ESPON

EUROPEAN UNION

Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

FINAL REPORT //

DIGISER

Digital Innovation in Governance and Public Service Provision

Annex 1.1 Extended Methodology // April 2022

This FINAL REPORT is conducted within the framework of the ESPON 2020 Cooperation Programme, partly financed by the European Regional Development Fund.

The ESPON EGTC is the Single Beneficiary of the ESPON 2020 Cooperation Programme. The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States, the United Kingdom and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.

Coordination
ESPON EGTC: Martin Gauk, Caroline Clause

Authors
OASC: Martin Brynskov, Geni Raitisoja, Margarida Campolargo,
IS-practice: Hugo Kerschot
Politecnico di Milano: Prof. Grazia Concilio, Dr. Irene Bianchi, MSc. Francesco Fagiani, Dr Matteo Fontana, Dr. Ilaria Mariani, Dr. Michelangelo Secchi, with the support of MSc Mathyas Giudici, MSc Giulia Mussi, MSc Federico Rita
CPC: Dr. Isaac Sserwanja, Bin Guan, Dr. Reza Akhavan
Deloitte: Diogo Santos, Jean Barroca, Ana Vaz Raposo, Ana Robalo Correia, Andreas Steinbach, João Carvalho Fachada

Advisory group
Kadri Jushkin (Ministry of Finance Estonia), Eedi Sepp (Ministry of Finance Estonia), Akim Oural (Lille Metropole), Paulo Calçada (Porto Digital), Markku Markkula (Helsinki-Uusimaa Region), Lodewijk Noordzij (Eurocities), Wim De Kinderen (ENoLL), Olli Voutilainen (Finnish Ministry of Economic Affairs and Employment), Tanguy Coenen (imec), Martin Brynskov (Aarhus University), Gianluca Misuraca (Krems University), Serge Novaretti and Stefanos Kotoglou (EC-DG Connect), Bert Kuby (Committee of the Regions), Paresa Markianidou (Technopolis Group)

Information on ESPON and its projects can be found at www.espon.eu.
The website provides the possibility to download and examine the most recent documents produced by finalised and ongoing ESPON projects.

Published on paper produced environmentally friendly

ISBN: 978-2-919816-68-2

Graphic design by BGRAPHIC, Denmark

Contact: info@espon.eu

Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

FINAL REPORT //

DIGISER

Digital Innovation in Governance and Public Service Provision

Annex 1.1 Extended Methodology // April 2022

Contents

List of figures and tables

List of figures

List of tables

List of maps

Abbreviations

API	Application Programming Interface
DESI	Digital Economy and Society Index
DIGISER	Digital Innovation in Governance and Public Service Provision
DIGISURVEY	The survey deployed during DIGISER with 255 respondent cities
DPSVI	Digital Public Value Service Index
EAB	European Advisory Board
EDCI	European Digital City Index
EIF	European Interoperability Framework
ESPON	European Spatial Planning Observation Network
EU	European Union
EU ODP	European Union Open Data Portal
FUA	Functional Urban Areas
GDC	Green Digital Charter
GDP	Gross Domestic Product
GDPpc	Gross Domestic Product per Capita
GDPR	General Data Protection Regulation
ICC	Intelligent City Challenge
ICT	Information and Communications Technology
KPI	Key Performance Indicator
LAU	Local Administrative Units
LEA	Learning Technology Accelerator
NUTS	Nomenclature of Territorial Units for Statistics
OASC	Open and Agile Smart Cities
OECD	Organisation for Economic Co-operation and Development
OGD	Open Government Data
PA	Public Administration
PCP	Pre-Commercial Procurement
Q_	Question (in Digiser Survey)
R&D	Research and Development
SAB	Scientific Advisory Board
SAG	Scientific Advisory Group
SDGs	Sustainable Development Goals
SEM	Structural Equation Modelling
SI	Service area Index
T-LL	Triple-Loop Learning
ToR	Terms of Reference
UNDP	United Nations Development Programme
Reference Sample	It refers to 156 cities intended to be the best approximation attainable that could be considered as representative of the variety of European cities.

1 Intro

This Annex to the Final Report of DIGISER (D4) reports all the information related to the work carried out by the research team of the Politecnico di Milano, aimed at developing and testing a set of composite indexes capable of capturing and synthetically describing the performance of cities in the digital transition and their ability to drive this transition towards the creation of public value.

This index (or set of indexes), labelled "Digital Public Service Value Index" (DPSVI), is one of the main outputs of DIGISER and its development has also been documented in depth in the Inception Report, where the conceptual bases of the DPSVI have been exposed, in the Interim Report, where the related Data Model has been built starting from the concept has been explained in depth, and in the Draft Final Report, that included the first version of the data model that has been updated and refined in the final months of the research project.

In summary, the DPSVI is conceived as a multi-level composite index, developed on top of primary data collected through a survey (DIGISURVEY) targeting European cities. These data are processed and combined to feed a system of composite indexes that provide a synthetic assessment of the performances of European cities in relation to complex phenomena underlying digital transformation. In addition, a specific subset of indexes has been developed to explore in detail the state of the art of digital transformation through different service areas (SI - Service Index).

The DPSVI has been used in almost all the project's output as a compass to explore complex challenges and phenomena related to the digital transformation of governance methods and public service delivery in European cities, reported in the main DIGISER Final report and in the DIGISER Policy Handbook, as well as in dedicated annexes that explore systematically all the indexes composing the DPSVI (Annex 1.2.1 and Annex 1.4 to DIGISER Final Report).

All these documents are published on the ESPON website at https://www.espon.eu/DIGISER.

This technical annex reports extensively the methodology used to develop the DPSVI, including the theoretical definition of the index, the design of the data model, the data collection process, the mathematical computing of indexes and their statistical validation, as well as the data visualization methods implemented.

2 The DPSVI framework

The “digital” dimension of public services has been long interpreted as a driver of innovation and changes since it became evident that ICT represents a vital tool in the governance balancing act as buildings, transport networks and utility systems (Economist Intelligence Unit, 2010). Over the last decades, a novel vision emerged of the public sector activated by ICT in public services where principles such as information sharing, transparency, openness, and collaboration became key concepts with relevant organizational and policy implications. This slow, yet steady, process has considerably contributed to making more complex and demanding the reflection on governmental capacity in terms of competences required, institutional/organizational arrangements and policy actions' responsiveness and appropriateness.

Within this framework, an effective and deep observation and analysis of the role played by digital innovation of public services needs to be framed within a more complex and longer process of technology-enabled public sector reform (Ferro et al., 2013), able to capture the complexity of the service creation process and its capacity to contribute to possible responses to global societal challenges. Providing (digital) public services by capturing the powerful potentials offered by the ICT fast advancements and development represents a crucial manner to make cities protagonists of the very urgent transition every city, every public institution should feel responsible for.

The key question targeted in the work is, therefore: **are the ICT growing potentials effectively adopted in services conception and provision and turned into opportunities for a public sector reform to be aligned with the urgent socio-technical transition?**

This interrogative represents both a specification of an overarching and more fundamental question about how the technological “infrastructuring” of public administrations may be turned into value for society and the critical interpretational driver for the conceptual development of the **Digital Public Service Value Index.**

2.1 The Digital Public Service Value Index: a transitional perspective

The **DPSVI** acquires the key meaning of a digital transition capacity index, i.e., evaluating the capacity of a public authority to translate the growing ICT potentials into transitional opportunities of the public sector in general and of the related socio-technical system (Geels, 2005, 2011; Geels and Schot, 2007) in particular.

The operational translation of such a “dilemma” result in three key research questions.

1. ***How can digital transformation generate long-term innovation in public sector organizations?*** This question refers to the capacity of the digital transformation of services to also activate organizational restructuring and innovation (Avgerou, 2000; Poole and Van de Ven, 2004; Deserti and Rizzo, 2019). The creation of new digital services or the digital innovation of existing ones is an opportunity for reflection and learning at the institutional level, and challenges institutional organizations towards more flexible and open structures being collaborative, transparent, experiment-prone, and capable (Van der Voet et al., 2016; Plesner et al., 2018; Elliot, 2020).
2. **How does public sector organizational innovation generate public value in local contexts?** From a transition perspective, the digital innovation of services represents a means to drive changes in practices and behaviours in everyday life (Shove et al., 2012; Chilvers et al., 2018). Coherently with the shared interpretation of any innovation process as a value generation process (Hansen and Birkenshaw, 2007), innovation -especially public service innovation- should bound the value generation process to the situated perspectives of local contexts and the different stakeholders that operate at that level. Citizens groups, small organizations and innovators are co-producers of such public values based on the principle that beneficiaries are also the experts of their needs (Krogstie, 2006; Emaldi et al., 2017).
3. **What paths and key enablers can make best innovation practices replicable and scalable?** Public administrations neither act alone nor in vacuum environments; their action spaces are strongly affected by several factors like market pressure. This is especially true in the ICT for public service provision and creation (Albury, 2005), by experience of similar public administrations within the current cities marketing global competition or by their belonging to national/international networks enabling experiences exchange and collaboration (Campbell, 2013). In these dynamics,

cities represent sources and drivers of (new) practices replication and diffusion, as well as replicants or active adopters of (new) practices developed by other cities.

The three research questions underlying the development of the Digital Public Service Value Index are able to indicate the way towards sets of indexes and may contribute to explicit them by focussing on the key mechanisms of socio-digital transition: scaling-up, scaling-deep, and scaling-out (Riddell and Moore, 2015; Omann et al., 2019).

Research questions underlying the definition of a DPSVI	Focus
How digital can transformation generate long-term innovation in public sector organizations?	Organizational Change and Performance (***Scaling-Up***)
How does public sector organizational innovation generate public value in local contexts?	Local Context Change and Performance (***Scaling-Deep***)
What paths and key enablers can make best innovation practices replicable and scalable?	Relational capacity: Replication and Transfer (***Scaling-Out***)

Table 1 - Mapping DPSVI categories over the DIGISER research questions

The introduction of a transition perspective and the related research questions suggest looking at the DIGISER analysis as a transformational learning (Bateson, 1973) or Triple-Loop Learning (T-LL)[1] process, to be activated through data collection activities at the scale of local institutions. In transition theory, learning is central as it can enable, accelerate, and guide socio-technical transformations (Loorbach, 2010; Loorbach and Rotmans, 2010).

In this view, systemic change –targeted as a transition to improvement – requires cognitive energy and learning outcomes to be situated into action at multiple levels. The level of learning, and the degree to which it has been embedded into actions, routines, practices, and behaviours (both at the institutional and at the individual levels) reflect the maturity of a transition. In other words, the more changes are embedded and internalized in the subject, whatever complex is what is learnt, the better Triple Loop Learning is achieved. The more disruptive is the change to be achieved, the more Triple-Loop Learning needs to engage all involved actors, from individuals to organizational and institutional infrastructure, up to the societal scale (Johannessen and Wamsler, 2017).

In T-LL, each learning loop (single, double, triple) has been conceptualized by some authors (Sinek, 2009; Engelbart, 2002) as a possible joint view of three learning modes. They focus on the goal each loop reflects on - the “what”, the “how”, and the “why” - as shown in the graph below (see Figure 1).

[1] Triple-Loop Learning is required when problems are wicked and unstructured and especially when the deep underlying causes and context have to be considered in redefining, relearning, and “unlearning” what we have already learned before (Gupta, 2016). In T-LL, iterative questionings and modifications help to shift the perspective, ideally leading to a systemic change, in coherence with any transformation or innovation process within the perspective of transition. In Stacey’s terms, T-LL is manifested as a form of collective awareness (Stacey, 2007); the relationship between organizational structure and human behaviour changes as the organization learns how to learn and understands more about the values and assumptions which lie below the patterns of actions (Kahane, 2004). Triple-Loop Learning allows not only individuals, but also organizations to question whether the values and assumptions are locking them into a recurring cycle in which today’s solutions become tomorrow’s problems. In this way, the values, as well as the strategies and expectations, can be modified (Argyris and Schön, 1978).

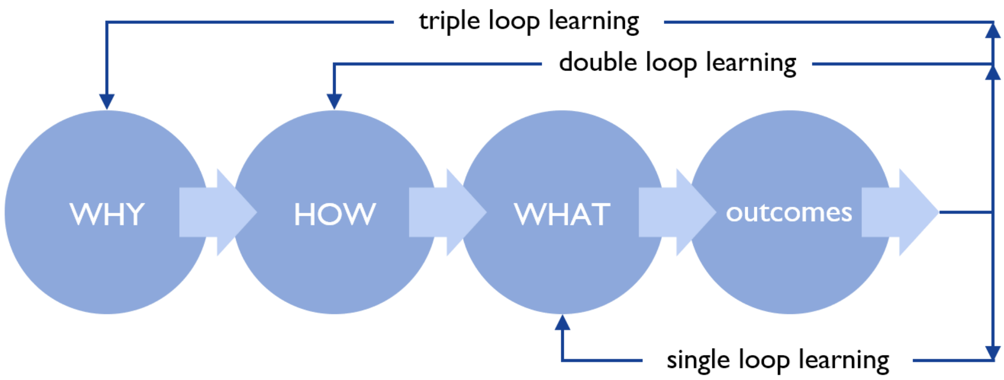


Figure 1 - Triple-Loop Learning and the "what, how, and why" questions

Looking at the T-LL in terms of the three reflection levels able to activate learning into organizations, the DIGISER concept has been developed conceiving the Digital Public Service Value Index as structured in coherence with the "what", "how" and "why" questions (see Figure 2). This conceptual setting is reflected also in the survey for data collection (see Chapter 3), making it work as much as possible as a learning infrastructure, supporting reflection especially for those Public Administrations that will be the focusses of the analysis.

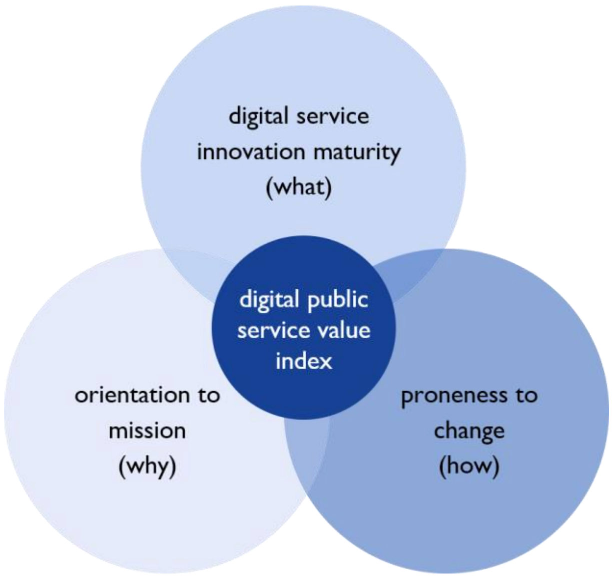


Figure 2 - Conceptual structure of the Digital Public Service Value Index

1. **Digital service innovation maturity**. Representing the "what", the "digital service innovation maturity" is the concrete object of the DIGISER analysis. "*Digital innovation is about the creation and putting into action of novel products and services; by digital transformation we mean the combined effects of several digital innovations bringing about novel actors (and actor constellations), structures, practices, values, and beliefs that change, threaten, replace or complement existing rules of the game within organizations and fields*" (Hinings et al., 2018). DIGISER mainly refers to two main elements: the advancement in technological infrastructuring, i.e., the product; and the changes in the structures, practices, values/beliefs it requires or activates, i.e., the process. Advancements in technological infrastructures ask for new services models and interactions. These two components, in turn, require a change in the processes, structures, practices, value and culture of the public administrations.
2. **Proneness to change**. The shift from reactive to proactive service delivery mechanisms is enabled by the transition from e-government to digital government, where the use of digital technologies is assumed as an integrated part of governments' modernisation and innovation strategies, creating public value through the engagement of a broad ecosystem of stakeholders (OECD, 2017). This

shift is only possible if organisations have a strong orientation to changes, i.e., low internal resistances, strong competences, high availability to learn (see Fernandez and Rainey, 2006). In DIGISER conceptual structure, proneness to change therefore represents the "how", which defines the way chosen to guarantee both an innovation process and an effective exploitation of the growing beneficial potentials of digital transformation.

3. **Orientation to mission**. Exploring the "why" represents the final aim of every reflexive public action (Argyris and Schön, 1978). Starting from this assumption, "orientation to mission" (Mazzucato, 2018) is used to define the horizon to achieve in terms of systemic change as an answer to one or more societal challenges local authorities are asked to face. It represents the overarching perspective the innovation of public services should be contributing to. In short, "orientation to mission" represents the transition driver of service innovation, and it offers the key values that should be mobilized by the services and their digital innovation.

In the following section, the triplet "digital service innovation maturity", "proneness to change", "orientation to mission" is analysed in richer details.

2.2 Inside the DPSVI structure

As illustrated in the previous paragraph, DIGISER conceptualises the Digital Public Service Value Index by focussing on three components, "digital service innovation maturity", "proneness to change" and "orientation to mission", that will be described in detail in the following paragraphs. They have been specified as follows:

- **Digital service innovation maturity** is described through the **digital maturity** and the **level of service embedment.**
- **Proneness to change** is described by **change management** and **innovation governance.**
- **Orientation to mission** is mainly described through the alignment to **Sustainable Development Goals.**

These three elements of the Digital Public Service Value Index are deeply inspired by the socio-technical transition perspective (Geels, 2005, 2011; Geels and Schot, 2007), that has been adapted and operationalised by the three research questions described in the previous paragraph. The three research questions represent a productive driver to the identification of indexes composing the Digital Public Service Value Index by leveraging on the three key mechanisms: scaling-up, scaling-out and scaling-deep. These mechanisms *"underscores the complexities and complementary nature of the strategies involved in advancing large systems change"* (Riddell and Moore, 2015: 3), and together they can explain: (i) how a socio-technical transition works and (ii) how one innovation can contribute to transition by activating changes, transformations, learning dynamics and synergies with other innovations at multiple levels.

Scaling-up - Organisational change and performance. This mechanism entails modifications of the organisational structures, routines, and practices, and it impacts policies, rules and laws, and organisational routines. Scaling-up mechanisms can be grounded in different levels of critical reflection (Argyris and Schön, 1978). In line with the T-LL scheme illustrated above (see Figure 1), they can refer to changes in the actions undertaken to support service development and provision ("'what"), but also to modification in how innovations are managed and decisions about digitalisation and innovation governance processes are taken within the PA organisational structure ("how"). Focusing on the role of digital transformation as a driver of change, DIGISER explores in particular how scaling-up mechanisms can contribute to support long-term innovation within public sector organisations.

Scaling-deep - Local context change and performance. Scaling-deep refers to impacts generated on cultural roots, and it is related to the notion that *"durable change has been achieved only when people's hearts and minds, their values and cultural practices, and the quality of relationships they have, are transformed"* (Riddell and Moore 2015: 3). In the context of DIGISER, scaling-deep mechanisms are understood in terms of public value generation. They look specifically at the capacity of institutions to generate innovation in their context of reference, and at the dynamics through which public sector organisational innovation effectively impacts local context dynamics. Notably, scaling-deep mechanisms are affected by the capacity of PAs to support services that meet context-specific needs, which in turn depends on "context readiness", which is shaped by socio-demographic factors, as well as by the degree of digital capacity of local actors (including service end-users) and by the type and quality of existing digital infrastructures.

Scaling-out - Relational capacity: replication and transfer. This mechanism emphasises replication and dissemination of innovations in different communities (Riddell and Moore, 2015) and deals with the spread and (re)production of innovative values, ideas, and tools across the multiple levels of interactions characterising socio-technical systems (Geels and Schot, 2007). In line with DIGISER research questions (Table 1), scaling-out mechanisms are related to the paths and enablers that allow for innovation practices to be replicated somewhere else e.g., to the mechanisms through which cities reproduce, replicate, and adopt digital service procedures or innovation practices developed in different contexts[2].

Scaling mechanisms play a role in the concept specification that is twofold.

On the one hand, they represent the **changes and transformation that a public authority achieves to activate** by governing their contexts through flexible, adaptive, learning-prone, and context-sensitive schemes, and by managing relations and interactions with other actors, including public subjects (other institutions at local or higher levels), private actors and citizens. This first dimension foresees a proactive role of public institutions, which drive innovation process generation and are engaged in spreading innovation across the multiple levels of socio-technical systems (see Geels and Shot, 2007; Geels, 2020). In this case, scaling mechanisms allow explore different transition pathways that may emerge within service innovation processes. First, scaling-up mechanisms allow investigating the capacity of public institutions to proactively generate innovation dynamics through the modification of their internal governing mechanisms, of organisational routines, of decision-making processes and of the are taken and tools are developed and adopted. The capacity of PAs to support long-term organisational innovation primarily depends on their "proneness to change", and particularly on their capacity to "manage change", e.g., through the acquisition of new competences and skills, the redefinition of legal and funding schemes, or the modification of internal governance structures. Second, scaling-deep mechanisms enable exploring how institution-led innovation can support public value generation and capturing the dynamics through which innovation is adopted and used by local actors across the public, private and civic realms. Finally, DIGISER assumes that "the role of public managers is not necessarily to accomplish all public innovations themselves, but rather to facilitate and align constellations of diverse actors to address various societal challenges" (Bugge et al., 2019: 4). Accordingly, scaling-out mechanisms are used to look at how PAs generate and spread innovation. The capacity of institutions to replicate and transfer innovation practices and modes ultimately depends on their position within existing relational networks, and more specifically by their level of interconnection with other agents acting across service sectors and governance levels.

On the other hand, **scaling mechanisms represent the dynamics that a service creation (ideation, design, experimentation, implementation, supply) or innovation may require to generate an effective response to the societal needs it is created for**. In this second set of innovation pathways, the role of PAs changes. On the one hand, it consists in 'detecting' innovation signals developed in different arenas (scaling-out) and in adopting and adapting them in a way that allows responding to context-specific needs. On the other hand, it requires PAs to embed innovation in their actions through a modification of their internal mechanisms and procedures (scaling-up).

Considering the roles that they play and the relevance they have as for the coherence with the DIGISER research questions, **scaling mechanisms are considered as a cross-cutting interpretative category**. In particular, they are related to two elements specifying the DIGISER concept, namely the "level of service embedment" and the "change management" (see Figure 3).

[2] Achieving innovation in the public sector can be difficult and requires additional, targeted support and resources. In recent years, there has been a significant growth in the type and number of organisations and structures dedicated to supporting innovation in the public sector (OECD, 2017). These are known as teams, units, labs, networks to name a few. Among these, innovation-focused networks and innovation labs have attracted most of the attention. Networks can support and motivate public sector innovation by creating a space where innovators can share ideas, practices, and challenges for implementing innovations. Dedicated innovation units/labs can help address some of the barriers to innovation: e.g., compensate for the lack of innovative leaders and champions and help overcome rigidities in the reward and incentive systems that can often hinder innovative performance in the public sector. They can foster the creation of organisational knowledge about how to apply innovation processes and methods, and support more collaborative and harmonious approaches in problem solving. This can help address departmental silo thinking by adopting cross-cutting, inter-disciplinary approaches, bringing together different or new tools, methods, and skills. (OECD, 2018: 198)

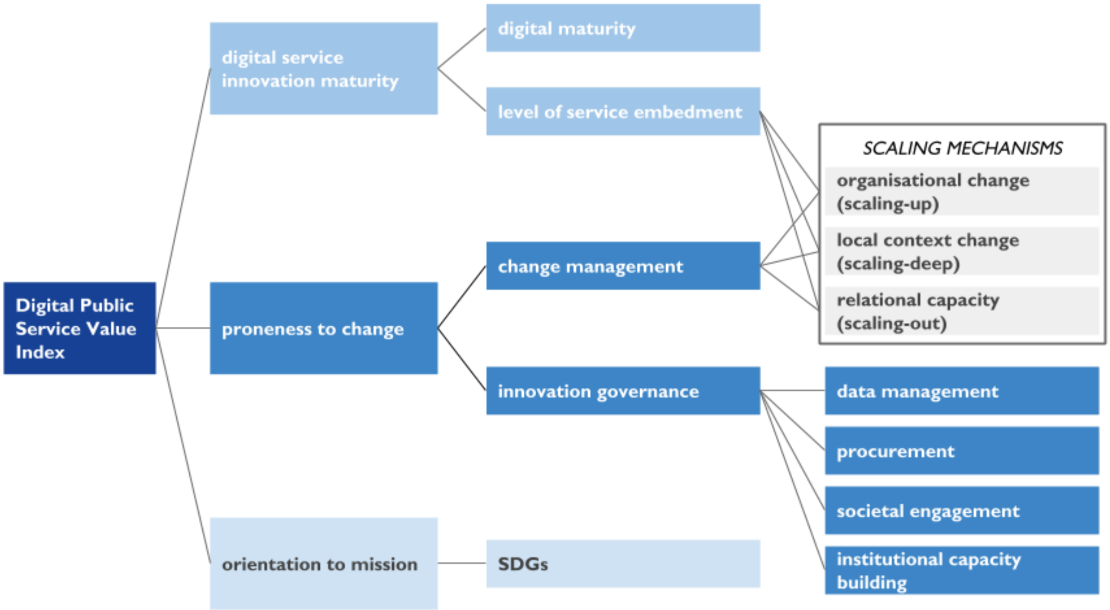


Figure 3 - DPSVI Conceptual Triplet

2.2.1 Digital service innovation maturity

Digital technologies are profoundly affecting people's lives and how they interact with public infrastructures (Welby, 2019). These technologies, their growing availability and performances, the wide use of data, the broad offer of services provided by a large variety of actors are re-shaping the value supply chain of public service and the associated concept of public good. Also, "o*ver the past decades, countries have enacted large-scale public sector reforms to prioritise digitalisation[…], investing considerable resources to adopt new practices to modernise their services and make them more responsive to citizens' needs*" (OECD, 2019: 146).

Exploring Public Service means to deal with one of the two key roles of the Public Administrations: the "*management and implementation of the whole set of government activities dealing with the implementation of laws, regulations and decisions of the government and the management related to the provision of public services"* (UNDP, 2015: 2). For what concerns the latter, digital technologies play a crucial innovative role, as they place increasing and new demands and expectations on the public sector. Furthermore, the fast evolution of technologies continuously offers new opportunities towards digital government, transparency, and openness. Accordingly, even if the digital transformation of government and services has now achieved an advanced state of maturity, realising the full potential of these technologies still represents a key challenge for governmental organisations (DESI, 2019; DESI, 2020). Public service innovation constitutes an integral part of digital government strategies and more and more "*relies on a digital ecosystem comprised of government actors, non-governmental organisations, businesses, citizens' associations and individuals, which supports the production of and access to data, services and content through interactions with the government (for example, open data platforms common to several governmental institutions* (OECD, 2019: 146).

Most recent DESI reports (2019; 2020) show that, from the user side, the demand for digital public services is growing, witnessing that societal digital literacy is growing together with the digital transformation and maturity process. In this dwelling of growing demand for and evolving offer of digital services two elements appear relevant and contribute to determine **digital service innovation maturity**. The first is **digital maturity,** which is defined by the level of digital infrastructure and transformation (i.e., what technologies and to what extent services are digitally offered and used). The second refers to the **level of service embedment** and consists in the level of adoption of the digital service and in its internalization in the public administration organization and setting (i.e., how far the digital service is accessible and adopted by most of the citizens; to what extent the digital service potentials are fully exploited by the skilled organization and affect the public administration renewal and innovation). Together, these two dimensions specify what has been recently defined *digital readiness* of innovative public services (European Commission, 2020) explored through four dimensions: technological, societal, organizational, and legal (p. 7).

- **Digital maturity** mainly attains to the extent to which public administrations embrace new digital technologies and deliver innovative public services. Digital maturity is usually referred to the four layers of the European Interoperability Framework (EIF), aligned with user centricity principles defined by the Tallinn Declaration in 2017 to ensure that the adoption of new technologies does not lead to creation of new silos or compartmentation. Digital maturity considers the distinction between mature technologies and emerging technologies, these last playing a relevant role in describing to what extent the public authority challenges itself while developing new services.
- The **level of service embedment** reflects the role played by the service in driving changes in public authorities. The three scaling mechanisms reflect here a different perspective. Scaling-up mechanisms are related to the achievement of the public authority to supply the service autonomously, reflecting the completion of a process of adaptation and renewal throughout service development. The scaling-out mechanisms reflect the public authority's capacity to drive service adoption by others, either in case it has been entirely and autonomously developed, or it represents the result of an improvement process. In this respect, specific and dedicated experiences of sharing and collaborative networks are crucial and allow public authorities to access a large variety of services and related solutions opportunities. Finally, scaling-deep mechanisms reflect the level of adoption by the users in service development, so capturing changes in practices and behaviours that the service innovation aims to affect.

2.2.2 Proneness to change

The second dimension explored by the DPSVI concerns PA's **proneness to change**. As previously mentioned, (Fernandez and Rainey, 2006), the degree of proneness depends on a variety of factors, including organisational structuring and degree of internal resistances, attention towards capacity building and presence of adequate competencies, and availability to learn, i.e., to engage in iterative learning processes that encompass the different dimensions illustrated in the T-LL model (see Figure 1). In DIGISER, proneness to change is defined in relation to **change management** and with is specified considering specific **governance innovation** processes.

Change management is hereby defined by the capacity of PAs to *manage change* in order to engage into digital innovation processes, and to *shape change* (Rammel et al., 2004) by supporting innovation pathways through transitional scaling dynamics. On the one hand, change management in the DIGISER context refers to the capacity of PAs to put in play a set of actions, norms, policies, and tools either to proactively support innovation in (digital) service development and provision or to increase its capacity to detect and adopt innovation dynamics developed in different contexts. This notion implicitly acknowledges that innovation can originate either within the institution or within specific service domains. Accordingly, it relies upon the capacity of an organization to adapt its internal procedures in order to adjust to both internal and external circumstances (see scaling-up mechanisms), but also upon its ability to create spaces for other agents (both from other contexts and the local level) to engage along the different dimensions of governance innovation processes (as described in the following paragraphs). "Proneness to change", therefore, also includes the capacity *"to utilize innovative bottom-up developments in a more strategic way by coordinating different levels of governance and fostering self-organization through new types of interaction and cycles of learning and action for radical innovations offering sustainability benefits"* (Kemp et al., 2007: 3). On the other hand, change management refers to the capacity of an institution to support government modernisation and to modify its internal procedures and practices to *"create space for short-term innovation and develop long-term sustainability visions linked to desired societal transitions"* (Loorbach, 2010: 163). Concerning digitalisation processes, this ultimately relates to increasing its openness, transparency, and effectiveness in terms of digital service development and ICT-enabled service delivery.

The capacity of PAs to manage and shape change is affected by a variety of factors, including (i) the degree of awareness PAs have about their role and transitional potential; (ii) their commitment to change, e.g., in terms of proneness to experiment and to use advance ICT technologies, but also to activate new modes of governance; (iii) their capacity to act, e.g., with respect to the adoption of adequate tools and procedures (see "digital maturity") and (iv) their role and position in their network, e.g. in terms of capacity to develop policies and practices in the interaction of a variety of societal actors within innovation governance structures..

Also, "proneness to change" is explored in relation to **four innovation governance processes,** which reflect key challenging opportunities public authorities have faced in the last years. Those are:

1. **Data management.** Data (open and big) represent an un-precedent opportunity for growing availability combined with the growing computational and analytical potentials. Although public authorities have been exposed to the request for data disclosure, more recent reflections (Concilio and Molinari, 2019; Concilio and Pucci, 2021) also show the growing relevance played by data as a resource mainly having private owners and making cities compete at the market level.

2. (Public) **Procurement.** Public procurement represents one of the most important innovation channels for public authorities. The way public authorities run procurement procedures can reveal a lot on their innovation strategy and their proneness to learn.

3. **Societal engagement.** The role of citizens is gaining importance up to obliging public authorities to develop dedicated programs overcoming participatory approach and transforming societal engagement into collaborative city making towards new citizenship models.

4. **Institutional capacity building**. Organisational learning is a pre-requisite for innovation to emerge at the institutional level. Many elements contribute to institutional capacity building: employee skills and competences, the internal personnel mobility, collaboration and sharing, the organizational involvement in experiments and tests.

Given the growing value of data in today's societies and economies and their crucial role in governmental processes, effective **data management** strategy is becoming increasingly imperative towards better public services. As highlighted by the OECD (2018: 192), "*Open Government Data (OGD) can be a powerful lever for social and economic development. It can also be used to strengthen public governance by improving the design of public services with a citizen-driven approach, by enhancing public sector efficiency and by spurring public sector integrity and accountability. By ensuring OGD availability, accessibility and reuse by public, private and civic actors, governments can design more evidence-based and inclusive policies, stimulate innovation inside and outside the public sector, and empower citizens to take better-informed personal decisions".* In this context, *OGD policies are set "on ideas and principles that centre on making data from public bodies available to everyone in open, free and accessible formats*" (OECD, 2019: 148). Obstacles in the design and implementation of such policies emerge at the central/federal level, due to a great variety in "*the extent to which countries conduct initiatives to promote data re-use outside government (such as hackathons and co-creation events) and inside governments (via training and information sessions to civil servants)"* (OECD, 2018: 192); and to the fact that *, "few countries monitor the economic and social impact of open data as well as the impact of open data on public sector performance (...and to the possible existence of) an implementation gap in a number of countries where policy developments have been introduced very recently including notably in some of the eastern European countries such as the Czech Republic, Latvia, the Slovak Republic and Slovenia*" (ibidem). . Relevant challenges also emerge at the urban scale. As part of the rhetoric surrounding the Open Government and Smart City concept, cities are increasingly challenged in relation to data (e.g., management, governance, processing, storage, publishing), as per the growing power acquired by the data market and the great relevance assigned to data ownership rather than to data-exploitation know-how. Concurrently, policies call for more open data to foster service innovation and government transparency. More and more crucial is the policy framework they can develop to shift the data culture from ownership to exploitation (Walravens et al., 2021). Public authorities may become drivers for **data management** strategies that make cities less impacted by the (big) data market and transform cities into data ecosystems where: citizens become (big) data sources and literate users; private actors are exchanging information while transforming their services into public value production systems; public services are considered strategic data collection and utilization systems enabled by format and procedural standards that allow the data to be used by anyone; public authorities promote initiatives of data utilizations for the creation of innovative services (Concilio and Pucci, 2021).

