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Tentative Governance of Artificial Intelligence Regulation. Representing governance as a virtual network of documents.

Bilel Benbouzid, Lionel Villard, Philippe Larédo, Euan Adie

The paper wishes to test our ability to use quantitative methods to track emerging arrangements in the governance of artificial intelligence regulation. We position the paper in the conceptual approach proposed by Kuhlmann Stegmaier and Konrad (2018).

We see tentative governance as an encompassing approach that incorporates the different and complementary dimensions that have been highlighted about the reflexive, anticipatory, adaptive and distributive nature of governance arrangements. They also highlight the importance of experimental and exploratory approaches to governance setting, that often requires 'a balancing act' between centralized and decentralized approaches, top-down and bottom-up initiatives. In a practice-oriented view of processes, we consider the main results arrived at by Rip and colleagues about 'de facto' governance of nanotechnologies (see for a review, Rip, 2018): its distributive character, the constitutive role of bottom-up actions, strategies, and interactions; and a new pattern dealing with the internalization of requirements of "responsible development".

In this practice-oriented approach, work on AI governance has balanced and is still balancing between 3 main governance options: self-regulation with ethics principles guidelines focused on safety, transparence, fairness, responsibility and privacy; soft regulation linked to tools supporting AI regulation (testing, risk assessment, security standards dealing with robustness and explicability, certification of fairness); and hard regulation from rule of law.

In order to characterize the dynamics at work for Artificial intelligence, we delineate the "hybrid forum" (Callon & Rip, 1972) or "policy arena" or also "technological zone" (Barry, 2006) of the regulation of AI. For doing so we have taken web entities as representing actors and looked at their activity progressively building a map of hyperlinks that identifies 355 key nodes and 2695 links. This map integrates every place where positions confront each other, where irreversibilities are constructed and where market 'frameworks' are gradually being set; all different kind of actors contributing toward the formation of the rules of engagement that constitutes AI domains. In this presentation, we will show how we are building a dataset and then curating data on different actors, places and resulting networks of AI governance at worldwide level. Assembling content and citation network of heterogeneous documents from academia, policy consulting, legislative body, administration and business, we represent governance as a virtual network of documents, we analyze the hierarchical structures of the AI governance documents network and we show how co-citations and co-words analysis in heterogeneous document enable the mapping of knowledge network of strategic alliance actors.

The process of our research was as follows: In a map of hyperlinks, directions matter, and one striking phenomenon is that the EU appears as a core actor toward which many links are directed, while very few outgoing links can be observed. This has driven us to consider two complementary analysis based on a new publicly available source, OVERTON (https://www.overton.io) that gathers policy documents worldwide.

The first one is to analyse the sources that documents produced by the EU (and published by its publication office) mobilise: what types of documents (and in particular what academic science) and what key actors. We make there 3 hypotheses: (a) references to academic science are fragmented (many actors with limited influence); (b) there is a central role of a limited number of key 'mediating' actors (with probably a central role of thinktanks), and (c) the resources mobilised differ depending upon the theme addressed and the actor within the EC (for instance different DGs). We shall use the CORTEXT semantic tool to address this issue.

The second one is to look at the 'policy' production of the actors identified in our hyperlink map, and take advantage of one of the very important characteristics of Overton, that is to follow the use that is made of these documents in other policy documents that can be characterized by the actors that produce the latter. This will enable us to establish a 'network of influences' and the 'policy shaping' role of the producers identified in the hyperlink map. One central hypothesis lies in the central role of economic actors and think tanks located in the other side of the Atlantic.

We shall present the results of these 2 analyses and their implications for further analysing the 'de facto' proposals for governance arrangements.

