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R-Map
MAPPING THE EFFECTS OF REMOTE WORKING ARRANGEMENTS IN URBAN AND RURAL AREAS

D2.1

The R-Map model (v2)

University of Twente

31/03/2025

Funded by the European Union

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Project Information

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PROJECT OVERVIEW	R-Map aims to analyse the impact of remote working arrangements (RWAs) on the disparities between urban and rural regions in Europe. An Integrated Impact Assessment Framework (powered by the R-Map model) will be produced for the assessment of individual, social, economic, environmental and spatial impacts of RWAs. It will also allow decision-makers to monitor and assess how remote work arrangements affect people, communities, space, economy, and environment in urban and rural regions. Furthermore, R-Map will formulate policy recommendations on how to create environments conducive to remote work, that are tailored to the needs of local governments in both urban and rural settings.

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Abbreviations

Table 1: Abbreviations

RWA	Remote Working Arrangements
LAU	Local Area Unit
NUTS	Nomenclature des unités territoriales statistiques (Nomenclature of Territorial Units for Statistics)
COVID	Coronavirus Disease
HEU	Horizon Europe
PSM	Participatory systems mapping
CLD	Causal Loop diagram
FCM	Fuzzy Cognitive mapping
WP	Work package
BBN	Bayesian Belief Network
OSM	OpenStreetMap
GDP	Gross Domestic Product
Del	Deliverable
GIS	Geographic Information System
DAG	Directed Acyclic Graph

Executive Summary

Remote working, initially referred to as telework or smart work, has been a subject of research since the 1970s. The emergence of advanced information technology has facilitated professional work beyond traditional office spaces, impacting urban and rural dynamics, transportation, environmental factors, economic structures, and social relations. The COVID-19 pandemic accelerated the adoption of remote working arrangements, highlighting gaps in policies, regulations, and the need for systematic impact assessment.

The HORIZON-EUROPE-funded R-Map Project (Mapping, Understanding, Assessing, and Predicting the Effects of Remote Working Arrangements in Urban and Rural Areas) seeks to comprehensively analyse the spatial, economic, and social effects of remote working arrangements, across Europe. Conducted by an international consortium from Greece, Turkey, the UK, the Netherlands, Italy, Austria, and Belgium, the project aims to understand and forecast the consequences of RWAs while providing actionable recommendations for policymakers.

Understanding the interconnected social, spatial, and economic impacts of RWA presents a significant challenge due to the complexity of its cause-effect relationships. To address this, Task 2.1 and 2.2 focus on co-designing an integrated impact assessment framework—the R-Map model—which systematically maps these relationships and implementing the model. The R-Map model serves as a conceptual framework to assess the effects of RWAs on the spatial, economic, and social aspects of the urban-rural divide in EU regions, and the implemented causal chain illustrates how parts of the conceptual framework can be translated into a computer model. A co-design process to conceptualise the R-Map model engaged consortium partners, the R-Map Advisory Board, and domain and regional experts, ensuring an interdisciplinary approach. The implementation of the causal chain model built on the conceptual model. Key sub-objectives were:

- Knowledge Synthesis: Establishing a shared understanding of the urban-rural divide based on WP1 findings.
- Dimension Definition: Defining the spatial, economic, and social dimensions of the urban-rural divide in the context of R-Map.
- Key Factor Selection: Identifying critical factors influenced by RWAs across diverse regions.
- Factor Assessment: Semi-quantifying these factors with expert input to evaluate their significance.
- Arrive at a conceptual R-Map Model
- Formulate indicators and harmonize datasets to inform a causal chain
- Detail, implement and validate the R-Map Model

The co-design process incorporated a review of participatory and analytical methods, including Causal Loop Diagrams, Fuzzy Cognitive Mapping, Participatory System Mapping, and Bayesian Belief Networks. A review of public and unconventional datasets (e.g., social media data) and WP1.5 survey results was also conducted.

R-Map Conceptual Model Development

The model was co-designed using Participatory System Mapping, incorporating expert and experiential knowledge. The conceptual R-Map model features:

- Causal impact chains across spatial, economic, and social domains.
- A comprehensive causal network illustrating factor interdependencies.

The R-Map model distinguishes drivers of remote working (e.g., digital infrastructure, transport accessibility, taxation policies) from impacts across spatial, social, economic, and environmental domains. Key social impacts include health and well-being, caring responsibilities, and social cohesion. Spatial impacts include polycentricity, land consumption, multilocality, mobility patterns, and relocation. Economic impacts include employee productivity, access to labour markets, and regional economic development. Additionally, socio-economic impacts—work-life balance, workplace loneliness, cost of living, and tourist/digital nomad living space demand—were identified. Carbon emissions was incorporated later as an environmental impact.

The model maps causal relationships between factors such as health and well-being, work-life balance, workplace loneliness, mobility patterns, polycentricity, and regional economic development. It distinguishes between direct and indirect causal relationships in specific causal chains, identifying mediators, confounders and colliders that influence impact assessments. The temporality of impacts varies, with short-term effects observed in workplace loneliness and work-life balance, while long-term effects emerge in spatial planning, land consumption, and regional economic shifts.

Consensus among partners confirmed the strong effects of RWAs on health and well-being, mobility patterns, multilocality, polycentricity, social cohesion, work-life balance, workplace loneliness, access to labour markets, and local/regional economic development. The study also highlighted the role of digital infrastructure and transport accessibility as key drivers of RWAs and polycentricity's broad influence across spatial and economic domains. The identification of mediators, confounders and colliders, along with the semi-quantification of indicators, facilitates the transition of the conceptual R-Map model into a computational model. Bayesian approaches will be used to refine causal relationships and enhance predictive capabilities.

R-Map Model Operationalisation and Key Insights

The implementation process involves several key steps: (1) selecting indicators and proxy variables for the factors identified in the conceptual model; (2) harmonising datasets to ensure consistency in scale, format, and spatial resolution, with a focus on the NUTS-2 level; (3) identifying a representative causal chain for implementation, based on data availability and interpretability; (4) reformulating causal relationships including the introduction of relevant control variables, while preserving the original conceptual structure, and (5) building and validating the model as an operational statistical system. The R-Map model is implemented as a Bayesian network in the Python programming environment, treating the conceptual structure as a graph-based representation of probabilistic relationships between variables. The model integrates two primary data streams – empirical indicators derived from harmonised datasets; and stakeholder-informed priors, gathered through participatory activities and surveys conducted during Task 2.1. These inputs allow the Bayesian framework to quantify both expert-derived assumptions (as priors) and data-derived likelihoods, resulting in posterior distributions that capture the strength and uncertainty of relationships across the causal network. This structure supports both diagnostic analyses (i.e., identifying drivers of outcomes) and predictive analysis (e.g. simulating scenarios with predefined inputs).

As a proof of concept, the analysis focuses on a specific causal chain: from RWA to Regional Economy, also incorporating factors such as tourism demand and transport accessibility, sequenced temporally based on the relative immediacy of their impacts as identified in survey data. We also run the model to investigate the influence of the different drivers on RWA, including digital infrastructure accessibility, industry composition, demographics and country-fixed effects to capture variation in institutional frameworks. While significant drivers of RWA are identified—such as digital infrastructure, industry composition, youth demographics, and country-specific effects—the downstream influence of RWA on regional GDP is found to be statistically inconclusive within the current framework, likely due to data constraints and time-lagged impacts.

Implications and Future Research Directions

The findings obtained underscore the need for finer-grained data over multiple time points as macroeconomic impacts of RWA may manifest only over longer time horizons. The incorporation of spatial dependencies is proposed as a methodological enhancement to explore potential neighbourhood spillover effects, which are particularly relevant in regional development and cohesion policy contexts.

Looking forward, the R-Map model will serve as the foundation for regional case studies under WP4. The framework is designed to be scalable and extensible, allowing for the integration of new datasets, updated causal chains, and refined indicators. Moreover, the model's structure supports its evolution into an interactive platform, equipped with modules for data harmonisation, visualisation, and user interface functionalities. These enhancements will increase the model's accessibility and utility for both academic research and evidence-based policymaking.

1. Introduction

Remote working, in early studies often referred to as telework or smart work, can be defined as professional working that takes place outside the office/workspace with the use of IT technology. The occurrence and effects of remote working have been researched already since the 1970s (Adobati and Debernadi 2022). A strong focus of research conducted on remote working has ever since been on the multitude of potential positive or negative impacts of remote working on e.g. spatial arrangements in cities and regions, transport infrastructure and mobility on employees, environmental impacts such as air and noise pollution and carbon emissions, and economic and social impacts for both employers and employees, among other impacts.

The COVID-19 pandemic at the beginning of the 2020s gave a massive push not only to various remote working arrangements and technologies but also boosted research on both. Key findings (Krasilnikova and Keitel 2022) highlighted significant policy gaps and a lack of regulations and procedures to implement remote working arrangements (RWA). Further findings revealed that impacts of RWA can differ quite strongly between countries and regions, between economic sectors and can impact gender inequalities.

With the ongoing rapid development of information and communication technologies including the adoption of AI in many economic sectors, the way of working will further change profoundly in many branches, and it is likely to assume that flexible working arrangements are continuously increasing with remote working becoming a natural part of it. Considering that, it is essential to better understand the diverse impacts of remote working to devise suitable remote working policies harvesting its positive outcomes and impacts on societies and countries and mitigating the negative impacts.

1.1 Background and project context

This report is written in the context of the HORIZON-EUROPE (HEU) funded **R-Map Project (Mapping, understanding, assessing and predicting the effects of remote working arrangements in urban and rural areas**) (Project 101132497 — R-Map), which is conducted by an international consortium of academics and professionals from Greece, Turkey, UK, Netherlands, Italy, Austria and Belgium. The overall goal of the R-Map project is to understand, forecast and suggest ways to address the impacts of remote working arrangements on the spatial (including environmental), economic and social facets of the urban-rural divide in Europe. This goal first requires a comprehensive understanding of the diversity of RWA across Europe and the diversity of impacts and effects resulting from them which has been accomplished in WP1 (Deliverables 1.1-1.4).

Considering the insights of different RWA across Europe and the variety of impacts in the spatial, social and economic domains, an impact assessment model needs to be developed that allows to map, analyse and estimate future impacts of RWA and their relations under changing conditions. For this task, a basic impact assessment framework is required that is broad enough to cover the diversity of impacts and RWA across Europe and at the same time sufficiently flexible to be applied to varying contexts of diverse European regions. The development of the overall impact assessment framework and model is part of WP 2 while the application and contextualization of the R-Map model to various European regions is done in WP 4 of the R-Map project.

That said, in WP2 the development of the impact assessment framework and R-Map model relies strongly on the knowledge obtained in WP1, i.e. the insights about RWA across Europe and the elicitation of impacts of RWA on the spatial, social and socio-economic domain, as reported in scientific literature and observed in practice. The goal of the project is to base the development of the R-Map model not solely on scientific insights reported in the literature as the evidence on RWA impacts is partly in its infancy and currently deriving novel insights resulting from the COVID-19 pandemic, but also include experiential and professional knowledge from regional and domain-specific experts through a co-design process.

1.2 Objectives and scope of Work Package 2 and Tasks 2.1 and 2.2

The goals of WP2 entitled “Design of the R-Map model” are (i) to develop an Integrated Assessment Framework (the R-Map model) for assessing social, spatial and economic impacts of remote working arrangements at the European level, (ii) to develop a typology of EU regions based on how remote working arrangements have affected the spatial, economic and social facets of their urban-rural divide, and (iii) to define a taxonomy of economic and social impacts of remote working arrangements.

The objective of the here reported Task 2.1 is to co-design the R-Map model for assessing the effects of RWA on the spatial, economic and social facets of the urban-rural divide in EU regions. This objective entails the sub-objectives of (1) synthesizing the knowledge produced in WP1 to agree on a common understanding of the urban/ rural divide, (2) defining the spatial, economic and social dimensions of the urban-rural divide in the context of R-Map, (3) selecting the key spatial, social and economic factors of the urban/ rural divide that are affected by remote working arrangements in the different regions, and (4) assessing and semi-quantifying these factors in terms of their importance drawing on expert knowledge. Output of Task 2.1 is the conceptual design of the R-Map model including semi-quantified cause-effects impact chains across domains and an overview of suitable data sources and sets to inform the selected impacts.

Task 2.1 started with a review of participatory model-building methods and statistical methods for integrated impact assessment. Then, a review of publicly available datasets to inform spatial, social and economic factors representing impacts of remote working arrangements was conducted. This review also entails the inspection of unconventional data sources such as data derived from social media platforms, and an exploration of the data quality resulting from the large-scale survey conducted in WP 1.5. The co-design process as such consisted of 1 day co-design workshop at the University of Twente in September 2024, and 4 online (technical) workshops with consortium partners, advisory board members and domain and regional experts in which each iteration of the R-Map model was discussed and reflected upon. In between the workshop session, all partners were involved in the co-design via an online survey and review tasks.

The objective of the here reported Task 2.2 is to detail, implement and validate the R-MAP-model for assessing the effects of remote working arrangements on the spatial, economic and social dimensions of the urban-rural divide in EU regions. The R-Map conceptual model arrived at Task 2.1 serves as the foundation for Task 2.2. More specifically, Task 2.2 is structured around three core sub-objectives: (1) formulating indicators for the identified spatial, social and economic factors in Task 2.1, (2) prepare and harmonize data sets to inform these indicators (either quantitatively or qualitatively), and (3) implementing the integrated R-Map model. The key output of Task 2.2 is the R-Map Integrated Assessment Framework, which formalises the conceptual structure into a working model capable of supporting empirical analysis and policy-relevant insights.

In addition to the sub-objectives above, several critical steps were undertaken to operationalise the R-Map model:

1. Development of indicators and proxy variables aligned with the conceptual factors identified in Task 2.1;
2. Harmonization of datasets to ensure consistency in spatial resolution (primarily at the NUTS-2 level), format, and coverage;
3. Selection of a representative causal chain for implementation, guided by data availability and interpretability;
4. Reformulation of causal relationships, incorporating control variables as necessary, while maintaining coherence with the conceptual structure;
5. Construction and validation of the model as an operational statistical system.

The R-Map model is implemented as a Bayesian network using the Python programming environment, in which the conceptual model is translated into a graph-based statistical representation of interrelated variables. The model synthesises two principal data streams: empirical indicators derived from harmonized datasets; and stakeholder-informed priors, elicited through participatory processes and surveys conducted in Task 2.1. This Bayesian approach enables the integration of expert-informed assumptions (priors) with data-driven evidence (likelihoods), generating posterior distributions that quantify the strength, direction, and uncertainty of causal relationships. The resulting model facilitates both: diagnostic analysis—to identify the most influential drivers of observed outcomes, and predictive simulation—to explore hypothetical policy or behavioural scenarios based on predefined input values.

1.3 Project partners and others contributing to the report

The co-design of the R-Map model was a collaborative effort led by the UT team. It actively involves all partners of the project consortium and the R-Map Advisory Board, as well as domain and regional experts to accommodate the inter- and transdisciplinary nature of the topic. All experts participated in the 1-day co-design workshop at the UT and the subsequent online validation workshop (see for details section 2.3 and annex table 1 for a detailed list of participants). Also, the so-called sister projects of the R-Map project, the WinWin4WorkLife (WW4WL) project (https://winwin4worklife.eu) and the REMAKING project (https://remaking-project.eu) were contacted and invited to contribute to the co-design process during the online validation workshop. From these, WW4WL accepted the invitation and contributed valuable inputs to the process.

1.4 Outline of the report

Section 2 outlines the methodological approach used for the development of the R-Map conceptual model. It presents the rationale for selecting suitable participatory modelling and integrated impact assessment methods, establishes the relevant terminological and methodological framework, and details the co-design process employed to develop the R-Map model for assessing the social, spatial, and economic impacts of Remote Working Arrangements (RWAs). Section 3 provides a comprehensive description of the resulting conceptual R-Map model, including an in-depth discussion and analysis of the selected factors and the causal relationships that link them. Section 4 presents a critical review of the existing data sources available to inform and quantify the model's factors, serving as the empirical foundation for the model's operationalisation.

Section 5 focuses on the implementation and operationalisation of the R-Map model, including the steps taken to translate the conceptual framework into a functioning statistical model. Section 6 offers a critical reflection on the model's outcomes, evaluating its scientific contribution, practical strengths, and acknowledging potential limitations and challenges in its application. Finally, Section 7 concludes the report by summarising the main findings and providing an outlook on future research directions and planned follow-up activities.

2. Methodology - Conceptual model development (Task 2.1)

Section 2 reports on the methodology applied in Task 2.1. The objective of Task 2.1 is, in short, to conceptually develop the R-Map model as an integrated assessment model of remote working impacts. The basis for the model development is the literature review and expert consultation conducted in WP1 and the experiential knowledge of the entire R-Map consortium, the advisory board members and other invited experts. The methodological approach we choose is a participatory model-building approach using causal mapping methods embedded in a co-design process.

The section starts with a review of participatory causal mapping methods for integrated assessment (section 2.1). Section 2.2 summarizes the overall methodologic approach to the task and provides conceptual definitions and the key terminology. Section 2.3 reports the implemented co-design process.

2.1 A review of causal mapping methods for integrated impact assessment

In this section, we elaborate on the different causal mapping methods that can be utilized for integrated impact assessment. We discuss the most relevant methods with respect to the co-design of the R-Map integrated impact assessment model.

A causal diagram that represents cause-effect relationships within a system helps in understanding a certain phenomenon, e.g. impacts of remote working arrangements (Cunningham, 2021). Developing such a diagram requires integrating expertise derived from multiple sources, including theory, scientific models, expert input, personal observations and experiences, evidence from literature, intuition, and hypothesizing. As emphasized by Pearl & Mackenzie (2019), data alone cannot establish causality within a system; causal inference relies on constructing a causal diagram to examine the relationships of cause and effect within a system or phenomenon. Pearl (2009) specifically refers to directed acyclic graphs (DAGs), often used to structure Bayesian Networks and counterfactual analysis.

The co-design approach (Section 2.3) that is aimed at, in this task emphasizes the importance of participatory methods for constructing causal maps, involving experts and stakeholders to collectively identify system components and relationships. Participatory causal mapping encompasses a range of methods, from qualitative to quantitative, including Causal Loop Diagrams, Participatory System Mapping, Fuzzy Cognitive Mapping, and Bayesian Belief Networks. These methods are sometimes referred to as mind mapping, cognitive mapping, system mapping, or causal diagrams (Barbrook-Johnson & Penn, 2022).

As Barbrook-Johnson & Penn (2022) highlight, causal mapping techniques can be viewed as methods that help produce simplified models composed of a set of elements, the relationships between them, and the system boundaries being examined. Some approaches, like Causal Loop Diagrams, Participatory System Mapping, and Fuzzy Cognitive Mapping, prioritize a system-wide perspective. Others, such as Bayesian Belief Networks (BBNs), focus more explicitly on designing and assessing interventions. Methods also vary in their level of quantitative analysis and ease of stakeholder participation. Figure 1 below illustrates how different system mapping techniques can be positioned based on their degree of quantification and the ease of participant involvement. In practice, often a combination of system mapping methods is used to address a particular question.

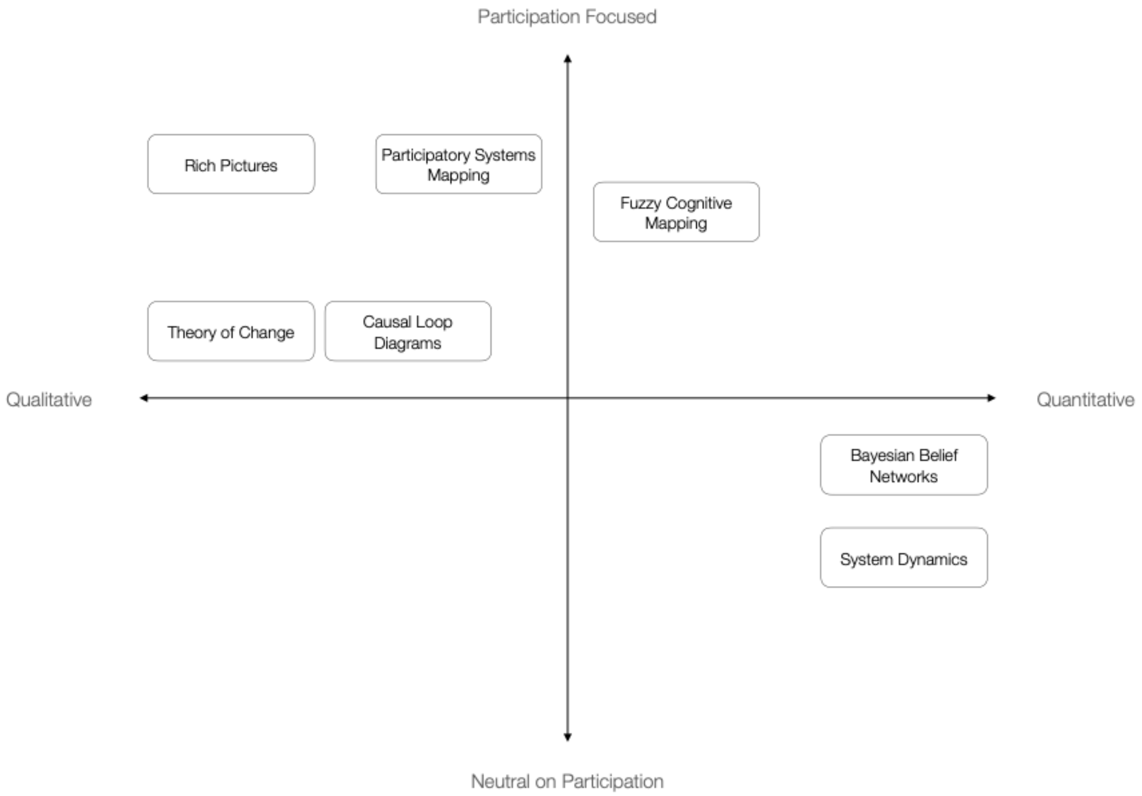

Figure 1: The different system mapping methods, adapted from Barbook-Johnson and Penn (2022)

In the following, we provide a brief overview of selected methods—Causal Loop Diagrams, Participatory System Mapping, Fuzzy Cognitive Mapping, and Bayesian Belief Networks—which are particularly relevant for the development of the R-Map model. These methods strike a balance between qualitative and quantitative approaches, enabling maximum co-creation while maintaining a high level of quantitative sophistication. By combining methods in a causal mapping exercise, we can secure broad inputs without compromising analytical rigor. These methods are presented in their increasing quantitative sophistication, moving from qualitative to quantitative approaches. For each method, we highlight its respective strengths and weaknesses, forming the basis for our selection criteria and linking the problem to the most suitable approach, as detailed in section 2.2. An overview of additional methods, such as Rich Pictures, Theory of Change, and other system mapping techniques, can be found in Barbrook-Johnson and Penn (2022).

Before delving into the methods, we introduce and define the common components of causal maps, as represented in Figure 2.

Network: A network consists of nodes (boxes) connected by edges (links). In causal system maps, these edges are typically directed, meaning they take the form of arrows pointing from one node to another

Nodes: These represent the key elements or variables in the system being analysed. These are the boxes within a network where edges meet.

Links (a.k.a. edges): These are the connections or relationships between nodes, visualized as lines or arrows that indicate causality or influence

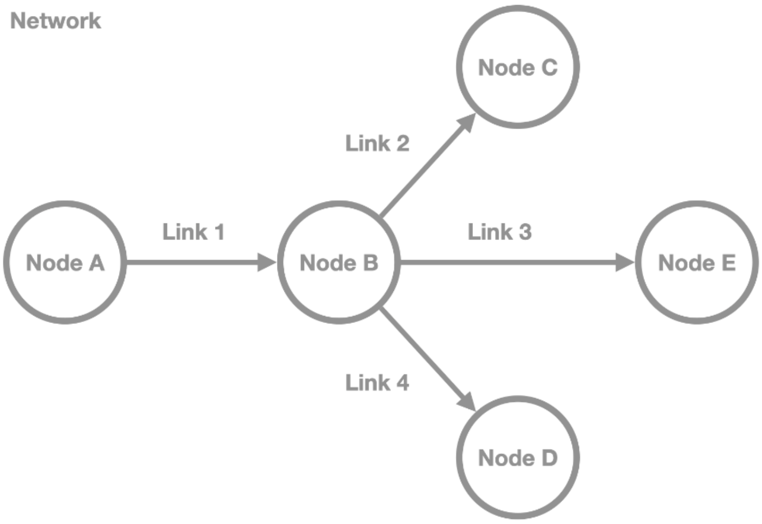

Figure 2: Components of a causal map – the network formed of nodes and (directed) links

2.1.1 Causal Loop Diagrams

Causal Loop Diagrams (CLDs), rooted in the System Dynamics approach to simulation modelling, are tools for visualizing and analysing the interdependencies and feedback dynamics within a complex system (Penn et al., 2013; Sterman, 2000). They are situated roughly in the middle of the qualitative-quantitative spectrum of causal mapping methods (Figure 1), leaning more towards the qualitative side. They provide insights into the dynamics of a system, with a particular focus on feedback loops as a central component and organizing structure for complex systems. Due to their emphasis on feedback loops and the strict use of variables for nodes, CLDs are a natural stepping-stone to simulation methods such as stock-and-flow diagrams and system dynamics (Barbrook-Johnson & Penn, 2022).

At the core of a CLD are nodes, which represent variables or system elements, arrows that depict causal relationships between them, and feedback loops (as depicted in Figure 3). The boxes, or nodes, can be anything that makes sense to consider as increasing or decreasing along a scale. Each arrow indicates the direction of influence, with a "+" signifying a positive relationship (where both variables increase or decrease together) and a "−" representing a negative relationship (where one variable increases while the other decreases, and vice versa). These relationships intertwine to form feedback loops, which can be classified as either reinforcing loops (R) that amplify changes through positive feedback or balancing loops (B) that stabilize the system through negative feedback. In a reinforcing loop, change in one direction is compounded by more change. For example, money in a savings account generates interest, which increases the balance in the savings account and earns more interest. Balancing loops, in contrast, counter change in one direction with change in the opposite direction. Balancing processes attempt to bring things to a desired state and keep them there, much as a thermostat regulates the temperature in a house.

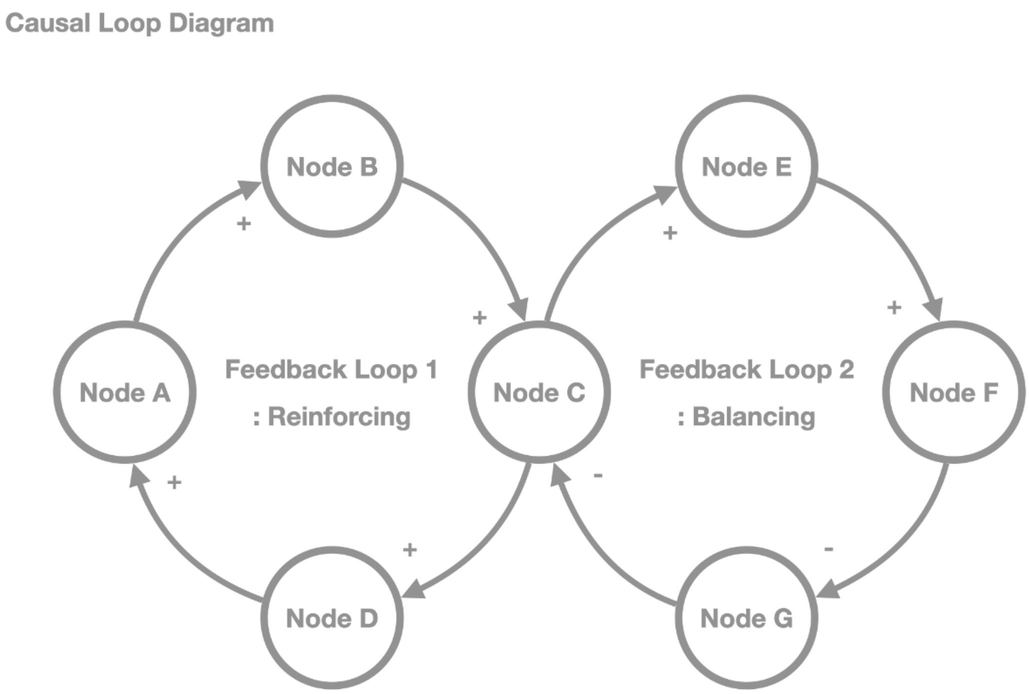

Figure 3: Components of a Causal Loop Diagram (CLD): nodes, links and feedback loops

An example relevant to R-Map is the relationship between the number of hours spent working remotely (used here as a working definition of Remote Work Arrangements, or RWAs) and polycentricity, as illustrated in Figure 4. A positive relationship can be mapped, where increased hours of remote work enhance the likelihood of individuals relocating or engaging in activities across multiple localities (multilocality). These immediate outcomes, in turn, may contribute positively to the emergence of new centres and the process of decentralization, collectively referred to as polycentricity. However, unlike causal loop diagrams (CLDs), which primarily emphasize feedback loops, this example does not include such a loop. The components integrated from various methods, including CLDs, will be discussed later in accordance with our specific requirements.

As Barbook-Johnson and Penn (2022) highlight, CLDs can be constructed in a participatory manner, where discussions during workshops serve as data. However, due to the rigour required to focus on a system's feedback loops in a participatory setting, decisions are often made by the modeler or researcher. On the downside, Causal Loop Diagrams (CLDs) can be limiting due to their strong emphasis on feedback loops, which can concentrate a lot of power in the hands of the researcher, particularly during the creation of these loops. If feedback loops are not present or significant in the examined system, this method may be less effective. Additionally, being positioned in the middle of the qualitative-quantitative spectrum means that CLDs do not provide any quantitative analysis. As a result, without quantitative data, it can be challenging to meaningfully understand how multiple feedback loops will interact.

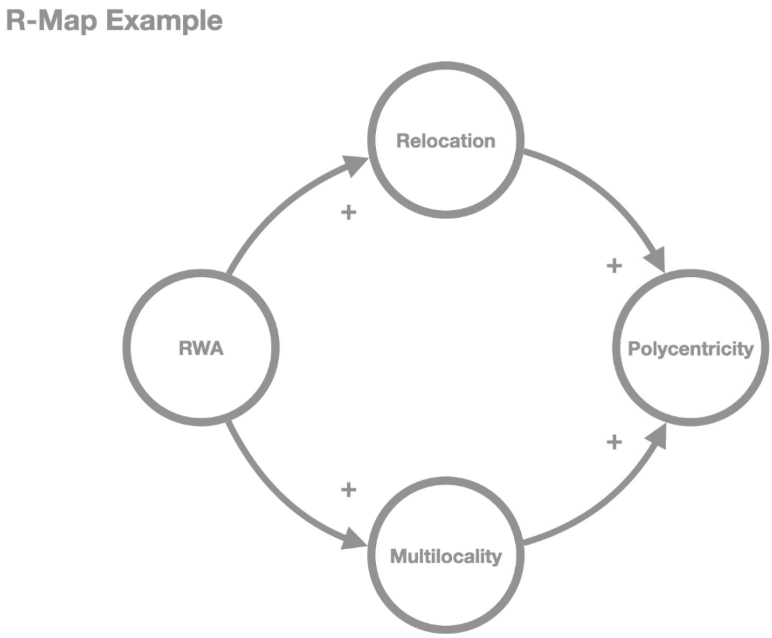

Figure 4: Example of a causal chain in the R-Map model and positive relationships between factors

2.1.2 Participatory System Maps

Participatory System Maps (PSMs) are causal models of a system represented by a network of factors and their causal relationships (Barbrook-Johnson & Penn, 2022). These maps are typically annotated and layered with detailed information about the factors and their connections. Technically, PSMs are directed cyclic graphs, meaning that the connections between factors are represented by directed arrows and feedback loops can exist within the network. The maps are developed by stakeholders, usually through a series of workshops and meetings, with the participatory nature of their creation being of utmost importance. The analysis approach also relies heavily on stakeholder input, network analysis principles, and an examination of the 'flow' and chains of causal relationships—often referred to as 'causal flow', thereby creating submaps focused on exploring specific questions or purposes in a highly participatory and iterative manner, which are brought together to create larger maps at times. The nodes in the map are referred to as factors. They can come from any relevant domain; they do not need to be explicitly quantifiable or supported by data, but they should be expressed as variables, i.e. elements in the system that can increase or decrease. There are often special types of factors, such as outcomes or functions of the system that are of interest, or interventions that can be controlled. The connections in the map represent causal relationships, which can be positive (i.e., if A increases or decreases, B changes in the same direction), negative (i.e., if A increases or decreases, B changes in the opposite direction), or uncertain/complex (i.e., where causal relationships depend on other factors or contexts, or where the relationship is strongly nonlinear). PSM are in the middle of the spectrum between flexible and qualitative methods such as rich pictures and theory of change, and more formal quantitative methods, such as Bayesian belief networks and system dynamics. They are likely to work best when using systems mapping in a participatory and flexible manner, but with a structure given by clear definitions of how the model works and how it can be analysed. The main steps in the process involve deciding on the aim of the project, defining the system boundary, stakeholder selection, process design, selecting focal and general factors, building the map, collecting factor and connection information, and validating the links. After the causal map is developed, these insights can be transitioned into a more quantitative model, which can then be further enhanced using data-driven indicators.

