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# Can spatial indicators fully explain car dependence? Evidence from Lombardy (Italy)

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ABSTRACT

Reducing car dependence is a critical challenge for transport and environmental policy, requiring a thorough understanding of its multidimensional nature. However, existing research often struggles to assess car-dependence's complexity comprehensively. This paper addresses that gap by applying Sensitivity Analysis (SA) techniques to a rich spatial dataset deployed across the Italian region of Lombardy, which encompasses diverse territories and mobility patterns. The proposed methodology combines moment-independent and variance-based SA methods to better suit observational data and identify key factors shaping car dependence. The resulting SA models show that car dependence cannot be fully explained by numeric variables alone and reveal unexpected causing factors that might point to deeper, underlying patterns. These findings highlight the limitations of purely quantitative approaches in comprehensively capturing the complexity of car dependence, reinforcing the need to complement them with context-based and qualitative approaches. In this way, the study contributes to a more robust understanding of the phenomenon across diverse territorial contexts, supporting more accurate strategies for developing or evaluating policies aimed at reducing car dependence.

## 1. Introduction

The increasing urgency of technological, environmental, and socio-urban challenges has made the reduction of car dependence a central objective in transport planning and policy. As the pursuit of a more sustainable, smart, safe, and equitable transportation system gains momentum (Hensher, 2024; Loorbach et al., 2021; Trygg & Grundel, 2025), understanding the societal reliance on private automobiles becomes critical. This perspective adds an essential dimension to ongoing debates on mobility transitions, which, beyond focusing on technological innovations such as electrification or automation, must also confront the socio-spatial processes which underpins widespread car choice.

### *1.1. Challenges addressing car dependence and methodological improvements*

The concept of car dependence can be framed as a complex and multifaceted phenomenon in which cars serve as the dominant mode of transportation for fulfilling activities and reaching needs (Sierra Muñoz et al., 2024). Far from being a purely transport-related matter, car dependence has been expanded by diverse research perspectives (Cremer-Schulte et al., 2024), including land use as well as behavioural studies or accessibility studies (Goodwin, 1996; Gorham, 2002; Mattioli et al., 2016; Pokharel et al., 2023; Wiersma et al., 2016). While the former strands have been primarily developed by scholars in the United States and Australia (Akbari & Nurul Habib, 2014; Asgari & Jin, 2022; Boeing, 2020; Kenworthy & Laube, 1996), the latter have been led by European research (Behren et al., 2018; Huby & Burkitt, 2000; Motte-Baumvol et al., 2010; Van eenoo et al., 2022a; Wiersma et al., 2016), showing varying insights across regions. Despite its theoretical richness, this car dependence academic diversity has resulted in a fragmented research landscape, characterized by multiple definitions, varying interpretations, and different operationalizations (Van Eenoo, 2025).

One key consequence of the conceptual complexity of car dependence is the wide range of metrics related to it, mostly derived from different sources rarely integrated together (Sierra Muñoz et al., 2024). As this lack of comprehensive focus limits the potential to translate the accumulated academic insights into effective planning tools and policy interventions, it also reveals a research gap. To address this, the present article builds on a conceptual framework that brings together the multiplicity of literature-based indicators and supports a methodological approach to numerically assess their relationships. This enables several

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objectives, covering different gaps: to identify the most influential variables, to examine how different indicators interact or contribute to the concept in distinct ways, and to evaluate the overall explanatory power of such quantitative, indicator-based approach.

Sensitivity analysis (SA) offers a promising methodological avenue to address car dependence conceptual challenges. As a well-established set of techniques for identifying key factors in complex datasets, SA is particularly useful when relationships between variables are not clearly established (Plischke et al., 2013). Its core objective is to determine which input parameters most strongly influence the output, by quantifying how uncertainty propagates through the model (Borgonovo, 2007). Additionally, SA contributes to improving model confidence by revealing sources of uncertainty, such as limited knowledge of the model's driving forces or constraints in sampling design (Lilburne & Tarantola, 2009). Despite its common use in transport engineering, the application of SA in mobility studies remains limited, mostly confined to networks modelling (Bao et al., 2016; Cantarella et al., 2019; Ciuffo et al., 2013; Juhász & Mátrai, 2024). This highlights a relevant potential for car dependence research, where complex, multivariate interdependencies hinder the assessment and comprehensive operationalization of the concept.

### 1.2. Aim and contribution of the paper

Quantifying and assessing car dependence is essential to develop a robust numerical understanding of the concept, capable of informing planning practice and guiding effective policies design. A key layer on that goal relates with the variety of territorial settings, which impose relevant spatial conditions shaping the phenomenon of car dependence. This notion orients the research towards regionally diverse contexts where exploring the contrast between different car-dependence-related metrics and the heterogeneous spatial setting. Using the Lombardy region (Italy) as a case study, the paper is able to approach car dependence comprehensively both through a variety of indicators and across different spatial contexts.

Following that guiding principle, this research aims to explore to what extent a quantitative approach, based on a broad car dependence-related indicators' dataset can adequately capture the phenomenon. To this end, the paper is structured as follows: Section 2 explores the concept of car dependence and its operationalization status. Sections 3 and 4 outline the selected methodological approach, based on a two-step SA framework, and the selected case study. Section 5 presents the results, followed by their discussion in Section 6. Finally, Section 7 provides the conclusions, summarizing key insights and implications for car dependence research.

## 2. Towards car dependence operationalization

Car dependence has attracted increasing attention in academia, as highlighted by recent critical reviews (Cremer-Schulte et al., 2024; Pokharel et al., 2023; Sierra Muñoz et al., 2024; Van Eenoo, 2025). These studies illustrate that previous literature has often treated car dependence in a fragmented manner, examining its various components without a cohesive framework. A key reason for this lack of integration is the absence of conceptual clarity, which directly impacts on how the term is operationalized and measured.

### 2.1. Car dependence assessment in previous research

While car dependence is closely related to social and transport inequalities (Belton Chevallier et al., 2018; Cao & Hickman, 2018; Carroll et al., 2021; van Dülmen et al., 2022), its operationalization in research relies on a variety of variables, each providing partial insights into the phenomenon. Some studies have explored car dependence through travel demand and the built environment (Blaudin de Thé et al., 2021; Cervero & Kockelman, 1997; McIntosh et al., 2014; Tian & Yin, 2025; Yin et al., 2025), while others have emphasized accessibility (Benenson et al., 2010; Fernández Núñez et al., 2024; Wiersma et al., 2016) or the contrast between spatial indicators and users' subjectivity or socio-demographic factors (Hamadneh & Jaber, 2023; Hunecke et al., 2008; Saadaoui et al., 2025; Thorhauge et al., 2020; Vega-Gonzalo et al., 2024; Zhao, 2011). Still other associate car dependence with high car use and ownership (Akbari & Nurul Habib, 2014; Asgari & Jin, 2022; Cao & Hickman, 2018; Jiang et al., 2017) or with low public transport supply (Langer et al., 2023; Van Eenoo et al., 2022b). While all of these contribute valuable perspectives, they are rarely combined within a single analytical framework.

The variation in assessment methods reflects a broader lack of consensus on how to define and measure car dependence (Cremer-Schulte et al., 2024; Sierra Muñoz et al., 2024). In the absence of shared conceptual foundation, research struggles to establish common metrics, which in turn limit the capacity to conduct more extensive quantitative analysis. Advancing a more integrated conceptualization is therefore essential to support robust quantitative assessment and inform policy design.

### 2.2. Car dependence scale and spatial aggregation

A key tension in the operationalization of car dependence lies in the scale of analysis (Cremer-Schulte et al., 2024). Mattioli et al. (2016) distinguished between different levels at which car dependence can be inferred, from spatial (macro) to activities (meso) and individual (micro) perspectives, which in turn deals with different data structures. As the former typically relies on spatially aggregated indicators, the latter draws on self-reported user data (Sierra Muñoz et al., 2024). This distinction introduces a methodological reflection dealing with the territorial extent and data sources, which imposes a critical constraint in car dependence research.