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Recruiting personnel for AI related jobs - the Effects on Operating Revenue and Productivity

Asta Bäck[1], Arash Hajikhani[1], Angela Jäger[2], Torben Schubert[2,3], Arho Suominen[1]

[1]VTT, Finland

[2]Fraunhofer Institute for Systems and Innovation Research ISI, Germany

[3]CIRCLE - Centre for Innovation Research, Lund University, Sweden

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Introduction

The use of digital technologies has revolutionized the ways of doing business for many firms and economic sectors (Brynjolfsson et al. 2018, Gal et al. 2019), with initial evidence showing that the adoption of ICT-related technologies can contribute to explaining differential developments in economic performance and productivity (van Ark 2015). Yet, in particular for artificial intelligence (AI) as one the most advanced uses of ICT, results are largely theoretical (Acemoglu and Restrepo 2018, Gries and Naudé, 2018) while empirical support is absent. That gap is clearly due to the lack of firm-level data on the use and adoption of AI-related technologies.

Job advertisements open a view on the skills required by the labour market at any given time. In this paper, we analyzed the job advertisements of Oikotie Oy's Job Advertisement service, one of the two leading commercial job advertisement services in Finland.In this paper, we look at the rate of AI adoption and the impact of AI adoption in Finnish firms by exploiting unique data on their job openings in 2016 obtained from a dominant Finnish job advertisement platform. This study aims to show an approach of deriving novel metrics from raw data to inform the impact digital and artificial intelligence skills have on the economy. We match this data to economic performance measures including productivity in 2019, which we collect from the ORBIS database. Our regression results based on a total of 605 firms show that AI-related job opened robustly and strongly increase the level of revenues and productivity.

Job data

The job ads dataset extends from 2013 to 2020 and contains 480,000 job advertisements. This period and particularly its second half were a period of growth in the number of job vacancies. The largest number of job advertisements in the dataset, slightly over 90,000, was in 2019. The most significant growth in the yearly number of jobs, over 20,000 jobs, occurred in 2017. The brisk growth also continued in 2018. For GDP, 2017 was also the period of rapid growth during the period considered; since then, annual growth has been lower.

The dataset includes full details of the job advertisement, created by the job poster, such as job titles, job descriptions and information of which company had posted the ad. The most significant challenge with the data is the use of recruitment agencies without identifying actual recruiting company.

Artificial Intelligence glossary

To identify job ads looking for AI related skills, we developed a three-tier glossary of terms and concepts describing AI. The glossary was build using publications where AI terminology and taxonomy were explained (Aristodemou et al. 2018; Brunette et al. 2009). Additionally, terms were picked from Stack Overflow survey results 2020[1], and from Wikipedia AI glossary[2]. Because the terms were of different levels of abstraction and specificity, the vocabulary was defined consisting of three tiers:

- Tier 1: Main general terms referring to AI (i.e., artificial intelligence, machine learning).
- Tier 2: Core technologies associated to AI (i.e., NLTK, Decision tree)
- Tier 3: Technologies that support or enhance AI solutions but not direct AI core technologies (i.e., Cloud, Database, Matlab)

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[1] Annual survey from software developers conducted by Stack overflow community: https://insights.stackoverflow.com/survey/2020

[2] https://en.wikipedia.org/wiki/Glossary_of_artificial_intelligence

The terms were defined in two languages (Finnish and English); many acronyms and product names were used as such in both languages and needed no translation.

The terms were searched in job titles and descriptions. Each job advertisement was linked to only one tier by starting from Tier 1, even though it might have had terms from Tiers 2 or 3. As a quality check, we assessed the job titles of the resulting dataset to check their relevance, and some ads were removed based on this before the analysis.

Joined data set for analyses

The data on AI-related job advertisements can be complemented with information from ORBIS data. ORBIS provides data on operational turnover as well as the number of employees, thereby also providing an approximate measure of the company's productivity. In this match, 999 firms are initially identified. After checking the data availability in the ORBIS data, the final data set contains information of 605 firms for further analysis including financial information in 2019 as well as information on whether a company has published AI related job ads in 2016 referring to AI in specific terms as used to identify tier 1 ads.