(Public) **Procurement** refers to techniques, structured methods, and means to streamline an organization's procurement process and achieve desired results while saving cost, reducing time, and building win-win supplier relationships. "*Governments continue to use public procurement to pursue secondary policy objectives while delivering goods and services necessary to accomplish their missions in a timely, economical and efficient manner. The high relevance of public procurement for economic outcomes and sound public governance, as implied by its large volume, makes governments use public procurement as a strategic policy lever for achieving additional policy goals, which aim to address environmental, economic and social challenges according to national priorities*" (OECD, 2018: 174). This is true at all government levels, as public procurement is one of the main demand-side innovation policies to support innovative goods and services. Information and communication technologies play a twofold role in procurement processes. On the one hand, they may represent the object of the procurement and how procurement processes are conducted may reveal important insights on the digital innovation strategies of the public authorities (e.g., the innovation perspective, the level of delegation, the ICT advancement challenge). On the other hand, ICT technologies may represent the supporting infrastructure of the procurement process (e-procurement) enabling "*governments to increase the transparency of public procurement activities as well as collect consistent, up-to-date and reliable data on procurement processes*" eventually feeding "*other government information technology (IT) systems through automated data exchanges, reducing risks of errors and duplication*" (OECD, 2019: 138). Within the first perspective, it is crucial to consider the role potentially played by "pre-commercial" **procurement** (PCP) as a means to use public needs as a driver for innovation. The concept was introduced as a response to the need to reinforce the innovation capabilities of the European Union while improving the quality and efficiency of public services: it is a very challenging and fascinating concept still having a complex implementation perspective in terms of standard procedures as well as in terms of interpretation (see Edquist and Zabala-Iturriagagoitia, 2015).

The notion of s**ocietal engagement**, while being characterized by a shared pool of keywords and concepts (e.g., transparency, efficiency, accessibility, inclusion, or even democracy), proved capable to absorb cultural influences from the contexts where it is materialized into policies and practices, cross-fertilizing itself with pre-existing political and cultural traditions (Sintomer et al., 2016). Narrowing down the extreme variety of approaches to societal engagement in complex governance (Fung, 2006), DIGISER focuses on two prevalent streams of literature and practices. The first one reflects on the political foundations of societal engagement. This stream focuses on the active participation of non-elected actors and stakeholders in public decision-making processes as a means to reinforce local democratic systems in response to the generalized crisis of institutions of representative democracy (Avritzer and Santos, 2005). In this first interpretation, DIGISER will observe and contextualize participatory democracy experiments seeking to engage urban actors to influence decision-making processes, as in the case of participatory budgeting, local stakeholder engagement in urban planning policies, local petitioning, and referendum mechanisms. The second stream approaches societal engagement from a co-design and co-creation perspective, considering urban actors as both consumers and producers of public services and generator of public value. This interpretation focuses on the "*constellation of design initiatives geared toward making social innovation more probable, effective, long-lasting, and apt to spread*" (Manzini, 2014: 65). Notably, while the implementation of participatory processes necessarily entails the active engagement of urban public authorities, the co-creation of public services can also be grounded on bottom-up initiatives generating public value, that can be eventually institutionalized at a later stage (Ibarra, 2007). Even though both approaches to societal engagement were pre-existing the recent digital transformation, both have been significantly affected by the widespread availability of digital technologies. Not only they provided new means and opportunity to engage people, but they also enhanced the potential active role of societal actors as providers of input and data, coproducers or owners of the services (Public Private People Partnership - PPPP) and unlocked new domains of engagement. A relevant example is provided by a new generation of collaborative platforms, which has been introduced and implemented by urban authorities with the purpose to extend e-participation opportunities (Sestini, 2012). The deployment of collaborative platforms by an urban authority entails several challenges regarding "hard" technological choices (e.g., code, licenses, data ownership) as well as interaction design choices that will be observed in DIGISER as an indicator of both the level of digital maturity and as proxies to understand the actual orientation to interoperability and openness. Another crucial dynamic refers to the multiplication of co-design and co-creation initiatives, many of them regarding projects and topics typical of digital transformation (e.g., the co-design of e-government services, or the active involvement of urban actors in the collection and publishing of new open data series), which are intended to be a relevant indicator of the vitality and integration of the urban innovation ecosystem.

Starting from the assumption that "organisations require both existing and novel organisational capabilities to utilise digital technologies in order to respond to transformation drivers" (Faro et al., 2019: 2), the exploration of **institutional capacity building** addresses both training and educational activities put in play to enhance the digital skills of civil servants and the proneness of PAs to enhance and mobilise their organisational and technological resources through the adoption of ICT technologies or the modification of internal rules and procedures (in relation with the scaling-up dimension, see Figure 3**Error! Reference source not found.**). Concerning the former, institutional capacity building focuses on the role played by employees' skills and competences, which is crucial when digital innovation is targeted, as *"civil servants need the ability, motivation and opportunities to contribute to innovation. Therefore, human resource management (Hm) is an important lever for supporting public sector innovation by enabling managers and front-line staff to formulate ideas that result in new and improved ways to deliver public services"* (OECD, 2017: 196). DIGISER, therefore, looks at the practices developed to enhance organisational capacity for innovation, such as *"incentive structures and awards; managerial and leadership approaches; organisational practices related to recruitment, training, mobility and compensation of employees; and job design factors such as autonomy and ways of working*" (ibidem), as one of the main factors contributing to "digital service innovation maturity". Attention is paid to the capacity of local government to support both flexibility (e.g., through smart working, and autonomy in service development and delivery (see "level of service embedment", in Figure 3**Error! Reference source not found.**). With respect to the latter, the proneness to proactively foster innovation through capacity building is assumed to be grounded into the PAs' capacity to engage into iterative learning processes (see the T-LL model, Figure 1**Error! Reference source not found.**) affected by internal and external constraints and pressures. In this direction, capacity building is affected by the relational capacity of an institution2.2, e.g., concerning collaboration schemes with other cities and networks, as well as to the participation to projects and programmes targeting service digitalisation objectives or facilitating a vast deployment of digital technologies.

2.2.3 Orientation to mission

DIGISER uses "**orientation to mission**" (Mazzucato, 2018), which has been recently receiving attention in the scientific domain and in the actual policymaking field, to explore the extent to which institutional actions intentionally answer to one or more societal challenges local authorities are asked to face. The mission-oriented approach to research and innovation policies refers to a methodology that aims to manage complex governance aligning it toward specific and explicit missions. This approach can be recognized when integrated policies and initiatives are aligned toward a clearly defined mission, (i.e., achieving a measurable goal or implementing a solution), targeting a specific and explicit societal challenge (i.e., reducing social exclusion in a given context). Differently from other approaches to innovation based on the simplistic equation that relate innovation to mere digital transformation, orientation to mission "*does not facilitate innovation merely by levelling the playing field with horizontal policies that prescribe no direction. On the contrary(… it provides) explicit technological and sectoral directions to achieve the 'mission'."* (Mazzucato, 2018a: 5).

At the institutional level, targeting missions requires inscribing research and innovation strategies in a larger strategical framework, associated with consistent regulatory and organizational provisions. In this perspective, public organizations must set long-term perspectives towards, and commitment to, clearly identified missions deducted through a process of prioritisation of societal targets and create conditions for very effective solutions to emerge, root and survive (Mazzucato, 2018b; European Commission, 2018).A sound orientation to mission is shaped through a differentiated set of initiatives being ambitious, cross-disciplinary, exploratory, and ground-breaking in nature and mixing narrowly defined actions, aimed at single, well-defined objectives with more broadly defined initiatives addressing societal challenges and targeting the transformation of the system as a whole. At the same time, to be successful, mission-oriented policies *"must also enable bottom-up experimentation and learning*." (Mazzucato, 2018a: 5).

Despite its fluidity and context-sensitivity, the notion of mission-oriented approach has been introduced in DIGISER after a critical reflection on the technology-driven assumptions underlying much of the research on the relation between digital transformation and societal innovation in recent years (Wyatt, 2017). The DIGISER perspective goes beyond simplistic techno-determinism and explores the purposes underlying digital transformation in public service provisions. In doing so, it seeks to research if public policies are oriented to societal goals and how much those goals are clearly defined, and their achievement adequately monitored.

In DIGISER, orientation to mission is interpreted in relation to **four key societal challenges**: scaling governments and markets to take the full advantage of the digital revolution; changing the government structure; government processes, service design and delivery; and skills and capacity (see DIGISER Final Report). These key challenges resonate with the dynamics investigated throughout the Project, with the support of the DIGISER conceptual framework (see Figure 3).

The exploration of "orientation to mission" is carried out indirectly with the support of quantitative raw data from the DIGISURVEY (see DIGISER Final Report) and - considering the extreme context-sensitivity of the phenomena - of in-depth qualitative methods. To better investigate "orientation to mission", DIGISER refers to the Sustainable Development Goals (SDGs), which are identified as a major, urgent set of societal challenges, in coherence with a recent framework to roadmap mission-oriented innovation policy for SDGs (Miedzinski, 2019). In particular, DIGISER tries to capture efforts put in play at the local level to enable and accelerate the transition towards the Sustainable Development Goals (SDGs).

As this this third conceptual and interpretative dimension of "orientation to mission" is only partially explored in DIGISURVEY, it is not included in the in the DPSVI Data Model (see Figure 6), but it is explored directly in the DIGISER Final Report based on the results of qualitative investigation carried out in the cities explored in the case studies (see DIGISER D3 Main Report, Chapter 3. and Annex 1.7 Case Studies at https://www.espon.eu/DIGISER).

2.3 Conceptual data model development

The DPSVI data model has been drawn upon the results of a preliminary Data gap review (reported in the Interim report of DIGISER) and to answer to solicitations developed within the conceptual framework.

The process of definition of the data model has been then developed considering both theoretical and practical concerns and required the development and discussion of several possible scenarios of data collection that have been finally selected involving both the client and the experts of the SAG. The main outcomes of this work can be summarized in 2 points.

- First, the research team decided to develop **a data model that is fed in first place by primary data collected directly through a survey,** allowing the research team to design an ad hoc questionnaire targeting specific research questions.
- Second, the team decided to consider the key processes introduced in the concept, namely th**e innovation governance processes (**Data Management, Procurement, Societal Engagement, Institutional Capacity Building) and the **scaling mechanisms** as the **starting drivers to the survey so implementing a "from processes to services" data model hypothesis.**

Combining the analytical perspective of the DPSVI with the potential availability of primary data a preliminary data map was drawn.

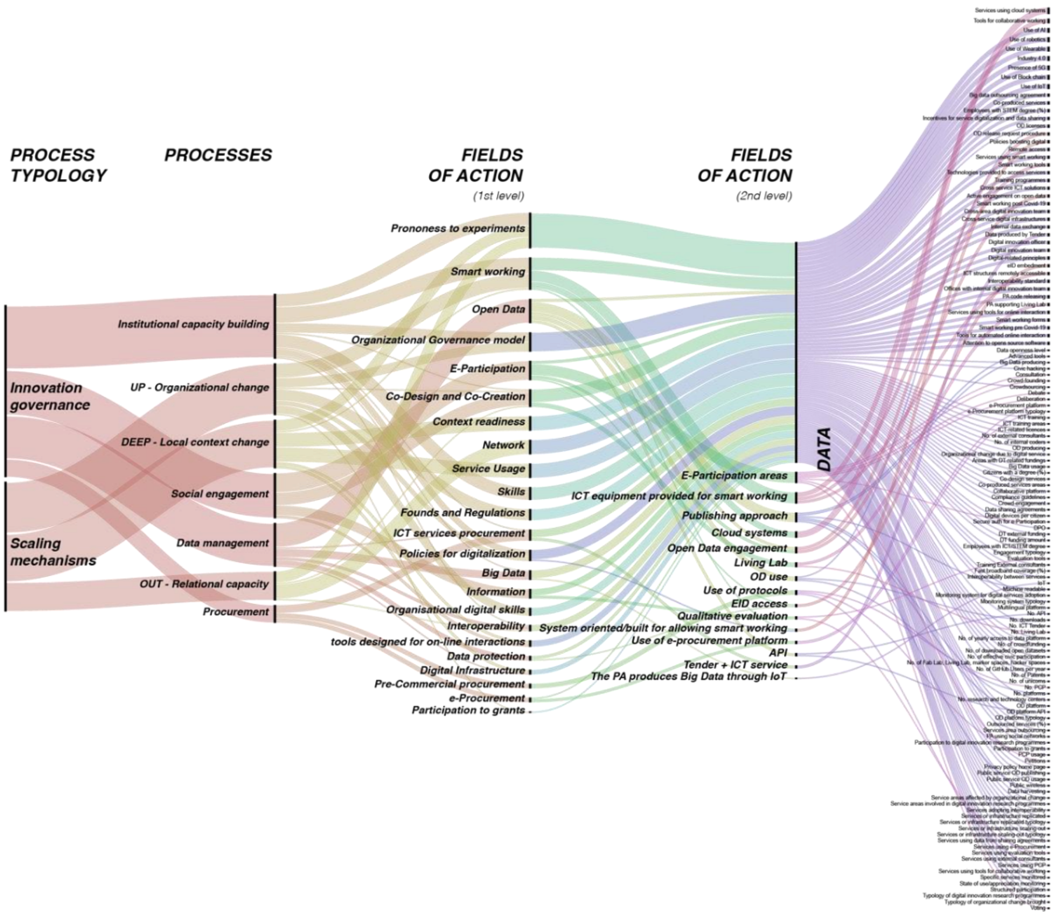


Figure 4 – DPSVI preliminary data map

Figure 4 clearly shows two process families representing the starting points of the data collection strategy. They refer to processes related to "innovation governance" and to "scaling mechanisms". As stated in the concept, the latter can be considered as a cross-cutting interpretative category, shared by both the process and the service perspectives.

These typologies are then articulated in a sub-hierarchy of respective fields of action. From this level, it is then possible to identify the terminal leaves of the conceptual data model, representing the single data units retrieved. Every data unit may inform more than one "position" in the hierarchy. In Figure 4, this fact is represented by the stroke thickness attributed to the curves connecting the second level of the fields of action to the data level.

The disaggregation according to processes and the one according to services are summarised and displayed in the Circular Dendrogram of Figure 5, where the process-related hierarchy is displayed using the branches of the dendrogram tree, while the connection to the service level is shown via the colours of the balls representing the entity. In this visualization, data that feed multiple points of the dendrogram are duplicated and identified via a black dot inside.

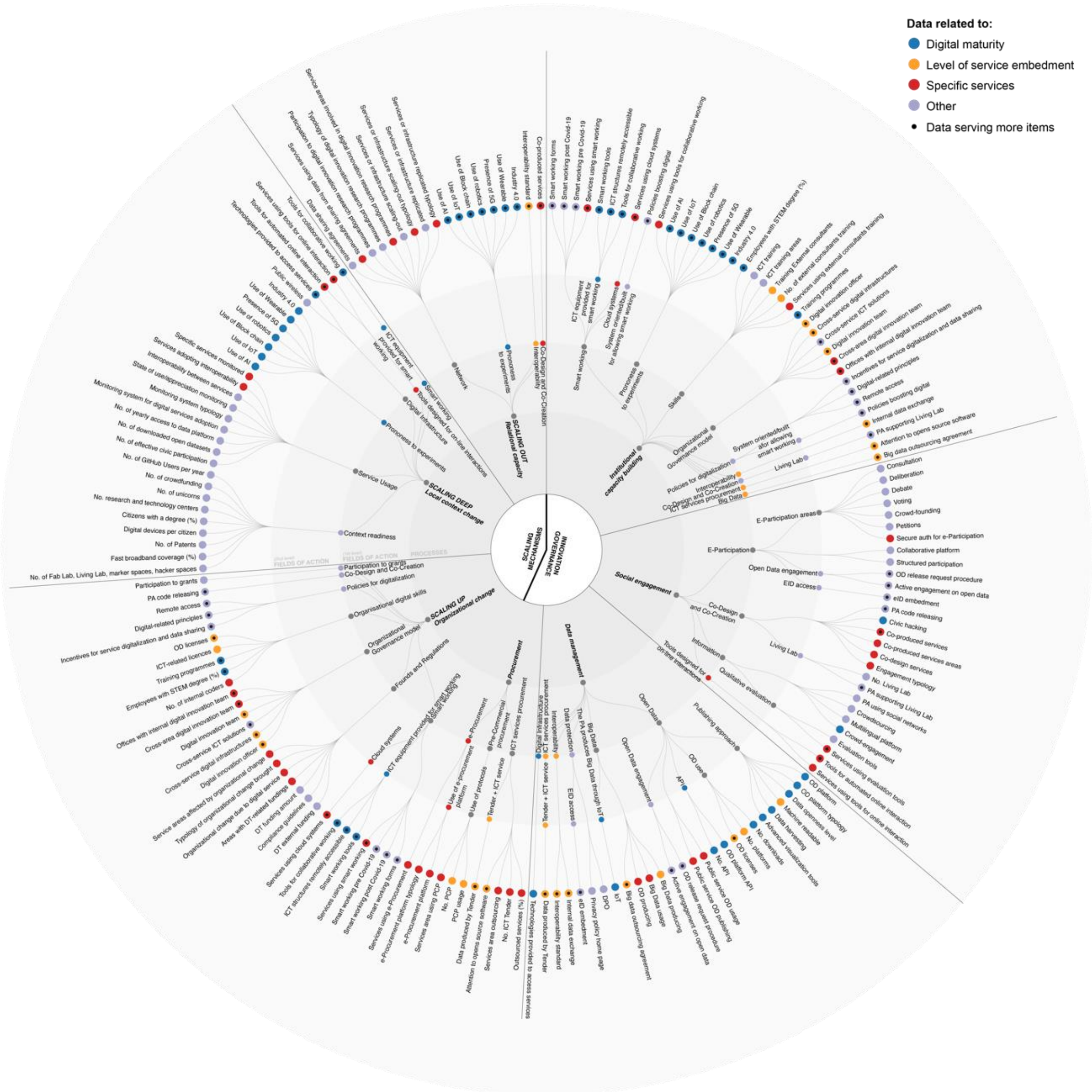


Figure 5 - Circular Dendrogram, combining the process and the service perspective

Focusing on those pieces of information that can only be acquired via a survey - and being the conceptual data model also a clustering dendrogram able to group the data into thematic entities - the hierarchy allows creating modules of items that can be seen as conceptually homogeneous. Being also a map in terms of conceptual relationships (and thus, of statistical correlation), the hierarchical structure, both in terms of processes and services, will constitute a theory-driven framework to inform the statistical analysis. The technique of choice, in this case, will be Structural Equation Modelling (SEM) (Kaplan, 2008), and specifically the use of measurement models to extract latent factors (which in our case will represent the “scores” of the cities in different categories) from data. Such a measurement model will be refined after the data collection phase via exploratory factor analysis techniques, and then validated via a confirmatory factor analysis. The creation of a validated measurement model (and connected factor calculation procedures), and so of a statistically validated scale to measure the Digital Public Service Value along its dimensions will allow the use of the designed survey as an instrument to evaluate such dimensions also on different cities and to provide them with a quick comparison with the representative sample of cities that we aim to analyse.

2.4 DPSVI data model

The DPSVI data model has been designed in order to answer to the solicitations developed within the conceptual framework and considering the constraint related to the data collection method adopted in DIGISER.

In summary, the DPSVI is conceived as a multi-level composite index, nourished by primary data collected through a survey (DIGISURVEY) targeting European cities. On the one hand, cities have provided a relevant base of data and knowledge that can be used directly to formulate analyses and interpret specific phenomena through the analysis of raw questions. On the other hand, these data are combined and used to feed a system of composite indexes that provide a synthetic assessment of the performance of cities in relation to complex phenomena.
Figure 6 provides an overview of the index tree that makes up the DPSVI.

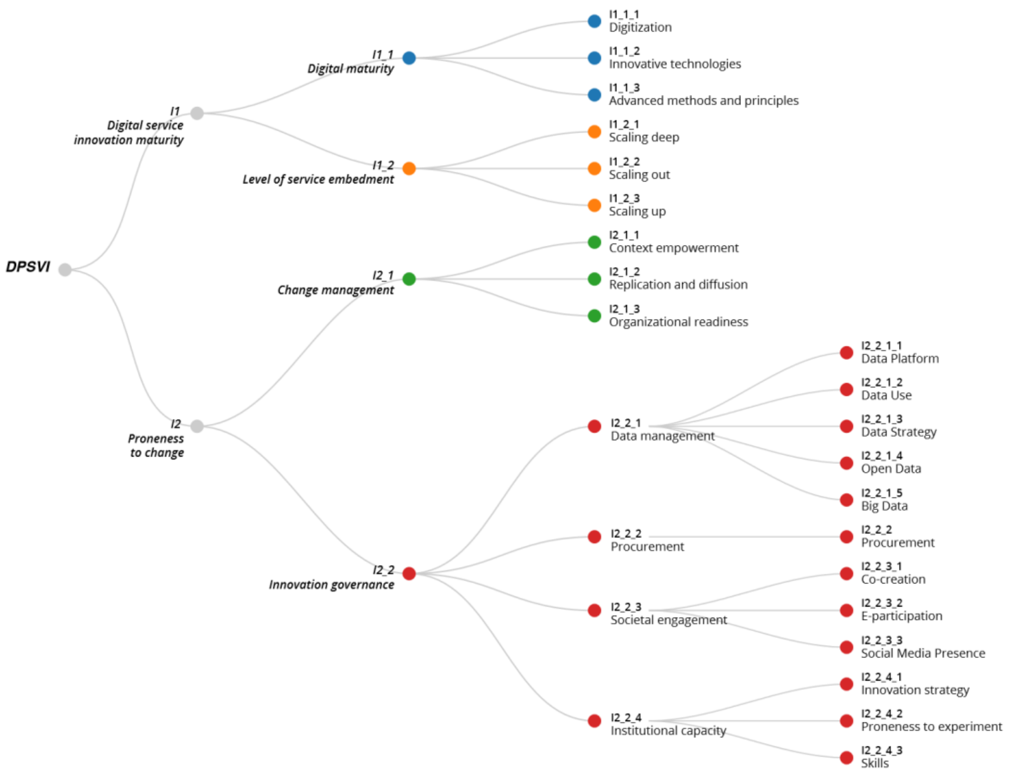


Figure 6 - DPSVI Structure

Overall, the DPSVI is composed of 31 Composite indexes that are organized in three groups:

- 3 Top Indexes: are the apical indexes including the DPSVI itself and the two pillars (I1 DIGITAL SERVICE INNOVATION MATURITY and I2 PRONENESS TO CHANGE)
- 21 Bottom Indexes: the indexes directly generated on top of DIGISURVEY data
- 7 Intermediate Indexes: the other indexes in intermediate positions

Code	Label	Level	Description
I1	**DIGITAL SERVICE INNOVATION MATURITY**	**Top**	**It explores the degree of penetration and maturity of technical and organizational innovation in public service delivery**
I1_1	Digital maturity	Intermediate	It assesses the level of digitalization of the public authority, intended not only as shift toward digital technologies, but also encompassing the related organizational change, namely the delivery of innovative public services
I1_1_1	Digitization	Bottom	It focuses on the degree of digitization of pre-existing internal procedures either ancillary or directly related to public service delivery
I1_1_2	Innovative technologies	Bottom	It explores the degree of adoption of innovative technologies (AI, blockchain, wearables, etc.)
I1_1_3	Advanced methods and principles	Bottom	It analyses the level of consistency of methods and principles used to increase the digitalization level of the public authority
I1_2	**Level of service embedment**	Intermediate	It indicates the extent to which the innovation of services is pervasive and has already generated changes
I1_2_1	Scaling deep	Bottom	It indicates the extent to which the innovation of services is pervasive and has already generated changes in the local context, at societal level
I1_2_2	Scaling out	Bottom	It indicates the extent to which the innovation of services has already generated changes either by replicating successful innovations from other contexts or exported elsewhere the innovations experimented locally
I1_2_3	Scaling up	Bottom	It indicates the extent to which the innovation of services is pervasive and has already generated changes within the organization of the public authority
I2	**PRONENESS TO CHANGE**	**Top**	**It assesses the inclination or readiness of the public authority to change and alter its behaviour, vision, procedures, and its preparedness to integrate and amplify innovations**
I2_1	Change management	Intermediate	The capacity of public administrations to put in play a set of actions, norms, policies, and tools either to proactively support innovation in digital service development and provision, or to increase its capacity to detect and adopt innovation dynamics developed in different contexts (within the context, or towards or from other contexts).
I2_1_1	Context empowerment	Bottom	It measures the effectiveness of the strategies, developed by the public authority, to ensure impacts of innovation within in the local context, at societal level, e.g. instillation of cultural values oriented to innovation and change; encouragement for the development of sustainable relationships
I2_1_2	Replication and diffusion	Bottom	It measures the effectiveness of the strategies developed to ensure replicability in other contexts to the innovations experimented locally, so to impact a larger number of citizens or communities
I2_1_3	Organizational readiness	Bottom	It measures the effectiveness of the strategies developed to ensure impacts of innovation within the organization of the public authority
I2_2	Innovation governance	Intermediate	It refers to the way in which the public authority uses transversal administrative processes (data management, societal engagement, public procurement, capacity building) as a leverage to promote cross-sectoral digital innovation
I2_2_1	Data management	Intermediate	It assesses the innovation capacity of data management strategies used by the public organization
I2_2_1_1	*Data Platform*	Bottom	It assesses the features of the data platform and the consistency between data management strategy and its underlying technical infrastructure
I2_2_1_2	*Data Use*	Bottom	It explores, from an operational perspective, how data are used by the public administration for the purposes of evaluation and monitoring, delivery, and anticipation and planning.
I2_2_1_3	*Data Strategy*	Bottom	It investigates whether the definition and the embrace of governance models effectively set appropriate and favorable conditions for data-driven, data-informed, or data-aware decisions and services for creating public value.
I2_2_1_4	*Open Data*	Bottom	It provides an overview of the degree of application of open data principles, practices, and framework, that are meant to improve performance and efficiency of government services in general
I2_2_1_5	*Big Data*	Bottom	It refers to the capacity of the city to generate, manage and use big data
I2_2_2	Procurement	Bottom	It assesses the level of digitalization of the public procurement processes within the public authority and their orientation to digital innovation

Code	Label	Level	Description
I2_2_3	Societal engagement	Intermediate	It provides an overview of the intensity and level of digitalization of societal engagement policies, and their impact on public service design and innovation
I2_2_3_1	*Co-creation*	Bottom	It gives the level of involvement of the citizens in service design and innovation
I2_2_3_2	*E-participation*	Bottom	It refers to the level reached by the municipality in involving citizens and/or communities through digital platforms
I2_2_3_3	*Social Media Presence*	Bottom	It provides information about how pervasive is the communication via social media by the municipality
I2_2_4	Institutional capacity	Intermediate	It refers to the institutional capacity of the public authority in relation to the experimentation and consolidation of digital innovation
I2_2_4_1	*Innovation strategy*	Bottom	It provides information about the agenda setting and pursuing capacity in relation to digital innovation strategies
I2_2_4_2	*Proneness to experiment*	Bottom	It analyses the readiness to experiment new organizational settings and methods within the public authority
I2_2_4_3	*Skills*	Bottom	It assesses the availability, within the public authority, of skills as key to the management of digital innovation

Table 2 - Composite indexes of DPSVI

3 Data collection

Data collection in DIGISER has been carried out following the lines defined in the conceptual research framework presented in the Interim Report of DIGISER (Chapter 3 of the DIGISER Inception Report), and from the results of the data gap analysis carried out at the beginning of the project (Chapter 2 of the DIGISER Inception Report).

The conceptual framework defined at high level the key research questions and hypotheses and frame the **Digital Public Service Value Index (DPSVI),** intended as a *key summary measure of the extent to which each urban public authority is actually adopting and scaling up best practices through open data, APIs, and standards, and thus increasing public value*[3]. In the inception report the DPSVI has been detailed as the combination of several sub-indices, each one targeting a subset of underlying questions and hypotheses.

The initial Data Gap Analysis - the mapping of available data developed for the Inception Report through and looking at several open databases and pre-existing research projects (see Chapter 2.3 of the DIGISER Inception Report) - showed the limited availability of relevant data at the adequate scale of analysis (i.e., the local level) and supported the option of a large-scale primary data collection.

As a consequence, the DIGISER team in accordance with the client, decided to proceed with the development and deployment of an online questionnaire called DIGISURVEY.

3.1 DIGISURVEY

The development and consolidation of DIGISURVEY followed a long and non-linear process as a result of three combined challenges.

- First, the kind of information and data necessary to answer the research questions have a degree of complexity that is unfit for an online questionnaire. This concern led to work on both the simplification of language and on the questionnaire logical structure itself, modifying the hierarchy of the questions that had to be reviewed from the perspective of the responders.
- Second, the typology of information researched and the lack of control on the accuracy and autonomy of responders generate a significant risk of collecting biased answers. To mitigate this risk, the formulation of questions has been carefully reviewed and in particular those more potentially sensitive to political biases. The most relevant decision regarded the exclusion of questions aimed at exploring the "orientation to mission" branch. After careful assessment, the DIGISER partners agreed that the quantitative questionnaire was not an adequate tool to grasp the complex and subtle insights regarding the techno-political agency in the cities surveyed, and entrusted task 4 (targeting a limited number of case studies) with the exploration of this dimension.
- Third, the numerous feedbacks received from partners and stakeholders and the requests of integration of additional topics and questions coming from the client and from the members of the EC included in DIGISER's advisory board finally modified in part the questionnaire, widening the original conceptual framework by introducing new topics of enquiry.

As a result, the questionnaire has been severely edited through an iterative process occurred from March to May 2021, where seven different versions have been produced. In its final version, the flow of the questionnaire does not precisely follow the structure of the DPSVI as it is presented in the conceptual model. On the contrary, the sequence of questions has been reorganized considering the perspective of the responder and the contiguity of information and data requested. Finally, a relevant number of questions has been hierarchically ordered and nested and would appear only under specific conditional criteria.

[3] The definition of DPSVI is elaborated on top of the definition provided in the Terms of Reference of DIGISER

3.1.1 Structure and content of the questionnaire

The final version of the questionnaire is structured around **9 sections** and includes **74 mandatory questions** and **54 nested questions** that could appear depending upon the answers to previous questions.

The 9 Sections refer to the following field of actions:

1. **General Information**: The scope of this section is to collect general information about the respondent public authority, its competences, and its responsibilities on public service delivery.
2. **Digital Innovation Strategy**: In this section, we want to find out whether the public authority have specific strategies in place to manage digital innovation, what effects digital innovation has had so far on the public authority and whether the public authority is part of a network of cities sharing knowledge and innovation.
3. **Financing & Procurement of Digital Solutions and Services**: Because digital innovation is closely linked to financing and procurement, we would like to find out more about how the public authority funds digital innovation and how procurement of digital innovation is organised.
4. **Institutional Capacity & Skills**: In this section, we want to know more about how the public authority organises work around digital innovation and if it supports employees to build the necessary set of skills.
5. **Data Management**: In this section, we would like to get better insights into how the public authority governs data, whether platforms to manage, analyse, model data are in place, how interoperable and accessible data are as well as whether the public authority is using or sharing big data.
6. **Citizen Engagement and Innovation Ecosystems**: As part of the DIGISURVEY, we would like to find out more about the public authority's innovation ecosystem, as well as how it involves and informs citizens about innovation activities.
7. **Service Design**: In this section on Service Design, we would like to get a better understanding of how the public authority approaches the design and implementation of new (digital) services. Also, we want to learn more about what innovative technologies it has already implemented or is planning to implement in the near future.
8. **Digital Maturity**: In this part of the DIGISURVEY, we would like to get more insights on the offer of digital services in the public authority and how they impact the different service areas.
9. **The Impact of COVID-19**: Covid-19 has influenced everyone and every organization in the past year. We would like to get a better understanding of how the pandemic has affected the public authority and what role digital innovation has played.

Each section could include the following typologies of questions:

- Binary
- Single Choice
- Multiple Choice
- Likert
- Cardinal
- Matrix Single
- Matrix Multiple Choice

A specific set of questions have been introduced in all sections in order to explore in detail the performance of cities through different public service areas. These questions had the format of matrix as represented in Figure 7.

2.4 Is your public authority part of a (local, regional, national, EU) network of cities sharing operational digital solutions or open source code?
Note: If yes, please answer for each service area that applies. If not, please select "Not Applicable"

	Local	Regional	National	International	Not Applicable
*General Services / Administration	☐	☐	☐	☐	☐
*Building & Spatial Planning	☐	☐	☐	☐	☐
*Culture & Leisure	☐	☐	☐	☐	☐
*Education	☐	☐	☐	☐	☐
*Healthcare	☐	☐	☐	☐	☐
*Order & Safety	☐	☐	☐	☐	☐
*Social & Welfare Services	☐	☐	☐	☐	☐
*Transport & Mobility	☐	☐	☐	☐	☐
*Utilities	☐	☐	☐	☐	☐

Figure 7 - DIGISURVEY Service Area question

3.1.2 Survey deployment

DIGISURVEY has been distributed online through the platform EU survey, at the address: https://ec.europa.eu/eusurvey/runner/DIGIsurvey2021

EU survey is a free service based on open code supported by the European Commission's ISA² programme.

The expected time requested for filling the survey was about 1hr.

