# Revealing the Mysteries of Population Mobility Amidst the COVID-19 Pandemic in Canada: A Comparative Analysis with IoT-Based Thermostat Data and Google Mobility Insights

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## *Abstract*

**Background:** The COVID-19 pandemic saw the implementation of public health policies aimed at restricting human mobility to curb the spread of infection. Mobility is an often-overlooked determinant of human health and is linked to both infectious and chronic diseases. The development of tools to collect mobility data can unravel the complexities of human behavior and inform public health policies. Google has capitalized on its GPS-based location tracking to capture human movement out of the house during the pandemic: Google Mobility Reports has become the gold standard in mobility research. Yet, human mobility inside the home remains relatively unexplored. Here we investigated in-house mobility data from ecobee's smart thermostats during the COVID-19 pandemic in Canada.

**Objective:** This study aimed to assess the suitability of smart thermostat data through direct comparison with Google's residential mobility data.

**Methods:** Motion sensor data was collected from the ecobee "Donate your Data" program through Google's BigQuery cloud platform. Residential mobility data were obtained from the Google Mobility Report. The analysis focused on the Canadian provinces of Ontario, Quebec, Alberta, and British Columbia from February 15, 2020, to February 14, 2021. The data cleaning, analysis, and visualization used the MS Azure platform with Python and R coding languages. Changes in mobility above baseline were determined and compared between the two datasets. The statistical significance of the association was determined using Pearson's correlation and Spearman's correlation [34]. We analyzed day-by-day, week-by-week, and month-by-month seasonality patterns across both datasets and performed anomaly detection.

**Results:** Results showed significant changes in week-by-week and month-by-month population mobility for the selected provinces which tracked with pandemic-related policy changes. The ecobee data was significantly associated with Google data. Analysis of Google's day-by-day patterns found greater mobility changes on weekdays; this trend was not captured in the ecobee data. Anomaly detection found significant mobility deviations corresponding to policy changes and cultural festivities.

**Conclusions:** The findings from this study demonstrate that the Canadian stay-at-home order and work-from-home policies had a significant impact on population mobility. This could be captured using both out-of-house residential mobility data from Google and in-house smart thermostat data from ecobee. Therefore, smart thermostats are a valid tool to support intelligent monitoring of population mobility in response to policy-related changes.

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# Revealing the Mysteries of Population Mobility Amidst the COVID-19 Pandemic in Canada: A Comparative Analysis with IoT-Based Thermostat Data and Google Mobility Insights

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**Abstract**

**Background**: The COVID-19 pandemic necessitated public health policies to limit human mobility and curb infection spread. Human mobility, often underestimated, plays a pivotal role in health outcomes, impacting both infectious and chronic diseases. Collecting precise mobility data is vital for understanding human behavior and informing public health strategies. Google's GPS-based location tracking, leading to Google Mobility Reports, became the gold standard for monitoring outdoor mobility during the pandemic. However, indoor mobility remains underexplored. This study investigates in-home mobility data from ecobee's smart thermostats in Canada (February 2020 to February 2021) and compares it directly with Google's residential mobility data. By assessing the suitability of smart thermostat data, we aim to shed light on indoor mobility patterns, contributing valuable insights to public health research and strategies.

**Methods**: Motion sensor data were acquired from the ecobee "Donate your Data" initiative via Google's BigQuery cloud platform. Concurrently, residential mobility data were sourced from the Google Mobility Report. The study centered on four Canadian provinces—Ontario, Quebec, Alberta, and British Columbia—during the period from February 15, 2020, to February 14, 2021. Data processing, analysis, and visualization were conducted on the MS Azure platform utilizing Python and R programming languages. Our investigation involved assessing changes in mobility relative to the baseline in both datasets, with the strength of this relationship assessed using Pearson's and Spearman's correlation coefficients. We scrutinized daily, weekly, and monthly variations in mobility patterns across the datasets and performed anomaly detection for further insights.

**Results**: The results revealed noteworthy week-to-week and month-to-month shifts in population mobility within the chosen provinces, aligning with pandemic-driven policy adjustments. Notably, the ecobee data exhibited a robust correlation with Google's dataset. Examination of Google's daily patterns detected more pronounced mobility fluctuations during weekdays, a trend not mirrored in the ecobee data. Anomaly detection successfully identified substantial mobility deviations coinciding with policy modifications and cultural events.

**Conclusion**: This study's findings illustrate the substantial influence of the Canadian stay-at-home and work-from-home policies on population mobility. This impact was discernible through both Google's out-of-house residential mobility data and ecobee's in-house smart thermostat data. As such, we deduce that smart thermostats represent a valid tool for facilitating intelligent monitoring of population mobility in response to policy-driven shifts.

**Keywords**

Population-level health indicators, Internet of things, Public Health surveillance, mobility, risk factors, Chronic diseases

**Introduction**

The dynamics of human mobility are currently undergoing a remarkable transition. Rapid global urbanization, sedentary lifestyles, infectious diseases, air pollution, and climate change are some of the factors driving shifts in human mobility. Whether examined at the individual- [1,2] or population-level [3], human mobility patterns are associated with multiple public health and social issues. Dwindling mobility patterns are linked to chronic diseases including dementia and age-related physical decline. For infectious diseases, individual mobility is linked to the spread of infections like COVID-19. Human mobility data can therefore be an effective tool to comprehend the complexities of human health and behavior [4].

