**Public Interest in Sustainable Mobility: Evidence from Google Trends data**

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**Abstract**

This study explores how digital interest in sustainable urban mobility varies across countries, using Google Trends data as a proxy for modal preferences and intentions. We collect relative search volumes for 12 mobility-related keywords—classified under the Avoid–Shift–Improve (ASI) framework—across multiple countries and years (2018–2023). Through principal component analysis (PCA), we construct a *Sustainable Mobility Index* that synthesizes these search signals into a standardized indicator of interest. We then apply K-means clustering to identify territorial patterns in digital predisposition toward sustainable mobility, revealing regional clusters with distinct modal profiles. Finally, we estimate a panel data model to examine which structural, normative, and infrastructural factors are associated with higher levels of digital engagement with sustainable transport topics. Our findings contribute to the understanding of mobility as both a behavioral and perceptual phenomenon, and demonstrate the value of online search data as a scalable tool for assessing sustainability transitions.

*Keywords*: Mobility, Google Trends, Big Data

*JEL Classification*: R41, C53, Q56

**Introduction**

Cities have emerged as critical arenas for global climate action, accounting for approximately 70% of carbon emissions and consuming nearly two-thirds of the world’s energy (United Nations, 2020). Within this urban metabolism, transportation plays a particularly decisive role, currently responsible for 30% of global energy consumption, and thus represents a major challenge for the net-zero energy transition (International Energy Agency, 2020). Recent research underscores that this transition cannot rely solely on cleaner technologies or improved vehicle design. Even ambitious policies focused on electrification, retrofitting, and efficiency improvements are insufficient to meet climate targets unless accompanied by a rapid and large-scale reduction in car use (Winkler et al., 2023). Sustainable urban mobility, therefore, hinges not only on transforming vehicles, but on fundamentally rethinking mobility demand itself, through policy approaches that address infrastructural, behavioral, and institutional dimensions (Banister, 2008).

Mobility has traditionally been understood as the movement of people across space and time (Wang et al., 2022). However, this functionalist view has evolved to encompass a more complex understanding of mobility as a socially embedded phenomenon. It is not only a question of physical displacement, but a function of one’s capacity to access, interpret, and act upon available options—what has been described as *motility*, or the potential to be mobile within specific structural and cultural contexts (Kaufmann et al., 2004, 2014). It is well established that mobility opportunities are unevenly distributed across individuals and territories, shaped by infrastructure, spatial planning, and socioeconomic conditions (Duranton & Turner, 2011). From this perspective, any attempt to shift mobility demand must also consider how structural inequalities influence individuals’ ability—and willingness—to engage with more sustainable modes of transport.

In parallel with this growing interest in the multidimensional nature of urban mobility—economic, social, and political—the increasing availability of large-scale digital data has transformed how mobility is measured and understood (Batty et al., 2012). Sources such as mobile phone records, GPS traces, transit smartcards, and geolocated social media have enabled researchers to analyze movement patterns at unprecedented temporal and spatial resolution. These data have been used to uncover social disparities in accessibility, delineate activity spaces, and infer demographic traits and behavioral routines (Wang et al., 2022; Wu & Zhou, 2023). Yet these traces, while rich in *where* and *when*, remain largely silent on the *why*. From a broader perspective, mobility can be understood as a total social phenomenon—one that reflects evolving relationships between space, society, and subjectivity. The dissolution of the urban–rural dichotomy, the emergence of dispersed urbanization, and the centrality of transport and communication networks all contribute to mobility practices that are increasingly fluid, flexible, and socially unequal (Kaufmann, 2014).

While the importance of transforming mobility demand is widely acknowledged, less attention has been paid to how such shifts in interest or intention can be monitored and interpreted using emerging data sources. In this context, a key question arises: how can digital traces such as online searches help us understand the evolving public orientation toward sustainable and unsustainable modes of transport? Traditional instruments like travel surveys or census data offer limited temporal granularity and rarely capture early signals of change in perceptions or preferences. Google Trends, by contrast, offers a high-frequency, globally accessible, and geographically disaggregated dataset that has been widely recognized as a valuable proxy for public attention and behavioral intention, with demonstrated applications in fields such as epidemiology (Ginsberg et al., 2009) and economic nowcasting (Choi & Varian, 2012), well-being (Brodeur et al., 2021) or tourism (Havranek & Zeynalov, 2021). More broadly, the growing use of big data in the social sciences has opened new avenues for capturing issue salience at scale, particularly in contexts where traditional data sources are infrequent, costly, or unavailable (Mellon, 2013; Einav & Levin, 2014). Using the Avoid–Shift–Improve (ASI) framework as a conceptual guide (Bakker et al., 2014), this study categorizes transport-related search terms accordingly and investigates how, where, and under what conditions interest in these strategies varies across countries. In this sense, Google Trends represents a promising tool for detecting shifts in digital interest that may precede or accompany broader changes in mobility preferences and sustainability-related behaviors.