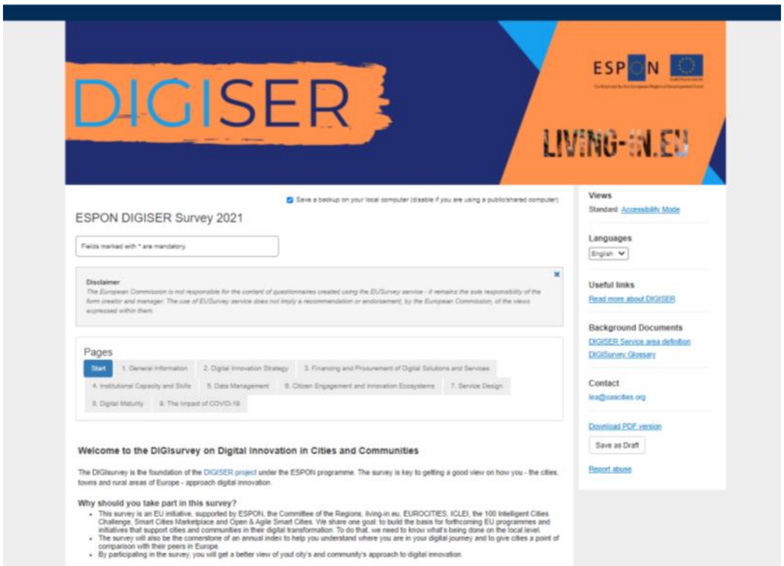


Figure 8 - DIGISURVEY splash page

3.2 Participant cities

While the DIGISURVEY was open to any city willing to participate, the research aimed to reach a minimum sample of cities that could be considered representative of the European scenario of digital transformation at local level.

3.2.1 Definition of city in DIGISER

DIGISER decided to adopt a multi-layer approach to the definition of the notion of 'city', reusing different conceptualization used in recent years by international institution and agencies as the EC, Eurostat, UN, OECD, and ESPON itself in research projects, datasets and studies that were analysed during the data gap analysis (see the Inception Report of DIGISER)

In particular, the definitions used in DIGISER tries to grasp the best geographical definition of cities according to the following order of priorities[4]:

- **Cities**: "is a local administrative unit (LAU) where the majority of the population lives in an urban centre of at least 50 000 inhabitants" (Eurostat, 2021);
- **Greater Cities**: "is an approximation of the urban centre when this stretches far beyond the administrative city boundaries" (Eurostat, 2021);
- **LAU**: local administrative units. Low level administrative divisions of a country below that of a province, region, or state. They may refer to a range of different administrative units, including municipalities, communes, parishes, or wards (Eurostat, 2021);
- **FUA**: consists of a city and its commuting zone. Functional urban areas therefore consist of a densely inhabited city and a less densely populated commuting zone whose labour market is highly integrated with the city (OECD, 2012) (Eurostat, 2021).

As a result, DIGISER accepted as valid participants all the Local Authorities with direct responsibility on any of these territorial definitions including the following categories:

- **Municipalities**
- **Sub-municipal authorities (Districts, parishes, etc.)**
- **Metropolitan authorities**
- **Unions/agglomerations of municipalities**

In order to define a compass to get oriented in the variety of competences and responsibilities of the public authorities participating to the survey, several filter questions were included in section 1 of the DIGISURVEY "General information".

All the public authorities that participated to the DIGISURVEY have been identified, validated, and associated with a NUTS 3 code and, where possible, with a LAU code. The association with these codes, widely adopted in the Eurostat statistical system, will be used to analyse the interplay between DIGISURVEY data and external data series, and is expected to enable further research opportunity and maximize the potential for reuse of data collected.

3.2.2 Reference sample

Following the directions of the original *Terms of Reference* of DIGISER, the research targeted since the early stage a reference sample of European cities. The reference sample is intended to be the best approximation attainable that could be considered as representative of the variety of European cities.

The reference sample plays a relevant role in the analysis and interpretation of the results of the DIGISURVEY. On one hand it will be used to describe an overall picture of the state of the art of digital transformation in European cities. On the other hand, it will be used to establish a benchmark to assess the results of single cities or groups of cities, allowing the measurement of their performance against average values computed for the reference sample.

The reference sample of cities has been composed using several statistical criteria:

- The sample should **cover all European countries**, proportionally to each country's population (i.e., larger countries equal more cities in the sample), with at least one city for each country of the ESPON space. For smaller countries with only one city listed the Capital is included in the sample.
- The sample should include **cities of all sizes** (according to OECD-EC classes) above 50.000 inhabitants, trying to counterbalance the bias toward large cities and metropolis that characterize most of the studies on public service innovation and digital transformation. Cities below 50.000 inhabitants will participate anyway to the DIGISURVEY, but their results will not be considered for the reference sample.

[4] https://ec.europa.eu/eurostat/web/cities/spatial-units https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Local_administrative_unit_(LAU)

- The overall sum of the inhabitants of the cities of the sample should account for at least **10% of the total EU population.**
- The sample should **avoid cities within the same province** (NUTS3 level).

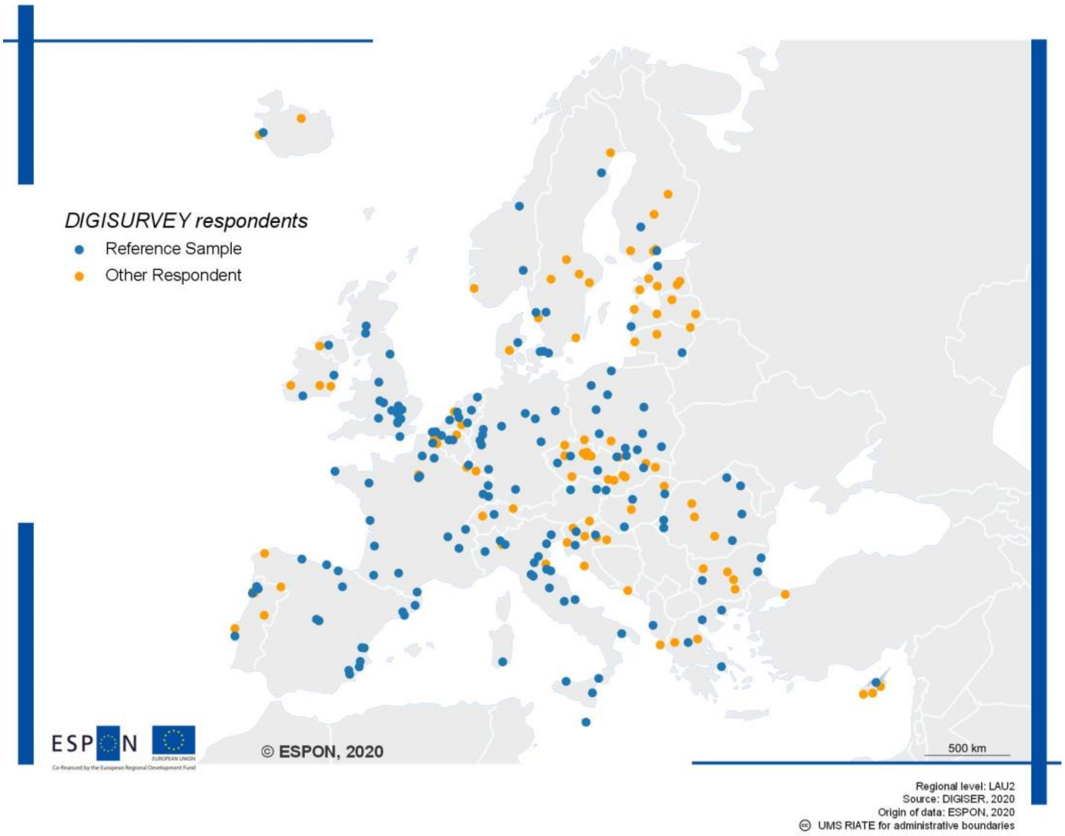
As a result, a reference sample of 170 cities have been defined a priori at the launch of the DIGISURVEY and the engagement campaign targeted primarily the cities included in this list.

The initial list of cities, driven also by concerns regarding the engagement of cities, prioritized **those cities that belong to city networks and organizations related to the promotion of digital transformation and public sector innovation**, including all those networks indicated as relevant by the members of the SAG[5].

All along the data collection stage, while the survey was open online, the research team monitored the rate of completion of the sample. The initial list of cities has been modified according to the actual participants to the survey. New cities that were included in the sample in substitution of other missing cities with equal statistical criteria.

3.3 Overview of data collected

At the date of December 3rd, 2021, DIGISURVEY collected 248 valid questionnaires filled by as many European local authorities.



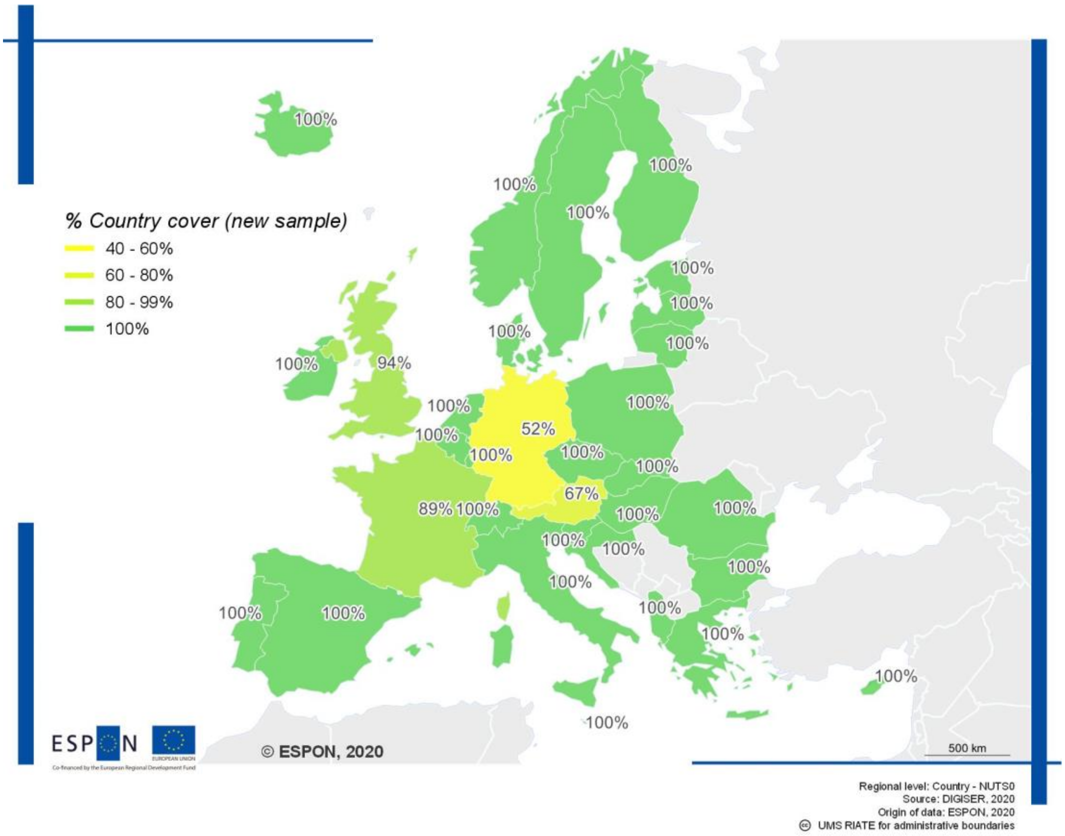
Map 1 - DIGISURVEY participant cities

Out of the **248 questionnaires collected**, **156 are validated as the reference sample**, that in this manner is completed above 90%.

As shown in Table 3 and Map 2, the main data gap related to the sample lies in the lack of responses of the cities in Germany, that responded less promptly to the engagement campaign accompanying DIGISURVEY.

[5] OASC, https://oascities.org/; Living-eu JBS, https://www.living-in.eu/; ICC, https://www.intelligentcitieschallenge.eu/; GDC; Eurocities, https://eurocities.eu/; Smart city marketplace, https://eu-smartcities.eu/ .

Nonetheless, despite this data gap the sample maintain sufficient integrity to allow interpretation and generalization (with the exception of in-depth analysis of the group of German cities).



Map 2 - DIGISURVEY sample saturation

Country	Country	Target	Collected	Complete	Missing	Respondent
AT	Austria	3	2	67%	1	3
BE	Belgium	5	5	100%	0	8
BG	Bulgaria	3	3	100%	0	7
CH	Switzerland	2	2	100%	0	3
CY	Cyprus	1	1	100%	0	4
CZ	Czech Republic	4	4	100%	0	11
DE	Germany	23	12	52%	11	13
DK	Denmark	3	3	100%	0	4
EE	Estonia	1	1	100%	0	6
EL	Greece	4	4	100%	0	7
ES	Spain	15	15	100%	0	16
FI	Finland	2	2	100%	0	7
FR	France	18	16	89%	1	18
HU	Hungary	3	3	100%	0	5
IE	Ireland	2	2	100%	0	6
IT	Italy	19	19	100%	0	21
LT	Lithuania	1	1	100%	0	3
LU	Luxembourg	1	1	100%	0	2
LV	Latvia	1	1	100%	0	6
MT	Malta	1	1	100%	0	1
NL	Netherlands	6	6	100%	0	8
NO	Norway	2	2	100%	0	3
PL	Poland	11	11	100%	0	13
PT	Portugal	4	4	100%	0	10
RO	Romania	6	6	100%	0	9
SE	Sweden	4	4	100%	0	11

Country	Country	Target	Collected	Complete	Missing	Respondent
SI	Slovenia	1	1	100%	0	5
SK	Slovakia	2	2	100%	0	9
UK	United Kingdom	18	17	94%	1	18
HR	Croatia	2	2	100%	0	6
TR	Turkey	0	0	0%	0	1
AL	Albania	1	1	100%	0	1
IS	Iceland	1	1	100%	0	3

Table 3 - DIGISURVEY sample saturation

4 Data Analysis

The data collected in DIGISER have been processed and analysed through different and complementary approaches aimed at exploring different dimensions of the digital transition of European cities, according to the conceptual framework presented in Chapter 2.

4.1 Raw data vs. composite indexes

The main distinction between the analytical approaches adopted regards the **direct use of raw data vs. the computation of composite indexes such as the DPSVI**:

4.1.1 Raw Data

Raw data are intended to be the data directly stemming from the questionnaires filled by cities. They constitute the basis of the composite indexes themselves but can even be interpreted without any specific mathematical and statistical processing. Their explanatory potential is limited to the specific topic of each question, even though in some case, findings at this very simple level can prove capable to support relevant inferences and analyses. Raw data can be also used as proxies to interpret larger phenomena, such as in the analyses carried out in the main DIGISER Final report, where these are used to provide a picture of the state of the art of European cities with respect to the Grand Challenges individuated by the SAG of DIGISER.

This report focuses on the methods used to generate the DPSVI and the other composite indexes and does not explore raw data. Nonetheless, raw data from the DIGISURVEY are made accessible through the delivery of the full DIGISER dataset to ESPON. In addition, the whole set of charts generated directly on top of raw data is made available as *DIGISER_D4_Annex 1.3 DIGISURVEY Questions Report (Q_Report)*, made accessible on the project's webpage.

4.1.2 Composite Indexes

Composite indexes consist of "scores" calculated through the processing of the raw data collected through the DIGISURVEY.

DIGISER developed two kinds of Composite Indexes[6]

I. **DPSVI – Digital Public Service Value Index**

The DPSVI and its other sub-indices, explained in detail in Chapter 2 of this Scientific Annex, are meant to be a concise **measurement of the performance of each city** with respect to several phenomena, that are explored through the combination and cross-checking of the answers to several single questions. The core data model for the computation of the DPSVI is the Data model described in Chapter 2.4. Despite indexes have been conceived as a mean to measure and assess the performance of cities at single level, the above-mentioned clustering of data collected can eventually enable large scale interpretations as well as generalizations of the findings.

II. **SI - Service Area Index:**

In addition to the DPSVI, an ad-hoc index has been developed with the purpose of **measuring the performance of different service areas** at the European scale with respect to several phenomena related to Digital Transformation.

The computation of indexes followed three steps that will be explained in detail in the following sub-chapters.

- **Mapping** In this first step the DIGSURVEY's questions and answers are mapped to the indexes

[6] During the early stage of the project the research team hypothesized to develop also an alternative method to compute the DPSVI, where all the values of cities were re-calculated against the average value of the Reference Sample of cities that could be considered as representative of European trends. The results of data collection induced the team to not proceed on this path and focus the effort on the standard "absolute" DPSVI.

- **Standardization**: this second step aims at transforming each question mapped to an index in a standardized value on the scale 0,00-1,00, converting the raw answers provided by the cities into numerical values via data coding and/or standardization techniques.
- **Aggregation**: in this final step the standardized numerical values obtained from the questions are aggregated and combined into indexes according to the hierarchy established in the Data Model. The value of indexes corresponds to a weighted average of the values of the questions aggregated.

The table below provides an overview of the different approaches to data analysis, highlighting the differences among the three typologies of indexes DIGISER computed.

Approach	Description	Observed unit	Processing	*Detailed results*[7]
Raw Data	Raw primary data directly referable to a specific question of the DIGISURVEY	City/Entity	na	*DIGISER_D4_Annex 1.3 DIGISURVEY Questions Report (Q_Report)*
DPSVI – Digital Public Service Value Index	Composite indexes measuring cites' performance in absolute values, against an ideatypical city	City/Entity	Standardization of questions on a scale 0.00-1.00/ Aggregation according to the DPSVI data model	*DIGISER_D4_ANNEX 1.2 DPSVI Reports **Error! Reference source not found.***
SI - Service Area Index	Composite indexes measuring the performance of different service areas	Service Area	Standardization of questions on a scale 0.00-1.00/ Aggregation according to the SI data model	*DIGISER_D4_ANNEX 1.4 Service Area Index Report*

Table 4 - Data analysis approaches overview

4.2 DPSVI computation

The DPSVI has been developed on top of the conceptual model explained in chapter 2.4

Overall, the DPSVI is composed of 31 Composite indexes that are organized in three groups (cfr. Table 2 - Composite indexes of DPSVI:

- 3 Top Indexes: are the apical indexes including the DPSVI itself and the two pillars (I1 DIGITAL SERVICE INNOVATION MATURITY and I2 PRONENESS TO CHANGE)
- 21 Bottom Indexes: the indexes directly generated on top of DIGISURVEY data
- 7 Intermediate Indexes: the other indexes in intermediate positions

4.2.1 Mapping questions and answers

The first step of data processing has been the detailed mapping of questions to the 21 Bottom Indexes, that are the ones directly generated on top of the raw data collected with the Digisurvey, while the other indexes are resulting from a successive aggregation between composite indexes. Figure 9 maps the detailed relation between the questions of the DIGISURVEY and the DPSVI structure and represents the logical basis for the statistical aggregation of data (described in detail in Chapter 4).

It is important to clarify that in several cases only a limited number of answers (of a given questions) have been mapped to indexes. In this manner the same question could have been used more than once but considering each time only a limited set of possible answers to which has been attributed a different meaning (and consequently a different numeric value). In summary the same question could have been standardized in different manners according to the indexes to which it is associated.

[7] Final version of the annexes will be made available at: https://www.espon.eu/DIGISER

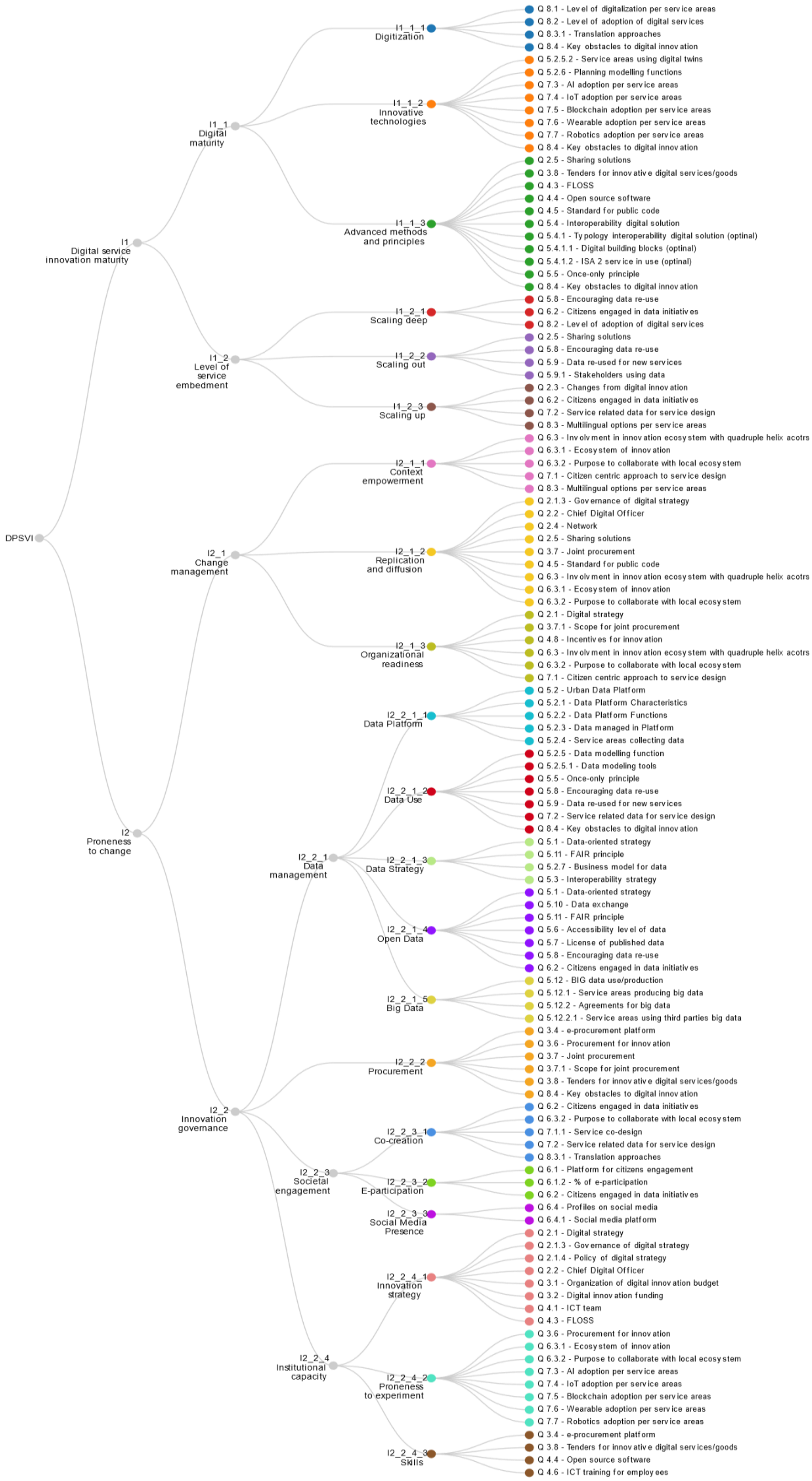


Figure 9 - DPSVI detailed structure – Questions

4.2.2 Standardization

To render the information gathered via the questionnaire processable via computational methods, each question, or group of answers, has been transformed into a number.

In practice, raw data have been replaced by a set of numerical values x_p, where $p = 1, \dots, P$ and P is the total number of questions, or groups of them.

This operation is usually performed in an ad-hoc way, given the specificities of each item of the questionnaire. Nevertheless, the following table provides a synthesis of the methods for data standardization adopted for each category of question.

Type of question	Standardization methods
Binary	Converted into dummy (0-1)
Single Choice	Converted to cardinal value (e.g., answer A = 1, answer B = 3, Answer 3 =0)
Likert Scales	Converted to correspondent ordinal (e.g., Low = 1, Medium-Low = 2, Medium-High = 3, High = 4)
Multiple Choice / Matrix	Converted into dummies, then (weighted) sum, propaedeutic yes/no are dropped.
Scalars	Normalised using external values (population, size of municipality) if representative of relative phenomena
Matrix – Service Level	Converted into dummies, then summed by column (i.e., process level), finally normalised over number of digitalised services

Table 5 - Standardization methods overview

It is important to clarify that in the case of single choice, multiple choice and matrix questions a different weight has been attributed to the answers for the purposes of standardization into a numeric value.

The appendix ***A.I.1 DPSVI Data model – Answers weighting in questions' standardization*** Includes a detailed table with all the information related to the standardization process underlying the DPSVI, including the detailed map of answers to indices and the weight attributed to each answer for standardization purposes.

Before aggregating the numeric answers, it is crucial to rescale them into a 0.00 –1.00 range, so to make them comparable. The mathematical operation that needs to be performed to move these different scales into a unique one, where 0 is the worst possible value and 1 is the best possible one, is the following:

$$x_p^{IT} = \frac{x_p - x_p^{min}}{x_p^{max} - x_p^{min}}$$

Where x_p^{IT} is the rescaled value, x_p is the original value mapped on a generic scale and x_p^{min}, x_p^{max} are, respectively, the minimum possible and the maximum possible value of datum x_p.

For example, if $\mathrm{x_p}$ is 0-1 valued (for instance, it is originated by a single-choice question), the standardisation is fairly simple since the formula becomes:

$$\mathrm{x_p^{IT}} = \frac{\mathrm{x_p} - 0}{1 - 0} = \mathrm{x_p}.$$

In a more complex case, such as the one of a Likert variable with four levels where the lowest possible value is 1 and the highest possible one is 4, the formula becomes:

$$\mathrm{x_p^{IT}} = \frac{\mathrm{x_p} - 1}{4 - 1}.$$

4.2.3 Aggregation

In this final phase the standardized values computed on top of the answers to DIGISURVEY questions, are aggregated via a mathematical procedure, with the goal of finally creating the indexes.

After having refined the data to be taken as input, in accordance with the standard literature for this kind of dimensionality reduction task, the indices are introduced as linear combinations of data, that is:

$$I = \frac{\alpha_{n_1^I} x_{n_1^I}^{IT} + \alpha_{n_2^I} x_{n_2^I}^{IT} + \dots + \alpha_{n_{N_I}^I} x_{n_{N_I}^I}^{IT}}{\alpha_{n_1^I} + \alpha_{n_2^I} + \dots + \alpha_{n_{N_I}^I}}.$$

The table published in appendix ***A.I.2 DPSVI Data model – Question aggregation relative weights*** illustrates the different relative weight attributed to each of the question composing an index.

4.3 Service areas Index (SI) computation

In addition to the main DPSVI, the research team explored an alternative and complementary analytical approach that shifted the point of view from the single city to the public service areas: instead of observing the way in which cities are performing on public value creation through digital innovation, the Service Index focuses indeed on the performance of several service areas.

The underlying research question aims at exploring to what extent each service area contributes to the digital transformation of the city, and what are the most advanced service areas in terms of digitalization.

In detail, DIGISER considered the service areas described in the appendix ***A I.3 SI Service Index – Detail of service areas,*** drawn upon pre-existing studies and classification[8] in the attempt to define a taxonomy applicable to different institutional systems where responsibilities and competences of local authorities can differ significantly.

Even though service areas are the items observed in this alternative analytical approach, nonetheless the database used to analyse them consists of the same primary data used in the computation of DPSVI and based on the answers of cities to the DIGISER Survey. In particular, the SI relies on 16 matrix or multiple-choice questions that collected the data per service areas, as exemplified by the following figure.

2.4 Is your public authority part of a (local, regional, national, EU) network of cities sharing operational digital solutions or open source code?

Note: If yes, please answer for each service area that applies. If not, please select "Not Applicable"

	Local	Regional	National	International	Not Applicable
*General Services / Administration	☐	☐	☐	☐	☐
*Building & Spatial Planning	☐	☐	☐	☐	☐
*Culture & Leisure	☐	☐	☐	☐	☐
*Education	☐	☐	☐	☐	☐
*Healthcare	☐	☐	☐	☐	☐
*Order & Safety	☐	☐	☐	☐	☐
*Social & Welfare Services	☐	☐	☐	☐	☐
*Transport & Mobility	☐	☐	☐	☐	☐
*Utilities	☐	☐	☐	☐	☐

Figure 10 - Example of a service-based multiple-choice matrix from DIGISURVEY

[8] Main references for the definition of the Service Areas were two studies carried out by the Committee of the Regions:
- Committee of the Regions, ed. *Regional and Local Government in the European Union: Responsibilities and Resources*. CDR - Studies, E-1/2001. Luxembourg: Office for Official Publications of the European Communities, 2000.
- Committee of the Regions. and European University Institute. *Study on the Division of Powers between the European Union, the Member States, and Regional and Local Authorities.* LU: Publications Office, 2008.

4.3.1 Mapping questions and answers

Alike the DPSVI itself, an analytical model has been designed to measure and interpret the state of the art of the digital transformation and organizational innovation in each service area.

The Service Index Data Model is structured as a hierarchical tree of indices fed directly by questions, where each sub-index aims to explore a specific phenomenon and is epistemically relevant for its interpretation.

Considering the relatively small base of data to be computed, the analytical model, represented in Figure 14, looks like simpler than the original DPSVI tree, and all the indices are positioned at the same (unique) level.

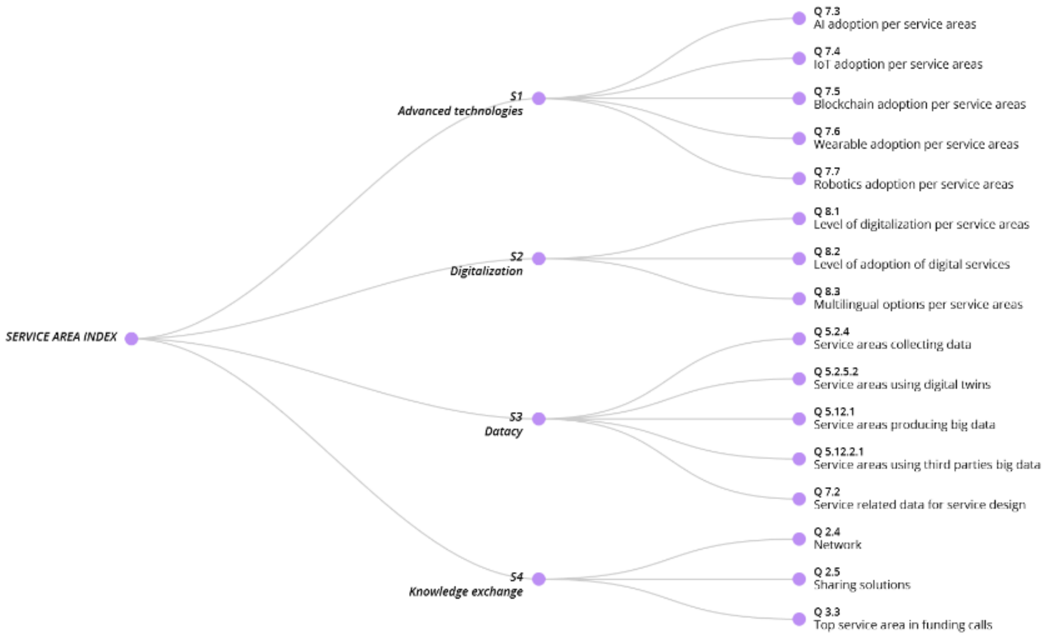


Figure 11 - Service Index data model

The 16 questions are combined to create composite 4 thematic indexes aimed at exploring a specific perspective on digital transformation in service areas. The four Indexes are then combined into a unique index (SI Index) that can be used to compare and assess the performance transversally to the four themes. The following table specifies the focus of each one of the sub-indexes.

Cod	Label	Description
S1	**Advanced technologies**	It reports the state of the art of the adoption and use of brand new and complex technologies as AI, IoT, Blockchain, Wearables, Robotics
S2	**Digitalization**	It assesses the level of digitalization of each service area in core and ancillary services and the level of actual usage of digital services by citizens and users
S3	**Datacy**	It focuses on the contribution of each service area to feed the open data ecosystem of their organization, as well as to their capacity to exploit the potential of open data and big data for service design and delivery
S4	**Knowledge Exchange**	It explores the role of each service area in disseminating, sharing, and exchanging knowledge regarding digital innovation both within the organization and with other public organizations

Table 6 – Definition of sub-indexes for Service Areas

4.3.2 Standardization

This phase aims at converting the raw answers provided by the cities into numerical values via data coding and/or standardization techniques.

As per the DPSVI, to render the information gathered via the questionnaire processable via computational methods, each answer, or group of answers, requires to be transformed into a given number. As a result, raw data are replaced by a set of numerical values x_p, where $p = 1, \dots, P$ and P is the total number of questions, or groups of them.

As above, this operation is usually performed in an ad-hoc way, given the specificities of each item of the questionnaire, nevertheless some general guidelines were followed. The following table provides a synthesis of the methods for data standardization that have been adopted for each category of answers.

Type of question	Standardization methods
Binary	Converted into dummy (0-1)
Single Choice	Converted to cardinal value (e.g., answer A = 1, answer B = 3, Answer 3 =0)
Likert Scales	Converted to correspondent ordinal (e.g., Low = 1, Medium-Low = 2, Medium-High = 3, High = 4)
Multiple Choice / Matrix	Converted into dummies, then (weighted) sum, propaedeutic yes/no are dropped.

Table 7 - Standardization methods overview

Before aggregating the numeric answers, it is crucial to rescale them into a $0.00 - 1.00$ range, so to make them comparable. The mathematical operation that needs to be performed to move these different scales into a unique one, where 0 is the worst possible value and 1 is the best possible one, is the following:

$$x_p^{IT} = \frac{x_p - x_p^{min}}{x_p^{max} - x_p^{min}}$$

Where x_p^{IT} is the rescaled value, x_p is the original value mapped on a generic scale and x_p^{min}, x_p^{max} are, respectively, the minimum possible and the maximum possible value of datum x_p.

4.3.3 Aggregation

In this final stage the standardized values computed on top of the answers to DIGISURVEY questions are aggregated via a mathematical procedure. After having refined the data to be taken as input, in accordance with the standard literature for this kind of dimensionality reduction task, the indices are introduced as linear combinations of data, that is:

$$I = \frac{\alpha_{n_1^I} x_{n_1^I}^{IT} + \alpha_{n_2^I} x_{n_2^I}^{IT} + \dots + \alpha_{n_{N_I}^I} x_{n_{N_I}^I}^{IT}}{\alpha_{n_1^I} + \alpha_{n_2^I} + \dots + \alpha_{n_{N_I}^I}}.$$

The following table illustrates the different relative weight attributed to each of the question composing an index.