The COVID-19 pandemic has served as an ideal case study to develop tools and knowledge in the field of human mobility research [5]. The World Health Organization (WHO) declared COVID-19 an international public health emergency in late January 2020 and subsequently declared it a pandemic on March 11, 2020. To curb the spread of COVID-19 and avoid overwhelming healthcare institutions [6], many countries implemented restrictions on human mobility including social distancing, self-isolation, closure of non-essential services, work-from-home policies, and travel restrictions [7,8]. In the early stages of the pandemic, digital data sources found that the decrease in human mobility was closely paralleled by a reduction in the incidence of COVID-19 [1,7,9–15]. Thus, the COVID-19 pandemic provides an ideal opportunity to measure and extract meaning from human mobility and how it is affected by restrictive policies.

The study of human mobility has historically been retrospective with limited study participants. Interestingly, it was the technological advancements in smartphones and wearable devices that have had the largest impact on the field [16]. These innovations now provide direct access to human location, trajectories, opinions, and interactions [17]. Human mobility can now be tracked passively in real-time from various sources: GPS-enabled smartphones, texts or photos via photo-sharing platforms like Twitter and Flickr, geolocation-enabled internet posts, public transport cards, satellite, flight traffic, and even credit card transactions. The data collected has a previously unprecedented level of detail, immediacy, and precision. These large data sets, equivalent to "big data" in volumes, are now being analyzed to describe human movement patterns, characteristics (such as sleep, stress, and activity), and interactions.

Google Maps is the most popular navigation app in the US and Canada. The app surpassed twenty-three million downloads in 2020 with 154.4 million monthly users. Google passively generates and collects over 20 million pieces of mobility data per day. The information has now been made available to researchers and policymakers through Google's open source 'COVID-19 Community Mobility Reports' [18]. The reported geographic movement, called macro-mobility, is grouped by category: retail and recreation, grocery and drug stores, parks, transit stations, workplaces, and residences [18]. While macro-mobility data is readily available through sources like Google's 'COVID-19 Community Mobility Reports', our understanding of micro-mobility at the population-level remains limited. This study aims to fill this gap by analyzing smart thermostat data, thereby providing a more comprehensive picture of human mobility patterns. This study leverages the unprecedented access to real-time human mobility data provided by smart thermostats, a source that has not been extensively utilized in previous research. The high level of detail, immediacy, and precision of this data allows for a more granular understanding of human mobility patterns, particularly in-house mobility (micro-mobility), which has been less explored compared to macro-mobility. Unlike Google's macro-mobility data, smart thermostat data can provide insights into in-house mobility patterns. This is particularly relevant in the context of the COVID-19 pandemic, where stay-at-home orders and work-from-home policies have significantly altered in-house mobility patterns.

Modular smart home thermostats offer a novel source of data on in-house human behaviours [19,20]. Not only can they report on indoor temperature, humidity, and air quality, but embedded motion sensors can capture mobility within the home. More than 90% of Canadian households had thermostats in 2018; most opting for programmable thermostats. Smart thermostats, often known as Internet of Things (IoT) devices, are a type of programmable thermostat that may be connected to the internet. *Ecobee* has the second highest market share for smart thermostats in Canada. *ecobee* has a program called Donate Your Data (DYD) in which subscribers can opt to make their anonymized data available for research purposes. DYD currently has 1 million users including over 172,000+ households in Canada. Here we sought to compare mobility data obtained from *ecobee* smart thermostats to the "gold standard" mobility data from Google during the COVID-19 pandemic in Canada. We explored day-by-day, week-by-week, and month-by-month seasonality patterns and applied anomaly detection to both datasets.

## Methods

### Data Sources

Google Mobility data were collected for each province in Canada from February 15, 2020, onwards to February 14, 2021 [18]. Google Maps uses aggregated and anonymized data to determine the daily total number of visits to specific destinations (Table 1) visited by individuals who have enabled their location history [18]. Daily values are compiled across individuals and are compared to the baseline value for that day of the week to determine changes in mobility. The baseline is the median of corresponding days over the five-week period from January 3 to February 6, 2020, [18]. Out of the six categories, we focused on residential data. We curated mobility data from *ecobee*'s "Donate your Data" (DYD) program from February 15, 2020, to February 14, 2021, to align with the Google Mobility Report publication dates. *Ecobee's* smart thermostats record in-house mobility via motion sensors. The DYD dataset supplied by *ecobee* is hosted in Google BigQuery. This study analyzed data from four provinces in Canada; Ontario, Alberta, Quebec, and British Columbia. This included 12,252 *ecobee* households. These four provinces constitute approximately 87% of the Canadian population [21]. The reliability and validity of the ecobee dataset were rigorously assessed in our prior studies, as detailed in our previously published research [20,22,23]." Information regarding Canadian policy implementation dates across provinces was obtained from a dedicated platform managed by the Canadian Government to share COVID-19 related information regularly [24].

### Ethical considerations

In accordance with ethical research standards, this study exclusively utilized secondary data, and therefore, no additional consent from human subjects was necessary for this research. The original informed consent procedures or Institutional Review Board (IRB) approvals for primary data collection explicitly permitted the secondary analysis conducted in this study. Furthermore, robust privacy and confidentiality safeguards were implemented to ensure the anonymity and de-identification of study data. Ethics approval for this study was duly obtained from the University of Waterloo Office of Research Ethics (#31377), attesting to our commitment to upholding the highest ethical standards in research."