Obtaining disaggregated data is costly and often results in small sample sizes or unequally covering larger spatial settings. While spatially aggregated data are commonly used "because of data availability and computational constraints" (Stępniak & Jacobs-Crisioni, 2017), they are also particularly suitable for wide regional analysis. Aggregated data can better capture structural patterns across territories that might otherwise be blurred in individual-level variations, thus enhancing the interpretability of the phenomenon. Indeed, most car dependence research, closely tied to spatial characteristics, has adopted a macro-level approach (Sierra Muñoz et al., 2024).

Empirically, several studies have demonstrated that aggregated data can provide tangible benefits. Such data can serve as a useful proxy when micro data is unavailable (Adjemian & Williams, 2009), assist in estimating disaggregated ridership in the absence of public transport ticketing data (Lizana et al., 2024) or even enhance the performance of disaggregated data: Ballis and Dimitriou (2021) have shown that, besides ensuring privacy, aggregated data can support the generation of synthetic granular information while Bwambale et al. (2020) demonstrated that aggregated metrics from census or mobile phone records improve the predictive capability of household surveys. Altogether, these studies underline the advantages of using aggregated metrics, supporting the spatial focus adopted in this research to examine car dependence through a macro-level territorial perspective, as defined by Mattioli et al. (2016).

The choice of a spatially-aggregated approach implies, however, the exclusion of individual-level metrics (e.g., attitudes and perceptions) due to data unavailability and potential issues on aggregation. While the relevance of individual-level analyses is acknowledged, a comprehensive spatial approach can still yield valuable insights when applied from a multidimensional standpoint (Sierra Muñoz et al., 2024). Moreover, as noted by Cremer-Schulte et al. (2024), spatially-based car dependence analysis provides an essential foundation for informing individual-level research.

### 2.3. Conceptual framework

The present paper builds on the idea that car dependence is not a fixed condition, but a dynamic process shaped by multiple territorial and societal factors. Following Goodwin (1995) and Sierra Muñoz et al. (2024), the analysis is grounded in a conceptual framework that structures car dependence concept through a cause-and-effect lens, distinguishing between structural factors that contribute to car dependence and its observable outcomes. Rather than treating car dependence as a static, proxy-based condition, the framework captures it as the multiple interactions among these causes and effects elements.

The framework organizes the study's indicators into four causing dimensions (i.e., accessibility, land use and form, transport supply, and sociodemographic factors) and one effect dimension, referring to transport demand. In this way, it assumes that territorial conditions such as limited transport options or dispersed urban settings contribute to increased car choice and attachment, generating multiple multidimensional interactions that form the core of the car-dependent process. Although the theoretical model from Sierra Muñoz et al. (2024) includes an additional effect dimension on opinions and experiences, this is not included due to the lack of individual-level data at the regional scale, acknowledging its omission as a key area for further research.

The operationalization of this framework involves examining the statistical relationships between these cause-and-effect indicators. Rather than relying on predefined assumptions on causal chains, the research uses SA to identify which causal indicators contribute most significantly to explain car dependence outcomes and to assess the overall explanatory capacity of the quantitative approach. This provides an empirical basis for testing the conceptual framework against given data, as further detailed in the following sections.

## 3. Methodology

The goal of testing a comprehensive quantitative approach of car dependence is achieved by means of SA. As a family of statistical methods, it is able to identify which inputs most strongly explain the effects and quantify their explanatory power across high-dimensional and heterogeneous datasets. While this makes it particularly suitable for complex concepts where many overlapping factors interact, like car dependence, the SA techniques have not yet been systematically applied to its analysis.

SA is designed to evaluate how variations in input variables affect the outputs of a model, reducing the dimensionality of large datasets (Saltelli et al., 2007). In contrast to traditional regression-based techniques, SA methods are sensitive to nonlinear, non-monotonic and interactive effects among the inputs, framing uncertainty in the mathematical models. In that way, SA is used as a diagnostic tool to assess the car dependence framework, verifying which factors (among 150+ indicators, see Section 4) explain car dependence and how robust those explanations are.

The car dependence indicators constitute an observational dataset, which requires standard SA techniques to be adapted. Usually, SA deals with synthetic, design-driven data, whose inputs are generated from random model samples, in contrast to fixed, pre-existing values (known as given data) on the study's dataset. It also involves potentially correlated inputs, which conflicts with the assumptions of the model's inputs independence (Mara & Becker, 2021) of most SA methods. The study combines two SA techniques executed consecutively to account for these limitations, presenting a methodology not only useful for addressing car dependence but for to apply SA to any large observation dataset.

The method for observational datasets proceeds in two stages:

- Stage 1: Borgonovo Delta Index (Borgonovo, 2007). It is a moment-independent method suitable regardless of correlation among inputs, which provides a robust ranking of all input variables considering the independence to the model output.
- Stage 2: Sobol's indices based on Bayesian Sparse Polynomial Chaos Expansion (BSPCE) (Shao et al., 2017). It provides an efficient variance decomposition of the output variance from each input, providing the final quantification of the most relevant variables and assessing the models' performance.

This two-step approach is designed to first prioritize the inputs variables (stage 1), preparing the datasets to the methodological assumptions required to assess their individual and interaction effects more precisely (Stage 2).

### 3.1. Stage 1: Borgonovo delta index

Borgonovo's delta is a density-based, global sensitivity indicator that is moment-independent that evaluates "the influence of input uncertainty on the entire output distribution" (Borgonovo, 2007), highlighting which parameters contribute most to uncertainty. Since the method considers the entire distribution (unlike variance-based, which only measure contributions to output variance), it is more robust in capturing non-linear and non-monotonic relationships. This makes the method particularly useful for complex systems, such as mobility behaviour or spatial configuration models.

This method outputs a delta index for each input-output pair, with higher values indicating stronger dependence among them (ranging from 0 to 1). Unlike variance-based methods, Borgonovo method is suitable regardless of eventual correlations among the parameters, which is a relevant feature for observational datasets. This stage is used to pre-screen variables, producing a ranking of variables' independence, which guides the subsequent variance-based stage. The method is implemented using the SALib Python library (Herman & Usher, 2017; Iwanaga et al., 2022), which offers a reliable framework for conducting global SA.

### 3.2. Stage 2: Sobol indices from BSPCE

The Sobol method (Sobol, 1993) decomposes the output variance into partial variances from each input variable and their interactions. Since this method expects inputs' independence, the input variables are added to the Sobol model one at a time, following the ranking produced by Borgonovo's delta method (see Section 3.3), applying the method sequentially and refining the analysis. In that way, the variance-based Sobol method address the limitations posed by the given-data. Additionally, as it requires decomposing the function linking inputs and outputs, the model follows the BSPCE algorithm developed by Shao et al. (2017), decomposing into an orthonormal polynomial basis efficient and effectively for SA (Mara & Becker, 2021). The method has been implemented following the approach used in SIML@B,[1] the European Commission's tool for SA (European Commission's Joint Research Centre et al., 2020; Tarantola & Becker, 2015).

The model outputs Sobol's indices, which range between 0 and 1 (higher values indicate greater sensitivity):

- First-order effects ($S_i$), reflecting the direct influence of each input variable
- Total-order effects ($ST_i$), which also accounts for interaction with other input variables.

The indices represent the variance decomposition of the output variable $y$ into partial variances from input variables $x_i$ (e.g., $V_{i1}$ as individual and $V_{i1i2}$ as mutual contribution), as shown in Eqs. (1)–3.

[1] https://web.jrc.ec.europa.eu/rapps/pub/simlab/

$$\mathrm{V_y} = \sum_{i_1=1}^{N_i} V_{i_1} + \sum_{i_1=1}^{N_i} V_{i_1 i_2} + \cdots + \mathrm{V}_{1\ \ldots\ N_i} \tag{1}$$

$$1 = \sum_{i_1=1}^{N_i} S_{i_1} + \sum_{i_1=1}^{N_i} S_{i_1 i_2} + \cdots + S_{1\ \ldots\ N_i} \tag{2}$$

$$\mathrm{ST}_{i_1} = \mathrm{S}_{i_1} + \sum_{i_2 \neq i_1}^{N_i} S_{i_1 i_2} + \sum_{i_3 \neq i_1, i_2}^{N_i} S_{i_1 i_2 i_3} + \cdots + S_{1\ \ldots\ N_i} \tag{3}$$

Moreover, the variance-based model offers diagnostic indicators that enhance the interpretability and robustness of the simulation, extending the capabilities of Borgonovo's delta:

- $\varepsilon_{training}$ quantifies the model's amount of unexplained variance, which should remain below a recommended threshold (e.g., 0.10)
- the estimated PCE variance ($V_y^{PCE}$) with the empirical output variance ($V_y$), which should remain of the same magnitude order.