The final dataset for assessing the impact of AI recruitment on productivity consists of 23 percent of large firms with 500 or more employees, 14 percent of larger medium sized firms with 250 to 499 employees, 24 percent of smaller medium sized firms with 100 to 249 employees and 28 percent of small firms with less than 50 employees. The sectors covered range from agriculture to transportation. The data consists of 26 percent of firms active in the information and communication sector, 15 percent manufacturers, 15 percent service providers of professional, scientific and technical services, 8 percent of firms offering private or public administrative services, and 36 percent of firms of all other sectors as financial service providers, education, trade. The data selection was driven by the availability of the main information in the ORBIS.

In order to assess the impact of recruiting AI related personnel on financial performance in terms of operating revenue and gross productivity, a time gap of three years is implemented. For the identification of the effects of recruiting AI related personnel on financial performance, we run heteroscedasticity-robust linear regressions of the firms' operating revenue resp. productivity measured as revenue per employee in 2019 on number of AI related job offers in 2016. We control for sector affiliation and firm size measured as number of employees. We take the log of the explained variables in order to avoid issues resulting from limited dependent nature of operating revenues and productivity.

Results and interpretation

The job data gives us the opportunity to get an overview of the development of the AI skills demand. Additionally, the joined data allows analysing the impact of the search for AI related competences on the firms' productivity. Thereby, the focus lies on the most recent data with the financial information of 2019 and the AI job ads in 2016.

First, looking at the occurrence of specifically AI related jobs (tier 1), the data suggest that it was still rarely needed in 2016. Out of all 605 firms, 92 percent did not open any specifically AI related jobs (tier 1). The remaining 8 percent of firms having opened AI related jobs had approximately 1.7 vacancies in 2016. Half of these firms published only one vacancy, 16 percent of them published 3, 4 or 5 AI related jobs in 2016. The demand for AI related competences does not differ considerably among the sectors. In manufacturing, around 9 percent of firms offered AI related jobs, in contrast to 4 percent of administrative firms; however, no significant difference is observable. In contrast, this demand for AI specialists is heavily related to firm size. Whereas smaller firms with less than 50 employees rarely put an offer out (3 percent), a considerable share of larger firms with 250 or more employees (14 percent) were looking for these kind of competences.

Secondly, the main results of the multiple analyses of the relation between of AI job ads in 2016 and performance in 2019 are displayed in Table 1. The first four models test the effects on operating revenues in 2019. The following four models test the effects on productivity (operating revenues per employees) in 2019. Model 1 and 5 provide a base line of the industrial context documenting on the one hand that both constructs depend somehow on firm size. On the other hand, it shows that firms of the manufacturing have higher operating revenues as well as a higher revenue per employee. Based on the information of firm size and sector affiliation around 54 percent of the variance of the revenues can be explained by the model, whereas only 2.6 percent of the variance of the productivity is explained.

In the other models, we include measures capturing the opening AI jobs three years prior: first taking into account the number of jobs offered (Models 2 and 6), secondly checking the type of impact by using categorical variables differentiating between one job offered or more (Model 3 and 7). Thirdly, we test whether the positive impact differ related firms size (Model 4 and 8). In general, we find significant coefficients for the AI Job offer measures with respect to the revenue as well as productivity. However, for productivity, the amount of jobs offered is not important but rather the fact having searched for AI competences itself counts. Regarding the revenues, the result is confirmed that more job offers are related to higher revenues three years later. Looking at these correlations for different firm sizes by controlling for the moderating effect of firm size, we find that for small firms, engagement in AI capabilities is neither related to turnover nor productivity. The moderating effects for small firms clearly counterbalance the negative effect of the absence of AI job offers; in terms of productivity, small firms are even more productive if they had not undertaken any such step. Medium-sized and larger firms, on the contrary, show higher productivity if they invested in AI skills. Finally, we find that in comparison to the baseline model including information on AI-related jobs, the explanatory power increases slightly while the impact of the context variables does nearly not change. The highest effect on productivity is linked to the sector, i.e. the market these firms are operating in.