Table 1. Google mobility data categories and their description as described on the website [18].

| **Category** | **Definition** |
|---|---|
| *"Grocery & Pharmacy* | *"Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies."* |
| *"Parks"* | *"Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens."* |
| *"Transit stations"* | *"Mobility trends for places like public transport hubs such as subway, bus, and train stations"* |
| *"Retail & recreation"* | *"Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theatres."* |
| *"Residential"* | *"Mobility trends for places of residence."* |
| *"Workplaces"* | *"Mobility trends for places of work."* |

### Data Preparation

*Ecobee's* data were transferred from Google's Big Query to the Microsoft Azure cloud services platform [25]. Data were prepared using Azure Databricks data analytics platform and Jupyter notebook using Python [26,27], detail explanation of the whole process has been mentioned in our previous studies [20,23,28]. Data cleaning, analysis, and visualization were done in R studio [29] (version 1.4.1106) with R software [30] (version 4.0.5) and data analysis packages tidyverse [31] and timetk [32].

Utilizing ecobee data, we established a baseline mobility value akin to the Google data preparation approach detailed earlier for seamless comparison. To ascertain daily in-house mobility, we computed the total number of activated sensors within each 24-hour timeframe by summing all sensor statuses. A table containing date records alongside the average count of activated sensors per date was then saved as a CSV file.

As the timestamp of the DYD dataset was in UTC format, the time zones in the dataset were converted by locating time zone information from the geolocation of the households in the metadata. In Quebec and Alberta, all the cities were in the same time zone. In the province of Ontario, six cities have different time zones than EST: namely, Drayton, Kenora, Kenora-Unorganized, Mitchell, Red Lake, Sioux Lookout cities (1% of the DYD dataset for Ontario). For British Columbia, 28 households were from different time zones than Pacific Standard Time and were excluded from the analysis. Once cleaned for the time zone, time-series data analysis was performed on the adjusted data on the households included in the study. These numbers are presented in Table 2.

Table 2 The number of households selected for the analysis by province.

| | **N, Before time zone cleaning** | **N, After time zone cleaning** | **Excluded num. of households for time zone difference** | **The proportion of household data by province (%)** |
|---|---|---|---|---|
| **Canada** | 21690 | 21690 | | |
| **Ontario** | 7145 | 7134 | 11 | 33 |
| **Alberta** | 3989 | 3989 | 0 | 18 |
| **British Columbia** | 449 | 421 | 28 | 3 |
| **Quebec** | 708 | 708 | 0 | 2 |

**Data Analysis**

To assess mobility variations, we aggregated daily province-level movement into weekly, monthly, and day-of-the-week periods and compared them to the respective baselines in both datasets. Time series plots were generated for each province using Google's residential and ecobee mobility data. The statistical significance of the relationship between the two data sources was determined through Pearson's and Spearman's correlation coefficients [33].

We conducted seasonal diagnostic tests utilizing the timetk [32] package in R software, tailored for time-series data analysis. Distinct approaches were employed to investigate daily, weekly, and monthly seasonality. To assess statistical significance [34] one-way ANOVA was employed.

For anomaly detection, we initially conducted seasonal and trend decomposition using the Loess method (STL)[32,35,36]. After removing trend and seasonality components, we performed anomaly detection on the residual data. Anomalies were identified based on the interquartile range (IQR), specifically the difference between the 75th and 25th percentiles, establishing the distribution of the remaining data. Default boundaries were set at 3X above or below the IQR, designating values beyond these limits as anomalies.

To examine data granularity, we analyzed mobility data by days of the week for both Google and ecobee datasets. Additionally, we aggregated mobility data into one-week intervals for all four provinces to explore seasonality in mobility changes following the onset of the COVID-19 pandemic.

**Results**

**Positive Association Between Google and *ecobee* Mobility Data**

Comparison of Google residential mobility data and ecobee mobility data across each province over a year revealed a positive association (Figure 1). Notably, the Google mobility data exhibited a recurrent weekly pattern, which was closely mirrored by the ecobee data (Figure 1). Both data sources exhibited a significant uptick in residential mobility, both indoors and outdoors, commencing around March 11, 2020, aligning with the declaration of the COVID-19 pandemic in Canada. It's worth noting that, given Canada's provincial health regulation framework [37], the official implementation dates of pandemic-related policies varied among the four provinces under investigation (March 17, 2020, for Ontario; March 16, 2020, for Quebec; March 17, 2020, for Alberta; and March 19, 2020, for British Columbia).

