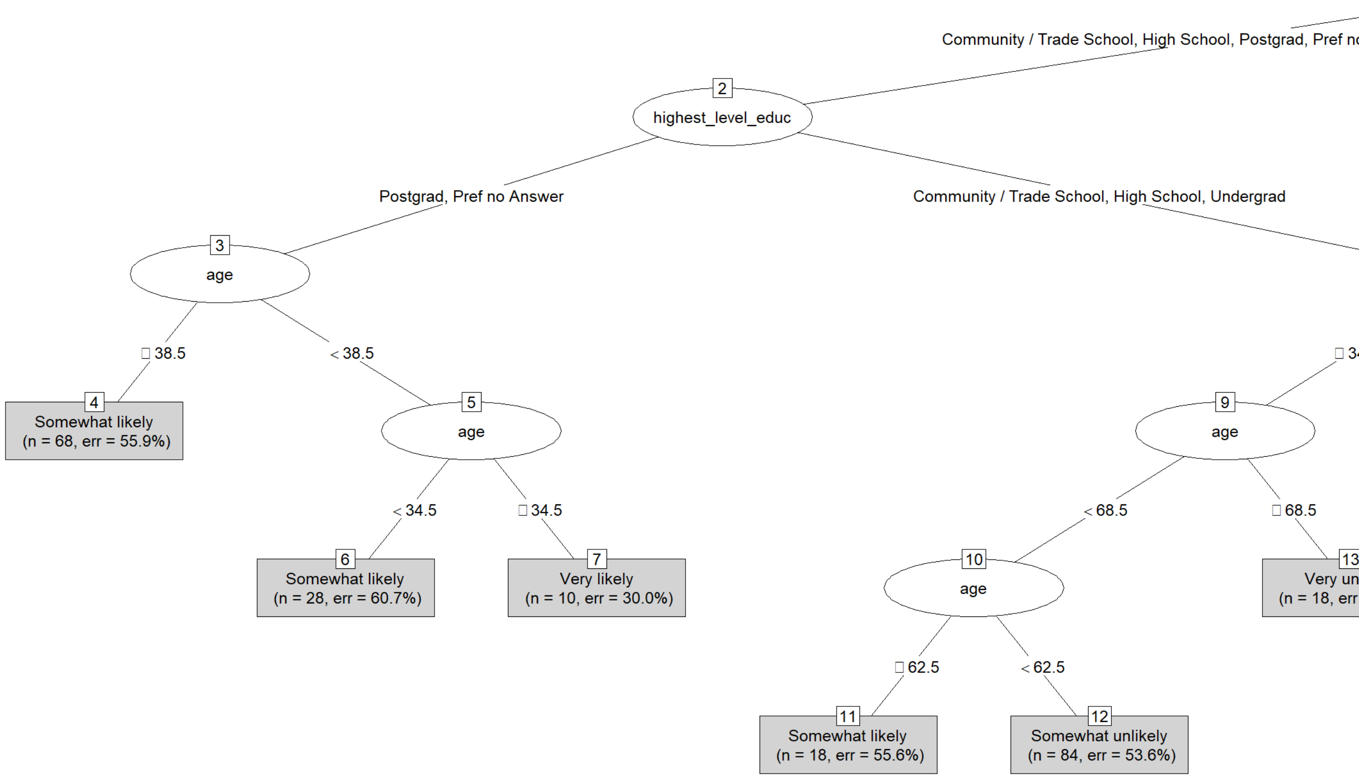
Model Estimation and Interpretation

The model predicts that younger individuals with higher education levels are more likely to adopt climate-friendly behaviors. The decision tree identifies key splits in the data and evaluates prediction reliability using error rates, providing insight into the impact of age and education on sustainable actions.

Transportation Actions

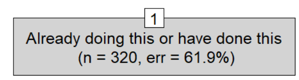
Likelihood of switching to an electric or hybrid vehicle

fig-ten reveals that education is the primary predictor for the likelihood of switching to an electric or hybrid vehicle. Individuals with "Some Community/Trade School" or "Some University" education are "Very likely" to invest, though with moderate variability (error rate 63.8%). Those with higher education show more age-based segmentation. Younger individuals under 35 years are more likely to invest, with a lower error rate (30%). Older individuals, particularly those over 69 years, are “Very unlikely” to invest. This model demonstrates how age and education interact to influence vehicle choice.



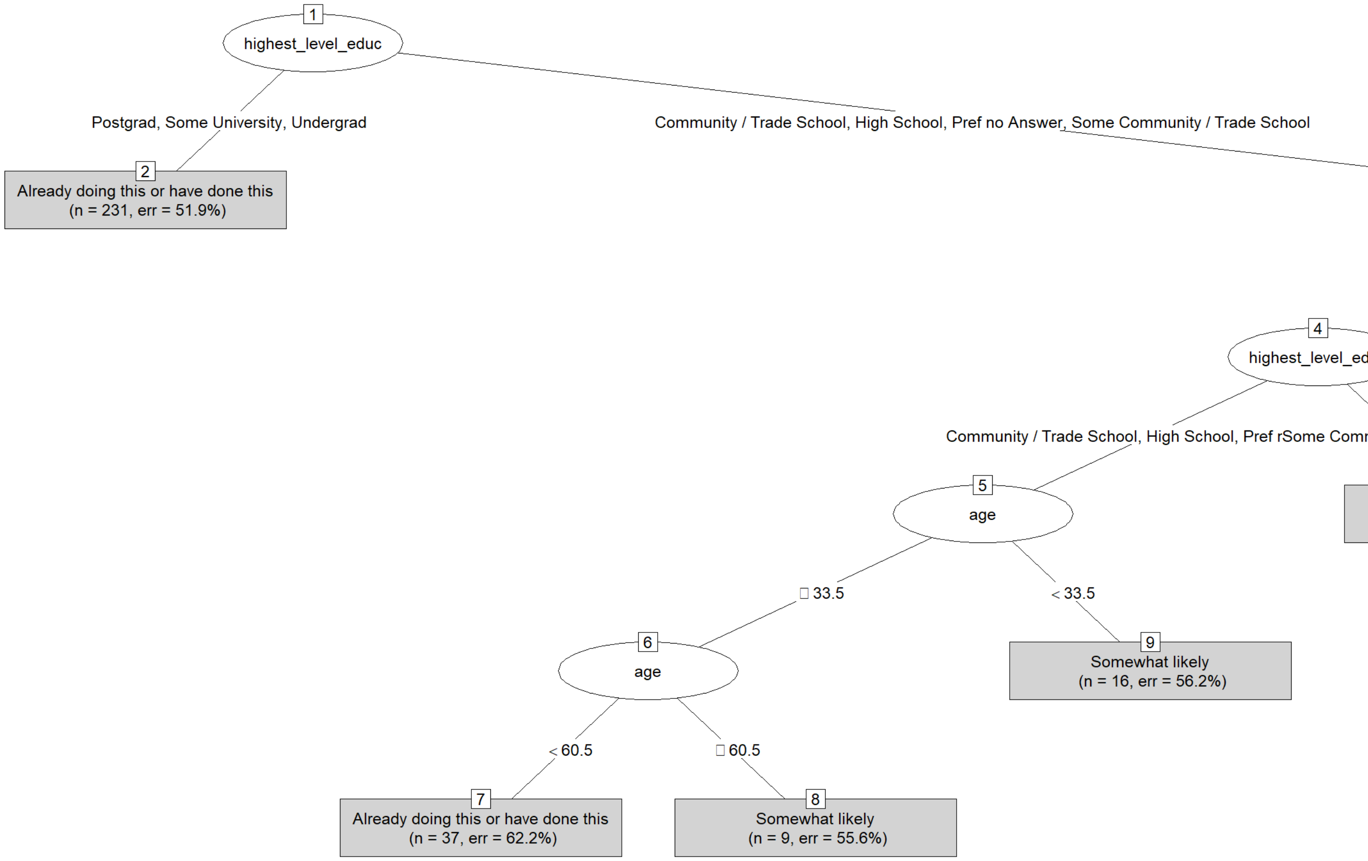
Likelihood of minimizing car use

fig-eleven shows that the likelihood of minimizing car use is consistent across the sample, with a high error rate (61.9%). The model classifies all individuals into the “Already doing this or have done this” category, indicating widespread adoption of this behavior, regardless of age or education