2.1.3 Fuzzy Cognitive Mapping

Fuzzy Cognitive Mapping (FCM), developed by Kosko (1992), is a semi-quantitative tool that integrates cognitive mapping and fuzzy logic to model and analyse complex systems. It is particularly effective for studying systems characterized by uncertainty, vagueness, or incomplete data, where interdependencies exist but are not empirically defined and bridges the gap between qualitative knowledge representation (Penn et al., 2013). FCMs are particularly useful in participatory settings, as they allow stakeholders to integrate diverse forms of knowledge, experiences, and perceptions into a single coherent model. FCM enables the construction of causal maps, where system components (nodes) and their relationships (edges) are represented. Participants collaboratively identify key system components, define relationships, and assign weights to capture both the causal structure and the relative importance of variables. These relationships are weighted on a scale from -1 to +1, indicating the strength and direction of influence.

FCMs are used to identify dominant drivers, feedback loops, and system behaviours under different scenarios. Nodes represent factors that can vary in magnitude (e.g., increase or decrease), while edges indicate causal links. Relationships may not require empirical data, making FCMs ideal for exploratory analyses. A distinguishing feature of FCMs is their focus on generating outputs that support scenario testing and projections or facilitating stakeholder discussions. This capability makes FCMs highly versatile for applications such as environmental management, policy analysis, urban planning, and risk assessment (e.g. Reckien et al. 2014).

As Barbook-Johnson and Penn (2022) highlight, there are two main approaches in FCM – causal and dynamic ones. The causal approach retains the original FCM framework, where link weights represent certainty in causal relationships. Factor values range from 0 to 1 (or sometimes -1 to 1), indicating the degree of activation or causation. For instance, a factor value of 1 suggests complete activation, while 0 indicates no activation. Edges reflect certainty about causation, with stronger magnitudes implying greater confidence. This approach answers questions like: “If we change one factor, how confident are we that other factors will change?” The dynamical approach focuses on how changes propagate through the system, producing dynamic representations of relative changes in factor values. Factor values, often any real number, reflect the magnitude of an effect, while edge weights (-1 to +1) represent the strength of influence. The model tracks system behaviour iteratively until factor values stabilize or form repeating cycles. This approach helps identify the most influential factors and how structural changes affect system dynamics. Both approaches use edge values to reflect the strength of causal relationships, but their interpretations differ. The causal approach emphasizes certainty in causation, while the dynamical approach examines the propagation of effects. In summary, FCM provides a flexible framework for exploring complex systems, accommodating uncertainty and facilitating participatory analysis. FCM has been used in a variety of different scenarios, including exploration of future scenarios of deforestation in the Amazon (Kok, 2009) and bio-based economy for the UK Humber region (Penn et al., 2013).

2.1.4 Bayesian Belief Networks

Bayesian Belief Networks (BBNs) are suitable for developing probabilistic causal models (Barbrook-Johnson & Penn, 2022). Like other methods, BBNs consist of nodes (representing variables, factors, or outcomes in a system) and edges (depicting the causal relationships between these nodes). Each node has defined states (e.g., on or off, high or low, present or absent) with associated probabilities of being in each state. These probabilities are determined based on the states of the connected nodes, which have causal arrows pointing toward them. In probabilistic terms, nodes are 'conditionally dependent' on the states of the nodes with which they share a causal connection. A key distinction of BBNs is their acyclic nature—arrows flow in only one direction, and no cycles or feedback loops are present. This sets them apart from other methods, such as Causal Loop Diagrams and Participatory System Maps, which incorporate cycles and feedback mechanisms. BBNs are directional probabilistic graphical models that model conditional dependence through directed edges, and conditional independence through missing linkages (Pearl, 2014). Using Bayes' theorem, BBNs address problems in complex systems by representing joint probabilities for the factor states in a model. The term "belief" reflects the subjective specification of probability distributions and relationships, distinguishing Bayesian probability from the frequentist approach, which relies on observed event frequencies.

We can define three types of linkages and nodes based on network positions (Pearl & Mackenzie, 2019) which are useful for identifying control variables in multivariate regression analyses. This helps satisfying the "back-door criterion", i.e. blocking all non-causal paths two variables of interest, and prevents overestimation, underestimation, or spurious correlations (Cunningham, 2021). The linkage types are as follows:

Fork linkage: $a \leftarrow b \rightarrow c$

Collider linkage: $a \rightarrow b \leftarrow c$

Chain linkage: $a \rightarrow b \rightarrow c$

In a fork linkage, factor *b* acts as a "confounder," and controlling for it makes *a* and *c* independent. In a collider linkage, *b* is a "collider," representing a common effect, and controlling for it can create spurious correlations. In a chain linkage, *b* is a "mediator" that can potentially be excluded from the model to simplify it, as it does not independently cause changes.

For instance, in the R-Map framework, consider a causal chain like the one discussed in Section 2.1.1, linking RWAs to polycentricity, with two additional factors influencing relocation. Figure 5 illustrates this acyclic structure, where nodes are assigned binary states (e.g., high/low) and conditional probabilities. The table accompanying the diagram displays the probabilities of polycentricity states as influenced by its two parent nodes—relocation and multilocality.

This BBN can be employed in two ways:

1. Downstream analysis: Changing the states of specific factors to simulate hypothetical scenarios and observing their impact on downstream nodes. For example, with high relocation and multilocality levels, there is an 80% probability of observing high polycentricity and a 20% probability of low polycentricity.

2. Upstream analysis: Investigating the probable states of contributing factors that lead to a specific outcome. For instance, analyzing the likelihood of different relocation and multilocality states that result in high polycentricity.

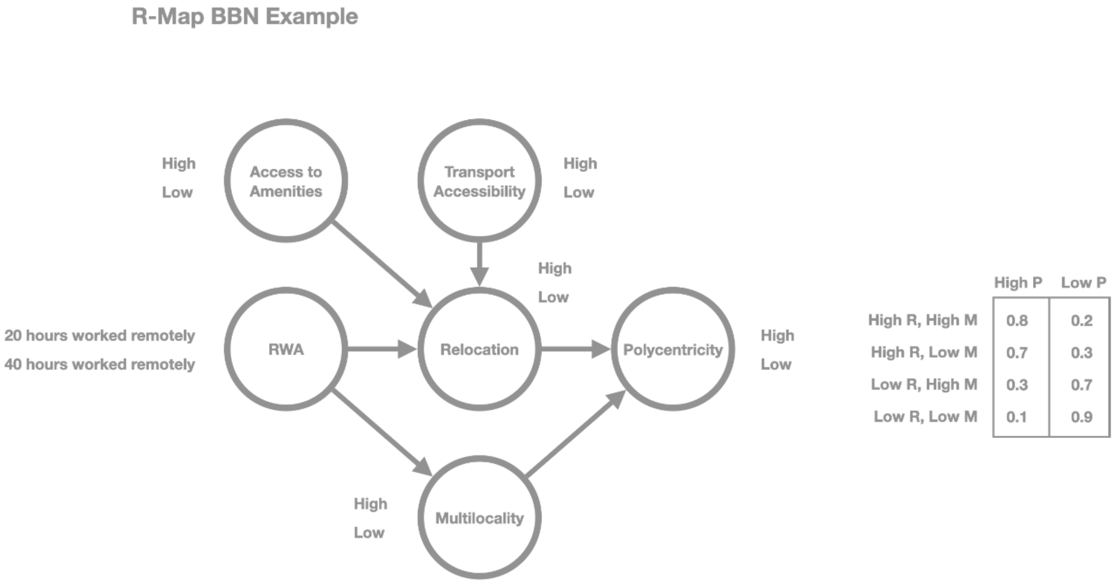

Figure 5: Example of a Bayesian Belief Network implementation in R-Map

While BBNs are highly versatile, they have certain limitations. Their acyclic nature prohibits feedback loops of any length, a constraint necessary for the mathematical calculations to remain valid. However, in complex systems where feedback loops are often key drivers of dynamics, this limitation can be partially addressed through "dynamic" BBNs, which represent the same variable at different time points using multiple nodes.

Despite this constraint, BBNs offer flexibility by incorporating broader system elements through conditional probabilities during map construction and analysis, even if these elements are not explicitly included in the network. This capability enhances their value, even when the network does not capture all potential factors. Additionally, a significant strength of BBNs is their ability to update probabilities as new data or evidence becomes available, making them particularly effective for adaptive analyses in dynamic and evolving systems.

2.2 Methodological approach and terminology

2.2.1 Methodological approach

The development of the R-Map model fulfils all 4 aspects that Penn et al. (2013) describe as the main characteristics of problems where causal mapping methods can help:

(1) when stakeholder behaviour and decisions are pivotal to a system's development,
(2) when detailed local knowledge is available but scientific data is lacking,
(3) when addressing complex 'wicked' problems with no definitive solutions, and
(4) when public or stakeholder participation is desirable or necessary.

The review of RWAs and their impacts conducted in WP1 of the R-Map project (D1.1 to 1.4) revealed that decisions and behaviour of stakeholders, e.g. policy makers, are crucial to how impacts play out in certain contexts. WP1 further showed that detailed knowledge of impacts is available across Europe and beyond, but scientific data and insights are limited to single case studies, often conducted in one region or country. The variety of impacts across these diverse case studies and contexts is a key indication of the wickedness of the problem next to its multi-disciplinary nature. This wickedness in turn requires the strong involvement of multiple stakeholders to address the challenges of impacts from RWA.

Based on the pros and cons of the different causal mapping methods elaborated above we conclude to use a Participatory Systems Mapping approach organized as a co-design process to develop the R-Map model. The PSM approach suits the iterative engagement of the R-Map consortium and other experts in the development of the R-Map model in a series of workshops. The given structure of workshops ensures a result within the limited time frame. The qualitative nature of PSM enables the contribution of stakeholders to the model despite the lack of data to quantify factors. Moreover, it retains critical details and serves as a foundation for transitioning to a more quantitative method—in this case, using a Bayesian approach (see section 5). The Bayesian setup allows us to address uncertainties in inferences and effectively manage missing variables through its probabilistic framework. A detailed description of the co-design research process is provided in section 2.3.

2.2.2 Terminology

For the participatory systems mapping approach embedded in a co-design process, we agreed on the following terminology.

The conceptual R-Map model is represented by a network of factors and their causal relationships. Factors included in the R-Map model need to fulfil the following characteristics (Table 2).

Table 2: Characteristics of Factors

Factors	Examples
Specific and measurable	In contrast to themes such as 'technology,' factors are more precise and measurable, like 'broadband access' or 'technological literacy'
Elements that are either **influenced by remote work** or have the potential to impact other factors influenced by remote work	Since the objective of this exercise is to examine the impact of remote working arrangements, the focus is on factors like 'employee productivity' rather than drivers like 'internet quality'—unless they also represent outcomes
Elements that **can increase or decrease** in value due to other factors or over time	Demographic variables such as 'age' and 'gender' are constants and do not qualify as impact factors. They will most likely be included as control variables
Preferably **neutral**, without indicating a positive or negative shift	Instead of using distinctions like 'formation (or reduction) of new social ties' it is more appropriate to use neutral terms like 'social ties', 'social network' or 'support network'
Continuous or categorical with multiple categories	We avoid binary categories since they provide limited utility for modelling. For example, 'gender equity' is a more useful factor than simply 'gender.'
Ideally, **state variables**, not events or processes	Similar to stock variables, factors represent states that can increase or decrease over time; they are not 'events' (which are one-time occurrences) or processes (like 'gentrification'). A process like gentrification is better analysed through specific state variables such as 'real estate prices' or 'net migration of communities.'
Relevant to the focus of the study	In this exercise, factors are relevant if they are significantly influenced by remote working arrangements or are sensitive to them. While gentrification might be an interesting phenomenon to study, unless there is substantial evidence or rationale to include it, it may fall outside the scope of this analysis

Factors can represent spatial as well as social or economic impacts of RWA. During a first screening of all potential factors as suggested in WP1, it became clear that some factors are rather suited to affect the implementation of RWA (such as digital infrastructure) while others are rather affected by the implementation of RWA (e.g. health impacts). To represent this distinction, we distinguish between drivers and impacts (see Figure 6).

Factors may occur as impacts that are affected by certain RWA (e.g. Health and Wellbeing) as well as drivers that affect the implementation of certain RWA (e.g. Digital Infrastructure Accessibility). For the sake of conceptual clarity, we separate in the conceptual R-Map model drivers from impacts as depicted in Figure 6.

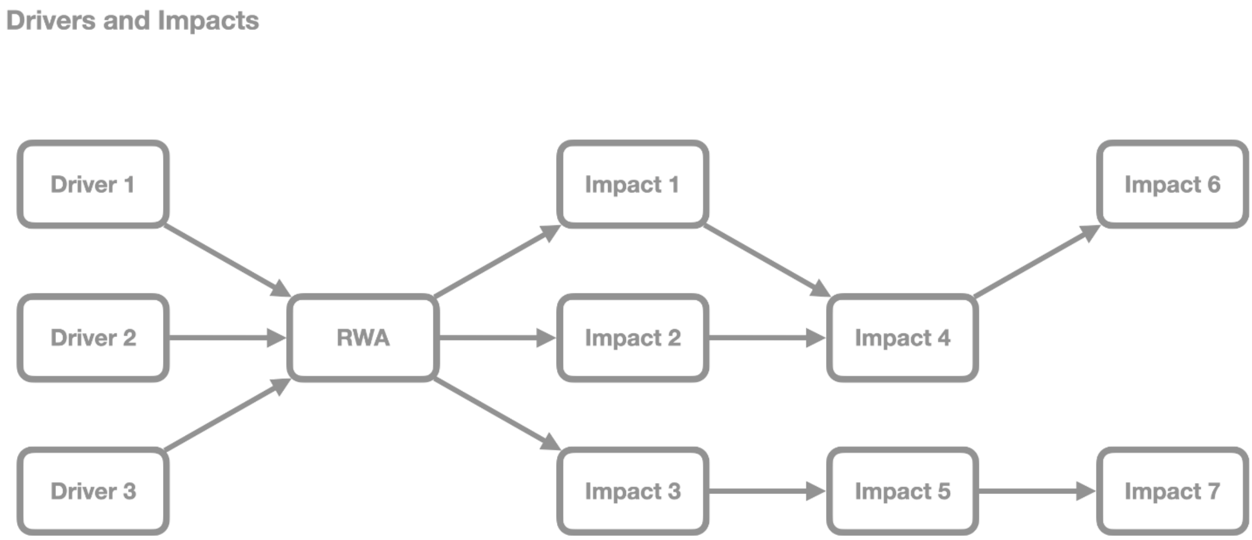

Figure 6: Separation of drivers and impacts

While drivers affect RWA directly and are mutually independent, factors are represented in the R-Map model as a network with causal relationships between them. The network of impacts results in cause-effect relationships between various impacts that can include mediating factors (mediators), confounding factors (confounders) and collider factors (colliders). A mediator is a factor that does not independently cause any change to other factors, confounders are factors that influence both the dependent variable and independent factors, and colliders are factors that are common effects in a specific causal chain (see Figure 7). Section 3.3.5 provides examples of causal chains in the R-Map conceptual model.

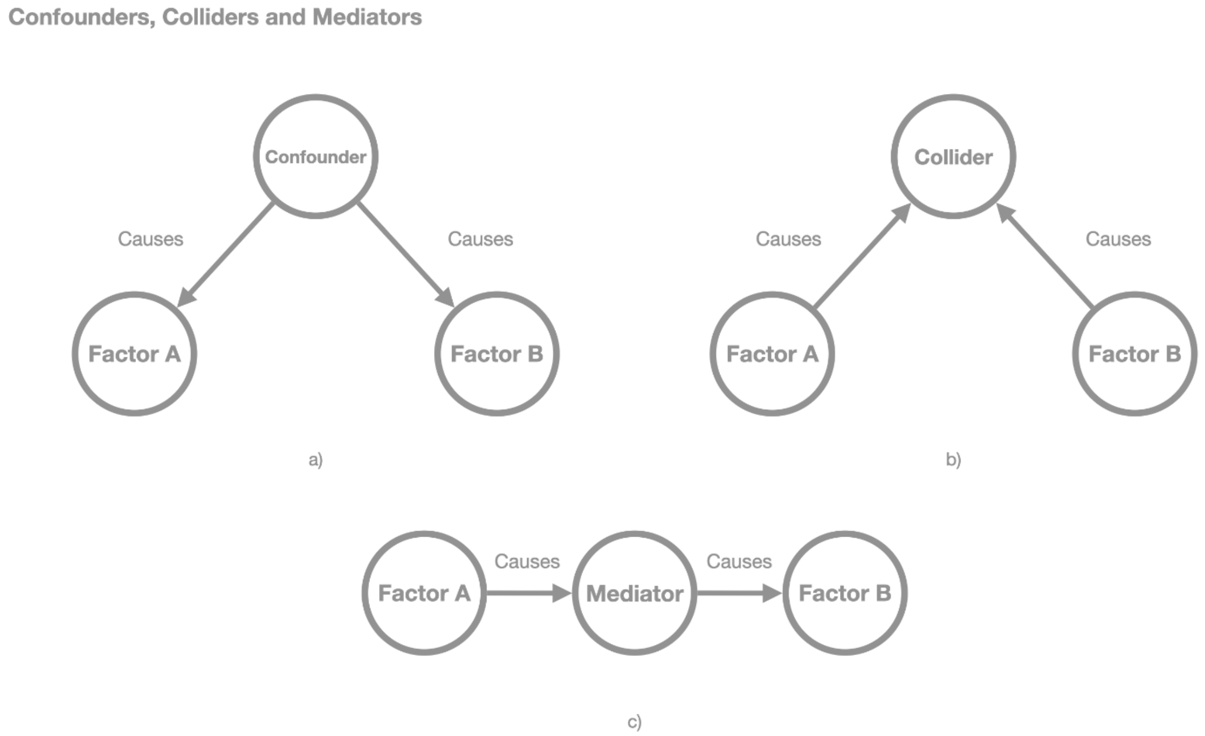

Figure 7: A factor acting as a a) confounder, b) collider and c) mediator depending on the network position in the map

The causal relations between the impacts are represented as links. These links can represent certain strengths of relation between two factors (weak, medium, strong relation), they can represent a positive (if factor A increases, factor B also increases) or a negative (if factor A increases, factor B decreases, and vice versa) relation, and they represent a relative temporality of the relation between two factors, i.e. these relations may occur either at short, medium or at the long term.

As discussed above, the impacts of RWA might differ in different contexts and constellations and vary if studied for certain sociodemographic groups or economic sectors. Impacts further differ concerning the specific RWA arrangements implemented. All these aspects are strictly speaking not part of the R-Map model but represent the so-called control variables that the R-Map model is to be checked for. A classification of typical control variables is provided in Table 3.

Table 3: Classification of Factors

Factors	Definition	Example
RWA	Metrics of professional working that takes place outside the office/workspace with the use of IT technology	The amount of time working remotely.
Branches/economic sectors	Single economic sectors having potentially specific RWAs	Industrial branches, services, education and training, etc.
Contextual factors	Spatial variations in impacts attributed to characteristics of the built and social environment	Urban or rural areas, countries, population density, etc.
Compositional factors	Differences in the composition of a group/region in terms of individual socioeconomic status or behaviour	Gender, age, income levels, household characteristics, etc.

2.3 The R-Map model co-design process

As outlined above, the goal of the co-design process is to (i) synthesize the knowledge produced in WP1 to arrive at a common understanding of the urban/ rural divide, (ii) define the spatial, economic and social dimensions of the urban-rural divide in the context of R-Map, (iii) select the key spatial, social and economic factors of the urban/ rural divide that are affected by remote working arrangements in the different regions and (iv) assess and semi-quantify these factors in terms of their importance drawing on expert knowledge and geographic context. In WP1 of the R-Map project, partners reported relevant impacts of remote working arrangements from broad literature reviews and expert interviews focusing on the social, spatial, and economic aspects of RWA that serve as input to the co-design process.

The co-design of the R-Map model is set forth through a series of workshops involving the consortium partners (UT, AUTh, UB, KU, SEERC, SURREY, RIM, Q-PLAN, WR, ARX), members of the advisory board of the projects, and other regional and domain-specific experts. The sequence of workshops includes one full-day physical workshop at the University of Twente with all consortium partners, the advisory board members and invited experts, three online workshops with the consortium partners, and a virtual validation workshop again with the advisory board, domain/ regional experts and potential users to present the results of the co-design process and seek feedback. In between the workshops, we sought additional input from partners via a survey and a request to revise and comment on factor definitions.

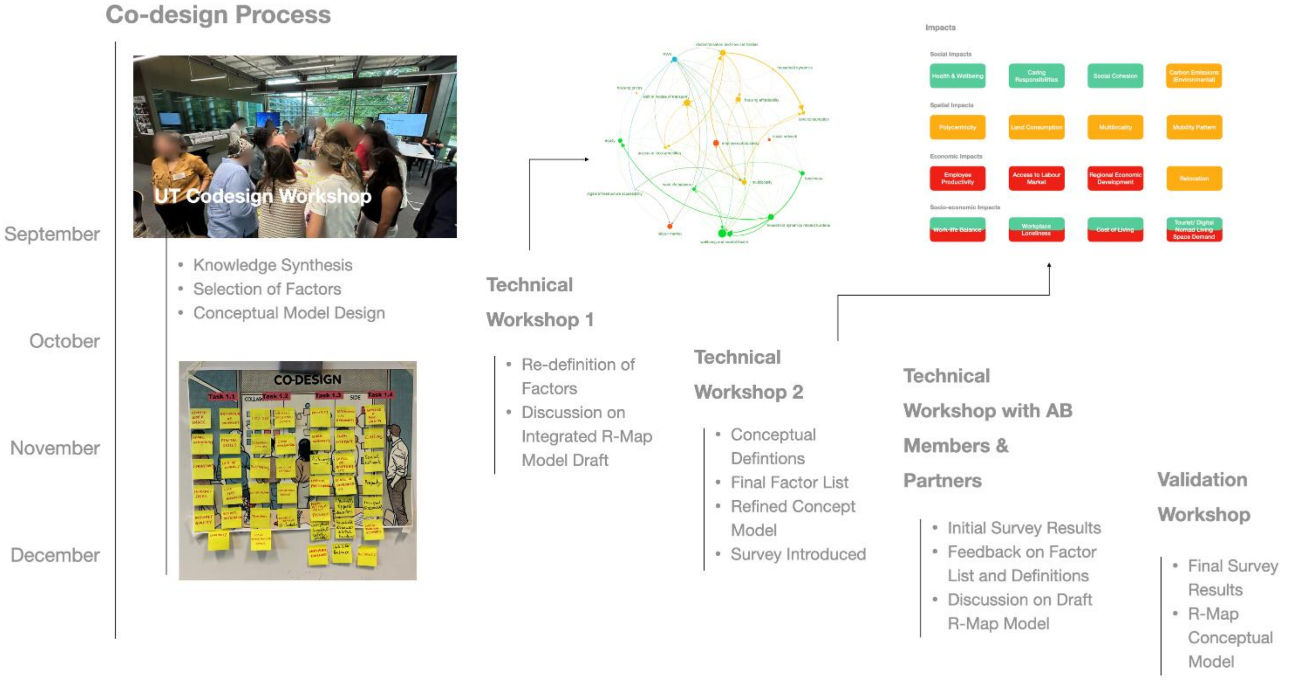

Figure 8: Schematic overview of the co-design process

2.3.1 The Co-design workshop at UT

The starting point of the development of the R-Map model was the one full-day co-design workshop at the UT with all consortium partners, AB members and invited regional and domain experts (see the full list of participants in Annex 1). The co-design workshop was conducted on September 4, 2024, at the UT in Enschede, the Netherlands.

The purpose of the workshop was to identify relevant factors from the reports of WP 1 and the experiential knowledge of all participants, to get acquainted with and practice the participatory system mapping method, and to draft relations between selected factors as a basis for the R-Map model. WP1 task leaders were requested to identify and present the ten most important factors from their studies as input to the workshop. The workshop was structured into two main steps (see Figure 9). The first step focused on knowledge synthesis, which involved the integration of scientific and experiential knowledge and the discussion of relevant factors. The second step introduced participatory systems mapping in groups to start the conceptual design of the R-Map model.

The workshop structure is described in Figure 9. The host's presentation outlined the exercise's objective, explained the terminology and methodology (see section 2.2), and described the tasks. Following this, each task leader (Task 1.1 to Task 1.4) presented their identified factors, after which participants were assigned one or two factors each. These factors were written on colour-coded cards, with each colour representing the various dimensions covered by the task leaders. The assignment of factors to participants was based on participants' expertise. The participants were then paired with someone with the same-coloured card to discuss and reflect on their factors in line with the host's instructions. This pairing promoted domain-specific discussions. Then, participants were distributed into mixed groups of 7 to 8 people across four tables, with an additional table for three online participants. The distribution ensured a balanced representation of participants from different backgrounds at each table. The task of this step was to discuss and refine, if necessary, the factors and add eventually missing factors in cross-disciplinary discussions. Once the factors were established across all tables, a joint plenary session was held to review the factors and eliminate redundancies. The participants then voted on the factors, ranking them based on their relevance to the project. Each participant had five votes to allocate. The top 15 factors, based on the voting results, were selected for the next stage of the exercise, where links were drawn between the factors. This process helped maintain manageability by limiting the number of links. In the final stage, participants, divided into the same breakout groups, used the selected 15 factors to draw causal directional links, redefining, omitting, or adding factors where necessary. The maps generated during the workshop are provided in the Annex (Annex 4, Figures 1 to 5). The criteria used to define factors are explained in section 2.2 (Table 2).

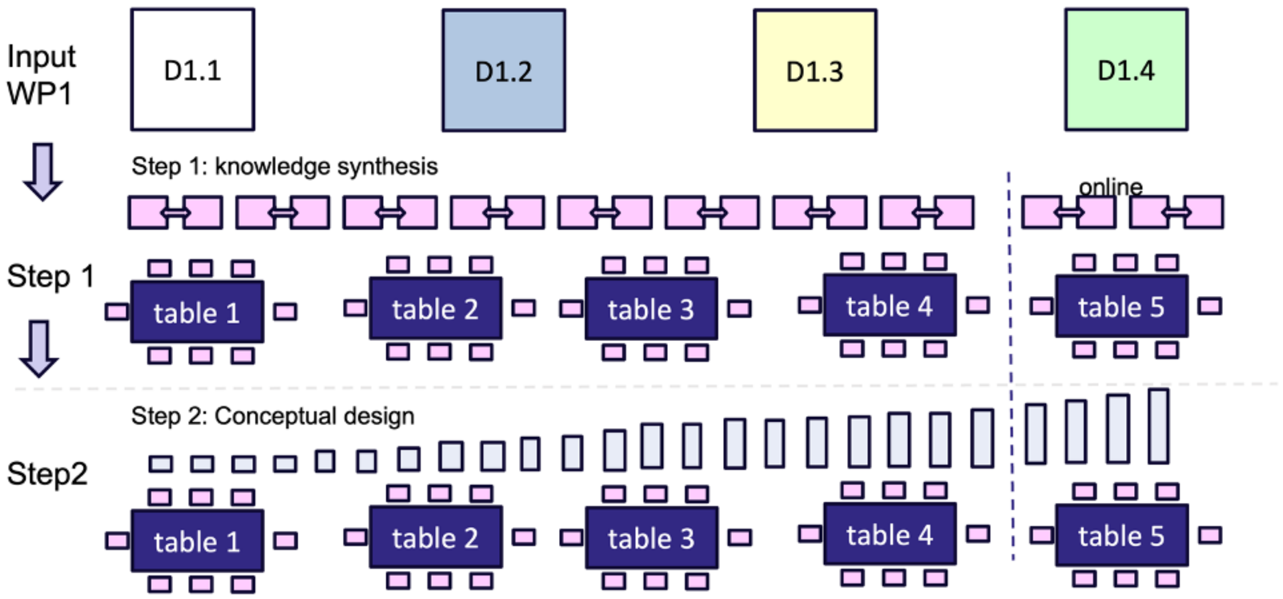

Figure 9: Workflow of the co-design workshop

2.3.2 First technical workshop

The purpose of the first technical workshop, conducted at the end of September 2024 online, was to consolidate and reflect on the results achieved in the co-design workshop at UT. Members of all consortium partners participated in the workshop. In preparation for the first technical workshop, the UT team rephrased a few original factors based on the results from the co-design workshop and started defining relevant factors that were identified through the voting at the co-design workshop.

First, the results from the participatory mapping exercise conducted in groups at the UT were presented and discussed. Part of the discussion was the rephrasing of single factors in line with the agreed characteristics of factors. Second, a consolidated network map of impacts that integrated the results from the 5 groups was presented. This integrated map served to discuss once again the distinction between drivers and impacts as well as the role of confounding and mediating factors in the R-Map model. Further various options to visualize the R-Map model were discussed.

At the end of the workshop, partners were asked to comment on the definitions of factors before the next workshop.

2.3.3 Second technical workshop

The purpose of the second technical online workshop, conducted in October 2024, was to finalize the selection and definition of factors included in the R-Map model and to focus on the participatory mapping of causal relations between factors. Members of all consortium partners participated in the workshop.

The final list of factors to be included in the R-Map model was presented in the workshop and approved by all partners. This final list resulted from the previous discussions and the comments of partners on definitions and rationale of factors. The second part of the workshop focused on the causal relation between factors. The already mapped relations were reviewed, and a few new ones were added. Also, a new visualization of the R-Map model, that presents impacts according to their temporality (short vs. long-term impacts) and their degree of aggregation (aggregated vs. disaggregated impacts) was discussed. Disaggregated impacts cause effects that are experienced on an individual or household level while aggregated effects occur at a region level.

To obtain detailed insights on the relevance and nature of causal relations between factors, the UT team set up a survey that asks to indicate the strengths (weak, medium, strong), temporality (short, medium, long-term), and directionality (positive, negative) of each already mapped link. Each R-Map consortium partner was asked to answer one survey before the next workshop, resulting in a sample of 10 answers.