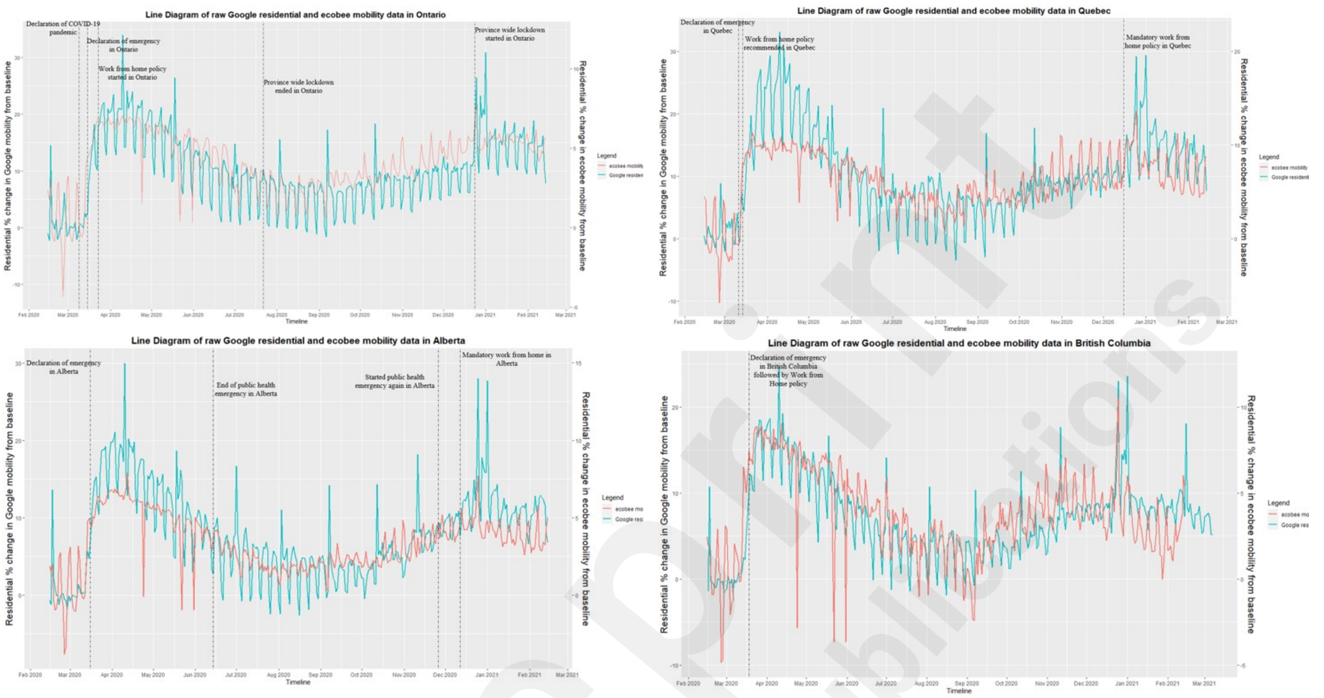
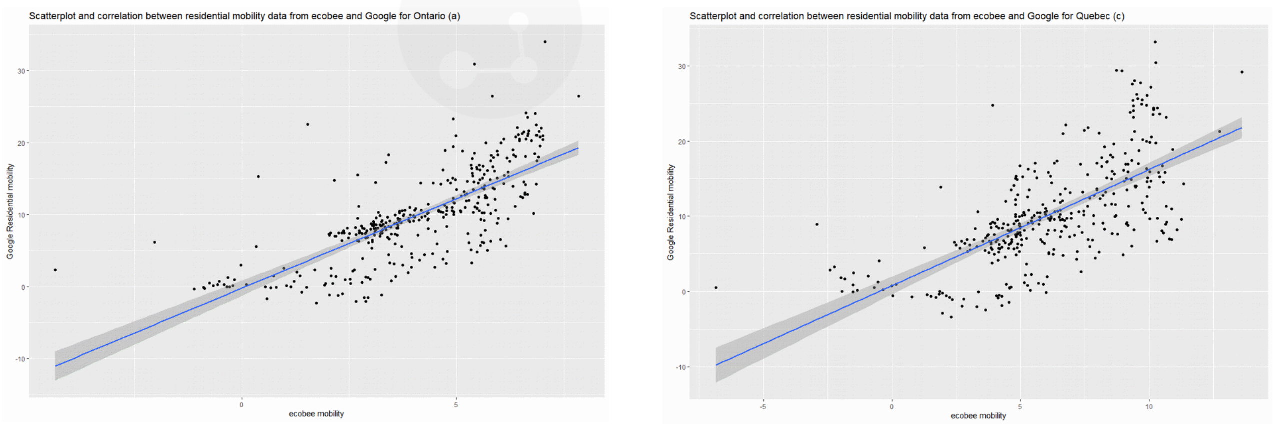



Figure 1 Association between Google residential mobility and *ecobee* mobility for a) Ontario b) Alberta c) Quebec d) British Columbia, Canada.

All provinces exhibited a notable increase in the percentage of mobility change coinciding with the commencement of the pandemic, as indicated by both Google and ecobee mobility data. Subsequently, from March 2020 to September 2020, a gradual decline in this trend was observed across all provinces in both datasets. Notably, a subsequent surge in residential mobility was linked to the onset of the second pandemic wave and the reinstatement of pandemic-related stay-at-home measures on specific dates [December 26, 2020 (Ontario); December 17, 2020 (Quebec); December 13, 2020 (Alberta); and October 19, 2020 (British Columbia)].