**Literature review**

*The Avoid–Shift–Improve Framework*

The concept of sustainable mobility emerged in the early 1990s as a response to the escalating social and environmental costs associated with motorized transport. As an alternative to the dominant “predict and provide” logic—which promoted continuous expansion of road infrastructure—this paradigm emphasized the need to manage travel demand, enhance accessibility, and reduce car dependency (Holden et al., 2019; Foltýnová et al., 2020). One of its most enduring conceptual tools is the Avoid–Shift–Improve (ASI) framework, which organizes strategies for reducing transport-related emissions and energy use into three complementary pillars: *avoiding* unnecessary travel, *shifting* to more sustainable modes, and *improving* vehicle technologies and fuels.

Since its introduction in the late 1990s, the ASI framework has been widely adopted by policymakers, urban planners, and sustainability researchers as a guiding principle for designing low-carbon mobility systems (Turan et al., 2024). Its appeal lies in its systemic orientation: rather than privileging technological innovation alone, it promotes a balanced approach that includes demand reduction and modal substitution. However, recent empirical assessments suggest a persistent misalignment between the framework’s priorities and real-world transport interventions. For instance, Jarre et al. (2024) find that “Avoid” strategies—those aiming to reduce travel demand through urban planning, telecommuting, or behavioral change—are consistently underrepresented in climate and transport policy portfolios. In a comparative analysis of national policy databases, only 6–22% of measures were classified as “Avoid,” compared to 33% focused on technological efficiency and a growing share of “Shift” strategies.

This imbalance is notable given the high potential of demand-side measures. Arnz et al. (2024), using integrated energy modeling, demonstrate that sufficiency-oriented approaches—encompassing both travel avoidance and modal shift—can achieve reductions in energy demand and emissions comparable to those expected from improvements in vehicle efficiency. Moreover, these strategies entail different societal trade-offs: while technological improvements often depend on private investment and consumer adoption, “Avoid” and “Shift” policies typically require public coordination and infrastructural change. As such, the ASI framework continues to offer a valuable lens not only for classifying interventions, but for interrogating the political and distributive dimensions of sustainable mobility.

More than three decades after its initial formulation, ASI remains a cornerstone in sustainable transport thinking. Its relevance is particularly salient in the context of global climate goals and the urgent need to reduce transport emissions beyond what efficiency gains alone can deliver. For this reason, integrating all three pillars—even bold Avoid/Shift strategies alongside technological Improve measures—is increasingly recognized as essential. As the present study explores interest in sustainable mobility across countries, the ASI framework provides a structured and policy-relevant basis for categorizing modal strategies and interpreting digital search behavior through the lens of systemic transition.

*From Behavior to Intention in Mobility*

Shifting travel behavior toward sustainability involves not just new infrastructure or technology, but also changes in attitudes, motivations, and intentions. Research on modal shift finds that convenience, cost, and personal norms all influence whether travelers choose alternatives to the private car. Environmental and climate awareness can be a powerful motivator: individuals concerned about climate change tend to drive less and show greater willingness to adopt sustainable modes (Mouratidis & Næss, 2024). Such findings suggest that raising climate awareness may translate into greater intention to use low-carbon transport. Indeed, environmental concern has been linked with increased public transit use habits and reduced car dependence over time (Bouscasse et al., 2018).

However, there is often a gap between pro-environmental intentions and actual behavior. Behavioral scientists note that daily travel is highly habitual and routinized; past car use can reinforce itself, making it harder for even well-intentioned individuals to change modes​. In developed countries, strong car-use habits significantly reduce the intention to switch to public transport, even when people acknowledge environmental benefits. This intention–behavior gap means that many who claim willingness to change their travel behavior struggle to do so unless convenient alternatives and supportive policies are in place. Studies measuring willingness to change modes confirm that breaking car habits requires not only personal motivation but also external enablers like improved service, infrastructure, and incentives. For example, surveys in urban areas have identified segments of travelers open to shifting from cars to biking or transit – especially when they are younger or more climate-conscious – but also point out perceived barriers (safety, reliability) that prevent follow-through.