Q_#	S1	S2	S3	S4
2_4	-	-	-	33%
2_5	-	-	-	33%
3_3	-	-	-	33%
5_2_4	-	-	29%	-
5_2_5_2	-	-	14%	-
5_12_1	-	-	14%	-
5_12_2_1	-	-	14%	-
7_2	-	-	29%	-
7_3	20%	-	-	-

Q_#	S1	S2	S3	S4
7_4	20%	-	-	-
7_5	20%	-	-	-
7_6	20%	-	-	-
7_7	20%	-	-	-
8_1	-	50%	-	-
8_2	-	25%	-	-
8_3	-	25%	-	-

Table 8 - Service Area Indexes - Relative weight of underlying questions

The final operation is the aggregation of the four Sx Indices into a higher-level general Service area Index (SI), where all sub-indexes have equal weight, resulting in the simple average of its inputs $x_p^{IT}, p = n_1^I, \dots, n_{N_I}^I$.

5 Analysis of the robustness of the DPSVI data model

The DPSVI has been built on top of a set of theoretical assumptions and hypotheses (cfr. Chapter 2) and the consequent data model followed a deductive approach.

To validate the robustness of the analytical framework the research team conducted an ex-post confirmatory analysis of the DPSVI data model.

Following the results of the validation analysis, the DPSVI data model has been updated and the indexes values have been re-computed accordingly.

5.1 Robustness analysis flow

The analysis was structured around four different steps, each one using different methods and techniques to explore and assess the statistic robustness of the data model used to compute the DPSVI.

	0	1	2	3
COMPONENTS	DATA PREPARATION	DATA ANALYSES	DATA VISUALIZATION	INTERPRETATION
INPUT	DIGISURVEY RAW DATA FURTHER INFO ABOUT CITIES LIST OF INDICES	CSV FILE WITH INDICES CSV FILE WITH QUESTIONS	THE TWO RData STRUCTURES	THE TWO RData STRUCTURES VISUALIZATIONS
FEATURES	From raw to numeric Standardisation Aggregation	Questions – Index relationship Index internal balance VS Redundancy Questions interactions	Boxplots Correlation tables Bar plots	Questions – Index relationship Index internal balance VS Redundancy Questions interactions Overall discussion
OUTPUT	2 CSV FILES WITH INDICES 1 FOR THE QUESTIONS 1 FOR THE NARRATIVES	2 RData FILES WITH A DATABASE STRUCTURE	VISUALIZATIONS AND A DASHBOARD	TO BE DISCUSSED IN A WORKSHOP -

Figure 12 - Robustness analysis flow

The analysis started with the first computation of DPSVI indexes, described in detail in Chapter 4, necessary to have a first batch of data to test and validate statistically; then several statistical techniques have been used to assess the robustness of the DPSVI model.

The focus is directed only to DPSVI bottom indexes (the last level of indexes directly generated on top of standardized questions – cfr. chapter 4.2.1) and the questions that compose them.

Three tasks are investigated for each “bottom” index:

- what is the contribute given by each question to the bottom index it feeds,
- whether each bottom index is internally well-balanced,
- if there are correlations between the questions composing each index.

To translate these inquiries into a statistical language several computations have been implemented.

5.1.1 Test 1 : Questions – Index relationship

The first test aims to explore the relation between each index and its underlying questions, measuring to what extent each question influences the index value.

To explore the relationship between each question inside an index and the index itself, a multiple regression for every block of questions is introduced, with the goal of extracting a representative value for the contribution of each question in the making of the index. The formula below shows, indeed, a linear additive model that aims at describing the values of the output variable (index value) in terms of input data (answers to index questions). To give a practical example, it is reported the case of subindex $I2.2.3.1$:

$$I_{2.2.3.1} = \beta_1 * q_{6.2} + \beta_2 * q_{7.1} + \beta_3 * q_{7.1.1} + \beta_4 * q_{7.2} + \varepsilon_{2.2.4.3}$$

The outcomes of this model are the $\beta's$, which correspond to the weights given to each question to compute the index, and the error ε, that accounts for the contribute not captured by the current combination. Note that, due to the structure of the indexes (see subchapter **4.2.2**), the linear combination perfectly covers the behaviour of the index, so the error term is always equal to zero.

The beta coefficients serve to accomplish a bigger purpose: the actual **decomposition of any index with respect to its underlying questions** can be visualised. For what concerns the answers distributions, a condensed and complete view of the data behaviour is obtained via boxplots. These plots emphasise the central range of variability and also allow a rather punctual overview of the data-points, as perceivable in Figure 13. Every coloured solid circle represents a data value (e.g., if the possible answers to a question are just "Yes" and "No", one will see only two coloured circles in correspondence of the numerical value translating the answer – for example in question 7.1 the dots are in 0 and 1), the grey boxes cover the range containing the central 50% of the data (called Inter-Quartile Range), namely the bottom line of the dark grey box is the 25^{th} percentile, the median corresponds to the change of the shade, and the 75^{th}percentile is the top line of the light grey box; finally the whiskers embrace the data contained in $1{,}5 \, * \, IQR$.

Then, the computation of the decompositions scaled by the β coefficients (Figure 13 on the right) is provided. Since in most of the cases the index is given by an average of the answers to its constitutive questions, implying the equality of the β coefficients, i.e. $\beta_i = \frac{1}{\#questions\ inside\ Index}$ $\forall i$, the relevance of such a choice may be hard to grasp. However, if a weight rebalancing happens, then the single contributions of the questions are no more equally distributed, and finally this choice reveals it usefulness.

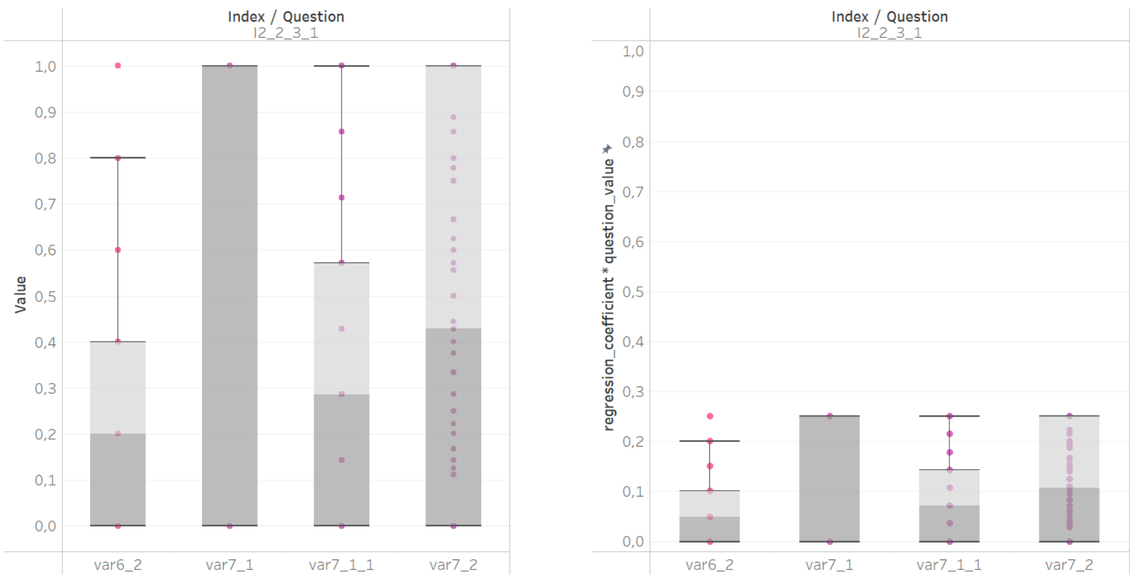


Figure 13 - Boxplots of answers distributions (right) and their "beta-scaled" version (left)

A tool that can help analysing the effect of each question is the **linear correlation coefficient** between a question and its wrapping index. From this computation a ranking among questions can be established, and it should be interpreted in the following way (proposing again the above example): "if one tries to explain the behaviour of index $I2.2.3.1$ only by means of one single question, the best performing question is 7.1, then immediately after we find $7.1.1$, a bit further away 7.2 and finally 6.2". This is not a mere ranking: not only does it provide an order for the best performing questions, but also reveals the scores that led to this rank.

	var6_2	var7_1	var7_1_1	var7_2
I2_2_3_1	0,5081	0,7534	0,7494	0,5883

Figure 14 - Index – Questions correlations

It is noticeable that the multiple regression can be seen as complementary to the correlation coefficient. This is because the first explores the index de-structured in all its questions while the latter analyses the specific contribution given by each single input question: in other terms it quantifies how the index behaviour reflects the behaviour of one single question.

5.1.2 Test 2: Index internal balance VS Redundancy

The second test aims to explore the internal balance of each index, validating the number of questions used to shape the index.

To tackle the issue of internal balance, two instruments, both based on the variability inside an index, are employed. To begin with, it is worth explaining in an unequivocal way the concept of "**equivalent number of independent questions**": given that an index is *a priori* designed with X questions, one may ask whether all of them cover distinct aspects and complement each other, or if there are (too) many superpositions. To give a precise, synthetic, and scientific answer, it is possible to research a new formulation of independent, perfectly complementary, and ideal questions, able to replicate the index. To achieve this, the existing questions are mixed, and it is important to stress the fact that the output will be a non-interpretable nor verbally reasonable set of new questions, but with the property of being complementary and perfectly additive. In this way, the variability of the index can be decomposed into these new components, and only at this point a decision about the "equivalent number" mentioned above can be taken. As a general rule, one selects the smallest number of new questions needed to cover a sufficiently close to 1 proportion of explained variance. Therefore, in the example of index $I2.2.3.1$, 3 is the selected value, as with three out of four equivalent questions, more than 99% of the variability is captured (see Figure 15). The interpretation of "sufficiently close" depends on the problem at hand and on the number of components involved; the typical thresholds considered are 90, 95 or 99%.

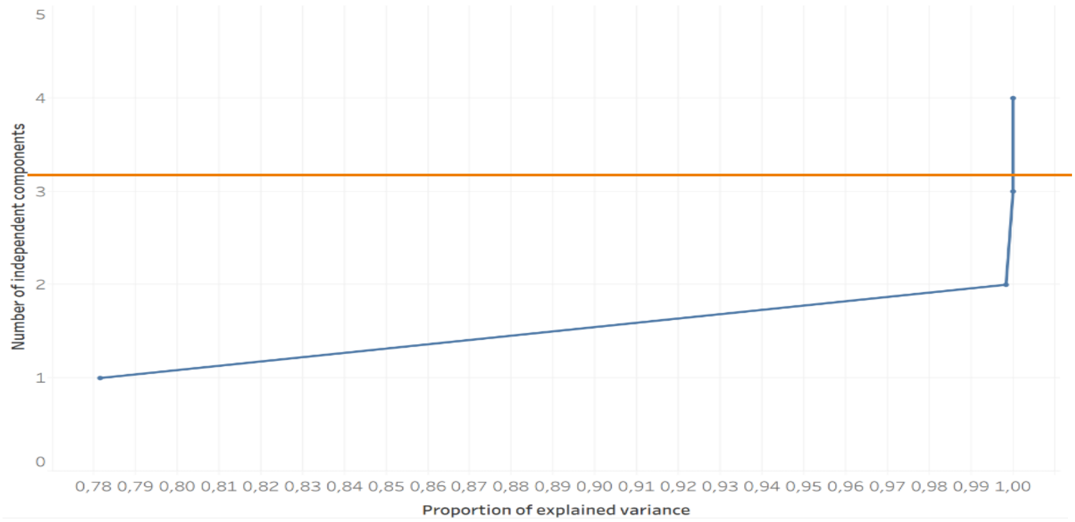


Figure 15 - Behaviour of the ideal set of independent questions declined in index I2_2_3_1

Second, we introduced the concept of **generalised variance**, a numerical value that measures the common variance of an object made up of multiple elements. According to the literature, the Kaiser-Meyer-Olkin index, an overall and summarising **measure of sampling adequacy,** is the most suitable index for the current scenario. In other words, according to this value, it is possible to have an indication of how suitable are, as a hole, the input variables that model the output.

According to Kaiser reasoning, the input data are to be considered:

- *from 0.00 to 0.49 unacceptable;*
- *from 0.50 to 0.59 miserable;*
- *from 0.60 to 0.69 mediocre;*
- *from 0.70 to 0.79 middling;*
- *from 0.80 to 0.89 meritorious;*
- *from 0.90 to 1.00 marvellous.*

However, this reasoning is not perfectly suitable with all the problems. Kaiser ranking is based on the importance given to the pair-wise correlation between all variables: a high KMO would imply that all the variables are well correlated with each other, no one excluded. From one hand, this could mean that the index is coherent within, yet this is instead something not completely desirable. In fact, high correlation can be translated with redundancy in this scenario. In the picture below the behaviour of the deepest subindexes is shown, most of them lay in the middle but few of them perform poorly, according to Kaiser.

Besides, a deeper and more detailed interpretation of this value will be given, also by comparing this result with the ones from the other analyses.

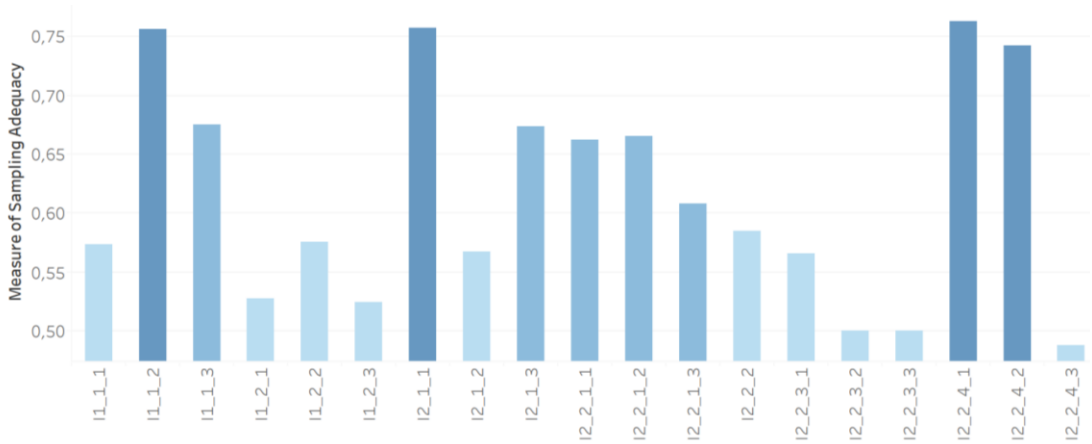


Figure 16 - KMO index for generalised variance

5.1.3 Test 3: Questions interactions

This test aims to assess the correlations between couple of questions within each index with the goal to verify the existence of questions behaving in similar manner.

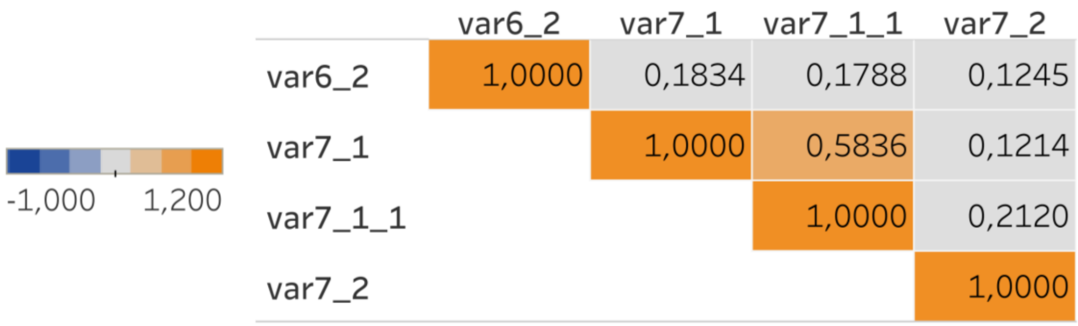
Finally, concerning the interactions between the questions inside the index, the computation of pair-wise correlations between couples of questions is proposed. The most powerful way of visualising these interactions is via a table filled with the calculated correlation values and coloured accordingly, in order to highlight, for examples, groups of strongly correlated variable.

Taking the absolute value of the correlation, the following classification can be drafted:

- *0.0 – 0.2* *negligible correlation*
- *0.2 – 0.8* [9] *moderate correlation*
- *0.8 – 1.0* *strong correlation.*

Figure 17 reports the usual example of index $I2.2.3.1$, where it is clear that between question 7.1 and $7.1.1$, which can be accessed only if one affirmatively answers to the former, there is a quite strong positive correlation. On the other hand, all the other questions do not manifest relevant similarities from a correlation point of view.

[9] This range is kept wide on purpose: there are several currents of thought in the literature.



	var6_2	var7_1	var7_1_1	var7_2
var6_2	1,0000	0,1834	0,1788	0,1245
var7_1		1,0000	0,5836	0,1214
var7_1_1			1,0000	0,2120
var7_2				1,0000

Figure 17 - Correlation matrix

5.2 Visualization of the outcomes of robustness analysis

The current subchapter complements the previous one in terms of comprehension and interpretation of the numerous outputs produced. Due to the elevate numerosity, they have been stored in two well-organised database structures, in a way that complies with the input requirements of the Tableau software. In fact, to facilitate the understanding of the numerical outputs, as already shown, a graphical support has been rendered for every index and for every feature. However, to smooth the navigation through this large number of plots, a dashboard has been introduced.

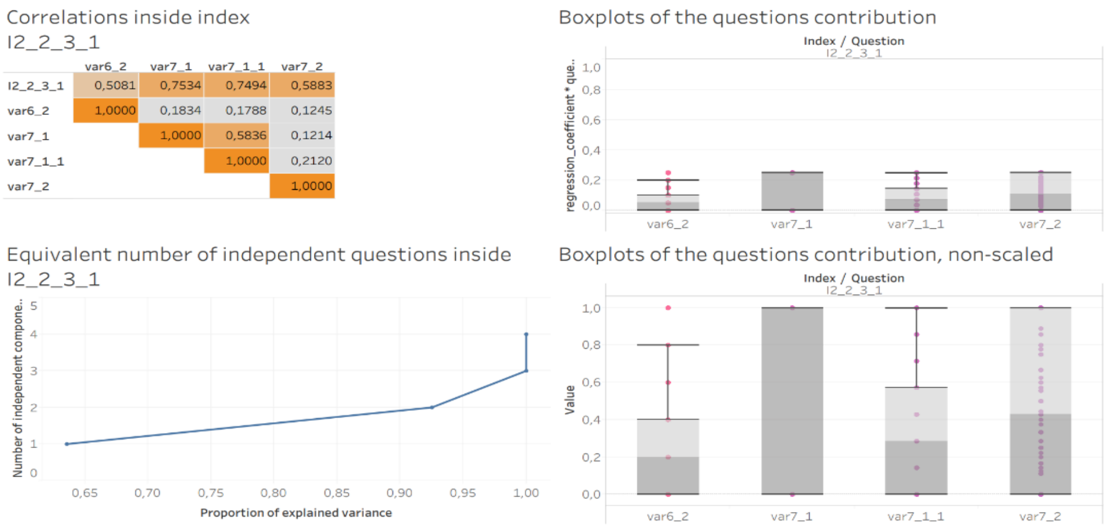


Figure 18 - Dashboard for robustness test

Figure 18 shows an exemplificatory page of the summarising dashboard, which can be explored in two directions: by moving the focus from index to index, separately for every plot, or by selecting a subset of the questions composing an index. This particular view has been designed to allow an immediate comparison of the main statistics computed, to achieve a complete and coherent interpretation of them. As a matter of fact, such a global perspective is crucial, since the investigated features happen to overlap a little in some cases, therefore, if the results points towards the same direction, then they enforce each other and empower the researcher's deductions, either positive (meaning that the index follows overall a desired behaviour and the initial assumptions and reasonings underlying its construction were founded) or negative. Otherwise, if discordant, they may draw one's attention toward possible unexpected responses, that could be generated by incomplete or biased initial hypotheses.

Beside the dashboard there are some other visualizations worth mentioning. For what concerns the single elements composing the above-mentioned dashboard, there are ad-hoc sheets for each of them, where even comparisons among different indexes within the same analysis are viable. Moreover, a page is devoted to the KMO visual representation, which is not included in the dashboard since already comprising all the indices, and a final booklet containing all the cited visualizations, accompanied with a brief description, concludes the work.

5.3 Input for the modification of the DPSVI tree

The aforementioned results can be used as input for a possible re-organization of the tree structure, at a low level. Examples of the drivers for this re-evaluation are the presence of too many highly correlated questions inside an index, something that can be seen from a too small number if equivalent independent variables, or from the last pair-wise internal correlations. Another problem may be an unexpected imbalance in the contributions given by single questions, noticeable from the index-questions correlations combined with the s; or again, the complete absence of correlation of an index with one of its internal questions, or eventually too low values of the KMO index. These many outputs become inputs of an articulate reasoning, which ultimately leads to the validation.

In summary, the kinds of input for the modification of the DPSVI tree that were considered by the DIGISER research team have been:

- Changes to the DPSVI structure
- Minor changes in answer mapping and standardization methods (Answer_Weight)
- Changes in question weighting for aggregation purposes

Using for example the index I2.1.1, the output of the validation techniques now become inputs and drivers for the modifications to practically happen. Firstly, one can start from Kaiser Meyer Olkin, being a very simple tool that provides just a number. Its value is 0.76 and suggests the indicator to be quite well-constructed. To better comprehend this, one has to widen the spectrum of investigation. First of all, it is coherent with the pair-wise analysis there are three out of five strongly correlated variables (block 6.3, 6.3.1, 6.3.2), which lift the KMO up. It does not reach 1 since the others (7.1 and 8.3) to manifest a low correlation with every other variable. Another similarity can be found with the computation of the equivalent number of questions, where the identified number is three. The fact that two of the uncorrelated and reformulated questions are redundant, is itself evidence of overlap of some questions or strong correlation between a few of them. Evidently, the “problematic” questions are those of group 6.3. Up to now, the proofs push towards the same direction, namely the reduction of weight of the overall 6.3's, and especially of the *parent* question.

To find the final confirmation, one has to the question-index dependencies. The predominant question is 6.3, and in general the index is polarised towards these three questions. Despite being crucial in the construction of the index, according to the urban science argument, they should not be the only ones that matter. The idea is to reduce the importance of 6.3, allowing a higher the contribution of 6.3.1 and 6.3.2 than 7.1 and 8.3. This is because the former two are considered to cover more relevant aspects of the Context empowerment than the latter ones. In the end the applied re-weighting is the following:

Question	New Weight	Computation
6.3	0.06	0.1 * 0.6
6.3.1	0.27	(0.9 * 0.6) * 0.5
6.3.2	0.27	(0.9 * 0.6) * 0.5
7.1	0.2	0.2 * 1

Table 9 - Robustness analysis - changes to the I2.1.1

The Computation column shows the rationale behind the weight choices: the block 3.6 is thought to be more relevant than the other two, so a priori they are set to account for the 60% of the indicator, and the remaining two 20% each. In particular, the block 6.3 is split into 10% on the parent and 90% on the two child questions.

Following the result of the robustness analysis the DPSVI model has been updated to the new model published in this report as Figure 6 and reported in detail in the *Appendix I: Detailed DPSVI Model,* and all the indexes have been re-computed according to the new structure and parameters.

5.4 Post-hoc analysis

In addition to the robustness analysis, the research team carried out other statistical experiments aims to further explore and unveil possible statistical biases enrooted in the DPSVI data model.

In this perspective, two kinds of possible approaches have been explored seeking for design and contextual variables that could have eventually influenced the results of the data analysis.

5.4.1 Internal correlations

First, an internal correlation analysis has been carried out, seeking for patterns of consistent behaviour between different indexes. The goal is two-folded: on one hand to detect possible biases depending by the underlying questions (that could influence the behaviour of indexes) and on the other end to identify possible explanatory relation that could enrich the interpretation of data. The specific objective of this statistical analysis is the research of the so-called spill-over effects, responding to the followings "Are there indicators such that their changing affects other indicators in the opposite part of the tree?", or "Does an implemented manoeuvre apt to improve the performances in a specific aspect of the digital maturity of a city, have an effect also in another, apparently distant, field? In which direction? And of what intensity?".

This analysis is based on the **pair-wise correlations** between indicators. These correlations are intended across the two halves of the DPSVI tree (cfr. Figure 6 - DPSVI Structure), namely between a sub-indicator originating from I1 - Digital Service Innovation Maturity - and another one among the ones branching from I2 - Proneness to Change. These correlations are evaluated respecting the hierarchy, meaning that the comparisons happen between indices at the same level. The application of this guideline can be recognised in Figure 19, where three block are identifiable:

- the top-left one comprises the **bottom level** indexes
- the middle one concerns the **intermediate level** indexes
- the bottom-right corner has the the value of **top** indexes directly stemming from the root

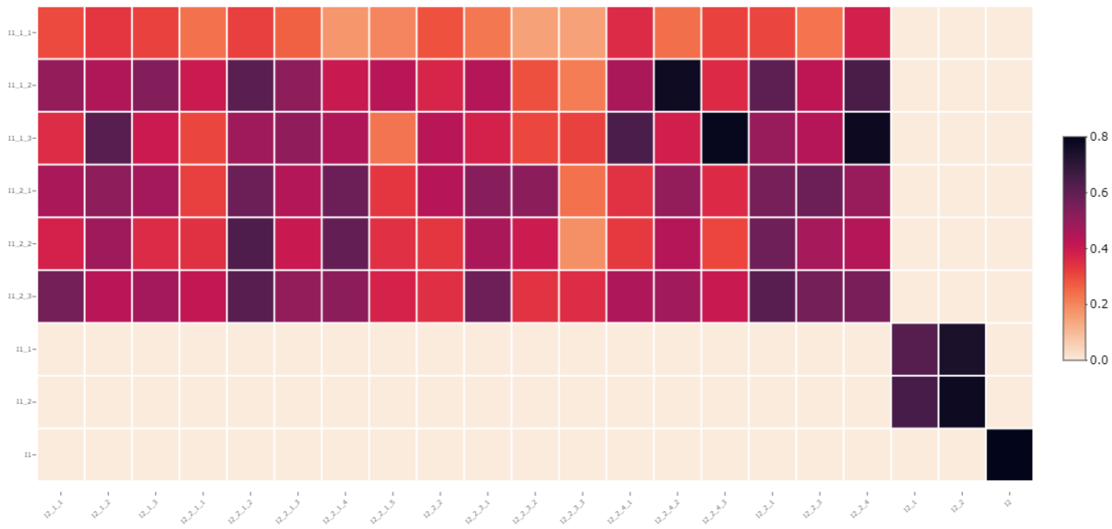


Figure 19 - Internal correlation analysis

It is evident that the intermediate and top indices show higher correlations, like in the cases of I1-I2, I1.1 and I1.2 with both I2.1 and I2.2). This behaviour is not surprising and seems quite reasonable. Indeed, these top indexes are the result of consecutive averaging processes of other indicators, that in turn are correlated themselves, even if in a less pronounced way as the figure shows.

The analysis at the bottom level - thus inside the biggest block – is more relevant due to the major theoretical independency of these couples of indicators. Nonetheless some interesting spill-over effects are visible like the ones reported in the table below where the most relevant correlations (above 0.6) are reported.

K factor	**Index branch 1**	**Index branch 2**
0.7773	I1_1_3 “Advanced method and Principles”	I2_2_4 “Institutional Capacity”
0.6453	I1_1_2 “Innovative Technologies”	I2_2_4 “Institutional Capacity”
0.6200	I1_1_3 “Advanced method and Principles”	I2_1_2 “Skills”
0.6162	I1_2_3 “Scaling up”	I2_2_1 “Data Management”
0.6071	I1_1_2 “Innovative Technologies”	I2_2_1 “Data Management”

Table 10 - Internal correlation analysis

These data suggest two main inferences:

- Several major digitalization processes are directly correlated with the skills diffused in the city, and in particular with the institutional capacity of the public organization steering the digital transformation. In this sense this data seem to confirm one of the main research hypotheses of DIGISER: the accessibility and availability of digital technologies is not a sufficient condition to generate organizational and societal transformation.
- Data Management (which is composed by a large number of questions and is a very “robust” index) seem to be correlated to the experimentation of innovative technologies (where data management technologies are considered) and is a major driver of the scaling up mechanisms, capable to influence the transition of digital innovations within the structure of the public organization.

5.4.2 Univariate models

Additional univariate models were tested to interpret the possible influence of external variables on cities' performances.

Appendix II: Univariate models reports extensively the analysis carried out on the indicator I1 – Digital Service Innovation Maturity, as an example of potential future research agenda based on the data collected in DIGISER.

6 Data Visualization

All the data collected through the DIGISURVEY as well as all the Indexes generated on top of these raw data – Including 31 DPSVI and 5 SI indexes - are going to be published on the ESPON database[10] and will be made accessible and consultable through the standard visualization methods that are available on the ESPON portal.

In addition, DIGISER implemented several methods to visualize data collected through the DIGISURVEY and the related indexes both for internal purposes of analysis and interpretation and for public dissemination of the results.

The following table summarizes the methods currently implemented - explained in detail in the following subchapters – and the related report/annex where charts and maps are visualizable.

Data Visualized	Format	Description	Annex to D4
DIGISURVEY Raw Data	pdf	Static report including several standard visualizations for each question composing the DIGISURVEY. Matrix questions have a dedicated set of charts.	Annex 1.3
DPSVI	web	Dynamic dashboards allowing the exploration of all the 31 DPSVI indexes for each single city and for the main clusters (Country, GDPPC, Population).	Na
DPSVI	pdf	Static report including 2 maps and several standard visualizations for each of the 31 DPSVI indexes through several clusters (Country, GDPPC, Population, Case studies).	Annex 1.2
Service Index	pdf	Static report including 2 maps and several standard visualizations for each of the 5 Service indexes (Country, GDPPC, Population).	Annex 1.4
Narrative reports	pdf	A narrative report for each city generated automatically according to the scores achieved in the different domains of DPSVI	Annex 1.6

Table 11 - Visualization methods overview

All annexes will be published on the ESPON website at: https://www.espon.eu/DIGISER

6.1 Raw data from the DIGISURVEY (Annex 1.3)

For each question included in the DIGISURVEY has been created a report that contains several tables and charts to explore the results by multiple point of views. Each Chapter corresponds to a question and is indeed labelled according to the number of the question in the original structure of the DIGISURVEY (e.g., the chapter related to the question number 3.5 will be labelled as Q_3.5).

In the Question Report, each matrix question is considered as a group of questions organized in a table, where the rows represent features of the matrix question, while the columns are a set of answers applicable to each row. Matrix question’s results could be explored as a whole, with the matrix report, or line by line as a simple question report.

[10] https://database.espon.eu/

6.2 Dashboards for DPSVI

During the project an interactive dashboard was built with the main purpose of allowing all DIGISER research team to explore directly DPSVI indexes. Dashboard facilitated the in-depth inspection of the data of the cities participating in the survey, focusing in particular on the visualization of single cities' performances.

A custom exploratory dashboard has been built using Microsoft PowerBI to enable experts to analyse and identify patterns and behaviours within the dataset. The tool has been developed using the Power BI Pro (version 13.0.17333.39) license connected to the workspace of the DataScience group of Politecnico di Milano.

Index visualized	Link
DPSVI	https://app.powerbi.com/view?r=eyJrIjoiM2Q5NjQwOTYtZTU4OC00ZTI4LThhM-mYtODcwZmI3MzEyNTIwIiwidCI6IjBhMTc3MTJiLTZ-kZjMtNDI1ZC04MDhlLTMwOWRmMjhhNWVlYiIsImMiOjh9&pageName=ReportSection

Table 12 - DPSVI Dashboard

In general terms the Dashboards offers several kinds of visualizations including simple charts (histograms and radars), and bidimensional semiotic squares (based on Greimas, 1983)

Simple charts highlight the composition and aggregation of indexes values. Histograms and radar charts allow visualizing multiple indexes (e.g., I1.1.1, I1.1.2, I.1.1.3) while a line (in the formers) or simple text value (in the latter) allows visualizing the upper-level index (e.g., I1.1). As for the previous graphs, Power BI enables the user to apply filtering on counties, population range, GDPPC range, and specific cities.

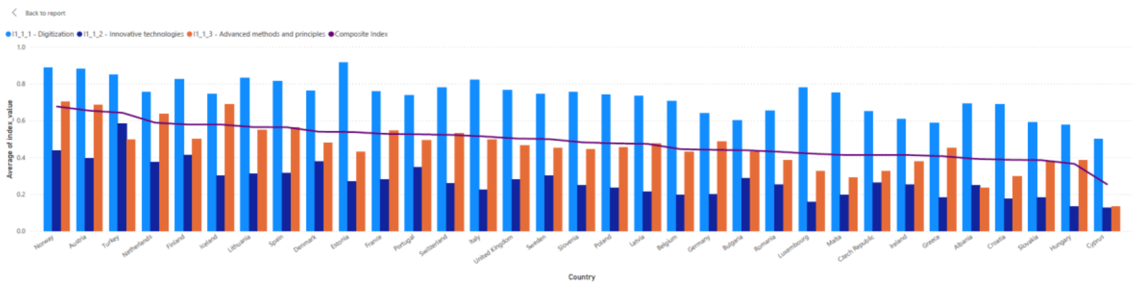


Figure 20 - PowerBI Dashboard - Histogram example

The second group is devoted to pointing out the position of the cities in semiotic squares (cfr. Semiotic squares interpretation in chapter 6.3.1). These graphs could be explored through filters on counties, population range, and GDP per capita range; specific filtering on cities names could also be applied.

The following table provides a detailed overview of all the visualization types available on the POWERBI dashboards.

