# Predicting the Likelihood of Climate-Friendly Actions: Insights from Age and Educational Attainment*

**An analysis of how demographic factors influence the adoption of sustainable behaviors**

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This study examines the relationship between demographic factors—age, education, and self-reported knowledge of climate change—and individuals' likelihood of engaging in climate-friendly behaviors. The analysis reveals that younger people and those with higher levels of education are more likely to adopt sustainable actions such as reducing car use and purchasing electric vehicles. However, the study also highlights that financial barriers and limited access to resources remain significant obstacles for broader climate action. These findings underscore the importance of tailoring policies and interventions to make sustainable behaviors more accessible to diverse demographic groups, promoting wider participation in efforts to combat climate change.

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## 1 Introduction

Climate change is one of the most urgent challenges we face today. From rising temperatures to extreme weather events, the planet is already feeling the consequences of human-driven environmental change (Intergovernmental Panel on Climate Change (IPCC) 2023). Yet, despite widespread awareness of these risks, many people still struggle to adopt behaviors that could help mitigate climate damage (Gifford 2011). This gap between knowledge and action is a central puzzle that governments, communities, and organizations are trying to solve (Kollmuss

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

and Agyeman 2002). If we are to tackle this crisis effectively, we need to better understand what stops people from acting, and how we can motivate change (Steg 2014).

This paper examines how specific factors—such as age, education, and self-reported knowledge of climate change—shape people's willingness to engage in climate-friendly actions (Schultz 2002). By analyzing data from a 2018 survey (City of Toronto 2024), we explore the connection between demographic characteristics and behaviors like reducing energy consumption, using greener transportation, and lowering waste. The survey also delves into what prevents people from adopting these behaviors, uncovering obstacles like cost, convenience, and skepticism about the power of individual actions (Gifford 2011). With this analysis, we aim to uncover how these factors interact and what they mean for efforts to encourage sustainable choices (Stern 2000).

The heart of this study is to measure how age, education, and knowledge of climate change influence the likelihood of adopting certain behaviors. We found that younger individuals and those with higher education levels are more likely to engage in actions like reducing car usage and adopting plant-based diets (Fulton 2022). However, older individuals are more inclined to take steps like cutting down on household energy use (Lee 2019). Beyond these demographic trends, we also discovered that barriers such as financial cost and doubts about the effectiveness of individual efforts often hold people back from taking action (Kollmuss and Agyeman 2002). These findings suggest that a "one-size-fits-all" approach to climate communication won't work. Instead, targeted strategies that consider demographic differences are essential for driving meaningful engagement (Steg 2014).

Understanding these patterns is crucial for crafting effective climate policies. By identifying which groups are more likely to act and which face significant barriers, we can better design interventions that speak to people's concerns and motivations (Stern 2000). The implications of this study go beyond simply knowing what people think about climate change—they offer a roadmap for shaping messages and policies that could shift behavior on a larger scale (Fulton 2022).

The remainder of this paper is structured as follows: Section **??** details the data and methods used in our analysis. Section **??** describes how we assess the factors influencing climate-friendly behaviors across demographic groups. **?@sec-results** highlights key differences in behavior based on age, education, and knowledge of climate change. **?@sec-discussion** discusses the findings, addresses the study's limitations, and suggests directions for future research. Section **??** concludes with a summary of the key takeaways and actionable recommendations for enhancing climate action engagement. Finally, Section **??** contains supplementary material.

## 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 and 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). Data cleaning and manipulation were primarily facilitated by the `tidyverse` package (Wickham, Averick, et al. 2024), which encompasses various essential tools. Within this suite, `dplyr` (Wickham, François, et al. 2024) was employed for data manipulation tasks such as filtering, summarizing, and joining datasets, while `readr` (Wickham, Hester, et al. 2024) provided efficient functionality for reading and writing rectangular text data. Specifically, the `write_csv` function from `tidyverse` was used to save the raw 2018 dataset. To handle Excel files, we incorporated the `httr` package for downloading files directly from online sources and `readxl` (Wickham and Bryan 2024), which enabled us to read Excel files seamlessly. Additionally, the `openxlsx` package was utilized to create a new Excel workbook with multiple sheets, allowing us to store the 2021 dataset in a structured format.

The `arrow` package was employed to handle large datasets efficiently, ensuring smooth data processing, while `forcats` was used for reordering factor levels to facilitate more insightful analyses and visualizations. In terms of data tidying, the `tidyr` and `stringr` packages allowed us to reshape and clean the data by managing character strings and handling missing values. The (Therneau and Atkinson 2024) and (Hothorn and Zeileis 2024) were used in to make the models. For the final documentation and report generation, the `knitr` package was instrumental in integrating R code and outputs into a cohesive and reproducible report format. This suite of R packages collectively enabled us to conduct thorough data management, manipulation, and analysis, ultimately contributing to the successful completion of the project.

## 2.1 Methodology

### 2.1.1 Data Collection

The data for this analysis comes from two surveys commissioned by the City of Toronto to assess residents' perceptions of climate change and their willingness to take community action. In 2018, Environics Research conducted n=404 online interviews with Toronto residents aged 18 and older between October 11 and October 18. Each interview lasted approximately 10 minutes. The sample was drawn from an online panel, with quotas set by region, age, and gender to reflect the city's population based on the 2016 Census, and minor weighting was applied. Due to the non-random nature of the online survey, no margin of error was assigned, though a random sample of this size would typically have a margin of $\pm 4.9$ percentage points, 19 times out of 20.