Likelihood of walking or cycling shorter distances

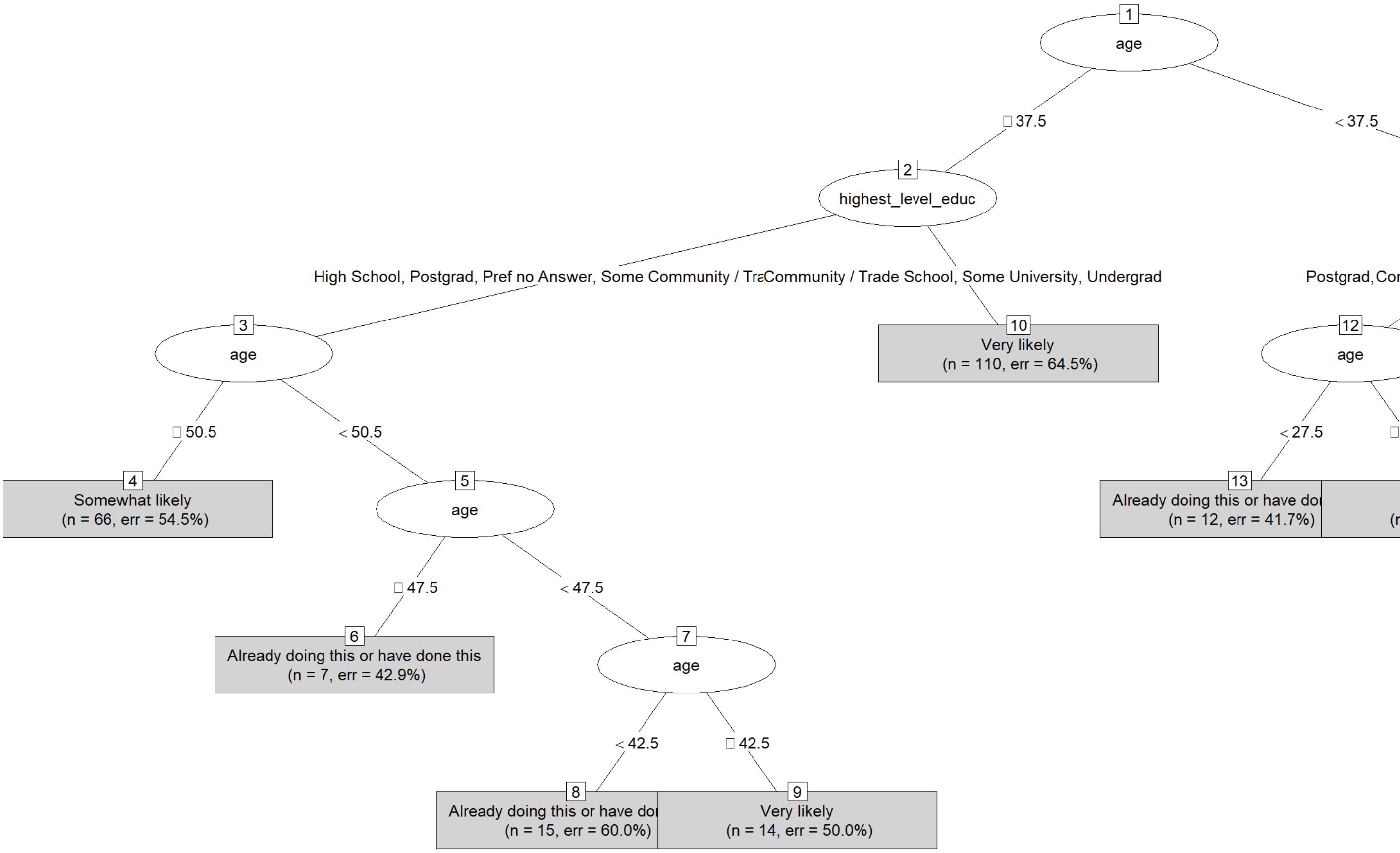
fig-twelve indicates that education is the primary factor influencing short-distance walking or cycling. Those with higher education (postgraduate, undergraduate, or some university) are more likely to engage in this behavior, with an error rate of 51.9%. For those with lower education, age plays a significant role, with younger individuals (under 66 years) more likely to walk or cycle, with an error rate of 60%. This model highlights how education and age together shape short-distance mobility, with error rates reflecting the model's predictive variability.



Waste and Product Actions

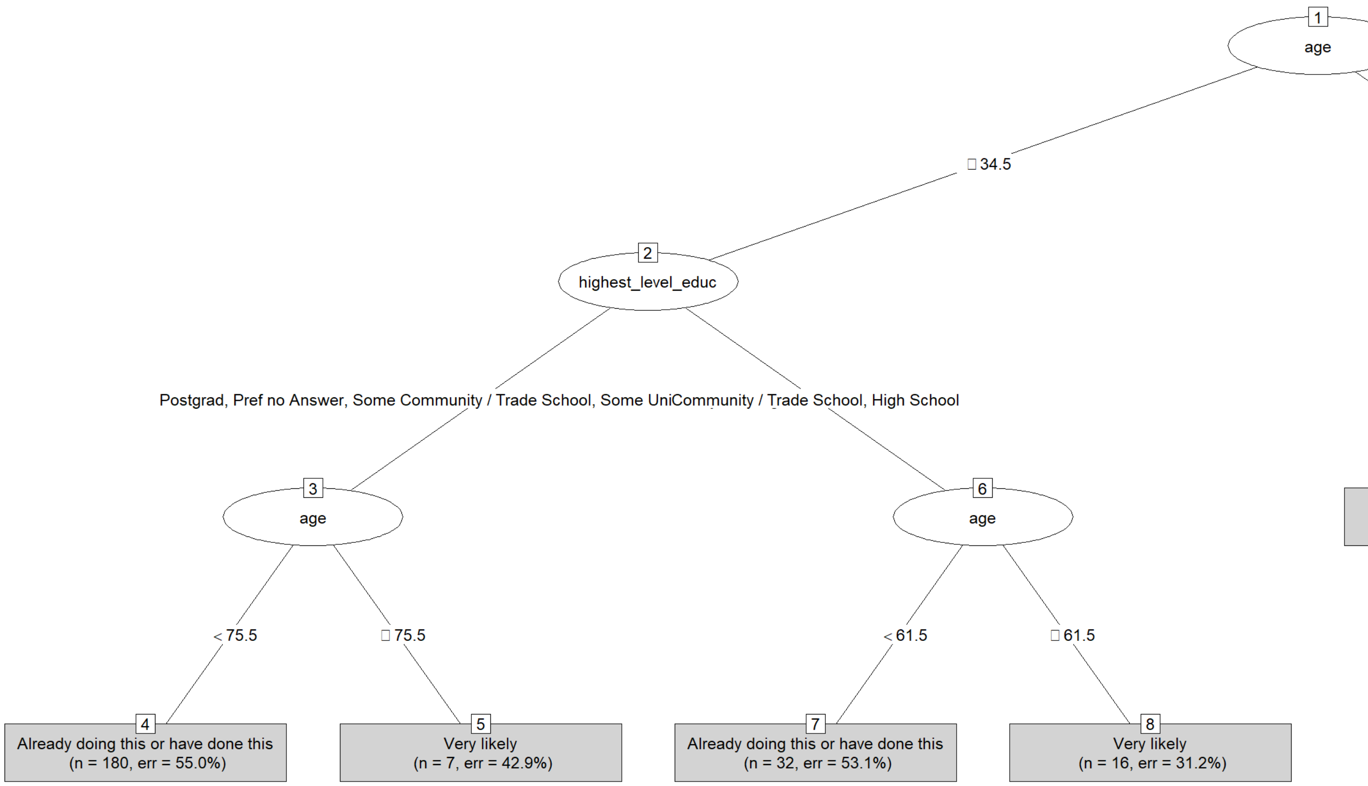
Likelihood of purchasing green products

fig-thirteen reveals that age is the initial split for green product purchasing behavior. Younger individuals (under 38 years) are more likely to purchase green products, with an error rate of 51.9%. Education further refines the prediction. Older individuals (over 38 years) are classified by both age and education, with postgraduate education leading to higher engagement in purchasing green products, with an error rate of 60%. This model shows how age and education influence consumer choices in sustainable products.