#	Type	Indices	Single Cities	Clusters
1	Semiotic Squares	DPSVI, I_1, I_2	Yes	Countries
2	Semiotic Squares	DPSVI, I_1, I_2	Yes	Population range
3	Semiotic Squares	DPSVI, I_1, I_2	Yes	GDPPC range
4	Semiotic Squares	DPSVI, I_1, I_2	Yes	-
5	Histogram (with upper-level index line)	All (except DPSVI)	No	Countries, Population range and GDPPC range
6	Histogram (no upper-level index line)	All (except DPSVI)	No	Countries, Population range and GDPPC range

#	Type	Indices	Single Cities	Clusters
7	Radar	All (except DPSVI)	No	Countries, Population range and GDPPC range
8	Histogram (with upper-level index line) and Radar	All (except DPSVI)	Yes	-
9	Histogram (no upper-level index line) and Radar	All (except DPSVI)	Yes	-

Table 13 - PowerBI Dashboards detailed content

6.3 DPSVI static reports (Annex 1.2)

The DPSVI is published in a set of 8 reports, each one exploring a part of the DPSVI tree that can be read either individually or altogether, as an unique extensive report of the DPSVI:

- DIGISER_D4_ANNEX 1.2.1 DPSVI
- DIGISER_D4_ANNEX 1.2.2 Digital Maturity
- DIGISER_D4_ANNEX 1.2.3 Level of Service Embedment
- DIGISER_D4_ANNEX 1.2.4 Change Management
- DIGISER_D4_ANNEX 1.2.5 Data Management
- DIGISER_D4_ANNEX 1.2.6 Societal Engagement
- DIGISER_D4_ANNEX 1.2.7 Institutional Capacity
- DIGISER_D4_ANNEX 1.2.8 Innovation Governance

These reports include a large number of charts and maps that are generated on top of the indexes that make up the DPSVI and in some cases referred to the same underlying questions

The charts used to represent DPSVI indexes are relatively simple, being limited to radars, columns, box plots. All charts include a legend reporting the following key information:

Index observed	Index type	Index level	Data Sample	Cluster
Indicates the code and the label of the index observed	*Indicates the type of index as either:* • DPSVI • SI	*Indicates the Index position in its Data model:* • Top • Intermediate • Bottom	*Indicates the sample that the data refers to* • All respondents • Reference sample	*Indicates the series showed in the charts and listed in the legend* • Capital cities • Reference sample • Population • GDPPC • Country

Table 14 – DPSVI Index charts legend

Data are presented grouped in clusters. The cluster considered in the report could be the followings:

- **None**: no cluster, the data refers to the entire sample
- **Capital cities**: comparing the results of capital cities with all the other respondents.
- **Reference sample**: compared results of reference sample and all other respondents.
- **Population**: compared results among cities by population size
- **GDPPC**: compared results among cities by GDP per capita size
- **Country**: compared results among countries
- **Authority Type**: compared results among different types of local government
- **Case Studies**: 10 selected cities also surveyed through qualitative methods

6.3.1 Semiotic squares interpretation

Only for the three Top Indexes of the DPSVI ("DPSVI", "Proneness to Change" and "Digital Service Innovation Maturity", cfr. **Error! Reference source not found.**), published in DIGISER_D4_ANNEX 1.2.1 DPSVI a different set of visualization is provided, with a specific epistemic value.

Semiotic squares are used to provide cities with feedback about their attitudes and behaviours in relation to DIGISER processes and process typologies. Also, they are used to help respondents visualise how they are currently performing in terms of proneness to change and digital service innovation maturity.

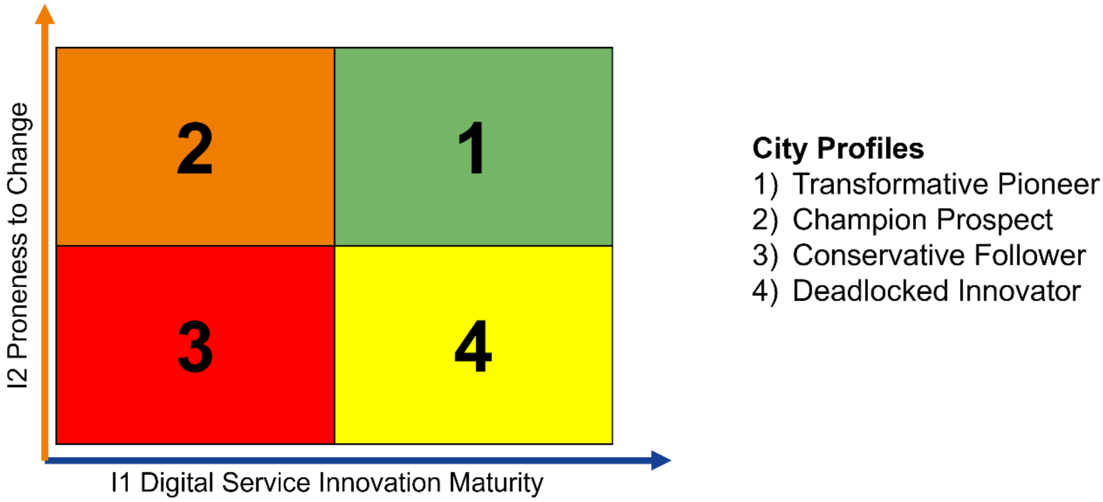


Figure 21 – Semiotic square quadrants

To facilitate the interpretation, bisectors are associated with ideal-typical profiles, that characterise each cartesian quadrant. Those are:

1. **Transformative Pioneer**
   Innovative and aware / Change prone
   The transformative pioneer displays a high level of technical and digital-enabled organizational innovation in public service provision and delivery. Also, the pioneer uses digital technologies as an integrated part of governments' modernization and innovation strategies.
   This profile is aware and ready to actively support changes in organizational behaviors, attitudes, and procedures to face challenges related to the digitalization, and to drive pervasive and transformative service innovation practices.

2. **Champion Prospect**
   Conservative and unaware / Change prone
   The champion prospect has a strong orientation to change, as it is inclined and ready to modify behaviors, visions, and practices to foster and amplify innovation, as witnessed e.g., by efforts made to enhance data management, societal engagement, procurement, or institutional capacity-building.
   The champion prospect, how-ever, might need to work on its ability to actively support technological and organizational change and to improve the scalability and replicability of service innovation practices

3. **Conservative Follower**
   Conservative and unaware / Change reluctant
   The conservative follower has a low degree of penetration and maturity of technical and organizational innovation in public service delivery.
   Also, this profile does not seem to be particularly inclined nor ready to modify behaviours or attitudes to support organisational or technological innovation.

4. **Deadlocked innovator**
   Innovative and aware / Change reluctant

The deadlocked innovator displays a high level of technical and organizational innovation in public service provision and delivery.
The deadlocked innovator, however, might need to overcome organizational, societal, and legal barriers that constrain its space for action and do not allow this profile to fully grasp its transformative potential.

This characterisation is the same for all three quadrants, even if its specific meaning depends on the axes and on associated qualitative values, as specified in the following table.

	Semiotic square A: DPSVI	Semiotic square B: Proneness to Change	Semiotic square C: Digital Service Innovation Maturity
Quadrant I – Transformative pioneer	innovative and aware/change prone: The transformative pioneer displays a high level of technical and digital-enabled organisational innovation in public service provision and delivery. Also, the pioneer uses digital technologies as an integrated part of governments' modernisation and innovation strategies. In addition, this profile is aware and ready to actively support changes in organisational behaviours, attitudes, and procedures to face challenges related to the digitalisation process and to drive pervasive and transformative service innovation practices.	active and committed/open and flexible: The transformative pioneer has a pro-active attitude towards digitalisation. As a public administration, it strives to innovate transversal administrative processes (including data management, societal engagement, or institutional capacity-building) and to use them as leverage to support cross-sectoral digital innovation. It has developed and implemented effective strategies to ensure long-term transformative impacts in public sector organisations, generate value in the local context and make innovation practices replicable and scalable.	advanced and aware/advanced: The transformative pioneer can enhance the overall digitalisation of the public administration, not only supporting a technological shift but also achieving digital-enabled organisational change. This profile succeeded in digitalizing pre-existing internal procedures, adopting new technologies and in using advanced methods and principles to foster organisational innovation. Also, in these Public Administrations digital services are accessible and adopted by most of the citizens, are fully exploited by skilled employees and have been successfully replicated also in other contexts.
Quadrant II – Champion prospect	conservative and unaware/change prone: The champion prospect has a strong orientation to change, as it is inclined and ready to modify behaviours, visions, and practices to foster and amplify innovation, as witnessed e.g., by efforts made to enhance data management, societal engagement, procurement, or institutional capacity-building. The champion prospect, however, might need to work on its ability to actively support technological and organisational change and to improve the scalability and replicability of service innovation practices.	passive and not committed/open and flexible: The champion prospect is not fully using transversal administrative processes to drive cross-sectoral innovation. Even if it might be very successful in developing sectoral innovation strategies, it has a limited capacity to use them to orient broader innovation governance processes. It displays, however, an open and flexible attitude towards change management at the strategic, tactical land operational levels, and has a good capacity to ensure long-term transformative impacts in public sector organisations, generate value in the local context and make innovation practices replicable and scalable.	basic and unaware/advanced: The champion prospect is capable to develop and implement innovative services, that are widely accessible to citizens, that are exploited by public employees and that have also been adopted in other contexts. Despite this high level of internalisation of digital settings in the public administration organisation and setting, the champion prospect has not yet succeeded in achieving digital-enabled organisational change, as it failed to challenge itself while developing new services.

	Semiotic square A: DPSVI	Semiotic square B: Proneness to Change	Semiotic square C: Digital Service Innovation Maturity
Quadrant III – Conservative follower	conservative and unaware/change reluctant: The conservative follower has a low degree of penetration and maturity of technical and organizational innovation in public service delivery. Also, this profile does not seem to be particularly inclined nor ready to modify behaviours or attitudes to support organisational or technological innovation.	passive and not committed/locked-in: The conservative follower has a limited capacity to use transversal administrative processes to support and orient cross-sectoral innovation governance processes. Also, lock-in mechanisms (e.g., related to their scarce degree of awareness, to limited commitment to change and capacity to act, or to their role and position in their networks) do not allow this profile of PAs to fully support innovation in (digital) service development and provision or to increase its capacity to detect and adopt innovation dynamics developed in different contexts.	basic and unaware/basic: The conservative follower might rely on a good degree of technological innovation but fails in fostering digital-enabled organisational transformation. Also, due to technological, social, organisational, or legal barriers, the innovation of services is not pervasive and face problems in generating impacts that produce changes within the public administration, in the local context or in other contexts through replication.
Quadrant IV – Diligent employee	innovative and aware/change reluctant: The diligent employee displays a high level of technical and organisational innovation in public service provision and delivery. The prisoner, however, might need to overcome organisational, societal, and legal barriers that constrain its space for action and do not allow this profile to fully grasp its transformative potential.	active and committed/locked-in: The diligent employee is making significant efforts to enhance innovation governance and to support cross-sectoral governance innovation processes. It developed strategies and measures to enhance innovation e.g., in relation to data management, procurement, societal engagement and institutional capacity-building, and displays a positive attitude towards learning. As for the conservative follower, also in the case of the organisational prisoner lock-in mechanisms do not allow this profile of PAs to fully support innovation in (digital) service development and provision or to increase its capacity to detect and adopt innovation dynamics developed in different contexts.	advanced and aware/basic: The diligent employee embraces new digital technologies and delivers innovative public services, displaying a high degree of digital infrastructural innovation and a positive attitude towards organisational change. Due to technological, societal, organisational, and legal barriers, however, the prisoner cannot fully supply its services autonomously, nor achieve changes in practices and behaviours related to service innovation adoption by local users or by stakeholders acting in other contexts.

Table 15 - Semiotic squares ideal-typical profiles

Index observed	Index type	Index level	Data Sample	Clusters
DPSVI	Absolute	Top	All respondents	na

Figure 22 – DPSVI - Semiotic square example

6.4 Service Index report (Annex 1.4)

A static report in PDF format includes charts and graphical processing and visualization related to the Service Index (SI). It is a document that resemble the structure of DPSVI static reports and includes several types of visualizations related to the Service Index and the 4 underlying indexes.

Visualizations include histograms, radar, and combined charts, as in the following example.

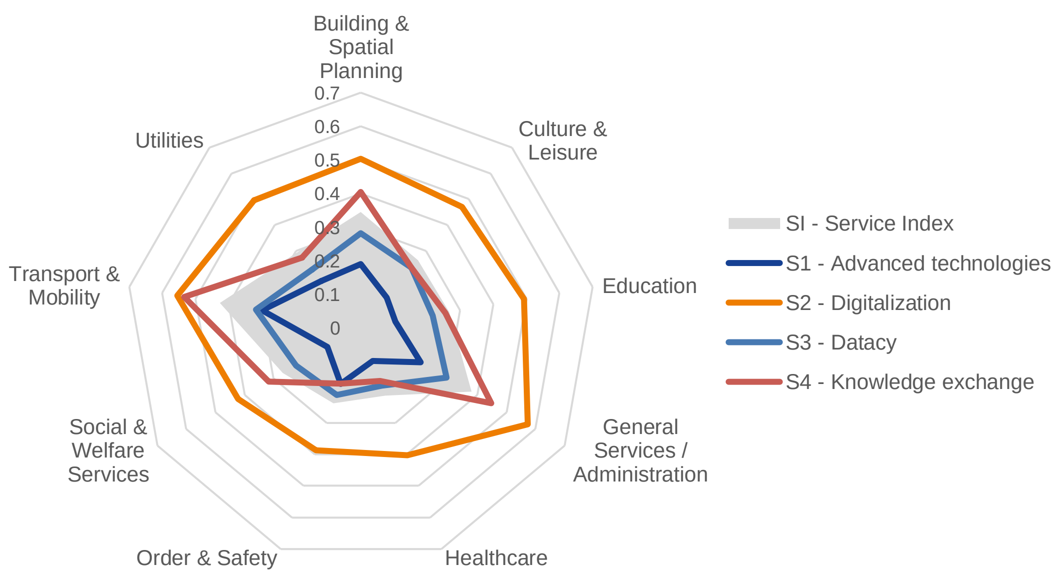


Figure 23 – Service Index – Radar example

6.5 Narrative feedback (Annex 1.5)

The last visualization method used in DIGISER aims at providing participant cities with a customized narrative feedback that can direct better strategies and policies, built upon their answers to the DIGISURVEY.

The indexes and data of the DPSVI analytical model have been translated into semi-automated narrative feedback. Shaped as a structured narrative description, the feedback is tailored to each public authority that answered the DIGISURVEY questionnaire. By its design, the narrative builds on the answers provided as well as their computation into indexes and sub-indices.

The concept on the ground of the narrative feedback is to provide public authorities with a proactive and constructive description of their activities and practices. The intent is to inform about their performances while situating their activities and practices in the broader scenario of digital innovation in the public sector. Therefore, the higher scope is to trigger a reflection on their multi-level and cross-sector attitude and behaviour toward digital innovation while feeding the mindset for potential medium and long-term changes and improvements.

Going beyond the provision of a mere number, which returns little information on the performance, each data is considered relevant and able to inform future strategies and strategies. The narrative description is therefore a complex interpretation that dynamically associates multi-level indexes and specific data to texts serving a descriptive function. Consequently, the narrative feedback develops embedding and elaborating information that is based on the interpretation of punctual data, namely answers to questions, and indexes and sub-indices, as computations at different levels of data aggregation.

The following figure provides an example of a narrative feedback for the index “Institutional Capacity” of an (anonymized) city.

INSTITUTIONAL CAPACITY

Institutional capacity is strongly related to transformation drivers, organisational ones included, influencing the adoption and management of digital technologies. It entails both training and educational activities put in play to enhance the digital skills of civil servants. Moreover, it affects the proneness of public administrations to enhance and mobilise their organisational and technological resources through the adoption of ICT technologies or the modification of internal rules and procedures. *Institutional capacity* considers therefore dimensions as *Innovation strategies*, *Proneness to experiment*, *Skills* and competences related to both digital management and information, and communications technology.
In this regard, **CityNameRemoved** has an overall **fair** capacity to experiment and consolidate digital innovation.

Innovation Strategy

In terms of *Innovation strategy*, **CityNameRemoved** provides a **good** level of information about the agenda setting and pursuing capacity.
CityNameRemoved has approved and published a digital innovation strategy, which covers only one public administration, and **is linked** to regional, national or European regulatory frameworks, strategies, directives. There is **a Chief Digital Officer, internal or shared with other public authorities,** coordinating the implementation of the digital innovation strategy, with **some budget dedicated**.
In terms of funding sources for digital innovation, the public authority reaches out to **a limited amount of funds**, and compared to the average, the per capita investment in ICT services is **very limited**. Moreover, **CityNameRemoved** has **no dedicated ICT team supporting one or more departments and services**; it **encourages** the use of Free/Libre and Open Source Softwares (FLOSS), and its IT set-up **offers** the possibility to implement open source alternatives.
No incentives are provided encouraging cooperation across service areas, regarding data sharing and data re-use, collaborative service design, ICT platform sharing, or cooperation among teams from various service areas.

Figure 24 - Example of narrative feedback

Appendix I: Detailed DPSVI Model

A.I.1 DPSVI Data model – Answers weighting in questions’ standardization

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_2.1	A1	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-	-	-	40%	-	-
Q_2.1	A2	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	30%	-	-
Q_2.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-
Q_2.1	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-
Q_2.1.3	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-
Q_2.1.3	A2	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	20%	-	-
Q_2.1.3	A3	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	30%	-	-
Q_2.1.3	A4	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	40%	-	-
Q_2.1.4	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
Q_2.2	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_2.2	A2	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_2.3.a	A1	-	-	-	-	-	7%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.a	A2	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.a	A3	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.a	A4	-	-	-	-	-	27%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.a	A5	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.b	A1	-	-	-	-	-	7%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.b	A2	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.b	A3	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.b	A4	-	-	-	-	-	27%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.b	A5	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.c	A1	-	-	-	-	-	7%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_2.3.c	A2	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.c	A3	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.c	A4	-	-	-	-	-	27%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.c	A5	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.d	A1	-	-	-	-	-	7%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.d	A2	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.d	A3	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.d	A4	-	-	-	-	-	27%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.3.d	A5	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.a	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.a	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.a	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.a	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.b	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.b	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.b	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.b	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.c	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.c	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.c	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.c	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.d	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.d	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.d	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.d	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.e	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_2.4.e	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.e	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.e	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.f	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.f	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.f	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.f	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.g	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.g	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.g	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.g	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.h	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.h	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.h	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.h	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.i	A1	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.i	A2	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.i	A3	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.4.i	A4	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.a	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.a	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.a	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.b	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.b	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.b	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.c	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_2.5.c	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.c	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.d	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.d	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.d	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.e	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.e	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.e	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.f	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.f	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.f	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.g	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.g	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.g	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.h	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.h	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.h	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.i	A1	-	-	17%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.i	A2	-	-	33%	-	100%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_2.5.i	A3	-	-	50%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_3.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.a	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.a	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_3.2.b	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.b	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.c	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.c	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.c	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.d	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.d	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.d	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.e	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.e	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.e	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.f	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.f	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.f	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.g	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.g	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.g	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.2.h	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-
Q_3.2.h	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-
Q_3.2.h	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-
Q_3.4	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	100%
Q_3.4	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-
Q_3.4	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-
Q_3.6.a	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-
Q_3.6.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-
Q_3.6.a	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	100%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_3.6.b	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-
Q_3.6.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-
Q_3.6.b	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	100%	-
Q_3.7	A1	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	75%	-	-	-	-	-	-
Q_3.7	A2	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	25%	-	-	-	-	-	-
Q_3.7.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-
Q_3.7.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-
Q_3.7.1	A3	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	50%	-	-	-	-	-	-
Q_3.8	A1	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-
Q_3.8	A2	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	50%
Q_3.8	A3	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	50%
Q_3.8	A4	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-
Q_4.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40%	-	-
Q_4.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	40%	-	-
Q_4.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-
Q_4.3	A1	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
Q_4.4	A1	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%
Q_4.5	A1	-	-	67%	-	-	-	-	67%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_4.5	A2	-	-	33%	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_4.6.a	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%
Q_4.6.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%
Q_4.6.b	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%
Q_4.6.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%
Q_4.6.c	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	25%
Q_4.6.c	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%
Q_4.6.d	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_4.6.d	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	25%
Q_4.8	A1	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_4.8	A2	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_4.8	A3	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_4.8	A4	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.1	A1	-	-	-	-	-	-	-	-	-	-	-	43%	100%	-	-	-	-	-	-	-	-
Q_5.1	A2	-	-	-	-	-	-	-	-	-	-	-	29%	-	-	-	-	-	-	-	-	-
Q_5.1	A3	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.1	A5	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2	A1	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.1	A1	-	-	-	-	-	-	-	-	-	40%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.1	A2	-	-	-	-	-	-	-	-	-	30%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.1	A3	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.1	A4	-	-	-	-	-	-	-	-	-	10%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A2	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A3	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A4	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A5	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.2	A6	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A1	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A2	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A3	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A4	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A5	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A6	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.2.3	A7	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.3	A8	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.a	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.a	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.a	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.b	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.b	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.b	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.c	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.c	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.c	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.d	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.d	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.d	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.e	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.e	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.e	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.f	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.f	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.f	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.g	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.g	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.g	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.h	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.h	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.h	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.2.4.i	A1	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.i	A2	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.4.i	A3	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.a	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.a	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.a	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.a	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.a	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.b	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.b	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.b	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.b	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.b	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.c	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.c	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.c	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.c	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.c	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.d	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.d	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.d	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.d	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.d	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.e	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.e	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.e	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.2.5.2.e	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.e	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.f	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.f	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.f	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.f	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.f	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.g	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.g	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.g	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.g	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.g	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.h	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.h	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.h	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.h	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.h	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.i	A1	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.i	A2	-	38%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.i	A3	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.i	A4	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.5.2.i	A5	-	13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.6	A1	-	67%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.6	A2	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.2.7	A1	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2.7	A2	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.2.7	A3	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2.7	A4	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2.7	A5	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2.7	A6	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.2.7	A7	-	-	-	-	-	-	-	-	-	-	-	14%	-	-	-	-	-	-	-	-	-
Q_5.3	A1	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-	-	-
Q_5.3	A2	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-	-
Q_5.4	A1	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1	A1	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1	A2	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1	A3	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1	A4	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A1	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A2	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A3	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A4	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A5	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A6	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A7	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A8	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.1	A9	-	-	11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A1	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A2	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A3	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A4	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A5	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.4.1.2	A6	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.4.1.2	A7	-	-	14%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.5	A1	-	-	67%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.5	A2	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.6	A1	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-
Q_5.6	A2	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-
Q_5.6	A3	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-
Q_5.6	A4	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-
Q_5.6	A5	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-
Q_5.7	A1	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-
Q_5.7	A2	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-
Q_5.7	A3	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-
Q_5.7	A4	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-
Q_5.8	A1	-	-	-	100%	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-
Q_5.8	A2	-	-	-	-	100%	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-
Q_5.8	A3	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-
Q_5.8	A5	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-
Q_5.9	A1	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.9.1	A1	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.9.1	A2	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.9.1	A3	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.9.1	A4	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.9.1	A5	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_5.10	A2	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-	-	-	-	-
Q_5.10	A3	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-	-
Q_5.10	A4	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.11	A1	-	-	-	-	-	-	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-
Q_5.11	A2	-	-	-	-	-	-	-	-	-	-	-	33%	33%	-	-	-	-	-	-	-	-
Q_5.11	A3	-	-	-	-	-	-	-	-	-	-	-	17%	17%	-	-	-	-	-	-	-	-
Q_5.12	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-
Q_5.12.1.a	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.a	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.a	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.b	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.b	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.b	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.c	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.c	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.c	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.c	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.d	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.d	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.d	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.d	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.e	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.e	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.e	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.e	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.f	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.f	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.12.1.f	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.f	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.g	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.g	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.g	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.g	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.h	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.h	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.h	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.h	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.i	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-	-	-
Q_5.12.1.i	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.1.i	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	38%	-	-	-	-	-	-	-
Q_5.12.1.i	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-
Q_5.12.2	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-
Q_5.12.2.1.a	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.b	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.c	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.c	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.d	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.d	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.e	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.e	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.f	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_5.12.2.1.f	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.g	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.g	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.h	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.h	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_5.12.2.1.i	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-	-	-	-	-	-	-
Q_5.12.2.1.i	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-	-	-	-
Q_6.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1	A10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-	-	-	-
Q_6.1.2	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-	-
Q_6.1.2	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-	-	-	-
Q_6.1.2	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	50%	-	-	-	-
Q_6.2	A1	-	-	-	-	-	100%	-	-	-	-	-	-	20%	-	-	20%	-	-	-	-	-
Q_6.2	A2	-	-	-	50%	-	-	-	-	-	-	-	-	40%	-	-	40%	-	-	-	-	-
Q_6.2	A3	-	-	-	50%	-	-	-	-	-	-	-	-	40%	-	-	40%	100%	-	-	-	-
Q_6.3	A1	-	-	-	-	-	-	100%	100%	100%	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.1	A1	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.1	A2	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	50%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_6.3.1	A3	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.1	A4	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	50%	-
Q_6.3.1	A5	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.1	A6	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.1	A7	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A2	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A3	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A4	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A5	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A6	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A7	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A8	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.3.2	A9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-
Q_6.3.2	A10	-	-	-	-	-	-	-	-	25%	-	-	-	-	-	-	100%	-	-	-	-	-
Q_6.3.2	A11	-	-	-	-	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_6.4	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-
Q_6.4.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_6.4.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_6.4.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_6.4.1	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_6.4.1	A5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_6.4.1	A6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17%	-	-	-
Q_7.1	A1	-	-	-	-	-	-	100%	-	100%	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.1.1	A1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_7.1.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13%	-	-	-	-	-
Q_7.1.1	A8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9%	-	-	-	-	-
Q_7.2.a	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.a	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.b	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.b	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.c	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.c	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.d	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.d	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.e	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.e	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.f	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.f	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.g	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.g	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.h	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.h	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.2.i	A1	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_7.2.i	A2	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_7.3.a	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.a	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_7.3.b	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.b	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.c	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.c	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.d	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.d	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.e	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.e	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.f	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.f	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.g	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.g	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.h	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.h	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.3.i	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.3.i	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.a	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.a	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.b	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.b	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.c	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.c	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.d	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.d	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.e	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.e	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_7.4.f	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.f	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.g	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.g	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.h	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.h	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.4.i	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.4.i	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.a	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.a	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.b	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.b	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.c	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.c	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.d	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.d	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.e	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.e	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.f	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.f	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.g	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.g	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.h	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.h	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.5.i	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.5.i	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_7.6.a	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.a	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.b	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.b	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.c	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.c	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.d	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.d	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.e	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.e	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.f	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.f	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.g	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.g	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.h	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.h	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.6.i	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.6.i	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.a	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.a	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.b	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.b	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.c	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.c	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.d	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.d	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_7.7.e	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.e	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.f	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.f	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.g	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.g	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.h	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.h	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_7.7.i	A1	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33%	-
Q_7.7.i	A2	-	75%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	67%	-
Q_8.1.a	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.a	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.a	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.b	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.b	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.b	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.c	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.c	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.c	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.d	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.d	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.d	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.e	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.e	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.e	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.f	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_8.1.f	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.f	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.g	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.g	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.g	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.h	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.h	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.h	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.i	A2	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.i	A3	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.1.i	A4	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.a	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.a	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.a	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.b	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.b	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.b	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.c	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.c	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.c	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.d	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.d	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.d	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.e	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.e	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.e	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_8.2.f	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.f	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.f	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.g	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.g	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.g	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.h	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.h	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.h	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.i	A2	33%	-	-	17%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.i	A3	33%	-	-	33%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.2.i	A4	33%	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.a	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.a	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.b	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.b	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.c	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.c	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.d	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.d	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.e	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.e	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.f	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.f	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.g	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.g	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_8.3.h	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.h	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.i	A1	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.i	A2	-	-	-	-	-	50%	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.1	A2	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.3.1	A3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
Q_8.4.a	A1	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.a	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.a	A3	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.a	A4	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.a	A9	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.b	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.b	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.b	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.b	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.b	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.c	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.c	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.c	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.c	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.c	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.d	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.d	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.d	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.d	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.d	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q_#	A#	I1_1_1	I1_1_2	I1_1_3	I1_2_1	I1_2_2	I1_2_3	I2_1_1	I2_1_2	I2_1_3	I2_2_1_1	I2_2_1_2	I2_2_1_3	I2_2_1_4	I2_2_1_5	I2_2_2	I2_2_3_1	I2_2_3_2	I2_2_3_3	I2_2_4_1	I2_2_4_2	I2_2_4_3
Q_8.4.e	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.e	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.e	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.e	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.e	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.f	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.f	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.f	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.f	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.f	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.g	A1	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.g	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.g	A3	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.g	A4	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.g	A9	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.h	A2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-
Q_8.4.h	A3	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.h	A4	-	-	25%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Q_8.4.h	A9	-	-	50%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

DPSVI Data Model – Answers weighting in questions' standardization

A.I.2 DPSVI Data model – Question aggregation relative weights

Q.#	I1.1.1	I1.1.2	I1.1.3	I1.2.1	I1.2.2	I1.2.3	I2.1.1	I2.1.2	I2.1.3	I2.2.1.1	I2.2.1.2	I2.2.1.3	I2.2.1.4	I2.2.1.5	I2.2.2	I2.2.3.1	I2.2.3.2	I2.2.3.3	I2.2.4.1	I2.2.4.2	I2.2.4.3
2.1	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	100%	-	-
2.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2.1.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2.1.3	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	100%	-	-
2.1.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
2.2	-	-	-	-	-	-	-	50%	-	-	-	-	-	-	-	-	-	-	100%	-	-
2.3	-	-	-	-	-	40%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2.4	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-
2.5	-	-	100%	-	100%	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-
3.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
3.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
3.3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	10%
3.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3.6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	25%	-
3.7	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	100%	-	-	-	-	-	-
3.7.1	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	100%	-	-	-	-	-	-
3.7.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3.7.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3.8	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	30%
3.8.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-
4.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4.3	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-

Q.#	I1.1.1	I1.1.2	I1.1.3	I1.2.1	I1.2.2	I1.2.3	I2.1.1	I2.1.2	I2.1.3	I2.2.1.1	I2.2.1.2	I2.2.1.3	I2.2.1.4	I2.2.1.5	I2.2.2	I2.2.3.1	I2.2.3.2	I2.2.3.3	I2.2.4.1	I2.2.4.2	I2.2.4.3
4.4	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	30%
4.5	-	-	100%	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-
4.6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	30%
4.7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4.8	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-
4.8.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.1	-	-	-	-	-	-	-	-	-	-	-	100%	100%	-	-	-	-	-	-	-	-
5.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	-	-
5.2.1	-	-	-	-	-	-	-	-	-	80%	-	-	-	-	-	-	-	-	-	-	-
5.2.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.2	-	-	-	-	-	-	-	-	-	80%	-	-	-	-	-	-	-	-	-	-	-
5.2.3	-	-	-	-	-	-	-	-	-	80%	-	-	-	-	-	-	-	-	-	-	-
5.2.4	-	-	-	-	-	-	-	-	-	80%	-	-	-	-	-	-	-	-	-	-	-
5.2.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.5.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.5.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.5.2	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.6	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.7	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-
5.2.7.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.2.7.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.3	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-	-
5.4	-	-	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.4.1	-	-	60%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.4.1.1	-	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.4.1.2	-	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q.#	I1.1.1	I1.1.2	I1.1.3	I1.2.1	I1.2.2	I1.2.3	I2.1.1	I2.1.2	I2.1.3	I2.2.1.1	I2.2.1.2	I2.2.1.3	I2.2.1.4	I2.2.1.5	I2.2.2	I2.2.3.1	I2.2.3.2	I2.2.3.3	I2.2.4.1	I2.2.4.2	I2.2.4.3
5.4.1.2.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.5	-	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.6	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-
5.7	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-
5.7.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.8	-	-	-	20%	100%	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-
5.8.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.9	-	-	-	-	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.9.1	-	-	-	-	90%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.9.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.9.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5.10	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-	-	-
5.11	-	-	-	-	-	-	-	-	-	-	-	100%	100%	-	-	-	-	-	-	-	-
5.12	-	-	-	-	-	-	-	-	-	-	-	-	-	20%	-	-	-	-	-	-	-
5.12.1	-	-	-	-	-	-	-	-	-	-	-	-	-	40%	-	-	-	-	-	-	-
5.12.2	-	-	-	-	-	-	-	-	-	-	-	-	-	8%	-	-	-	-	-	-	-
5.12.2.1	-	-	-	-	-	-	-	-	-	-	-	-	-	32%	-	-	-	-	-	-	-
6.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-
6.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6.1.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-
6.1.3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6.2	-	-	-	20%	-	20%	-	-	-	-	-	-	100%	-	-	100%	100%	-	-	-	-
6.3	-	-	-	-	-	-	6%	10%	20%	-	-	-	-	-	-	-	-	-	-	-	-
6.3.1	-	-	-	-	-	-	27%	45%	-	-	-	-	-	-	-	-	-	-	-	13%	-
6.3.2	-	-	-	-	-	-	27%	45%	80%	-	-	-	-	-	-	100%	-	-	-	13%	-
6.3.2.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6.3.3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Q.#	I1.1.1	I1.1.2	I1.1.3	I1.2.1	I1.2.2	I1.2.3	I2.1.1	I2.1.2	I2.1.3	I2.2.1.1	I2.2.1.2	I2.2.1.3	I2.2.1.4	I2.2.1.5	I2.2.2	I2.2.3.1	I2.2.3.2	I2.2.3.3	I2.2.4.1	I2.2.4.2	I2.2.4.3
6.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-
6.4.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-
6.4.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6.4.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.1	-	-	-	-	-	-	20%	-	100%	-	-	-	-	-	-	-	-	-	-	-	-
7.1.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
7.1.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.2	-	-	-	-	-	20%	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
7.3	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-
7.3.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.4	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-
7.4.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.5	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-
7.5.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.6	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-
7.6.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7.7	-	100%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	-
7.7.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8.1	30%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8.2	30%	-	-	60%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8.3	-	-	-	-	-	20%	20%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8.3.1	10%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-
8.4	30%	100%	100%	-	-	-	-	-	-	-	-	-	-	-	100%	-	-	-	-	-	-