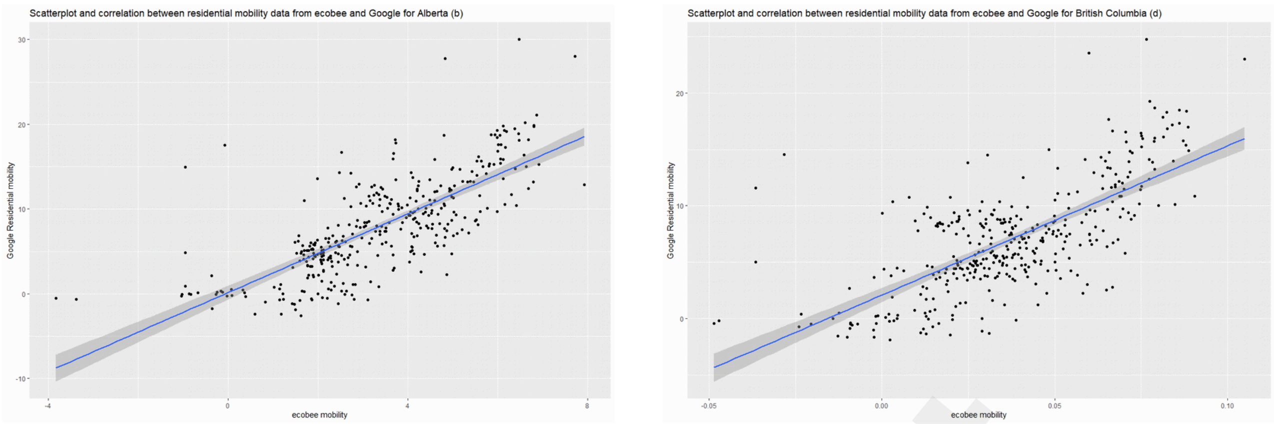



Figure 2. Correlation between residential mobility data from *ecobee* and Google for the province of a) Ontario b) Alberta c) Quebec d) British Columbia, Canada.

For each province, we calculated the correlation between Google's residential mobility data and ecobee's mobility data. The trend line displayed a linear relationship between the two datasets (see Figure 2). Pearson's and Spearman's correlation coefficients revealed a statistically significant association, ranging from 0.67 to 0.73 (refer to Table 3). Consequently, the data obtained from ecobee's smart home thermostat is demonstrably equivalent to Google's mobility data.

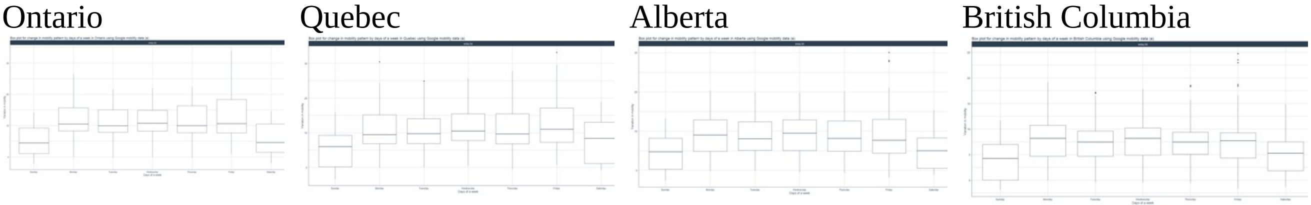
Table 3. Correlation between google and *ecobee* mobility data for Ontario, Alberta, Quebec, and British Columbia

| | **No of households** | **Pearson's Correlation coefficient (w/ 95% CI)** | **Spearman's rank correlation** |
|---|---|---|---|
| **Ontario** | 7134 | 0.73 (0.67-0.77) | 0.75 |
| **Alberta** | 3989 | 0.73 (0.69-0.78) | 0.76 |
| **Quebec** | 708 | 0.67 (0.61-0.73) | 0.70 |
| **British Columbia** | 421 | 0.69 (0.64-0.74) | 0.63 |

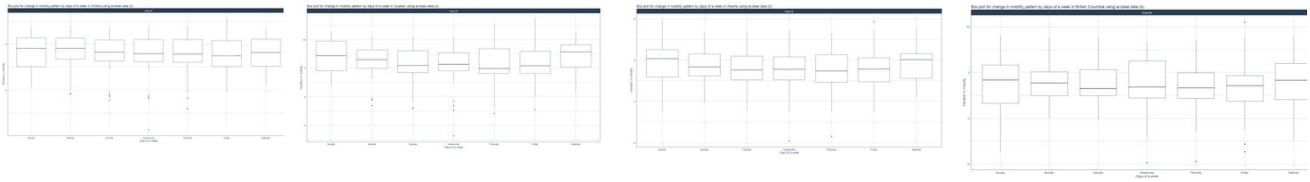
## Variations in Mobility by Day of the Week

There was a significant difference in daily mobility patterns across all four provinces when examining the Google residential mobility data set (Figure 3). Greater mobility changes were observed on the weekdays compared to weekends. One-way ANOVA test (Table 4) showed that day of the week had a statistically significant impact on residential mobility for all four provinces (Google). On the contrary, these differences in daily mobility were only observed in Quebec when we used *ecobee*'s mobility data.

Ontario Quebec Alberta British Columbia



Google



ecobee

Figure 3. Analysis of the a) Google residential and b) *ecobee* mobility data among days of a week in Ontario, Quebec, Alberta, and British Columbia.

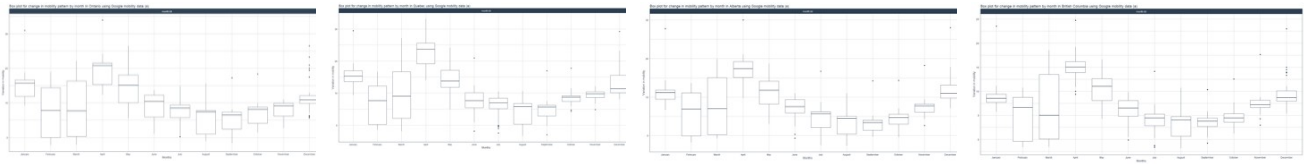
Table 4 The ANOVA test compares the day of the week’s impact on Google and ecobee mobility for the four provinces of Canada.