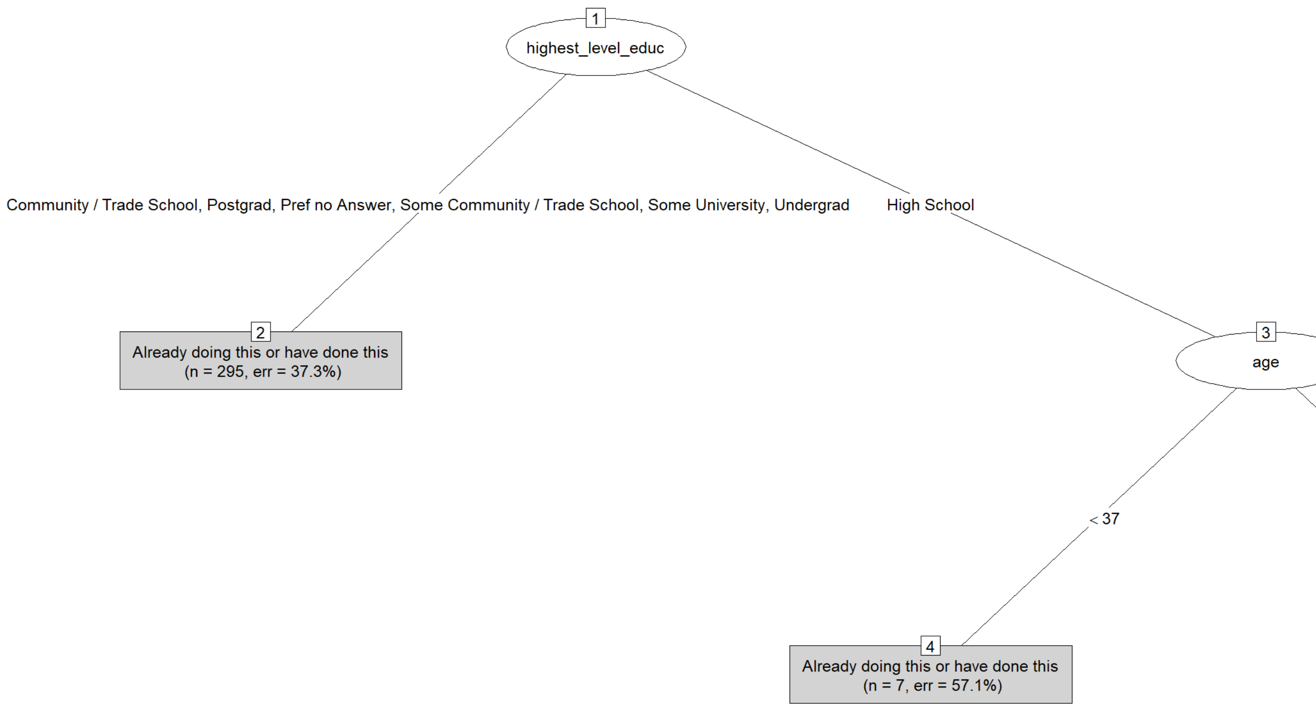
Likelihood of reducing waste by repurposing used product

fig-fourteen shows that age is the primary factor for waste reduction behaviors. Younger individuals (under 35 years) are more likely to repurpose waste, with an error rate of 57.1%. Education further refines the classification. Older individuals (over 35 years) show varied likelihoods based on education, with more highly educated individuals more likely to repurpose waste, with an error rate of 60%. This highlights the influence of both age and education on waste-reduction habits.



Likelihood of sorting waste correctly

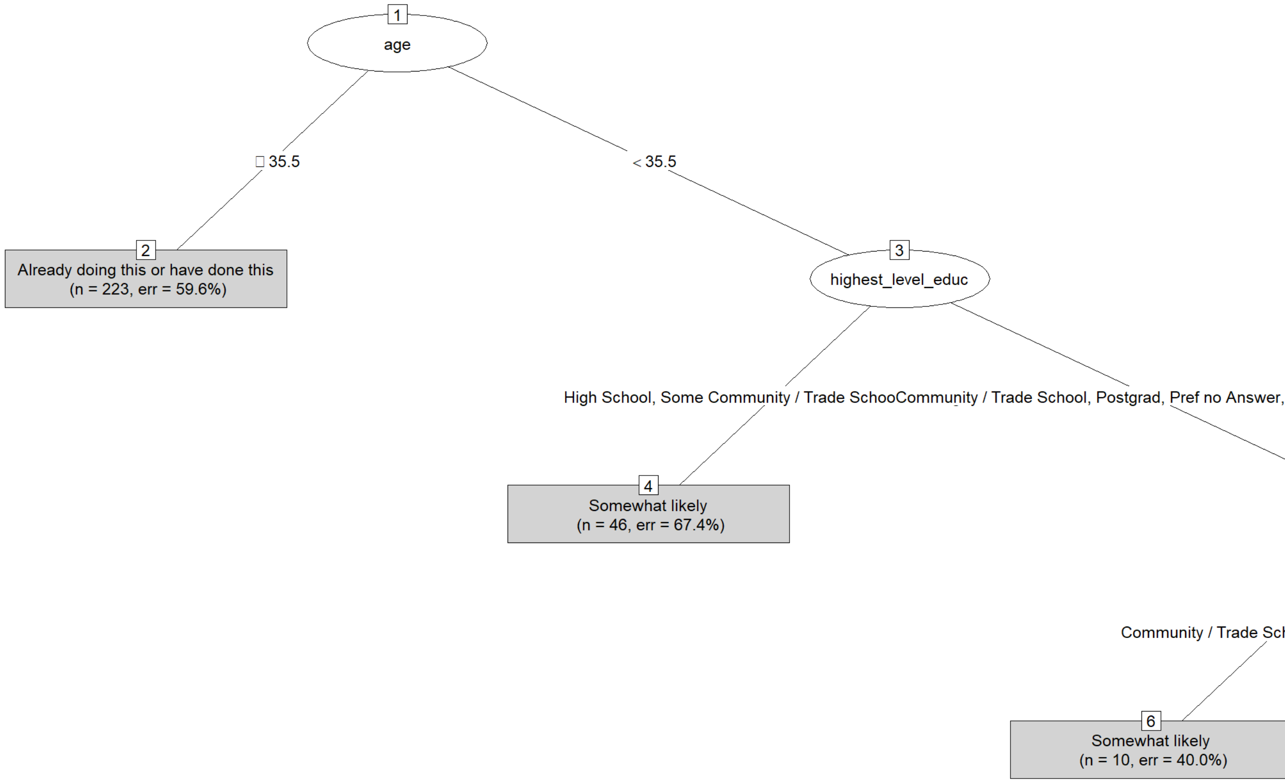
fig-fifteen identifies education as the primary factor for sorting waste. Those with higher education (at least community/trade school or postgraduate) are more likely to sort waste correctly, with an error rate of 37.3%. Age further refines the predictions for those with lower education levels, with younger individuals under 37 years being more likely to sort waste correctly, albeit with a higher error rate of 57.1%. Older individuals (37 years and above) are more likely to sort waste correctly, with an error rate of 35.3%. The model emphasizes the role of education in fostering proper waste-sorting behaviors, with age providing additional nuance.



Home and Lifestyle Changes

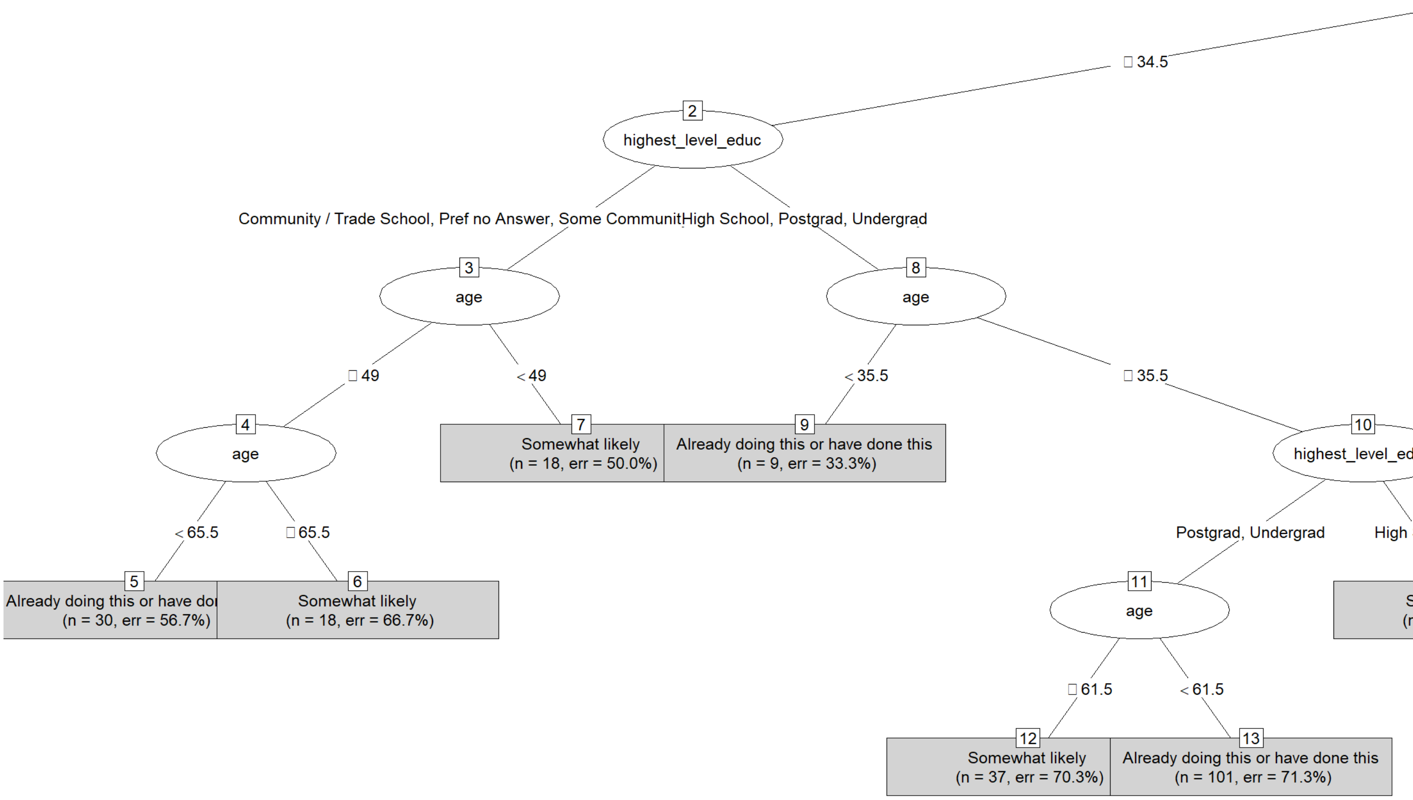
Likelihood of making home improvements

fig-sixteen shows that age is the key predictor for home improvement behavior. Individuals aged 36 years and older are predominantly classified as "Already doing this or have done this," with an error rate of 59.6%. For younger individuals (under 36), education plays a role: those with higher educational attainment ("Community/Trade School," "Some University," or "Postgraduate") are "Very likely" to make home improvements, with an error rate of 55%. Conversely, individuals with lower education levels are classified as "Somewhat likely," with a higher error rate of 67.4%. This model highlights how age and education interact to influence home improvement decisions.