These metrics are essential for evaluating model performance and reliability of the results, and they form a key part of the analysis proposed in the following section.

### 3.3. Iterative functional process

Borgonovo's delta and BSPCE Sobol Indices are combined into a sequential approach that leverages the strengths of both approaches, enhancing the overall robustness of the SA. This dual-method strategy is particularly suited to given data (Plischke et al., 2013), as it captures different sorts of interactions within the models while addressing potential correlations among variables.

The process applies Borgonovo and Sobol methods independently for each dependent variable, as the models require a scalar output and an array of inputs. The outcome of each dependent variable run yields individual metrics for each input variable. Additionally, the process also can be run independently for different sets of independent variables, allowing different simulations which provide some contrast among different input cases (see Section 4).

The process, which is graphically shown in Fig. 1, follows the following procedure:

- Application of Borgonovo's delta method to rank input variables.
- Iteratively run the Sobol BSPCE model, adding sequentially the top Borgnovo-ranked variables one by one.
- At each Sobol BSPCE model run, keep each sequentially-added variable if meets two optimizing conditions, otherwise they are excluded:
  - reducing the training error compared to the previous evaluation set run.
  - maintaining an acceptable output variances ratio ($0.5 < V_y^{PCE} / V_y < 5$).
- Once the models are run, compute the key output metrics:
  - The of the Sobol model unexplained variance ($\varepsilon_{training}$) for each dependent variable run, representing the model's explanatory power.
  - The independent variable score ($IVS_i$), an aggregated sensitivity score for each input variable across all dependent-variable ($d$) runs, shown in Eq. (4). This score is based on the total order Sobol indices results ($ST_i$) and it is weighted by the run's unexplained variance ($\varepsilon_{training,d}$), ensuring greater consideration is given to higher-performing models.

$$IVS_i = \sum_d IVS_{i,d} = \sum_d \frac{1 - \varepsilon_{training,d}}{\varepsilon_{training,d}} * ST_{i,d} \tag{4}$$

In this way, the iterative, self-refined process integrates moment-independent and variance-based methods, exploiting their respective strengths beyond their standalone performance. This methodological approach can be replicated in other given data contexts, offering a consistent framework for SA studies. In the following section, the specificities of the case study and its application are detailed.

## 4. Case study: Lombardy region

The SA methodology is applied to an extensive dataset specifically designed to capture car dependence comprehensively across the Lombardy region, the most populous and one the largest regions of Italy.

### 4.1. Spatial context

Lombardy features diverse urban, periurban and rural settings (see Fig. 2), encompassing Milan as its main metropolitan centrality. On the one hand, the region is characterized by intense mobility dynamics[2]: private motorised account for 64,5 % of all trips, while 68,2 % of trips involving crossing municipal or district boundaries. The average trip distance is 12.8 km, increasing to 17,4 km when considering main regional hubs, reflecting their role as major mobility attractors. On the other hand, Lombardy shows diverse socio-economic patterns and varying spatial densities: the case study region ranges from Milan's metropolitan core to sparsely populated areas shaped by different geographic conditions, such as the agricultural Po valley and the Alpine valleys (Balducci et al., 2017).

These structural conditions make Lombardy a relevant case study for research on car dependence. Recent work has already identified a wide diversity of car-dependent patterns across the region (Sierra Muñoz et al., 2026), varying markedly along the urban-rural continuum and shaped by heterogeneous socio-spatial configurations. In particular, that analysis also shows that local specificities, such as urban fragmentation, the influence of high-capacity road infrastructure or mismatches between accessibility, alternative transport supply and local needs, can nuance prevailing associations with the car dependence concept. Building on these findings, the present study explores to what extent SA can be capitalised on to identify new indicator relationships or underlying structural patterns emerging from Lombardy's territorial diversity.

Lombardy's spatial heterogeneity is also evident in its fragmented governance system, which shapes the transport and land-use policy landscape. The limited integration between land-use strategies led by local municipalities and transport measures planned at the regional scale amplifies the negative externalities of economic and settlement growth – strongly car-dependent and often unable to leverage public transport investments to guide territorial development strategies (Pucci & Vecchio, 2019). Transport planning also present significant contradictions across the region. On the one hand, Milan has introduced an urban toll and extensive low-emissions zones (Marchetti & Antonelli, 2024), significatively expanded its metropolitan rail network (Global Railway Review, 2024; Regione Lombardia, 2025) and deployed car-free schools streets (Bianchi & Moscarelli, 2024). On the other hand, policies at a regional level remain largely car-oriented, foreseeing the construction of approximately 1000 km of new high-capacity roads, compared to only with only 350 km of new or upgraded railway lines (Regione Lombardia, 2025).

At both regional and national levels, sustainable mobility strategies combine measures that often pull in opposite directions: alongside efforts to improve cycling infrastructure, expand public transport networks and foster intermodality, policy framework continues to plan road capacity expansions and subsidise the purchase of low-emission vehicles (Regione Lombardia, 2016; Servizio Studi della Camera dei Deputati,

[2] The presented values are derived from authors' own elaboration of the regional household travel survey (Regione Lombardia, 2021) data.