| | | Google | | | | Ecobee | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Province** | | **df** | **Sum of squares** | **F** | ***P*-value** | **df** | **Sum of squares** | **F** | ***P*-value** |
| Ontario | C(Weekday) | 6 | 3467 | 17.86 | <.001 | 6 | 10 | 0.458 | .84 |
| | Residual | 358 | 11579 | | | 358 | 1306 | | |
| Quebec | C(Weekday) | 6 | 2426 | 9.357 | <.001 | 6 | 130 | 2.364 | .03 |
| | Residual | 358 | 15471 | | | 358 | 3278 | | |
| Alberta | C(Weekday) | 6 | 1456 | 8.223 | <.001 | 6 | 22.9 | 1.123 | .348 |
| | Residual | 358 | 10566 | | | 358 | 1216 | | |
| British Columbia | C(Weekday) | 6 | 897 | 6.955 | <.001 | 6 | 14.9 | 0.371 | .897 |
| | Residual | 358 | 7673 | | | 358 | 2404 | | |

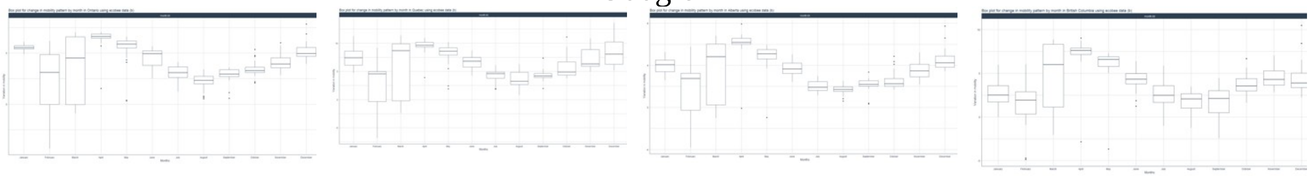
**Monthly Variations in Mobility**

To deepen our understanding of the pandemic-related changes in population behaviour, we aggregated the Google and *ecobee* data to analyze month-by-month mobility changes. Interestingly, in contrast to the differences observed between Google and *ecobee* mobility data for days of the week, month-by-month patterns were similar between the two data sets (Figure 4). Across all provinces, the change in mobility above baseline spiked in April 2020 consistent with the implementation of COVID-19 policies to curb social mobility. Also, the variability within the data, specifically for *ecobee* data, was reduced drastically from April 2020 onwards. The increase in residential and in-home mobility slowly declined from April 2020 to September 2020. A subsequent rise in mobility from October 2020 to December 2020 corresponded to the second pandemic wave and the re-implementation of pandemic-related stay-at-home policies. One-way ANOVA test showed a statistically significant change in both residential (Google) and in-house (*ecobee*) month-by-month mobility across all four provinces (Table 5).

Ontario Quebec Alberta British Columbia



Google



*ecobee*

Figure 4. Analysis of the a) Google residential and b) *ecobee* mobility data among month by month for Ontario, Alberta, Quebec, and British Columbia

Table 5 The ANOVA test compares month-by-month impact on Google and ecobee mobility for the four provinces of Canada.

| | | **Google** | | | | **Ecobee** | | | |
|---|---|---|---|---|---|---|---|---|---|
| Province | | **df** | **Sum of squares** | **F** | ***P*-value** | **df** | **Sum of squares** | **F** | ***P*-value** |
| Ontario | C(Month) | 11 | 6383 | 23.65 | <.0001 | 11 | 591.4 | 26.18 | <.0001 |
| | Residual | 353 | 8663 | | | 353 | 724.8 | | |
| Quebec | C(Month) | 11 | 9541 | 36.64 | <.0001 | 11 | 1372 | 21.61 | <.0001 |
| | Residual | 353 | 8357 | | | 353 | 2037 | | |
| Alberta | C(Month) | 11 | 5923 | 31.16 | <.0001 | 11 | 606.4 | 30.76 | <.0001 |
| | Residual | 353 | 6099 | | | 353 | 632.7 | | |
| British Columbia | C(Month) | 11 | 4062 | 28.83 | <.0001 | 11 | 1047 | 24.49 | <.0001 |
| | Residual | 353 | 4508 | | | 353 | 1372 | | |

**Week-by-Week Mobility Changes**

Beginning February 2020, the initial 5 to 6 weeks had a similar level of mobility across all four provinces (Figure 5). Google residential mobility declined from week 7 to week 10. Although there was a high level of data variability at week 7, this was lost in subsequent weeks. *Ecobee* in-house mobility followed a similar pattern but with a lag period of one week and a large degree of variability. Beginning at week 12 (corresponding to the week of March 16, 2020) Google residential data witnessed a sharp spike in residential mobility across all four provinces. This timing correlates to the date the pandemic was declared in Canada. A similar trend was observed for the *ecobee* data, however, mobility appeared to increase starting in week 11. Like the trends observed in month-by-month data (Figure 4), the elevated mobility steadily declined towards week 25 and stabilized above baseline until approximately week 40 (Figure 5). There was a subsequent steady increase in mobility from week 40 until the end of the year corresponding to the timing of the second wave of the pandemic in Canada. The *ecobee* mobility data showed a similar trend with the exception that the decline in mobility took place over a longer time period and with a shorter period of stabilization before rising again. An ANOVA analysis for the week-by-week mobility data showed a statistically significant difference between weeks for both datasets and for all four provinces (Table 6).

