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Issues and opinions

Bridging robotics/AI and real-world labs: A quantitative approach based on mining German newspaper articles☆

Martha Loewe [a], Ingrid Ott [a,b,c,*]

[a] KIT (Karlsruhe Institute of Technology), Institute of Economics, Chair of Economic Policy, Kaiserstr. 12, Karlsruhe, 76131, Germany
[b] IfW (Kiel Institute for the World Economy), Kiellinie 66, Kiel, 24105, Germany
[c] CESifo, Poschingerstr. 5, Munich, 81675, Germany

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ABSTRACT

Both, robotics/AI (RAI) and real-world labs (RWLs), are current topics in public innovation promotion policies, but are mostly treated in isolation. While RAI has a focus on a specific technology to serve society, RWLs address the institutional context including experimental learning of governments and societal perspectives. We are particularly interested in the interface between RAI and RWLs and the way media are reporting on these two domains. This reflects key aspects of the social debate in relation to RAI and RWLs. We base our analysis on the understanding that technology development and diffusion ultimately depend on institutional arrangements that are developed alongside or in lieu of market arrangements and also reflect societal needs. This paper uses quantitative text analysis to examine 3,800 German broadsheet newspaper articles in the period 2016–2023. We use Structural Topic Modeling (STM) with publication date and sub-corpus source as covariates to trace topic dynamics and topical prevalence contrast. We show that the dominant topic has changed over time from RAI ("Machine Learning and AI Development Methods") to RWL ("Real-World Labs for the Energy Transition"). We identify bridge topics and argue that these are diverse and include philosophical and legal considerations, public funding and specific application areas for robots, e.g. in schools. As indicators to identify the interface between the two domains (RAI, RWL), we propose a combination of topical prevalence contrast and eigenvector centrality and the use of psycholinguistic attributes to evaluate the topics. These elements could be broadly used to exploit possible complementarities for government experimental learning and when designing "smart regulation" which targets several fields simultaneously.

1. Introduction

Both, technology development and diffusion, ultimately depend on institutional arrangements that are developed alongside or in lieu of market arrangements and also reflect societal needs. Questions arise concerning the optimal institutional design which enables not only the development of technology, but also its diffusion. In line with the systems of innovation literature, the aim is to include in the analysis the perspective of as many actors as possible. In times of multiple crises and rapid change in an evermore complex world, new technologies, processes and policies are increasingly tested in designated spaces and scales under real conditions. These test rooms mostly refer to research and experimentation at the interface of science and society where primarily solutions are sought for societal challenges and transformation processes. There are various terms for this emerging research format, including "real-world lab" (RWL) and "regulatory sandbox".

According to the German Federal Government, real-world laboratories as regulatory sandboxes are regarded as an effective means for developing innovation-friendly framework conditions and as spaces to test the impact of various forms of small-scale regulations.

The "learning" element in this format refers to many stakeholders, explicitly including the government. In addition, the special role of society as a driver or inhibitor in the innovation process is emphasized. As with any new policy instrument, its impact needs to be reviewed. Ideally, the new policy instrument should fit seamlessly into existing contexts and mutually compatible funding instruments should be developed. There are (at least) two main challenges in this context. First, RWLs are heterogeneous and therefore context-specific. Given their focus on exploratory approaches and often small-scale and context-sensitive settings, regulatory sandboxes naturally fail to provide the

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* Corresponding author at: KIT (Karlsruhe Institute of Technology), Institute of Economics, Chair of Economic Policy, Kaiserstr. 12, Karlsruhe, 76131, Germany.
E-mail addresses: martha.loewe@partner.kit.edu (M. Loewe), ingrid.ott@kit.edu (I. Ott).

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indisputable evidence needed to motivate and defend government regulation at large. Second, quantifying the innovation induced by RWLs is demanding. There is a lack of data, and suitable indicators still need to be developed. There are a large number of well-established input/output indicators that reflect innovation activities of companies, including patents, publications, expenditure on research and development (R&D) personnel. However, it is much more difficult to find suitable indicators to measure the perspectives of society.

This paper combines the two perspectives of technological and institutional development while paying special attention to society. It analyzes how the two domains of RWL and RAI are linked in the media discourse that both informs and is shaped by society. The discussions thus reflect the attitudes of the general public. We also focus on the representation of the government in this discourse. The joint consideration of RAI and RWL contributes to the search of key overlaps and solutions to two major challenges that otherwise are mostly analyzed in isolation. For an effective design of policy instruments, it is also helpful to understand the attitudes of the general public towards certain topics. Especially in times of tight budgets, it is crucial to leverage synergies between different funding formats.

Methodologically, we use a method of quantitative content analysis, namely an unsupervised machine learning approach, called structural topic modeling (STM), that allows us to take into account exogenous covariates like the text source and the publication date of the articles. Our data consists of about 3,800 articles from German broadsheet newspapers published in the period from January 2016 to June 2023, reflecting a broad political spectrum.

The newspapers we selected all stand for professional journalism: they include a fact check, are neutral and follow the press code. These characteristics set our database apart from user-generated content. Newspapers are among the less biased sources for the study of evolving dynamics when monitoring trends and changes over time. Newspaper articles fulfill an important information function for the design of innovation-friendly regulation by political actors.

This paper offers six key novelties. First, we introduce the concept of bridge topics as a means to explore and identify links between two otherwise disparate domains. Bridge topics arise from a novel use of the topical contrast facility of the STM algorithm. The topical contrast facility was typically used to sort the documents in a corpus into two categories. For example, political speeches were classified according to the party affiliation of the speaker. However, we focus on the topics that the topical contrast facility of the STM algorithm cannot neatly classify, the topics that sit at the transition between the two classes. We call these topics “bridge topics” and use them to explore the links between the two disparate domains. Second, we enhance our network analysis with the concept of bridge topics. This enhanced version of a network analysis sheds further light on the structure of the relationship between topics. The network has two main clusters: one cluster with RWL topics and a second cluster with all other topics. The bridge topics are located at the margin of the second cluster and their edges link the two clusters. Third, we analyze our topics using four psycholinguistic indices featuring ratings regarding the pleasantness of a word, emotional arousal, abstractness and imageability. We combine this augmented sentiment analysis with the concept of bridge topics and find that two key bridge topics have particularly high pleasantness and emotional arousal values. Fourth, to our knowledge, this is the first study that captures the view and reception of RWLs by the general public based on a quantitative natural language processing analysis. Fifth, to our knowledge, this is the first study that captures the view and reception of RWLs *combined with* RAI by the general public based on a quantitative natural language processing analysis. Sixth, based on the concept of bridge topics and the example of RWLs and RAI, we offer two suggestions for developing policy instruments that encourage innovation, take the views of the affected constituencies into account and thus promote successful implementations, and reconcile competing funding priorities by identifying areas that serve both and investing in these.

Note that the first three key novelties concern the method, while the last three concern the content of this study.

We obtain the following results: We show that there is a variety of themes within our text corpus, ranging from philosophical considerations and science fiction over work place implications, specific application areas, machine learning methods, start-ups, funding, the energy transition and mobility. Structural topic modeling splits the collection of articles into topics automatically. However, the labeling of the topics and the interpretation of the results are based on extensive manual work and require critical reflection. We partition the entire text corpus into 32 topics and obtain the following results. First, the 32 topics can be assigned to the areas RWL or RAI to varying degrees, including bridge topics that are related to both dimensions, RWL and RAI. We consider these bridge topics to be particularly interesting against the background of joint perspectives on funding policy or regulation that could be more broadly based.

Second, we create a network that represents the structure of the relationships between the topics and highlights which of them are often discussed together within a newspaper article. We apply network indicators and uncover that “Philosophical Considerations on the Digital Transformation” followed by “Political Support for AI and Robotics in Germany” gain the most prestige within the network.