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Table 1: Main regression results (linear regression, robust standard errors)

	Log(Operating revenues in 2019)				Log(Productivity 2019)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of AI related job offers		0.567***				0.202**		
		(0.145)				(0.0897)		
One AI related job offered (1)			0.927***				0.406*	
			(0.331)				(0.220)	
More than one AI related job offered (1)			1.248***				0.454*	
			(0.403)				(0.247)	
No AI related job offers (2)				-1.209***				-0.338*
				(0.337)				(0.190)
Interaction: No offer x small firm				1.215*				0.726**
				(0.621)				(0.362)
No offer x medium sized firm				0.0146				-0.675
				(0.624)				(0.445)
Smaller firms (<50 employees) (3)	-4.268***	-4.145***	-4.152***	-5.324***	-0.307**	-0.264*	-0.263*	-0.975***
	(0.185)	(0.185)	(0.186)	(0.591)	(0.152)	(0.155)	(0.155)	(0.328)
Medium sized firms (50-249 employees) (3)	-2.106***	-2.003***	-2.014***	-2.021***	-0.0621	-0.0253	-0.0267	0.612
	(0.161)	(0.160)	(0.160)	(0.602)	(0.140)	(0.142)	(0.142)	(0.422)
Manufacturing (C) (4)	0.926***	0.962***	0.956***	0.955***	0.507***	0.519***	0.515***	0.520***
	(0.178)	(0.172)	(0.176)	(0.175)	(0.116)	(0.117)	(0.118)	(0.118)
Professional, scientific and technical services (M) (4)	-0.0774	-0.0588	-0.0857	-0.0881	0.0300	0.0367	0.0239	0.0192
	(0.144)	(0.142)	(0.141)	(0.141)	(0.108)	(0.108)	(0.106)	(0.104)
Administrative and support services; Public administration and defence; etc. (N O) (4)	-0.448*	-0.378	-0.398	-0.380	-0.332	-0.307	-0.316	-0.292
	(0.247)	(0.244)	(0.244)	(0.245)	(0.208)	(0.208)	(0.209)	(0.209)
Other sectors (A to S) (4)	0.176	0.217	0.201	0.212	0.134	0.149	0.143	0.149
	(0.180)	(0.180)	(0.180)	(0.181)	(0.155)	(0.155)	(0.156)	(0.156)
Constant	11.89***	11.73***	11.74***	12.93***	5.128***	5.069***	5.069***	5.413***
	(0.141)	(0.145)	(0.144)	(0.333)	(0.112)	(0.117)	(0.117)	(0.184)
Observations	605	605	605	605	605	605	605	605
Adj. R2	0.537	0.550	0.549	0.549	0.0258	0.0296	0.0287	0.0322

Coeff., robust SE in parentheses - Reference groups: (1) No AI related job offered in 2016, (2) AI related job offered in 2016, (3) Larger firm (4) Sector: J Information and communication, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Title:
Evaluating Policy Mix Characteristics with Text-based Metrics: The Case of Electric Mobility

Authors: Lindsay Mai, Asli Ates, Karoline Rogge
Affiliation: Science Policy Research Unit, University of Sussex

Relevance and core research question

Recently, policy mix thinking has witnessed a growing interest, including calls for bridging conceptual and methodological approaches between policy studies and transition studies (Kern et al., 2019). Broader conceptualisations of innovation policy mixes for sustainability transitions, which differentiate between long-term policy strategies and corresponding instrument mixes (Rogge and Reichardt, 2016) have also integrated policy mix design insights by building on its early contributions on policy mix characteristics, such as consistency and coherence (Howlett and Rayner, 2007). However, relevant empirical research studies remain largely qualitative in nature (Reichardt & Rogge, 2016; Rogge, 2018), at a time when policy mixes for sustainability transitions become increasingly complex, linking across various governance and sectoral levels, implying that a lack of policy coordination may inhibit the acceleration of such transitions.