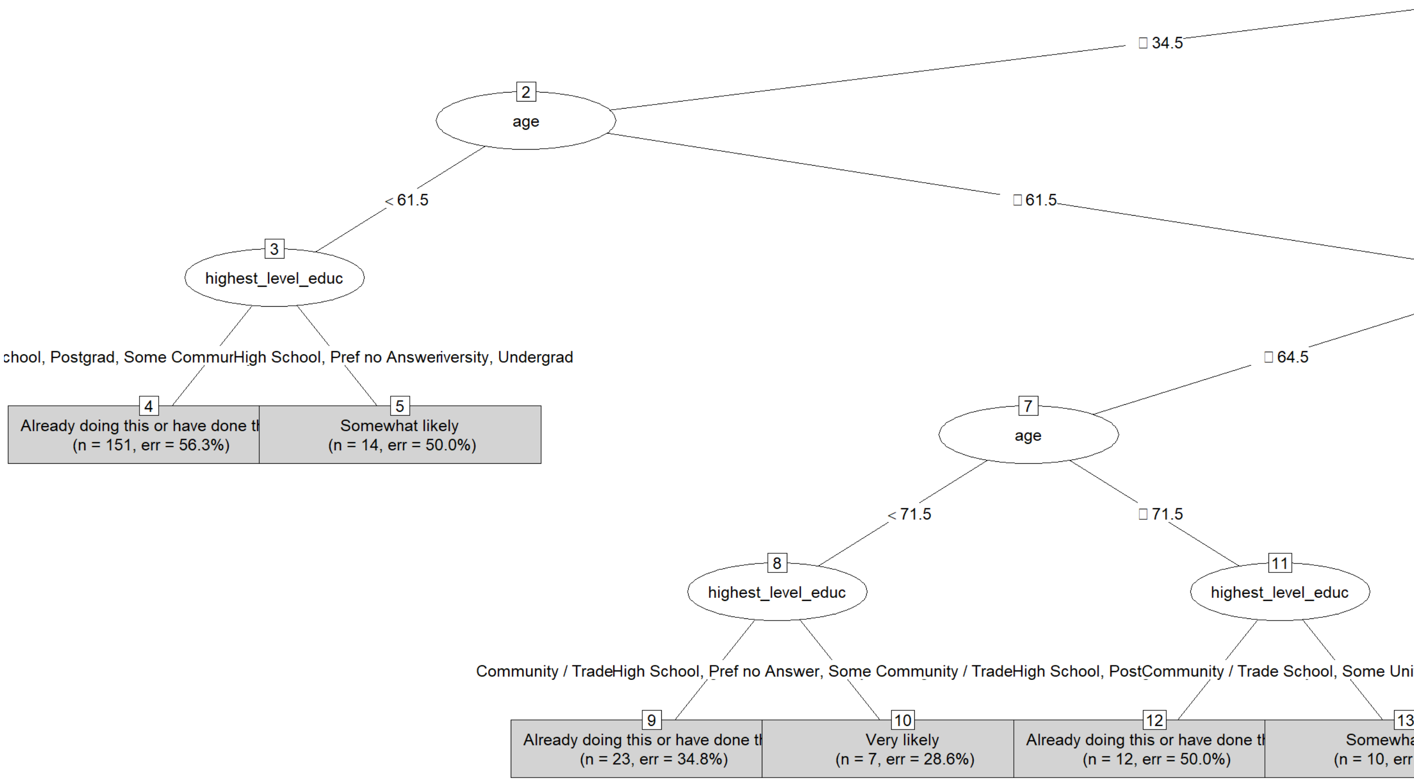
Likelihood of adopting meat alternatives

fig-seventeen demonstrates that age is the primary factor for adopting meat alternatives. Younger individuals (under 35 years) are more likely to adopt meat alternatives, with an error rate of 44%. For individuals aged 35 years or older, education becomes a key predictor. Those with community/trade school, undergraduate, or postgraduate education are more likely to adopt meat alternatives, with varying error rates, including "Somewhat unlikely" for younger individuals at 62.9%. This model highlights how age and education together shape dietary choices.



Likelihood of reducing hydro usage

fig-eighteen reveals that age is the primary predictor influencing hydro usage reduction. Younger individuals (under 35 years) are “Very likely” to reduce hydro usage, with an error rate of 60.9%. Older individuals (35 years and above) are further split by education and age, with those over 64 years also “Very likely” to engage in hydro conservation, with a lower error rate of 37.5%. Middle-aged individuals (35–64 years) with higher education are either “Already doing this or have done this” (error rate 56.3%) or “Somewhat likely” (error rate 50.0%). This model underscores the combined role of age and education in promoting energy-saving behaviors.



Results

Model Summary Table

fig-nineteen presents the accuracy of models predicting climate-friendly actions based on age and education. A threshold emerges from the data: models with accuracy above 50% are considered reliable, while those below require careful interpretation. Sorting waste correctly, with an accuracy of 59%, is the most reliable prediction, indicating a stronger association between demographic factors and this behavior. Models like home improvements (33%) offer limited predictive value but remain somewhat informative. In contrast, actions such as adopting meat alternatives (25%) or choosing electric or hybrid vehicles (25%) approach random chance, making their predictions less reliable for drawing meaningful conclusions.

Model	Accuracy (%)
Home Improvement	33
Reduce Hydro	28
Minimize Car	39
Electric / Hybrid Vehicle	25
Meat Alternative	25
Reduce Waste	39
Green Products	32
Walk / Cycle Short Distance	35
Sort Waste Correctly	59

Likelihood taking action by age

fig-twenty shows the relationship between age and the likelihood of engaging in various climate-related actions. The x-axis represents the age groups, and the y-axis indicates the percentage of respondents reporting different likelihood levels, from “Already doing this” to “Very unlikely”.