Therefore, transforming mobility demand hinges on both motivational factors (like climate awareness, personal norms) and situational factors (like habit disruption and viable alternatives). Effective interventions combine “soft” measures (education, awareness campaigns tapping into climate concern) with “hard” measures (policy and design changes that make sustainable modes the default)​ (Dasandi et al., 2024).

In sum, closing the gap from behavioral intention to action requires addressing psychological drivers and practical constraints – leveraging people’s growing willingness to change while dismantling the habitual and structural lock-ins that keep them in cars

*Big Data and the Limits of Mobility Insight*

The past decade has seen an explosion in digital trace data – from mobile phones, GPS devices, smart cards, and sensors – which has revolutionized how researchers study mobility. These passively collected big datasets capture travel flows at unprecedented temporal and spatial resolution, enabling analyses that were impractical with traditional travel surveys. For example, anonymized mobile phone records can now track population movements in near real time, revealing patterns of commuting, leisure travel, and even responses to shocks like pandemics​. Such data-driven approaches have opened new frontiers: planners and economists can observe actual behavior at large scales, calibrate models with high-frequency inputs, and identify granular trends (e.g. hourly congestion dynamics, or how mobility drops during a lockdown) that inform policy. However, the advantages of digital mobility data come with important limitations. One key issue is representativeness and bias – not everyone’s movements are captured equally. Studies have found that different data sources (e.g. different mobile carriers or apps) can vary significantly in their coverage of travel routes and populations, leading to biased mobility estimates if used alone (Chin et al., 2025). Another limitation is the lack of social context in pure digital traces. While we can observe where and when people travel, we often lack information on who they are (demographics, income) and why a trip is made. This makes it challenging to interpret equity implications or motivations behind observed patterns. Researchers have begun to bridge this gap by combining digital mobility data with other datasets or using clever proxies. For example, studies in urban areas link phone-based movement data with neighborhood socio-economic indicators to uncover mobility inequalities: one study in Shenzhen, China found that lower-income groups and migrant workers travel significantly less (shorter distances and fewer trips) than wealthier residents, reflecting unequal access and mobility opportunities (Pan & He, 2023). researchers must be cautious about inherent biases and missing context; methodological innovations (data fusion, bias correction, privacy-aware surveys) are crucial to ensure that big mobility data lead to accurate and equitable knowledge​ When used carefully, these data can help diagnose issues like accessibility gaps or urban mobility inequalities that were previously hard to quantify, guiding more inclusive and effective transportation planning.

*Google Trends in the Social Sciences*

Google Trends (GT) data has gained increasing popularity in the social sciences, particularly after 2014, reflecting a broader shift toward the use of internet search data as a tool for analyzing public interest and behavior (Hölzl et al., 2025). Hölzl et al. (2025) identify three key constructs that GT data can capture in social science research: issue salience, attitudes, and behavior. *Issue salience* refers to the level of public awareness or attention to a specific topic; *attitudes* reflect the positive or negative sentiment toward an issue, individual, or phenomenon; and *behavior* denotes either the engagement in offline actions or the expression of intention through search behavior. Among these, most GT-based studies focus on issue salience as a proxy for public interest.

A major methodological advantage of GT data lies in its capacity to capture actual search behavior, thereby bypassing some of the limitations of self-reported survey data. Unlike surveys, GT does not rely on respondents' comprehension of questions, memory accuracy, or willingness to provide socially acceptable answers. As such, it avoids cognitive biases and social desirability biases, offering a more unfiltered window into public concerns and interests. For instance, internet search data has been used to study sensitive or stigmatized topics that are often underreported in surveys, including racism (Stephens-Davidowitz, 2014), sexism (Owen & Wei, 2021), and voting behavior (Askitas, 2015a, 2015b; DiGrazia, 2017).

In fields closely related to this study, GT data has been applied to track temporal patterns of interest in climate change (Anderegg & Goldsmith, 2014, Ngheim et al., 2016).. For example, Anderegg and Goldsmith (2014) analyzed the popularity of various climate-related search terms, selecting those that best matched the public framing of environmental issues and that achieved the highest relative search volume across permutations. Their study demonstrates how GT data can be aligned with longitudinal survey data to assess issue salience, following methodological strategies outlined by Mellon (2013).