2.3.4 Third technical workshop

The purpose of the third technical online workshop was to discuss the results of the partner survey on the relevance and nature of causal relations between factors and to finalize the conceptual design of the R-Map model. Members of all consortium partners participated in the workshop.

10 partners had answered the survey on causal relations between factors. The following characteristics of the relations were analysed through the survey

- Degree of Consensus on Causal Relationship: Does Factor A cause a change in Factor B?
- Strength of Causal Relationship: What is the strength of the relationship between Factor A and B?
- Type of Causal Relationship: Does an increase in Factor A cause an increase in Factor B?
- Temporality of the Relationship: How long does the relationship take to realize?

Overall, the results of the survey confirmed many of the assumed relationships. Further, a large degree of agreement between partners regarding the cause-effect relations of impacts from RWA was found.

The final part of the third workshop focused on the revision of the R-Map model based on the results of the partner survey. Single relations were removed due to a low level of agreement on the relevance or direction of the relations or a large degree of uncertainty.

2.3.5 Validation workshop with experts and advisory board members

The purpose of the validation workshop was to present the ongoing conceptual development of the R-Map model to experts outside the R-Map consortium and to obtain feedback on the relevance and significance of the results obtained. Next to the consortium partners, the validation workshop was attended by some advisory board members and three representatives of the sister project WinWin4WorkLife (https://winwin4worklife.eu). As input to the discussion the entire co-design process and results obtained were presented. The focus of the presentation was on the identified factors, the results from the partner survey, and the draft conceptual R-Map model.

The overall outcome of this validation was a large degree of confirmation of the results and findings from the co-design process. The advisory board members confirmed that their expectations raised during the co-design workshop at the UT were overall met. The members of the sister project stated that they work on their project with a very similar set of factors they consider relevant. Upon their recommendation, one additional factor (relocation) was added to the set of factors which makes a specific cause-effect chain in the R-Map model much better understandable to others.

3. The conceptual R-Map model

The section elaborates on the result of the co-design of the R-Map model. In section 3.1 the knowledge and insights collected in WP1 are summarised. Section 3.2 provides a detailed discussion of the selected factors included in the R-Map model while section 3.3 elaborates the conceptual design of the R-Map model. Section 3.4 finally looks into the transition to Task 2.2 where the conceptual R-Map model is going to be implemented.

3.1 Knowledge synthesis from WP1

WP1 of the R-Map project focused on "setting the scene" by examining the current state and prospects of remote working arrangements (Task 1.1), analysing the spatial effects of RWA across the EU and specific regional case studies (Task 1.2), assessing its impacts on working and living conditions (Task 1.3), and gaining a deeper understanding on potential socio-economic effects of RWA (Task 1.4). Key outcomes were summarized in reports (Deliverables 1.1 to 1.4), which are briefly summarized below. Following this, we highlight the key impact factors proposed by each partner as inputs for Task 2.1.

3.1.1 Deliverable 1.1: Current status and emerging trends of remote working arrangements in Europe and beyond

Deliverable 1.1 outlined that the nature of work is transforming as traditional offices give way to flexible environments like homes, co-working spaces, and informal settings. This shift, accelerated by COVID-19 and technological advancements, expands the global talent pool but also highlights disparities in access to remote work. These disparities stem from factors such as labour policies, infrastructure, digital skills, and socioeconomic development, with rural areas and less developed economies lagging compared to urban centres. The key findings are listed below.

- **Infrastructure and Skills Gaps**: Rural areas often lack digital infrastructure and skilled human capital, limiting their participation in remote work.
- **Policy Disparities**: While many EU countries have similar remote working policies, differences in governance, implementation, and protections of employees (e.g., health, safety, and privacy) persist. An effective monitoring of the governance and implementation of remote working arrangements is considered essential.
- **EU Digitalisation Goals**: Regional disparities in infrastructure and technology hinder the EU's vision of a unified digital market and digital sovereignty.
- **Stakeholder Consensus**: Remote work is here to stay, requiring clear legal frameworks and inclusive policies addressing rights, safety, and costs for remote workers.
- **Corporate and Cultural Impacts**: Remote work is reshaping corporate culture, managerial styles, and internal policies, underscoring the need for further research into its long-term effects.

3.1.2 Deliverable 1.2: Spatial implications of remote working arrangements across Europe and beyond

Deliverable 1.2 examined how the shift to remote work is reshaping urban and rural landscapes, influencing housing preferences, mobility patterns, energy use, and spatial dynamics. It focused on the driving factors behind new working spatialities, with an emphasis on place-based policies and insights from case studies and local actor interviews to contextualize regional impacts. The key findings mentioned are:

- **Emergence of New Working Spatialities**: Remote work has led to the rise of coworking spaces, digital hubs, and multilocality (operating across multiple locations). These trends are reshaping urban development, land use, real estate, mobility, social interactions and community dynamics.
- **Urban and Rural Transformations**: Urban centres, particularly central business districts, are declining, while suburban and peri-urban areas are experiencing growth, revitalizing smaller cities. Housing demand is shifting towards suburban and rural areas with more space and better living conditions, reflecting changing preferences.
- **Urban-Rural Dynamics**: Remote work can either bridge or widen the urban-rural divide, depending on how well opportunities are integrated into local economies and supported by policies.
- **Mobility**: Changes in commuting patterns (decrease of daily commute, longer commutes, altered peak hours etc) have been observed due to increased remote work.
- **Remote work's environmental impact is mixed**: reduced commuting emissions are potentially offset by higher home energy use, raising sustainability concerns.

3.1.3 Deliverable 1.3: Potential effects of remote working arrangements on the working and living conditions

Deliverable 1.3 findings revealed that remote work impacts workplace dynamics, living conditions, individual health and well-being. Organizational factors, such as engagement, satisfaction, and workplace culture, are explained to be closely tied to mental health which requires careful monitoring. The key findings are listed below:

- **Workplace Dynamics and Well-being**: Remote work can foster detachment from workplace culture, widening gaps between remote and on-site employees.
- **Living Conditions and Family Dynamics**: Altered relationships with environmental factors and service access affect living conditions. Caregiving responsibilities and gender norms heavily influence remote work experiences, with women often struggling more to balance work and caregiving.
- **Work-Life Balance and Health**: Remote work improves flexibility, reducing stress and fatigue, but extended working hours can offset the benefits of reduced commuting. Positive health behaviour (e.g., physical activity, diet, and sleep) is susceptible to blurred work-life boundaries, risking harmful habits. Organized remote work can improve mental health and behaviour but risks isolation and loneliness.

3.1.4 Deliverable 1.4: Understanding the potential socio-economic effects of remote working arrangements

Deliverable 1.4 details that many organizations are already advanced in implementing remote work, though differences exist between the public and private sectors and between large employers and SMEs. Remote work often shifts certain costs to employees, intentionally or unintentionally, and its benefits and drawbacks are unevenly distributed based on characteristics like gender, age, caregiving responsibilities, and home location. Emerging trends, such as digital nomadism remain underexplored, particularly regarding challenges like taxation and social security, which are amplified in cross-border contexts. The key findings are mentioned below under the categories of social, economic and socio-economic impacts:

1. **Social Impacts**: Gender and Age – Women gain flexibility but face higher stress and mental health challenges. Younger workers struggle with performance; older workers need telework training and gradual adaptation. Social isolation and unsuitable workspaces impact older workers' well-being.

   Work-Life Balance – Flexible hours support family life but blur work-home boundaries, reducing focus and productivity. Balancing professional responsibilities with childcare can be stressful.

   Social Network – Social isolation is a significant concern due to remote work impacting productivity, performance and well-being

2. **Economic Impacts**: Tax, Social Security, Pension, Salary parity and Insurance – Equitable pay models updated social security, and insurance policies for remote-specific risks (e.g., ergonomic injuries and cybersecurity) are essential.

   Property Market – Remote work drives suburban and rural housing demand and land values, reducing urban office use and land values in city centres.

3. **Socio-economic Impacts**: Transport and Accessibility – Reduced commuting lowers costs, stress, emissions, alleviates congestion and boosts gender equity and inclusivity for individuals with disabilities
   Regional Development: Decentralization supports smaller cities, boosts local economies, and enhances employment resilience.

3.1.5 Factors suggested by Del. 1.1 to 1.4 for UT co-design workshop

Each WP1 partners responsible for a Deliverable (1.1 to 1.4) was asked to suggest approximately 10 most important factors, i.e. the most relevant impacts from remote working arrangements, as input to the co-design workshop. The identified factors are shown in Table 4.

Table 4: Key factors identified by WP1 task leaders as input to the UT co-design workshop

Task/Deliverable	Suggested Factors
1.1	Remote work index; legal inadequacy; connectivity; internet speed; internet quality; affordability of internet; digital skills; cost of living; good life enablers; gender distribution; seniority
1.2	City size; suburbanisation; multilocality; urban decentralisation; land consumption; land-use change; gentrification; urban-rural divide; transport; local infrastructure stress; energy demand
1.3	Wellbeing and mental health; precarity level; autonomy; non-attachments degree; sustainable occupational health and safety services in RWA; flexibility types; household dynamics-related burden; work-life balance; presenteeism; workplace loneliness; level of inequalities; level of accessibility; RWAs literacy; awareness level; technological readiness; labour participation opportunities; work intensity
1.4	Gender; age; caring responsibilities; social network; property market; transport and accessibility; local tourism economy; insurance

During the co-design workshop at the UT, these factors were discussed and revised in mixed groups with experts and advisory board members (co-design process step 1). The goal of the discussion was to agree on the set of factors in a wider group and to revise them according to the defined characteristics of factors (see Table 1 in section 2.2.2; see the revised list of factors that the group agreed on in Annex 2).

3.2 Relevant factors in the R-Map model (Drivers and Impacts)

As explained above, the R-map model distinguishes factors into drivers and impacts, with additional classifications as confounders or mediators based on their network position (see section 2.2). In the following, the final selected factors resulting from the co-design process are presented and discussed. The challenges of the co-design process were to capture the multitude and diversity of impacts resulting from remote working arrangements in the R-Map model, select the most relevant factors, and define the factors precisely to avoid any misconception. Another boundary condition of the co-design process was to agree on a limited set of factors (around 15 to 20 impacts) to be included in the R-Map model to achieve a workable model that allows quantifying impacts of RWA in Task 2.2.

The factors and their classifications are further detailed in the following subsections. A list of factor definitions, which was utilized as a collaborative document for discussions, is provided in Annex Tables 3 and 4.

3.2.1 Drivers

The co-design process identified four key drivers of remote working arrangements: digital infrastructure accessibility, access to local amenities, transport accessibility, and taxation/social insurance regulations.

1. **Digital Infrastructure Accessibility**: the driver was initially suggested under internet quality (e.g. speed, bandwidth) and internet affordability by Del. 1.1 and revised and consolidated in the discussions during the co-design workshop. The factor captures the access to high quality (in terms of speed and coverage) and affordable internet. Citing Eurofound (2022), Task 1.1 identifies technical infrastructure (e.g., broadband accessibility) as a relevant driving factor which might explain variations in the prevalence of telework noted across different countries, and between urban and rural areas.

2. **Access to Local Amenities**: The factor was added during table discussions in the co-design workshop by two groups who called it 'access to local amenities and opportunities' and 'city facilities (transport, health care, amenities)'. It was merged into one factor during the plenary session and recognized as a significant factor during the voting process. Streamlining with a suggestion of Task 1.2, as to what all elements comprise amenities, the factor was finally understood as access to green areas, shopping, recreation, education, sports and community facilities, co-working spaces, etc. The factor is also understood to cover the dimension of quality of life incorporating the factor 'good life enablers', suggested by Task 1.1.

3. **Transport Accessibility**: The impacts on transport and mobility from remote work were identified as significant by Tasks 1.2 and 1.4. However, during discussions in the co-design workshop, it was classified as a significant driver, which rather influences the relocation decision of employees and thus can be characterised as a driver of RWAs. It is understood as a measure of the ease of reaching (and interacting with) destinations or activities distributed in space. A place with "high accessibility" is one from which many destinations can be reached with relative ease. It also covers aspects of accessibility to work and travel time and costs.

4. **Taxation, Social Security, Insurance Regulations**: This factor was originally suggested by Task 1.4, and emphasized by other partners during the technical workshops. This factor serves as a broad container term that encompasses economic drivers of RWA including taxation, social security, pensions, and insurance which play out differently in different contexts. The factor captures different regulations and laws governing how individuals and businesses are taxed, including income, sales, and corporate taxes, which are typically set at the country or regional level. The factor encompasses tax rate differences between countries, double tax arrangements, social security and insurance framework. As mentioned above, D1.1 elaborates that while many EU countries have similar remote work policies, differences in governance, implementation, and worker protections (e.g., health, safety, and privacy) persist, requiring effective monitoring. Further as elaborated in D1.4, remote work necessitates the development of new remuneration models that are equitable and motivating. Furthermore, insurance policies, originally designed for physical workplaces need to be updated to cover remote work environments, ensuring workers' rights and protection regardless of the work location. Due to its role as a policy lever, this factor is understood to be a driver.

3.2.2 Impacts of RWA

As analysed in WP1, impacts of RWA occur across various domains. During the co-design process, the R-Map team agreed to distinguish spatial, social, economic and socio-economic domain impacts. The spatial domain also includes one environmental factor (carbon emissions) to avoid having a 5th domain. Along these four dimensions, the selected factors representing the impacts of RWA in the R-Map model are discussed in detail below. For an overview of factors that result from the co-design process (section 2.3) see Figure 10.

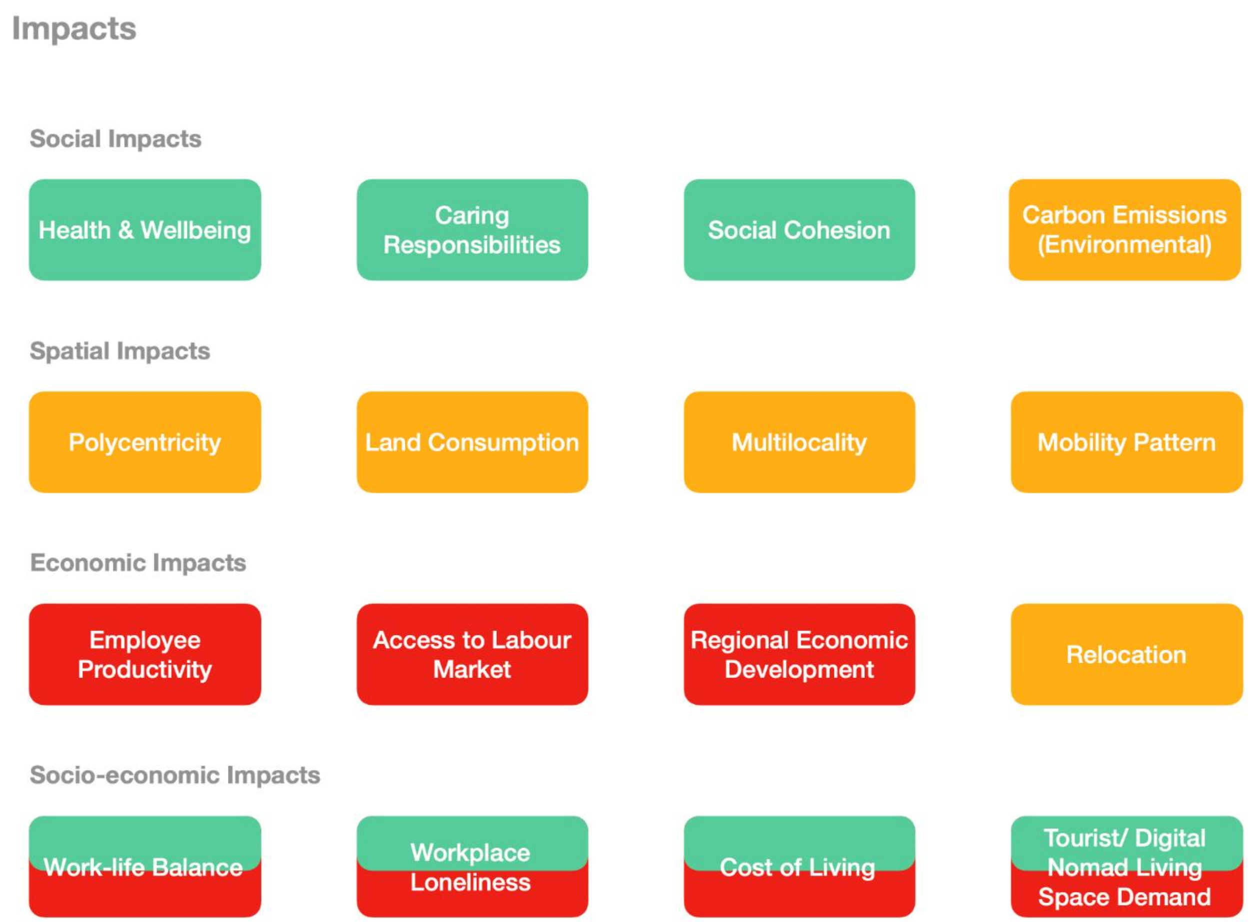

Figure 10: Impact factors included in the conceptual R-Map model

3.2.2.1 Spatial impacts

The spatial impacts of RWA include factors that describe changes in land use, transport patterns and spatial manifestation of socioeconomic factors. Five spatial impacts are identified: polycentricity, land consumption, multilocality, mobility patterns, and relocation, with carbon emissions later added as an environmental impact.

1. **Polycentricity**: The factor was originally suggested by Task 1.2 as suburbanisation, urban decentralisation and new centralities and was subsequently clubbed into polycentricity, considering the preferences of state variables over processes in the interest of measurement. Polycentricity can be understood as a spatial phenomenon where at a regional scale multiple centres of similar size and importance exist, and at an urban scale, multiple neighbourhoods or sub-centres of similar importance exist. As described in D1.2, polycentricity could be a multi-scale phenomenon. At a regional scale, it implies the rise of small/medium-sized cities due to RWAs, while at a metropolitan scale, it implies decentralization towards the outskirts of the city. D1.2 recognises the emergence of new spatialities due to multilocality or relocation. These trends are reshaping urban development, land use, and the real estate market. Further, the report defines decentralization as the migration of (high-skilled) workers outside of the city centre to the immediate/inner suburbs within commuting distance, which can in turn lead to urban sprawl. The report cites Hölzel et al. (2023) and claims of a notable shift in the demand for office space during the COVID-19 pandemic. Similarly, Mariotti et al. (2021) and Biagetti et al. (2024) highlight the decrease in human presence in central neighbourhoods and increased demand for housing in less congested and more affordable areas outside urban cores.

2. **Land Consumption**: Also originally suggested by Task 1.2, land consumption can be understood as the expansion of built-up area for human settlements. Task 1.2 defines land consumption in terms of the expansion of residential areas into previously undeveloped areas (due to more affordable housing options, less congestion and proximity to nature). They report that multilocality exacerbates land consumption by increasing the number of vacant or intermittently occupied homes.

3. **Multilocality**: D1.2 defines multilocality as the maintaining of residences and activities in multiple geographic locations at the same time. It cites Greinke and Lange (2022), who in their study in three rural districts in Germany, report that multilocality prevents complete relocation from rural to urban areas due to strong ties to family and friends. The potential impacts discussed include housing prices being driven up, new construction, reduced affordability and vacancy in rural areas (Greinke and Lange, 2022; Weichhart and Rumpolt, 2015); increased land consumption, travel distance and car-based commute, benefits to local economy, but pose a challenge in developing strong social ties and engagement in local civic activities (Danielzyk et al., 2020).

4. **Mobility Patterns**: Like the driving factor taxation, social security, insurance regulations, the factor mobility pattern also acts as a broad container term. Originally the factor was suggested by Task 1.2 as 'transport infrastructure' and by Task 1.4 as 'transport and accessibility'. Task 1.2 further elaborated that the factor stands for a shift in mobility and car usage patterns. More specifically, it stands for changes in the usage of public transport, and increased reliance on private vehicles. This is also suggested by Deliverable 1.4. The factor was rephrased initially during the co-design workshop as 'shifts in modes of transport' based on the Swedish experience which suggests the maximum shift was observed in the usage of different modes of transport than any other commuting behaviour. However, based on interviews conducted for Task 1.2, the Dutch experience suggests a shift in the purpose of commuting as well. Therefore, the factor was defined broadly as - patterns of human movement

facilitated by public or private transportation, encompassing two aspects: the choice of transport modes and the purpose of trips.

5. **Relocation**: The factor was added after the workshop with the sister project, AB members and regional experts. The sister project WinWin4WorkLife (WW4WL) acknowledged the synergies in the two projects and more specifically their focus on similar dimensions, with 'relocation' as an important component in their study. We also observed 'relocation' studied as an important mediating factor between remote work and housing and the real estate market. Additionally, it also allowed us to clarify the R-Map conceptual model, as will be elaborated further. Thereafter, upon further discussions with the partners, the factor was introduced and can be understood as the decision to move someone's place of living.

6. **Carbon Emissions**: The factor was added during the second technical workshop with the project partners. The impacts of RWA on carbon emissions were already studied several years ago. It is mainly affected by the travel behaviour of employees and their locational choices. Therefore, the above-outlined factors of mobility pattern, multilocality and polycentricity are mediating factors to carbon emissions. Various studies conducted during the COVID-19 pandemic revealed a decrease in carbon emissions due to a higher share of home working and reduced commuting activities by car (Roberto et al. 2022). In certain contexts, this energy saving might be eaten up by increased energy consumption during homework and other behavioural changes of remote workers (Marz and Sen 2022).

3.2.2.2 Social impacts

Social impacts represent the impacts of RWA on the life and living conditions of the employees. Three social impacts were identified including health and well-being, caring responsibilities, and social cohesion. These are described below.

1. **Health and Wellbeing**: Originally suggested by Task 1.3, the factor is defined as capturing impacts on physical health, mental health, social and family, work-related needs, and health behaviours - physical activity, diet, and sleep (according to EU-OSHA, 2023). Also, as mentioned in D1.3, the WHO emphasizes a holistic approach to well-being, encompassing physical and mental health as well as social dimensions to promote overall health and quality of life (WHO, 1948; Topp et. al., 2015). It further details that remote working arrangements encompass specific working conditions and organizational structures that generate psychosocial factors. These factors could potentially serve as sources or conditions that expose individuals to various biopsychosocial influences. Psychosocial factors, in turn, are closely linked to biological outcomes, potentially impacting health, illness, and the development of diseases.

2. **Caring Responsibilities**: The factor was originally suggested by Task 1.4 and Task 1.3 under the term - 'household dynamics-related burdens.' Upon subsequent discussions, the term 'caring responsibilities' was decided due to its neutral phrasing, aligning it with the criteria of defining factors.

The factor, as defined in D1.3, captures responsibilities including housework, childcare, and care for elderly, relatives, among others.

3. **Social Cohesion**: The factor was originally suggested by Task 1.4, as social network, and pertained more to workplace support networks. Upon subsequent discussions, the workplace component was isolated from the factor (termed as workplace loneliness, defined below) and was defined neutrally as the presence or absence of social ties or social support networks, referring both to physical and digital ties. This factor has potential implications for individual well-being, mental health, loneliness and productivity

3.2.2.3 Economic impacts

Economic impacts capture the effects of RWA on economic productivity and opportunities of employees as well as factors characterising the economic productivity of regions as a whole. Economic impacts include employee productivity, access to labour markets, and local/regional economic development. These are described below.

1. **Employee Productivity**: The factor was originally suggested by Task 1.3 as 'work intensity and productivity balance' and during subsequent discussions separated into 'employee productivity' and 'work life balance'. As suggested by Task 1.4, the factor could be realized at two levels – micro- (individual level) and meso-level (organizational level). While at an individual level, the factor refers to how efficiently and effectively a worker or a group of workers contributes to accomplishing organizational goals, at a meso-level the factor means the achievement of goals by a particular organization.

2. **Access to Labour Market**: The factor was suggested during the co-design workshop and was voted as having a significant impact. The factor was defined as access to a diverse and competitive labour force from an employer's perspective. It also has relevance for employees, who have a wider range of possibilities of getting a job because of RWAs. The factor also captures labour participation at a societal level - participation of disabled people and inclusiveness. The dynamics of the labour market, including changes in demand for new jobs, also form a part of this factor.

3. **Local/ Regional Economic Development**: The factor was suggested by Tasks 1.1 and 1.4 during follow-up discussions on factor definitions and could be understood as the economic development of a region through which it can improve its economic, political, and social welfare state. As reported in D1.4, remote work fosters regional development by decentralising economic activities and establishing work centres in non-metropolitan areas. Areas with higher remote job shares show greater employment resilience, supporting local economies through stable spending and economic growth, particularly in smaller cities.

3.2.2.4 Socio-economic impacts

Given the interconnection between social and economic factors, the study also distinguished four socio-economic impacts. They capture impacts at the interface of social and economic conditions of employees and include work-life balance, workplace loneliness, cost of living, and tourist/ digital nomad living space demand. These are described below:

1. **Work-life Balance**: The factor was originally suggested by Task 1.3 as 'work intensity and productivity balance' and during subsequent discussions separated into 'work-life balance' and 'employee productivity.' D1.3 describes 'work-life balance' as the ability to balance between professional responsibilities and personal life - as time management and boundary settings between work and personal life, and its impact on family and social life. It is understood that work-life balance involves not only time management but also workload-related flexibility when needed. There are two key interfaces: a work-related supportive side and a life-related supportive side, each including various supportive services.

2. **Workplace Loneliness**: The factor was suggested by Task 1.3 and was separated from 'loneliness' in general and personal social ties as captured by the factor 'social cohesion.' Defined in Del.1.3, workplace loneliness is characterized by a lack of information quality, supportive leadership, supportive conditions for job demands, and individual psychological states. It is understood that as new ways of working evolve, the definition of the "workplace" is also changing. Employee services related to these "new workplace" aspects play a critical role in supporting job engagement, task completion, and providing network support when needed.

3. **Cost of Living**: Originally Task 1.1 suggested the factor 'cost of living', the factor 'housing affordability' was suggested during the codesign workshop and eventually the two were assimilated into 'cost of living' as it was considered more holistic. The factor can be broadly defined as the amount of money that a person needs to pay for basic needs such as food, shelter, and energy.

4. **Tourist/ Digital Nomad Living Space Demand**: Task 1.4 suggested the factor 'local tourism economy' originally, however, it was not adjudged as amongst the most significant factors during the co-design workshop. During subsequent discussions, the impact on tourism, specifically from digital nomads, was highlighted as a relevant dimension to be included by multiple partners. Therefore, the factor was added to cover the demand for living space from the increased number of tourists and digital nomads.

3.3 The final conceptual R-Map model

In this section, the final conceptual R-Map model is presented. The elaboration of the network of causal relations between the various impacts of RWA that built the core of the R-Map model, was done in two steps during the co-design process in parallel to the identification of RWA impacts presented above: the first draft causal network of the R-Map model was developed during the co-design workshop at the UT. Further refinement and validation of the R-Map model were done throughout the series of technical workshops and intermediate tasks fulfilled by the partners. Key information for the latter was the partner survey on cause-effect relations conducted between the second and third technical workshops.

Below, first, the results of the partner survey are presented and discussed. Then the final R-Map model is elaborated. To determine causal relations between factors the R-Map partners were asked in the survey to provide their view on (i) the existence of causal relations between two specific factors, (ii) the strength of the causal relations, (iii) the type of causal relations, and (iv) the temporality of the relationship (see section 3.3.3). Results from the analysis of causal relations between factors help in the semi-quantification of the R-Map model (see section 3.3.2)

3.3.1 Degree of consensus on causal relationships

Figure 11 shows the results of the first question of the survey which was - does Factor A cause a change in Factor B, with the option of answering 'yes', 'no' or 'I don't know'. We associate a value of 1 with each 'yes' mentioned and sum the values per causal relationship to arrive at the heatmap. The heatmap representation captures the directional graph with the y-axis depicting the factors where a link emanates from and the x-axis depicting a factor where it terminates. Due to its directional nature, the heatmap is not symmetric along the diagonal. Three classifications – high (values 9 and 10), medium (values 6 to 8) and low (values less than 6) consensus – were made based on quantiles, such that the number of values in each class is approximately the same.

Figure 11: Degree of consensus on causal relationships

The identification of the direction of links reveals a strong consensus on the effect of RWA on several impact factors, specifically, health and wellbeing, mobility pattern, multilocality, polycentricity, social cohesion, tourist/digital nomad living space, work-life balance, workplace loneliness, access to labour market, and local/regional economic development. Additionally, there is significant agreement on the influence of various social and socioeconomic factors on health and well-being—such as social cohesion, work-life balance, workplace loneliness, caring responsibilities, cost of living, and access to local amenities—establishing health and well-being as a broader, final impact beyond immediate outcomes.

Both digital infrastructure and transport accessibility are seen as key drivers for RWA by all partners. Furthermore, multilocality and polycentricity are identified as critical bridges across domains, influencing a wide range of factors. There is strong agreement that polycentricity impacts spatial factors such as land consumption and mobility patterns, as well as economic factors such as access to the labour market and local/regional economic development. Similarly, there is broad consensus that multilocality is connected to the spatial factor of polycentricity and the economic factor of local/regional economic development. High agreement also exists on the role of digital infrastructure accessibility as a key driver of mobility patterns and polycentricity, a relationship further clarified through the introduction of the factor of relocation.

3.3.2 Strength of causal relationships

A high consensus among partners of a causal relation between single impacts or driving factors does not allow to make any conclusions on the strengths of this relation. Therefore, in the second question of the survey we asked about the strength of a given relationship between Factor A and B, with the possibility of answering ‘weak’, ‘medium’, ‘strong’ or ‘I don’t know’ A weight of 1, 2 and 3 was associated respectively with the answers ‘weak’, ‘medium’ and ‘strong’ and was summed per causal relationship to arrive at the heatmap. Also, if respondents replied ‘yes’ in the previous question and specify ‘I don’t know’ in the second question, we also assign a weight of 1. We use the quantile criteria here as well, to specify five categories, including very strong (values 23 to 25), strong (values 19 to 22), medium (values 17 and 18), weak (values to 11 to 16) and very weak (values less than 11). The results are depicted in the same format as above in Figure 12.

Most important findings are that RWA have the strongest causal relations with the impacts: health and wellbeing, work life balance, workplace loneliness, and access to labour markets. They are further also strongly related to the impacts of mobility patterns, polycentricity, tourist living space demand, and employee productivity. Another interesting finding is that social cohesion is a weakly linked to RWA despite the strong consensus of the relation elicited in the figure below.