A I.3 SI Service Index – Detail of service areas

General / Administration	
Included Service Sectors	***Example of a digital solution***
Certification/registration	*Certify/register personal information online*
Information	*Find information online*
Taxation & fees	*Declare taxes, pay fees online*
Interaction	*Provide feedback/information online*
	Follow council meetings (streaming)
	Participate in process (eVoting, streaming)
Business services	*Certify/register business information online*
Building & Spatial Planning	
Included Service Sectors	***Example of a digital solution***
Strategic/Land use planning	*Consult data and plans (GIS)*
	Apply for permits and trace progress
	Consult/participate (streaming, teleconference)
	Predictive modelling
	Car Share
	Fleet and Ride Share
	Person-to-Person Car Rental
	Real-Time Tracking of Journey inside and in stations (Cloud, Big Data, AI, IoT)
	Notifications on service interruptions
Construction	*Apply for permits, register and certify*
	Legal: building codes for smart buildings
Transport & Mobility	
Included Service Sectors	***Example of a digital solution***
Parking	*Pre-Booking & Reservations*
	Dynamic Availability & Smart Payment
	EV Charging
	Towing and removal
Traffic Management	*Real-Time Traffic Information and Management (Cloud, Big Data, AI, IoT)*
	Road User Charging (IoT)
	Connected Vehicles
	Connected Traveller
	E-Call Road Assistance
	Digital Information Boards

Logistics	*Crowdsourced Logistics*
Delivery	*Apps*
	Robots & Drones
Public Transport	*Multimodal Transportation Information (Apps)*
	Route Management and Planning
	Autonomous Transport Systems [Robotics, Big Data, AI, IoT, 5G]
	Dynamic Availability & Smart Payment
	Bike/Scooter Share
Utilities	
Included Service Sectors	***Example of a digital solution***
Waste disposal	*Route Management and Planning*
	Smart Sensor Bins and RFID Tags (IoT)
	Volume/Frequency-Based Payment System
Water (clean & waste)	*Smart meters*
	Public Health Monitoring (Smart Sensors)
	Quality Monitoring (Smart Sensors)
	Leak & degrading infrastructure detection
	Maintenance planning (automated geolocation of failures)
	Infrastructure repairs (robotics)
Elecriticty	*Smart meters and consumption monitoring*
	Electronic billing
	Smart Energy Grid
Internet	*Public wifi (4G, 5G)*
	Package stations
Street lighting	*Smart lampposts*
Road maintenance	*Apps to communicate about road conditions*
	Snowplow, cleaning (route planning)
Heating	*Real time energy demand information and management*
	Smart Thermal Grid
	Smart energy systems
	Smart buildings
Social & Welfare Services	
Included Service Sectors	***Example of a digital solution***
Social Housing	*Registration, process management*
Building smart monitoring and management	
Social assistance	*Registration, process management*
Water (clean & waste)	*Smart meters*

Public Health Monitoring (Smart Sensors)	
Quality Monitoring (Smart Sensors)	
Healthcare	
Included Service Sectors	***Example of a digital solution***
Public health services	*Registration, ticketing, booking, access to records*
	Remote assistence, Digital/virtual rehabilitation, health-related data monitoring
Outpatient services	*Registration, ticketing, booking treatments, access to records*
	Health-related data monitoring
Education	
Included Service Sectors	***Example of a digital solution***
Pre-primary education	*Enrolment*
Primary/secondary education	*eLearning*
	eBooks
Culture & Leisure	
Included Service Sectors	***Example of a digital solution***
Cultural services	*Ticketing, booking access, digital guides (app), service evaluation*
Recreation and sporting activities	*Ticketing, booking access, service evaluation*
Tourism services	*Ticketing, booking access, digital guides (app), service evaluation*
Emergency response	*Real Time Call Centers*
	Drones
Order & Safety	
Included Service Sectors	***Example of a digital solution***
Emergency preparedness	*Emergency preparedness plans (Digital Twin, IoT, VR)*
Public safery	*Facial recognition (IoT, Drones, AI)*
Police	*Crime prediction modelling (AI)*
	Recording (Bluetooth, Cloud Computing)
	GPS tracking

Appendix II: Univariate models

This analysis is developed with the aim of doing inference on some external variables. They include the population of a city and the belonging or not to (at least) one network of cities. These two are available at the same aggregation level of the cities. Another external variable is the gross domestic product per capita, which is instead referred to the province of the city, and not precisely to the city itself. Not only are some hypotheses of linear correlation discussed, via a linear model, but also more general ones. In fact, for every explored dependence, a baseline tentative is done via linear models. Then, non-linearity is allowed through the generalised additive models (introduced by Hastie and Tibshirani, 1986). The latter model is selected to guarantee a high degree of interpretability and communicability of the results, while granting nonlinear dependencies. The strength of the GAMs is the additivity: despite allowing non-linearity between the output and each variable, the final model is obtained by adding these terms. So, it is easy to separately analyse the non-linear terms. These analyses deserve attention since provide useful and intuitive tools to explore correlations and dependencies between the enquired phenomena and some variables that may, or may not, be their drivers.
In this annex, the analysis of index I1 is presented, although the same work has been carried out for the other indicators too.

Univariate: POP + Country_CODE

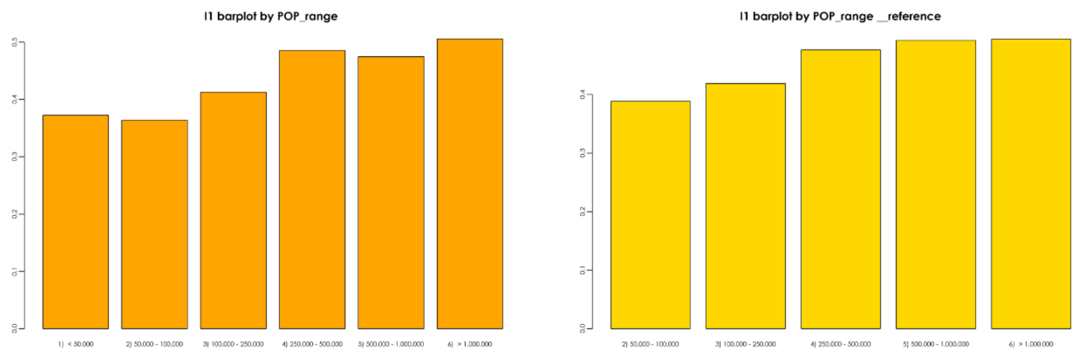


Figure 25: Barplots summarising the distribution of I1 versus some predefined clusters of population. Plot produced with all respondents on the left, and only the cities belonging to the statistical sample.

The couple of barplots in Figure 25summarises the distribution of I1 versus some predefined clusters of population. The plot on the right is done considering just the 155 cities belonging to the so-called reference sample, which does not take into account cities with less than 50 000 inhabitants, and it should cover more homogeneously all the other population ranges. The other plot instead is obtained with all the respondent cities, which do not show a clear pattern, yet it seems that there is a considerable up-shift for cities with more than 250 000 inhabitants. Despite being interesting to compare the average trend noticed in the global sample and the statistical one, these barplots flatten out the characterising variability of the various cities of the same cluster. In fact, suppose that there is a wide underlying variability but the cluster dimension is large, the averaging effect dominates and shades this variability. On the other hand, for the smaller clusters, leveraging elements that move the mean significantly are likely to be found, especially if the leveraging data point is extremely far from the rest of the data points. Therefore, the following regression analyses will be useful to statistically prove any evidence of this kind.

Linear Model

The first proposed model is the linear model where I1 is the output, and the regressors are the base−10 logarithm of the population datum and the categorical variable representing the country. Such a model is meaningful for various reasons. Firstly, it is the best in terms of R^2_{adj} and statistical significance of the estimated coefficients. It outperforms the models without the logarithmic transform, or with, for example, a double logarithm or even a square root. Secondly, it provides a neat, simple and easily interpretable overview of the relation between the population and the current indicator. Moreover, the country factor allows to address a crucial research question, namely the existence of a single European reality, against a differentiation of behaviour country by country. As just mentioned, the Country variable is of a factor-type, thus to insert it in a regression model in a way that delivers a more natural interpretation of the country coefficients, the so-called Deviation Encoding[11] is applied. Thanks to it, the resulting model can be seen as a “grand mean” term, i.e. a reference value and, plus a set of deviations from it, one for each country. It is important to specify that by grand mean it is intended the mean of the country means. To practically achieve such a result, the encoding works in the following way: assuming n levels of the considered factor variable, an equivalent set of n−1 contrasts is built, therefore the first n−1 levels are mapped into n−1 dummy variables. The remaining one is built “by contrast”, so it assumes a value equal to −1 in correspondence of each dummy. When performing a linear modelling the first n − 1 deviations are directly readable from the model summary, since they coincide with the regression coefficients, then to retrieve its deviation it is enough to sum the reverse of the n − 1 coefficients, since the sum of all the deviations is 0, as long as a model including all of them is nothing but the reference itself. This model confirms a positive dependence between I1 and the logarithm of the population variable, and in many cases the Country line needs to be shifted, up or down. In fact, from this summary it seems that a unique European trend does not appear to be realistic, but country by country the performances differ, as the following ANOVA model summary in Table 16 summarises.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
(Intercept)	1	45.58	45.58	3666.396	< 2e-16	***
Country_CODE	32	1.48	0.05	3.726	3.72e-09	***
log10(POP)	1	0.30	0.30	24.528	1.45e-06	***
Residuals	221	2.75	0.01			

Table 16: ANOVA table of the population linear model.

[11] see, for example, the UCLA website of Advanced Research Computing for Statistical Methods and Data Science https://stats.oarc.ucla.edu/r/library/r-library-contrast-coding-systems-for-categorical-variables/#DEVIATION.

```
Formula: y ~ log10(POP) + Country_CODE

Residuals:
     Min       1Q   Median       3Q      Max
-0.31290 -0.06349  0.00000  0.07658  0.29433

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.020622   0.081948   0.252 0.801546
log10(POP)       0.033582   0.006781   4.953 1.45e-06 ***
"AL" Country_CODE1  -0.099891   0.108494  -0.921 0.358211
"AT" Country_CODE2   0.119268   0.063165   1.888 0.060310 .
"BE" Country_CODE3   0.016326   0.037248   0.438 0.661603
"BG" Country_CODE4  -0.064276   0.041906  -1.534 0.126508
"CH" Country_CODE5   0.034098   0.063112   0.540 0.589556
"CY" Country_CODE6  -0.208966   0.055040  -3.797 0.000190 ***
"CZ" Country_CODE7  -0.059250   0.033903  -1.748 0.081916 .
"DE" Country_CODE8  -0.034319   0.031467  -1.091 0.276633
"DK" Country_CODE9   0.136195   0.054843   2.483 0.013759 *
"EE" Country_CODE10  0.107722   0.040420   2.665 0.008266 **
"EL" Country_CODE11 -0.104152   0.041970  -2.482 0.013824 *
"ES" Country_CODE12  0.025229   0.028041   0.900 0.369252
"FI" Country_CODE13  0.100999   0.042010   2.404 0.017033 *
"FR" Country_CODE14  0.017496   0.027204   0.643 0.520803
"HR" Country_CODE15 -0.093960   0.045305  -2.074 0.039244 *
"HU" Country_CODE16 -0.173171   0.049331  -3.510 0.000542 ***
"IE  Country_CODE17 -0.038957   0.045169  -0.862 0.389361
"IS" Country_CODE18  0.101726   0.063805   1.594 0.112294
"IT" Country_CODE19 -0.007763   0.025560  -0.304 0.761634
"LT" Country_CODE20  0.078211   0.063108   1.239 0.216542
"LU" Country_CODE21 -0.035726   0.077261  -0.462 0.644243
"LV" Country_CODE22  0.039416   0.046007   0.857 0.392511
"MT" Country_CODE23 -0.045901   0.077035  -0.596 0.551888
"NL" Country_CODE24  0.109632   0.035975   3.047 0.002589 **
"NO" Country_CODE25  0.163680   0.063150   2.592 0.010181 *
"PL" Country_CODE26 -0.033630   0.031761  -1.059 0.290825
"PT" Country_CODE27  0.043497   0.035596   1.222 0.223021
"RO" Country_CODE28 -0.072818   0.037220  -1.956 0.051675 .
"SE" Country_CODE29  0.023025   0.033994   0.677 0.498901
"SI" Country_CODE30 -0.019689   0.045321  -0.434 0.664394
"SK" Country_CODE31 -0.057679   0.038909  -1.482 0.139654
"TR" Country_CODE32  0.042547   0.112780   0.377 0.706342
"UK" ---            -0.00892
Obtained by summing the opposite coeff of every country.

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1115 on 221 degrees of freedom
Multiple R-squared:  0.3941,Adjusted R-squared:  0.3036
F-statistic: 4.356 on 33 and 221 DF,  p-value: 1.681e-11


Shapiro-Wilk normality test

data:  lm_temp$residuals
W = 0.99159, p-value = 0.1532
```

Table 17: Summary table of the results of the linear model in the population case, produced with the help of R software.

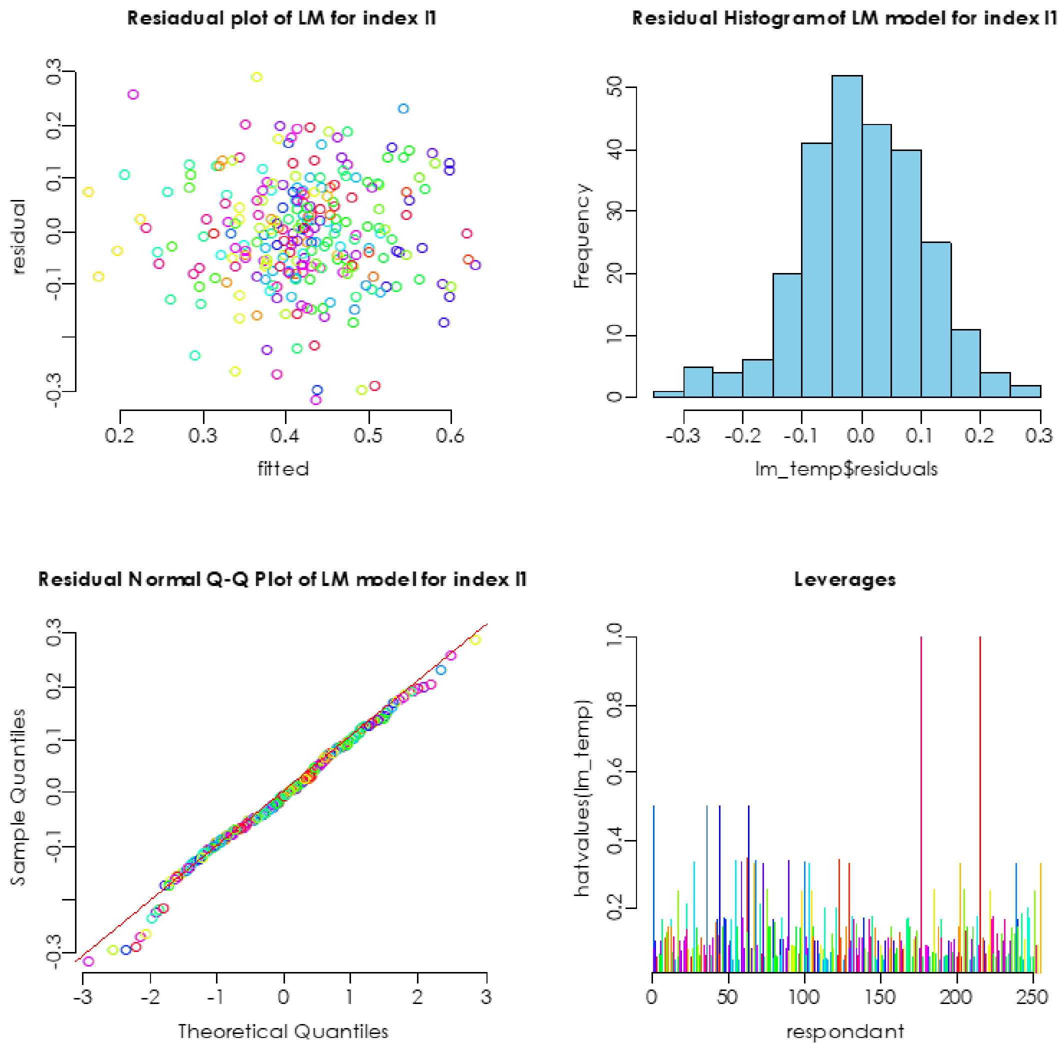


Figure 26: Analysis of the residuals of the LM with population, via typical plots.

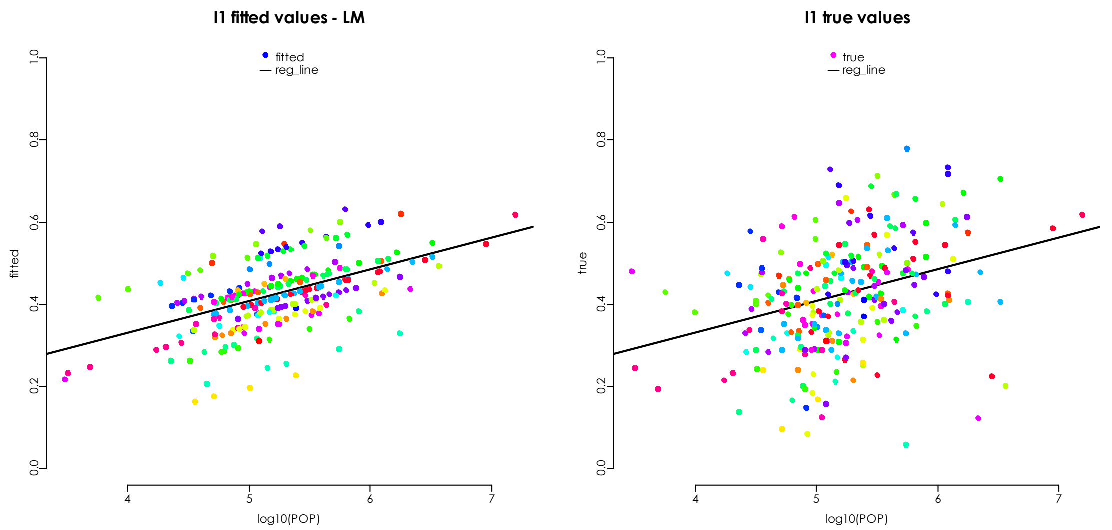


Figure 27: Scatter-plots of fitted values (left) and true values (right) of I1 versus the logarithm of the population; the straight line is the estimated regression line.

In these two plots (cfr., Figure 27) a logarithmic scale has been used on the *x*-axis, to provide a cleaner and clearer visualization. This scale implies that, a value of $\log_{10} POP = x$ corresponds to an actual value of $POP = 10^x$, e.g. $x = 4$ means that $POP = 10\,000$. In the left plot (fitted values) there are shown the linear regression line in black, and all the values computed by the estimated linear model, coloured according to the country they belong to. On the other hand, the right plot show what is the target, so the true values of the index at hand. An interesting insight is given by the spreading of the true values against the fitted ones: the former ones are more widely spread along the y-axis, while the latter are more shrunk. This is the direct reflection of a statistical evidence brought by the model: it is able to capture around 30% of the variability of the data[12]. It means that the population (a city-specific information) and the country variables do not account for all the variability of the indicator, but there is something left which cannot be referred to them. In particular, it follows that the 70% left cannot be tackled by variables of a larger aggregation level than the single city. Thus, the inclusion of the minute city representation in the model is crucial, since each of them in fact possesses a characteristic and intrinsic behaviour that eludes the country terms. It is worthy underlining once again that the country contributions are confirmed to be statistically significant and deserve to be kept in consideration. They provide a substantial differentiation to be added on top of the basic European level, as it can be seen by the two plots below (Figure 28).

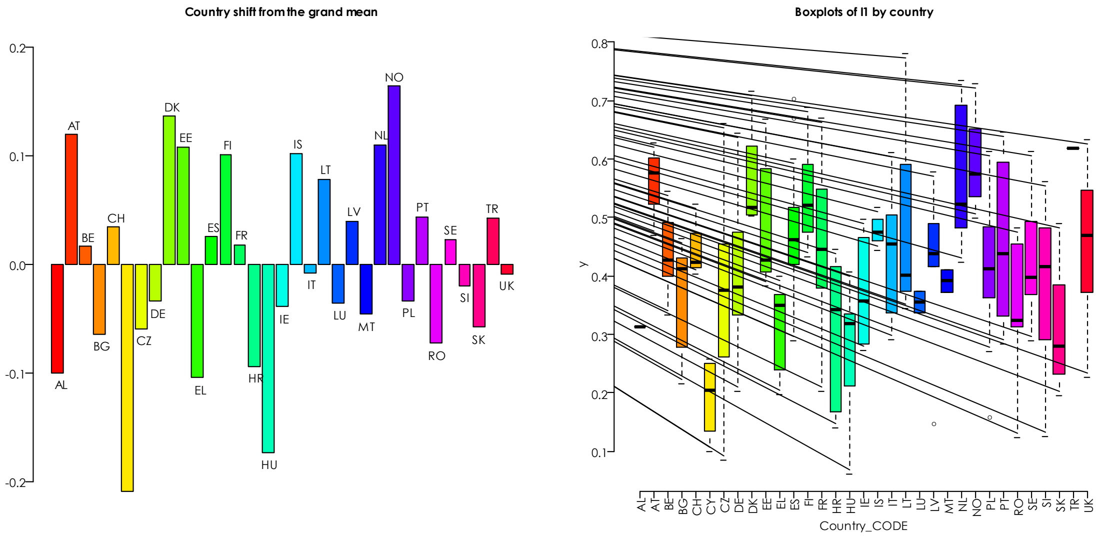


Figure 28: Barplot of the estimated values of the coefficient values, on the left, where 0 represents the European level; boxplots of the distribution of the index values by country on the right.

Generalised Additive Models

At this point, a more general model is attempted, both to explore also non linear dependencies and to allow a better fit in the regions where the data are less dense. Due to the categorical nature of the country variable, the non-linearity can be applied only to the population term. In this case it has been decided to leave it non transformed, since the model itself is able to capture any form of non-linearity by using smooth curves. Here, after the summary Table 18, the GAM curve is shown (Figure 29), and in the following the scatter plots (Figure 30). The wider and wider confidence interval at 95% around the estimated curve, represented by the dashed lines, is caused by the scarcity of cities with more than 5 million inhabitants. The European final regression curve, bold black line in the plots, shows a clear initial linear behaviour, which translates into a logarithmic positive dependence of the I1 index on the population. Then the following "hill" that occurs in correspondence of $\log_{10} POP \in [5.5, 6.5]$ highlights a sudden loss of such a dependence, thus from a certain, large, number of inhabitants, the index stops to grow along at the same pace.

[12] Information brought by the R^2-adjusted of the model, see Table 17: Summary table of the results of the linear model in the population case, produced with the help of R software.

```
Family: gaussian

Link function: identity

Formula: y ~ s(POP, bs = "cr") + Country_CODE

Parametric coefficients:

                Estimate Std. Error t value Pr(>|t|)

(Intercept)     0.417997   0.013452  31.072  < 2e-16 ***

Country_CODE1  -0.080177   0.107410  -0.746 0.456195

Country_CODE2   0.141074   0.064103   2.201 0.028799 *

Country_CODE3   0.030241   0.038533   0.785 0.433415

Country_CODE4  -0.051867   0.042926  -1.208 0.228243

Country_CODE5   0.049707   0.063168   0.787 0.432189

Country_CODE6  -0.196947   0.055289  -3.562 0.000451 ***

Country_CODE7  -0.046858   0.035309  -1.327 0.185868

Country_CODE8  -0.020358   0.033296  -0.611 0.541556

Country_CODE9   0.137300   0.055026   2.495 0.013328 *

Country_CODE10  0.105585   0.040940   2.579 0.010563 *

Country_CODE11 -0.095774   0.042740  -2.241 0.026040 *

Country_CODE12  0.035602   0.030202   1.179 0.239753

Country_CODE13  0.102148   0.042833   2.385 0.017940 *

Country_CODE14  0.022564   0.029161   0.774 0.439889

Country_CODE15 -0.082142   0.046147  -1.780 0.076462 .

Country_CODE16 -0.161400   0.050285  -3.210 0.001528 **

Country_CODE17 -0.030501   0.045739  -0.667 0.505578

Country_CODE18  0.108096   0.063690   1.697 0.091074 .

Country_CODE19  0.003726   0.028041   0.133 0.894417

Country_CODE20  0.084044   0.063042   1.333 0.183868

Country_CODE21 -0.020957   0.076891  -0.273 0.785449

Country_CODE22  0.051373   0.046768   1.098 0.273209

Country_CODE23 -0.046148   0.076867  -0.600 0.548889

Country_CODE24  0.118818   0.037752   3.147 0.001877 **

Country_CODE25  0.168625   0.063139   2.671 0.008138 **

Country_CODE26 -0.033676   0.033423  -1.008 0.314763

Country_CODE27  0.048639   0.036594   1.329 0.185178

Country_CODE28 -0.071901   0.038584  -1.863 0.063735 .

Country_CODE29  0.036151   0.035236   1.026 0.306034

Country_CODE30 -0.006709   0.045971  -0.146 0.884094

Country_CODE31 -0.065858   0.039201  -1.680 0.094382 .

Country_CODE32 -0.230345   0.378412  -0.609 0.543346

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '
' 1

Approximate significance of smooth terms:

         edf Ref.df     F p-value

s(POP) 3.199  3.547 9.161 3.7e-06 ***

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '
' 1

R-sq.(adj) =  0.326   Deviance explained = 41.9%

GCV = 0.014026  Scale est. = 0.012035  n = 255

Shapiro-Wilk normality test

W = 0.99199, p-value = 0.1815
```

Table 18: Summary table of the results of the GAM in the population case, produced with the help of R software.

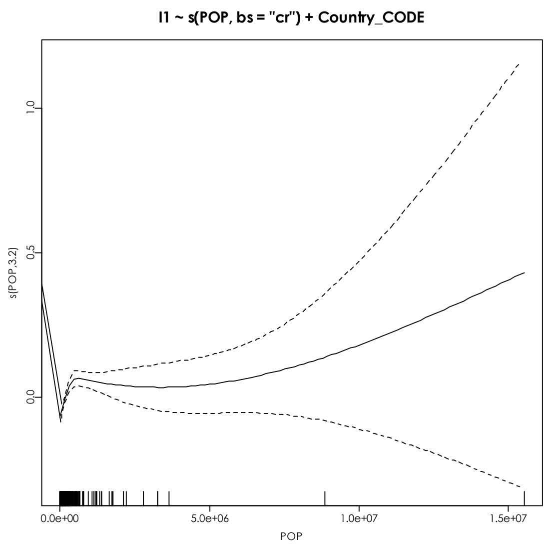


Figure 29: The estimated GAM curve for I1 versus the population.

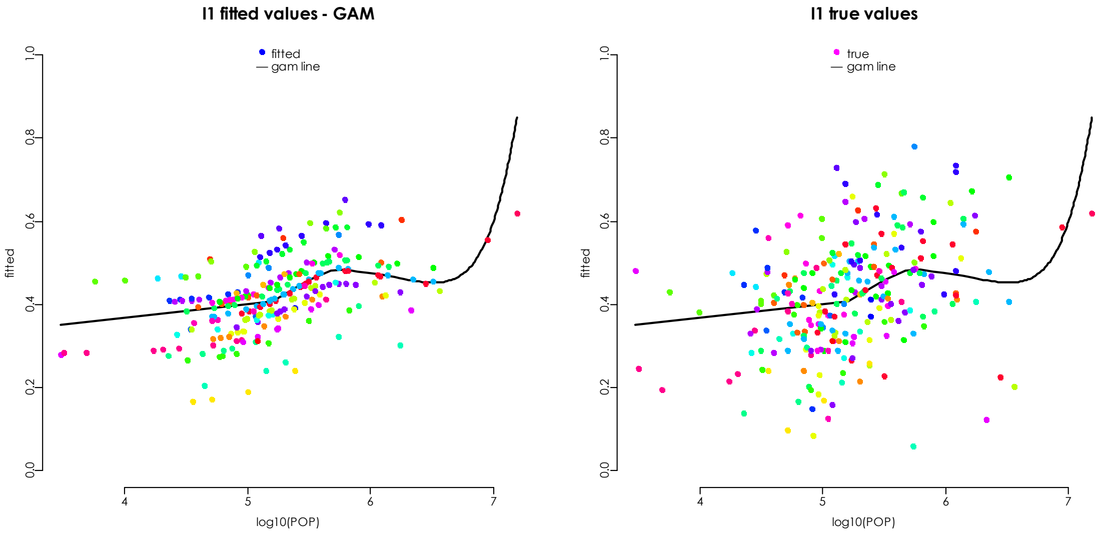


Figure 30: The regression curve, the fitted (left) and true values (right) of I1.

Figure 31 focus again on the country contribution. On the left, there is the representation of the deviation from the average European behaviour of each considered country estimated with the nonlinear model, whilst on the right it is shown the comparison of the estimation of the deviations by the two introduced models. The estimated coefficients are very similar, with the exception of Turkey (penultimate country on the right). This result is particularly due to the presence of regression line underestimates the index value of Istanbul.

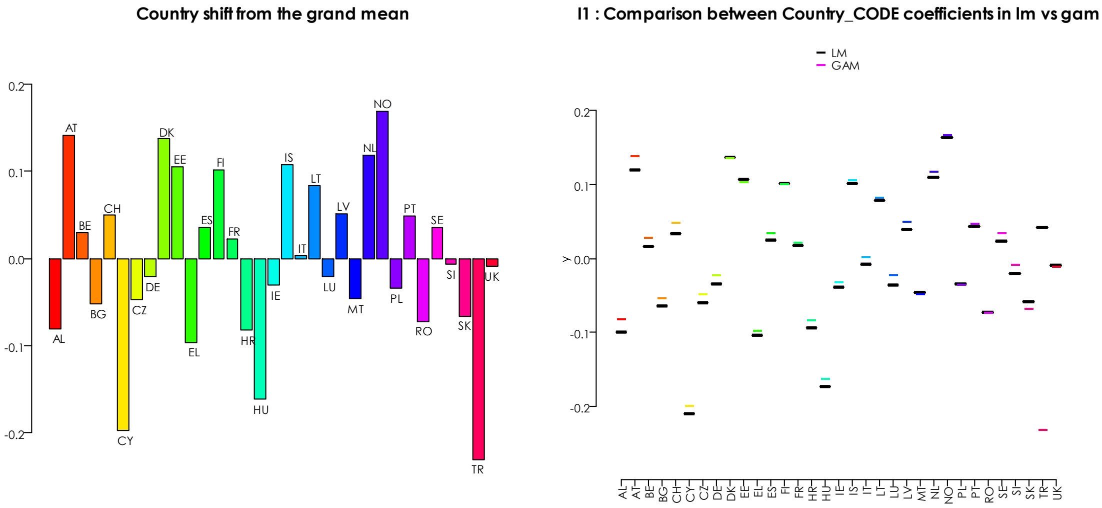


Figure 31: The country contributions estimated with the GAM, and the comparison with the LM results.

Univariate: GDPpc + Country_CODE

Linear Model

Moving to the investigation of the GDPPC, the same baseline model is attempted, with the $log_{10}GDPPC$ as numerical input variable, and the country as factor. Once again, the ANOVA summary in Table 20 and the model summary of Table 19, confirm the significance of all the coefficients, country-related too. Also, the residual plots seem to confirm the statistical significance of the model (see Figure 32)

```
Formula: y ~ log10(GDPPC)+ Country_CODE

Residuals:

      Min        1Q    Median        3Q       Max

-0.290475 -0.072823 -0.005998  0.073672  0.296496

Coefficients:

                 Estimate Std. Error t value Pr(>|t|)

(Intercept)    -0.264403   0.209834  -1.260  0.20898

log10(GDPPC)    0.156114   0.047548   3.283  0.00119 **

Country_CODE1   0.004806   0.117007   0.041  0.96727

Country_CODE2   0.086585   0.066538   1.301  0.19452

Country_CODE3  -0.024922   0.039686  -0.628  0.53067

Country_CODE4   0.015163   0.049611   0.306  0.76017

Country_CODE5  -0.047756   0.068740  -0.695  0.48795

Country_CODE6  -0.229475   0.056449  -4.065 6.67e-05 ***

Country_CODE7  -0.034928   0.035636  -0.980  0.32810

Country_CODE8  -0.066778   0.034823  -1.918  0.05644 .

Country_CODE9   0.079860   0.059256   1.348  0.17913

Country_CODE10  0.102080   0.042314   2.412  0.01666 *

Country_CODE11 -0.088998   0.043886  -2.028  0.04377 *

Country_CODE12  0.042364   0.028646   1.479  0.14059

Country_CODE13  0.078536   0.044585   1.761  0.07954 .

Country_CODE14  0.007574   0.028543   0.265  0.79097

Country_CODE15 -0.068465   0.048554  -1.410  0.15992

Country_CODE16 -0.108650   0.052803  -2.058  0.04080 *

Country_CODE17 -0.094694   0.048276  -1.962  0.05107 .

Country_CODE18  0.006738   0.066555   0.101  0.91945

Country_CODE19 -0.001963   0.026274  -0.075  0.94052

Country_CODE20  0.114848   0.065563   1.752  0.08121 .

Country_CODE21 -0.159232   0.083986  -1.896  0.05927 .

Country_CODE22  0.062710   0.050863   1.233  0.21892

Country_CODE23 -0.034689   0.079241  -0.438  0.66199

Country_CODE24  0.098638   0.038626   2.554  0.01133 *

Country_CODE25  0.108802   0.068181   1.596  0.11197

Country_CODE26  0.020366   0.033617   0.606  0.54526

Country_CODE27  0.051058   0.037216   1.372  0.17147

Country_CODE28 -0.012647   0.042439  -0.298  0.76598

Country_CODE29 -0.023245   0.036393  -0.639  0.52366

Country_CODE30 -0.029810   0.046563  -0.640  0.52270

Country_CODE31 -0.078726   0.039773  -1.979  0.04901 *

Country_CODE32  0.238813   0.112426   2.124  0.03477 *

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘
’ 1

Residual standard error: 0.1148 on 221 degrees of freedom

Multiple R-squared:  0.3582,Adjusted R-squared:  0.2623

F-statistic: 3.737 on 33 and 221 DF,  p-value: 2.323e-09

Shapiro-Wilk normality test

data:  lm_temp$residuals

W = 0.99634, p-value = 0.8203
```

Table 19: Summary table of the results of the LM in the GDPPC case, produced with the help of R software.

```
               Df Sum Sq Mean Sq  F value    Pr(>F)

(Intercept)     1  45.58   45.58 3461.101  < 2e-16 ***

Country_CODE   32   1.48    0.05    3.517 1.92e-08 ***

log10(GDPPC)    1   0.14    0.14   10.780  0.00119 **

Residuals     221   2.91    0.01
```

Table 20: ANOVA table of the GDPPC linear model.