Ontario Quebec Alberta British Columbia

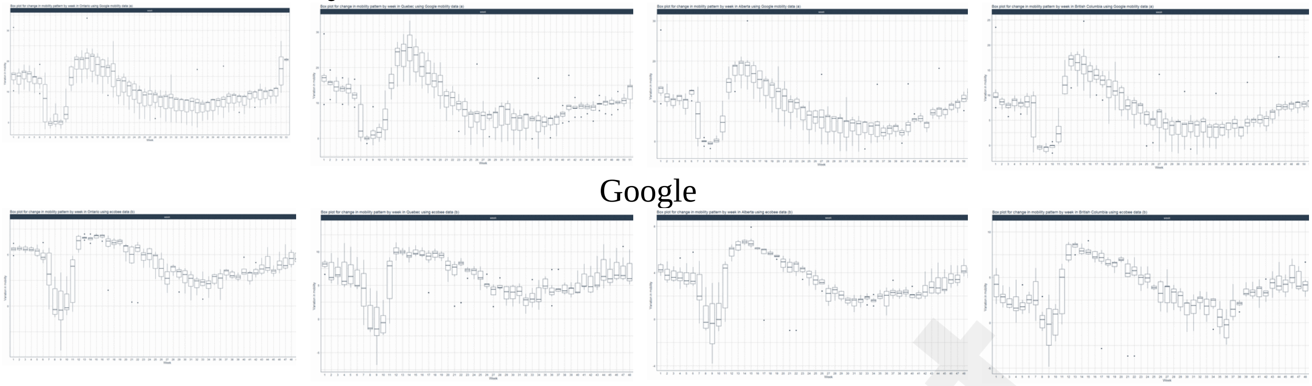



Figure 5. Analysis of the a) Google residential and b) *ecobee* mobility data among week by week for Ontario, Alberta, Quebec, and British Columbia

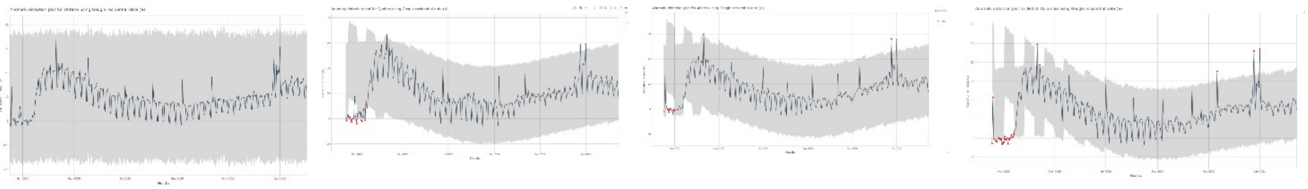
Table 6 The ANOVA test comparing week by week impact on Google and ecobee mobility for the four provinces of Canada.

| | | **Google** | | | | **Ecobee** | | | |
|---|---|---|---|---|---|---|---|---|---|
| Province | | **df** | **Sum of squares** | **F** | ***P*-value** | **df** | **Sum of squares** | **F** | ***P*-value** |
| Ontario | C(Week) | 52 | 10140 | 12.4 | <.0001 | 52 | 992.9 | 18.43 | <.0001 |
| | Residual | 312 | 4906 | | | 312 | 323.2 | | |
| Quebec | C(Week) | 52 | 13582 | 18.88 | <.0001 | 52 | 2375 | 13.79 | <.0001 |
| | Residual | 312 | 4316 | | | 312 | 1034 | | |
| Alberta | C(Week) | 52 | 8961 | 17.57 | <.0001 | 52 | 927.3 | 17.84 | <.0001 |
| | Residual | 312 | 3061 | | | 312 | 311.9 | | |
| British Columbia | C(Week) | 52 | 6558 | 19.49 | <.0001 | 52 | 1675.8 | 13.53 | <.0001 |
| | Residual | 311 | 2012 | | | 312 | 742.9 | | |

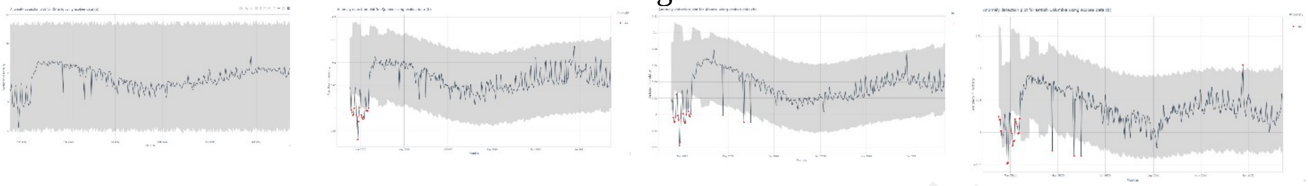
### Social Mobility Policy Restrictions and Festive Periods Create Mobility Anomalies

To determine whether Google and *ecobee* data analysis could pick out behavioural anomalies in mobility associated with policy changes, we performed an anomaly detection analysis (Figure 6). Neither Google residential data nor *ecobee* in-house mobility data showed any anomaly within 2020 for Ontario. For Quebec, Alberta, and British Columbia anomalies were found at the beginning period in both the Google and *ecobee* data. Notably, these corresponded with the dates of COVID-19-related policy changes. In Alberta and British Columbia, *ecobee* 's in-house mobility analysis captured anomalies in May and June 2020 which correspond to phase-wise reopening plans and the lifting of social restrictions. Interestingly, Google residential data were able to capture anomalies corresponding to festive periods like Christmas and New Year in Quebec, Alberta, and British Columbia. These anomalies were not seen in the *ecobee* data. Overall, these results demonstrate the ability of Google's residential data and *ecobee's* thermostat data to capture notable shifts in population behaviour as a result of policy changes and cultural festivities.