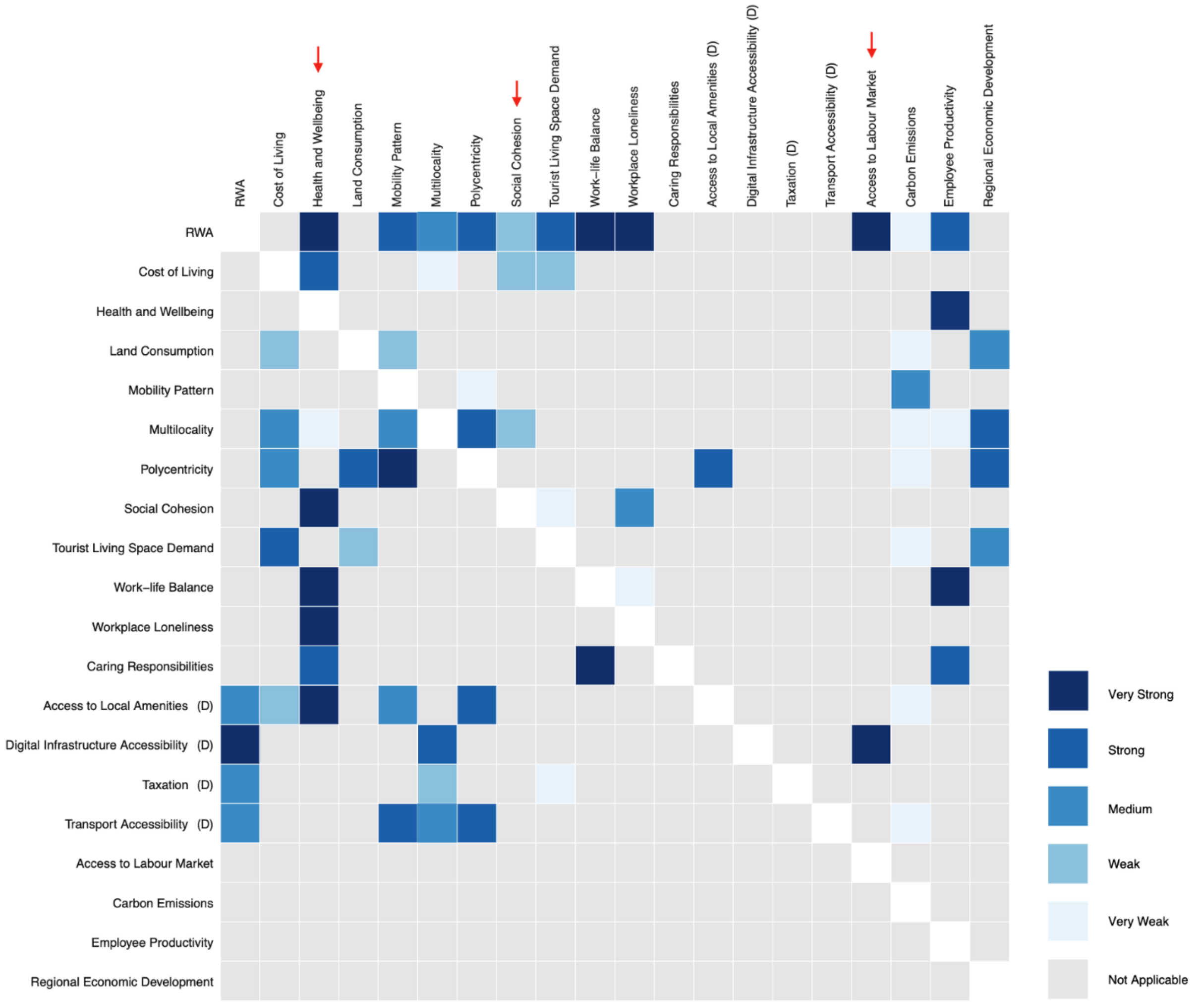

Figure 12: Strength of causal relationships

Most important findings are that RWA have the strongest causal relations with the impacts: health and wellbeing, work life balance, workplace loneliness, and access to labour markets. They are further also strongly related to the impacts of mobility patterns, polycentricity, tourist living space demand, and employee productivity. Another interesting finding is that social cohesion is weakly linked to RWA despite the strong consensus of the relation elicited in the figure above.

Other very strong causal relations elicited by the partners are health and wellbeing on employee productivity, and polycentricity on mobility patterns, social cohesion, work life balance, workplace loneliness. The driver access to local amenities strongly correlates with health and wellbeing, and the driver digital infrastructure accessibility with access to labour markets. Overall, health and wellbeing is the factor that is strongly affected by a number of impacts, which makes this factor a key final impact of the R-Map model. Also, the factor carbon emissions is affected by 8 other impacts though often only mapped as a weak link. This is potentially because the factor carbon emissions was added a little later in the process to the set of factors, and so/thus not all partners had assessed causal relations to it in the survey.

3.3.3 Type of causal relationships

For developing the R-Map model it was crucial to assess whether the mapped causal relations between factors are positive or negative. To address this issue the partners had to assess the type of causal relationships between two factors by answering the question whether an increase of factor A causes an increase or a decrease of factor B, with the possibility of answering 'yes', 'no', or 'I don't know'. Partners were also allowed to enter 'mixed' in the comments if they believed that the relationship varies depending on the context. For broad, container factor terms, an additional step was undertaken to refine their definitions and to clarify what constitutes an increase or decrease in the respective factors. Specifically, this refinement was applied to the following factors:

1. Mobility Pattern: The scope was narrowed to focus specifically on the usage of public transport.
2. Taxation, Social Security, and Insurance Regulations: The definition was streamlined to address tax benefits associated with remote working.

The results are shown below in Figure 13. All mapped causal relations are shown on the y-axis with length of the bar chart indicating the number of partners having assessed the relation and in colour the results of the assessment per partner (green= positive relation, red=negative relation, beige=I don't know). The figure further shows the degree of consensus among partners on the type of relation: the longer the green or red colour per bar, the higher the degree of consensus. In case of shorter bars, not all partners assessed the causal relationship to/that exist.

Overall, a large number of relationships is conclusively positive. The highest degree of consensus exists on the positive relation of work-life balance, social cohesion, and access to local amenities, with health and wellbeing. High consensus exists also on the positive relations between multilocality and polycentricity, health and wellbeing and employee productivity, and digital infrastructure accessibility and RWA. For several other relations, some partner did not confirm the positivity of the relations which might have to do with their scientific background and knowledge.

Overall, 10 of the mapped relations are assessed by the partners as conclusively negative. The highest consensus exists on the relation of workplace loneliness to health and wellbeing, and caring responsibilities to work-life balance. In total, 14 relations got a mixed assessment by the partners. Reasons for this differential view on relations can be the varying experiential knowledge and experience of partners with respect to the relations, different mental models of contexts these relations are applied to by partners, and varying interpretations of factors by partners. The latter is potentially aggravated by the purposely broad definition of factors that in some cases serve as container terms for more than one concrete impact indicator. For the overall R-Map model developed in this task the relations are to be excluded from the model, given the uninformative prior in such cases within the Bayesian setup may produce uncertain results. For the application of the model in different contexts and regions in WP4 of the R-Map project these relations will have to be re-examined.

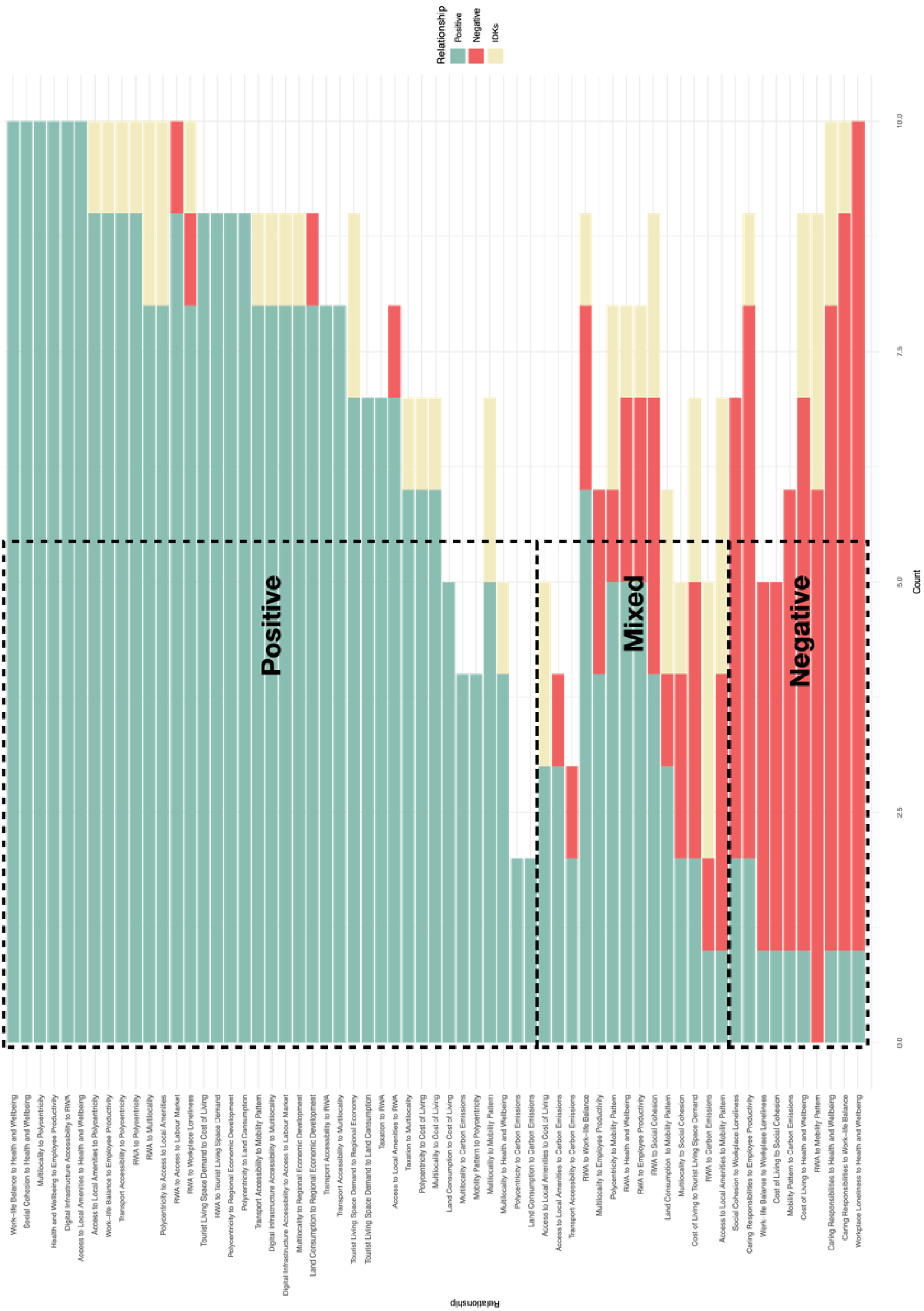

Figure 13: Type of causal relationships – positive, negative or mixed

3.3.4 Temporality of causal relationships

Finally, the temporality of the mapped causal relations was assessed by the partners in answering the questions of how long a relation between factor A and factor B takes to realise. The distinction between factor relations at a temporal scale is crucial for eliciting cause-effect chains over several factors from the here-assessed one to one relations.

Figure 14: Relative temporality of causal relationships

The results of the question are visualised in Figure 14, distinguishing causal relations into the categories of short, medium, and long-term. This temporality is mapped on the x-axis with drivers being plotted on the very left and long-term effects of RWA being plotted on the far right of the graph.

It is important to mention that the temporality of the relations is mapped in Figure 14 in relative, not absolute terms. Temporality should further be understood in terms of the domain, i.e. spatial impacts may take longer to be realised, than impacts in the social domain. For example, health and well-being, identified as a medium-term impact and positioned one step beyond immediate effects such as workplace loneliness and work-life balance, is manifested considerably sooner than polycentricity.

Additionally, the final assessment presented in Figure 14 is evaluated relative to RWAs and other associated impacts. For instance, while the majority of partners indicated that the causal relationship between RWAs and polycentricity unfolds over the long term, a similar time frame was identified for the relationship between polycentricity and land consumption. Consequently, in relation to RWAs and land consumption, polycentricity is classified as a medium-term impact.

Overall, we can conclude that the partner survey provided valuable insights for the analysis of causal relations between factors that help with the conceptual design of the R-Map model and its semi-quantification. For the co-design process we can constitute that the results of the survey rather confirmed the initial mapping of relations done during the co-design workshop at the UT. Moreover, a large degree of agreement between partners exists regarding the causal relations between impacts of RWA. Nevertheless, a high agreement does not necessarily translate into a strong causal relationship, which underlines the quality of the survey for developing the R-Map model.

3.3.5 The final conceptual R-Map model

Based on the results of the partner survey on the consensus of causal relations between factors and their respective strengths, certain links of low relevance were excluded from the R-Map model. The criteria for retaining or omitting links in the R-Map model were as follows:

1. Exclusion of very weak links: Links identified as very weak, based on survey responses regarding the strength of causal relationships (Figure 12), were omitted. For example, links such as multilocality to employee productivity and work-life balance to workplace loneliness were excluded under this criterion.

2. Exclusion of redundant links: Links that are redundant due to being already captured by another causal chain were removed. For instance, the link between caring responsibilities and employee productivity was excluded, as it was determined to be mediated by work-life balance.

3. Minimizing loops: To ensure clarity and facilitate modelling in Task 2.2 as Bayesian Networks, loops were excluded wherever possible. In cases of two-way relationships, the dominant direction was retained. For example, while a bidirectional relationship was identified between cost of living and tourist/digital nomad living space demand, the link from cost of living to demand was weak, whereas the reverse direction was strong. Therefore, the link from "tourist/digital nomad living space demand" to "cost of living" was retained, and the reverse link was excluded.

4. Focus on RWA-driven causal changes: As mentioned, links mediated by RWAs were prioritized in the conceptual model to emphasize causal changes driven by remote work, aiding discussions on this theme. For instance, while strong connections were identified between access to local amenities and digital infrastructure accessibility, these were temporarily excluded.

5. Exclusion of mixed relationships for modelling in Task 2.2: Links characterized by mixed relationships (Figure 13), while retained in the conceptual R-Map model, will be excluded from the modelling exercise in Task 2.2.

After semi-quantifying the causal relationships between factors and classifying them, a directed network was generated, resulting in the conceptual R-Map model presented in Figures 15 and 16. To facilitate focused discussions, a simplified representation was adopted, wherein all causal links from drivers to impacts were mediated through RWAs. This approach emphasizes the scope of the task, which is limited to understanding causal relationships stemming from RWAs. While direct relationships between drivers and impacts are of interest and may be utilized in Task 2.2, the primary objective of Task 2.1 was to map causal relationships emanating from RWAs and between impact factors.

Figure 15 represents the factors as nodes and the causal relationships as directed arrows, with their weights reflecting the strength of relationships as indicated by partners in the survey. Arrows associated with carbon emissions have been moved to a class above the one indicated in the survey, to correct for the later inclusion and subsequent underrepresentation in the survey. It can be seen in Figure 15 that the factors of health and wellbeing, cost of living, and regional economy are the key final impacts of remote working arrangements, indicated by a high number of incoming (receiving) links. Further, it can be observed that spatial impacts are rather intermediate impacts resulting in social, economic and socio-economic impacts.

Figure 15: The conceptual R-Map model (a)

Figure 16 further depicts these relationships by their type—positive, negative, or mixed. Most of the causal relationships included in the R-Map mode are positive relations, i.e. when the factor where the link starts increases also the factor where the link terminates increases. While this is not so important for the conceptual design of the R-Map model, it needs to be taken into account when it comes to the modelling of impacts and the translation of factors into indicators.

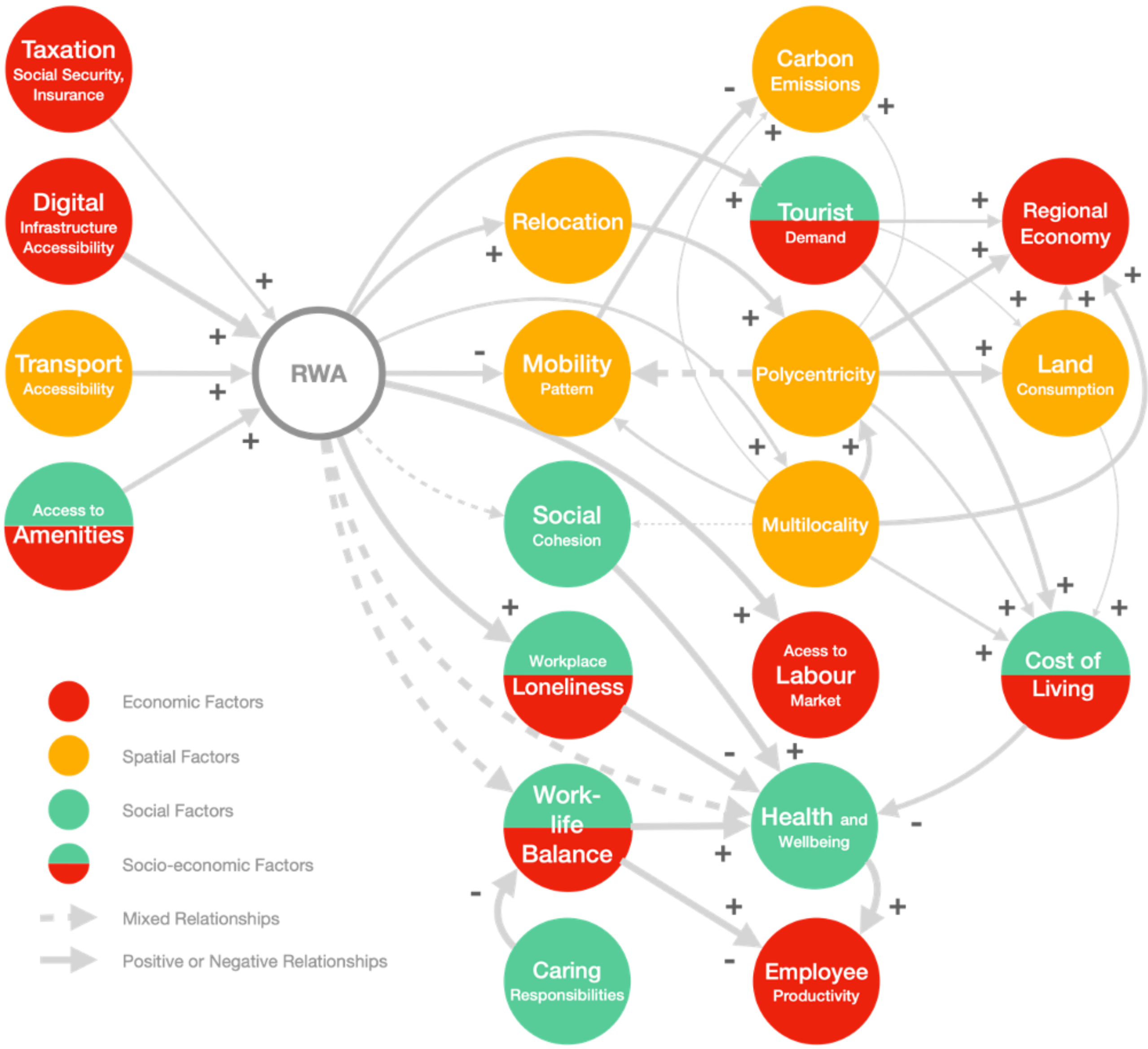

Figure 16: The conceptual R-Map model (b)

To analyse how changes in Remote Work Arrangements (RWAs) and other drivers influence final impacts, and to assess the significance of intermediate factors in this process, specific causal chains can be isolated from the R-Map model.

Causal chains can be described as pathways of influence that originate from a root cause and lead to an impact, passing through multiple intermediate factors. A causal chain can have several causal paths. These causal chains can be used to identify confounders and mediating factors. Figure 17 illustrates an example of a causal chain from RWAs to the cost of living, highlighting the following causal paths:

1. RWA > Tourist Demand > Cost of Living
2. RWA > Relocation > Polycentricity > Cost of Living
3. RWA > Relocation > Polycentricity > Land Consumption > Cost of Living
4. RWA > Multilocality > Polycentricity > Cost of Living
5. RWA > Multilocality > Cost of Living
6. RWA > Mobility Pattern < Polycentricity > Cost of Living
7. RWA > Mobility Pattern < Multilocality> Cost of Living

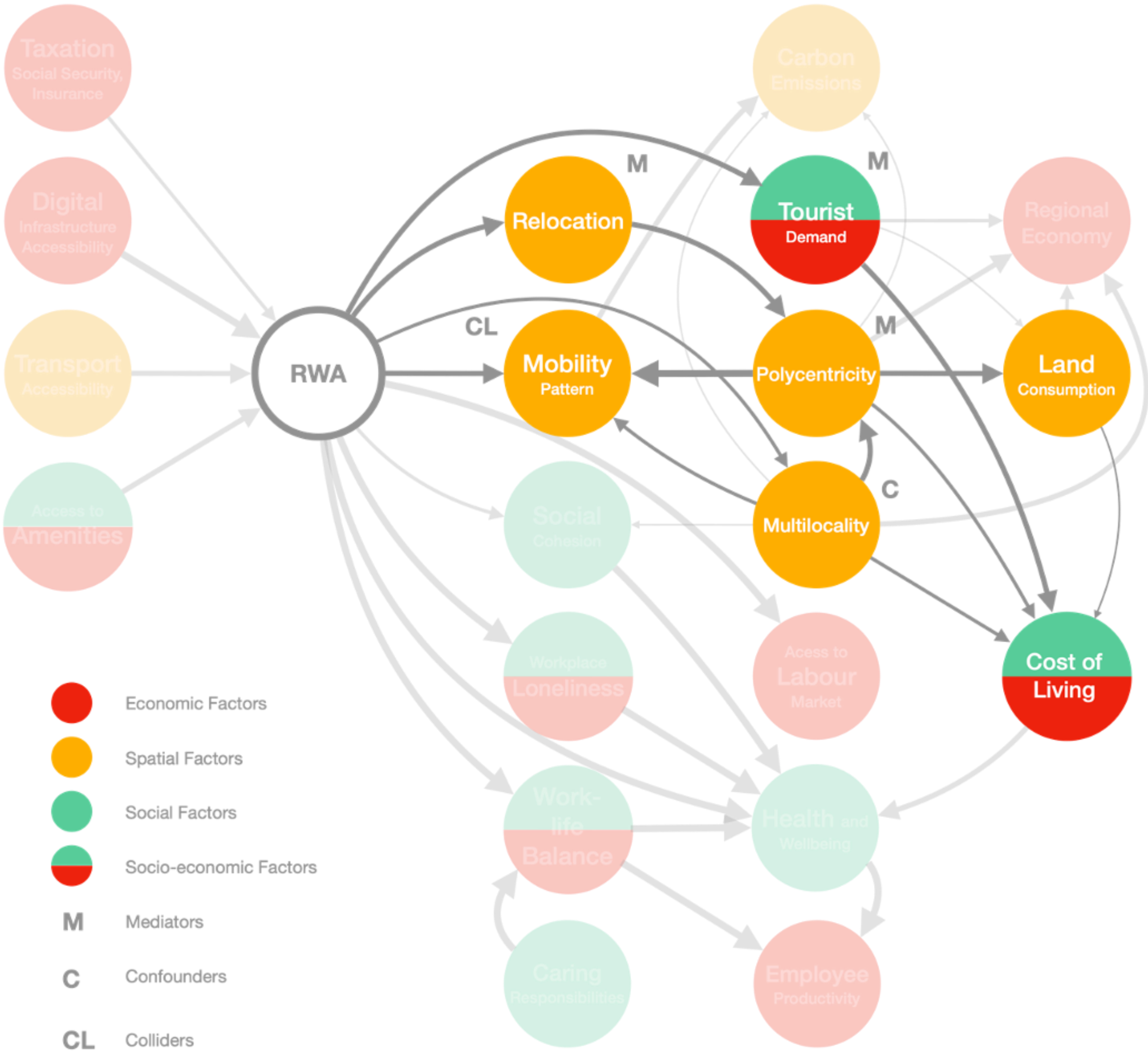

Figure 17: A causal chain from RWA to cost of living in the R-Map conceptual model

In terms of factor types and their implications, we make the following few observations:

1. Mobility Pattern as a Collider
   Mobility pattern acts as a collider or common effect in the causal chain. Controlling for it would violate the back-door criterion, resulting in spurious correlations. Therefore, it should be excluded in a multivariate regression analysis in a Bayesian setup.

2. Multilocality as a Confounder
   Multilocality serves as a confounder between polycentricity and the cost of living. Consequently, it is critical to control this factor in the analysis to prevent biases and ensure valid causal inferences.

3. Tourist Demand as a Mediator
   Tourist demand can be classified as a mediator in the causal chain. However, since not all tourist demand is driven by remote work and is influenced by external factors beyond the causal map, it cannot be excluded outright. A more effective approach is to introduce additional control variables to better understand their contribution to the final impact (i.e., cost of living).

4. Relocation as a Mediator
   Similar to tourist demand, relocation can be classified as a mediator in the causal chain, and one which is not entirely driven by remote work. Therefore, it should not be excluded from the analysis. Instead, other control variables should be introduced to isolate their role in influencing the cost of living.

5. Land Consumption as a Mediator
   Land consumption is strictly a mediator between polycentricity and the cost of living. Since land consumption can be safely assumed to be driven entirely by polycentricity, it may be excluded from the analysis if the focus is solely on understanding the impact of remote work on the cost of living. However, this exclusion should only be considered after controlling for variables that drive polycentricity.

By distinguishing between confounders, mediators, and colliders within a specific causal chain, the analysis can be structured to prevent spurious correlations, maintain valid causal pathways, and ensure a robust understanding of the relationships between RWAs, intermediate factors, and final impacts. This approach can also be extended to other causal chains, allowing for a detailed assessment of the effects of various factors on specific final impacts of interest, such as health and wellbeing, carbon emissions, employee productivity, or the regional economy.

3.4 Computational implementation of the conceptual R-Map model

The R-Map conceptual model serves as the foundation for Task 2.2 (Section 5), which focuses on distilling, detailing, implementing, and validating the R-Map model. Specifically, Task 2.2 involves formulating indicators and proxies which are in the form of measured data for the factors identified in Task 2.1 and harmonizing datasets as inputs for the implemented model; the datasets so far identified are outlined in the subsequent section. The implemented model is a reduced version or subset of the conceptual model. The reason is that the scope of the model is constrained by the availability of relevant data and certainty of causal relationships. After the indicators are developed, the causal relationships are reformulated using these specific indicators, ensuring alignment with the R-Map conceptual model. This step is essential, as some factors may have multiple indicators, and additional control variables may need to be introduced. This is further elaborated in Section 5.

The R-Map model is implemented with the rationale of treating the conceptual model shown in Figures 15-16 as the graph-based representation of statistical relations among factors, while the statistical relations are modelled using a Bayesian approach. Hence, both surveyed knowledge and measured indicators from datasets are treated to capture people's belief and actual measurements at the same time. Insights from the survey regarding the types of causal relationships are utilized as the model priors in the Bayesian setup, while likelihoods and posterior probabilities are derived from the data where available. This methodology also enables several analytical directions, such as assessing the significance of various factors in influencing specific outcomes (looking "up" the network) or predicting potential outcomes under hypothetical scenarios where certain factors take predefined values (looking "down" the network), as discussed in Section 2.1.4. Furthermore, additional model functionalities can include accommodating the addition of new factors and facilitate learning of the causal network structure.

As the R-Map model is designed as an integrated assessment framework for Europe, and most indicators are singular values at NUTS-3 or NUTS-2 levels, it is reasonable to anticipate model outputs in terms of singular values at these scales. However, as the project advances into regional case studies under WP4, more localized data can be collected, enabling detailed, context-specific analyses and/or predictions.

4. Data sources to inform the R-Map model

To perform an integrated assessment of spatial, social, and socio-economic impacts of RWA across Europe and to evaluate the impacts of remote working arrangements on different regions in WP4, the here identified factors need to be translated into measurable indicators and connected to data sets that inform these indicators for the different spatial units. This part of the work is conducted in Task 2.2 of the WP2. To prepare for this, Task 2.1 identifies suitable data sources that allow to inform the indicators of the R-Map model. Possible data sources for this are publicly available data sets published on open data portals including other HEU projects that publish open data sets as results of their research, data that is derived from the large-scale survey conducted in the R-Map project (Task 1.5), and unconventional data sources, for example data potentially derived from social media platforms such as LinkedIn or Twitter (now X). Suitable data sets from these different sources to inform factors in the R-Map model are discussed in this chapter.

To inform the R-Map model factors and indicators the data sets need to fulfil certain requirements. The following criteria were applied for selecting the data sets discussed below.

- The data needs to be publicly available and accessible
- The data needs to be available for different years to allow the analyses of changes over time (e.g. before and after the COVID-19 pandemic)
- The data needs to be available at sufficient spatial resolution. As the goal of the R-Map project is to assess the impacts of RWA at the regional level, the data is ideally available at NUTS3-level or NUTS2-level.
- The data needs to be available - ideally - for the entire EU to support a coherent and consistent assessment of RWA impacts across different case studies.

4.1 Open data sources

Open data sources provide access to publicly available data sets typically compiled and verified by governmental authorities. The following publicly available data sets are suitable to inform the R-Map model.

Eurostat (https://ec.europa.eu/eurostat/en/web/main/data), the statistical office of the European Union, provide high-quality statistics and data on Europe for a large variety of different topics and themes, including land use, economy, population and social conditions, transport, environment, among many other topics. Eurostat data is harmonized across all EU countries, available for longer time series, and provided at a high spatial resolution down to NUTS3 level, which makes it a rich and important data source for the R-Map Model.

The European Foundation for the Improvement of Living and Working Conditions (Eurofound) provides data and surveys on working conditions and sustainable work, industrial relations, labour market change and quality and life and public services in Europe (https://www.eurofound.europa.eu/en/data). The data offers a unique source of comparative information on the quality of living and working conditions across the EU and this is very valuable to inform the R-Map model. Several surveys that Eurofound conducts are done repeatedly and allow for the analysis of changes over time. The spatial resolution is often limited to country level, more detailed resolution needs to be checked and requested for single data sets.

OpenStreetMap (OSM) is an online open geographic database, regularly updated and provides detailed spatial data across the world maintained by a community of volunteers via open collaboration. While this spatial data cannot be directly used to inform specific factors or indicators of the R-Map model, it can be used to construct indicators. Examples are for instance a spatial data layer of road networks across Europe provided at https://www.globio.info/download-grip-dataset that can be helpful for assessing transport accessibility per region, or a spatial data set containing points of interest that might help assess the density of amenities per region in Europe.

The EU Social Progress Index (EU-SPI, https://ec.europa.eu/regional_policy/assets/social-progress/index.html#/) provides data for EU regions on a range of social and environmental aspects. The data sets include data on basic needs (housing, medical care) and foundations of wellbeing (information and communication, health) including environmental quality. They are available at NUTS2 level for the years 2016, 2020, and 2024 which makes it suitable to compare the situation before and after the COVID-19 pandemic.

The ESPON Data and Knowledge Portal (https://gis-portal.espon.eu/arcgis/apps/sites/#/espon-hub) provides data and indicators on European territorial development including a broad variety of topics such as population and living conditions, economy and labour markets, employment, transport and accessibility, among other topics. The data is publicly available at NUTS2 resp. NUTS3 level for different years, covering the entire EU territory.