In 2021, a second survey was conducted by Ipsos, a global market research company. This survey included n=1,400 Toronto residents aged 18 and older and used a mixed-method approach. The sample consisted of 1,000 respondents from an online panel, 300 recruited via cell phone and landline, and 100 online interviews conducted in Mandarin, Cantonese, and

Punjabi. This combination of methods aimed to enhance the survey's representativeness. For analysis, Version 2 of the 2021 dataset, which presents responses in a numeric format, was used.

### 2.1.2 Data Analysis

The primary focus of this analysis was the 2018 dataset, examining six key variables: age, education, extent informed, likelihood to take action, reasons for not taking action, and the best method for delivering information regarding climate change action. I analyzed these variables at the individual level in the 2018 dataset by calculating the percentages within each category, which provided a clear understanding of the distribution and trends within the population.

In addition, I compared the 2018 dataset to the 2021 summary data to assess changes over the years. By calculating the percentage distribution for each variable in both years, I was able to identify any shifts in public awareness, engagement, and preferences regarding climate change action. This comparison revealed whether there have been notable changes in factors like the public's level of information about climate change, their likelihood to take action, and their preferred communication methods.

This two-step approach allowed for a comprehensive understanding: a detailed exploration of the 2018 data combined with a broader comparison of trends between 2018 and 2021.

## 2.2 Features

### 2.2.1 Age

#### 2.2.1.1 Individual 2018

Figure **??** illustrates the age distribution of survey respondents in 2018. The histogram displays the frequency of respondents across different age groups, with the x-axis representing age intervals and the y-axis indicating the number of respondents within each interval. The distribution is relatively balanced, with two noticeable peaks around the 30–40 and 50–60 age ranges, suggesting these age groups are the most represented in the survey.

The vertical dotted lines in the figure highlight key statistical measures: the green dotted line represents the median age, while the blue dashed line indicates the mean age of the respondents. Both measures fall near the center of the distribution, reinforcing the observation that the sample is primarily composed of middle-aged individuals. Although the distribution appears fairly symmetrical, there is a gradual decline in respondent frequency after the age of 60, with fewer participants aged 90 and above, indicating a smaller representation of older individuals.

Overall, Figure **??** provides valuable context for understanding the demographic composition of the survey sample. The predominance of middle-aged respondents may influence the interpretation of survey results, particularly if age is a factor in attitudes, behaviors, or preferences related to the study.

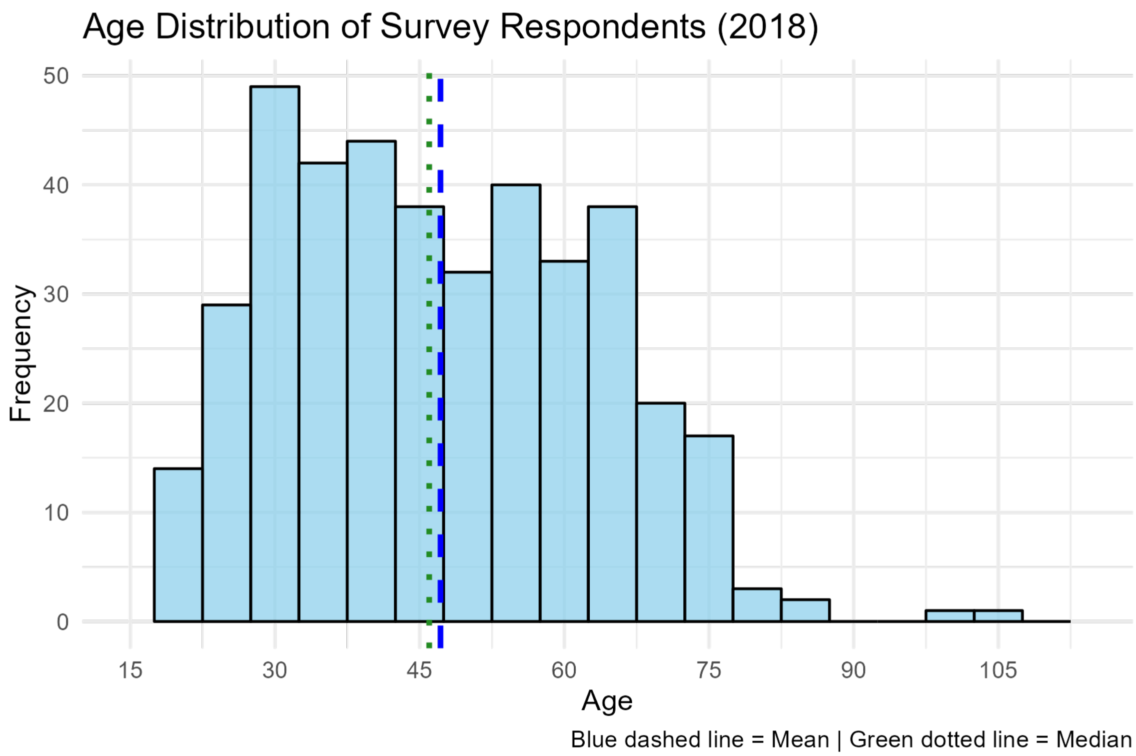


Figure 1: The histogram shows the distribution of age given the 2018 survey respondents.