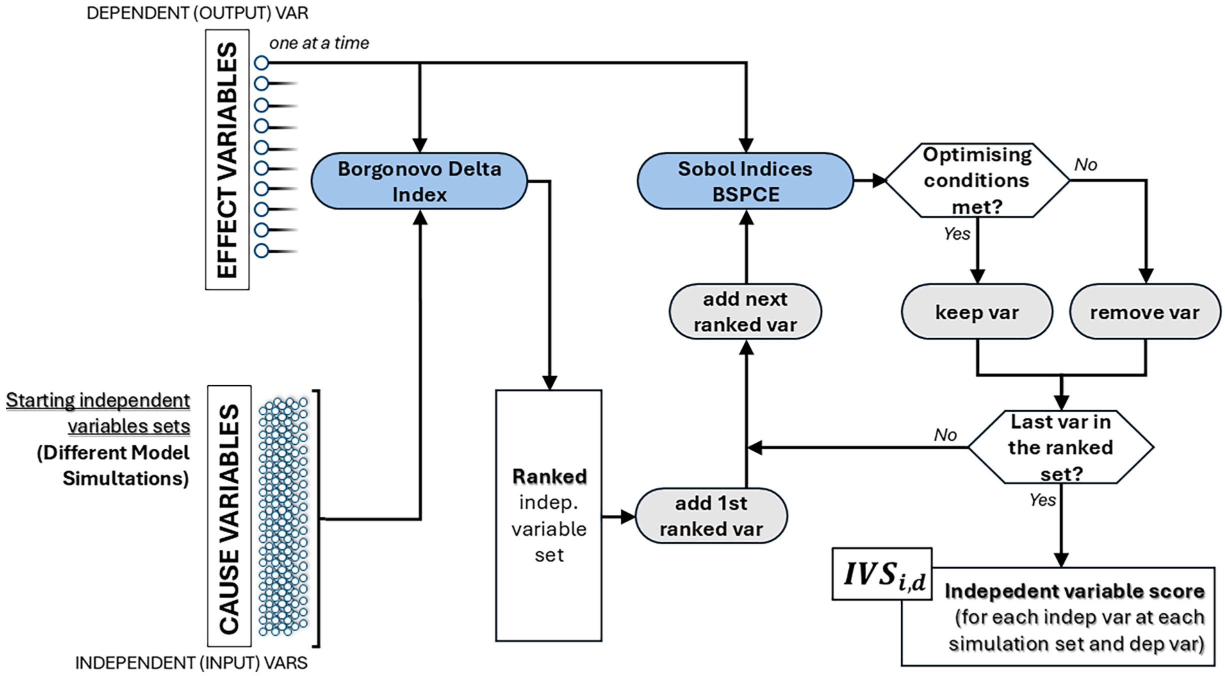



**Fig. 1.** SA iterative evaluation process schematic outline. (Source: own elaboration).

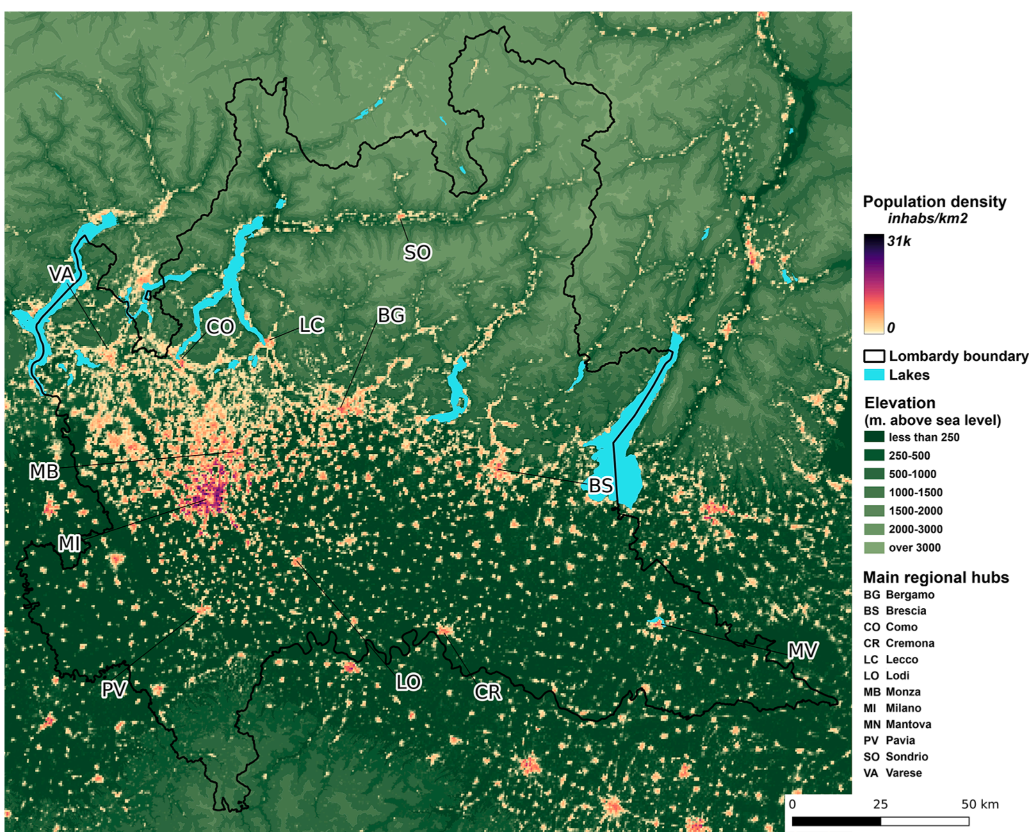



**Fig. 2.** Population density and main regional cities in Lombardy region (Source: own elaboration from Schiavina et al. (2022) GHSL population dataset).

2025). As a result, the regulatory and planning context shows no explicit or coherent strategy aimed at reducing car dependence and, in some cases, even promotes measures that risk reinforcing it.

Altogether, the region's heterogeneous context makes Lombardy an ideal case for investigating car dependence. In that way, the research approach is able to explore drivers potentially transcending local conditions, something especially relevant when strong and structured policies against car dependence are missing.

### 4.2. Dataset

Following the contextual features of Lombardy, the research dataset includes a wide range of indicators that reflect the multifaceted nature of car dependence, based on the dimensions introduced in Section 2. These indicators, drawn from existing literature, are deployed across over 1400 transport analysis zones (TAZ) within the region.

The dataset's primary data source is a regional transport survey (Regione Lombardia, 2021), which has resulted in diverse variables representing transportation demand from TAZ trip flows categorized by travel motivations and mode. Other indicators have been incorporated from various external datasets and libraries (Automobile Club d'Italia, 2023; Barrington-Leigh & Millard-Ball, 2019; Istituto Nazionale di Statistica - ISTAT, 2023; Istituto Nazionale di Statistica, 2023a, 2023b, 2017; Ministero delle infrastrutture e dei trasporti, 2022; Ministero dell'Economia e delle Finanze, 2023; OpenStreetMap contributors, 2023; Regione Lombardia, 2023, 2019; Schiavina et al., 2022; Transitland, 2023), which have been reconfigured to align with the TAZ framework. This allows for the comparison of territorial features on a common basis. To capture more fine-grained inputs, many indicators are derived from a 500 m squared-cell grid, covering homogeneously the region, with values then averaged by population into TAZ.

To apply SA, indicators were divided into independent and dependent variables, corresponding to cause-and-effect dimensions of car dependence (see Section 2 for more details):

- Dependent variables represent observed car dependence outcomes (e.g., modal share, motorization rate, etc.).
- Independent variables capture potential spatial or socio-economic causes of car dependence (e.g., density, accessibility, transport supply)

The operationalization of SA also required structuring the dataset to ensure the relevance and comparability of the results. On one side, a preliminary filtering was applied to the dependent variables to ensure they reflected meaningful outcomes of car dependence, leading to 9 key indicators from a pool of over 300. On the other, the 151 potential independent variables were organized into three simulation scenarios, introducing sensitivity to different modelling conditions. These scenarios are defined as follows:

- Sim 1: Uses the full set of 151 independent variables, with no restrictions.
- Sim 2: Applies a restricted set of 118 independent variables, excluding auxiliary-like indicators (e.g., metrics considered in composite indicators). The excluded variables are marked with an asterisk (*) in Table A.1.
- Sim 3: Uses the same Sim2, restricted set of 118 variables, while applying a topic-based restriction for best-independent variables choice. The 118 variables are divided into 23 topics, each representing a shared underlying metric (e.g., urban density, which can be measured through different definitions, such as population per TAZ surface versus urbanized surface area, among others). Within each topic, multiple combinations of variables may be defined, but only one combination per topic is permitted in each simulation run. This constrain prevents the inclusion of redundant or overlapping variables, enhances model clarity and allows the identification of the most effective indicator for each metric.

Table A.1 in the Appendix details the full list of variables, their topic membership, their combination belonging (if applicable), and whether they belong to the full or restricted set.

## 5. Results

The results presented in Table 1 illustrate the unexplained variance for each variance-based simulation, highlighting the most performing one in bold for each variable. Overall, the unexplained variance usually remains consistent across different simulations for each dependent variable, indicating the robustness of the models despite variations in the inputs' sets to some extent. Notably, Sim 3 results suggest that imposing constraints on the variables' combinations does not offer significant advantages: even when Sim3 performs better, the improvement over other simulations is marginal. The main difference arises when comparing Sim 1 and 2, representing the use of the full set versus the restricted set of variables, respectively. The performance varies depending on the dependent variable. Specifically, the full dataset models perform significantly worse with commuting average distance, while it excels for modal share in non-commuting trips and self-containment index. However, there is no clear conclusion regarding the optimal framework for SA simulations.

**Table 1**
Results of unexplained variance for each simulation and dependent variable.

| *Output variables (Car-dependence effects)* | **Sim 1** *162 vars no combs constrain* | **Sim 2** *118 vars no combs constrain* | **Sim 3** *118 vars with combs constrain* |
|---|---|---|---|
| **Age of 1st License** | **0385** | 0386 | 0390 |
| **Commuting average distance** | 0715 | **0576** | 0592 |
| **Average distance by private-motorized means** | 0546 | 0559 | **0545** |
| **Non-commuting[1] average distance** | 0344 | **0314** | 0458 |
| **Private-motorized modal share in commuting trips** | 0451 | **0396** | 0431 |
| **Motorization rate** | 0675 | 0681 | **0675** |
| **Private-motorized modal share in non-commuting trips** | **0521** | 0607 | 0647 |
| **Self-Containment Idx (internal trips for working/Workers)** | **0370** | 0476 | 0596 |
| **Driving license rate** | **0294** | 0329 | 0343 |

[1] Commuting trips refer to work and study reasons, while non-commuting refer to leisure and private affairs.