Third, we apply a sophisticated sentiment analysis that evaluates the topics based on the four psycholinguistic attributes arousal, valence, abstractness and imageability. We find that, disregarding the timeline, dominant (i.e. large and prestigious) topics have a positive connotation and are less abstract.

Fourth, the proposed approach facilitates zooming in on different broader themes. In the field of mobility, for example, we can show which facets of the media discourse have a positive connotation and which are presented more negatively.[1] A differentiated analysis is also possible in the areas of “future work” and robot assistance systems (in private households, in schools).

This paper contributes to a better understanding of the attitudes of the general public based on quantitative indicators. It especially highlights the bridge topics as a potential element of smart regulation. Such an element of smart regulation can add further important perspectives for the development of flexible, but well-founded and data-based regulation and policy instruments for innovation promotion beyond the classic innovation indicators. Our analysis contributes to implementing smart regulation based on quantitative evidence of the attitudes of the general public as reflected by the media reporting. Ideally, smart regulation increasingly integrates the attitudes of the general public while developing public policy choices for innovation systems.

The remainder of this paper is organized as follows. We begin with an introduction of the building blocks of this paper, namely robotics/AI and real-world labs and reflect on some related literature in Section 2. In Section 3, we briefly introduce the applied method, Structural Topic Modeling, and expound in detail our data sources, the preprocessing steps and the model specification. In Section 4, we present the main results regarding labeling, dynamics, topic prevalence contrast, correlation and sentiment analysis, and discuss these results. Section 5 presents some policy implications, critically reflects on the methodology used and hints to future perspectives, while Section 6 concludes.

[1] Sustainability related reporting is positively connoted while reporting on autonomous driving is negatively connoted, as texts on autonomous mobility tend to focus on accidents.

2. Building blocks and related literature

This paper is based on several building blocks. It links robotics and AI to the well-established economic framework of general purpose technologies. RWLs are linked to the theory of innovation systems with a focus on the government as learning agent and the combined perspective of technological and institutional innovations. We use quantitative text analysis to capture the mood in society regarding RAI and RWLs and to identify topics in a huge amount of text data. We trace the dynamics of the topics we identified and explore their correlations. Based on this approach, we develop a concept that allows to search for synergies between the technological and institutional dimensions along the innovation process. In this section we provide more details on these building blocks and the associated key literature.

AI is broadly accepted as the currently most important General Purpose Technology (GPT) with the benefits of a long-run gain in aggregate productivity and increased global welfare and the challenges of adjusting well-established procedures and boundary conditions which is both time consuming and costly. According to Bresnahan and Trajtenberg (1995), who coined the term of GPTs, they are characterized by pervasiveness, an inherent potential for technical improvements and innovational complementarities. Pervasiveness entails that GPTs are used as inputs by many downstream sectors and innovational complementarities mean that the productivity of R&D in downstream sectors increases as a consequence of innovation in the GPT. These characteristics undoubtedly apply to AI and their embedding in robots brings an explicit technological perspective into play.

There are only a few RWLs that have a technical focus, including the "Real-World Lab Robotics Artificial Intelligence" at the Karlsruhe Institute of Technology (RAI; more below), that investigates the determinants of the innovation adoption and diffusion processes of humanoid robots into everyday life and public spaces on the basis of specific fields of application. The potential for automation in the service sector is high and it is desirable to understand and to exploit this potential. One major challenge is the heterogeneity of the fields of robot application. In addition to the technological challenges, the area of data protection, for example, poses a major challenge. The question is how to organize (regulate) innovation processes intelligently so that they are legally compliant on the one hand and thus provide planning security for innovating companies, and on the other hand allow sufficient freedom to experiment with a wide variety of formats and thus enable innovation in the first place. For innovation diffusion, the robots need to be adapted given specific constraints and individual requirements. It is not yet clear exactly what these are, and a RWL is a natural format to test them.

Bresnahan and Trajtenberg (1995) already pointed out the implications regarding reorganizations of well-established practices and work arrangements, not only in the application sectors but also beyond. They implicitly addressed discussions that currently are framed in the context of social innovation, though they did not name them explicitly. Another point already addressed by Bresnahan and Trajtenberg (1995) is the need to co-design institutional and organizational arrangements to fully exploit the welfare potential of GPTs and to influence the present and future pace of innovation. Bekar, Carlaw, and Lipsey (2018) applied an evolutionary approach and argued that GPTs transform the structure of the economy and today's knowledge society.

However, this literature does not address issues around regulatory learning. Instead, given certain boundary conditions, it sees the government as a "benevolent social planner" that pursues the goal to internalize prevailing horizontal and vertical externalities, resolves issues resulting form coordination failure and tends to maximize overall welfare. One might conclude that the complementary perspective between economy, government and society is already implicitly included in the early reasoning on GPTs, though it is not yet clearly spelled out.

Nowadays, we take for granted such a joint consideration of innovation and policy conditions, including research, the economic and the societal perspective (compare e.g. Grubb et al., 2021). In particular, it has also been recognized that the co-evolution between technology development and institutional design requires the state, just like innovating companies, to test, evaluate and continuously develop its instruments. This is where RWLs come into play as modern tools.

In 2019, the German Federal Ministry for Economic Affairs and Energy defined real-world labs as "test spaces for innovation and regulation" (BMWI, 2019). Since 2018, the federal government has been prominently promoting the format of real-world laboratories as an explicit instrument for innovation. Before that there was already support for real-world labs at the level of individual federal states at varying degrees. Regulatory sandboxes, understood as research settings for developing, testing and evaluating solutions to societal problems, play an important role in the development of technologies that meet societal needs.

In 2020, the Council of the EU chose regulatory sandboxes and experimentation clauses as instruments for an innovation-friendly, future-proof and resilient regulatory framework to address disruptive challenges in the digital age. In 2024, the federal government in Germany worked toward the adoption of a so-called real-world laboratory law (Reallabor-Gesetz). The key points here are defining overarching standards for RWLs, legal foundations for new RWLs in important areas of innovation, experimental clause checks and a one-stop-shop for RWLs as a central point of contact for practice and knowledge transfer. The concept is also based on the results of expert reports, on discussions with representatives of European governments, federal and state ministries, business, research and civil society.

Currently, RWL are seen in the scientific literature as modern representations of innovation systems (compare e.g. Ott, 2024). Regarding the literature on innovation systems, this paper is most closely related to Technical Innovation Systems (TIS).[2] The TIS concept is concerned with the emergence of novel technologies and can be traced back to the seminal paper of Carlsson and Stankiewicz (1991). A common feature of RWLs and the TIS literature is their acknowledgement that innovation systems cannot be fully understood without considering their contexts (compare Bergek et al., 0000). Research on TIS already includes the institutional and organizational changes that in addition to technology-push and demand-pull perspectives are seen as essential drivers behind the generation, diffusion, and utilization of technological innovation. The TIS framework already includes notions of change and dynamics thereby pointing to the emergence and developments of institutions.

In line with the spatial or the technical perspective, another key outcome of the theory of innovation systems has been the identification of so-called "functions". They refer to processes that need to run smoothly for the innovation system to perform well (compare Bergek, Jacobsson, Carlsson, Lindmark, & Rickne, 2008; Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007 or Hekkert & Negro, 2009). From the seven functions identified in the literature mentioned above, the following three may be particularly useful in understanding the role of RWLs: guidance of the search that considers societal embedding, preferences and expectations, the creation of legitimacy, and the importance of protected niches where learning can occur. Protected learning niches are typically provided by firms. We introduce the government as a provider of protected niches in this paper.[3]

In principle, RWLs are not limited in their applications and can represent technological, spatial and/or topical foci, thereby challenging the identification of overarching similarities of this new experimentation format (compare Schäpke et al., 2018).

[2] Other prominent perspectives include a focus on specific sectors or on a special spatial range (regional, nation, global).

[3] The other four functions include entrepreneurial activity, knowledge development, knowledge diffusion, and resource mobilization (compare Hekkert & Negro, 2009 for details on the full list of functions).