**Data**

*Google Trends*

Google Trends (GT) provides data on search activity, reflecting the popularity of a given keyword as the "search interest in a particular topic, within a specific location and time frame." Instead of reporting absolute search volumes, GT normalizes data into an index ranging from 0 to 100. This normalization process allows for comparisons over time without being affected by the general increase in search queries since 2004. The index is adjusted daily based on the total number of searches in each region, accounting for seasonal fluctuations. The highest search interest within the selected period is assigned a value of 100, while all other values are scaled relative to this peak. As a result, the GT index facilitates meaningful comparisons across time periods, geographic regions, and multiple search terms, thereby mitigating biases associated with raw search volume data.

However, Google assigns a value of 0 to data points where search volumes fall below a certain undisclosed threshold. According to the company, this measure is intended to protect user anonymity (Google News Initiative, 2024). Consequently, a 0 value may indicate either a complete absence of searches for a term or a search volume too low to be reported. This poses a challenge for analyzing terms with inherently low search frequency, as their time series may contain numerous missing or zero values, limiting their interpretability and consistency in long-term trend analysis. Literature identifies three major challenges when using Google Trends (GT) in social science research: internal validity, reliability, and generalizability (Höltzl et al., 2025).

*Internal validity*

Internal validity refers to whether search volumes accurately reflect real-world behaviors and attitudes or merely indicate temporary interest, which may be influenced by external factors such as media coverage, social trends, or changes in search terminology.

Previous research has explored the connection between online search behavior and urban mobility, suggesting that keyword popularity can serve as a proxy for movement patterns (Kostakos et al., 2013). Their findings indicate that search terms are often semantically relevant to specific locations, reinforcing the idea that online interest may be linked to physical mobility. However, their results have also highlighted limitations in using high-frequency (e.g., hourly) search data, as circadian rhythms (daily activity cycles) can generate strong correlations across all locations, reducing the ability to differentiate mobility trends effectively. Daily aggregated data has proven to be a more reliable approach in this context. While search data is collected at a national scale, there is evidence that pedestrian flows at specific locations exhibit strong correlations only with relevant search queries, suggesting that search behavior is not entirely random but reflects actual movement patterns.

*Reliability (Sample variation)*

Another major concern when using Google Trends (GT) data is measurement reliability, as Google's internal algorithms and scaling methods remain undisclosed, limiting transparency in how search data is sampled. Rather than considering the entire set of searches within a given period, Google Trends applies a sampling process with unknown characteristics. As a result, the same query can yield different time series across extractions, introducing inconsistencies that may affect the interpretability and reproducibility of models built with this data (Choi & Varian, 2012; Cebrián & Doménech, 2024). There are three main sources of sampling errors of Google Trends data: search popularity, smaller geographic regions and higher data frequency (Eichenauer et al., 2022, Cebrián & Doménech, 2024). Eichenauer et al. (2022) shows that monthly data is noisy if the population is smaller than 10 million inhabitants. Moroeover, weekly and daily data instability is almost similar in magnitude

A key technical limitation of Google Trends is its caching mechanism, which returns the same sample if a query is repeated within 24 hours. This can prolong data collection efforts and reduce data freshness when conducting real-time analyses (Cebrián & Doménech, 2024). To mitigate the impact of sampling variation, previous studies recommend aggregating multiple extractions over different days to stabilize the data and improve consistency (Carrière-Swallow & Labbé, 2013; D’Amuri & Marcucci, 2017; Eichenauer et al., 2022).

*Comparison of terms and generalization*

A key technical limitation of Google Trends is its restriction to a maximum of five search terms per query, which complicates the comparison of multiple terms simultaneously. Moreover, because Google normalizes each dataset independently, search trends extracted separately cannot be directly compared. To address this issue, we incorporate a control term into each dataset.

The selected control term must exhibit a stable search trend over time and have a higher search volume than any of the terms of interest to ensure that it is assigned the highest relative search index value across datasets. By normalizing all search term values relative to this control term, search trends across different datasets become comparable, allowing for accurate cross-term analysis without distortions from Google’s independent scaling process. In this study, we select Wikipedia as the control term due to its consistent search interest over time.

Finally, it is important to acknowledge that search trends may not be fully representative of the general population, as internet access and reliance on Google vary across sociodemographic groups. This introduces a potential selection bias, particularly in regions with lower internet penetration (Höltzl et al., 2025).

