

# 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.

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### 0.1 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

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\*Code and data are available at: [https://github.com/LexiKnight/toronto\\_climate/tree/main](https://github.com/LexiKnight/toronto_climate/tree/main).

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 ??.

## 0.2 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.

### 0.2.1 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), `whilereadxl` (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.

### 0.2.2 Methodology

#### 0.2.2.1 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.

### **0.2.2.2 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.

## **0.2.3 Features**

### **0.2.3.1 Age**

#### **0.2.3.1.1 Individual 2018**

Figure ?? 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

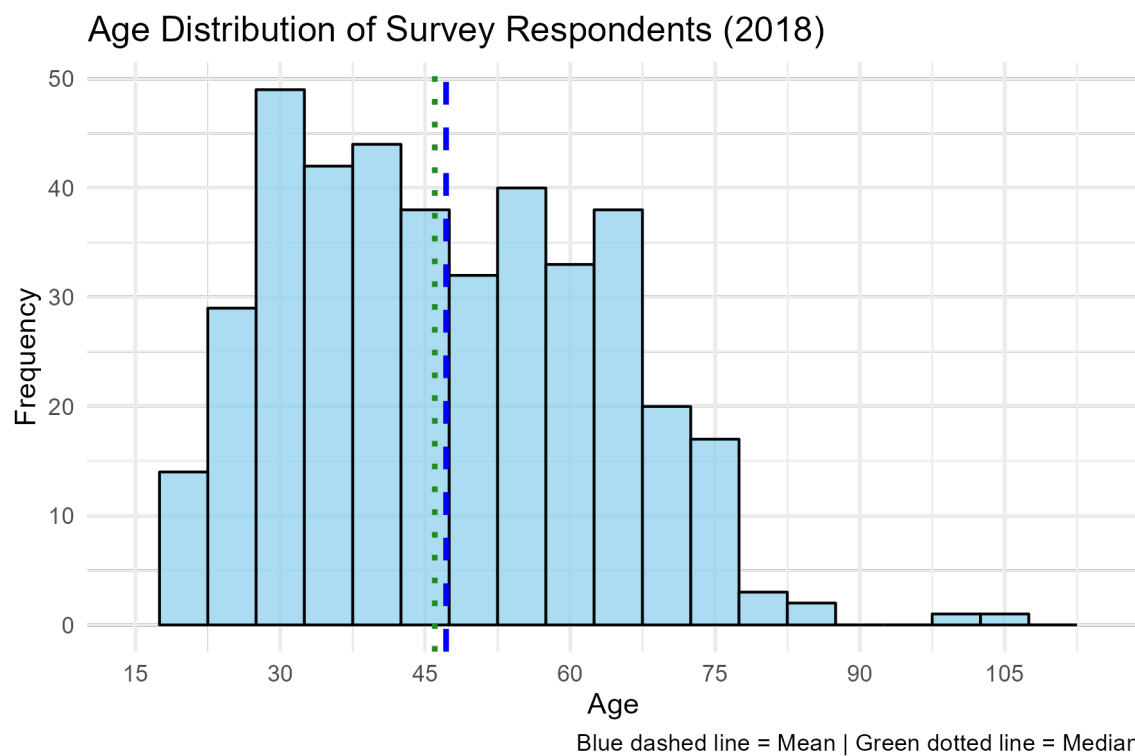


Figure 1: Distribution of age given the 2018 survey respondents. The mean and median of the sample is indicated with dashed and dotted lines respectively.