Regulatory sandboxes allow researchers or innovating firms to interact with diverse stakeholder groups to co-design and test socio-technical solutions by creating a less-regulated environment for a certain time period. Ideally, regulatory sandboxes contribute to gaining a deep understanding of the psychological and social processes affected by technological innovations and of user preferences, to explore desired and undesired effects of technology, but also to inspire, design and especially to test the efficacy of policy tools. As a "test space for innovation and regulation" the latter feature explicitly addresses the aspect of regulatory learning.

What do flexible modern regulatory instruments look like that offer long-term orientation without being too rigid? Like all economic policy instruments, they must be free of contradictions, have a targeted and timely effect and fit into existing regulation; they are also often embedded in an international context. One special feature of regulatory sandboxes is the claim to be effective at the interface with society. In addition to market signals, the social environment and their acceptance are essential for successful innovations.

Despite these ambitious large-scale requirements, regulatory sandboxes are a highly context-sensitive approach to studying socio-technical co-adaptation that is still novel. As a consequence, given their context-specificity, it is challenging to delineate conclusions that are valid in a larger context. Currently, most RWLs have a strong environmental focus and only a few address the diffusion perspective in the context of technologies. Due to increasing computing capacity and miniaturization, modern robots are flexible, easy to operate and become able to navigate autonomously, even in unstructured environments. Rapidly decreasing costs combined with shortages of skilled labor in many fields, including care for the elderly, education and health care, are important drivers of the diffusion of so-called "service robots". These robots perform useful tasks for humans or equipment excluding industrial applications.[4] The diffusion of service robotics currently exceeds the diffusion of industrial robots and the International Federation of Robotics sees dominating future market potentials in this diverse field (compare IFR, 2023). However, service robots are not a new phenomenon and their evolution can be traced technologically in patent data (compare Savin, Ott, & Konop, 2022). The technology is very heterogeneous in terms of complexity, possible applications and prices which makes one-size-fits-all considerations impossible. In order to better understand their application potentials, it is necessary to jointly take into account the respective technological possibilities, the needs of customers and the regulatory environment. While the potential and the requirements for industrial robots are generally clearly specified, the situation is different with service robots, where the full application potentials, diffusion potentials and obstacles are often not clear ex ante.[5] This is where the RWL RAI comes in.

The "Real-World Lab Robotics Artificial Intelligence" at the Karlsruhe Institute of Technology (KIT) operates at the interface between real-world labs on the one hand and technological development and innovation in the fields of robotics and AI on the other hand (Nierling et al., 2023). The real-world lab deploys humanoid robots to various settings in the public square, including day care centers (Krebs et al., 2023; Rudenko et al., 2024), schools and museums, and gives members of the general public the opportunity to interact with them in the context of diverse experiments. Through these experiments, accompanying research, and citizens' dialogues, the researchers gain new insights into the preferences, expectations, desires and fears of potential users and take these observations into account while developing the design of the next generation of AI robots. Interacting with individuals is at the heart of this approach to exploring the attitudes of the general public. It inspired us to take an integrative look at two major funding lines of the German government, which were set up independently of each other and are usually analyzed independently of each other.

This study complements the work of "Robotics AI" by taking a bird's eye view. We aim to develop perspectives on how experimental learning can be used to combine previously unconnected perspectives, especially from the point of view of experimental governmental learning. In this way we contribute to a potential design of smart regulation, understood as the examination of forward-looking regulatory approaches and forms that transcend disciplinary and sectoral boundaries and pose questions for the future. Another goal consists in quantifying some elements of smart regulation. This addresses a major shortcoming in the evaluation of RWLs, on the one hand, and in the scaling of insights, on the other.

Our core idea is to explicitly search for synergies between two prominent future fields (RAI and RWL) that have the particularity of combining technological and institutional innovations. In addition to the perspective of innovation systems, the discipline of future studies and the concept of "weak signals" can also provide a conceptual framework within which the development of suitable indicators can take place. A few ideas on this can be found in Section 5.

In this paper, we use the term "real-world lab" in the widest possible sense, including *all* alternative definitions, as the newspaper articles that we analyze are not concerned with precise definitions, but with the concept as such. Other terms for similar concepts include "urban lab", "innovation lab", "future lab", or "transformation lab". Our analyses have in mind technical RWLs and allow us to simultaneously address the joint development of technology and institutions. As mentioned above, we contextualize this for robotics and AI.

In our analysis, we take advantage of the fact that the strong link between innovation and economic, political, and socio-cultural factors is expressed in the public media discourse. Thus we capture societal information. Despite the immense growth of social media and the associated importance it has as a source of information for many people (compare DellaVigna & Ferrar, 2015), newspapers are among the less biased sources for the study of evolving dynamics when monitoring changes and trends over time. It is also well recognized that individuals update their expectations when new information becomes available. The media can thus be collectively viewed as a suitable representation of the contents of discourses, notwithstanding that it might be biased (compare e.g. Gentzkow & Shapiro, 2010, Lehotský, Černoch, Osička, & Ocelík, 2019 or more recently Cage, Hengel, Hervé, & Urvoy, 2024). The media encompass a body of constantly evolving ideas and concepts that are generated, replicated, and adapted into practices that shape our understanding of reality. They serve as a proxy for discourse content, collectively acting as an arena for claims-making competition. Walgrave and Van Aelst (2006) already pointed to the fact that the media influence how political actors evaluate a variety of conditions and circumstances and thus affect the political process. It is important to be aware of the fact that contents in the media are produced in the exchange between political and social agents with journalists and may be biased, as certain issues are pre-selected and highlighted and others are neglected. However, this aspect is beyond our analysis.

From a technical perspective, the evaluation of topics discussed in the media is increasingly (partially) automated. Due to the rising power of modern computers, the ever growing availability of large amounts of data and the further development of unsupervised machine learning methods, text as data has become a prominent source for analysis (e.g. Gentzkow, Kelly, & Taddy, 2019; Gentzkow & Shapiro, 2010; Kelly, Papanikolaou, Seru, & Taddy, 2021, for a critical reflection see Grimmer & Stewart, 2013). Prominent methods for automated content analysis build on so-called topic models. The Structural Topic

[4] For a precise definition of service robots and further sub-classifications, compare ISO 8371:2012, 2.11 (private use; synonyms are personal or domestic use) and 2.13. (professional use).

[5] Due to the multitude of forms, structures and application areas of service robots, it is sometimes not easy to delimit service robots from industrial robots. For example, in logistics, robots are used in non-manufacturing environments, such as logistic centers, hospitals or warehouses but also to transport parts within factories.

Model (STM) is an unsupervised machine learning method that facilitates extracting information from (large) textual data. Currently, the use of STMs by social scientist is exploding, as STMs allow to add meta data to the text data. This additional data may be include a time stamp and the text source, and it can be used for tracing trends and relationships between topics.

This study takes the bird's-eye view on society and analyzes the main themes in public reporting and discussion about RAI and RWLs. In doing so we provide a comprehensive perspective that combines technological and institutional innovations while keeping the general public in mind. Policy conditions include the cultural and societal environments. Societal environments are reflected in the public discourse in newspapers, social networks, television, position papers and public speeches. However, a solid and state-of-the-art quantification of these phenomena is still missing. A key novelty of the paper is explicitly bridging the perspectives of two important fields that usually are discussed, analyzed and also funded as isolated topics. We posit that this may have important implications for governmental learning in the context of creating the design of policy instruments and governmental funding schemes.

3. Methods and data

3.1. STM as a method of automated content analysis and link to recent developments in NLP

At the intersection of data science, computational linguistics, and social sciences, we observe the emergence of a multitude of different algorithms for natural language processing (NLP) for automated content analysis. Prominent examples are generative models that use large amounts of data and exploit information on word usage and other information. These models are constantly being improved and are increasingly able to process further information, like syntax, word embeddings or document-specific covariates, beyond the simple evaluation of word frequencies.