The ESPON data portal also provides several highly aggregated indices composed of available data. That might serve to inform single R-Map indicators. The good life enabler index is for instance compiled of indicators that are partly also included in the R-Map model. The documentation of the construction of the index might serve as a good basis for targeting suitable data sets to be included in the R-Map model (ttps://archive.espon.eu/sites/default/files/attachments/ESPON%20Working%20Paper%2C%20Is%20Our%20Life%20Good%20Enough.pdf

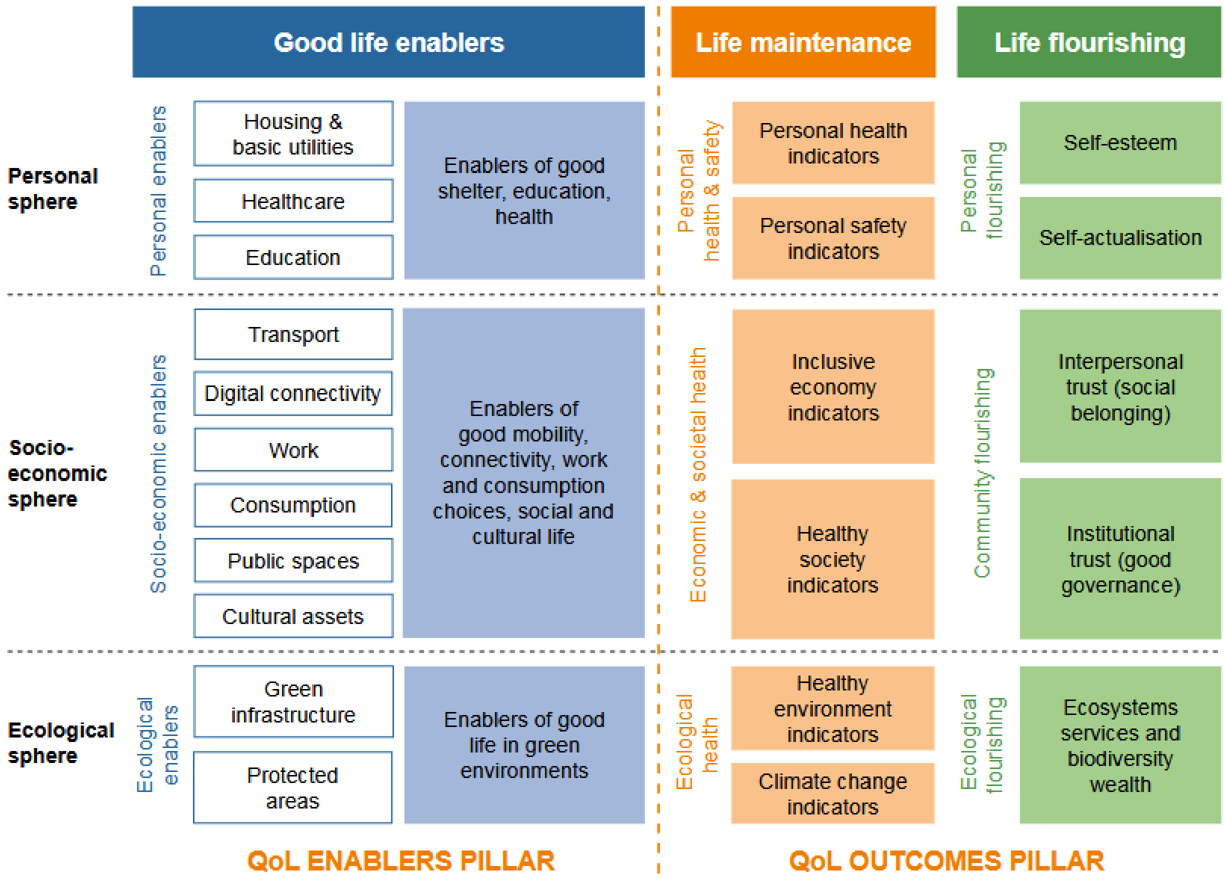

Figure 18: The framework for good life enabler index (source: ESPON 2021)

Europe-wide data sets that are produced and made publicly available in the context of other HEU projects might be also relevant data sources to inform indicators of the R-Map model. For instance, the LOCALISED project (https://www.localised-project.eu/), which aims at downscaling decarbonisation trajectories consistent with the EU's net-zero targets to local levels, has published an open data set via a data sharing API on Github that contains also small-scaled sociodemographic and socioeconomic data as well as data on industries and services https://github.com/FZJ-IEK3-VSA/LOCALISED-Datasharing-API-Client. Most of the data, that originally stems from public data portals such as Eurostat etc, has been downscaled and disaggregated from a broader spatial resolution to NUTS3 and even Local Area Units (LAU), which increases the relevance of the data of the R-Map project.

4.2 Large-scale survey on remote workers' perceptions, requirements, and location choices (WP1, Task 1.5)

In WP1, as part of/in Task 1.5 of the R-Map project a large-scale survey was conducted to collect primary data on remote workers' perceptions, requirements, and factors influencing location choices. The survey aimed to create a comprehensive dataset by targeting approximately 20,000 participants, which could inform subsequent stages of the project. Initially, the survey focused on European participants; however, due to limited responses, it was expanded to include similar countries such as the United States, Canada, and Australia.

The questionnaire captured various aspects of remote work, including hours worked remotely per week, industry background, gender, workplace preferences and drivers, commuting distances and modes, as well as participants' current work and home location (municipality level). It also inquired whether respondents had relocated their place of work or residence due to remote work and, if so, the corresponding municipalities before and after the change. To ensure data privacy, participants were anonymized. Respondents were asked to provide municipality names in a textual format. However, this introduced challenges with data consistency, requiring substantial data cleaning efforts.

4.2.1 Data processing and matching

To associate municipalities with spatial administrative boundaries, a two-pronged strategy was employed:

1. For European municipalities, responses were matched with Local Area Units (LAUs) and linked to their respective NUTS-3 regions.
2. For non-European municipalities, responses were matched with GADM (the Database of Global Administrative Areas).

Furthermore, municipalities were classified into urban-rural categories for proceeding tasks and dissemination purposes. For Europe, the NUTS-3 typology was used, classifying regions as predominantly urban, predominantly rural, or intermediate. For non-European municipalities, the Degree of Urbanisation framework was applied (The European Commission & United Nations Human Settlements Programme, 2021), categorizing level 2 administrative areas (approximating municipal scales) into categories such as urban centres, dense urban clusters, semi-dense urban clusters, suburban or peri-urban, rural cluster, low-density rural, very low-density rural, and water.

4.2.2 Insights and inputs for Task 2.2

The results of this large-scale survey are potentially a rich data set to inform the quantification of indicators for the R-Map model (Task 2.2, Section 5), particularly as such a survey was never done before. The data set can especially help explore some of the following key research questions:

1. Relocation due to remote work: Assessing the extent to which remote work influences residential relocation and its relationship with hours worked remotely.
2. Distance of relocation: Determining how far individuals are willing to relocate from their workplace based on the extent of remote work.
3. Job location choices: Exploring whether individuals are willing to secure jobs farther from their homes and how this correlates with remote working hours.
4. Regional attractiveness: Evaluating the ability of regions to retain or attract remote workers.

5. Commuting behaviour: Analysing commuting mode choices in relation to commuting distances and transport accessibility.

These inquiries can be further enriched by integrating other open datasets mentioned previously, allowing for an investigation into factors such as access to amenities, transport accessibility, digital infrastructure availability, and taxation in shaping relocation decisions. Additionally, this data can be used to assess whether relocation results in actual land consumption, leveraging built-up area data from sources such as the Global Human Settlement (GHS) dataset. This dataset provides a unique foundation for advancing understanding of remote work's spatial and socio-economic impacts, offering critical insights for policy and planning.

4.2.3 Insights from LinkedIn poll on remote work preferences and impacts

Complementary to the large-scale survey, a LinkedIn poll was conducted by the R-Map project, garnering approximately 5,500 responses. This poll sought to further explore the workplace and location preferences of remote workers, as well as the perceived impacts of remote work on productivity and job satisfaction. Key findings from the poll include:

1. Positive impact on productivity: Respondents overwhelmingly reported that remote work had a positive effect on their productivity.
2. Enhanced job satisfaction: An even stronger positive response was observed regarding the impact of remote work on job satisfaction.
3. Preference for suburban or rural living: A significant preference emerged for suburban or rural areas over urban areas, indicating a tendency towards less densely populated living environments.
4. Flexibility in work schedules and location: Respondents expressed a positive sentiment toward the flexibility remote work offers in terms of choosing work schedules and locations.
5. Varied support preferences: Opinions varied on the type of support deemed beneficial for remote working, with preferences ranging from ergonomic office supplies to mental health and wellness initiatives.

These insights underscore the importance of employee productivity and health and well-being as key final impact factors. Additionally, the preference for less densely populated areas reflects a centrifugal shift away from urban centres, highlighting the evolving spatial dynamics associated with remote work.

4.3 Unconventional data sources

To complement traditional datasets, we explored the potential of leveraging unconventional data sources to inform key factors included in the R-Map model. This included examining the data policies of social media platforms such as X (formerly known as Twitter), LinkedIn, and Threads, as well as open datasets shared within developer communities on platforms like Kaggle. Additionally, other sources offering transport, movement, walkability, and cost-of-living data at urban or regional scales were also considered.

4.3.1 Social media platforms and open data repositories

1. X (formerly Twitter): Previously, X provided free access to its API and geolocated tweet collection, enabling sentiment analysis, and topic and keyword modelling (Saura et al., 2022), which could offer insights into public perceptions of remote work. However, these services have transitioned to a paid model, limiting their accessibility for research purposes.
2. LinkedIn: As a platform rich in data on job postings and trends related to remote work, LinkedIn could have been a valuable resource. However, its free API services have been discontinued, restricting open access to such information.
3. Threads (Meta): Threads, a newer social media platform similar to X, still allows limited free API usage. Although its user base is smaller compared to X, it remains a potential avenue for sentiment analysis and other exploratory studies.
4. Kaggle: Kaggle hosts various developer-contributed datasets, including historical tweets and job postings in specific industries. While these datasets provide an opportunity to examine certain trends, their reliability and comprehensiveness remain, like for other social media data, uncertain, especially for nuanced analyses like assessing the spatial or economic impacts of remote work.

4.3.2 Other unconventional data sources

We also investigated platforms providing urban and regional-scale data on transport, movement patterns, walkability, and cost of living. For instance:

1. Google Maps API: Previously a viable option for accessing Points of Interest (POI) data, this has also shifted to a paid service, limiting its feasibility for large-scale, cost-effective research.

2. Mobile Phone Data: Aggregated and anonymized data from European Mobile Network Operators (MNOs) provides insights into stationary points and flows using unique identifiers linked to location and timestamps. Despite its utility, access is restricted and typically available only for specific studies under GDPR-compliant frameworks.

3. Mobility Data Repositories: Mobility data at the national and European levels presents a valuable resource for analyzing transport and movement patterns. National initiatives include Germany's Mobility Data Space, the Netherlands' iSHARE, and France's Bison Futé. The European Mobility Data Space (EMDS) initiative provides a unified framework for data interoperability and sharing in the mobility and transport sectors. Supported by the deployEMDS project under the EU Digital Europe Programme, EMDS facilitates multimodal mobility, traffic management, and sustainable urban mobility assessments, building on the groundwork of PrepDSpace4Mobility. However, the project will be fully operational only by 2026, requiring reliance on national repositories in the interim. City-level datasets include specific datasets, such as UTD19 curated by the Institute for Transport Planning and Systems at ETH Zurich, which provide detailed traffic flow data at the city level.

4. Remote Sensing Data: Satellite-based remote sensing data, particularly nighttime imagery from SDGSAT-1, offers the potential for detecting traffic volumes and analyzing urban mobility patterns. SDGSAT-1 is accessible for scientific purposes, making it a promising resource for mobility studies. However, its temporal coverage poses a challenge for continuous or high-frequency analysis, limiting its ability to capture dynamic trends comprehensively.

5. Property and Job Listings Data: Web scraping of property websites and job listing platforms offers insights into housing and commercial property trends, relocation patterns, market demand, and remote work-related roles. However, legal and ethical considerations must be addressed to comply with data usage policies, and data cleaning is required to handle inconsistencies across platforms.

6. Other data sources:
   Walkability Indices: Open sources like Walk Score provide valuable data on walkability, which can inform indicators related to access to local amenities.
   Quality of Life Metrics: Studies such as the "Regional Quality of Living in Europe" (Lagas et al. 2015) offer insights into regional quality of life metrics, which can inform indicators related to cost of living.

While unconventional datasets provide unique insights into mobility patterns, housing markets, and employment trends, they come with challenges such as limited access, temporal coverage gaps, and data compliance requirements. Despite these hurdles, integrating these datasets with traditional sources can significantly enhance our understanding of the spatial and socio-economic impacts of remote work. Future efforts should focus on overcoming access barriers, fostering partnerships, and ensuring data quality to maximize their potential.

5. The R-Map Model Implementation and Operation

5.1 Recap of the R-Map model rationale

Task 2.2 aims to implement of the R-Map model; it treats the model conceived in Task 2.1 as the conceptual foundation. The implementation focuses on distilling, detailing, implementing, and validating the R-Map model. Specifically, Task 2.2 further involves identifying and consolidating indicators and proxies which are in the form of measured data for the factors identified in Task 2.1 and harmonizing datasets as inputs for the implemented model; the indicators and corresponding datasets identified are outlined in section 5.4.2. The implemented model is a reduced version or subset of the conceptual model, considering that the scope of the model is constrained by the availability of relevant data and certainty of causal relationships. After the indicators are developed, the causal relationships are reformulated using these specific indicators, ensuring alignment with the R-Map conceptual model. This step is essential, as some factors may have multiple indicators, and additional control variables may need to be introduced.

The R-Map model is implemented with the rationale of treating the conceptual model shown in Figure 16 as the graph-based representation of statistical relations among factors. The statistical relations are modelled using a *Bayesian* approach. More concretely, the conceptual model which represents key factors and relations within a system in terms of nodes and directed links among them, is translated and implemented as an operational statistical model, namely a *Bayesian network* in *Python* programming language. This modelling core brings the quantitative inference and predictions about how one set of factors as drivers, influence another set of factors as impacts, through their probabilistic relations to remote working arrangements (RWA).

Hence, both co-created knowledge (gathered from consortium members) and measured indicators from datasets are treated to capture people's perception or belief towards the factor relations, along with actual measurements of factors at the same time. Insights from the co-created knowledge gathered in 2.1 regarding the types of causal relationships are utilized as the model priors in the *Bayesian* setup, while *likelihoods* and *posterior* probabilities are derived from the data where available. This methodology also enables several analytical directions, such as assessing the significance of various factors in influencing specific outcomes (looking "up" the network) or predicting potential outcomes under hypothetical scenarios where certain factors take predefined values (looking "down" the network), as discussed in Section 3. Furthermore, the model can accommodate the addition of new factors and facilitate learning of the causal network structure.

As the R-Map model is designed as an integrated assessment framework for Europe, and most indicators are singular values at NUTS-3 or NUTS-2 levels, this task anticipates model outputs in terms of singular values at these scales. However, as the project advances into regional case studies under WP4, more localized data can be collected, enabling detailed, context-specific analyses and/or predictions. At the same time, the implemented R-Map model is equipped with a regression analysis, which by nature can be extended into many forms such as *spatial regression* by taking advantage of the spatial information in the datasets, and generate results that are also spatially discriminative, hence, can be visualized as maps.

In presenting the R-Map implementation, the report explicitly distinguishes between the R-Map model conceptualized in Task 2.1, and a full-fledged platform with extended functionalities of data harmonizations, storage, visualization and user interfaces, which will be realized through an extended workflow. The report also elaborates on its potential of being extended to a user-friendly platform with sample functionalities, including data harmonization and storage, preliminary data exploration, model input preparation, and model output processing and storage, that can be added on top of the core model.

5.2 Prepare inputs for modelling

In order to implement the model, both the datasets as the inputs and the conceptualized model should be represented properly in a computer. There are two important pieces of raw data for the R-Map modelling. One is the harmonized spatial dataset (which will be illustrated later regarding data harmonization) encoding indicator or proxy values of the factors. And the second is people's perception (e.g. represented by partners involved in workshop of Task 2.1) towards the relations among the factors obtained through workshops and surveys from work-package 1 of the project. These two types of data provide inputs for the factors at the nodes and relations along the links shown already in Task 2.1.

However, these datasets cannot be directly loaded into the model for the nodes and links. In fact, there is not yet a suitable model structure to load the data. Hence, the first step in the implementation is to create such a model structure, specifically a model frame with the necessary components of nodes and links to hold the data, so that the data can be structured resembling the structure of the model. In the R-Map model implemented in *Python*, the structure of the matrices created in Task 2.1 is used to derive how factors are linked. For instance, as shown in Figure 19 below, the entire matrices from Task 2.1 encoding how people see the strength and direction of links provide the information about whether factors are linked and can be viewed and transformed into binary encoding of factors and links. In the centre of the figure, a subset of the factors and the relations are shown in a binary matrix. This already captures a practical situation, where it is difficult to include all the factors in the actual modelling due to limitations such as data availability. Since the R-Map model is acyclic and non-reinforced (not allowing looping over one factor itself), the matrix should be asymmetric and registered with null values along the diagonal. Although it can still be visualized as a network such as that of Task 2.1 (as on the right-hand side of the figure), the actual structure is entirely registered in the binary matrix. The factor names are also passed down into either the rows or columns of the binary matrix in another *Python List* consistent with the numbering sequence [0, 1, 2, ...] as shown in the figure 19. In this way, data from the GIS table with certain factor name (normally on the top of each column) will be registered and numbered accordingly in the binary matrix.

Given the model structure that is created, loading the information of relations for the links is more implicit than loading the factor values to the nodes. Firstly, the relations registered as people's perception towards the causal links is largely categorical, such as ranking of discrete level of strengths, and direction of either positive or negative relation. They need to be translated into coefficients of relations, or probability of coefficients in the case of *Bayesian Network*. Secondly, the relations are not registered as part of the model structure as in a matrix in Figure 19, instead, they are parameters used in the process of modelling, hence, loaded in parallel with the model configuration. This will be shown in section 5.3, where the parameters of relations are used in the *likelihood function* specified for the *Bayesian regression* model.

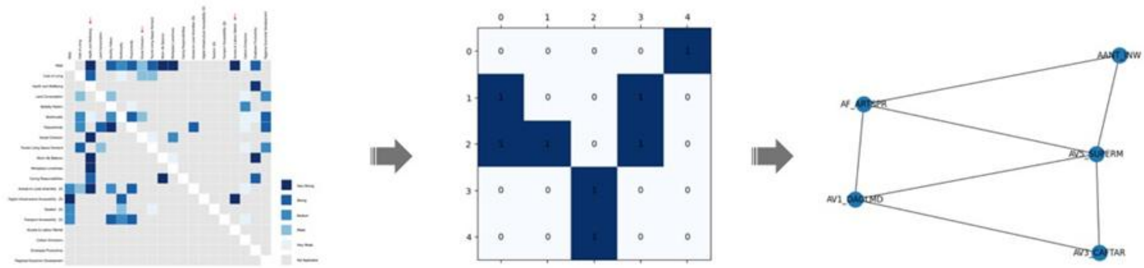

Figure 19: Matrix to be "translated" into model structure as a "placeholder"

5.3 Modelling: The core model algorithms

The R-Map core model follows the setup of the classic *Bayesian Network* but also differs from the classic model with its characteristics. The classic *Bayesian Network* represented as a *directed acyclic graph* (*DAG*), consists of nodes linked by arrows, where each node is a factor or variable, and a directed arrow links two dependent nodes with the cause pointing towards the effect. Instead of the actual values of a factor or variable, each node encodes the probabilities of *discrete* events or status of the factor or variable at each node, conditioning on events that are considered as causes, which are linked by directed arrows. Hence, the probability at each node can be either a probability or conditional probability distribution depending on the presence of *parent* nodes as the causes. Any pair of nodes that are not linked are conditionally independent variables. For instance, in the example in Figure 20 below, the status of factor *B*, which takes a binary form $P(b)$ and $P(\sim b)$, is conditioned on the other two parent-factors *L* and *C*, hence a *conditional probability* $P(B|L,C)$. The value of each probability, e.g. $P(B = b|L = T,C = T)$, is given in a *conditional probability table*. The status for factors L and C are also given in their own table, but not in conditional probability form as no *parent* factors are present for them. Most importantly, any inference about a certain event, such as "What is the probability of the status *C* given an observed consequence as a status of *B*" in the form of $P(C = T|B = T)$, can be derived through *Bayesian inference* as the joint probability of the two events normalized by the marginal probability of the consequence as $P(C = T,B = T)/P(B = T)$.

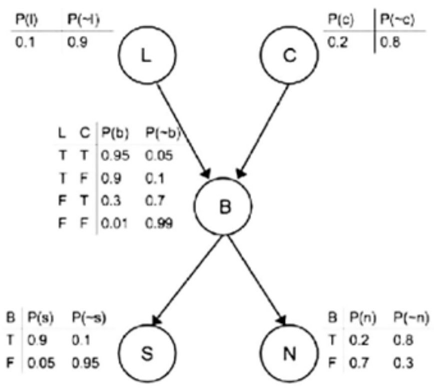

Figure 20: The classic setup of a Bayesian Network represented as a Directed Acyclic Graph (DAG)

5.3.1 The R-Map model as a modified Bayesian Network

The implementation of the R-Map model follows exactly the structure of a *Bayesian Belief Network.* At each of the nodes, it encodes the probabilistic distribution of the factor values that can be either continuous or discrete, and the links stipulate relations among the factors. However, the spatial data to be loaded onto each node is not the distribution but actual measurements or observations. Further, people's perceptions towards the factor relations are explicitly gathered as co-created knowledge, which must be encoded as available information along the links. Hence, the *prior knowledge* is more or less along the links rather than at the nodes. Given the *Bayesian Network* structure and its similarity to the rationale of BBN, the configuration of the conditional probabilities and their computation should be adapted and differ from the original BBN setup.

The R-Map core model differs from the setup shown in Figure 20 in a few ways. First of all, each of the nodes in the network graph encodes actual values of a factor, which can be either discrete or continuous, as opposed to probabilities of discrete status of the factor. In the case of continuous values, it can be population density values of all the spatial units on a map covering a certain geographic region. Imagine one of the harmonized datasets, such as those that can be visualized as maps but are essentially stored as GIS relational tables (or commonly referred as attribute table), or as a column of an attribute in the table. Although it is not the probability of a discrete status, it is still a *distribution of values* which can be approximated by a *probabilistic density function*. It is similar to how a probabilistic function represents a histogram of values. This narrows down the essential difference between the conventional setup of the *Bayesian Network* and the one in the R-Map model.

Secondly, both the practical (in the sense of supporting decision- and policymaking) and scientific values of the R-Map model are to understand how one or one set of factors influence the other, rather than just computing the outcome probabilities of factor status at each node. Then knowledge regarding what is going on along the edges, such as strength and directions of the relations, becomes the primary goal of the modelling. The workshop and survey collecting perceptions regarding factor relations from Task 2.1 largely focused on obtaining such knowledge. This means the characters of the edges should also be explicitly modelled, whereas the conventional *Bayesian Network* are only parameterized by conditional probability tables at the nodes. In the case of Figure 6, this forces conditional probability $P(B|L,C)$ to be modified into $P(B|L,C,\beta_l,\beta_c)$ with the relations along arrows from *L* and *C* explicitly parameterized.

Ultimately, putting the differences in the configuration of both the nodes and edges, it leads to the modification of modelling itself, where the probability distribution of parameters along the edges should be estimated in the first place before modelling the actual values at the nodes. While the factor values are considered to be given at each node in the case of the R-Map model, estimating parameters such as β_l and β_c can be considered as estimating a *posterior distribution* of $P(\beta_l,\beta_c|B,L,C)$, with values at node *L*, *C* and *B* (e.g. continuous values such as population density, age or housing property values) and *prior knowledge* of $P(\beta_l)$ and $P(\beta_c)$. Such modelling rationale naturally links to *Bayesian regression* as $P(\beta_l,\beta_c|B,L,C) \propto P(B|L,C,\beta_l,\beta_c)P(\beta_l)P(\beta_c)$, where $P(B|L,C,\beta_l,\beta_c)$ is considered as the *likelihood function*. Any *predictive distribution* regarding the actual values of *B* can be derived by using the *posterior distribution* of the parameters of β_l and β_c as updated knowledge of the relations together with the *likelihood function* and newly observed *L* and *C*.

At the most generic level, estimating the *probability*, *conditional probability* or *joint probability* of an event in the conventional *Bayesian Network* is essentially equivalent to estimating the probability of values at each node of the R-Map model, where an extra layer of edge parameters needs to be estimated as well. This modification is fundamental as: (1) it captures interesting perceptions towards relations among factors as opposed to only the factors themselves; and (2) the *Bayesian regression* can be extended easily into different forms such as to include spatial and temporal information as covariates, leading to modelling outcomes also spatially and temporally informed, and ready to be visualized on maps.

5.3.2 The priors, likelihood functions and estimation

In a very simple scenario without the loss of generality, the implementation of the R-Map model in *Python* can be illustrated by three nodes with two of them as the drivers and one as the impact, mimicking a multi-factor network of the smallest size. As shown in Figure 21, the factor *Mobility Patterns* (*M*) is influenced by *Transport Accessibility* (*T*) and *Digital Infrastructure Accessibility* (*D*). Preferably, the indicators or proxies found for these factors are continuous measurements, for instance, some normalized index for *T* and *D*, and *M* is measured as distance travelled as one of several potential dimensions of mobility pattern. Then the conditional probability of *M* taking specific values is given as $P(M|T,D,\theta_t,\theta_d)$, where θ_t and θ_d encode parameters of relation of T→M, and D→M, respectively. In practice, they are modelled as probability distributions serving as *prior distributions* of the parameters as shown along the arrows in the Figure.

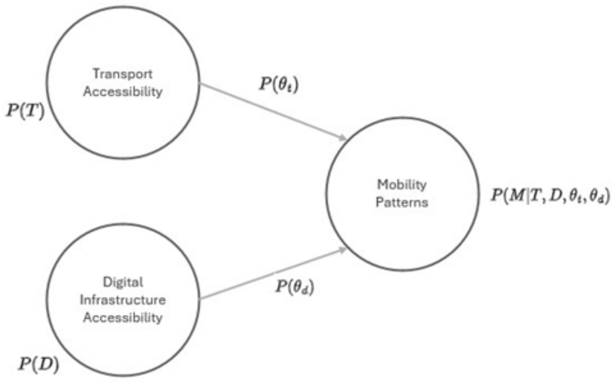

Figure 21: Oversimplified model components highlighting terms of the building block algorithm

As mentioned above, estimating the *posterior distributions* of the parameters goes before the estimation of the *predictive distribution* of factor values. Hence, it can be the first building block algorithm of the R-Map model with the form of:

$$P(\theta_t,\theta_d|M,T,D) \propto P(M|T,D,\theta_t,\theta_d)P(\theta_t)P(\theta_d). \tag{1}$$

The terms on the right-hand side need further specifications. Again, as mentioned above, while such modelling configuration naturally links to *Bayesian regression*, the likelihood function $P(M|T,D,\theta_t,\theta_d)$ can be specified exactly as a regression model subject to model complexity choices. For instance, in the first trial implementation of the R-Map, it can be a linear likelihood in the form of:

$$P(M|T,D,\theta_t,\theta_d) \sim \mathrm{N}(T\theta_t + D\theta_d, \delta^2), \tag{2}$$

where a simple multi-variate linear regression model is used along with assuming a Gaussian noise δ^2.
Once the *posterior distributions* of the parameters are estimated, they can be plugged back into the *Bayesian setup* along with the *likelihood function* to make *predictive distribution* for the values of the target factor in the form of:

$$P(M_*|T_*,D_*,M,T,D) = \int P(M_*|T_*,D_*,\theta_t,\theta_d)P(\theta_t,\theta_d|M,T,D)d\theta_t d\theta_d, \tag{3}$$

where $\cdot_*$ are new datasets of either drivers or impacts in the context of the R-Map model. Basically, with the regression setup, the *predictive distribution* uses the *likelihood function* of exactly the same form but averaging over all possible parameters according to the *posterior distribution* of the parameters.

Obviously, the simple linear *likelihood function* $T\theta_t + D\theta_d$ set in this case can be extended into a lot more sophisticated form with *T* and *D* being projected to higher dimensional *feature space*, such as $(T, T^2, T^3, \ldots)$, and other information can be attached together with them, for instance, the geographic locational information, which always comes along in all spatial datasets, and such setup can be turned into spatial regression flexibly.

5.3.3 Operationalize the estimation

As illustrated above, such a minimal representation in Figure 21 is sufficient to capture important modelling elements under the *Bayesian* formalization with the building block algorithms shown in Equation (1), (2), and (3). The report shows the operationalization of the model, where inputs are fed into the model, and estimation being generated with the algorithms applied.

Once the datasets are properly harmonized as mentioned later in Section 5.7, the values of a given factor can easily be read as a single column of the GIS relational table. By drawing a connection of Figure 21 and Figure 22 below, this can also be imagined as loading a map of values at a certain granularity (e.g. at NUT-3 level) in a given region into each node. Since the values in a column of a table or on a map themselves already yield data distributions considering in the forms of a histogram or being approximated by some probabilistic distributions, they carry statistical information automatically. A more complicated step is loading information for the parameters along the arrows encoding the relations among the factors. Such information, in its very raw form, namely the perceptions about the characters of the relations in the form of co-created knowledge such as positivity/negativity, strength, and degrees of agreements, need to be transformed into proper probabilistic distributions. In Figure 22 below, one can imagine that the matrices generated in Task 2.1 encoding the relation characters have already been "translated" into statistical characters such as the *mean* or *standard deviation* of a distribution if Gaussian model is used for distribution approximation. Then for the *prior distribution* of a parameter, taking $P(\theta_t)$ for an example, multiple matrices should be used to read different statistical characters, where the *means* can be registered in one and the *standard deviation* can be registered in another.

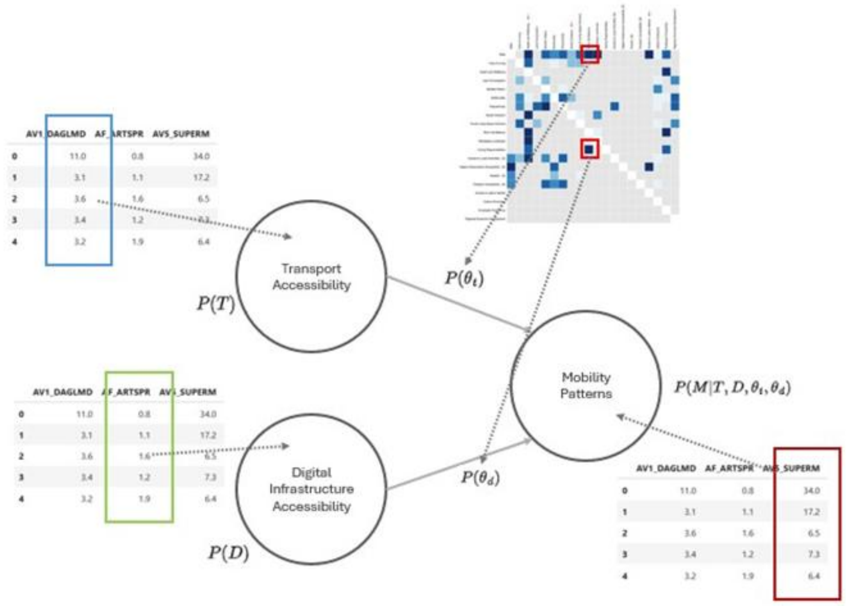

Figure 22: Inputs prepared from the harmonized datasets being fed into the model

Once the values from tables and matrices are properly loaded, the *prior distribution* and *likelihood function* specified in Equation (1) can be computed to derive the posterior distribution of the parameters and essentially be visualized as below in Figure 23. In the case of two driving factors, there are two regression coefficients shown as *slopes* (slope0 and slope1) in the figure. Since itis a linear regression model specified as shown in Equation 1, there is also an *intercept* parameter apart from the slopes in practice, which is not explicitly written down in the equation. Also, the noise level δ is estimated but shown as the variance $\sigma = \delta^2$ in the figure below.

Up to this phase, the report described how to achieve the estimation and computation of the R-Map model, but here only a very small subset of the model is illustrated. The entire estimation should be replicated over a rather large model in practice when more factors and links are included. All of the estimations about the *predictive distributions* taking place in the next step are built on top of the *posterior* estimation of the parameters. Hence, both data preprocessing/preliminary exploration, and model choice are decisive.