Transportation Actions

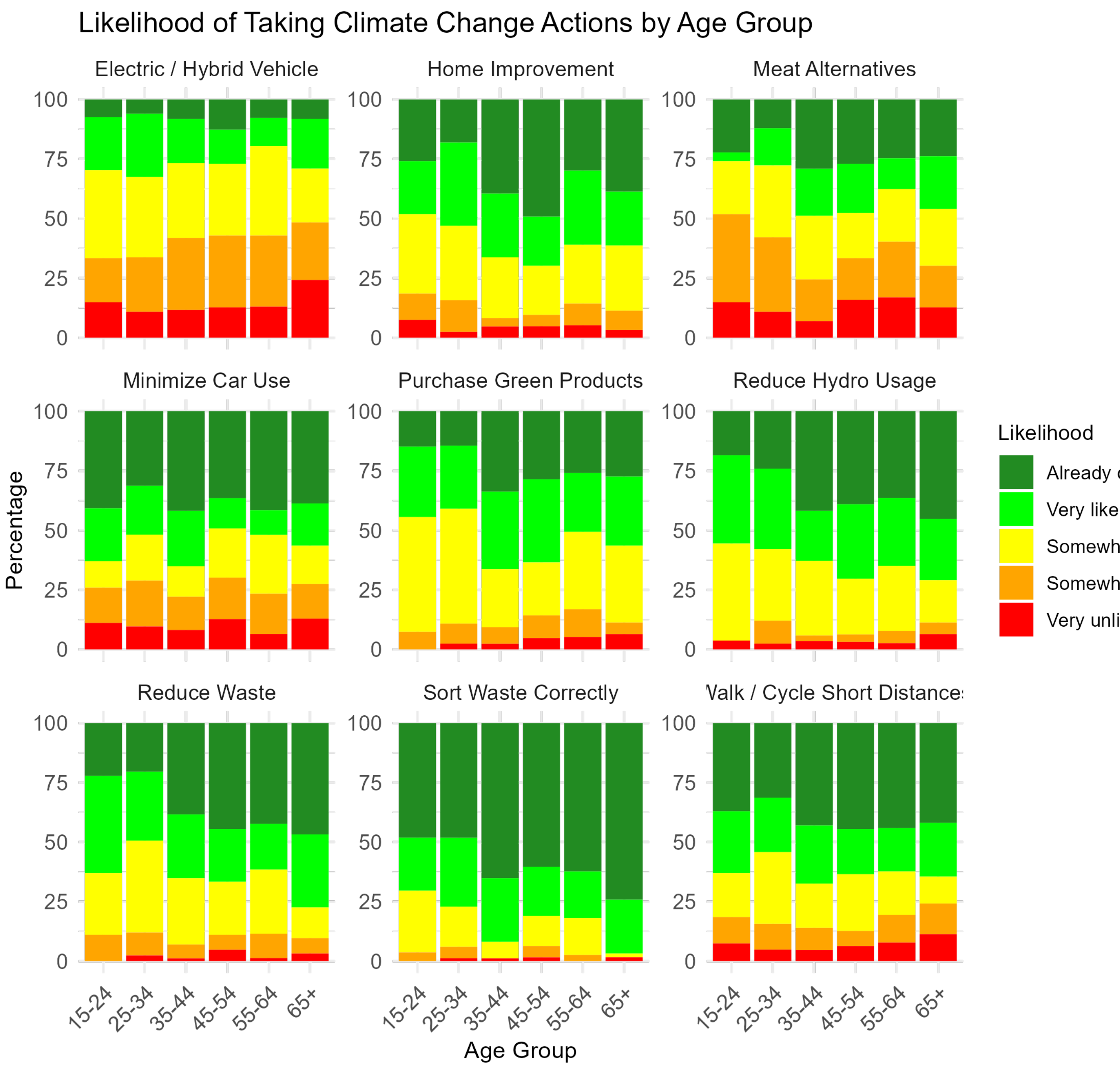
In the category of transportation actions, the results reveal that for electric and hybrid vehicles, there is little difference between age groups in terms of the likelihood of adopting this behavior, but older individuals, particularly those aged 65+, are more likely to report being “very unlikely” to do so. For minimizing car use, individuals across all age groups report similar levels of engagement, with relatively consistent percentages already minimizing their car use. However, older individuals, particularly those in the 45-54 and 65+ age groups, are more likely to report being “very unlikely” to minimize car use. For walking or cycling short distances, the trend shows that all age groups, except for those aged 25-34, report similar levels of engagement, with a slight decrease in adoption among the 25-34 age group. Conversely, older individuals, especially those aged 65+, are more likely to report being “very unlikely” to engage in walking or cycling for short distances.

Waste and Product Actions

When examining purchasing green products, individuals aged 35 and older report higher engagement in this action, with many already purchasing green products or expressing a strong likelihood of doing so. Notably, those aged 45 and above are the least likely to adopt this behavior, with a significant percentage indicating they are “very unlikely” to do so. For reducing waste, older age groups show higher levels of engagement, with individuals aged 35 and above reporting the highest rates of already taking this action. The 45-54 age group, however, is the least likely to engage in this behavior. Sorting waste correctly is overwhelmingly supported by all age groups, with at least 75% in each category already doing or being very likely to take action. The incidence of individuals reporting being "very unlikely" to sort waste correctly is minimal across all age groups.

Home and Lifestyle Changes

For making home improvements aimed at increasing energy efficiency, middle-aged individuals (35-54) are the most likely to report having already made improvements or being very likely to do so. Across all age groups, at least half of the respondents are already engaged in or very likely to engage in energy-efficient home improvements, though younger individuals (15-24) are less likely to take this action. Regarding adopting meat alternatives, younger individuals, particularly those aged 15-24, are the least likely to reduce meat consumption with plant-based alternatives. In contrast, individuals aged 35 and older show higher levels of adoption or strong intention to adopt this behavior. Lastly, for reducing hydro usage, there is a clear increase in the likelihood of engagement with increasing age. Older individuals, particularly those aged 65+, are more likely to report already reducing their hydro usage or being very likely to do so, though the 65+ age group also reports the highest percentage of being "very unlikely" to reduce hydro usage.



Likelihood of Taking Climate Change Actions by Age Group
Electric / Hybrid Vehicle
Home Improvement
Meat Alternatives
Minimize Car Use
Purchase Green Products
Reduce Hydro Usage
Reduce Waste
Sort Waste Correctly
Walk / Cycle Short Distances
Percentage
0
25
50
75
100
15-24
25-34
35-44
45-54
55-64
65+
Age Group
Likelihood
Already d
Very like
Somewh
Somewh
Very unli

Likelihood taking action by education

fig-twenty-one displays how the likelihood of engaging in climate-friendly actions varies by educational attainment. The x-axis represents the proportion of respondents in each education category, while the y-axis lists the educational levels, from low to high educational attainment. Each action is shown across separate facets, revealing how education level correlates with engagement in each behavior.

Transportation Actions

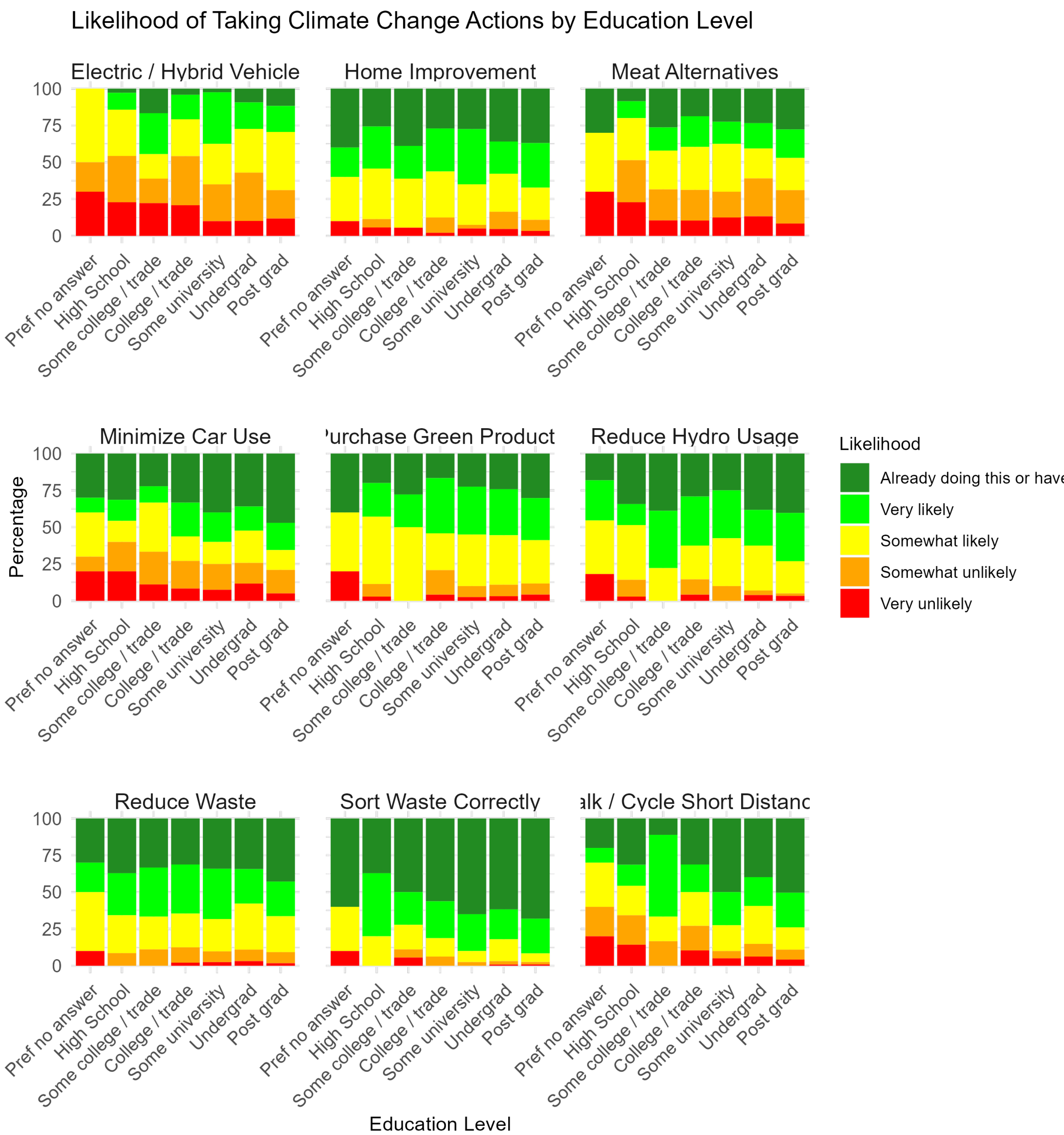
In the category of transportation actions, the likelihood of adopting electric or hybrid vehicles does not significantly vary across age groups, but older individuals, particularly those aged 65+, are more likely to report being "very unlikely" to adopt this action. When considering minimizing car use, responses show relatively consistent engagement across all age groups, with similar percentages already engaging in this action. However, older age groups, particularly those aged 45-54 and 65+, are more likely to report being "very unlikely" to minimize their car use. For walking or cycling shorter distances, the trend is fairly consistent across age groups, with all groups showing similar levels of adoption, except for those aged 25-34, who report slightly lower engagement. Older age groups, particularly individuals aged 65+, are also more likely to report being "very unlikely" to engage in walking or cycling for short distances.