Meanwhile, the availability of machine learning techniques and their latest applications in policy studies have provided new venues of interpreting large and evolving volumes of policy texts which may help capturing this increasing complexity (e.g. Anastasopoulos et al 2020's topic modelling on budget narratives; Shaffer 2018's extraction of institutional design from legislative text). While it is promising to adopt these data-intensive applications to systematically assess policy mix characteristics, so far empirical applications have been limited. With this paper, we aim to close this gap by proposing and testing suitable data-intensive approaches to identify policy mix characteristics – specifically consistency, coherence and credibility – in emerging cross-sectoral fields with particular great degrees of uncertainty and complexity. In addition, based on publicly available policy and consultation documents we also suggest how to identify relevant actors active in such newly emerging STI policy subsystems. Our research question thus can be summarised into how data-intensive analytics can be harnessed to enhance our understanding of policy mixes in newly emerging, cross-sectoral policy fields.

Theoretical background

To overcome policy implementation quandary, scholars in policy studies and policy makers have become "increasingly aware that the real potential of a new policy instrument to improve policy outcomes lies not in its isolated application, but in the contribution it makes to an existing policy mix" (Howlett and Rayner, 2007: 1). This is particularly apparent in STI policies where there are often competing technological innovations (with their corresponding institutional logics) in response to the same policies. For instance, in the rollout of zero-emission vehicle mandate in California as a technology-forcing regulation since 1990s, there have been contests for resources, political supports, and consumer interests among different technological innovations, notably between battery-powered electric vehicles and fuel cell electric vehicles in the wider context of socio-technical system (Stokes and Breetz, 2018;

Trencher, 2020). The weaving of different policy instruments (such as subsidies for research and development, fuel standards, etc.) and strategies (namely state government plans in economic development and energy transitions) often interact with new policy instruments to shape the STI subsystem dynamics and lead to different trajectories of innovation development and thus transitions.

Policy mixes have been discussed in various streams of literatures. In policy design theories, policy mixes are understood as “complex arrangements of multiple goals and means which, in many cases, have developed incrementally over many years” (Kern and Howlett, 2009: 395). In innovation studies, Flanagan et al. (2011: 704) point out the focus on “trade-offs between policies as they impact upon the extent to which the ultimate intended goals or outcomes of innovation policy are realised, in a particular space and at a particular time”. In transition studies, policy mixes have been analytically defined as “combination of the three building blocks elements, processes and characteristics, which can be specified using different dimensions”, in which the ‘elements’ consist of policy strategies and instruments (or instrument mixes) whereas the different ‘dimensions’ range from policy fields, governance levels, geography, to time (Rogge & Reichardt, 2016: 1622; Rogge, 2018). Further theoretical discussions centre around what are the ‘characteristics’ of policy mixes and how these may influence their policy outcomes and socio-technical impacts; these ‘characteristics’ include consistency among instrument mixes and multiple policy objectives, coherence of policy processes, credibility of policies, as well as comprehensiveness of policy mix elements and the decision making processes (Howlett and Rayner, 2007; Rogge & Reichardt, 2016; Rogge, 2018).