Plugging the estimation outcome of Equation (1) into Equation (3) should produce new distributions $P(M_*)$ in the case of the example in Figure 21. However, it can be more interesting, as already mentioned, to include the spatial information such as geographic locations in the *likelihood function*, in this example it is the *linear regression* function specified in Equation (2). Thus, the *spatial regression* can be configured as the *likelihood function* given large flexibility in specifying the form of the regression. Since the geographic locational information comes naturally along inside of the relational table and is attached as extra columns of *geometric* attributes, it should always be rather convenient to extract such information along with the other factor values as inputs into the model. This is considered as one possible extension of the current trial version of the R-Map model.

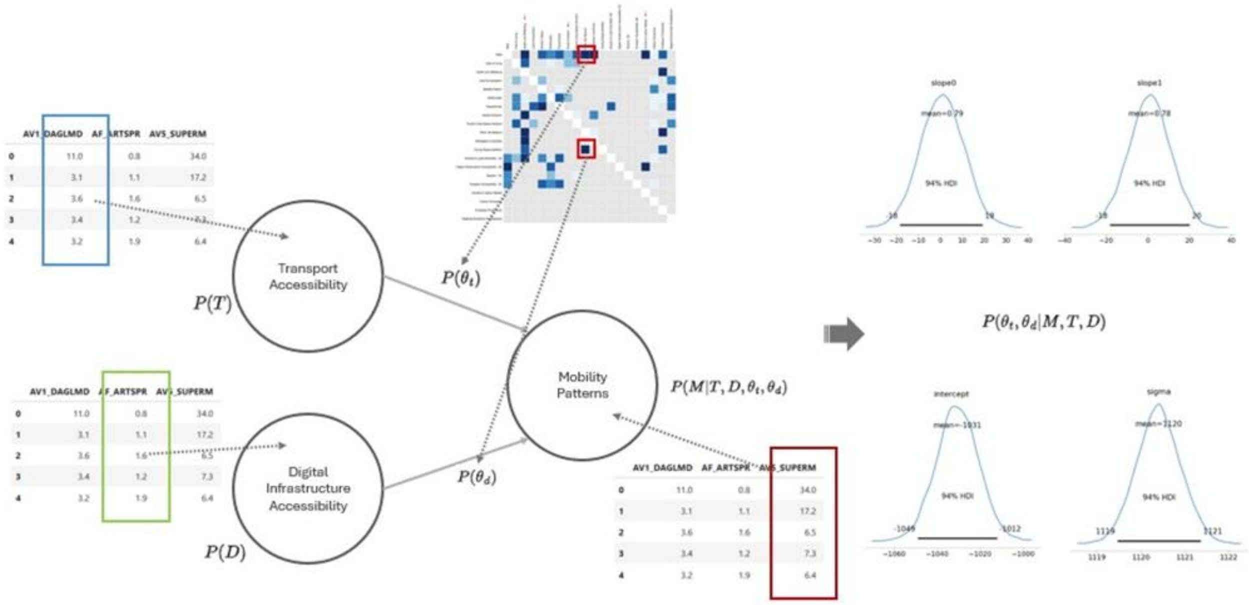

Figure 23: Estimating the posterior distribution of relation parameters. Schematic flow of data from the database tables into the nodes as input, and statistical distribution of the parameters are generated as the outcomes

5.4 Illustration of one causal chain

5.4.1 Selection of subset network of the R-Map conceptualization

To illustrate the approach, we focus on a specific causal chain within the R-Map framework—namely, the pathway from RWA to the Regional Economy. This pathway was selected due to the relatively higher reliability and availability of proxy indicators along this chain, in comparison to alternative pathways. Crucially, the relationship between RWA and population change—and, by extension, between RWA and relocation—is of particular interest. The variable 'relocation' functions as a key mediator, influencing both short- and long-term effects, such as polycentricity, cost of living, and regional GDP (see Figure 24). While direct origin–destination data capturing relocation flows attributable to remote work is not available, the conceptual model (Figure 25) positions relocation strictly as a mediating factor between RWA and population change. Therefore, population change is employed as a proxy to capture the downstream effects of relocation in this causal chain.

Importantly, the decision to focus on a spatial-economic causal chain is also motivated by practical considerations around data resolution and interpretability. Many social indicators are either only available at the national level or are highly context-specific and influenced by individual-level variation, making them unsuitable for regional aggregation and statistical modelling. For example, work–life balance could theoretically be proxied using Eurostat data on the *average number of usual weekly working hours in the main job*; however, this data is reported only at the national level. Moreover, a key control variable for work–life balance—individual caring responsibilities—is not captured in available regional datasets, limiting the reliability of this proxy in assessing downstream impacts such as employee productivity. Similarly, while health and well-being could be approximated at the NUTS-2 level using indicators such as *hospital days of in-patients*, these aggregate metrics fail to reflect the heterogeneity of individual experiences and the contextual drivers of well-being. Without the ability to control for intervening factors such as work–life balance or caregiving obligations, reliance on such proxies may introduce spurious relationships and obscure meaningful inferences. Consequently, the RWA-to-Regional Economy causal chain provides a more analytically robust and spatially interpretable pathway for investigation, given both data availability and conceptual clarity at the regional level.

A key consideration in focusing on a specific causal chain is the need to incorporate appropriate control variables to accurately assess final impacts. This requirement informed our decision during the co-design process to distinguish between "factors"—defined as quantities that may increase or decrease as a result of changes in RWA or any dependent variables—and control variables, which are introduced later in the analysis. The inclusion of these control variables necessitates a reinterpretation of certain causal relationships and their corresponding linkages, as reflected in the extended network structure shown in Figure 25. The control variables presented here are derived from multiple sources: the literature review undertaken in WP1 (subject to data availability), insights gathered from survey responses and stakeholder input during the WP1 co-design process, and additional reflections contributed by project partners in WP2. It is important to emphasize that this represents one possible operationalization of the causal impact pathway from RWA to the Regional Economy, rather than a definitive model. As further data and research emerge, the framework can be refined to enhance the precision of impact estimations. The Bayesian Network probabilistic modelling approach is particularly well-suited for this task, as it allows for the integration of new variables without compromising the coherence of the model—such variables will, by design, demonstrate limited influence if they are not strongly supported by the data. Additionally, as discussed later, the functionality of network learning can be incorporated into subsequent stages of the research to further strengthen the model's adaptability and empirical grounding.

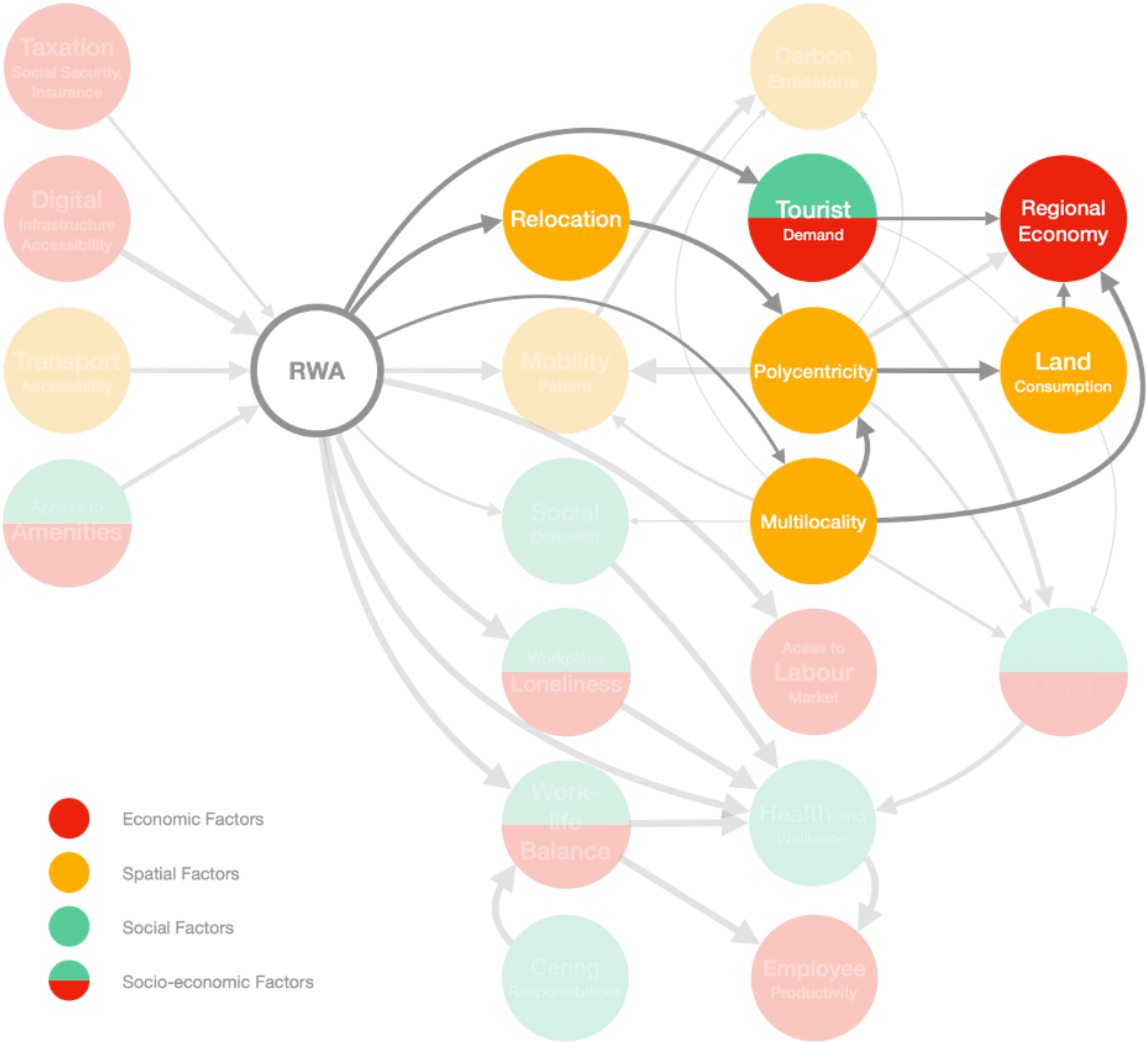

Figure 24: Key causal chain – RWA to regional economy

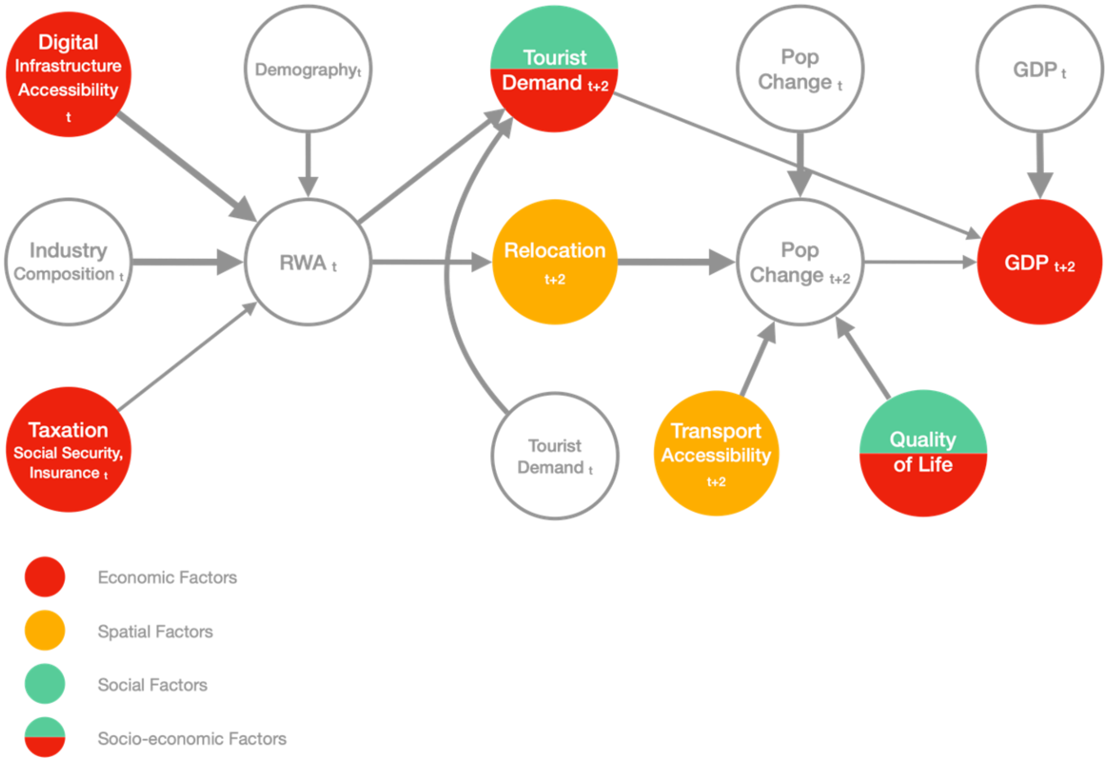

Figure 25: Focal causal chain from RWA to regional economy with incorporated control variables

5.4.2 Description of the indicators and corresponding datasets

A detailed overview of the datasets used is provided in Section 4. Beyond identifying and processing the available datasets, we also developed a set of indicators—both direct and proxy—to represent specific factors within the model. Table 5 presents the proposed list of indicators, focusing on those factors for which reasonable and data-supported proxies could be established. In parallel, Table 6 presents the associated control variables. It is worth noting that for two factors—caring responsibilities and social cohesion—no meaningful proxies could be identified from available data sources. These omissions reflect broader limitations in regional-level social data and underscore areas for potential future data development. It is also important to note that the large-scale survey conducted as part of WP1 played a pivotal role in guiding key model assumptions. Specifically, it informed the identification of sectors with high remote work potential and clarified the relationship between relocation distance for residence and employment context.

Table 5: Key indicators and corresponding data sources for identified factors

No.	Factor	Potential Indicators and Proxies	Spatial/ Temporal Granularity	Spatial Coverage	Dataset

1.	RWA	Annual change in percentage of the population working from home more than at least half of the days over the reference period of four weeks	NUTS-2 / 2020	EU	Eurostat[1]
		Percentage of employed adults working at home	NUTS-2 / Annual	EU	Eurostat
		Percentage of employed adults working at home by sex, age groups, number of children and age of youngest child	National / Annual	EU	Eurostat
2.	Transport Accessibility	Ease of access to destinations as proxied through from street network analysis - average closeness or betweenness centrality	Local / Cross-sectional	EU	Street network data from OSM (derived from Geofabrik[2]), UTD19 traffic data[3]
		Ease of access to work locations as proxied through from street network analysis – average network step depth from business districts or travel time and cost	Local / Cross-sectional	EU	Street network data from OSM (derived from geofabrik)
		Average travel time to cinema, shops, stations, banks, pharmacies, hospitals, schools	NUTS-3 / Cross-sectional	EU	ESPON
		Total road and rail network length	NUTS-2 / Annual	EU	Eurostat
3.	Digital Infrastructure Accessibility	Percentage of households with internet access at home	NUTS-2 / Annual	EU	Eurostat
		Percentage of employees with internet for business purposes by sector	NUTS-2 / Annual	EU	Eurostat

4.	Access to Local Amenities	Territorial Quality of Life – Good Life Enabler Index	NUTS-2 / 2019	EU	ESPON
		POIs (Points of Interest) - interpolated	Local / Cross-sectional	Germany	Eurostat
		Liveability index - Regional Quality of Living (2015)	Cities, NUTS-2 / Cross-sectional	EU	Eurostat, Lagas et al. (2015)
		Average travel time to cinema, shops, stations, banks, pharmacies, hospitals, schools	NUTS-3 / Cross-sectional	EU	ESPON
5.	Taxation, Social Security, Insurance Regulations	Country fixed-effects capturing country-level variations in institutional contexts	National	-	-
6.	Access to Labour Market	Job postings	NUTS-2 / 2008 - 2015	EU	Eurostat
7.	Cost of Living	Cost of living score - interpolated	Cities / Cross-sectional	EU	Eurofound/ Eurostat
8.	Land Consumption	Change in the total built-up area	Local / 5-year interval	EU	Global Human Settlement (GHS), EOC Geoservice Maps[4]
9.	Mobility Pattern	Modal usage proxied through car ownership	NUTS-2 / Annual	EU	Eurostat
		Modal usage proxied through regional loading unloading of rail passengers	NUTS-2 / 5-year interval	EU	Eurostat
		Mean duration of commuting time one-way between work and home by sex and age	National / Annual	EU	Eurostat
10.	Polycentricity	People Concentration Index[5] capturing flows of relocation of population	NUTS-2 / 2018	EU	ESPON
		POIs (Points of Interest) - interpolated	Local / Cross-sectional	Germany	Eurostat

11.	Multilocality	People Concentration Index capturing flows of relocation of population	NUTS-2 / 2018	EU	ESPON
12.	Tourism	Number of bed places occupied in tourist accommodations	NUTS-2 / Annual	EU	Eurostat
		Number of bed and breakfast establishments	NUTS-2 / Annual	EU	Eurostat
		Nights spent in tourist accommodations establishments	NUTS-2 / Annual	EU	Eurostat
13.	Work-life Balance	Average number of usual weekly hours of work in main job, by sex, age, professional status, full-time/part-time and economic activity	National / Annual	EU	Eurostat
		Employed persons having more than one job by sex	National / Annual	EU	Eurostat
14.	Health and Wellbeing	Hospital days of in-patients	NUTS-2 / Annual	EU	Eurostat
15.	Carbon Emissions	Greenhouse gas emissions	NUTS-2 / Annual	EU	Eurostat
		Air emissions accounts for greenhouse gases by sector	National / Annual	EU	Eurostat
		Nitrogen dioxide concentrations - interpolated	Cities / Cross-sectional	EU	Eurostat
17.	Employee Productivity	GDP per inhabitant (labour productivity*proportion of people employed)	NUTS-3 / Annual	EU	Eurostat
18.	Regional Economy	GDP	NUTS-3 / Annual	EU	Eurostat
		Employment	NUTS-3 / Annual	EU	Eurostat
		Employment by sex, age and educational attainment level	NUTS-2 / Annual	EU	Eurostat

		Household Incomes	NUTS-2 / Annual	EU	Eurostat

1. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20210923-1

2. https://download.geofabrik.de

3. https://utd19.ethz.ch/

4. https://geoservice.dlr.de/web/maps/eoc:wsfevolution

5. https://gis-portal.espon.eu/arcgis/apps/sites/#/espon-hub/datasets/9404846ba61b57c08438043b4d66e936/explore?layer=0

Table 6: Key control variables and corresponding data sources

No.	Factor	Potential Indicators and Proxies	Spatial/ Temporal Granularity	Spatial Coverage	Dataset
1.	Demography	Population by age and sex	NUTS-3 / Annual	EU	Eurostat
		Population by sex, age and educational attainment level	NUTS-2 / Annual	EU	Eurostat
		Population change	NUTS-3 / Annual	EU	Eurostat
2.	Industry Composition	Total employment in sectors including finance and insurance, information and communication, scientific and technical activities, and arts, entertainment and recreation	NUTS-2 / Annual	EU	Eurostat
3.	Science and Technology	R&D personnel and researchers by sector of performance, sex	NUTS-2 / Annual	EU	Eurostat
		Patent applications by sector	NUTS-2, NUTS-3 / Annual	EU	Eurostat/ PATSTAT[6]

4.	Business Demography	Business demography by NACE Rev. 2	NUTS-3 / Annual	EU	Eurostat
		Employer business demography by NACE Rev. 2	NUTS-3 / Annual	EU	Eurostat
5.	Crime	Police-recorded offences	NUTS-3 / Annual	EU	Eurostat

6. https://www.epo.org/en/searching-for-patents/business/patstat

Given the data limitations—specifically, the availability of Remote Working Arrangement (RWA) data only for the year 2020—this analysis adopts a cross-sectional design. Temporal sequencing of certain factors is informed by their proximity to observable impact, as identified through the survey conducted in Task 2.1. The factors temporally advanced include: tourism demand, population change, regional GDP, and transport accessibility. Due to the absence of direct data on population relocation attributable to RWAs and acknowledging its role as a mediator rather than an observable outcome in the causal chain, we instead rely on net population change and regional GDP as proxies for estimating impacts on the regional economy. Rather than including exhaustive control variables for GDP, tourist demand, and population change, an autoregressive specification is employed to reduce the dimensionality of the model while retaining explanatory robustness.

The data pre-processing of Eurostat datasets involved several standard cleaning procedures: harmonization of column names, reconciliation of geographic identifiers with NUTS-2 nomenclature (particularly where updates have occurred), and aggregation or subsetting as required. Missing data are imputed using the mean of the respective indicator within a given NUTS-2 region. As an illustrative example, the preparation of data related to employment in sectors with high remote work potential followed a multi-step process. First, we queried employment statistics by NACE sector from the Eurostat database. We then ensured consistent column naming across datasets and matched NUTS-2 codes to their corresponding regional names by joining with an auxiliary dataset. Subsequently, we filtered the dataset to retain only employed persons, and then subset the data to include only the four sectors identified in WP1 as exhibiting a high propensity for remote work. These sector-specific employment values were then aggregated by NUTS-2 region and by year. Finally, we removed all observations where the NUTS-2 code ended with the suffix "ZZ", which indicates placeholder or non-standard regional entries. The resulting metric was then used as an indicator of industry composition.

Two primary causal pathways linking RWA to regional GDP were tested:

RWA → Relocation → Population Change → Regional GDP

RWA → Tourist Demand → Regional GDP

The following factors and associated indicators have been used (as summarised in the accompanying table):

Remote Working Arrangement (RWA): RWA is operationalised as the annual change in the percentage of individuals who 'usually' work from home, based on the Eurostat definition. 'Usually' refers to individuals who perform any productive work related to their current job at home for at least half of their working days within a reference period of four weeks. This data is available at the NUTS-2 level from Eurostat for the year 2020.

Digital Infrastructure Accessibility: Measured as the percentage of households with home internet access, using Eurostat data at the NUTS-2 level.

Industry Composition: Derived from Eurostat employment statistics at the NUTS-2 across four sectors which were identified via the large-scale survey in WP1 as having a high propensity for remote work - finance and insurance, information and communication, scientific and technical activities, and arts, entertainment and recreation.

Demographic Controls: Age, gender, and education-related variables are used to account for differential propensities to engage in RWA. These include: percentage of the population aged 20–34; percentage with tertiary education (levels 5–8); and total male and female population figures per NUTS-2 region, all sourced from Eurostat.

Quality of Life: In line with the recommendations of Task 1.1, we adopt quality of life as a key factor in the model, in place of the more narrowly defined concept of access to amenities. This decision is driven by both the holistic nature of the Quality of Life construct and the availability of robust data. Quality of life is proxied using the Territorial Quality of Life – Good Life Enabler Index, developed by ESPON (available for 2019 at the NUTS-2 level). This composite index captures multiple dimensions of well-being by integrating personal, social, and ecological indicators, including elements such as housing affordability, access to basic utilities, education, and healthcare services, among other regional determinants of well-being.

To further enrich this measure, we incorporate regional crime statistics—specifically, police-recorded offenses as reported by Eurostat—in order to account for additional dimensions of perceived and actual safety within regions.

Tourist Demand: Estimated using the number of bed places occupied in tourist accommodations, sourced from Eurostat at the NUTS-2 level.

Transport Accessibility: Proxied by the total length of road and rail networks in each NUTS-2 region, based on Eurostat data.

Taxation, Social Security, and Insurance Contexts: Recognizing country-level variations in RWA adoption (as highlighted in Deliverable D1.1), a country-level dummy variable is introduced to capture these institutional differences in a simplified form.

Finally, standardization (z-score normalization) on numeric variables is performed prior to the model run, ensuring comparability across units.

5.4.3 Model run and initial results

As described previously, running the model requires first translating the identified causal chains into a relationship matrix, as illustrated in Figure 26. Alongside the structural representation, a separate matrix is constructed to encode the strength (or weight) of the inter-factor causal relationships. To assess the upstream influence of parent variables on regional GDP in 2022 (i.e., “looking up” the network), the R-Map model is run with regional GDP in 2022 set as the focal outcome. The network identifies three immediate parent nodes for this variable: population change (2022), tourist demand (2022), and GDP (2020). As shown in Figure 27, GDP in 2020 emerges, as expected, as the most influential predictor. Population change in 2022 contributes positively, though the effect is extremely modest. Tourist demand in 2022, in contrast, does not exhibit statistical significance.

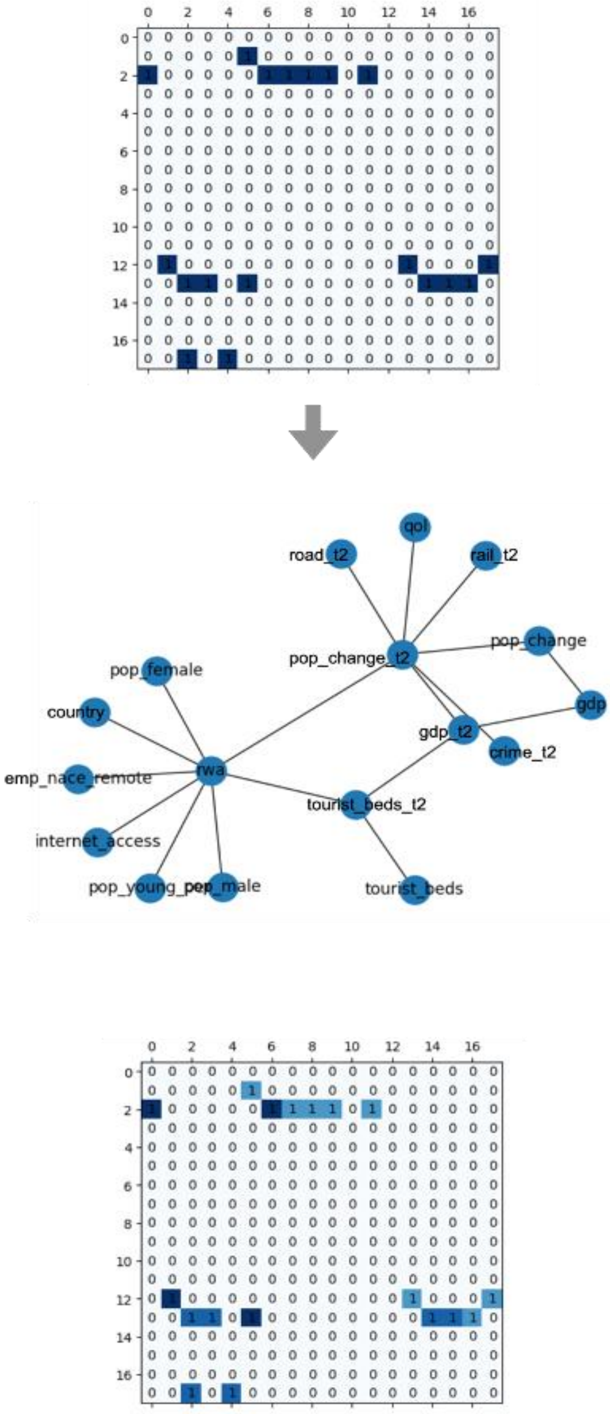

Figure 26: Causal Relationship Matrices (top and middle) and Weight Matrices (bottom), where the underlying values range from 0 to 1 (as reflected by the colour gradient), but are displayed as rounded values of 0 and 1 for visual clarity.

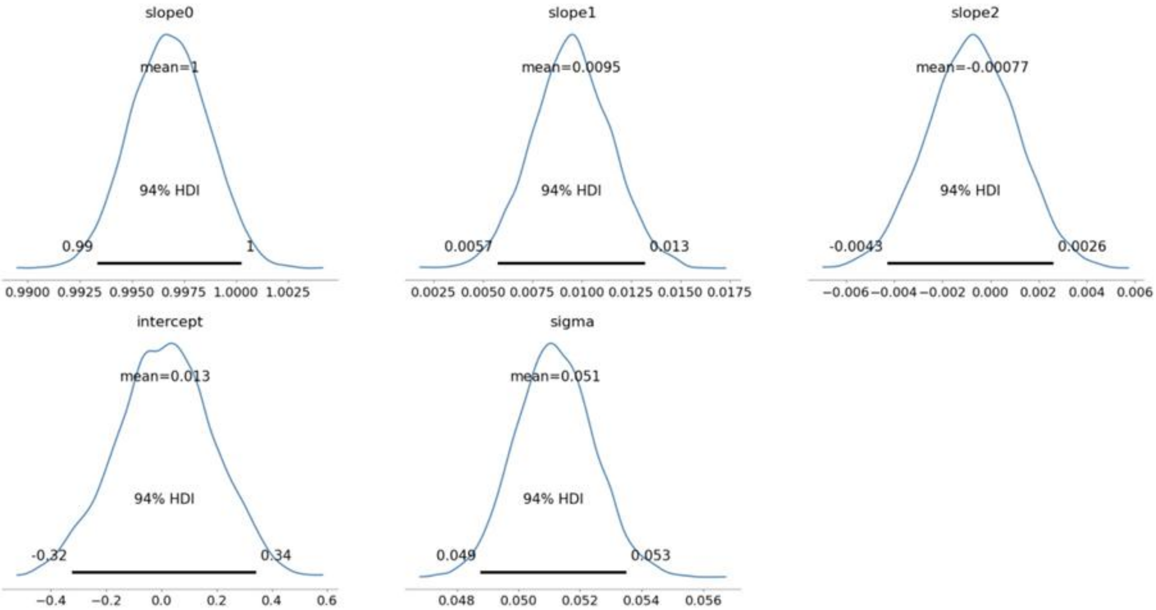

Figure 27: Parent Nodes' Influence on Regional GDP (2022). Slope 0, 1 and 2 correspond to GDP in 2020, population change in 2022 and tourist demand in 2022, respectively.

Since both population change and tourist demand are influenced by RWA in the network, a subsequent step focuses on assessing the significance of RWA in shaping these intermediate variables—effectively "looking down" the network. These results are presented in Figures 28 and 29. In Figure 28, population change in 2020 is confirmed as a strong and significant predictor of population change in 2022. While RWA (2020) and quality of life (2020) show moderately positive and negative associations respectively, neither effect is statistically significant—their coefficients are not distinguishable from zero. Transport accessibility (proxied by road and rail network length) and crime rates similarly display negligible influence, with low and statistically insignificant coefficients. Figure 29 presents the analysis of tourist demand in 2022. Here, tourist demand in 2020 is the most robust and statistically significant predictor. The influence of RWA in 2020, while directionally positive, is not statistically significant—its effect size is small and indistinct from zero.

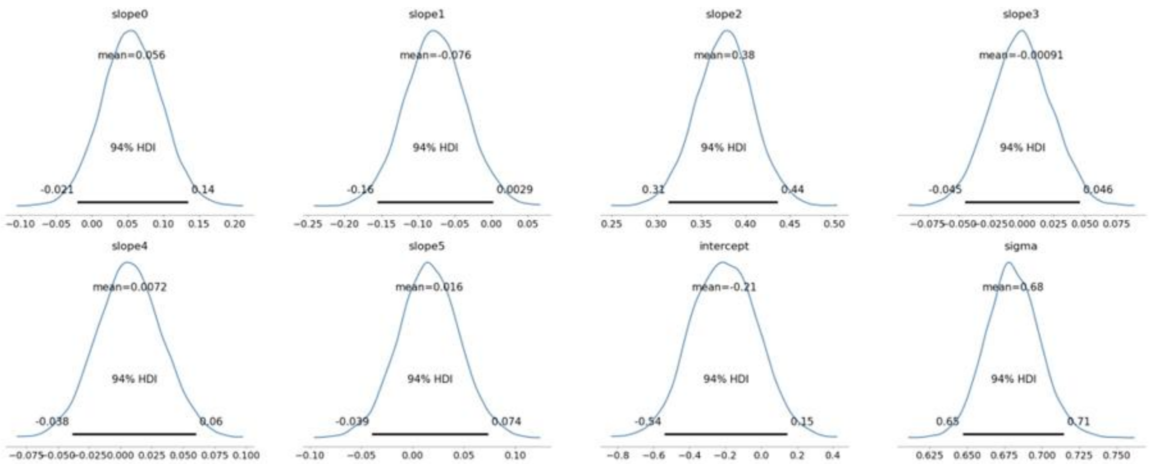

Figure 28: Determinants of Population Change (2022). Slope 0, 1, 2, 3, 4 and 5 correspond to RWA in 2020, quality of life, population change in 2020, total rail length in 2022, total road length in 2022 and crime in 2022, respectively.