In this paper, we use the Structural Topic Model (STM). This section gives a brief overview on its predecessors, describes the key logic, its strengths and weaknesses and also mentions some recent developments in this field. In addition, we explain why we used STM as a method to analyze our content and search for overlaps and synergies between the two prominent policy fields of RAI and RWL.

The Structural Topic Model (STM) allows to estimate topic models with document-level covariates.[6] STM is a probabilistic model based on the bag-of-words approach, where documents are mapped to a distribution of their words, whereas the syntactical structure and the order of the words are disregarded. Topic models are mixed-membership models: they assume that each document is a combination of several topics with varying proportions, documents are not attributed to just a single topic. The algorithm partitions the distribution of words in the corpus into k topics. Topic models are unsupervised: given the number of topics k, they create a partition of the distribution of the words in the corpus into k parts based on variational inference, without any prior thematic input of the modeler. This method is particularly suited for exploratory research with limited a priori assumptions.

STM is based on a variety of probabilistic topic models, including the following: (i) Latent Dirichlet Allocation (LDA) was introduced in the seminal paper of Blei, Ng, and Jordan (2003). LDA is a generative probabilistic model that represents documents as combinations of topics, where each topic is a distribution of words. Dirichlet and multinomial distributions are used to model the topic-word and the document-topic distributions. Though it is a standard method for discovering topics in a large corpus of text without additional metadata, it suffers from some key weaknesses: topics are uncorrelated, the distribution of words is assumed to be constant, and text within a document alone can determine the topics of the document. (ii) Correlated Topic Modeling (CTM) was introduced in the seminal work of Blei and Lafferty (2007). CTM pictures a web of topics which are all connected in some way. It extends the LDA by allowing for correlation between topics. Technically, a logistic normal distribution is applied. (iii) Dynamic Topic Modeling (DTM) was introduced in the seminal work of Blei and Lafferty (2006). DTM extends LDA to model how topics evolve over time. The algorithm incorporates time stamps in the modeling process, allowing the distribution of topics to change over different time slices.

The STM as a natural language processing method for automated content analysis was introduced in the seminal work of Roberts et al. (2014) and subsequent works Roberts, Stewart, and Airoldi (2016a), Roberts, Stewart, and Tingley (2016b) or Roberts, Stewart, and Tingley (2019). The STM extends the topic models listed above by facilitating the inclusion of metadata. Metadata provide additional non-textual details about each document. They are encoded as covariates, can be added to the text data and exploited to gain further insights. There are two types of covariates: topical prevalence covariates affect the shares of a document that are associated with different topics, and topical content covariates refer to the specific words of a topic. The STM model can use both types of covariates, either of them or none of them; in the latter case, the model reduces into an implementation of the CTM of Blei and Lafferty (2007). Roberts et al. (2019, p3) provide the mathematical representation of the generative process for each document based on a given vocabulary for an STM model with k topics. A list of scientific papers that apply the STM in a variety of contexts can be found on the webpage on STM.

NLP is a rapidly evolving field with a variety of methods for automated content analysis and efforts to improve the efficiency of algorithms. STM belongs to a cohort of methods for automated content analysis, including word embeddings, text clustering and knowledge graphs. Word embeddings are a representation of words as vectors in a multi-dimensional space, where the distance between vectors is a measure for the similarity and relationship between the respective words. Modelers can draw on several existing methods to generate word embeddings, including but not limited to Word2Vec (Mikolov, Chen, Corrado, & Dean, 2013), a method based on a neural network to predict the surrounding words of a target word in a given context, and GloVe ("Global Vectors for Word Representation", Pennington, Socher, & Manning, 2014), which uses global statistics to create embeddings. Word embeddings are used for various NLP tasks. They are relevant for our context, as they can lead to more semantically coherent clusters when partitioning texts into clusters. However, word embeddings are of limited use for domain-specific texts, as many domain-specific words do not have pre-trained vectors (out of vocabulary words). We decided against word embeddings for two reasons. The vocabulary in our corpus is domain-specific and thus has many out of vocabulary words. Moreover, as German is a richly inflected language, similar benefits can be achieved through lemmatization. We applied lemmatization in our text preprocessing steps (see Section 3.3).

Text clustering is the process of grouping a collection of texts into clusters based on the similarity of their content. There are numerous algorithms to achieve this task, including K-Means (Jancey, 1966; Lloyd, 1982; MacQueen, 1967) and DBSCAN (Density Based Spatial Clustering for Application with Noise, Ester, Kriegel, Sander, & Xu, 1996).

Xie and Xing (2013) proposed a unified framework that combines topic models (LDAs) with text clustering: the multi-grain clustering topic model, where each text cluster is an LDA. This model was tested on two datasets that are widely used as a benchmark in document clustering and the model performed better in terms of clustering accuracy than most other document clustering methods it was compared with. However, as detailed above, the structural topic model (STM)

[6] The stm package of R also includes tools for model selection, visualization, and estimation of topic-covariate regressions.

takes into account not only the texts themselves, but also exogenous information related to the texts, like the publishing date and the name of the newspaper. This exogenous information is encoded in covariates and is crucial for our analysis, especially the key novelty of bridge topics. Therefore we chose to forego other text clustering methods and use an STM.

Knowledge graphs are representations of information as semantic networks (Collins & Quillian, 1969; Quillan, 1963), where vertices denote entities (objects, events, concepts) and edges denote relationships between entities. Since Google introduced their knowledge graph in 2012 (Singhal, 2012), knowledge graphs have garnered much attention in both, academia and industry (Schneider et al., 2022). In NLP, they are used for natural language understanding (e.g. semantic parsing, text analysis, text classification), and natural language generation (e.g. machine translation, question generation, generation of text summaries). Building a knowledge graph based on text data typically requires the following steps: (i) sentence segmentation, (ii) part of speech tagging, (iii) extraction of entities and their relationships, and (iv) creating a graph based on the entities and their relationships from the previous step. Most often the resulting graph is too complex and filters are applied to reduce the graph and thus gain the desired knowledge. The definition of filters relies on expert knowledge in the respective field. One of the advantages of knowledge graphs for text analysis is the consideration of the syntactic structure of sentences. This approach has the potential to achieve a better semantic representation of the text than bag-of-word approaches used in topical models. However, the definition of filters requires expert knowledge and thus introduces bias.

Li, Zamani, Zhang, and Li (2019) introduced a topic model with knowledge graph embedding (TMKGE), a Bayesian nonparametric model, aiming to find more coherent topics by taking advantage of the knowledge graph structure. Experiments on three public datasets showed that the TMKGE performed better in terms of topic coherence and document classification accuracy compared with other topic modeling methods. However, the STM was not among the topic models the TMKGE was compared with. Further, in the experiments with the TMKGE, text preprocessing was omitted. Topic coherence can be greatly improved by exploiting linguistic domain knowledge, especially lemmatization and stop word removal (see Section 3.3). Additional experiments with text preprocessing are necessary to better determine the advantage of the TMKGE for topic coherence. Moreover, the TMKGE does not account for covariates, a crucial feature of the STM that we leverage for developing the notion of bridge topics.

Some efforts to improve the efficiency of NLP algorithms focus on reducing the dimensionality of the text corpus. The most prominent approaches are Non-Negative Matrix Factorization, Top2Vec and BERTopic. Non-Negative Matrix Factorization (NNMF) is based on the seminal work of Lee and Seung (1999) or Bojanowski, Grave, Joulin, and Mikolov (2017) and suggests an algebraic approach that factorizes a document-term matrix into two lower-dimensional matrices (document-topic and topic-word), subject to the constraint that these matrices have no negative entries. The advantage of this algorithm are topics that are easier to interpret. Top2Vec was first introduced by Angelov (2020) and creates jointly embedded topic, document, and word vectors in a lower-dimensional space. Topics are discovered by clustering these vectors. Top2Vec utilizes deep learning techniques for word embeddings (e.g., Doc2Vec) and then applies clustering on these embeddings. The method is effective for detecting semantic similarity and capturing nuanced topics in the text. The model BERTopic is based on Grootendorst (2022) and leverages BERT (Bidirectional Encoder Representations from Transformers) embeddings and a clustering algorithm to generate dense topic representations. The BERTopic algorithm uses BERT for embedding documents, UMAP for dimensionality reduction, and HDBSCAN for clustering. The method is suitable for high-quality embeddings and finely grained topic extraction. Additional information is given in Egger and Yu (2022) or Raman et al. (2024).