At a first sight given to Figure 33, the positive dependence between the GDPPC and the indicator stands out. Thus, on average, the higher the gross domestic product per capita, the larger the index value. Furthermore, by deepening a little the analysis, a similar reasoning to the one done for the population model can be built.

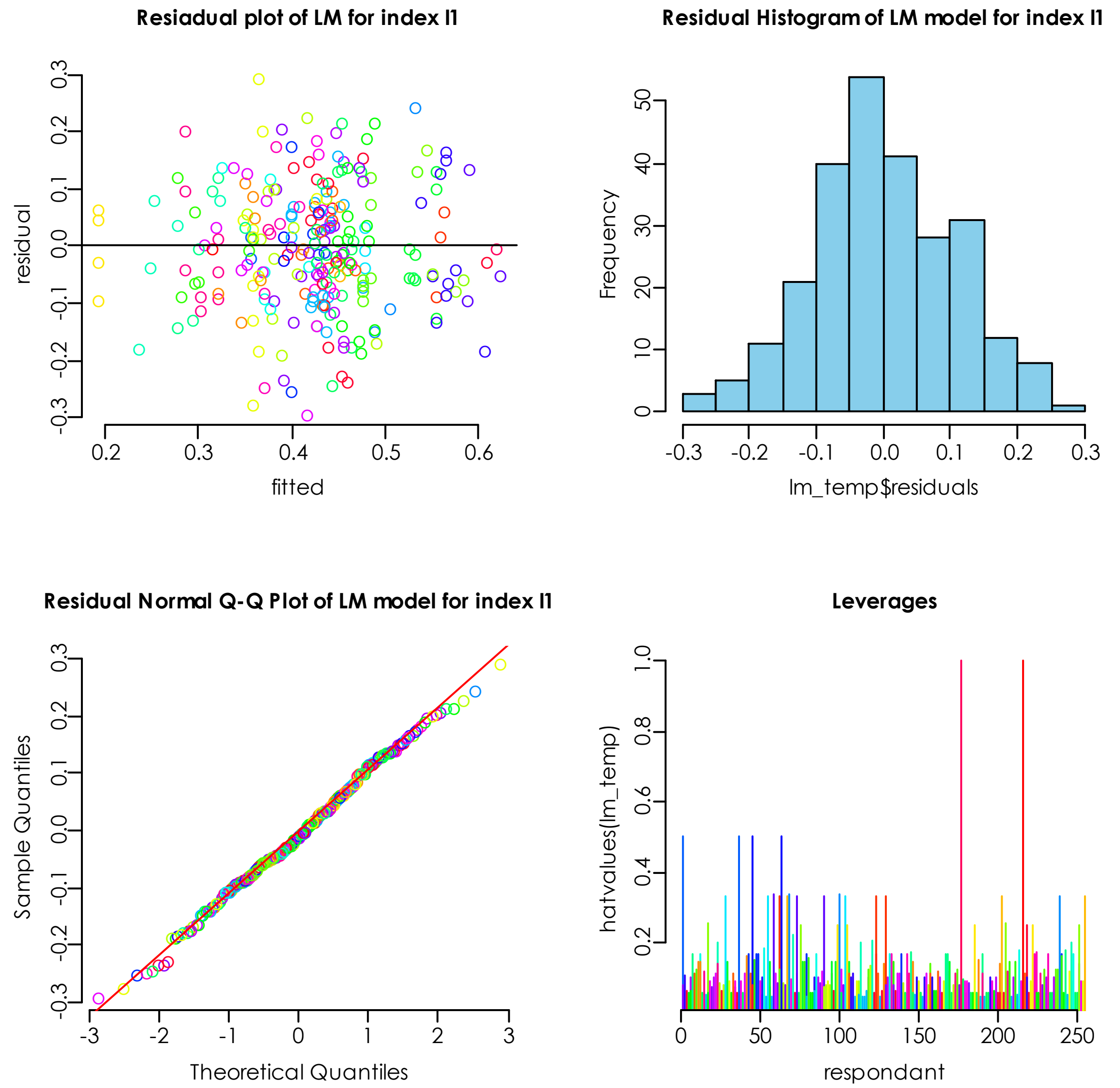


Figure 32: Analysis of the residuals of the LM with GDPPC, via typical plots. Error! Reference source not found.

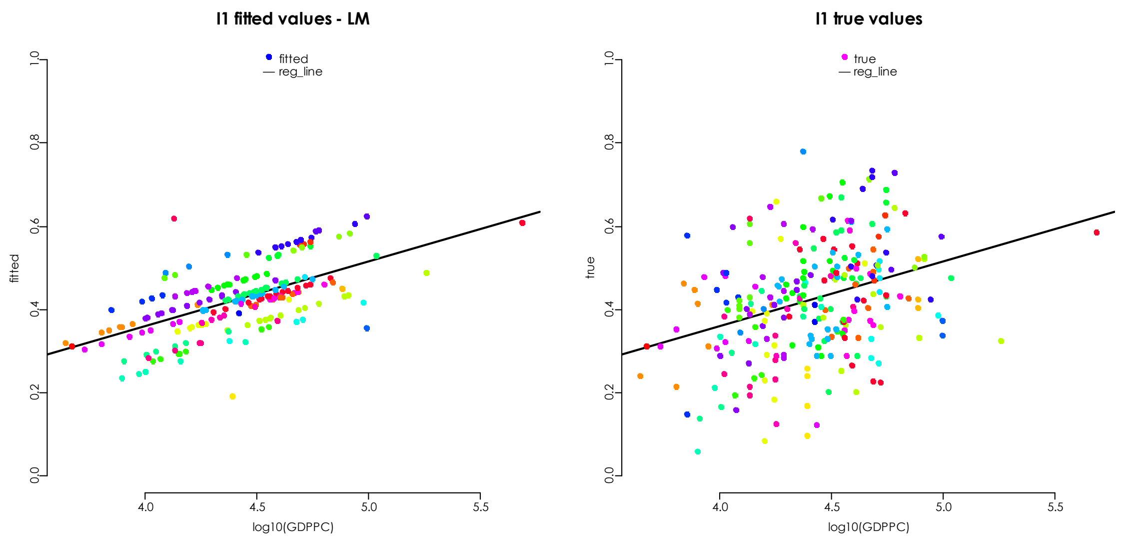


Figure 33: Scatter-plots of fitted values (left) and true values (right) of I1 versus the logarithm of the GDPPC; the straight line is the estimated regression line.

The linear model is able to reproduce a fraction of the total variability of the data around 26%. So, once again, every city can be partially described by a contribution proper to the country, and for the largest part, by a behaviour depending only on itself, the so-called city-effect. As mentioned above, the country contribution is not to be ignored, rather it gives an interesting insight on average behaviours, that can also be compared with the ones retrieved in the previous population model (cfr., Figure 34).

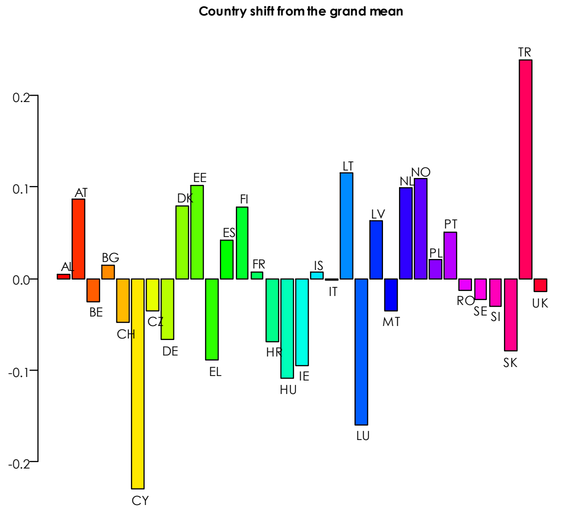


Figure 34: The country contributions estimated according to the GDPPC-based regression.

Generalised Additive Models

The results of the nonlinear additive model produced by considering the country factor (forced to be linearly modelled) and the GDPPC as inputs are here presented. The first plot shows the estimated smooth curve of dependence between GDPPC and I1 (Figure 35), while Figure 36 contains the estimated curves plotted on a logarithmic scale, and the usual scatter plots of fitted and true values.

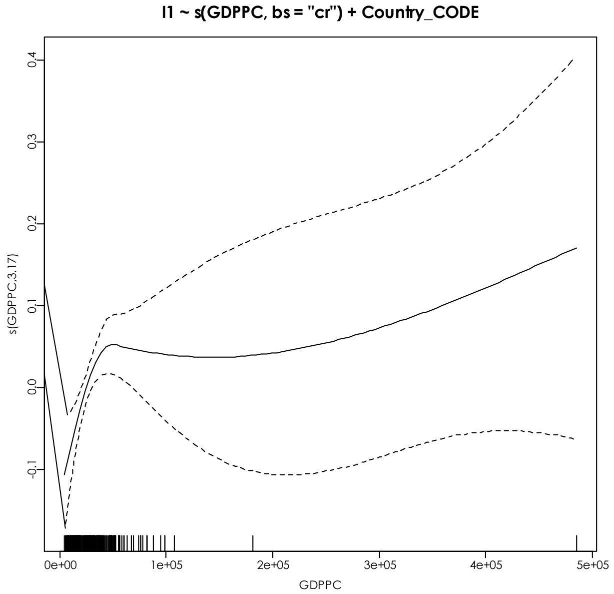


Figure 35: The smooth GAM curve of I1 as a function of GDPPC.

```
y ~ s(GDPPC, bs = "cr") + Country_CODE
Parametric coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     0.428120   0.009910  43.203  < 2e-16 ***
Country_CODE1  -0.009683   0.116045  -0.083   0.9336
Country_CODE2   0.077419   0.067368   1.149   0.2517
Country_CODE3  -0.037785   0.040739  -0.927   0.3547
Country_CODE4   0.014290   0.049736   0.287   0.7741
Country_CODE5  -0.023378   0.070038  -0.334   0.7389
Country_CODE6  -0.235824   0.057218  -4.121 5.34e-05 ***
Country_CODE7  -0.031561   0.036367  -0.868   0.3864
Country_CODE8  -0.065384   0.035163  -1.859   0.0643 .
Country_CODE9   0.085970   0.059843   1.437   0.1523
Country_CODE10  0.107943   0.042997   2.510   0.0128 *
Country_CODE11 -0.088430   0.044097  -2.005   0.0462 *
Country_CODE12  0.034760   0.030009   1.158   0.2480
Country_CODE13  0.065945   0.045584   1.447   0.1494
Country_CODE14 -0.002174   0.029502  -0.074   0.9413
Country_CODE15 -0.063598   0.049019  -1.297   0.1959
Country_CODE16 -0.106138   0.053015  -2.002   0.0465 *
Country_CODE17 -0.096977   0.048686  -1.992   0.0476 *
Country_CODE18 -0.002301   0.067395  -0.034   0.9728
Country_CODE19 -0.011319   0.027348  -0.414   0.6794
Country_CODE20  0.118362   0.065820   1.798   0.0735 .
Country_CODE21 -0.112905   0.087920  -1.284   0.2004
Country_CODE22  0.067841   0.051553   1.316   0.1896
Country_CODE23 -0.043590   0.079699  -0.547   0.5850
Country_CODE24  0.088823   0.039740   2.235   0.0264 *
Country_CODE25  0.125616   0.069042   1.819   0.0702 .
Country_CODE26  0.022605   0.034168   0.662   0.5089
Country_CODE27  0.054245   0.038130   1.423   0.1563
Country_CODE28 -0.010333   0.042810  -0.241   0.8095
Country_CODE29 -0.038983   0.037992  -1.026   0.3060
Country_CODE30 -0.031734   0.047214  -0.672   0.5022
Country_CODE31 -0.075156   0.040243  -1.868   0.0632 .
Country_CODE32  0.247060   0.112455   2.197   0.0291 *
UK    ---      -0.023626
Approximate significance of smooth terms:
           edf Ref.df     F p-value
s(GDPPC) 3.17   3.67 3.442  0.0119 *
---
R-sq.(adj) =  0.268   Deviance explained = 36.9%
GCV = 0.015236  Scale est. = 0.013075  n = 255
Shapiro-Wilk normality test
data:  gam_temp$residuals
W = 0.99706, p-value = 0.9233
```

Table 21: Summary table of the results of the GAM in the population case, produced with the help of R software.

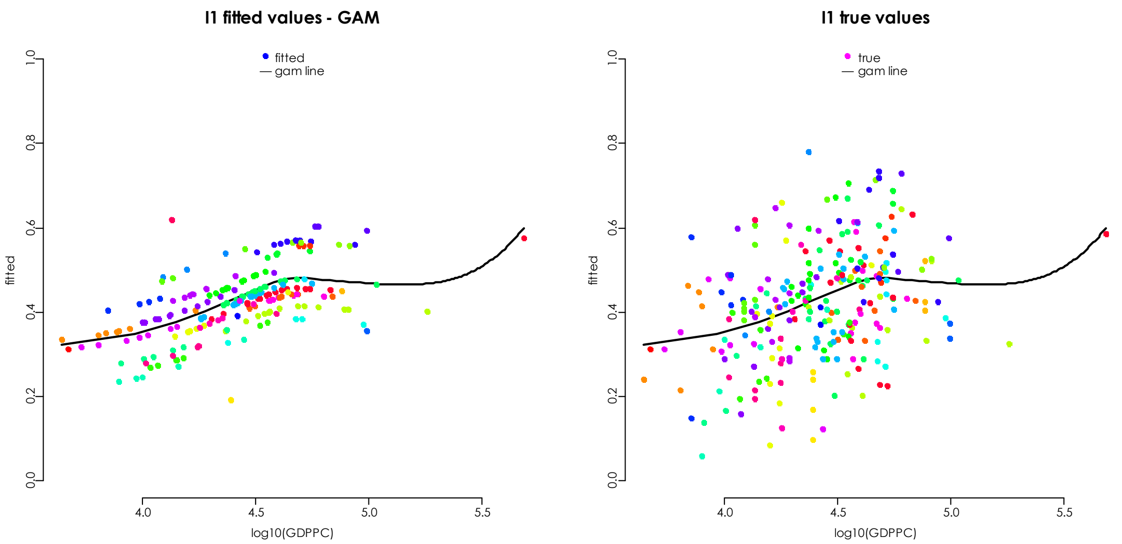


Figure 36 : Scatter-plots of fitted values (left) and true values (right) of I1 versus the logarithm of the GDPPC, and the estimated GAM regression curves.

Up to almost a GDP of 100 000€ per capita, the index grows in a logarithmic way, then it reaches a sort of plateau until the very extreme values on the right of the axis. The next plots (Figure 37) show again the contribution of the country factor in the nonlinear model and its comparison with the results obtained in the linear one. In this case the coefficients are very similar, between GAM and LM. The absence of relevant discordances is a source of confirmation of the importance of the country factor.

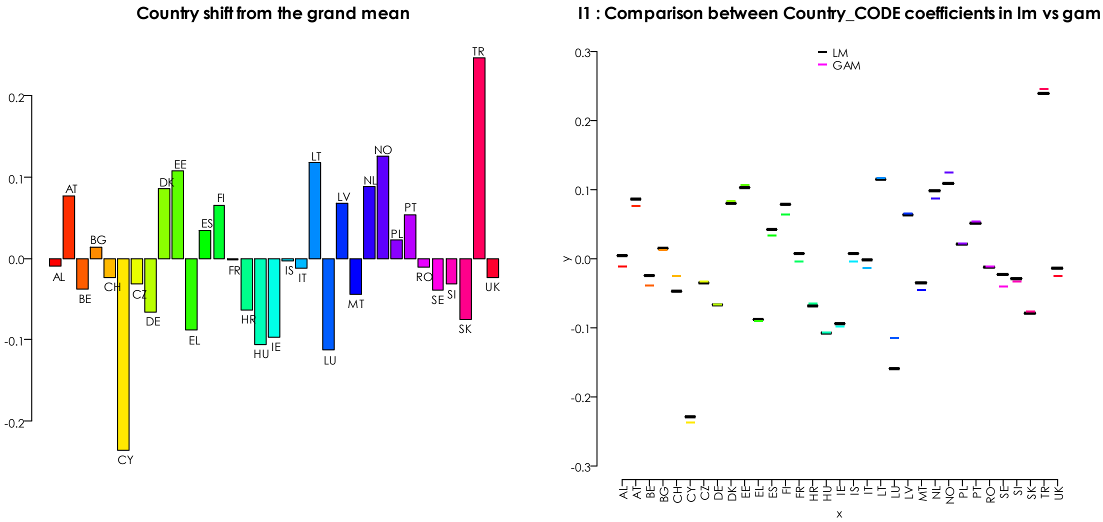


Figure 37: The country contributions estimated according to the GDPPC-based regression with the GAM, and the comparison with the LM coefficients.

Interactions: POP + POP:Network + GDPpc + GDPpc:Network + Network

At this stage, the inference analysis makes use of a slightly more sophisticated technique. It is implemented a multiple regression model that admits the interaction between some covariates (both population and GDPPC), and sees the country factor replaced by the dummy “the city belongs to at least one network of cities”, which for simplicity is referred to as Network. The goal is to understand if European network of cities positively impact the performances of their cities. The distributions of the data according to the Network dummy seem to behave quite differently, as it can be perceived in Figure 38.

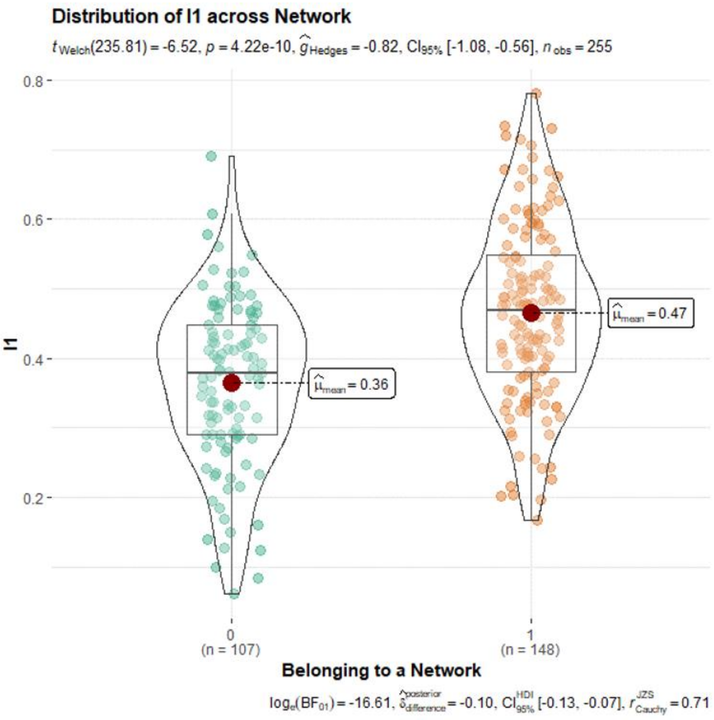


Figure 38: The distributions of I1 values according to Network, with the summaries provided by boxplots and violin plots.

Linear Model

In this section, quite a general formulation is taken into account to model the index, to give the most complete description possible, namely the numerical terms are included both interacting and not interacting with Network. In the following, the modelling equation and the summary in Table 5:

$$I1 \sim Network + \log_{10} POP + \log_{10} GDPPC + log_{10}POP{:}\,Network + \log_{10} GDPPC : Network$$

```
y ~ Network + log10(POP) + log10(GDPPC) + log10(GDPPC):Network + Network:log10(POP)
Residuals:
     Min       1Q   Median       3Q      Max
-0.34734 -0.08397  0.00677  0.07518  0.30499

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -0.073963   0.201272  -0.367   0.7136
Network              -0.231170   0.257800  -0.897   0.3707
log10(POP)           -0.003134   0.024863  -0.126   0.8998
log10(GDPPC)          0.104619   0.042634   2.454   0.0148 *
Network:log10(GDPPC) -0.011411   0.055081  -0.207   0.8360
Network:log10(POP)    0.068047   0.032037   2.124   0.0347 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1178 on 249 degrees of freedom
Multiple R-squared:  0.2376,     Adjusted R-squared:  0.2223
F-statistic: 15.52 on 5 and 249 DF,  p-value: 2.756e-13
```

```
Shapiro-Wilk normality test
data:  lm_temp$residuals
W = 0.99733, p-value = 0.9501
```

Table 22: Summary table of the linear model with interactions.

Looking at the end of the reported summary, it can be noticed that the percentage of explained variance in this more complex model is around 22.23%, lower than the one achieved in the univariate simpler models with one numeric regressor (either population or GDPPC) and the factor variable "Country_CODE". A possible explanation of this gap of at least 4 percentage points relies on the country contributions. In particular, including both GDPPC and population plus the new variable Network, and allowing for interactions, this current model can be considered quite complex and thorough, yet it does not achieve the same performance of much simpler models. There surely are sorts of redundancies (a certain degree of correlation bonds the POP and GDPPC variables), but the absent player is indeed the country factor, which, following this line of thoughts, must be considered as a game changer. There is a portion of variability of the indicator, a shade of its behaviour, that is only captured by such a structured variable. So once again, the relevance of an explanatory variable at a higher level than the city level is confirmed. At this point is time to deeply analyse the latest model, to reach an understanding of the coefficient values, and to do so one can take a look at the set of plots below. Firstly, a few comments on the coefficients found from the linear modelling: the most relevant and influential ones are the GDPPC and the interaction between the network and the population, both reporting a positive dependence of the index with the regressor considered. On the other hand, the network dummy, the population and eventually the GDPPC-network interaction are not significant from a statistical point of view. In particular, the latter two are also very small in magnitude – note that all these three coefficients are negative, so as the input variable grows, the index decreases (much more slowly).

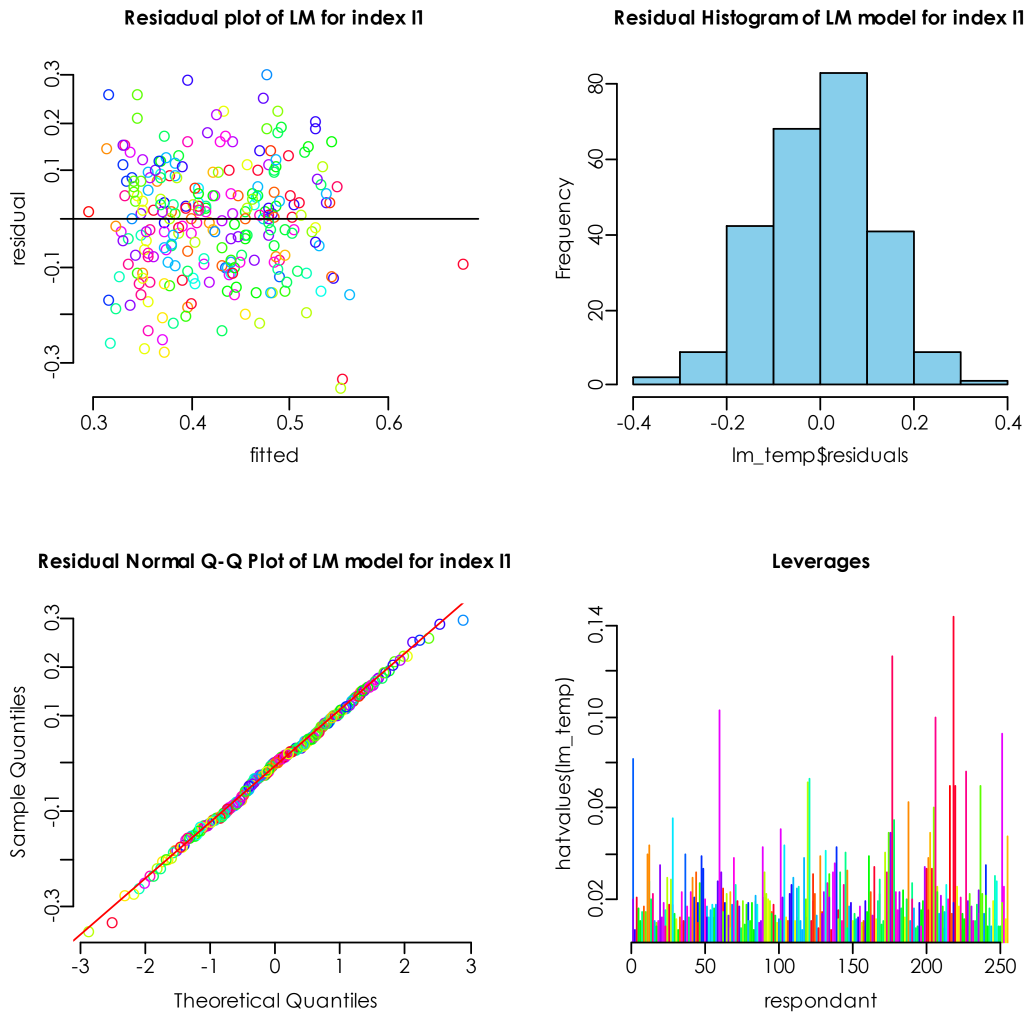


Figure 39: Analysis of the residuals of the interaction LM with network, via typical plots.

Case by case, the behaviour of the regression lines added to the following scatter plots will be discussed, paying attention to their direction, which is a direct effect of the combination of sign and intensity of the estimated regression coefficients. An initial note regards the blue line reported in these boxes. It is not exactly the computed regression line from the complete model, but the estimated line by letting only POP vary, and fixing all the other input parameters, namely the Network and the GDPPC. For start, the focus is addressed to the cities inside a network, as Figure 40 shows. In this case, the GDPPC value is fixed at its average, with the average taken on only the cities in a network. The regression curve in this scenario is the following:

$$I1 \sim \beta_0 + \beta_{Net} + (\beta_{POP} + \beta_{POP:Net}) \cdot \log_{10} POP + (\beta_{GDPPC} + \beta_{GDPPC:Net}) \cdot \log_{10} GDPPC \qquad (1)$$

which becomes, substituting the estimated coefficients and under the assumptions made above:

$$\widehat{I1} = -0.0740 - 0.2312 + (-0.0031 + 0.0680) \cdot \log_{10} POP + (0.1046 - 0.0114) \cdot \log_{10}\left(\overline{GDPPC}_{Net}\right).$$

The plots clearly highlight the main features noticeable in the formula (see Figure 40): the dependence between $log_{10}\, POP$ and the indicator I1 is positive. Despite the intercept is downshifted because of -0.2312 from network, the fact that all the cities inside networks have larger values of POP implies that the overall distribution of data, both of the true and the fitted values, is placed upper on the y-axis than the one of no-network cities (cfr.,Figure 41).

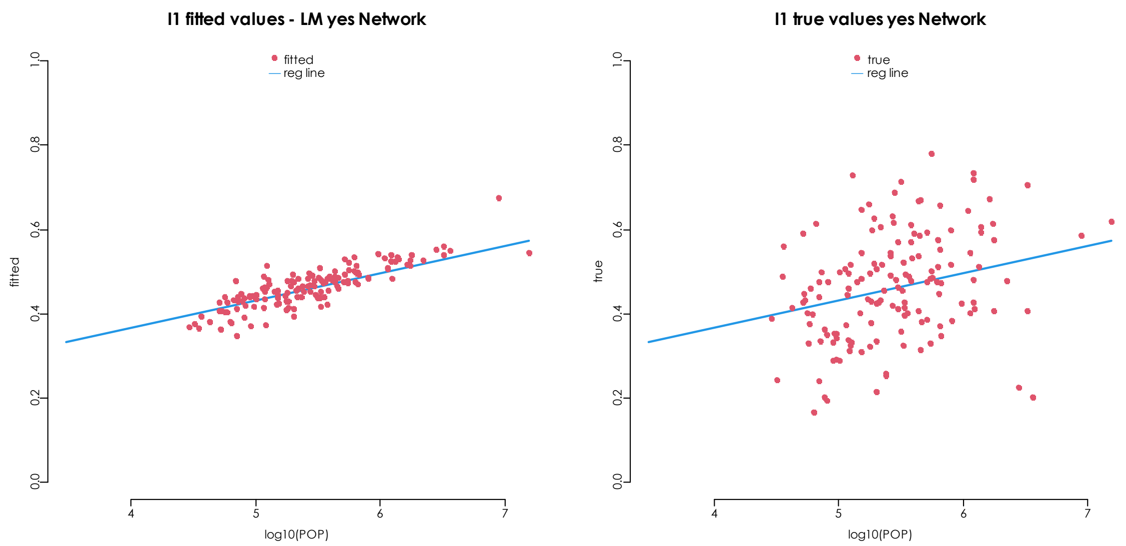


Figure 40: In-Network cities: regression line and scatter plots of estimated and true values.

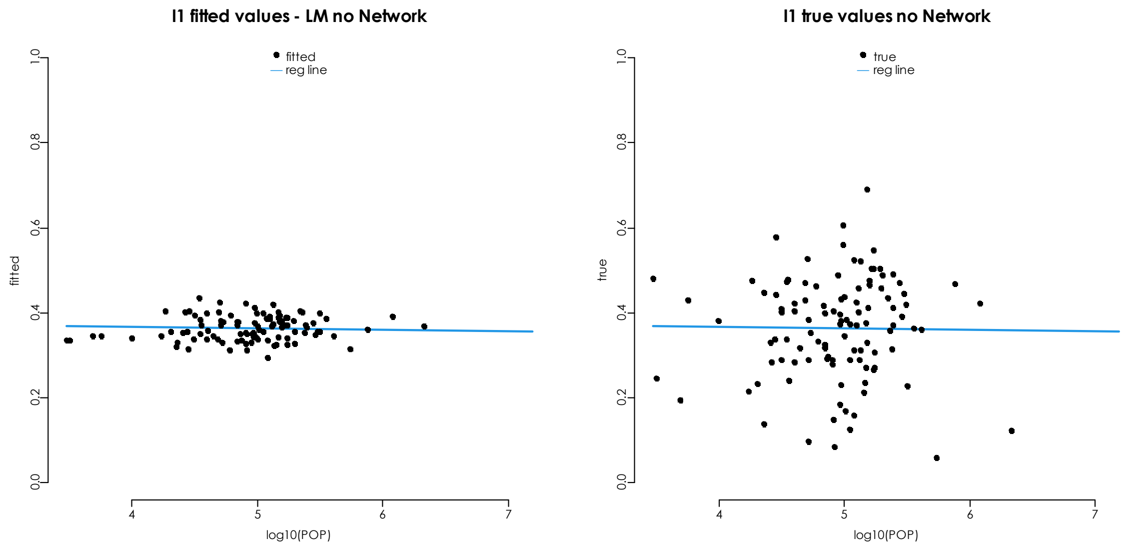


Figure 41: Out-of-Network cities: regression line and scatter plots of estimated and true values.

On the other hand, the cities outside any network manifest a substantially different behaviour with respect to the population. The slope of the regression line is imperceptibly negative, so being outside a network means that the dimension of a city in terms of number of inhabitants, does not affect the performances in the Digital Service Innovation Maturity measured by I1. Similarly, the formula that holds for such model is:

$$I1 \sim \beta_0 + \beta_{POP} * log_{10}\, POP + \beta_{GDPPC} * log_{10}\, GDPPC \qquad (2)$$

$$\widehat{I1} = -0.0740 - 0.0031 \cdot \log_{10} \overline{POP}_{Net} + 0.1046 \cdot \log_{10} GDPPC$$

Changing the perspective by letting vary GDPPC and fixing POP at its “yes-network” average value, the dependence of I1 on the independent variable (*x*-axis) is positive, but in this case the distribution of the points does not part evidently from the one of “no-network” observations. Therefore, differently from what has just been observed in the POP-regression, the Network variable does not separate the observations depending on its value (see the right plots of the following two pictures), and therefore the contribution of GDPPC can be fairly considered independent on Network. This statement is further confirmed by the lack of significance of the interaction coefficient “GDPPC:Network”.