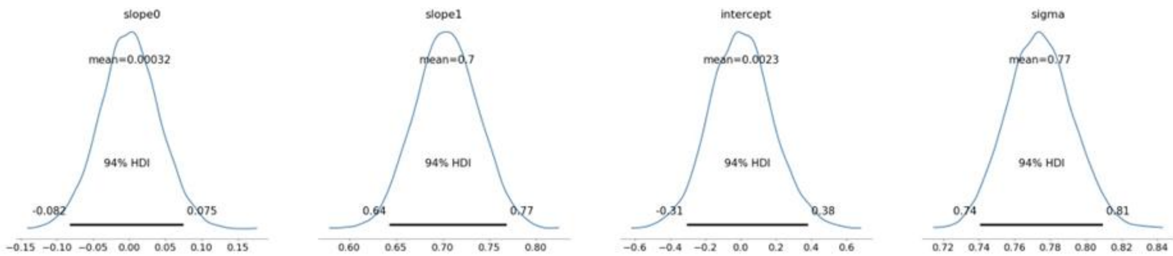

Figure 29: Determinants of Tourist Demand (2022). Slope 0 and 1 correspond to RWA in 2020 and tourist demand in 2020, respectively.

To further investigate the drivers of Remote Working Arrangements (RWA), the model is run with RWA in 2020 as the focal factor. Country-fixed effects are incorporated by introducing a factorised country-level variable. As shown in Figure 30, demographic variables, specifically the overall male and female population, emerge as the strongest predictors—male population displaying a negative effect, and female population a positive one. This divergence may reflect underlying gender-based differences in occupational structures and remote work feasibility. In addition, internet access, employment in sectors with high remote work potential, and the share of population aged 20–34 all display statistically significant positive associations with RWA. At the national level, Figure 31 highlights substantial positive fixed effects for several countries, including Germany, Finland, France, Ireland, Italy, Belgium, and Portugal. Furthermore, negative country-level effects are observed in Switzerland, Norway, Iceland, and several Eastern European countries, such as Cyprus, Croatia, Hungary, and Latvia.

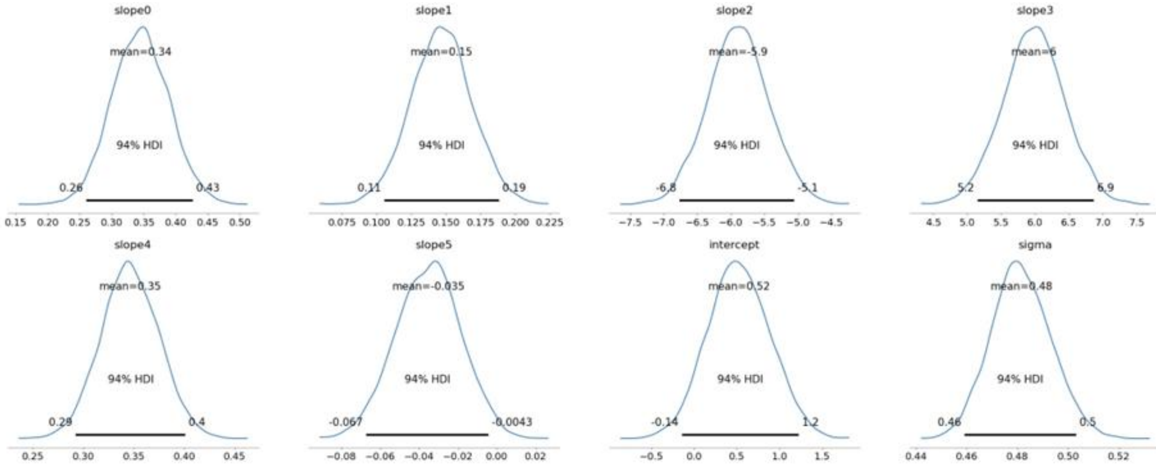

Figure 30: Key Drivers of RWA (2020). Slope 0, 1, 2, 3 and 4 correspond to internet access in 2020, employment in sectors with high remote work potential in 2020, total male population in 2020, total female population in 2020 and percentage of population aged 20-34 in 2020, respectively.

5.5 Interpretation of model outputs

While the model does identify significant drivers of RWA—including demographics, digital infrastructure, sectoral employment, and country-specific institutional contexts—its downstream influence on regional GDP remains statistically inconclusive within the examined causal chains. This limitation likely reflects the time lag required for such macroeconomic effects to materialize. In addition, introducing spatial dependencies would enable the exploration of neighbourhood spillover effects—a particularly relevant consideration in regional development analysis.

From a modelling perspective, these preliminary results highlight several priorities for subsequent work, including, addressing data gaps and increasing temporal and spatial resolution, advocating for open access to proxy indicators that better capture relocation, telework adoption, and related structural changes, and testing the model across different territorial scales for generalizability. Furthermore, future methodological enhancements could include – causal structure learning from data, incorporation of spatial dependencies to capture neighbourhood effects, and use of hierarchical Bayesian models to improve robustness across scales and contexts.

In summary, while initial results do not confirm a statistically significant link between RWA and regional GDP —at least within the scope of the current cross-sectional data and model assumptions, they provide crucial insights into the determinants of RWA and lay the foundation for more nuanced, dynamic, and spatially-aware modelling approaches in future research.

country	mean	hdi_3%	hdi_97%
AL	0.005	-1.853	1.900
AT	0.065	-0.630	0.741
BE	0.607	-0.059	1.244
BG	0.018	-1.977	1.839
CH	-0.883	-1.538	-0.285
CY	-1.604	-2.266	-0.903
CZ	-0.668	-1.228	-0.150
DE	1.019	0.504	1.546
DK	0.388	-0.179	0.927
EE	-0.290	-0.929	0.307
EF	-0.008	-1.834	1.905
EL	0.289	-0.174	0.764
ES	-0.325	-0.756	0.100
FI	1.070	0.623	1.513
FR	0.750	0.362	1.160
HR	-0.898	-1.367	-0.430
HU	-0.663	-1.057	-0.298
IE	2.061	1.625	2.471
IS	-0.651	-1.199	-0.078
IT	0.880	0.528	1.249
LI	0.007	-1.918	1.858
LT	-0.238	-0.777	0.314
LU	1.356	0.807	1.905
LV	-1.230	-1.835	-0.692
ME	-0.014	-1.900	1.841
MK	-0.295	-0.874	0.272
MT	0.771	0.173	1.341
NL	-0.316	-0.762	0.155
NO	-1.181	-1.632	-0.694
PL	0.267	-0.228	0.741
PT	0.736	0.233	1.271
RO	-0.381	-0.875	0.179
RS	0.163	-0.486	0.843
SE	-0.437	-1.009	0.135
SI	-0.085	-0.706	0.558
SK	-0.006	-0.615	0.649
TR	-0.030	-0.675	0.612

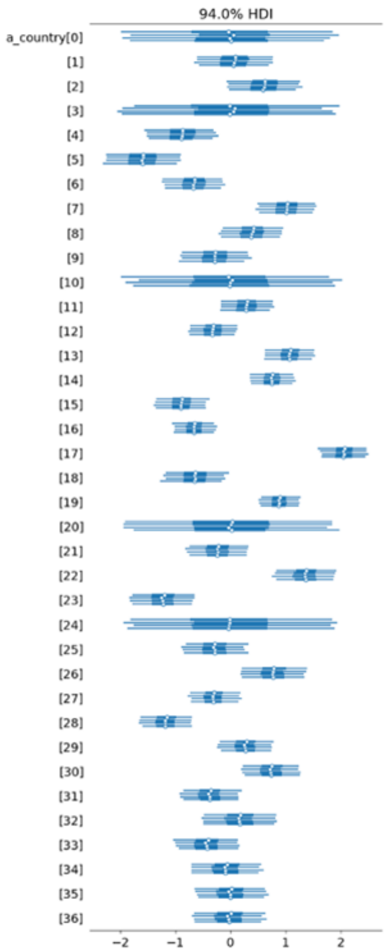

Figure 31: Country-Level Effects on RWA

5.6 Extending the R-Map model to the platform

The model conceptualization in Task 2.1, which has been implemented here in Task 2.2 forms the core of the R-Map modelling. While both scientific insights and policy implications can be derived from the modelling, it is by no means an operational platform that can be used and adapted to different modelling contexts, where new data inputs and model hypotheses are often encountered.

Hence, apart from the modelling itself, other functionalities are needed for users to include new datasets, from which the model could read data, and both inputs and outputs can preferably be stored and visualized. At the same time, the model can be fine-tuned and adapted according to user demands. Thinking about such type of functionalities for not only modelling experts but also a wider community of users, it already means, if not a sophisticated software design, but a design of *modularized functionalities* that are to be built on top of the modelling core and can be exposed with a user-friendly interface. Below is a list of *modularized functionalities to be* added on both ends of the modelling core of the *Bayesian network*:

- *Data harmonization and storage*: Spatial data in different formats from different sources are to be standardized to ensure compatibility, consistency and interoperability. It specifically addresses discrepancies in formats, spatial units/scales, temporality, semantics.
- *Preliminarily data exploration*: Before stacking multiple datasets and feeding them all together into the model, it is necessary to examine basic statistics of each dataset so that to build preliminary knowledge about data quality (e.g. in terms of missing entries in spatial units, or existence of outliers), uncertainties, and simple linear correlations between sample pairs of variables.
- *Inputs preparation for modelling*: The *Bayesian network* uptakes input data with explicit definitions upon *prior* and *likelihood distributions* or functions. In the setup of the R-Map model, these are to be loaded into the model from different sources. The *prior distributions* regarding factor relations are registered in matrix, and inputs indicators as variables are to be read from the harmonized datasets, so that a *likelihood function* can be built by using these variables, hence, they need be extracted and get prepared to be fed into the model. And this requires extra *application programming interfaces* (APIs) as a set of *modularized functionalities* to achieve.
- *Modelling*: This is the core of the R-Map model. In the R-Map model, the *Bayesian network* differs slightly from the conventional *Bayesian Belief Network.* At each node of the R-Map model it takes continuous values of a factor as opposed to the probability of a discrete status, whereas the belief or *prior knowledge* is set to capture the relations among factors rather than the status of individual ones. This equips R-Map with a character of mixing conventional *Bayesian Network* and *Bayesian regression models and* can be extended into spatial and temporal domains as the regression can easily be modified into spatiotemporal-based.
- *Outputs of inference and predictions, and storage*: Once the model is fit or trained (in the context of data science) with existing datasets, it can be used to simulate different scenarios of possible modifications of factors, such as the drivers, to predict corresponding possible outcomes or impacts. These scenarios can be useful information to assist decision-making and need to be stored. Just as the module of *data harmonization*, the storage will ensure standardized formats, spatial units/scales, temporality, and semantics.

These *modularized functionalities* form the guideline of the design of the R-Map *platform*, rather than the core model alone. As an illustrative example, as shown below in Figure 32, each one of these *modularized functionalities* is expected to be equipped with APIs as the actual functions aiming at specific tasks, such as aggregating or disaggregating spatial units through *resampling* algorithms in harmonizing data in different spatial units. The development of such functionalities may extend well into further WPs, but are still closely linked to Task 2.1 and 2.2. One should note that this is not an exhaustive and accurate list of functions in each of the module, but just a demonstration of how they are connected to form the guideline of design. In the following sections, all modules of functionalities apart from the R-Map core model will be walked through with more details.

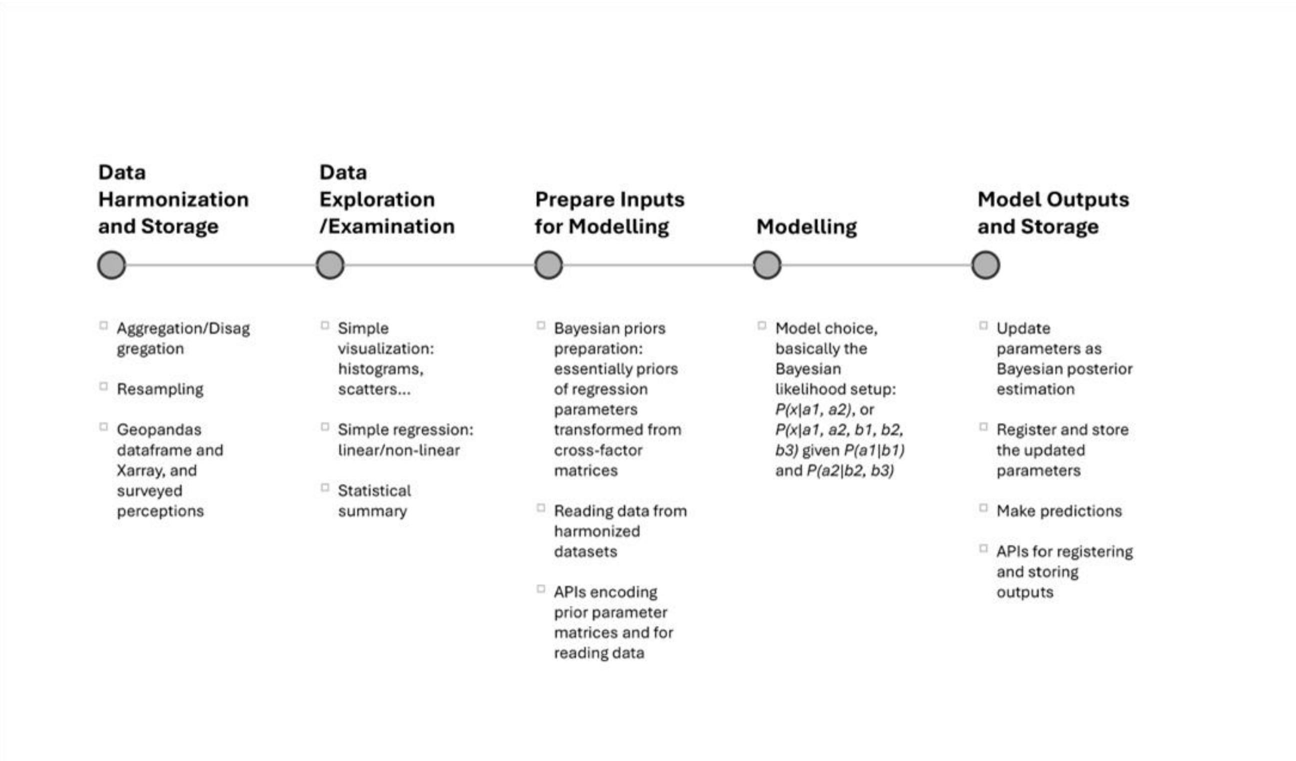

Figure 32: Major components and key functionalities of the R-Map model implementation for extending the model to a platform

5.7 Data harmonization and storage

5.7.1 Preliminary handling

Before putting the datasets from different sources in different formats together for data harmonization, preliminary check will be conducted to examine data quality and metadata. Many datasets come along with data quality documentations, which provide reference for screening data and identifying missing data.

5.7.2 Database formats and storage

The input to the R-Map model needs to be consistent in formats, spatial units/scales and without ambiguous semantics. Even if the model can take inputs from different time points, for instance, population data from both t_1 and t_2 are used to include temporal effects, it is crucial that these datasets should be resampled into consistent spatial units so that boundaries can be aligned once properly georeferenced. Visually, as shown below in Figure 33, the harmonized datasets should be with same granularity. Taking datasets in the Netherlands as an example, all the data in raster or vectors (polygons, polylines and points) should be resampled into the same spatial units, in the case below, the municipality boundaries, which is an even higher resolution than the NUT-3 level. At the database level, such vector data is stored as regular GIS relational data, with rows as instances of observation, which is the spatial units in this example, and columns as attributes harmonized from different data layers. In *Python* implementation of the R-Map model, this table is loaded as a *GeoPandas dataframe*, but can certainly be exported into common formats of *Geopakage* (**.gpkg*), *GeoJSON*, *CSV*, etc.

Figure 33: Harmonizing multi-source datasets in different formats into consistent spatial granularity and finally stored as a GIS relational table. Using Discrete Global Grids (DGG) like the H3 Hexagonal Grid as seen in the left, is currently considered for the ultimate harmonization of scales and discretization of data and probability distributions

Not all the datasets should be harmonized into vector format. Raster or gridded datasets are also allowed in storage, which can be resampled flexibly resampled into NUT2 or 3 level on demand in later phases rather than losing the original details soon as being stored. They should be with the same requirement of being consistent with resolution. When raster datasets are stored, they can simply be *GeoTIFF*, but once loaded in the *Python* implementation of the R-Map model, the *Xarray* is preferred.

In both cases of vector and raster data harmonization and storage, the metadata will also be standardized with common metadata schemas (e.g. ISO). So far, with the absence of many possible datasets and proxies, this metadata handling has not been implemented yet but still envisioned as the final activity by the end of WP2.

5.8 Preliminarily data exploration

Directly sending data into models would generate outcomes that are difficult to be interpreted. Almost always, knowing the data before modelling is beneficial for reliable interpretation of modelling outcomes and detecting spurious results. Understanding the data means knowing not only the quality of itself, but also the statistical nature of the data, simply because many models such as the R-Map are statistical, hence, the conclusions to be derived are also statistical by nature.

5.8.1 Visualizing basic stats: Histograms, box plots, scatters

Some simple statistical characters such as probability distributions and extreme values ranges can easily distort the outcomes of statistical analysis, such as correlation analysis. Most models assume that the data follows a certain distribution, like the normal distribution. But extreme values are, by definition, in the tails of the distribution. If the model isn't designed to handle those tails properly, the presence of extreme values can throw off the estimates. For example, the mean is sensitive to outliers. The problem also applies to model fit. If a model is trying to minimize squared errors, like in linear regression, a single extreme value can have a large influence on the regression line. The line might be pulled towards the outlier, making the model less accurate for the majority of the data. Another thing is that extreme events are rare. So in the dataset, there might not be enough of them to model their behaviour accurately.

Such statistical characters can be preliminary explored through visualizing histograms of the data, or box plots of it. One can even visualize the scatter plots without drawing correlations statistically to see how distributions and extreme values behave visually.

5.8.2 Correlation analysis

One step further into data exploration is to examine pair-wise correlations before drawing upon multiple factors together to inspect more complicated relations. This is because a significant correlation is a precondition for hypothesizing a causal relationship, in the absence of which there is no point for going further into the trouble of updating causal Bayesian links. Such one-to-one elementary correlation analysis is sufficient to build ideas about how strong and uncertain the correlation can be even within a pair of factors, and how such correlation would drift towards extremes. For instance, as shown in Figure 34 below, given some data of any two factors indicated by variable x and y, as soon as the scatter plot is visualized, extreme values or outliers can be further discussed. By further choosing a regression model, such as a linear model as shown in the figure, the uncertainty of the linear model of $p(y|x)$ can be quantified. In the figure, a few sample models drawn from a quantified interval of the model fit uncertainty is shown. It gives a sense of reliability of using statistical regression-based analysis, which impacts later the interpretation and conclusion regarding the linear relationship between two factors.

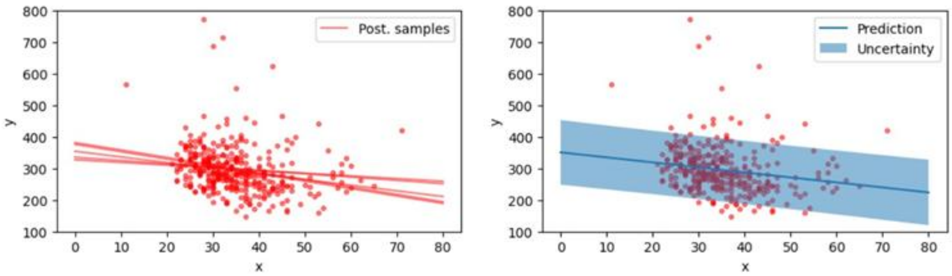

Figure 34: Preliminary exploration of simple statistics through pair-wise correlation

However, such preliminary exploration can move a few steps further not only due to the statistical nature of the data, but also regarding the model choice. As another illustration, an undesirable complex model is intentionally used to show how model complexity can overfit the data at hand and expectedly produce spurious accuracy assessment in a later phase, which in turn produces misleading interpretations and conclusions (Figure 35).

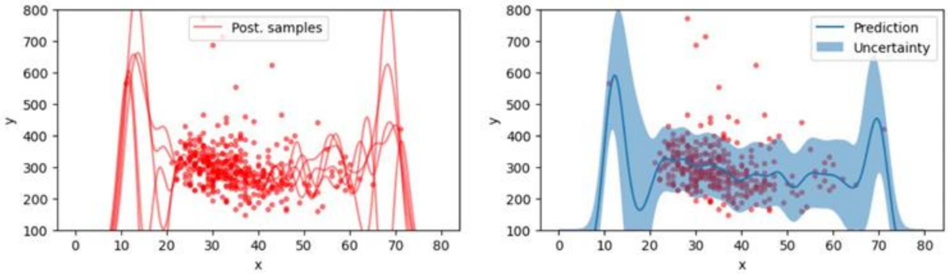

Figure 35: Preliminary exploration of simple statistics through pair-wise correlation

5.9 Outputs of inference and predictions, and storage

Very similar to the first modularized functionality of data harmonization and storage as illustrated in section 5.7, the modelling outcomes should be harmonized and stored considering the issue of formats, spatial and temporal units/scales, and sematic clarity. For vector data, shapefiles are common but have limitations. It is recommended to employ the more commonly used GeoPackage or GeoJSON. For raster, format in GeoTIFF is standard. Considering the potential of creating a large number of scenarios and the issue of data sharing, cloud-optimized formats like COG for scalability can also be considered.

Together with data harmonization, what can be envisioned but not implemented yet is designing the database. This is especially true if the model along with the reproduction of the modelling activities are to be sustained and maintained long-term. Traditional GIS databases like PostGIS (PostgreSQL extension) are important, and so are cloud solutions like Google Big Earth Engine or AWS S3 for large datasets. Version control might be tricky with large datasets. Hence, platform or repository with both version control and large data handling capacity is expected, such as the Git LFS. Metadata and documentation are crucial. Standards like ISO should be set.

6. Reflections on the R-Map model

The development of the conceptual R-Map model for assessing the impacts of Remote Working Arrangements (RWAs) required a careful balance between complexity and tractability. While the aim was to develop an integrated assessment framework to capture impacts resulting from RWA, it was essential to keep the scope of the model manageable without significantly compromising the number of key factors. The implemented co-design approach proved to help capture the rich and diverse experiential knowledge of the involved partners, advisory board members and domain experts and merge it with the comprehensive insights from literature and expert interviews collected in WP1. To structure this effort, methodologies and terminology from participatory systems mapping were applied, enabling the construction of a conceptually grounded and stakeholder-informed model. The resulting conceptual R-Map model laid the foundation for implementation. Given practical limitations—particularly regarding data availability and interpretability—the implementation focused on a representative causal chain as a proof-of-concept, using a Bayesian approach for operationalisation.

6.1 Relevance value and validity of the R-Map model

To avoid misconceptions about the purpose and the making of the R-Map model, it is imperative to consider the "doubly-complex" nature of the phenomenon that it aims to model. Furthermore, it is critically important to note that it is not only meant to be "a model of" a phenomenon but "a model for" contemplating our interferences with and our situation concerning a phenomenon. In other words, we are not aiming to make a replica of a large geographical system to predict its behaviour over time but rather aiming to explicate a collective understanding of the inner workings and mechanisms underlying some complex and intertwined chains of causes and effects in such a way as to get a grip on how our policies and arrangements may help or hamper our abilities to steer such complex dynamics of change. The double complexity label is borrowed from Portugali (2011) in reference to complex phenomena that are not only complex from a geographical (spatial, temporal, social) point of view but also from an anthropogenic dynamic stance brought about by political aspirations, visions, and decisions of governance and planning bodies. In other words, here we are not only dealing with getting a grip on "how things change" but also on "how to change things". Simply put, the model cannot possibly satisfy those who seek an accurate and comprehensive (scientific) large-scale impact assessment model, nor will it satisfy those who are looking for easy-to-remember lessons or catchy conclusions for policy development in the form of linear rules of thumb.

Thus, our modelling endeavour is based on a stance in between these two extremes, i.e. the geographical modelling science and policy analysis. The main goal of this task is to consolidate "a model architecture" for a Bayesian Network in Task 2.2 that can be reasonably traced back and justified concerning the findings of the partners from the literature as well as their experiential knowledge and expert intuition about the pertinence of the factors and their causal connections to one another. As far as expert opinions and literature findings are concerned, the partners from the sister project WinWin4WorkLife, who were invited as peers to our meetings to double-check our findings, confirmed that the resultant model architecture and its constituent factors conform to their findings and expert intuitions. Likewise, the preliminary implementation results are consistent with the findings of WP1, particularly concerning the drivers of RWA. Nonetheless, the model's ultimate utility (or futility) in capturing the urban–rural divide and for policy analysis requires further development through Tasks 2.3 and 2.4 and the regional case studies planned in WP4. These future efforts will allow for finer-grained data integration and context-specific model refinement, essential for validating and expanding the framework. At this stage, the model should be seen as a minimal yet expandable system, offering a foundation for an adaptive and scalable integrated assessment tool. Given the fact that the implementation of the R-Map model is only a subset of what has been conceptualized in Task 2.1, interpreting the model outcome back to the context of reality should always be with caution. As long as the *prior knowledge* of the factor relations are constrained by the co-created knowledge or perceptions, the implementation of the model does not guarantee a quantitative consistency across geospatial locations and scales as people's perceptions may not capture such location and scale sensitive dynamics. This in turn highlights the value of using *Bayesian* based modelling approach to leverage information in the measurements, or actual data, to balance out epistemological limitations. Yet, the challenge of finding reliable datasets as indicators or proxies for the factors leaves potential gaps between the indicators that can be found and the actual desirable data expected for each of the factors. Enforce an interpretation of derived relationships from poorly selected proxies apparently generates misleading conclusions and may further misinform potential strategies for policymaking.

However, from a qualitative level, the model as it is right now can be considered to be a useful representation of a collective systemic understanding of a complicated matter (a doubly complex system), i.e. the compound impacts of remote working arrangements and the way through which multiple short-term and mid-term effects of RWA at disaggregated geospatial resolutions (local phenomena) seem to lead to longer-term and more aggregate impacts (global issues). In that sense, the model architecture per se can be already used as a reflective device for policy analysis and deliberations in participatory or democratic decision-making processes.

6.2 Limitations of the R-Map model

We acknowledge several important theoretical and practical limitations of the R-Map model that cannot be simply addressed by mere larger investments in time and effort, but rather those require a different approach or different studies altogether. The first limitation is of a theoretical and methodological nature resulting from the inherent inadequacy of reliance on the collective intuition of a group of experts for understanding or mapping all relevant factors of influence and impact, not least due to the limited state of research in several dimensions relevant to RWAs. Even if the scope of the R-Map model was to be confined to a single domain perspective such as the economic impacts of remote working, a much deeper approach would be required to address the entirety of the subject; let alone the difficulty of collating the various sorts of impact factors at inherently incommensurate spatial or temporal scales or social bearings. Thus, instead of the disciplinary representativeness or adequacy of the model, its integrality is claimed in two senses: the multi-disciplinary integration of views and the operational integration potential of the model in participatory policy development cycles. The second limitation of the model mainly arises out of the incompatibility and incommensurability of the spatial and temporal scales of analysis and the definition of the indices on the one hand and the contextual impertinence of the indices when used in atypical social and political/administrative contexts other than those typically considered as globally frequent or pertinent.

The model architecture per se can be judged here in terms of its inherent limitations being related to the impossibility of ensuring a complete (diverse and inclusive) representation of stakeholders and their views in two important steps: 1) defining what factors must be included in the model architecture (the nodes), and 2) defining what links (causal relations) need to be modelled (to be eventually quantified) in the model. In the absence of a presumably perfect or complete benchmark, we are effectively settling for a rather pragmatic approach to the consolidation of the conceptual model. We firstly relied on the reports made by the consortium partners in WP1 (which are based on a wide literature review) to curate a set of potentially relevant factors to be included in the model; asked the partners to help us sift through the list of potentially relevant factors to pick a handful of more relevant ones; contemplated together with the consortium partners on which links are the most important ones to be modelled; and out of those links we chose a handful of the least ambiguous ones.

There are still several limitations and challenges that remain concerning the current modelling effort, particularly in relation to the quantification of conditional probabilities within the classical Bayesian framework and therefore our choice of a Bayesian regression approach. A key constraint lies in the limited availability of reliable indicators or proxy variables at spatial and temporal scales that are sufficiently commensurate and compatible to support wide-ranging geographic analysis. Perhaps the most significant theoretical limitation—one that cannot feasibly be addressed within the scope and timeframe of this project—is the expectation that the complex model architecture could enable simulation of impacts at mid- to long-term time horizons. While such network-based architectures are well suited to representing interconnected systems, the absence of relevant time-series data and the practical constraints associated with running iterative simulations through a Bayesian Network preclude any meaningful longitudinal analysis at this stage. Consequently, the initial implementation relies on a "before-and-after" snapshot approach, rather than a dynamic, temporally continuous simulation.

The challenge of finding proper indicators or proxies also poses the limitation of the practical value of the model. A proxy with poor representativeness of a factor leaves potentially significant gaps in interpreting the modelling outcomes into the original context of the model hypothesis. Together with the uncertainty of model hypothesis, such data or proxy representativeness adds another layer of uncertainty of how far such R-Map model implementation can reach either end of scientific validity and practical policy informing.

Moreover, it must be acknowledged that the implementation of the R-Map model is not immune to the risk of ecological fallacy. Although the co-design process provides reasonable confidence that certain causal relationships between RWAs and their effects exist at the aggregate level, it cannot be definitively asserted that these effects would not have occurred in the absence of RWA. While the current operationalisation incorporates an autoregressive specification as a partial workaround to control for baseline conditions, it underscores the importance of having high-frequency temporal data capable of being detrended to isolate the effects of pandemic-induced shocks on the organisation of work. This challenge is well illustrated in the findings of the Netherlands Environmental Assessment Agency (Planbureau voor de Leefomgeving), whose report on the consequences of remote working for living, working, and mobility (Buitelaar et al., 2021) leverages significantly more granular data to disentangle such effects. Therefore, any application of the R-Map model must be accompanied by a clear articulation of the uncertainties and limitations inherent in the current version of the model.