Table 1
Search terms related to "Reallabor" that were used in the German newspaper texts.

Language	Terms
German	Techniktest, Feldexperiment
English	Regulatory sandbox, Transition lab, Urban lab, Future lab, Innovation lab, Living lab, Social-Design lab, Real-World lab

Despite these novelties, in this paper we have decided for STM as our method of choice, because, to the best of our knowledge, this model is the only algorithm that facilitates the identification of links between two distinct domains. The STM as a method that exploits covariate information has already been applied in a variety of contexts, including studies of the relationship between science and technology in nanotechnology (compare Kang, Yang, Lee, Seo, & Lee, 2023), drinking water quality (compare Sohns, 2023), media analyses (compare Lehotský et al., 2019, technology legitimacy of wind power (compare Dehler-Holland, Okoh, & Keles, 2022), and the media discourse of hydrogen in the context the war against Ukraine (compare Loewe, Quittkat, Knodt, & Ott, 2024). Studies closest to this paper are Agrawal et al. (2022), Dehler-Holland et al. (2022), Loewe et al. (2024) and Zhang, Cao, Ji, Gu, and Wang (2022).

In this paper, we especially exploited the "topical prevalence contrast" facility of the STM algorithm which allows to better understand the roots of the topics, i.e. the underlying sub-corpus, and we used it in a new way (see Section 4.3 for more details). Our study is based on 3,801 German newspaper articles that were published from January 1, 2016 to June 30, 2023. We included two covariates: the publication date and an indicator variable that shows whether the article belongs to the Robotics/AI corpus or to the Real-World Lab corpus. The resulting model offers insights into the main themes in the German media reporting and the associated public discourse about robotics/AI and RWLs from 2016 to mid 2023 and sheds light on the linkages between the two domains as well as their dynamics.

3.2. Data

Our collection of newspapers (corpus) consists of two sub-collections, related to real-world labs and robotics/AI respectively. The initial search for newspaper articles for the Real-World Lab corpus focused on articles in the largest German broadsheet newspapers that are read nation-wide, including *Süddeutsche Zeitung (SZ)*, *Frankfurter Allgemeine Zeitung (FAZ)*, *Die Tageszeitung (TAZ)*, *Die Welt*, *Handelsblatt* and *Neue Zürcher Zeitung (NZZ)*. This set of newspapers covers the political spectrum from moderately left to moderately right and includes a financial newspaper (*Handelsblatt*) and a conservative Swiss publication that is widely read in Germany (*NZZ*). Using the query "Reallabor", we retrieved the articles from *Neue Zürcher Zeitung*, *Die Tageszeitung* and *Die Welt* from the academic database Nexis Uni and downloaded the articles from *Handelsblatt*, *Frankfurter Allgemeine Zeitung* and *Süddeutsche Zeitung* from the respective newspaper databases. However, this first search yielded only a small number of articles. Thus we extended our search in two dimensions: we added local newspapers that are published in cities with real-world lab activities and we included keywords that are semantically related to "Reallabor". The local newspapers included *Aachener Zeitung* (North Rhine-Westphalia), *Darmstädter Echo* (Hesse), *Hamburger Abendblatt* (Hamburg), *Lausitzer Rundschau* (Brandenburg), *Sächsische Zeitung Stammausgabe Dresden* (Saxony), and *Stuttgarter Zeitung* (Baden-Württemberg). We downloaded the articles from *Hamburger Abendblatt* from the newspaper database and retrieved the articles of all other local newspapers from the academic database Nexis Uni. Table 1 gives the list of terms related to "Reallabor" that served as keywords for the extended search. Fig. 1 displays the resulting number of articles by year and newspaper.

The highest number of articles were published in 2021, followed by 2020. The German government represented by the Federal Ministry for

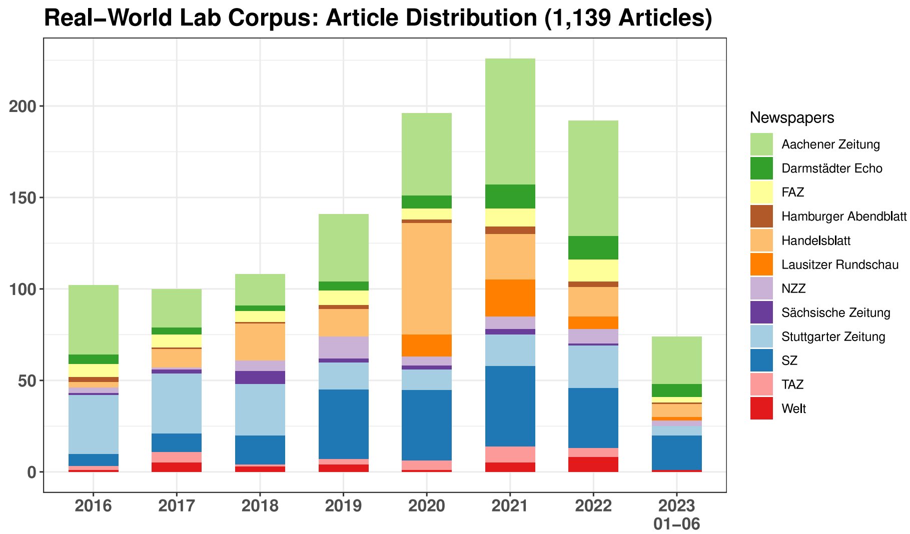

Fig. 1. The distribution of 1,139 newspaper articles published in twelve German newspapers from January 1, 2016 to June 30, 2023 that feature the keyword “Reallabor” or one of the related terms. The related terms are given in Table 1.

Table 2
Real-world lab milestones initiated by the German Federal Ministry for Economic Affairs and Climate Action.

Date	Milestone
December 2018	Launch of the Strategy for Real-World Labs (or Regulatory sandboxes)
February 2019	Real-World Lab 2019 Innovation Award Competition
July 2019	Presentation of the Innovation Award
June 2021	Publication of a revised funding concept for “Real-World Labs for the Energy Transition”
September 2021	Publication of a concept for a new Real-World Lab Law
November 2021	Real-World Lab 2022 Innovation Award Competition
May 2022	Presentation of the Innovation Award

Economic Affairs and Climate Action promoted real-world labs through several initiatives that explain the increased attention to this topic in the general public. Table 2 provides an overview of the respective milestones.

We noticed that some articles that were published in a nation-wide newspaper were reprinted in one or two local newspapers. We decided to keep the second and third copy of these articles in order to be able to track the number of articles that were published in local newspapers. We found that 54.8% (613 from 1,139) of the articles in the Real-World Lab corpus were published in the six local newspapers.

For the Robotics/AI corpus, we used the query “Robot* OR robot* OR künstliche Intelligenz OR Künstliche Intelligenz” and retrieved articles from the same newspapers like for the Real-World Lab corpus. The search yielded 8,375 articles. We noticed that many articles mentioned robotics or AI only in passing and some were duplicates. We removed duplicates and kept only articles that contained both terms, “k/Künstliche Intelligenz” and “r/Robot*”, and at least one of the terms more than once, resulting in a data set with 2,662 articles. Fig. 2 shows the number of articles by year and newspaper.

Notably, the highest number of articles were published in 2018 and 2019, as the German government launched the National AI Strategy for Germany in 2018 and Germany and France signed a joint AI roadmap in 2019. It is also noteworthy, that the number of articles published in the first six months of 2023 is only slightly lower than the number of articles published in the twelve months of 2022. With the release of ChatGPT end of November 2022, generative AI as implemented in large language models attracted the attention of the general public and was widely reported on in 2023.