Ontario Quebec Alberta British Columbia



Google



ecobee

Figure 6. Analysis of the a) Google residential and b) *ecobee* mobility data among days of a week for Ontario, Alberta, Quebec, and British Columbia

## Discussion

The aim of this study was to investigate the potential application of in-house mobility data obtained from ecobee sensors in comparison to residential Google mobility data. The most significant differences between datasets were observed, particularly when mobility was analyzed by the day of the week. While Google's residential data exhibited a significant correlation with the day of the week across all four provinces, ecobee's data showed a significant impact only in Quebec. However, when scrutinized on a monthly and weekly basis, consistent findings were observed across all provinces and datasets. A notable surge in in-house and residential mobility occurred between March and April 2020, coinciding with the initiation of pandemic-related policy changes in Canada. These mobility shifts gradually diminished until September 2020, and the onset of the second wave of the pandemic, coupled with the reinstatement of social policies, corresponded with increased mobility from October to December 2020. In summary, a statistically significant association between the two datasets was identified. Anomaly detection analysis provided evidence supporting the capability of both datasets to detect deviations in population mobility, capturing events such as emergency declarations, reopening phases, and festive days like December 25 (Christmas) and January 1 (New Year's Eve). These findings underscore the benefits of employing public health surveillance mechanisms, especially during health emergencies of pandemic proportions.

Historically, monitoring individual mobility has been hampered by insufficient sample sizes, difficulty in collecting data, recall bias, and privacy concerns [43–45]. The advent of smartphones, wearable devices, and the IoT has paved the way for researchers to capture individual geolocation and movement within the home (micro-mobility) [46–50]. For both micro- and macro-mobility, it is necessary to integrate data from multiple sources [51]. Thermostat-based IoT data, such as the ecobee DYD data reported here, can provide new opportunities for calculating population-level mobility indicators. IoT is a modern, passive sensing tool that can quantify in-house movement. Understanding in-house movement is particularly relevant given that people now spend more than 80% of their time indoors [4,52]. The use of these large datasets, combined with geographical data and timestamps [16,17], has the potential to unravel different dimensions of human behavior and lifestyle. In-house mobility data have the capacity to measure changes in sleep [5,53], physical activity [54], sedentary behaviors [55–57], and movement patterns [58] with greater detail and granularity. Motion sensors are a next-generation tool with a wealth of opportunities for application in the field of public health. Integrated into smart cities, motion sensors have the power to detect overall human mobility from various sources. Data collection will enable effective planning and implementation of responsive and preventative public health strategies [47].

Monitoring real-time population mobility is important in public health as it plays a significant role in both chronic and infectious diseases. A dwindling mobility pattern is a predisposition to various chronic diseases including dementia and age-related physical decline. For infectious diseases, individual mobility is directly proportional to the transmission of infections like COVID-19 [59]. Although the "Stay at Home" and "Work-from-Home" strategies were promoted globally to curb the spread of COVID-19, it is still unclear to what extent individuals complied with policy restrictions. Mobility data analysis has the potential to provide real-time information about the impact of such policies on individual and population behaviour [12,60,61].
However, a notable limitation of our study was the absence of socio-demographic information in the ecobee dataset. Consequently, our analysis was confined to spatiotemporal dimensions, and we were unable to examine the impact of socio-demographic features, including age, gender, and occupation. Varied perceptions surrounding infectious diseases, vaccinations, social mobility, and government policies across cultural and socioeconomic groups highlight the need for caution when generalizing the results [42]. Although the data was collected across four Canadian provinces, encompassing 87% of the population, the demographic represented by those with smart home thermostats likely skews towards a specific group—namely, young, tech-savvy individuals with higher socioeconomic status, who may be more inclined to work from home. Therefore, caution should be exercised in generalizing the reported results. Additionally, challenges arise in separating mobility patterns in multi-person households and eliminating sensor activation due to factors such as animals, rapid airflow, or other noises.

In conclusion, the real-time monitoring of population-level mobility using smartphones and IoT sensors has emerged as a recent development in public health, primarily in response to the COVID-19 pandemic. This study investigates the utility of IoT-based mobility data, specifically from smart thermostats, for assessing individual mobility within the context of social isolation policies. The findings demonstrate a close alignment between thermostat mobility data and the data presented in the Google Mobility Report, affirming its value as a mobility monitoring tool. The acquisition of real-time mobility data from smart thermostats has the potential to enhance our understanding of the intricate social determinants of health, providing valuable insights for the formulation of public health policies.

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**Data Availability**

The Google mobility data can be readily accessed by the public through the following link https://www.google.com/covid19/mobility. In contrast, access to ecobee data is restricted to researchers and scientists through a Data Sharing Agreement. If you are interested to accessing ecobee data, please email the research division of the ecobee at research@ecobee.com or visit the following link https://www.ecobee.com/en-ca/donate-your-data.

**Authors' contributions**

KS and PM conceived and designed the study, KS performed data extraction, cleaning, and analysis. KS wrote the paper under supervision of PM, JD, SM and SL. All the authors have reviewed and approved the final manuscript and provided edits and feedback to strengthen it.

**Conflict of interest**

None declared.

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