Examining the results by dependent variables reveals some surprising findings. Notably, outputs that are frequently studied in car dependence literature, such as modal share and motorization rate, do not rank highly and are associated with higher unexplained variance. The most effective dependent variables in terms of performance are driving license rate and non-commuting average distance, with self-containment index, age of first license and commuting motorized modal share following closely. Additionally, less-researched variables, like average distance, appear significant only when related to non-commuting purposes, encompassing a broader range of motivations and destinations. Despite these insights, the overall results indicate a substantial amount of unexplained variance. The best performing model achieves only 29 % of unexplained variance, which falls significantly short of the theoretical recommendations (10 %), highlighting a key finding from Table 1.

The results also explore the Sobol-based scores by variable, presented in Table 2 and Fig. 3 for the top-ranked variables. These scores highlight the primary variables emerging from the models, which are crucial for quantifying car dependence in this study. A noteworthy finding when comparing different models is the superior performance of Sim2, whose variables obtain average higher scores than those in Sim1 and, particularly, Sim3. This simulation, the only one with restricted combinations, exhibits weaker scores for its variables. This is partially due to its lower unexplained variance weights and fewer relevant variables. Still, the results show that the highlighted variables are not constant across the models for each simulation, appearing only in a few simulations. In fact, variables at each simulation have an average appearance rate (models where the input effectively mobilizes output variance) of 2.20 for Sim1 and Sim2, 2.13 for Sim3.

Regarding the main variables themselves, the models yield varied results. Variables related to cyclability consistently emerge at the top

**Table 2**
15-Top variables Sobol-based scores for each simulation.

| | Sim 1 | | | | Sim 2 | | | | Sim 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *162 vars no combinations restriction* | | | | *118 vars no combinations restriction* | | | | *118 vars with combinations restriction* | | | |
| *Rank* | **Variable** | **Dim.** | **IVS** | **#Ap.** | **Variable** | **Dim.** | **IVS** | **#Ap.** | **Variable** | **Dim.** | **IVS** | **#Ap.** |
| *1* | Cyclable routes elevation percentage | TRS | 1656 | 4 | Cycl. routes detour (route/ euclid dist) | TRS | 1824 | 2 | Foreigners rate | SOD | 0870 | 3 |
| *2* | Distance to nearest hardware store | ACC | 1495 | 3 | Cyclable routes elevation percentage | TRS | 1724 | 4 | Cyclable routes length over 4 % steep | TRS | 0800 | 3 |
| *3* | Built Surf. to Urbanized Surf. Ratio | LUF | 1438 | 2 | Employment rate | SOD | 1642 | 3 | Accessibility to tram and light rail trips | TRS | 0670 | 3 |
| *4* | Accessibility to non-Milan bus trips | TRS | 1404 | 1 | Accessibility to tram and light rail trips | TRS | 1635 | 2 | Distance to closest kindergarten | ACC | 0600 | 2 |
| *5* | Accessibility score to banks & ATMs | ACC | 1297 | 1 | Large households (over 2px) ratio | SOD | 1541 | 4 | Acc. Score to restaurants | ACC | 0573 | 1 |
| *6* | Foreigners rate | SOD | 0911 | 2 | Accessibility score to banks & ATMs | ACC | 1459 | 1 | Railway Service Score | TRS | 0540 | 2 |
| *7* | Large households (over 2px) ratio | SOD | 0889 | 4 | Land use mix (urbanized land, all uses) | LUF | 1284 | 1 | Large households (over 2px) ratio | SOD | 0537 | 3 |
| *8* | Accessibility to all transit trips | TRS | 0601 | 2 | Distance to nearest hardware store | ACC | 1200 | 4 | Average income per household | SOD | 0491 | 3 |
| *9* | Nodal sparsity in 3 km radius | LUF | 0531 | 2 | Distance to nearest hospital | ACC | 1133 | 1 | Built Surf. to Urbanized Surf. Ratio | LUF | 0489 | 2 |
| *10* | Acc. Score to bars and coffee shops | ACC | 0475 | 1 | Network circuicity log (1.5–2 km band) | LUF | 0962 | 2 | Average income per taxpayer | SOD | 0452 | 2 |
| *11* | Average income per taxpayer | SOD | 0409 | 3 | Foreigners rate | SOD | 0947 | 2 | Density (Pop/Urb. area, avg.1.5 km radius) | LUF | 0424 | 2 |
| *12* | Density (Pop/Urb. area, avg.1.5 km radius) | LUF | 0402 | 2 | Average income per taxpayer | SOD | 0631 | 2 | Network circuicity log (1.5–2 km band) | LUF | 0406 | 1 |
| *13* | Over-65 rate | SOD | 0394 | 2 | Density (Pop/Urb. area, avg.1.5 km radius) | LUF | 0602 | 2 | Distance to nearest post office | ACC | 0397 | 1 |
| *14* | Land use mix (all land, urban uses) | LUF | 0376 | 2 | Distance to nearest freeway access | TRS | 0487 | 2 | Density (Pop/Urb. area, avg. 0.5 km radius) | LUF | 0339 | 1 |
| *15* | Urbanized areas in 1500 m radius | LUF | 0371 | 2 | Accessibility to all transit trips | TRS | 0470 | 1 | Employment rate | SOD | 0296 | 3 |

Notes.
Dim: Dimension (TRS: Transport Supply; LUF: Land use and form; ACC: Accessibility; SOD: Sociodemographic).
IVS: Independent Variable Score.
#Ap: Number of appearances in each simulation models.

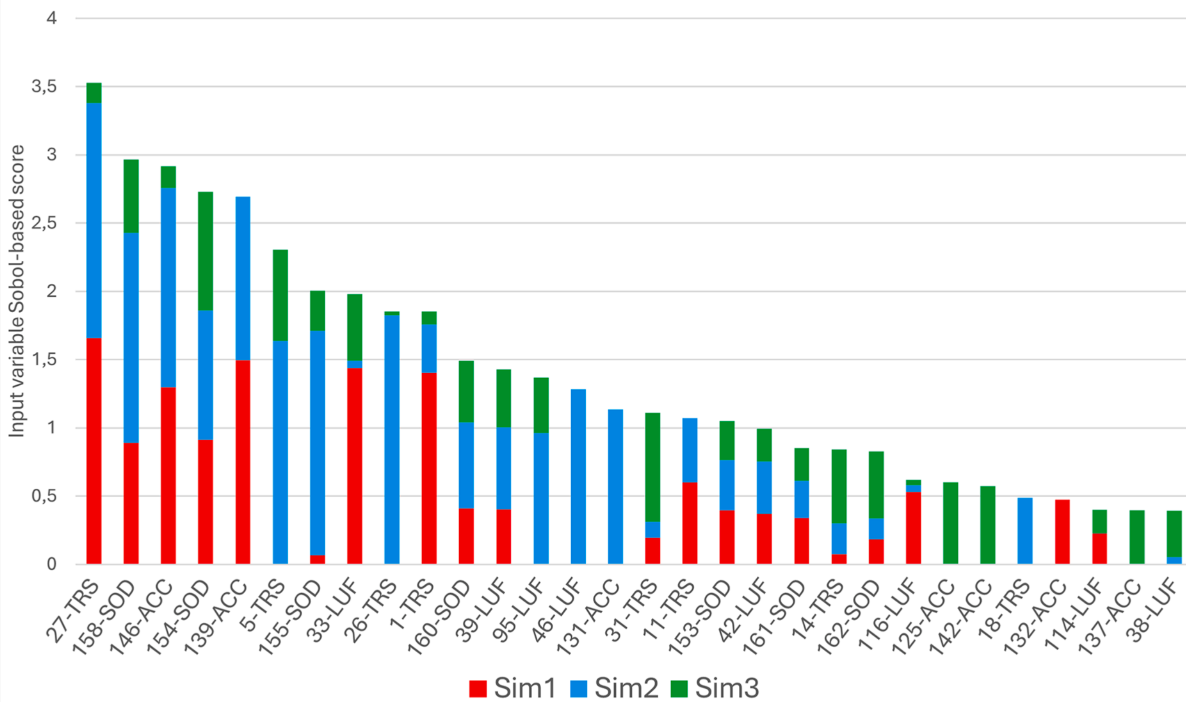
positions in all three models, which are constructed based on average insights of all routes shorter than 6 km between inhabited polygons. Specifically, the key variables include the elevation percentage of the routes (sum of routes elevation divided by the sum of actual routes length) and the percentage of the routes' length over 4 % steep. Although these variables were initially constructed as indicators for cycling, they highlight a clear focus on orography, indicating that territorial flatness or hilliness might be strongly associated with car dependence. Additionally, the detour rate of cycling routes (comparing the length of routes with the Euclidean distance between origins and destinations) also appears as a relevant bike-related factor. This indicator could be also related to orography, as flat places can have straighter and less winding roads, as well as to the morphology of the network.