Waste and Product Actions

Regarding purchasing green products, individuals aged 35 and older show higher levels of engagement, with a significant proportion already purchasing or expressing strong intentions to do so. Conversely, individuals aged 45 and older exhibit lower likelihoods, with a higher percentage reporting being "very unlikely" to adopt this behavior. For reducing waste, older age groups (35 and above) are more likely to have already taken action or express high intentions to do so. However, the 45-54 age group stands out as the least likely to engage in this action. Sorting waste correctly is a behavior that is overwhelmingly practiced across all age groups, with at least 75% of individuals from every age category reporting that they are already doing it or are very likely to do so. The percentage of individuals reporting being "very unlikely" to sort waste correctly is minimal across all age groups.

Home and Lifestyle Changes

For making home improvements to increase energy efficiency, individuals in the 35-54 age range are the most likely to report having already made improvements or being very likely to do so. In general, at least half of the sample across all age groups reports that they are already engaged in or very likely to make energy-efficient home improvements, although younger individuals (15-24) are less likely to take this action. When it comes to adopting meat alternatives, individuals aged 35 and above are more likely to reduce meat consumption with plant-based alternatives, while those aged 15-24 are the least likely to engage in this behavior. For reducing hydro usage, older age groups, particularly those aged 65+, report the highest rates of already engaging in or being very likely to engage in this action. However, the 65+ age group also reports the highest percentage of being “very unlikely” to reduce hydro usage.


Likelihood of Taking Climate Change Actions by Education Level
Electric / Hybrid Vehicle
Home Improvement
Meat Alternatives
Minimize Car Use
'urchase Green Product
Reduce Hydro Usage
Reduce Waste
Sort Waste Correctly
alk / Cycle Short Distanc
Percentage
100
75
50
25
0
Pref no answer
High School
Some college / trade
College / trade
Some university
Undergrad
Post grad
Education Level
Likelihood
Already doing this or have
Very likely
Somewhat likely
Somewhat unlikely
Very unlikely

Discussion

Overview of Climate Change Perspectives

This paper explored how various demographic factors—such as age, education, and climate change knowledge—affect individuals' engagement in climate-friendly behaviors. Through a comprehensive analysis of survey data from 2018 and 2021, we uncovered surprising patterns and deeper insights into the influences that drive people to adopt more sustainable actions. By investigating the interplay of these factors, we aimed to shed light on how societal changes, particularly in the context of climate action, reflect evolving values and behaviors.

What We Learn About the World

Age and Climate-Friendly Behaviors

Initially, we anticipated that younger individuals would lead the way in adopting climate-friendly actions. While younger people did excel in behaviors like walking or cycling and adopting meat alternatives, the older demographic demonstrated more significant commitment to long-term sustainable actions, such as making energy-efficient home improvements and reducing waste. This unexpected finding revealed that age influences sustainability in complex ways: younger people may embrace immediate, accessible actions, while older individuals engage in more transformative, lasting efforts. This highlights that climate action is a multi-generational effort, with each age group contributing in its own way.

The Role of Education in Sustainable Actions

We initially hypothesized that higher education levels would lead to greater engagement in climate-friendly behaviors, and the data largely supported this. Individuals with higher educational attainment were more likely to adopt green products and engage in waste reduction. However, some behaviors, such as reducing meat consumption, were less influenced by education and more affected by lifestyle preferences and cultural norms. Education acts as a strong catalyst for sustainability, but it works in conjunction with other factors, such as age and socio-economic status, to shape climate action. This reminds us that while education is a powerful tool for promoting sustainable behaviors, it is not the only factor at play.

The Influence of Climate Change Knowledge

To effectively encourage individuals to take climate action, it's crucial to consider the most popular and impactful methods of communication. Based on the findings from both 2018 and 2021, the most common methods for engaging individuals in climate-friendly behavior are ad campaigns, city newsletters/emails, and the official torontoca website. However, there has been a notable shift towards more diverse, digitally-focused strategies. Social media platforms, particularly Instagram and Twitter, have seen a significant increase in usage since 2018. These platforms allow for more dynamic, engaging, and personalized communication, which can be particularly effective for reaching younger demographics. Smith and Brown (Smith and Brown 2023) discuss how digital media can drive climate action by engaging youth through interactive and tailored content, offering an effective way to reach younger individuals who are more digitally engaged. Traditional methods, such as newsletters and brochures, continue to play a role but are becoming less dominant. To maximize engagement, a multi-channel approach that blends digital and traditional communication methods will likely resonate best with the broadest audience, particularly when targeting specific age groups and education levels.

Weaknesses of the Study

One limitation of this study is its reliance on self-reported survey data, which can be biased by social desirability or recall errors. Respondents may overestimate their commitment to sustainability or exaggerate their behaviors to align with societal expectations. Additionally, the use of summary data instead of individual-level data constrained our ability to explore complex interactions between socio-economic factors and climate behaviors. Future studies that utilize individual-level data and more objective measures, such as energy consumption records, would provide a clearer picture of the drivers behind climate action.

Survey data also presents challenges related to non-response bias, where certain demographic groups may be underrepresented, skewing results. Additionally, the framing of questions can influence responses, which could introduce variability in the data. The inability to verify self-reported behaviors further limits the reliability of the conclusions drawn from such datasets. Despite these challenges, surveys remain a valuable tool for understanding attitudes and behaviors, but their findings should be interpreted with caution and complemented with more direct forms of data collection.

Future Directions

To build on these findings, future research should focus on identifying the barriers that prevent certain groups from engaging in climate-friendly actions. By examining factors such as income, access to resources, and perceived obstacles to sustainability, we can tailor interventions to address specific needs. For example, financial incentives or public infrastructure improvements could make sustainable behaviors more accessible and feasible for low-income individuals. Longitudinal studies will also help track how climate awareness influences sustained behavioral changes over time, offering insights into the effectiveness of educational and policy interventions.

Lastly, incorporating objective data such as energy usage and transportation patterns could complement self-reported behaviors and validate the findings. This integrated approach would provide a more comprehensive understanding of how demographic factors shape sustainable actions, ultimately informing more effective climate policies.

Conclusion

This paper examined how age, education, and climate-friendly behaviors intersect, revealing that while younger individuals engage in more immediate actions like walking and adopting meat alternatives, older individuals tend to adopt long-term sustainable practices such as energy-efficient home improvements and waste reduction. Education plays a significant role in fostering sustainable behavior, though it works alongside other factors like income and lifestyle. The rise of digital media, especially social platforms, is crucial for engaging younger generations in climate action. Despite challenges such as biases in self-reported data, the study highlights the need for targeted strategies and multi-channel communication to drive climate action across diverse groups.

Appendix

Idealized methodology

Survey objectives

The primary objective of this study is to explore the factors influencing the likelihood of individuals engaging in climate-friendly behaviors. Specifically, the study aims to identify the age groups that are least likely to participate in sustainable actions and investigate how education levels impact climate-friendly behaviors. The research also seeks to determine whether individuals who report being relatively informed about climate change causes are more likely to take action to mitigate it. The underlying assumption is that individuals with greater knowledge of climate change should be more inclined to adopt behaviors that reduce its impact. Additionally, the study will examine the barriers that prevent people from engaging in sustainable behaviors, with the goal of identifying strategies to make these actions more accessible, affordable, and easy to adopt. The overarching aim is to develop solutions to increase the likelihood of participation in climate-friendly behaviors by removing existing barriers and promoting sustainability across different demographic groups. Part of this involves determining the most effective platforms for disseminating information about climate change, specifically by identifying which communication methods resonate most with different age groups. The research will also explore the role of education systems in fostering climate awareness and encouraging sustainable actions from a young age. Ultimately, the findings aim to provide actionable solutions to promote wider participation in climate-friendly actions, contributing to the fight against climate change.

Sampling approach

This study will target a diverse set of respondents across various age groups and demographic characteristics to gain a comprehensive understanding of climate-friendly behaviors and their drivers. The sample will be stratified to ensure representation across youth and adult demographics, enabling a comparison of climate knowledge and behaviors between generations. The study will start by sampling youth as young as age 12. This age group is chosen because children are old enough to understand the basics of climate change and the actions required to address it but still impressionable enough for their behaviors to be influenced by education and social interventions. By including participants starting at age 12, we aim to assess how effective climate change education in schools is and whether it is shaping climate-friendly behaviors in the younger generation.