For this study we combined the two corpora as we are interested to uncover the connections between robotics and AI and real-world labs. Fig. 3 shows the distribution of the articles in the combined corpus by year and newspaper.[7] Fig. 4 provides information about the sub-corpus shares in the combined corpus.

3.3. Preprocessing

Raw text data is routinely preprocessed before it is used as input in a model. We carried out the following procedure: First, we applied lemmatization. Lemmatization is the process of reducing a word to its canonical form. German is a richly inflected language and many words have the same canonical form. For example, the lemma (canonical form) of all the following words is “groß”: “größer”, “größte”, “größeres”, “größten”. We performed lemmatization manually. Second, we included a small number of bigrams. The unit of analysis in his study is a single term. However, given the subject matter, we included the following bigrams to preserve their meaning: “Vereinigte Staaten”, “Silicon Valley”, “Wall Street”, and “Science Fiction”. We concatenated the two terms to create a single term with camel case. For example, we mapped “Vereinigte Staaten” to “VereinigteStaaten”. Third, we removed punctuation marks. We wished to preserve the names of German member states, so we removed the hyphen and concatenated the two words, generating new compound words written in camel case. For example, “Baden-Württemberg” became “BadenWürttemberg”. Fourth, we removed numbers. Fifth, we removed stop words. Stop words are words that appear frequently in natural language, but carry little meaning for the purposes of our analysis. They include articles (“der”, “die”, “das”), pronouns (“er”, “sie”, “es”), prepositions (“unter”, “über”) and first names. We used a standard stop word list for the German language and extended it by a custom stop word list.[8] We included the search

[7] Note that there was no overlap between the two sub-corpora.
[8] To illustrate, we listed some example words from the custom stop word list in Appendix A.

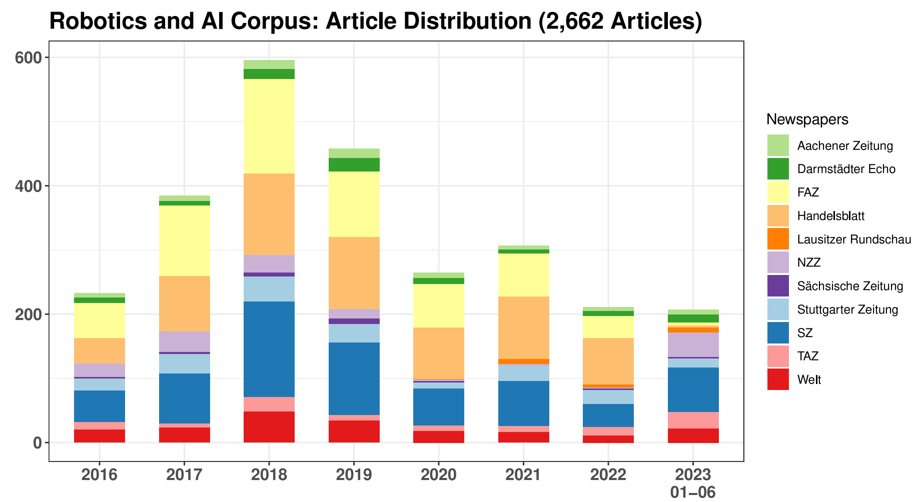

Fig. 2. The distribution of 2,662 newspaper articles published in twelve German newspapers from January 1, 2016 to June 30, 2023 that feature the keywords *r/Robot** and *k/Künstlich* Intelligenz*.

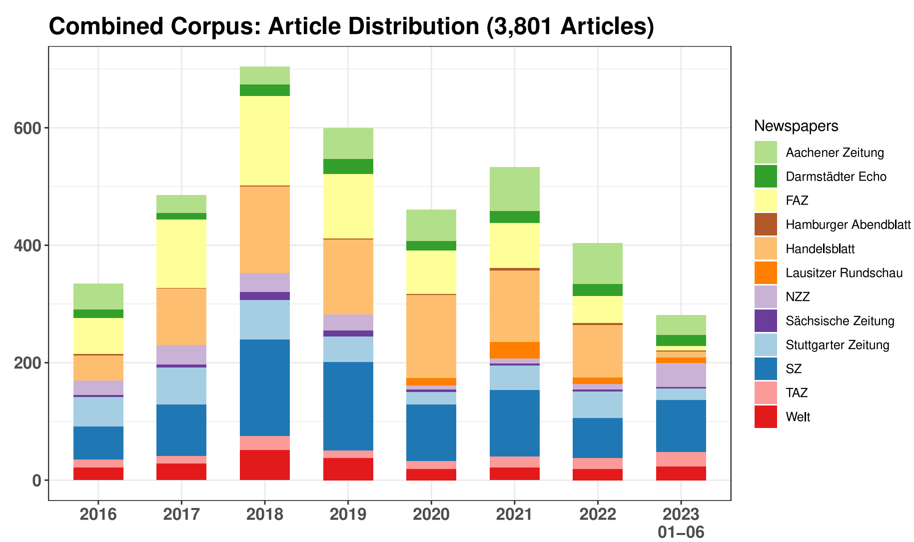

Fig. 3. The distribution of 3,801 newspaper articles published in twelve German newspapers from January 1, 2016 to June 30, 2023 that feature the keywords *r/Robot** and *k/Künstlich* Intelligenz* or *Reallabor* or one of the related terms.

terms in the custom stop word list for better results. Sixth, we removed short words with less than four letters. Seventh, we dropped terms that featured less than 30 times in the corpus. The contribution of these words to the topics in the model is negligible, the algorithm becomes faster without loss of statistical information. Note that we decided against transforming all words to lower case, since we wanted to preserve nouns, which are spelled with capital letters in German. Words that are capitalized since they appear in the first position of a sentence are mapped to their canonical forms through lemmatization.

After preprocessing, a vocabulary was created with all terms and their frequencies in the corpus. Each document was represented as a vector of terms and their respective frequencies. The vectors were combined to a matrix, the document-term-matrix. Thus the preprocessing steps facilitated mapping the articles to a mathematical representation. Fig. 9 in Appendix B illustrates the preprocessing process.

3.4. Model specification

We chose to leverage the Structural Topic Model (STM) to evaluate the content of our newspaper article collection and to uncover hidden structures in the content. We used the R package stm, an implementation of the STM algorithm (Roberts et al., 2019). The input of the model is the document-term matrix and optionally, metadata in the form of covariates. The output of the model are topics and estimates about the relationships between the topics and the included covariates. Topics are probability distributions over all terms in the vocabulary and documents are probability distributions over all topics. Thus each topic is a combination of terms with varying proportions and each document is a combination of topics with varying proportions.