Any policy making and implementation processes of policy mixes are carried out by policy actors and are influenced by state and non-state stakeholders. Arguably, the characteristics of policy mixes are resulting from competing governing resources related to authority, nodality, treasure and organisations (Howlett and Rayner, 2007), which are configured in (networks of) actors and become more complex when these are originating from different socio-technical systems. Existing theoretical perspectives to understand the role of actors in policy changes notably include, among others, the ‘advocacy coalition framework’ (ACF) (Weible, et al., 2011). The ACF concept of ‘belief systems’ of different coalitions in a policy subsystem may contribute to the analysis of policy mixes (Gomel & Rogge, 2020), for instance, rendering a more nuanced explanation on the consistency (or inconsistency of policy strategies and instruments. However, it remains largely unexplored how advocacy coalitions can serve to explain the dynamics of policy change in interconnecting policy subsystems (or socio-technical systems) in sustainability transitions. Conversely, the credibility of policy mixes could be investigated through the lens of power relations among actors, whose roles for sustainability transitions have been discussed in the context of a ‘multi-actor perspective’ (Avelino & Wittmayer, 2016). Such a focus on power relations among multiple actors could also help explain the consequential level of consistency among instrument mixes and between instruments and strategies.

System contexts, on the other hand, structure and condition the policy making and implementation processes of policy mixes. Rosenbloom (2020: 336) pointed out the “pressing need to generate more sustained interest in the dynamics occurring across rather than within (socio-technical) systems”, “as sustainability challenges and the transformative changes they necessitate stretch well beyond the boundaries of individual socio-technical systems”. The role and structuring of policy mixes are particularly prominent in cross-system contexts as there can be clashes or conflicts among pre-defined policy objectives, instrument designs following different system logics, and instrument interactions across policy or socio-technical (sub-)systems. To conceptualise multi-system dynamics, Raven (2007) began by articulating four types of multi-regime interactions, i.e. competition, symbiosis, integration, and spill-over. McMeekin et al. (2019) further suggested the idea of 'knock-on effects' of one (sub-)system to other (sub-)systems that create architectural changes at the system or regime level, whereas Rosenbloom (2019) illustrated changing positions of actors affiliated to the systems resulted from the symbiotic and competitive patterns of cross-system interactions. However, there have been few studies looking into how policy mixes are affected by or are contributing to the increasingly interconnecting multi-system context.

Research case

We investigate our research question for the increasingly interconnecting energy-mobility system and ongoing sustainability transitions, including influences of digitalization. As country of analysis, we have chosen the United States (U.S.) and in particular the federal state of California as pioneering region for the decarbonisation, electrification and digitization of transport. That is, we have selected the case of the increasingly interconnecting electricity and mobility systems to analyse with a novel, data-intensive methodological approach how the policy mixes in these policy fields have been designed on a regional and national level. In doing so, we focus on system overlaps and how these have been considered in policy making and implementation, and analyse the corresponding implications for policy mix characteristics. More precisely, with this case study we examine empirically (i) how policy mixes are juxtaposed in the dynamics of actor networks and interconnecting system contexts, (ii) whether these policy mixes have been designed in a consistent, coherent and credible manner, or how these characteristics are manifested in policy making and implementation processes, and (iii) to what extent these policy mixes represent comprehensiveness in processes and elements.

There are limited STI studies on policy mixes in the U.S., among which seven studies investigated cross-system policies, and only two of these involved intersections of electricity and mobility (Bose Styczynski, & Hughes, 2019; Jaccard & Goldberg, 2014). While most of these studies perform qualitative analysis, there are three studies conducting quantitative assessments; however, only one of them can be broadly considered as data-intensive applications as the simulation model was built with parameters estimated from historical data (Jaccard & Goldberg, 2014). Very few of these studies distinguish between the concepts of instruments and strategies (with the rare exception of Burke & Stephens, 2017).

While we are testing our new data-intensive approaches for the case of the US, the research is set up in a way to pay attention to possible standardisation of the methodological approach, and is intended to be applied at a later point also to Germany, the UK and China.

Methodological approach and data

Recent review studies in sustainability transitions have started to investigate the potential of data-intensive applications (e.g. Abduljabbar et al 2019, Asokan et al 2020, Müller-Hansen et al 2020). However, as pointed out by the panel, critical attention is still limited regarding methodological issues such as ethical use and management of data, privacy concerns in data mining, validity, as well as replicability and reproducibility of results. For example, Di Bella et al. (2018) probed into the question of whether ‘big data’ offered opportunities of “defining traditional or new social indicators” by analysing metadata of relevant academic articles, which concluded that discussion on statistical rigor among works involving ‘big data’ is still lacking.