In addition to youth, adults aged 18 and older will also be included to provide insight into longer-term behavioral trends, which may have been shaped by earlier education or a lack of education on the subject. The sampling will be stratified according to age, education level, income, and geographic location to capture a broad spectrum of experiences and perspectives on climate change and sustainability. Age groups will be divided into the following ranges: 12-17, 18-24, 25-34, 35-44, 45-54, 55-64, and 65+, while education levels will range from middle school to postgraduate education. Income will be categorized as low (<$30,000), middle ($30,000–$99,999), and high (>$100,000), and participants will also be grouped based on urban, suburban, or rural geographic locations. This stratified sampling approach ensures a diverse representation of individuals, allowing for meaningful comparisons of climate knowledge and behaviors across different demographic groups.

Respondant recruitment

Participants will be recruited using a multi-channel approach to ensure broad representation across various age groups and geographic locations. For youth aged 12-17, recruitment will occur through schools, with cooperation from middle and high schools. District educational boards or individual teachers will be approached to distribute information about the survey, and parental consent will be obtained before participation. To recruit adults, online surveys will be distributed via social media, email lists, and relevant climate-focused online communities. Additionally, outreach will be conducted in community centers and public spaces to capture respondents from rural or underserved areas. Flyers, local advertisements, and community events will help ensure that the sample is representative of both urban and rural populations.

Incentives such as gift cards or a donation to a climate-focused charity will be offered to participants to encourage engagement and improve response rates, especially among younger participants who may be less inclined to participate without an incentive.

Data Validation

To ensure the validity and reliability of the data, several validation mechanisms will be employed. Responses will be reviewed for internal consistency, such as cross-checking whether respondents who claim high levels of climate change knowledge also report engaging in corresponding climate-friendly behaviors. Participants who provide inconsistent answers or fail to complete the survey will be excluded from the analysis. Additionally, respondents may be contacted for clarification if their answers are ambiguous or incomplete. This will ensure that the data accurately reflects the participant's true attitudes and behaviors.

Weighting and Data adjustments

The data collected will be weighted to account for any imbalances in demographic representation within the sample. Statistical weighting will adjust for factors such as age, education level, income, and geographic location to ensure the sample accurately reflects the broader population. Weighting will correct for any over- or under-representation of specific demographic groups, allowing for more generalizable findings. Additionally, data will be adjusted for non-response bias, with greater weight given to underrepresented groups (e.g., certain age groups or income levels) to correct for gaps in participation.

Budget

The budget for this study will cover several key areas essential for effective data collection and analysis. A portion of the budget will be allocated to the survey platform and software tools needed for data collection, such as online survey tools and platforms for both youth and adult respondents. Since incentives are critical to encouraging participation, especially from younger individuals, funds will also be used to provide gift cards or donations to climate-related charities as incentives. To reach a diverse demographic, outreach costs will also be factored in, including the production and distribution of flyers, local advertisements, and outreach at community centers or schools. Lastly, resources will be dedicated to data analysis, including the purchase of statistical software like SPSS or R for cleaning, coding, and analyzing the responses. The final portion of the budget will cover any miscellaneous costs such as obtaining parental consent forms, printing, and mailing physical surveys or communication materials.

Survey design

The survey design will be structured to capture a range of demographic and behavioral data in order to address the research objectives. The survey will begin with demographic questions to capture essential background information, including age, education level, income, and geographic location. These variables will allow the analysis to identify how climate-friendly behaviors and knowledge vary across different groups. The primary focus will be on participants' climate change knowledge, specifically assessing their awareness of its causes, impacts, and potential solutions. Respondents will be asked to rate their perceived level of knowledge about climate change on a Likert scale, ranging from "not informed" to "very informed." They will also be prompted to identify key contributors to climate change, as well as actions individuals can take to mitigate its effects.

The next section of the survey will focus on climate-friendly behaviors, asking respondents to self-report on their engagement in specific actions such as reducing car use, purchasing electric vehicles, eating plant-based meals, recycling, and reducing household energy consumption. These behaviors will help determine the extent to which knowledge of climate change is translating into actions, as well as highlight potential gaps in engagement.

Following this, the survey will include a section on barriers to sustainable behaviors, exploring factors that may be preventing individuals from adopting more climate-friendly actions. Participants will be asked to identify reasons such as cost, convenience, lack of knowledge, or skepticism. This will allow the study to pinpoint the most significant obstacles to widespread adoption of sustainable practices and provide insight into potential solutions.

The final section will focus on how respondents prefer to receive information about climate change. Given the varying effectiveness of different communication channels for different age groups, the survey will include questions on the most effective platforms for disseminating climate change education, such as social media, school programs, TV ads, and email. By identifying these preferences, the study will be able to recommend the most suitable methods for spreading climate change awareness tailored to specific demographics.

Each section of the survey will include a combination of multiple-choice, Likert scale, and open-ended questions to capture both quantitative and qualitative data. The open-ended responses will allow for more nuanced insights into the reasons behind individuals' climate-related behaviors and barriers. The design will aim to balance simplicity with comprehensiveness to ensure that the survey is engaging and easy to complete while still gathering sufficient data to answer the research questions effectively.

Tradeoffs and limitations

While this methodology is designed to be comprehensive, there are inherent trade-offs and limitations that must be considered. One key limitation is the reliance on self-reported data. Since participants will be answering questions based on their own recollections and perceptions, there is the potential for bias, such as over-reporting sustainable behaviors or under-reporting barriers to climate action. This could skew the findings, particularly if individuals respond in a socially desirable manner. Additionally, while efforts will be made to capture a representative sample, there is a possibility of sampling bias, especially in rural areas or among specific income groups who may have limited access to the survey. This could affect the generalizability of the results. Further, survey fatigue is a potential issue, particularly with younger participants who may lose focus or fail to complete longer surveys. To mitigate this, the survey will be kept concise, though the breadth of questions may still pose challenges. Finally, while statistical weighting and adjustments for non-response bias will be implemented, there is always some degree of uncertainty regarding the effectiveness of these methods in fully correcting for bias or imbalances in the sample. These limitations must be taken into account when interpreting the findings of this study.

Idealized survey questions

Thank you for your participation in the 2024 Climate Change Survey. This survey aims to gather information about public attitudes and behaviors related to climate change, with a focus on understanding the factors that influence people's engagement in climate-friendly actions. Your participation is entirely voluntary, and you may withdraw at any time, for any reason, with no questions asked.

This survey collects data regarding your awareness of climate change, the actions you take to mitigate it, and the barriers that may prevent you from engaging in more sustainable behaviors. The data you provide will be kept confidential and will be used solely for research purposes. This survey is anonymous, and your responses will not be traceable back to you. The goal of this survey is to better understand the motivations, challenges, and opportunities related to climate action, with a view to improving strategies for promoting sustainability.

If you have any questions or concerns about this survey or its methodology, please feel free to contact Lexi Knight via email at lexi.knight@mail.utoronto.ca. Any correspondence will remain confidential and will not be shared with any external parties.

Screening and Consent:

By checking this box, I consent to this survey collecting information about my awareness of climate change, the actions I take to address it, and the factors that influence my behavior for research

Correspondence will not be shared with any external parties. - I consent.

Demographic Information: 1. Whats your age? 12-17, 18-24, 25-34, 35-44, 45-54, 55-64, 65+, Prefer not to say 2. What is the highest level of education that you've completed? Some high school, High school diploma, Diploma / post secondary certificate (college, trade school). Bachelor's degree, Master's degree, Doctorate degree.

Climate Change knowledge and Awareness: 3. How would you rate your knowledge of the causes of climate change? Very informed, Somewhat informed, Neutral, Somewhat Uninformed, Very uninformed. 4. How confident are you in your understanding of how to mitigate climate change through individual actions? Very confident, Confident, Neutral, Somewhat confident, Not confident.