The model is specified by the number of topics k and the definition of covariates. The number of topics k must be chosen carefully. We determined k iteratively: we generated two sets of candidate models

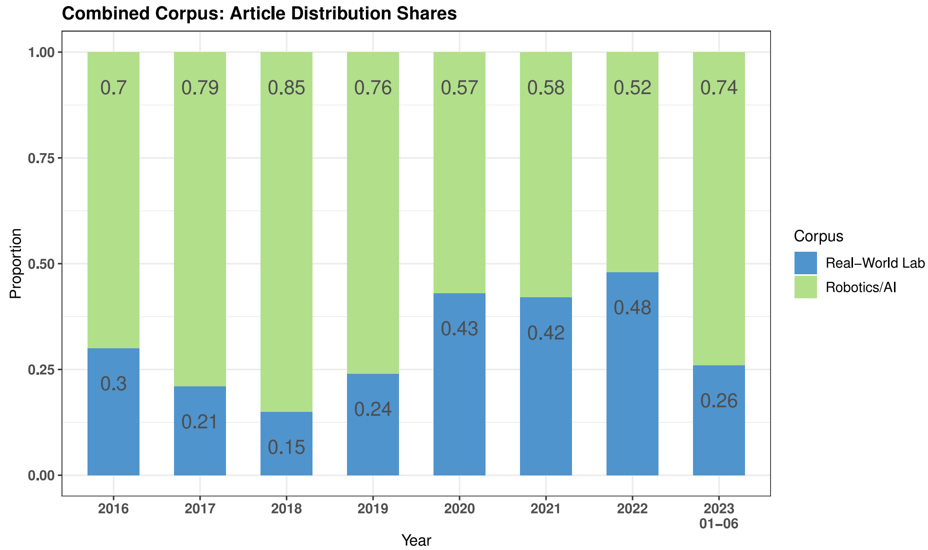

Fig. 4. The articles in the combined corpus originate from two separate searches that resulted in the Robotics/AI and the Real-World-Lab corpora. Shares of the original corpora in the combined corpus by year.

and selected the model with the best topic quality. Topic quality is a combination of semantic coherence and exclusivity of words to topics (Roberts et al., 2019, 2014). Semantic coherence measures the degree to which the content of a topic is meaningful. In a topic with high semantic coherence the most widely used words frequently occur together. Exclusivity measures the uniqueness of the terms in a topic compared to the terms in the other topics. A topic with high exclusivity has many terms that are unique to this topic. For our analysis, we chose the model with $k = 32$, as it performed best in terms of semantic coherence and exclusivity.[9]

We included two covariates: an indicator variable showing whether the article belongs to the Robotics/AI or the Real-World Lab corpus and the publication date. The indicator variable was used to model the prevalence contrast of the topics given the two underlying corpora. The topical prevalence contrast is a measure that determines whether a topic is categorized as a Robotics/AI topic, an integrated topic or a Real-World Lab topic.[10] The integrated topics are of particular interest for this study.

Based on the publication date, for each day in the time range, the algorithm estimates the shares of every topic using the least squares method on a polynomial of degree ten. Note that the shares of all topics add up to 1 for each day. Including this covariate facilitates an analysis of topic dynamics that traces the change of topic shares over time. Topic shares represent the relative importance of the topics at a specific time, where prominent topics have high shares. The fluctuation of topic shares reveals the topics that shape or dominate the discourse at a particular point in time. Fig. 10 in Appendix C illustrates the modeling process.

4. Results

4.1. Topic labeling, top terms and topic proportion

We surveyed the 32 topics in our model and labeled them manually. We chose the labels after closely reading the five most important articles in each topic.[11] and inspecting the respective word clouds.[12]

Table 3 provides an overview of our 32 topics, the six most frequent words per topic, and the topic proportions disregarding the timeline.[13] Note that the topic numbers are an output of the algorithm and may serve as a short reference for the topics. The top three topics are T3, labeled “Machine Learning and AI Development Methods”, T30, labeled “Philosophical Considerations on the Digital Transformation”, and T5, labeled “Digitization of Business Processes” with overall proportions of 5.87%, 5.17% and 4.68% respectively. T3 and T5 are Robotics/AI topics, which is expected, given that the share of the Robotics/AI corpus is 70% of the combined corpus. T30 is a topic that draws heavily on both corpora and is therefore considered a bridge topic. T28, labeled “Real-World Labs for Ecofriendly Mobility in Aachen” is the Real-World Lab topic with the overall highest proportion (4.15%) in the combined corpus.

Broader themes include “Robots and AI Applications in Professional Contexts” (T5, T6, T8, T11, T17, T20, T22, T29, T31, T32), “Government and Private Funding” (Topics T1, T7, T10, T16, T25, T27), “Real-World Labs” (T9, T15, T18, T28), “The Work Place” (T2, T26), “Robots and AI in Private Households and Schools” (T19, T23), “Robots and AI in Movies, Art and Literature” (T4, T21), and “Theory” (T3,

[9] For details on the iterative process for selecting the value of $k = 32$, see Appendix D.

[10] In the past, the method of topical prevalence contrast was used to clearly highlight differences in content between topics. Respective studies include several content contexts, like political speech, technological transformation, and media reporting, different text corpora (single corpora and combined corpora) and various languages (German and English in the examples briefly discussed below). In addition to the seminal work of Roberts et al. (2019), that refers to political speech from various parties, Scheu (2023) applied STM and in particular the perspective of “topical prevalence contrast” to a combined text corpus that includes abstracts of international patents and trademarks. Her analyses examined a field of high technology (robotics), low technology (footwear) and musical instruments with the goal to trace the sources of technological evolution over time beyond the use of structured data. Ott and Vannuccini (2023) analyzed the technology field of remote sensing and used the abstracts of international patents. The topics were then contrasted against the background of their affinity to the ICT sector (data affinity) or to economic sectors (e.g. private, public). Loewe et al. (2024), on the other hand, used a corpus of German newspaper articles, which were selected based on keywords. In this work a temporal shift of topics was studied in order to understand how the war of aggression against Ukraine has affected media coverage.

[11] Note that each article is assumed to be a distribution of topics with various shares s. Given a topic T, the most important articles for T are those with the highest values for s_T.

[12] The word clouds of selected topics are displayed in Appendix E.

[13] A table with the topics ordered by Topic Number is given in Table 4 in Appendix F.

Table 3
Topics and their proportions (Disregarding the timeline), ordered by proportion.

Topic label	#	Top words	Proportion
Machine Learning and AI Development Methods	3	Maschine, System, lernen, Algorithmus, Computer, menschlich	0.0587
Philosophical Considerations on the Digital Transformation	30	brauchen, wissen, Frage, Welt, Zeit, denken	0.0517
Digitization of Business Processes	5	digital, Digitalisierung, Unternehmen, Daten, Technologie, nutzen	0.0468
Artificial Humans in Movies and Literature	4	Maschine, menschlich, Buch, Leben, Welt, Menschheit	0.0454
Relationships between Humans, Machines and AI in Art Exhibitions	21	Kunst, Künstler, Film, zeigen, Ausstellung, Bild	0.0435
Real-World Labs for Ecofriendly Mobility in Aachen	28	Stadt, Aachen, Templergraben, Straße, Innenstadt, Auto	0.0415
Robots in Production	22	Unternehmen, Industrie, Bosch, Konzern, Produktion, Siemens	0.0391
Autonomous Cars	17	Auto, autonom, fahren, Fahrzeug, Tesla, selbstfahrend	0.0375
Digitalization and Automation Consequences for the Workplace	26	Arbeit, Digitalisierung, Arbeitsplatz, Maschine, Automatisierung, Beruf	0.0367
Real-World Labs for the Energy Transition	9	Wasserstoff, Energie, Projekt, Strom, Energiewende, Region	0.0356
Future Lab in Aachen - the Whole City as a Future Lab	15	Aachen, RWTH, Future, Stadt, Projekt, Veranstaltung	0.0350
Political Support for AI and Robotics in Germany	27	Deutschland, Europa, deutsch, Forschung, Wirtschaft, Industrie	0.0331
Lethal Autonomous Weapon Systems	31	autonom, Russland, System, ethisch, Waffe, Entscheidung	0.0321
Softbank (Japanese Tech Investor)	25	Japan, Dollar, Unternehmen, Softbank, Toyota, Fond	0.0320
Tightening of Investment Controls in the High-Tech Sector (USA, EU, Germany)	10	China, Land, Unternehmen, Europa, Amerika, Staat	0.0306
Real-World Labs for Sustainable Mobility in Baden-Württemberg	18	Stuttgart, Projekt, Baden, Campus, Idee, Württemberg	0.0300
Robots in Space and Robot Development	29	entwickeln, Forscher, arbeiten, Forschung, System, Entwicklung	0.0292
Chatbots and ChatGPT	6	Text, Chatbot, ChatGPT, Nutzer, Software, schreiben	0.0287
Service Robots and Assistance Systems	20	Darmstadt, Pepper, Einsatz, Patient, Pflege, helfen	0.0284
Regular Airspace Pilot Projects in Germany	12	Hamburg, Bahn, Berlin, Drohne, deutsch, Projekt	0.0278
Robots and AI in Private Households	19	Gerät, Smartphone, Amazon, Nutzer, Alexa, Produkt	0.0274
Government Funding for Research on AI and Climate Change	1	Hochschule, Universität, Professor, Studierender, Dresden, Forschung	0.0270
Google	14	Google, Amazon, Unternehmen, Konzern, Facebook, SiliconValley	0.0260
Fair Pay Innovation Lab	2	Mitarbeiter, Unternehmen, Kollege, arbeiten, wenig, Gehalt	0.0256
Covid Mass Vaccination as a Field Experiment	13	Pandemie, Corona, Krise, zeigen, Studie, wenig	0.0229
Robotics and AI in Construction, Agriculture and Policing	8	Landwirtschaft, Labor, Feld, Tier, wenig, Pflanze	0.0223
Fintech and Legal Tech	32	Kunde, Bank, Produkt, Blockchain, digital, Branche	0.0222
Tech Start-Ups	16	Start, München, Gründer, Firma, Unternehmen, Investor	0.0202
Digitalization in Urban Development	11	Stadt, smart, City, Zukunft, urban, Wohnung	0.0193
Digitization, Robots and AI in Schools	23	Kind, Schule, Schüler, lernen, studieren, digital	0.0172
AI and Robotics Cutting-Edge Research Funding in Bavaria	7	Bayern, Corona, Söder, München, Woche, gelten	0.0138
Digital Transformation Leaders	24	Unternehmen, Deutschland, gründen, Konzern, digital, Innovation	0.0128