With mounting data and new data-intensive analytics, requirements for indicators are also changing. While indicators have been defined as “measures that provide specific information about the property or state of a system” (Cottrill & Derrible, 2015: 47), boundaries between traditional and novel types of indicators are unclear. In the framing of data-intensive science as latest wave of the scientific discovery paradigm (Bell et al., 2009), justification and proper use of indicators in scientific measurements appear to be missing. Constructing, designing or adopting any indicators are barely mentioned in the review articles surveying data-intensive tools and analytics (e.g. Philip Chen & Zhang, 2014). To understand nascent indicators, Wouters et al. (2018) proposed the term “social media metrics” to denote both data and indicators related to the use, reception and impact of social media, and text-based metrics have been constructed to conduct sentiment analysis (Zhang et al, 2012). At the same time, traditional semantic metrics (e.g. word counts) seem to remain relevant on newly generated text data (de Souza, et al., 2019). These innovative and traditional indicators (or metrics) could serve as useful device and tools to measure policy mix characteristics with a comprehensive uptake of large volume of data generated from multiple systems that are related to a wide range of policy actors and stakeholders, while paying attention to aforementioned issues of data management.

This article seeks to address these gaps and puzzles by making use of natural language processing (NLP) and social network analysis (SNA) techniques to measure policy mix characteristics, which then support the evaluation of policy making and implementation processes in an emerging cross-sectoral field. To compose suitable indicators for the mapping of policy mixes in cross-system dynamics of sustainability transitions and the evaluation of their characteristics, we begin with systematically and critically reviewing around 160 studies published on key academic journals in innovation studies, policy studies, public administration and transition studies, to identify rationale for data-intensive applications and any emergent or traditional indicators adopted to conduct the analysis. We then adopt an embedded case study research design to shed light on how policy mixes on a regional and national level differ and interact (which in turn may shape policy outcomes), by focusing on energy-mobility transition policies in the state of California and competing (or synergetic) federal initiatives at the national level, i.e. the U.S..

As main data sources we draw on policy texts (developed and promulgated between the year 1990 and 2020) which are complemented with texts extracted from government press release, political speeches and policy consultation records (from the same timeframe).

Data analysis includes the following three steps:

First, to map out actor networks and innovations in system contexts, we apply named entity recognition in NLP on the retrieved textual data, followed by network construction and computation of network statistics with SNA techniques.

Second, to examine policy mix coherence and consistency, we interpret results from topic modelling on time-series textual data featured with defined elements (i.e. instrument types or policy strategy) and actor groups (i.e. types of policy makers and co-sponsors). In addition, we gauge the comprehensiveness of the policy mix by issue frequency and network density to identify any policy gaps or weakly designed areas.

Third, to assess credibility of policy mixes, we employ sentiment analysis with relevant text-based metrics on consultation responses and policy discussion. In particular, it is pertinent to examine how innovations at the intersections among electricity, mobility and ICT systems have emerged in the discourses and how they have been negatively or positively connotated in policy discussion.

Thereby, this article explores novel methodological ways of process tracing through semi-automated computational text analysis. Recognising the limitations of automated techniques, qualitative assessment is conducted to validate our findings.

Expected results, conclusions and policy issues

Expected findings from the empirical analysis include the network expansion and brokerage of policy actors, the level of coherence and consistency and the perceived credibility among various instrument mixes and overarching strategies and its relations with changes in policy mixes (i.e. reform, renewal, discontinuation, or obsolete), as well as identification of different patterns of interactions between energy and mobility systems as observed across different policy timeframes. With this research practice, we also aim to illustrate and introduce new methodological protocols of how policy mix characteristics can be measured and evaluated.

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