*Data collection strategy*

To ensure the semantic and cultural relevance of the analyzed terms, we compiled a country-specific and language-specific set of keywords. We focused on seven countries with high levels of urbanization and data availability: Spain, France, Italy, Germany, Portugal, the United Kingdom, and the United States. Keywords were translated into common, everyday language in each country and conceptually organized under the ASI framework:

* **Avoid** (avoiding trips): working from home, online shopping, grocery store/restaurant near me.
* **Shift** (modal shift): searches related to car, taxi, bus, bicycle.
* **Improve** (technological efficiency): electric car, hybrid car, car charging, fuel consumption.

The selection was designed to capture both intentional behaviors and structural conditions that influence mobility decisions. The full list of keywords per country is provided in Appendix 1.

**Methods**

*Sustainable mobility index*

We use Google Trends to collect relative search volumes for a set of sustainable mobility keywords over the 2018–2023 period. To synthesize these signals, we apply principal component analysis (PCA) to the search data and construct a *Sustainable Mobility Index*—a standardized variable with a mean of zero and a standard deviation of one. The resulting index captures how many standard deviations a given country's search interest in sustainable mobility deviates from the overall mean, serving as a proxy for digitally expressed interest in sustainable transport behaviors.

*Clustering Sustainable Mobility Countries*

To identify territorial patterns in digital interest toward sustainable mobility, we applied the K-means clustering algorithm to the values of the Sustainable Mobility Index across countries. K-means is an unsupervised learning method widely used in regionalization and pattern recognition tasks due to its simplicity and efficiency. The algorithm partitions observations into *k* clusters by minimizing within-cluster variance, assigning each data point to the nearest cluster centroid based on Euclidean distance (Saputra et al., 2020).

A critical step in the application of K-means is determining the optimal number of clusters (*k*), which is not known a priori. To address this, we used the **elbow method**, a heuristic technique that evaluates the percentage of variance explained as a function of *k*. The goal is to identify the value of *k* beyond which increasing the number of clusters yields diminishing returns in model improvement.

Specifically, we calculated the **sum of squared errors (SSE)** for different values of *k*, where SSE measures the total squared distance between each point and its assigned cluster centroid:

*Panel data model*

To investigate the structural and contextual factors associated with digital interest in sustainable mobility, we estimate a panel data model using the *Sustainable Mobility Index* as the dependent variable. The dataset includes annual observations for a set of countries over the 2018–2023 period.

The model specification takes the following form:

Where the Sustainable Mobility Index for country *i* in year *t*, it​ is a vector of explanatory variables, captures country-specific effects, controls for year-specific shocks, and ​ is the error term.

We consider a set of independent variables drawn from the Avoid–Shift–Improve (ASI) framework:

* **Avoid-related factors**: urban density, average commute times, and telework adoption rates.
* **Shift-related factors**: public transport coverage, cycling infrastructure per capita, and modal split indicators.
* **Improve-related factors**: electric vehicle adoption rates, fuel prices, and carbon intensity of transport.

In addition, we include controls for socioeconomic development (e.g., GDP per capita, education level), digital infrastructure (e.g., internet penetration), and environmental concern (e.g., national climate policy scores or environmental attitudes, where available). Depending on the outcome of the Hausman test, we estimate the model using fixed or random effects. Year fixed effects are included to account for common global shocks (e.g., COVID-19, energy crises). This modeling approach allows us to examine whether structural, normative, or policy-related factors are systematically associated with a higher (or lower) level of digitally expressed interest in sustainable urban mobility.

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**Appendix 1**

**Data Download Strategy**

Since Google Trends internally normalizes values and limits the number of queries per IP address, we implemented a data extraction strategy inspired by the method proposed by Stephens-Davidowitz (2014):

For each keyword *x*, we downloaded three distinct time series:

1. searches for *x*
2. searches for a control term (Wikipedia)
3. searches for *x + control term*

This approach enables subsequent imputation of missing values (i.e., values below the privacy threshold) and facilitates comparisons across terms and countries using regression techniques.

To increase the robustness of the time series, we repeated the download process multiple times (samples), incorporating proxies, random delays, and rotating countries to minimize the risk of query blocking. Data were collected at a **monthly frequency** between **January 2018 and January 2025**.

**4. Data Organization**

Each extraction is documented with a sample identifier, country, search term, and conceptual label (x, w, xw). The data are stored in .csv files, organized by country and series type (x, w, xw). This structure enables the construction of comparable panel datasets across countries and supports transparent robustness analysis.