Other relevant results are related to socio-demographic factors, whose main variables are consistently present across three simulations. Notably, the ratio of large households (those with three or more members), emerges as the second overall indicator. With lower but still significant results, foreigners' rate and average income per taxpayer also show consistent results across the simulations. This consistency underscores the importance and effectiveness of these socio-demographic indicators in the study. On the other hand, accessibility variables align more closely in Sim1 and Sim2, with significant results for banks (even if appearing only in six models) and hardware stores. The first amenity metric relates to the accessibility score, which quantifies their balanced proximity by awarding one point for each amenity within 400 m and gradually reducing the score to zero at 3 km network distance. In contrast, hardware stores' metric is based on the distance to the closest one, representing a different approach to measuring accessibility. These indicators are more relevant than the ones related to different services and other comprehensive metrics integrating all amenities (such as the sum of accessibility scores).

Finally, the results indicate limited relevance for land use and form indicators, which score lower and play a secondary role. The rate of built surface to urbanized area scores higher, while density, a key variable in literature, ranks 12th. Among the set of density indicators, the one highlighted is the surrounding population (in a 1.5 km radius) divided by urbanized surface, suggesting to some extent that assessing density in terms of proximity and urbanization may be more insightful. The alternatives of other transport modes, despite extensive researched in literature, does not score high either: the results focus on specific means of transport, as tram services on one side and non-Milan bus services on the other. Then, results suggest that traditional land use and transport indicators, if not neglecting their importance, might be nuanced by territorial morphology, sociodemographic and accessibility factors.

## 6. Discussion

Applying SA to car dependence indicators sustains this phenomenon's intricate and multifaceted nature. The extensive and multidisciplinary dataset used in this study, which integrates different dimensions within a single analytical framework, has its own value in providing broad insights. Beyond the specific results of the models, SA findings allow to further reflect on their implications, considering the relevance of the variables considered, the territorial extent or wider dynamics shaping car dependence, altogether being able to enrich and nuance knowledge from existing literature.




**Legend**

**Cause Dimensions:** TRS (Transport Supply), LUF (Land use and form), ACC (accessibility), SOD (Sociodemographic)

**Variables: 27**: Cyclable routes elevation percentage, **158**: Large households (over 2px) ratio, **146**: Accessibility score to banks & ATMs, **154**: Foreigners rate, **139**: Distance to nearest hadrware store, **5**: Accessibility to tram and light rail trips, **155**: Employment rate, **33**: Built Surf. to Urbanized Surf. Ratio (all area), **26**: Cycl. routes detour (route/euclid dist), **1**: Accessibility to non-Milan bus trips, **160**: Average income per taxpayer, **39**: Density (Pop/Urb. area, avg.1.5km radius), **95**: Network circuicity log (1.5-2km band), **46**: Land use mix (urbanized land, all uses), **131**: Distance to nearest hospital, **31**: Cyclable routes lenght over 4% steep, **11**: Accessibility to all transit trips, **153**: Over-65 rate, **42**: Urbanized areas in 1500m radius, **161**: Average income per inhabitant, **14**: Railway Service Score, **162**: Average income per household, **116**: Nodal sparsity in 3km radius, **125**: Distance to closest kindergarten, **142**: Acc. Score to restaurants, **18**: Distance to nearest freeway access, **132**: Acc. Score to bars and coffee shops, **114**: Nodal sparsity in 2km radius, **137**: Distance to nearest post office, **38**: Density (Pop/Urb. area, avg. 0.5km radius)

**Fig. 3.** 30-Top variables total Sobol-based scores, summing up each simulation values. (Source: own elaboration).

### *6.1. Variables related to car dependence*

The SA results highlight different independent variables related to car dependence. Among them, orography emerges as a significant factor, representing an important and somewhat unexpected finding that raises questions about the specific ways in which geomorphology impacts car dependence. While it is straightforward that geomorphology has shaped territorial development and city planning (Pica et al., 2024), its direct relationship with transport has received little scientific attention in car dependence literature (Cremer-Schulte et al., 2024). In the case of this study, the higher concentration of people in flatlands aligns with the intuitive idea that mountain areas, being more sparsely populated, involve greater transport distances and further challenges which lead to higher car-dependence effects. However, this finding prompts further questions: is geomorphology acting merely as a proxy for other latent factors, either generalizable relations or specific to the Lombardy region? Or, instead, does it hold deeper implications that have remained unexplored in literature and only becoming apparent through a comprehensive statistical and quantitative approach? These questions fall beyond this paper extent and requires further research.

One possible reason for the prominence of orography in this analysis lies in the region-wide perspective adopted. While such a broad scope is valuable to capture car dependence across a range of contexts, it may also obscure other dynamics. On one hand, orography might be entangled with specific landform, accessibility and socio-demographic features that SA does not capture as decisively as orography itself. On the other hand, certain patterns may only emerge under more homogeneous territorial conditions. Conducting SA over smaller or more uniform areas could help reveal trends potentially masked by geomorphological diversity, yielding different insights and greater explanatory power.

In fact, the strong influence of orography, combined with its relationship to urban morphology, might explain the lower significance of variables traditionally emphasized in literature. Some of them include population density (Ewing & Cervero, 2010; Saeidizand et al., 2022; Wiersma et al., 2016) and other transport modes service (Shen et al., 2016; Van Eenoo et al., 2022b; Yin et al., 2019), that may overlap with the flatness of the territory. The emergence of variables as potential proxies, integrating more direct indicators of car dependence effects, might also be applicable in other cases: foreigners' rate, although studied in literature (Toasin et al., 2016; Zhao, 2011), could be really indicating socio-demographic patterns related to car dependence. Additionally, the high relevance of specific amenities could indicate specific contexts related to car dependence: banks might be significant due to their concentration in high-activity urban centres, while hardware stores might be more relevant in suburban settings. These findings suggest further exploration of these particular indicators to uncover potential underlying connections and assess their validity in different regional contexts.

However, other prominent indicators in the models align with established literature, particularly regarding socio-demographic factors. Income is frequently used as a control variable able to provide context about further behavioural issues (Van Eenoo et al., 2022b; Zhao, 2011). Additionally, the rate of large households, which ranks second, is well documented in literature (Asgari & Jin, 2022; Boeing, 2020; Limtanakool et al., 2006) and relates to specific practices of car dependence (Mattioli, 2014; Mattioli et al., 2018; Thorhauge et al., 2020). The prominence of these variables suggests that a deeper understanding of car dependence may require greater attention to personal and contextual aspects shaping mobility practices.

Framing the dependent variables, those with the highest explanatory power are the driving license rate and the non-commuting average distance. Although their results remain above the 10 % statistically recommended threshold, they may still reflect meaningful insights into how car dependence is framed – particularly considering that these indicators are not typically emphasised in literature. On one hand, the driving license rate may represent how essential car use becomes in areas where alternatives are lacking, acceptably matching with the independent indicators from the dataset. On the other hand, the non-commuting average distance (including shopping, caregiving or leisure destinations) holds considerably greater explanatory power compared than its commuting counterpart. Interestingly, this relationship is reversed when considering modal share indicators, although these are generally associated with higher levels of unexplained variance.