6.3 Disclaimer: What is the R-Map model and what is it not?

In the spirit of the well-known adage— *"all models are wrong, but some are useful"* (a paraphrased version of George Box's classic observation)—the R-Map model is no exception. It is not intended to serve as a deterministic or all-encompassing prediction tool, nor should it be mistaken for a "crystal ball" capable of accurately forecasting the full socio-economic and environmental impacts of Remote Working Arrangements (RWAs). Rather, its value lies in its potential as a decision-support tool within the context of Participatory Policy Evaluation (PPE). In Task 2.1, we have focused on capturing the collective understanding (based on insights produced in WP1) of the project partners, advisory board members and invited experts as a de-facto group of experts of the existing systemic and causal relationships between factors that are somehow related to the remote working arrangements (RWA), from the most immediate and disaggregated effects to the mediators and the ultimate and aggregate impact factors of the changes in the society, economy, and environment. In this sense, the full potential of our approach is yet to be tested in scaling up participatory system modelling workshops. Even though conducting such mass-scale participatory modelling workshops falls beyond the scope of the current project, the idea of scalability is still part of the ethos of our modelling approach. Since the beginning of the modelling process, we did not have the illusion that such complex and systemic relationships could be possibly captured into any traditional regression-based approaches grounded in frequentist probability theory. Such models, even when effective in making ex-post predictions, typically lack explanatory power regarding the mechanisms underlying complex, multi-level dynamics—particularly those at the intersection of social, spatial, and economic change. Furthermore, frequentist models typically lack the flexibility to incorporate new incoming data dynamically. Moreover, they are structurally incapable of incorporating the experiential and intuitive knowledge of expert participants, which is central to understanding the lived realities and policy implications of RWAs. Thus, in Task 2.1 we aimed at making a model as a reflective medium by which a group of experts or potentially a much larger group of stakeholders can share and delineate their collective understanding of how one driver or factor leads to another to impact our living environment in their social, spatial, economic or socio-economic aspects. However, this collective understanding of the causal directional linkages between the factors cannot be mistaken for the "true" way in which these factors relate to one another, for it is clear that our collective understanding of the world, no matter how large our collective, cannot be assumed to represent the objective truth (rhetorically speaking). Therefore, the focus shifts from replication of real-world dynamics to policy relevance.

The model as a predictive tool will be almost certainly wrong in one way or another, but it can be a useful medium for collectively reflecting on the efficacy of our public and private policies surrounding the relatively new widespread phenomenon of remote work. This consideration motivates a wider validation approach that will not solely focus on the quantitative validation of the predicted patterns but also on the qualitative validation of the model in terms of ascertaining its usefulness for practical policy analysis tasks. In epistemological terms, in this approach, we seek to utilize the multitude of views and foci of the expert participants to highlight the important links between factors among a multitude of other rather less important links. In other words, we are employing the human intuition of the participants to sieve through the very overwhelmingly large pool of potential factors and their links to find the most important factors and their links. This innately human capability is arguably the most significant hallmark of natural intelligence that provides an advantage to all possible quantitative approaches in that it can efficiently ignore noise and trivia to focus on what matters from a decision-making standpoint concerned with the sustainability of our new ways of life and the potential long-term implications of remote working if spread much more dispersedly and deeply into the fabric of our human society at large.

From a practical standpoint, the challenge is not computational capacity, but rather data readiness. Attempting to model too many factors—especially across geographies and time—introduces significant hurdles in data curation, spatial harmonisation, and the identification of reliable indices or proxies. Even if such a large-scale model were technically feasible, it might be less effective as an explanatory tool. This is a commonly known issue in systems modelling literature about Large Scale Models that excessively detailed models may reduce interpretability and hinder engagement from non-technical audiences—limiting their educational and deliberative potential.

6.4 On the quantification of the R-Map model

Due to the immense challenges in data collection, data collation, harmonization, discretization, and even mere probabilistic interpretation of existing data distributions, we have inevitably made quite a few pragmatic choices to go forward with the modelling endeavour to showcase the partial quantification of the R-Map model towards creating a back-end for the intended policy analysis tool/dashboard to address Objectives 3, 4, and 5 of the project. However, it must be noted that reaching high accuracy, explanatory power, and reliability at the same time without undergoing multiple additional iterations of model building, evaluation, theorization, and justification (according to the famous cycle of Design Science Research as proposed by Pfeffers et al. (2007) is not realistic. In particular, we envisage that the back-end modelling requires further progress in the following directions:

- **Spatial [and Temporal] Data Harmonization:** utilizing Discrete Global Grids (DGG) can provide a globally consistent and convenient framework for discretizing spatial data and allow for harmonization of inputs of the processes, be they probability distributions or geographical distributions of context variables.
- **Methodical Generalization of the Bayesian Belief Network**: the current quantification approach is a mixture of the BBN model architecture and Bayesian Regression, specifically, Bayesian regression nested within a BBN structure.
- **Technical Generalization of the Back-end Model**: the current set up of the R-Map model is such that changing the input model architecture (the DAG network) is not impossible but requires manual work in Python. However, the aim is to generalize and vectorize the model so much so that the model architecture can be inserted as an input variable (a tensor/matrix) and that the policy-analysts using the model can perform inquiries for investigating different qualitative understandings of the impact causal chains.

In short, every feature of the dashboard tool or the policy analysis front-end has to be effectively developed in tandem with a methodical possibility incorporated within the backend model. These methodical developments themselves require iterative cycles of mathematical work and Python workflow development. Nevertheless, the most important bottleneck ahead of the developments, be they methodical or technical is the identification of suitable datasets that can be ideally extracted from two snapshot moments of before & after the introduction of RWAs as well as sufficient spatial resolution.

7. Conclusions

The most concrete conclusion to be drawn from task 2.1. and 2.2. are the consolidated R-Map model presented in Figure 16 and the entire workflow for the implementation, illustrated for one causal chain. The conceptual model shows the set of most important factors and their systemic or structural links or causal relationships leading to major impact factors relevant to the general public at global scales. This model architecture can be said to have emerged organically or to have been collectively discovered through a series of disciplined conversations deeply rooted in local and experiential knowledge of the participants from diverse geographical contexts and their idiosyncrasies. Hence, the structure of the model can be taken as a reliable agenda for quantitative research in the next steps of the process.

As extensively explained in the discussion on the limitations of the R-Map model, at this stage of development, one cannot make clear-cut conclusions about [how exactly] what leads to what in terms of the impacts of RWA. In that sense, the conclusions are rather methodological and intermediary rather than being final, factual, and revealing in terms of causal explanations or predictions. The most important conclusion so far is that the combination of PSM and Bayesian approaches to causal and probabilistic graphical modelling are suited to the complicated/wicked problem of policy analysis and integrated (i.e., multi-sectoral) impact assessment at hand. During implementation, the R-Map model differentiates itself from the conventional BBN and has been equipped with its own characters regarding encoding explicitly people's perceptions towards the relations among the factors along the links of the Bayesian networks, which can be modelled by integrating Bayesian regression among the factors. Technically, such adaptation of the original BBN structure brings flexibility of extending the modelling of the relations and factors by using different regression models, which can be simply extended as spatial regression problems to produce geographically discriminative patterns, and it can readily be mapped and visualized. Obviously, such flexibility is a "double-edged sword" that also brings the problem of model choice and arbitrary hypothesis. Hence, the boundary of extending such Bayesian network should be discussed further along with the future insights expected from following tasks.

Apart from the model implementation, challenges of finding proper datasets as indicators or proxies of the factors have been encountered. Despite such challenges, one can see that the frequentist statistical alternative approaches to this problem would only make it more confusing, more reductive, less participatory, and arguably less explanatory and thus less useful as to the purpose of the model as a policy analysis and deliberation tool. Based on the formal implementation of the R-Map model and illustration of one causal chain, we argue that we have gained methodological confidence that the R-Map model is gradually taking a useful shape while we are systematically sifting through a multitude of things to be included in the model in favour of highlighting and eliciting the essential variables that can help us get a grip of the transitional impacts brought about by the RWA. There is yet much quantitative work to be done on both the model and data but so far, the model architecture has stabilized into a shape that can be arguably labelled as collectively validated, systematically consolidated, and technically viable. It must be noted that the very scoping and identification of the inner systemic links in such a large-scale impact assessment model is far from trivial, especially when regarded from a usability and utilitarian perspective of prospective stakeholders.

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9. Annex

9.1 Annex 1

The table below lists the names of participants in the co-design workshop.

#	First Name	Last Name	Partner Institute
1	Margarita	Angelidou	Q-PLAN
2	Henk	Bouwman	METREX
3	Mariana	Faver	Architecture Urbanism Bureau Thuis (AUBT) (AB member)
4	Katharina	Fellnhofer	RIM
5	Johannes	Flacke	UT
6	Lisa	Fontanella	UB
7	Mandy	Fransz	RWW (WFA)
8	Barbara	Glinser	Centre for Social Innovation (AB member)
9	Theodora	Istoriou	AUTH
10	Ozge	Karanfil	KU
11	İlker	Kayı	KU
12	Eirini	Kelmali	SEERC
13	Sibel	Kiran	KU
14	Anna	Konstantinidou	WR
15	Vidit	Kundu	UT
16	Richa	Maheshwari	University of Liège
17	Konstantina	Mataftsi	WR
18	Thomas	Mone	AUTH
19	Pirouz	Nourian	UT

20	Hakan	Orer	KU
21	Karen	Oude Hengel	Netherlands Organisation for Applied Scientific Research (TNO), (AB member)
22	Panagiotis	Papanikolaou	Arx.Net
23	Karin	Pfeffer	UT
24	Dimitra	Plastara	AUTH
25	Georgia	Pozoukidou	AUTH
26	Elli	Roma-Athanasiadou	Q-PLAN
27	Efstratios	Stylianidis	AUTH
28	Vinod	Subramaniam	Twente Board
29	Jasmijn	Tiemersma	CBS
30	Dimitris	Tselios	NOMAD365 (AB member)
31	Cihan	Urhan	Turkish Confederation of Employer Associations (TİSK) (AB member)
32	Jon	Wang	UT
33	Anders	Wilandson	Stockholm Region (AB member)
34	Shi (Tracy)	Xu	SURREY
35	Savas	Zafer Sahin	Citizens' Assembly of Ankara (AB member)
36	Nikos	Zaharis	SEERC

Annex Table 1: Co-design workshop participants.

9.2 Annex 2

The table below shows the different factors as agreed during table discussions in the co-design workshop.

Table	Factors
1.1	Decentralisation and new centralities, diversification/ land-use change, urban sprawl/densification and land take, access to local amenities and opportunities, demand for larger housing, digital infrastructure accessibility, caring, access to support network, total number of burnouts, housing affordability, co-living and community building
2.1	Shift in modes of transport, acceptability, cost of living, multilocality, communication and information quality, work life balance capacity, accessibility to public services, individual characteristics, urban/rural divide, gender distribution, household dynamics related burdens
3.1	Internet quality (affordability) and performance, flexibility (location), flexibility (work time), loneliness, insurance, level of inequalities, city size
4.1	Level of digital capacity, digital infrastructure, gentrification, care responsibilities, land consumption, energy demand, attachment and commitment, gender equality, city facilities (transport, health care, amenities), health & safety outside office, employee productivity, precarious job conditions, labour market, mental health
5.1	RWA literacy, autonomy (individual), labour participation, connectivity, precarity, inequality

Table 2: Key factors arrived at after table discussions in the UT co-design workshop

9.3 Annex 3

The table with impact factor definitions is provided below.

#	Factor	Type	Definition	Rationale
1.	Health and Wellbeing	Social Impact	Task 1.3 defines health and wellbeing as outcomes (impacts) including physical health, mental health, social and family, work-related needs, and health behaviours - physical activity, diet, and sleep (according to EU-OSHA, 2023a). Also, the WHO emphasizes a holistic approach to well-being, encompassing physical, mental, and social dimensions to promote overall health and quality of life (WHO, 1948; Topp et. al., 2015)	As described, remote working arrangements encompass specific working conditions and organizational structures that generate psychosocial factors. These factors could potentially serve as sources or conditions that expose individuals to various biopsychosocial influences. Psychosocial factors, in turn, are closely linked to biological outcomes, potentially impacting health, illness, and the development of diseases.
2.	Polycentricity	Spatial Impact	The spatial phenomenon where at a regional scale multiple cities of similar size and importance exist; and at an urban scale multiple neighbourhoods or centres of similar importance exist	As described by T1.2, polycentricity could be a multi-scale phenomenon. At a regional scale, it implies the rise of small/medium sized cities due to RWAs, while at a metropolitan scale it implies decentralisation towards the outskirts of the city
3.	Land Consumption	Spatial Impact	Land consumption can be defined as the expansion of built-up area for human settlements. Task 1.2 defines land consumption in terms of expansion of residential areas into previously undeveloped areas (due to more affordable housing options, less congestion and proximity to nature)	
4.	Work-life Balance	Socio-economic Impact	Time management and boundary settings between work and personal life, and the impact on family and social life; the ability of balance professional responsibilities with personal life (report T1.3 p. 56)	Work-life balance involves not only time management but also workload-related flexibility when needed. There are two key interfaces: a work-related supportive side and a life-related supportive side, each including various supportive services

5.	Caring Responsibilitie s	Social Impact	Defined in D1.3 as caring responsibilities, that includes housework, childcare, care for elderly, relatives.	
6.	Employee Productivity	Econom ic Impact	Employee productivity refers to how efficiently and effectively a worker or a group of workers contribute to accomplishing organizational goals	
7.	Multilocality	Spatial Impact	T1.2 defines multilocality as the maintaining of residences and activities in multiple geographic locations.	Greinke and Lange (2022), in their study in three rural districts in Germany, report that multilocality prevents complete relocation from rural to urban areas due to strong ties to family and friends. The potential impacts discussed include housing prices being driving up, new construction, reduced affordability and vacancy in rural areas (Greinke and Lange, 2022; Weichhart and Rumpolt, 2015); increased land consumption, travel distance and car-based commute, benefits to local economy, but pose a challenge in developing strong social ties and engagement in local civic activities (Danielzyk et al., 2020a; Dittrich Wesbuer et al., 2015).
8.	Workplace Loneliness	Socio-econom ic Impact	Defined in report T1.3 as workplace loneliness (in RWA (p. 174), characterized by lack of information quality, supportive leadership, supportive conditions for job demands, and individual psychological states.	As new ways of working evolve, the definition of the "workplace" is also changing. Employee services related to these "new workplace" aspects play a critical role in supporting job engagement, task completion, and providing network support when needed.
9.	Cost of Living	Socio-econom ic Impact	The amount of money that a person needs to pay for basic needs such as food, shelter, energy	

10.	Mobility Pattern	Spatial Impact	Patterns of human movement facilitated by public or private transportation. This factor mainly encompasses two aspects: the choice of transport modes and the purpose of trips	A shift has been observed in modal split, purpose of trips due an increase in remote work
11.	Access to Labour Market	Econom ic Impact	Defined as access to a diverse and competitive labour force for an employer. It also has a relevance for employees, who now have a wider access to job opportunities	
12.	Social Cohesion	Social Impact	Defined as the presence or absence of a social ties or social support network. It can be both digital and physical social ties	The factor has potential implications on individual well-being, mental health, loneliness and productivity.
13.	Local or Regional Economic Development	Econom ic Impact	Economic development of a region through which a region is capable to improve its economic, political, and social welfare.	Areas with higher remote job shares show greater employment resilience, supporting local economies through stable spending and economic growth, particularly in smaller cities, as reported by T1.4
14.	Tourist/ Digital Nomad Living Space Demand	Socio-econom ic Impact	The demand for living space from increased number of tourists and digital nomads because of remote work	
15	Carbon emissions	Spatial (Env.) Impact	The amount of CA emitted into the atmosphere resulting from transport activities	

Annex Table 3: Definition of impact factors

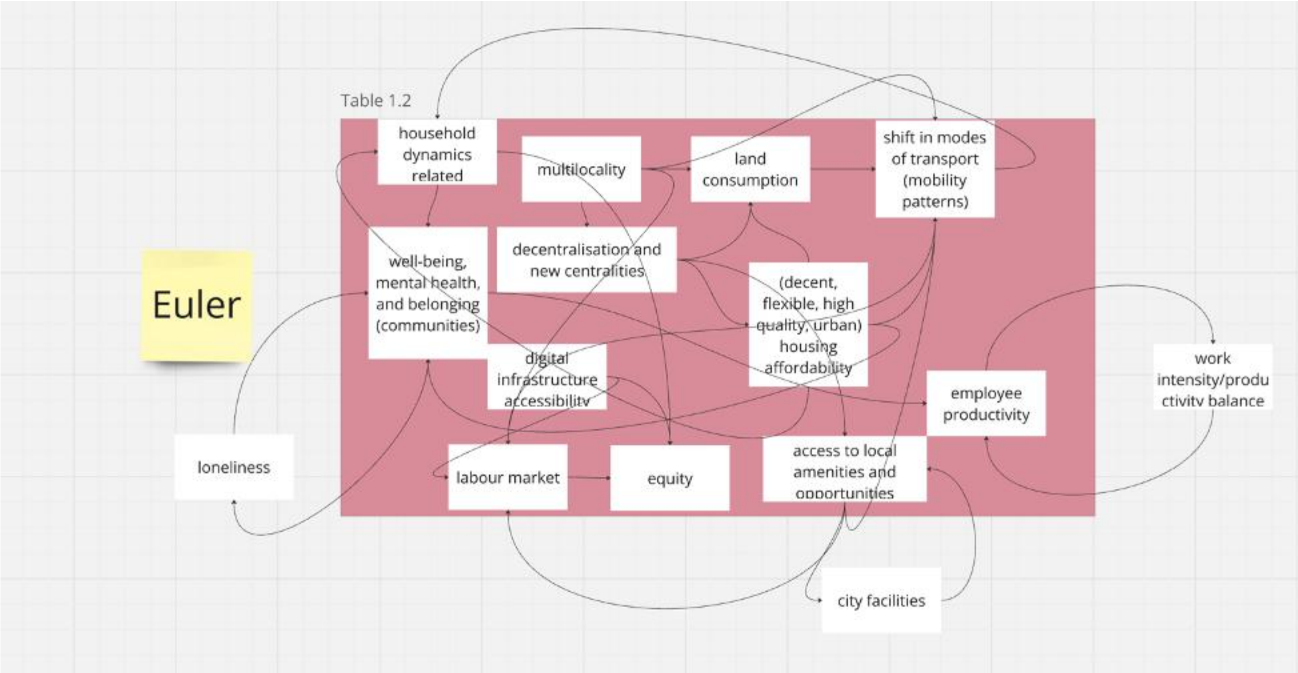
The table with driver factor definitions is provided below.

#	Factor	Type	Definition	Rationale
1.	Digital Infrastructure Accessibility	Driver	The factor can be defined as access to high quality (in terms of speed and coverage) and affordable internet	Eurofound (2022a) identifies technical infrastructure (e.g., broadband accessibility) as a possible factor which might explain variations in the prevalence of telework noted across different countries, and between urban and rural areas
2.	Access to Local Amenities	Driver	Access to green areas, shopping, recreation, education, sports and community facilities, co-working spaces, etc. Access to local amenities can have a direct implication on the quality of life.	
3.	Transport Accessibility	Driver	Transport accessibility refers to a measure of the ease of reaching (and interacting with) destinations or activities distributed in space. A place with "high accessibility" is one from which many destinations can be reached with relative ease.	
4.	Taxation, Social Security, Insurance Regulations	Driver	Rules and laws governing how individuals and businesses are taxed, including income, sales, and corporate taxes. The factor encompasses tax rate differences between countries, double tax arrangements, social security and insurance frameworks	

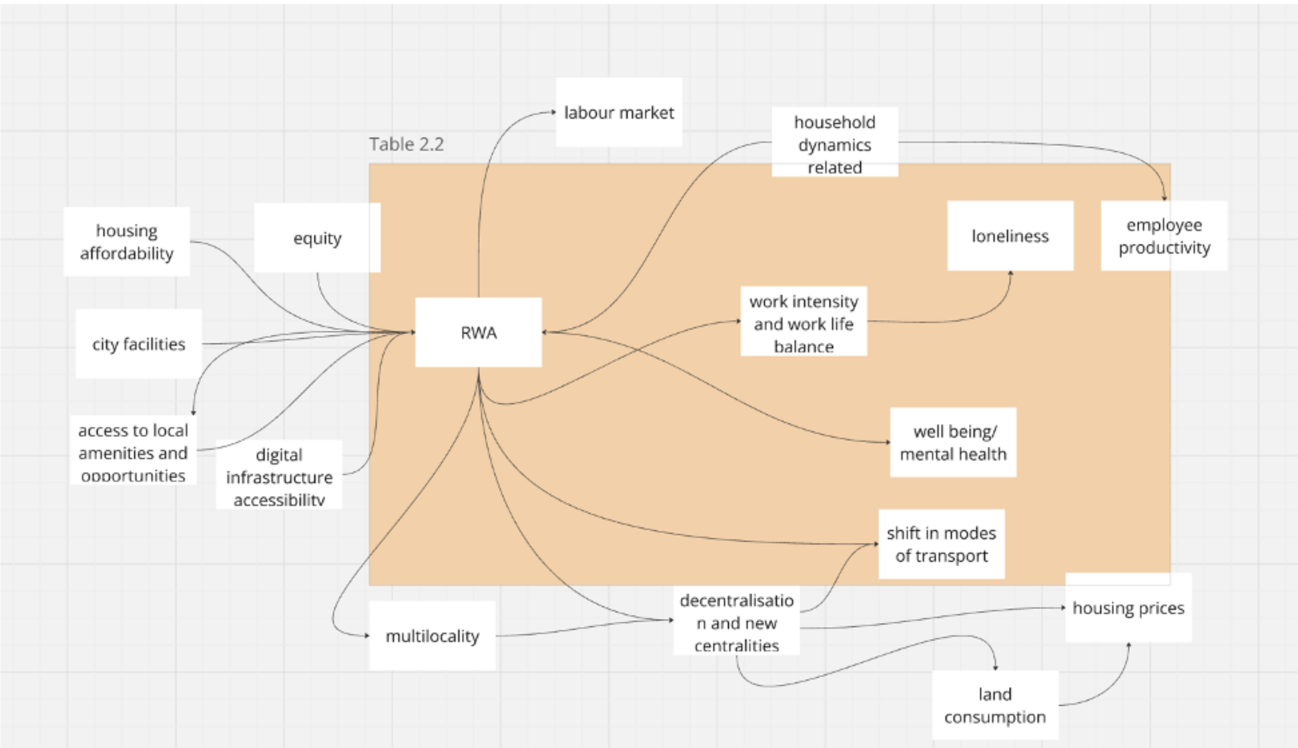
Annex Table 4: Definition of driver factors

9.4 Annex 4

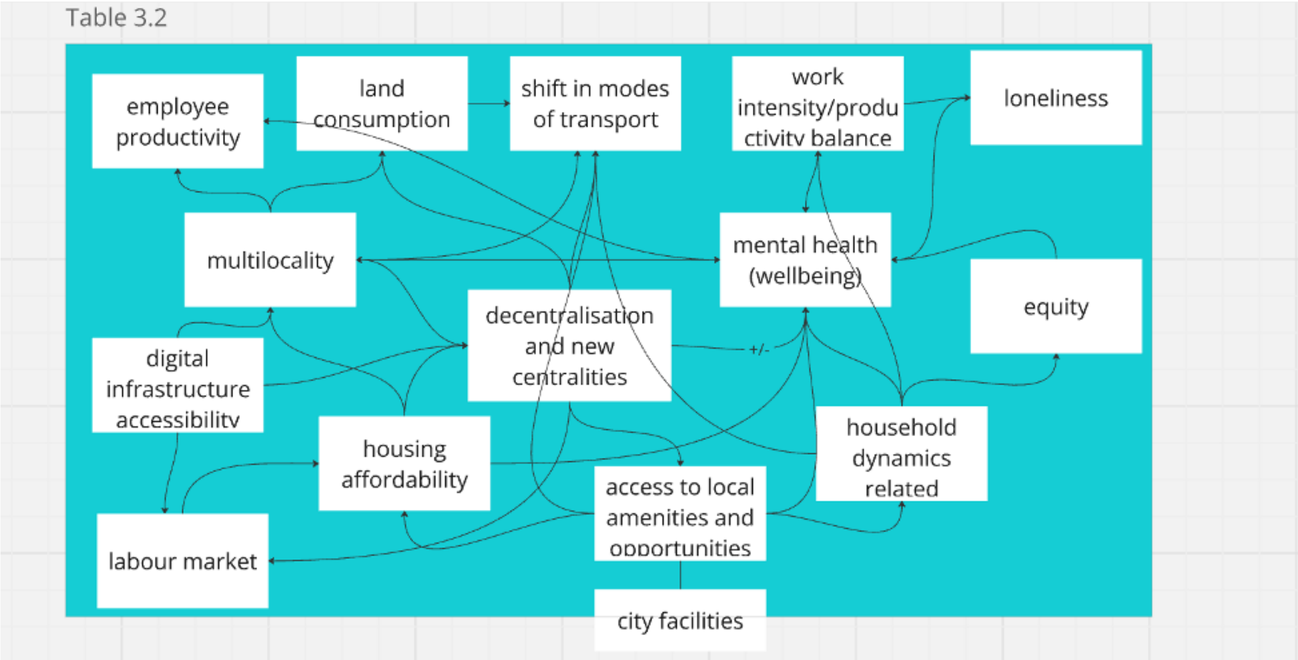
The causal maps generated on each of the tables in the co-design workshop.



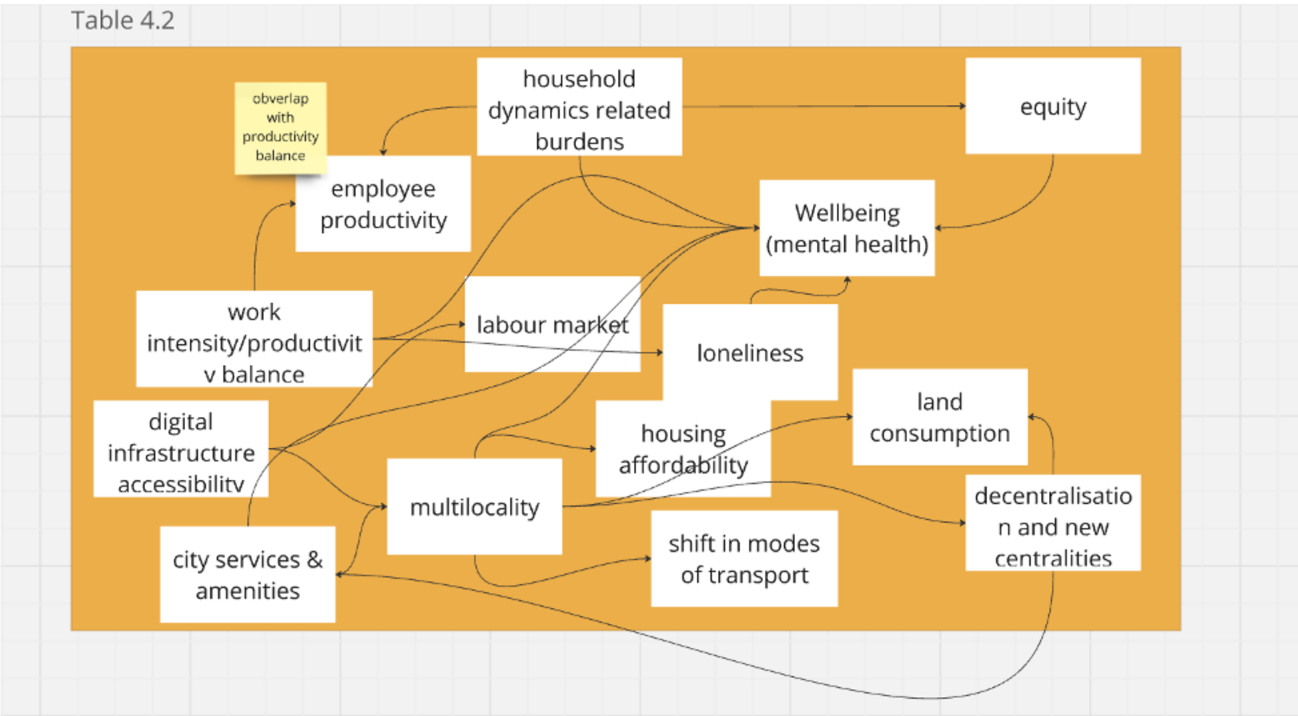
Annex Figure 1: Causal Map generated on Table 1.2



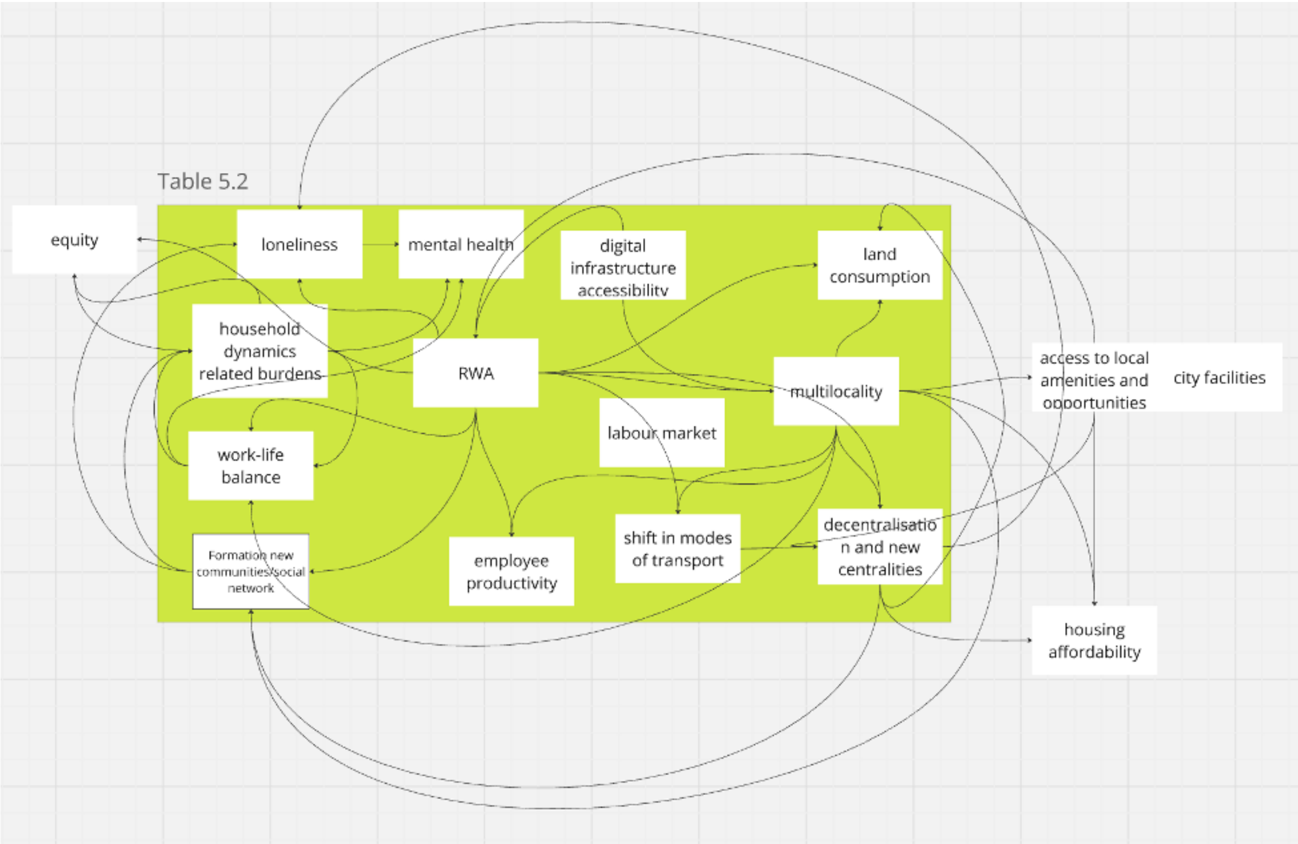
Annex Figure 2: Causal Map generated on Table 2.2



Annex Figure 3: Causal Map generated on Table 3.2



Annex Figure 4: Causal Map generated on Table 4.2



Annex Figure 5: Causal Map generated on Table 5.2

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