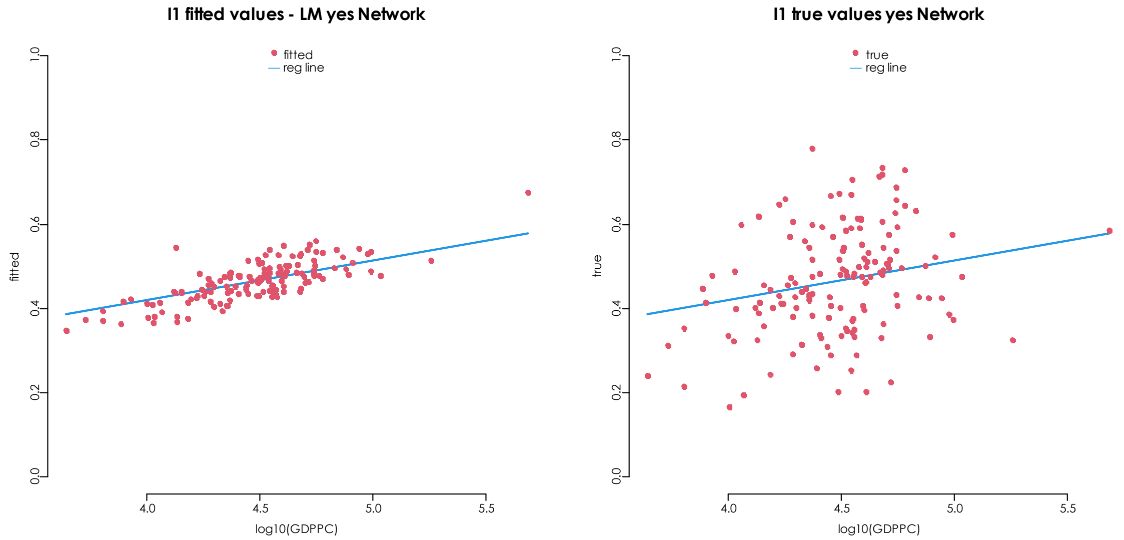


Figure 42: In-Network cities: regression line and scatter plots of estimated and true values.

To conclude, the graphical representation of the fitted values of the cities outside any network deserves a note: the black dots are almost attached to the regression line (see Figure 43). This fact is a reflection of the microscopic coefficient associated to the $log_{10}\,POP$ term. Conversely, the plot in the above Figure 26, referred to in-network cities, is characterised by a positive and much larger coefficient associated to the population, due to the presence of the interaction term. As a result, the population effect is more evident and the fitted values are pushed much away from the blue line. To conclude, both population and GDPPC are positively correlated with I1, and in addition, there is an interesting relation between population and network.

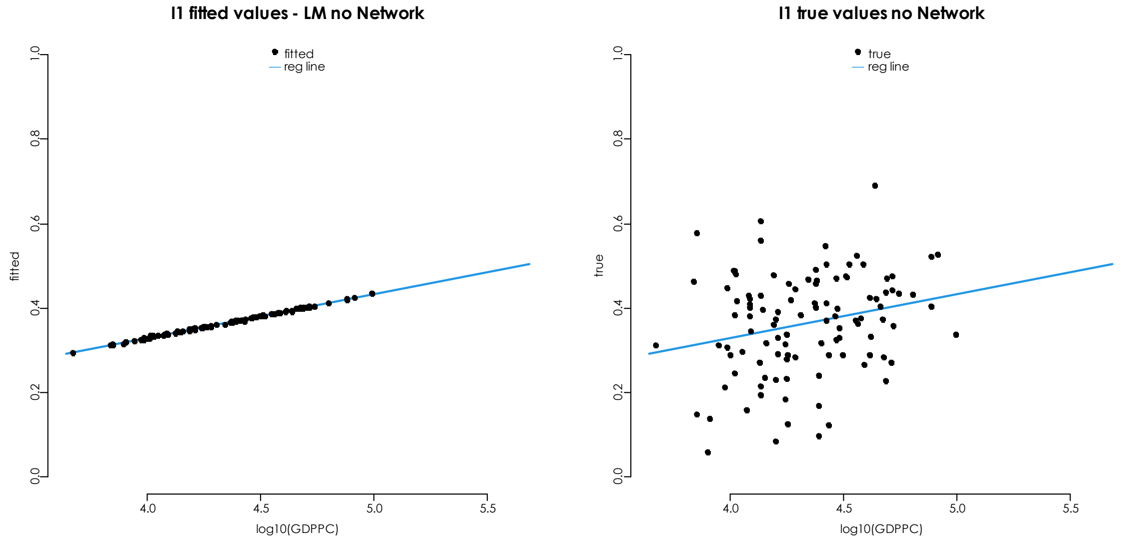


Figure 43: Out-of-Network cities: regression line and scatter plots of estimated and true values

Generalised Additive Models

```
Formula:
y ~ s(POP, bs = "cr") + Network + s(GDPPC, bs = "cr") + s(I(POP * Network), bs = "cr") + s(I(GDPPC * Network), bs = "cr")
Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.35166    0.08057   4.364 1.91e-05 ***
Network      0.12257    0.13830   0.886    0.376
---
Approximate significance of smooth terms:
                        edf Ref.df     F p-value
s(POP)                4.939  5.690 1.764  0.0996 .
s(GDPPC)              1.000  1.000 5.448  0.0204 *
s(I(POP * Network))   8.084  8.589 1.903  0.0497 *
s(I(GDPPC * Network)) 3.508  4.032 4.204  0.0025 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R-sq.(adj) =  0.299   Deviance explained = 35.1%
GCV = 0.013546  Scale est. = 0.012508  n = 255
Shapiro-Wilk normality test
data:  gam_temp$residuals
W = 0.99374, p-value = 0.3683
```

Table 23: Summary table of the interaction GAM.

The GAM approach suggests a slightly different perspective, possibly more accurate, since not only it can account for a distinction in the slope, caused by the Network variable, but also a allows for completely different shapes of the functions. In fact, a part from the pure GDPPC additive term which is estimated to be linear, all the others are associated to different smooths. As a result, this modelling strategy rewards the statistician with an increase of the percentage of explained variability: from the 22% of the linear model, to the current 30%. First of all, the results of the out-of-network sample are investigated: the smooth curve below, shows an oscillating behaviour, the index grows along with the population, for cities up to 250 000 inhabitants, then there is a decrease of the same proportion up to 500 000, and again a rise and then a fall, but more delicate. This plot (Figure 45), compared with the one from the linear model, which estimated a behaviour independent of the population, delivers a more accurate result, unveiling what is behind it.

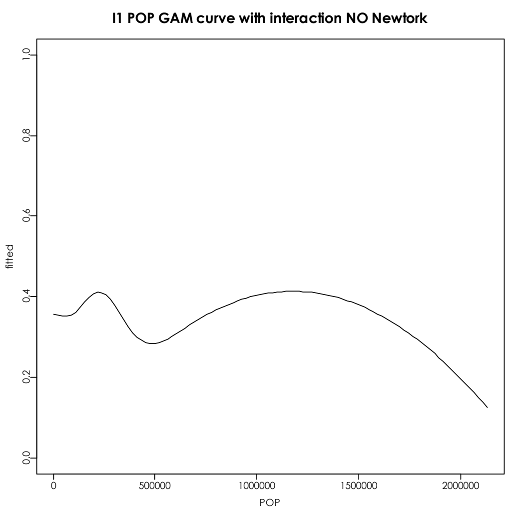


Figure 44: Out-of-Network cities: GAM regression line vs population.

The two scatter plots of Figure 45 represent the distribution of the fitted valued by the GAM (on the left) and of the true values of I1.

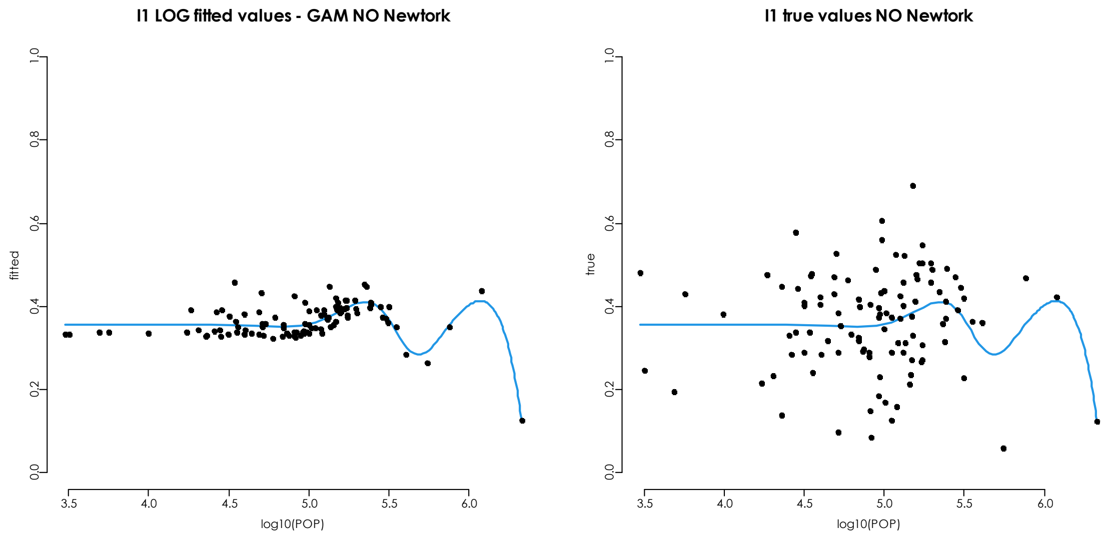


Figure 45: Out-of-Network cities: regression line and scatter plots of estimated and true values.

Moving to inside-network cities (cfr.,

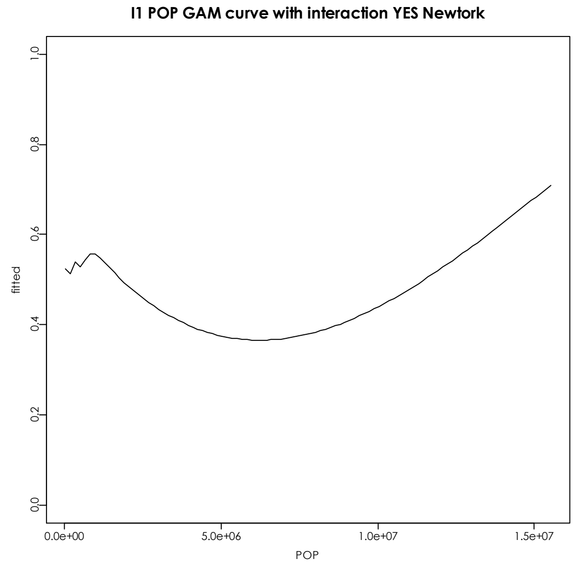


Figure 46 and Figure 47), the curve grows up to 1 million of inhabitants, and only after that there is a decrease, before a final ascent. Therefore, these cities are much more positively influenced by the growth of inhabitants, than those outside networks. A note, the final growing behaviour can be recorded thanks to the presence of a higher number of bigger cities inside networks than outside. However, looking at the left plot below, an underestimation of the index values, especially in correspondence of small values of population.

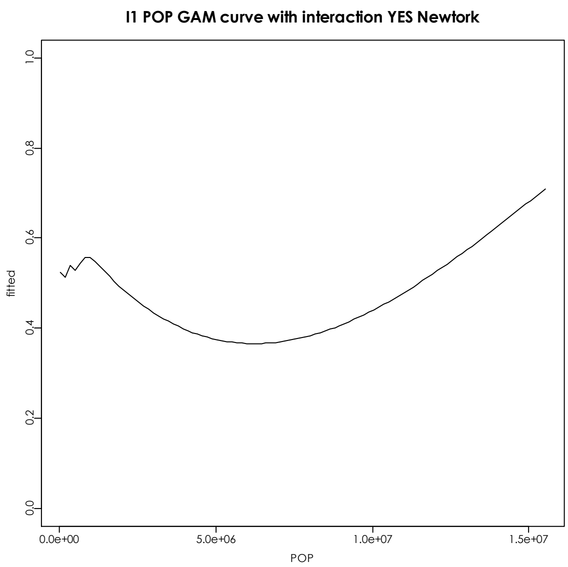


Figure 46: In-Network cities: GAM regression line vs population.

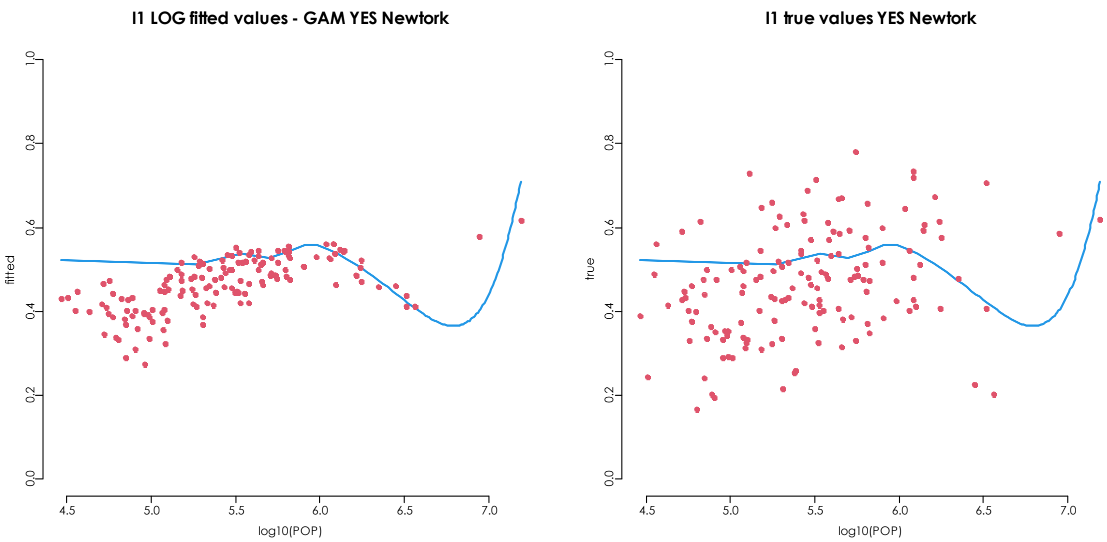


Figure 47: In-Network cities: regression line and scatter plots of estimated and true value.

When the focus is addressed to the relation between the gross domestic product per capita and the indicator I1, a positive, very light, linear dependence is found (cfr., Figure 49). Thus, as the GDPPC grows, a very small increase in perceivable in the indicator, in perfect agreement with the results obtained with the linear model. Conversely, the distribution of the fitted values is different from before, more spread around the estimated regression curve, rather than almost attached to it (see Figure 43). The reason lies in the dependence between population and I1 in out-network cities: that curve is neither linear nor horizontal, so it adds a source of variability that was almost absent in the linear modelling previously proposed.

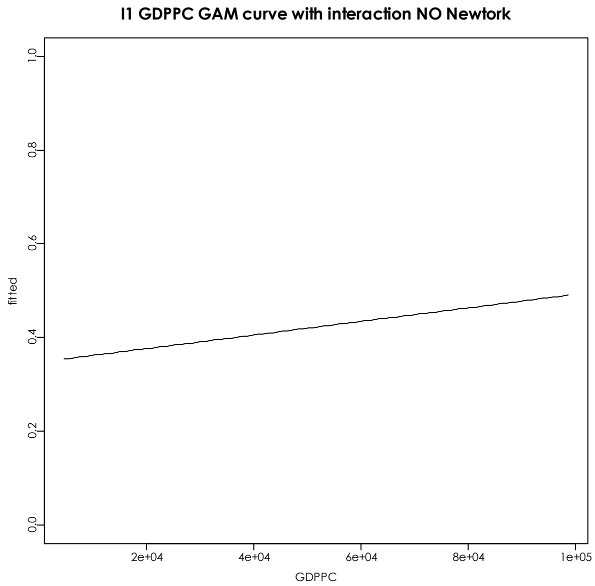


Figure 48: Out-of-Network cities: GAM regression line vs GDPPC.

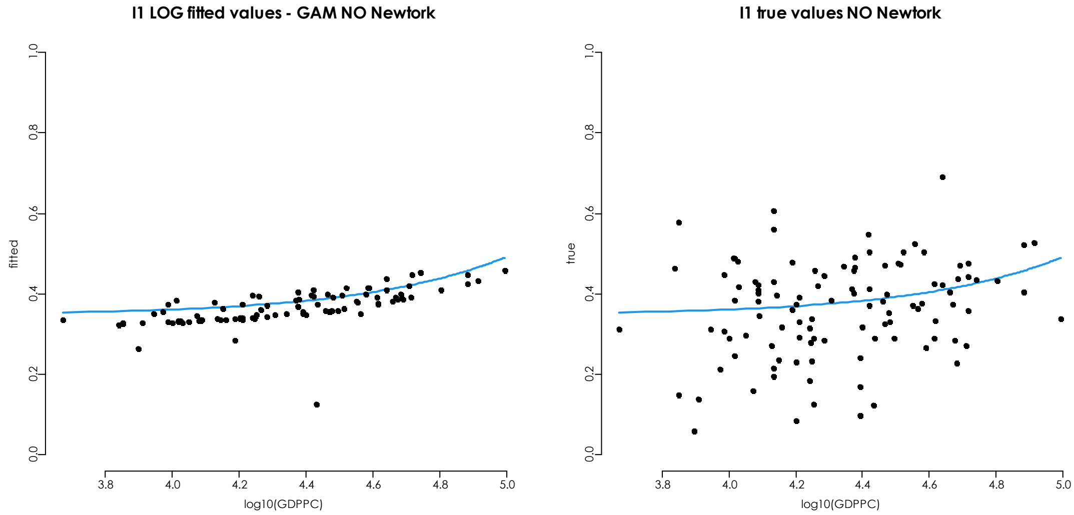
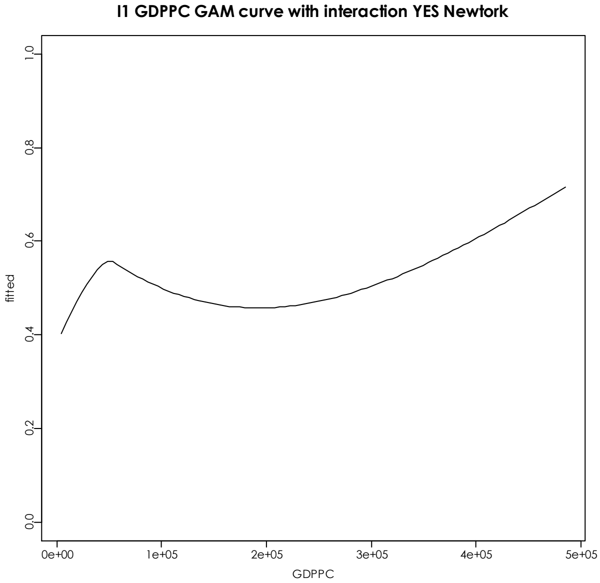


Figure 49: Out-of-Network cities: GAM regression line and scatter plots vs GDPPC

At a first sight, looking at Figure 51, the cities inside a network show, on average, a better performance all along the distribution of the GDPPC, than those outside any network. However, even if also in this case one can say that the GDPPC is a positively correlated variable with the indicator, evidently the trend is more visible for the poorer cities. However, after the initial steep ascent, for smaller amounts than 100 000€, there seems to be a inversion of tendency, before a final rise. Needless to say, this final rise is fitted on a very limited amount of data, therefore the uncertainty about the estimated curve in that interval is huge.

Figure 50: In-Network cities: GAM regression line vs GDPPC



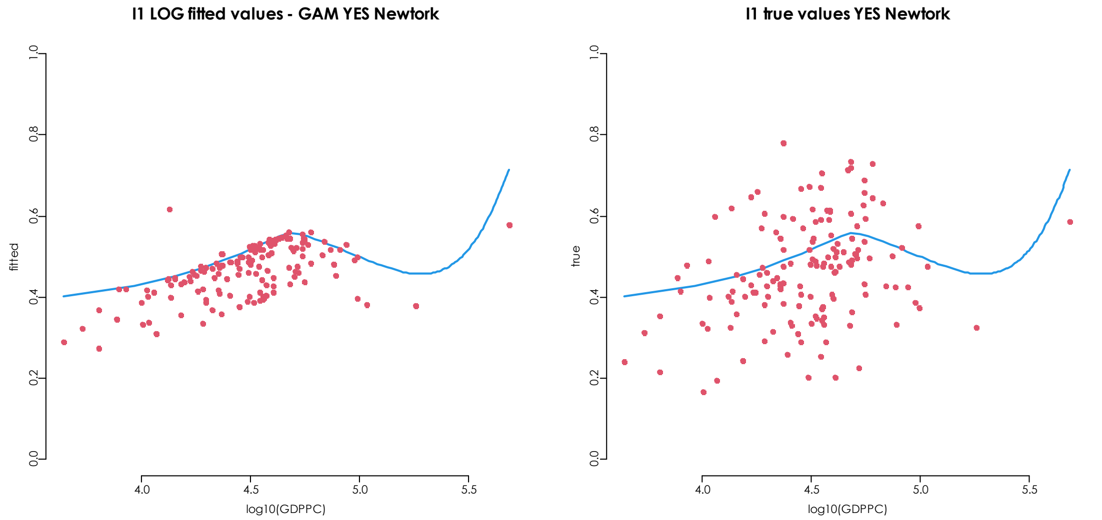


Figure 51: In-Network cities: GAM regression line and scatter plots vs GDPPC

To sum up, the generalised additive models provide more accurate results, because of their nature, but in many cases the liner model remain a valuable option. In fact, there are not significant performance drops by using them, and moreover there are well known by many stakeholders, therefore they can be better understood from the public. However, from a purely statistical and modelling point of view, the additional value brought by the GAM should be taken into consideration. Upon a limited cost of admitting non linear smooth functions for each regressor, finer results are obtained, especially in those regions for which there is scarcity of observations. The overall analysis on these external variables is satisfying, in the sense that the statistical results are solid and significant, and many interesting insights are achieved on the data. First of all, it is once again stressed that the country is a relevant factor: it provides a diversification not negligible. A unified European reality cannot be identified, for what concerns both the level of digital service maturity. On the other hand, belonging to a European network of cities can be a decisive added value. As a consequence, one way to improve the performance of cities in digital innovation may be to involve them inside these networks. Finally, the evidences collected about population and GDPPC can be summarised in the following way: in general a positive dependence is observed, but in a localised interval of values. As population and GDPPC approach higher and higher values, the measured performance does not grow perpetually. On the contrary, it is typically observed a phase of saturation of the performance, especially for the population. This behaviour is indeed not surprising. Intuitively, larger cities may need to be managed in a smarter way, and richer cities could and have more resources to invest in digitization. Yet it is reasonable that the major changes happen between administrating 100 000 inhabitants and 1 000 000 and not from, for example one million to 5 million. The result regarding the richest cities can be a starting point to develop a research in this matter, to understand if there might be some room of improvement, and in case, why it has not been filled yet.

References

Albury, D. (2005). Fostering Innovation in Public Services. *Public Money & Management 25 (1)*, 51-56.

Argyris, C., & Schön, D. A. (1978). *Organizational learning: a theory of action perspective.* Massachusetts: Addison-Wesley Pub. Co.

Avgerou, C. (2000). IT and organizational change: an institutionalist perspective. *Information Technology & People 13 (4)*, 234-262.

Avritzer, L., & Boaventura de Sousa, S. (2005). Opening Up the Canon of Democracy. In B. d. Santos, *Democratizing democracy: beyond the liberal democratic canon.* London: Verso.

Bateson, G. (1973). *Steps to an Ecology of Mind: Collected Essays in Anthropology, Psychiatry, Evolution and Epistemology.* London: Jason Aronson Inc.

Bogost, I. (2007). *Persuasive Games: The Expressive Power of Videogames.* The MIT Press.

Bugge, M. M., Fevolden, A. M., & Klitkou, A. (2019). Governance for system optimization and system change: The case of urban waste. *Research Policy 48 (4)*, 1076-1090.

Campbell, T. (2012). *Beyond Smart Cities. How Cities Network, Learn and Innovate.* Abingdon: Earthscan.

Chilvers, J., Pallett, H., & Hargreaves, T. (2018). Ecologies of participation in socio-technical change: The case of energy system transitions. *Energy Research & Social Science 42*, 199-210.

Concilio, G., & Molinari, F. (2019). The unexploitable smartness of open data. *Paper presented at the Annual Aesop Conference. Venice 9-13 July*.

Concilio, G., & Pucci, P. (2021 furthercoming). The data shake: an opportunity for experiment driven policy making. In G. Concilio, P. Pucci, L. Raes, & G. Mareels, *The Data Shake. Opportunities and obstacles for urban policy making.* Springer International Publishing - PoliMI SpringerBriefs.

Concilio, G., Pucci, P., & Raes, L. (2021). *The Data Shake. Opportunities and obstacles for urban policy making.* Springer International Publishing - PoliMI SpringerBriefs.

Deserti, A., & Rizzo, F. (2019). Embedding Design in the Organisational Culture: Challenges and Perspectives. In M. N.-C. Guy Julier, *Design Culture Objects and Approaches* (pp. 39-51). London: Bloomsbury.

Deterding, S., O'Hara, K., Sicart, M., & Nacke, L. (2011). Gamification: Using Game Design. Elements in Non-Gaming Contexts. *Extended Abstracts on Human Factors in Computing Systems*, 2425-2428.

Economist Intelligence Unit. (2010). *ICT for City Management. Using information and communications technology to enable, engage and empower city stakeholders.* Singapore: The Economist Intelligence Unit.

Edquist, C., & Zabala-Iturriagagoitia, J. M. (2015). Pre-commercial procurement: A demand or supply policy instrument in relation to innovation? *R& D Management 45(2)*, 147-160.

Elliott, I. C. (2020). Organisational learning and change in a public sector context. *Teaching Public Administration 38 (3)*, 270-283.

Emaldi, M., Aguilera, U., López-de-Ipiña, D., & Pérez-Velasco, J. (2017). Towards Citizen Co-Created Public Service Apps. *Sensors (Basel) 17 (6)*, 1265.

Engelbart, D. C. (2002). *Improving our Ability to Improve: A call for investment in a new future.* Singapore: World Library Summit.

European Commission. (2018, May 08). *European Commission.* Retrieved from Mission-oriented research and innovation. Inventory and characterisation of initiatives: final report: https://op.europa.eu/en/publication-detail/-/publication/3b46ce3f-5338-11e8-be1d-01aa75ed71a1/language-en

European Commission. (2020, September 14). *European Commission.* Retrieved from A multi-dimensional framework to evaluate the innovation potential of digital public services. A step towards building an innovative public services observatory in the EU: https://op.europa.eu/es/publication-detail/-/publication/cd56ca1d-f6fc-11ea-991b-01aa75ed71a1

European Commission. (2021, January). *DESI - Digital Economy and Society Index*. Retrieved from European Commission: https://ec.europa.eu/digital-single-market/en/digital-economy-and-society-index-desi

European Commission. (2021, January). *Digital Economy and Society Index (DESI) 2019*. Retrieved from European Commission: https://ec.europa.eu/digital-single-market/en/news/digital-economy-and-society-index-desi-2019

Eurostat. (2021, January). *Category: Regions and cities glossary*. Retrieved from Eurostat statistics explained: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Category:Regions_and_cities_glossary

Faro, B., Babak, A., & Cetindamar, D. (2019). Continuous Transformation of Public-sector Organisations in the Digital Era. *American Conference on Information Systems.*

Fernandez, S., & Rainey, H. G. (2006). Managing Successful Organizational Change in the Public Sector. *Public administration review 66 (2)*, 168-176.

Ferro, E., Caroleo, B., Leo, M., Osella, M., & Pautasso, E. (2013). The Role of ICT in Smart Cities Governance. In P. Parycek, & N. Edelmann, *Conference Proceedings: CeDEM13 Conference for E-Democracy and Open Government.* Edition Donau-Universität Krems.

Fung, A. (2006). Varieties of Participation in Complex Governance. *Public Administration Review 66 (s1)*, 66-75.

Geels, F. W. (2020). Micro-foundations of the multi-level perspective on socio-technical transitions: Developing a multi-dimensional model of agency through crossovers between social constructivism, evolutionary economics and neo-institutional theory. *Technological Forecasting and Social Change 152, 119894*.

Geels, F. W., & Schot, J. (2007). Typology of sociotechnical transition pathways. *Research Policy 36 (3)*, 399-417.

Gupta, J. (2016). Climate change governance: history, future, and triple-loop learning? *Wiley Interdisciplinary Reviews: Climate Change, 7(2)*, 192-210.

Hastie, T. & Tibshirani, R, (1986) Generalized Additive Models, Statistical Science, 1, pp. 297–310.

Hansen, M. T., & Birkinshaw, J. (2007). The innovation value chain. *Harv Bus Rev 85 (6)*, 121-30, 142.

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization 28 (1)*, 52-61.

Huotari, K., & Hamari, J. (2012). Defining gamification: a service marketing perspective. *12: Proceeding of the 16th International Academic MindTrek Conference*, (pp. 17-22).

Ibarra, P. (2007). Participación y poder : de la legitimación al conflicto. *Democracia participativa y desarrollo humano*, 33-53.

Johannessen, Å., & Wamsler, C. (2017). What does resilience mean for urban water services? *Ecology and Society 22 (1)*.

Kahane, A. (2007). *Solving Tough Problems: An Open Way of Talking, Listening, and Creating New Realities.* Berrett-Koehler Publishers.

Kemp, R., & Loorbach, D. (2006). Transition Management: A Reflexive Governance Approach. *Reflexive Governance for Sustainable Development, Cheltenham, UK and Northampton, MA, USA: Edward Elgar*.

Krogstie, J. (2006). Citizens, from consumers to prosumers: e-Government Services typologies revisited. *Workshop at Nordichi 2006: User involvement and representation in eGovernment Projects.*

Loorbach, D. (2010). Transition Management for Sustainable Development: A Prescriptive, Complexity-Based Governance Framework. *Governance Int. J. Policy Adm. Inst. 23*, 161-183.

Loorbach, D., & Rotmans, J. (2010). The practice of transition management: Examples and lessons from four distinct cases. *Futures 42 (3)*, 237-246.

Manzini, E. (2014). Making Things Happen: Social Innovation and Design. *Design Issues 30 (1)*, 57-66.

Mazzucato, M. (2018a). Mission-Oriented Innovation Policy: Challenges and Opportunities. *Industrial and Corporate Change, 27 (5)*, 803-815.

Mazzucato, M. (2018b). *Mission-Oriented Research & Innovation in the European Union. A problem-solving approach to fuel innovation-led growth.* Brussels: European Commission. Directorate-General for Research and Innovation.

Miedzinski, M., Mazzucato, M., & Ekins, P. (2019). A framework for mission-oriented innovation policy roadmapping for the SDGs: The case of plastic-free oceans. *UCL Institute for Innovation and Public Purpose, Working Paper Series (IIPP WP 2019-03)*.

Moore, M.-L., & Riddell, D. J. (2015). Scaling out, Scaling up, Scaling deep: Advancing systemic social innovation and the learning processes to support it. *Journal of Corporate Citizenship 58*.

OECD. (2017). *Government at a Glance 2017.* Paris: OECD Publishing.

OECD. (2019). *Government at a Glance 2019.* Paris: OECD Publishing.

Omann, I., Kammerlander, M., Jäger, J., Bisaro, A., & Tàbara, J. D. (2019). Assessing opportunities for scaling out, up and deep of win-win solutions for a sustainable world. *Climatic Change 160*, 753-767.

Plesner, U., Justesen, L., & Glerup, C. (2018). The transformation of work in digitized public sector organizations. *Journal of Organizational Change Management 31 (5)*, 1176-1190.

Poole, M. S., & Ven, A. H. (2004). *Handbook of Organizational Change and Innovation.* Oxford University Press.

Rammel, C., Hinterberger, F., & Bechthold, U. (2004). Govern-ing Sustainable Development. A Co-evolutionaryPerspective on Transitions and Change. *GoSD workingpaper 1*.

Rothbauer, P. M. (2008). Triangulation. *The SAGE Encyclopedia of Qualitative Research Methods*, 893-895.

Schein E. H. (1985) Organizational Culture and Leadership. Jossey-Bass Publishers, San Francisco

Sestini, F. (2012). Collective Awareness Platforms: Engines for Sustainability and Ethics. *IEEE Technology and Society Magazine 31*, 54-62.

Shove, E., Pantzar, M., & Watson, M. (2012). *The Dynamics of Social Practice: Everyday Life and How It Changes.* London: SAGE Publications Ltd.

Sinek, S. (2009). *Start with Why: How Great Leaders Inspire Everyone to Take Action.* Penguin Publishing Group.

Sintomer, Y., Röcke, A., & Herzberg, C. (2016). *Participatory Budgeting in Europe: Democracy and Public Governance.* Routledge.

Stacey, R. D. (2007). *Strategic Management and Organisational Dynamics: The Challenge of Complexity to Ways of Thinking about Organisations.* Pearson Education.

Stafford-Smith, M., Griggs, D., Gaffney, O., Ullah, F., Reyers, B., Kanie, N., . . . O'Connell, D. (2017). Integration: the key to implementing the Sustainable Development Goals. *Sustainability Science 12*, 911-919.

UNDP. (2015). *Public Administration Reform Practice Note.* UNDP.

Voet, J. V., Kuipers, B. S., & Groeneveld, S. (2016). Implementing Change in Public Organizations: The relationship between leadership and affective commitment to change in a public sector context. *Public Management Review 18 (6)*, 842-865.

Walravens, N., Ballon, P., Compernolle, M. V., & Borghys, K. (2021 forthcoming). Data ownership and open data: the potential for data-driven policy making. *G Concilio, P Pucci, L Raes*.

Welby, B. (2019). The impact of digital government on citizen well-being. *OECD Working Papers on Public Governance, No. 32, OECD Publishing, Paris*.

Wyatt, S. (2017). Making Policies for Open Data: Experiencing the Technological Imperative in the Policy World. *Science, Technology, & Human Values 42 (2)*, 320-324.

Zichermann, G., & Cunningham, C. (2011). *Gamification by Design: Implementing Game Mechanics in Web and Mobile Apps.* O'Reilly Media, Inc.

Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

espon.eu

ESPON 2021

ESPON EGTC
11 Avenue John F. Kennedy
L-1855 Luxembourg - Kirchberg
Grand Duchy of Luxembourg
Phone: +352 20 600 280
Email: info@espon.eu
www.espon.eu

The ESPON EGTC is the Single Beneficiary of the ESPON 2020 Cooperation Programme. The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States, the United Kingdom and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.