These findings underscore the relevance of being able to drive as well as non-mandatory trips in everyday mobility patterns, despite historically gathering less attention in policy (Convery & Williams, 2019; Wöhner, 2022). Longer distances to these types of destinations may drive individuals to rely on car use (and ownership) for a broader range of trip purposes, even in contexts where alternatives might be available. In that context, the lack of structured policies regarding car dependence in Lombardy might be exacerbating these outcomes, tending to an increased regionalisation of mobility supported by new high-capacity and speed road infrastructure.

### 6.2. *Variance-explanatory power of quantitative approach to car dependence*

In general, the high levels of unexplained variance observed across all models are far from the statistically recommended threshold, which leads to a significant finding: the study's quantitative approach to car dependence has important limitations, as it cannot ensure that addressing causing variables of the phenomenon will significantly impact the effects. Despite the identified patterns, the results show that the whole complexity of car dependence cannot be fully explained with numeric variables alone, nor from a purely spatial approach. This result has important implications as it questions the possibility to use models and other quantitative tools to forecast the impact of transport and land-use policies on car dependence and its effects, or at least it suggests complementing quantitative approach with psycho-social information and context-related qualitative analyses. For instance, the latter could be based on the direct engagement of the citizens directly affected by the policies under discussion (e.g. via living labs or other citizens' engagement activities).

The limited results of the SA may also stem from the diverse conditions of the dataset and the methodology. Firstly, the theoretical framework assumes that car dependence can be modelled as a process where a wide range of cause indicators produce measurable effects. While this integrated variables' approach aims to overcome the lack of comprehensive focus on car dependence, the interpretation of its results pushes forward a novel issue: when considered together, certain indicators may act as proxies for more complex underlying qualities such as urban vitality or easiness of reaching places, introducing nuances into the theoretical framework. This would imply that the causal indicators may have interlinkages and non-uniform relationships with the dependent variables, requiring further investigation. This is particularly relevant given that some well-documented dependent variables have shown low levels of explained variance.

Secondly, the absence of indicators covering the preferences, perceptions and other subjective factors behind car dependence pose a significant limitation. Leaving behind a relevant dimension of car dependence potentially represents a lack on the features providing explanatory power to the models. However, indicators related to these subjective factors are typically derived from surveys and individual-based studies (Behren et al., 2018; Sohn & Yun, 2009; Van Eenoo et al., 2022b; Zhao, 2011), posing particular difficulties when attempting to populate extensive spatial datasets and presenting a challenge for detailed, comprehensive spatial approaches.

Third, the territorial scope of the study spans over 1400 transport zones, encompassing heterogeneous settings from sparse mountain villages to dense metropolitan areas, which may complicate the extraction of generalizable trends. The orography-related findings support this insight, as well as the fragmented regional policies related to car dependence. Additionally, using transport analysis zones as statistical units for spatial aggregation may introduce biases due to aggregation and administrative boundaries (Jacobs-Crisioni et al., 2014). Although many indicators have been averaged based on population, exploring different scales and more homogeneous sub-regions could offer a different understanding of the uncovered input relationships. Further focus on these aspects could enhance the robustness and generalizability of the findings.

## 7. Conclusions

The study has presented a methodology combining two SA approaches to explore a comprehensive car dependence dataset for the Lombardy region, providing an operational alternative to existing dispersed quantitative research.

### 7.1. *Key findings and contributions*

The results highlight a range of variables not frequently associated to car dependence in the existing literature, despite limitations related to the overall explanatory power of the models. These findings underscore the need to reconsider metrics and indicators that have been overlooked, but not only. The role of orography, in fact, recalls the strong territorial embeddedness of car dependence, a matter that sometimes is difficult to combine with large numeric or statistical studies. However, the macroscopic, spatial approach is not sufficient to obtain a full picture of the car dependence phenomenon, suggesting that research on car dependence cannot be limited to aggregated and spatial analysis, requiring further detail in other directions.

Although the relatively high levels of unexplained variance prevent the study from drawing definitive conclusions, the findings remain valuable for advancing the understanding of car dependence in various ways. On one hand, addressing car dependence requires embracing its inherent complexity and considering a broader range of related metrics, including those that have received limited attention so far. On the other, the results underscore the importance of integrating indicators that capture users' perceptions, attitudes and daily practices, a dimension that is often absent from large-scale spatial analysis but may help account for part of the levels of unexplained variance. While the need to bridge macroscopic approaches with individual-level insights constitutes a transferable methodological lesson, the specific variables identified are contingent on the Lombardy case study. Nevertheless, these findings may still provide analytical guidance for other territories when interpreted in light of their local socio-spatial conditions.

### 7.2. Limitations and future research

The findings also imply further consideration of the methodological limitations. SA helps identify which inputs are more relevant to address the outputs but gives no information about the nature or direction of these relationships. In other words, while significant variables emerge, the method does not clarify whether their effects are positive, negative or more complex. This limitation suggests a need for further research to numerically and qualitatively explore these dynamics. Also, this limitation relates to exploring potential proxy behaviours and subsequent revision of the theoretical framework among the input variables. This could provide different insights on how to address those indicators.

Beyond expanding SA methods, further research should address the socio-psychological dimensions of car dependence, which remain underexplored and emerge as potential reason for the study limitations. One avenue involves incorporating subjective-based indicators into SA. However, such data are often difficult to collect at large regions or unmanageable to be integrated within aggregated transport zone frameworks. To address this limitation, addressing car dependence at smaller scales appears pertinent, involving more place-based approaches through user perception surveys, interviews or focus groups. Recent studies have emphasized the relevance of subjectivity through perception in navigating car-dependent settings (Blandin et al., 2024) and how context-based mobility solutions can be effective to shape travel behaviour (Stiebe et al., 2025). In parallel, investigating the emerging role of practices (Selzer & Lanzendorf, 2022; Van Eenoo & Boussauw, 2023) or the influence of specific territorial morphology on car dependence could not only provide a more holistic understanding of the phenomenon but also inform more tailored and effective interventions.

### 7.3. Research implications and prospects

This research has approached car dependence from a broad territorial perspective, enabled by the use of spatially aggregated data. Such data have proved useful to advance the understanding of car dependence at the regional scale, though highlighting how this type of data alone is insufficient for a complete policy monitoring and assessment. In this sense, the study clarifies the value and limitations of regional-scale quantitative approaches and contributes to building a shared ground for assessing car dependence across multiple dimensions, while fostering greater awareness of their policy linkages and constraints.

The study reveals that car dependence cannot be fully explained by numeric variables alone and question the sole reliance on modelling tools to anticipate land-use and transport interaction, emphasizing the complexity of the phenomenon. The identified limitations of purely quantitative approaches highlight the importance of qualitative, context-based research, showing the way for more robust, actionable and tailored insights for both academic inquiry and practical policy-making. By integrating qualitative and quantitative methods, future research can provide comprehensive understanding and effective strategies to reduce car dependence.

## Declaration of generative AI and ai-assisted technologies in the writing process

During the preparation of this work the authors used generative AI tools (GPT-5 mini and earlier versions) exclusively to improve readability and language quality. No content, analysis, interpretations or conclusions were generated by the AI. All AI outputs were carefully reviewed, edited and validated by the authors, who take full responsibility for the content of the manuscript.

## CRediT authorship contribution statement

**Jaime Sierra Muñoz:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Louison Duboz:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Biagio Ciuffo:** Writing – review & editing, Validation, Supervision, Conceptualization. **Paola Pucci:** Validation, Supervision, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The dataset used in this study is publicly available at https://doi.org/10.17632/jx48cs6276.1 (Sierra Muñoz, 2025).

## Appendix A. Dataset variables

Table A1.