Climate-Friendly Action: 5. Which of the following climate-friendly actions do you regularly engage in? (Select all that apply). Reduce personal vehicle use (e.g., carpooling, using public transport, biking or walking shorter distances), Use / install energy-efficient appliances / devices (e.g., LED bulbs, smart thermostats), Eat a plant-based diet or reduce meat consumption, Recycle and compost, Purchase eco-friendly products (e.g., sustainable clothing, eco-conscious brands), Use renewable energy sources (e.g., solar panels, wind energy), None of the above, Other. 6. How often do you consider the environmental impact of your purchases? Always, Often, Sometimes, Rarely, Never

Barriers to Sustainable Actions: 7. What factors prevent you from engaging in more climate-friendly behaviors? (Select all that apply) Cost of sustainable products or services, Lack of time, Lack of knowledge about how to make sustainable choices, Convenience (e.g., environmentally harmful options are more accessible), Skepticism about the effectiveness of individual actions, No barriers (I already engage in sustainable behaviors), Other (please specify) 8. Do you feel that climate-friendly behaviors are affordable for people in your community? Yes, No, Not sure 9. Which of the following reasons best describe why you do not participate in more climate-friendly actions? (Select all that apply) I do not believe my individual actions will make a difference, I find it too difficult to make sustainable choices in my daily life, It is too expensive to adopt sustainable behaviors, I don't know where to start or how to make a meaningful impact, Sustainable products or services are not easily available in my area, I do not feel that climate change directly affects me or my community, I am unsure about what actions are most effective in reducing climate change, I am not sure how to balance sustainable actions with my current lifestyle 10. If you have avoided taking climate-friendly actions, what do you believe would make it easier for you to participate in these behaviors? (Select up to three) Lower cost of sustainable products or services, More convenient access to sustainable options, Clearer information on how individual actions can make a difference, More education or awareness about climate change, Incentives (e.g., government subsidies, rewards) to take action, More social pressure or norms encouraging sustainable behavior, Other (please specify) 11. How much do you trust the information provided by the following groups on climate change? Government, Environmental NGOs, Local community organizations, Media (TV, online news), Social media influencers/bloggers, Scientists, I do not trust any of these sources 12. If the government provided more support for individuals to take climate-friendly actions, would this lead you to taking more environmentally friendly actions (e.g., incentives, education programs, reduced cost)? Yes, No, Not sure 13. How strongly do you agree with the following statement: "Taking climate-friendly actions is a personal responsibility." Strongly disagree, Disagree, Neutral, Agree, Strongly agree 14. How strongly do you agree with the following statement: "The government or businesses should take more responsibility for addressing climate change than individuals." Strongly disagree, Disagree, Neutral, Agree, Strongly agree 15. Do you think the reluctance to take action against climate change more due to a lack of knowledge about how to get involved, or is it primarily because sustainable actions are inconvenient for people? Lack of knowledge about how to take action, Inconvenience of sustainable actions, Both, Neither, Unsure

Education and Information: 16. How effective do you think current school programs are in educating students about climate change? Very ineffective, Somewhat ineffective, Neutral, Somewhat effective, Very effective 17. Which platforms do you find most effective for receiving information about climate change? Social media (e.g., Instgram, Facebook, Twitter, TikTok), School programs, TV/Youtube, News articles, Websites, Podcasts, Community events, Email newsletters.

General Perception: 18. Do you believe that individual actions can make a significant difference in combating climate change? Yes, No, Not sure

19. In your opinion, which of the following should be prioritized to encourage more sustainable behaviors? (Select up to two), Making sustainable actions more affordable, Providing more education and awareness about climate change, Improving the accessibility of sustainable options, Encouraging government policies and incentives for sustainable behaviors, Creating a societal norm where sustainable actions are expected and practiced

Confirmation Message

Thank you for your response. We greatly appreciate the time, effort, and honesty you dedicated to completing this survey. Your answers have been successfully recorded and will contribute significantly to our research!

Additional data details

After data collection, the responses will be cleaned, coded, and analyzed using appropriate statistical methods. Analysis will focus on identifying correlations between demographic factors (age, education, income, geography) and engagement in climate-friendly behaviors. The data will also be examined for patterns in barriers to participation and preferences for information delivery. These findings will provide the basis for actionable recommendations to improve climate change education and encourage greater participation in sustainable behaviors.

Simlation Process {sec-simulation-process}

For the purposes of this study, I simulated data to investigate various factors related to climate change behaviors, including demographics, education levels, awareness of climate change causes, and preferences for communication methods. The simulated dataset consists of 404 entries, each representing an individual. To create this dataset, I used the `tidyverse` and `arrow` packages in R and set a seed value `(set.seed(853))` to ensure the results were reproducible. I generated the following variables:

The age variable was sampled randomly from a range between 18 and 100 years old. For education, I created several categories, such as "high school or less," "some community college/trade school," and "postgraduate/professional school," with an option for "prefer not to answer." The informed variable was categorized into four levels, from "extremely informed" to "not at all informed," reflecting the extent to which individuals felt knowledgeable about climate change causes. To capture the likelihood of engaging in climate-friendly actions, I simulated the likelihood of taking action variable, with responses ranging from "already doing this or have done this" to "very unlikely." Finally, the communication method variable explored how individuals preferred to receive climate-related information, with options such as "Toronto.ca website," "social media platforms," and "advertising campaigns," among others.

I used random sampling to generate values for each of these variables, ensuring a broad range of responses. After generating the data, I summarized it to verify its structure and consistency. The dataset was then saved as a `.parquet` file for further analysis. This approach allowed me to simulate a diverse set of responses and explore potential relationships between demographic factors, climate awareness, and willingness to engage in climate-friendly behaviors, all while maintaining the flexibility of synthetic data.

Data cleaning

2018 Individual Data

The cleaning process for the 2018 individual data began with selecting six key questions from the survey, focusing on variables that would provide insights into individual perceptions and behaviors regarding climate change. The corresponding columns were extracted and renamed with meaningful, descriptive names for clarity. The selected variables included age, the extent to which individuals consider themselves informed about the causes of climate change, the likelihood of taking specific climate actions, reasons for inaction (if they indicated they were unlikely to act), the highest level of education completed, and preferred methods for the city to deliver information about climate change and climate action.

After selecting and renaming the columns, minor formatting inconsistencies were addressed. For instance, a missing space in the "verylikely" response category was corrected to "very likely." Additionally, certain values were reformatted to ensure compatibility with visualization tools, making the dataset easier to plot later. Unlike other datasets that often contain missing values or duplicate entries, this dataset was notably clean. There were no missing responses, and all questions were answered, allowing for a comprehensive analysis of survey participants' perceptions and behaviors. The dataset offered valuable insights into individuals' likelihood of engaging in climate actions and their preferred communication channels for climate information.

Throughout the cleaning process, no observations were removed, as every response was preserved to accurately represent the survey data. Despite encountering a few incorrect variable formats, these were easily corrected without data loss. The dataset provided a rare opportunity to analyze a complete and consistent set of individual responses, enabling a thorough exploration of both demographic characteristics and personal perceptions related to climate change.

2018 Summary Data

Cleaning Process for the 2018 Summary Data To create the 2018 summary data, I built off the cleaned 2018 individual data. This approach was necessary because the 2021 data was only available in summarized form, not at the individual level. By summarizing the 2018 data in a comparable format, I could facilitate a meaningful comparison between the two years. The first step involved loading the cleaned 2018 individual dataset and mimicking the structure of the 2021 summary data as closely as possible.

For age, I created the same age categories used in the 2021 dataset to ensure consistency between the two datasets. I then calculated the percentage of individuals within each age group and created a table summarizing this information. Similarly, I summarized the highest level of education completed by respondents, presenting it as a percentage of the total. However, a slight inconsistency emerged during this process, as the education levels and their descriptions differed between 2018 and 2021. Despite this discrepancy, I aligned the categories as closely as possible to maintain comparability.

Next, I calculated the percentage of respondents who reported feeling informed about the causes of climate change and summarized the likelihood of taking various climate actions. This step was somewhat more complex, as the dataset contained nine different actions, each rated on a five-point scale of likelihood. I created a table showing the percentage likelihood of taking each specific action. Additionally, I analyzed the reasons respondents provided for being unlikely to take certain actions, which were only collected if they had indicated "unlikely" in the previous question. These reasons were summarized as counts rather than percentages, reflecting the conditional nature of the responses.

Finally, I summarized the preferred methods for receiving climate-related information from the city, presenting this data as a percentage. This comprehensive summarization of the 2018 individual data provided a consistent and comparable dataset for analyzing trends and changes in perceptions and behaviors between 2018 and 2021.

2021 Summary Data

The cleaning process for the 2021 summary data focuses on ensuring consistency and accuracy for six specific variables: age, education, extent informed, likelihood to take action, and reasons for not taking action. I first extracted data from the relevant sheets and columns in the 2021 raw dataset using read_excel from the tidyverse. For each category, I selected specific rows and converted raw data into percentages. The age and education data were cleaned and saved into separate data frames (age_summary_21 and education_summary_21), while other categories like "extent informed" and "likelihood to take action" required cleaning across multiple columns, with data transformation into percentages. Missing values and outliers were handled by filtering invalid entries and ensuring all values were consistent.

Instead of merging datasets for 2018 and 2021, I aligned the 2018 summary data to match the structure and categories of the 2021 data to facilitate comparison. This alignment was necessary because the categories and structure of the two datasets differed, and I modified the 2018 dataset to resemble the 2021 format as closely as possible, allowing for a more direct comparison. By focusing on ensuring that categories and percentages were comparable between years, I preserved the integrity of both datasets.

Finally, I saved each cleaned dataset into formatted tables using tinytable for LaTeX compatibility. These cleaned datasets were essential for analysis, ensuring that all variables were represented as percentages without any missing or erroneous data. This process also ensured that the dataset was ready for comparison with the 2018 data, with clear, consistent categories across both years.

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