**Table A.1**
Dataset variables considered in the model with its dimensions, topic and combinations categories.

| Type | Dimension | Topic | Variables [combinations] |
|---|---|---|---|
| Output | Transport demand | - | Commuting average distance, Private motorised trips average distance, Non-commuting average distance, Motorisation rate, Private motorised modal share in commuting trips, Private motorised modal share in non-commuting trips, Self-containment index (internal working trips/TAZ workers), Drivers rate, First-license average age |
| Input | Transport supply | Public transport trips | Accessibility to non-Milan bus trips [103], Accessibility to Milan urban transit trips [103], Accessibility to north-east bus trips [103], Accessibility to regional train trips [101, 103], Accessibility to tram and light rail trips [102], Accessibility to metro l trips [102], Accessibility to railway trips [102], Accessibility to bus trips [102], Accessibility to cable transport trips [102], Accessibility to all transit trips [104], All transit trips access, exclud. urban Milan [101], |
| | | Train access | Distance to closest train station [202], Railway Service Score [201], |

(continued on next page)

**Table A.1** (*continued*)

| Type | Dimension | Topic | Variables [combinations] |
|---|---|---|---|
| | | Road density | TAZ-based road density [302], Grid cell averaged road density [301], TAZ-based, urbanised area road density [303], |
| | | Freeway access | Distance to nearest freeway access [401], |
| | | Cycling infrastructure density | Cycling lanes surface density (whole TAZ) [502], Cycling lanes network link dens. (whole TAZ) [503], Cell-based cycling lanes surface density [501], Cell-based cycling lanes network link dens. [504], Cycling lanes surface density (Urbanised TAZ) [505], Cycling lanes network link dens. (Urbanised TAZ) [506], |
| | | Cycling quality | Available cycle routes (under 6 km) [602], Cycl. routes detour (route/euclid dist) [602], Cyclable routes elevation percentage [602], Cyclable routes distance-on-cycl. lane ratio [602], Cyclable routes distance-on-road ratio [602], Cyclable routes distance-on-street ratio [602], Cyclable routes lenght over 4 % steep [602], Cycling quality score (stepness, cycl. lanes) [601], |
| Input | Land use and form | Compactness | Built Surf. to Urbanised Surf. Ratio (all area) [702], Built Surf. to Urbanised Surf. Ratio (urban area) [701], |
| | | Density | Density (Pop/all-TAZ area) [802], Density (Pop/built-surf area) [801], Density (Pop/urbanised area) [803], Density (Pop/area, avg. 0.5 km radius) [804], Density (Pop/Urb. area, avg.1.5 km radius) [805], Density (Pop/Built area, avg.1.5 km radius) [806], |
| | | Population around | Population in 1500 m radius (pop-averaged) [901], |
| | | Urbanised area around | Urbanised areas in 1500 m radius (pop-averaged) [1001], |
| | | Built density around | Built surface in 1500 m radius (pop-averaged) [1101], |
| | | Land use mix | Land use mix (all land, all uses) [1202], Land use mix (all land, urban uses) [1203], Land use mix (urbanised land, all uses) [1204], Land use mix (urbanised land, urban uses) [1201], |
| | | Residential mix | Residential type mix [1301], |
| | | Dense residence supply | Share of dense residence over total area [1401], Share of dense residence over residential area [1402], |
| | | Sprawl metrics | number of cycle-basis edges within TAZ*, number of bridge edges within TAZ *, number of deadends edges within TAZ*, number of selfloop edges within TAZ*, length of cycle-basis edges within TAZ*, length of bridge edges within TAZ*, length of deadends edges within TAZ*, length of selfloop edges within TAZ*, length of edges within TAZ*, euclidean distance sum from edges within TAZ*, number of nodal degree 1 nodes within TAZ*, number of nodal degree 3 nodes within TAZ*, number of nodal degree 4 or more nodes within TAZ*, number of nodes within TAZ*, number of nodes within TAZ*, avg nodes quantity 0.5 km around each TAZ node [1502], eucl. dist sum nodes 0.5 km around each TAZ node*, netw. dist sum nodes 0.5 km around each TAZ node*, avg nodes quantity 0.5–1 km around each TAZ node [1502], eucl. dist sum nodes 0.5–1 km around each TAZ node*, netw. dist sum nodes 0.5–1 km around each TAZ node*, avg nodes quantity 1–1.5 km around each TAZ node [1502], eucl. dist sum nodes 1–1.5 km around each TAZ node*, netw. dist sum nodes 1–1.5 km around each TAZ node*, avg nodes quantity 1.5–2 km around each TAZ node [1502], eucl. dist sum nodes 1.5–2 km around each TAZ node*, netw. dist sum nodes 1.5–2 km around each TAZ node*, avg nodes quantity 2–2.5 km around each TAZ node [1502], eucl. dist sum nodes 2–2.5 km around each TAZ node*, netw. dist sum nodes 2–2.5 km around each TAZ node*, avg nodes quantity 2.5–3 km around each TAZ node [1502], eucl. dist sum nodes 2.5–3 km around each TAZ node*, netw. dist sum nodes 2.5–3 km around each TAZ node*, average nodal degree of TAZ nodes [1502], dead ends node fraction [1502], Network circuicity log (0–0.5 km band) [1502], Network circuicity log (0.5–1 km band) [1501, 1502], Network circuicity log (1–1.5 band) [1501, 1502], Network circuicity log (1.5–2 km band) [1501, 1502], Network circuicity log (2–2.5 km band) [1501, 1502], Network circuicity log (2.5–3 km band) [1501, 1502], bridge edges length fraction [1501, 1502], non-cycle edges length fraction [1501, 1502], non-cycle edges fraction [1501, 1502], bridge edges fraction [1501, 1502], selfloop edges fraction [1502], sinuosity (avg links lenght to euc. distance in TAZ) [1502], Nodes sum (0–0.5 km from each polygon)*, Nodes sum (0–1 km from each polygon)*, Nodes sum (0–1.5 km from each polygon)*, Nodes sum (0–2 km from each polygon)*, Nodes sum (0–2.5 km from each polygon)*, Nodes sum (0–3 km from each polygon)*, Nodal sparsity in 0.5 km radius [1502], Nodal sparsity in 1 km radius [1502], Nodal sparsity in 1.5 km radius [1502], Nodal sparsity in 2 km radius [1502], Nodal sparsity in 2.5 km radius [1502], Nodal sparsity in 3 km radius [1502], Routing circuicity (netw.dist/euc) in 1 km radius [1502], Routing circuicity (netw.dist/euc) in 3 km radius [1502], Sprawl index [1503], |
| Input | Accessibility | Accessibility | Acc. Score to supermarket and groceries [1602, 1604], Distance to closest supermarket or grocery shop [1603], Acc. Score to primary schools [1602, 1604], Distance to closest primary school [1603], Acc. Score to kindergartens [1602, 1604], Distance to closest kindergarten [1603], Acc. Score to pharmacies [1602], Distance to closest pharmacy [1603, 1604], Acc. Score to hospitals [1602], Distance to nearest hospital [1603, 1604], Acc. Score to bars and coffee shops [1602, 1604], Distance to closest bar or coffee shop [1603], Acc. Score to park and open spaces [1602, 1604], Distance to closest park or open space [1603], Acc. Score to post offices [1602], Distance to nearest post office [1603, 1604], Acc. Score to hardware stores [1602], Distance to nearest hardware store [1603, 1604], Acc. Score to sport facilities [1602], Distance to closest sport facility [1603, 1604], Acc. Score to restaurants [1602, 1604], Distance to closest restaurant [1603], Acc. Score to cultural venues [1602, 1604], Distance to closest cultural venue [1603], Accessibility score to banks & ATMs [1602], Distance to closest bank or ATM [1603, 1604], Acc. Score to clothing shops [1602, 1604], Distance to closest clothing shop [1603], All accessibility score sum [1601, 1605], All distance to closest facilities sum [1601, 1606], |
| Input | Socio-demographic | Child ratio | Children rate [1701], |
| | | Over65 ratio | Over-65 rate [1801], |
| | | Foreigner ratio | Foreigners rate [1901], |
| | | Employment ratio | Employment rate [2001], |
| | | Age ratio | Average age in TAZ [2101], |
| | | Household size ratio | Average persons quantity per household [2202], Large households (over 2px) ratio [2201], |
| | | Income | Average income per taxpayer [2301], Average income per inhabitant [2302], Average income per household [2303], |

Note: The indicators tagged with "*" represent the auxiliary-like variables excluded in the restricted set of indicators.

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