T30). These are the main themes in the German media discourse about robotics, AI and real-world labs.

4.2. Topic dynamics

In addition to topic content, the results of the modeling exercise are estimates of the relationships between the topics and the covariates. The first covariate in our structural topic model is the publication date of the articles. Including this covariate facilitates an analysis that traces changes of topic shares over time. Topic shares can be seen as proxy for the relative importance of the topics at a specific time, where prominent topics have high shares. The change of topic shares identifies the topics that shape or dominate the discourse at a particular point in time. Fig. 5 displays the shares of the topics with the highest shares at some point in time between January 1, 2016 and June 30, 2023.[14]

From the start of 2016 to May 2019 the topic "Machine Learning and AI Development Methods" (T3) was the dominant topic. Disregarding the timeline, this topic has the highest overall share (5.87%)[15] and is based on articles on deep learning, artificial neuronal networks, evolutionary computation and the development of a general AI. It contains reporting on the technological progress in the development of AI. The topic "Artificial Humans in Movies and Literature" (T4) is the fourth most important topic overall and its shares vacillated depending on new movies being released and new novels being published and reviewed in the newspapers. It was the prominent topic for several months in 2019. The topic "Real-World Labs for the Energy Transition" (T9) began gaining attention mid 2018 and from the start of 2020 to October 2022 this topic remained one of the two top topics. From May 2020 to March 2021 the topic "Covid Mass Vaccination as a Field Experiment" (T13) superseded the topic about energy real-world labs as the top topic. The shares of topic "Chatbots and ChatGP" (T6) increased rapidly towards the end of the evaluation period and became the dominant topic in October 2022. We will discuss the results of this analysis in Section 4.6.

4.3. Topical prevalence contrast

The second covariate is an indicator variable showing whether the article belongs to the Robotics/AI or to the Real-World Lab corpus. This variable is used to elicit a topical prevalence contrast, a measure of the variability of topic coverage conditional on the sub-corpus. The results of our topical prevalence contrast analysis are given in Fig. 6.

The topics on the left-hand side draw mostly from articles in the Robotics/AI corpus. The topics that are most notably based on the Robotics/AI corpus include "Machine Learning and AI Development Methods" (T3), "Artificial Humans in Movies and Literature" (T4) and "Automation Consequences for the Workplace" (T26). The topics on the right-hand side are mainly based on articles in the Real-World Lab corpus. The three topics that are mostly based on the Real-World Lab corpus include "Real-World Labs for Ecofriendly Mobility in Aachen" (T28), "Real-World Labs for the Energy Transition" (T9), and "Future Lab Aachen - the Whole City as a Future Lab" (T15). All of these topics belong to the real-world lab theme. Note that these topics show a greater deviation from zero than the robotics/AI topics, indicating that they draw to a lesser extent from articles in the Robotics/AI corpus than vice versa.

[14] We omitted T15 and T28 from this graph, since these two topics are specific to Aachen and do not pertain to the whole country.
[15] Compare Table 3.

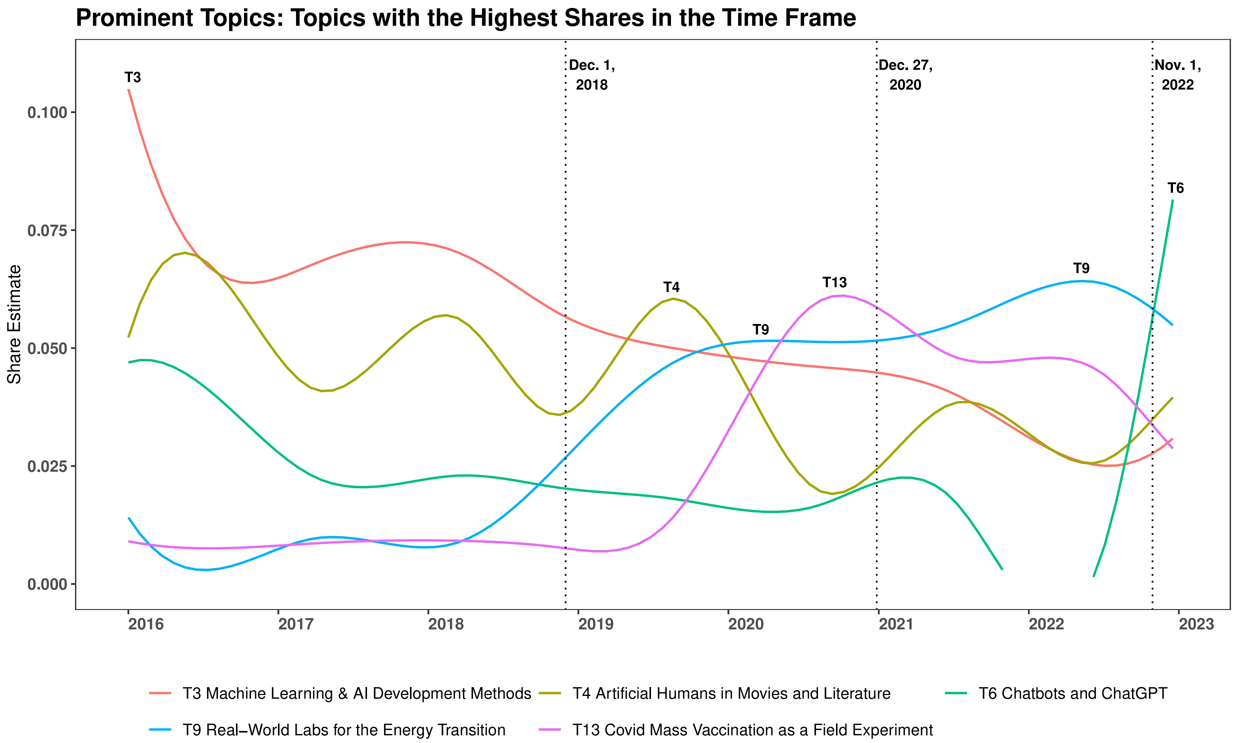

Fig. 5. Topic proportions change over time. This figure shows the shares of the topics with the highest shares at some point in the time frame. Topics with the highest shares dominate the reporting. The vertical dotted lines denote three important dates: Dec 1, 2018 (the launch of the Strategy for Real-World Labs by the German Federal Ministry of Economic Affairs and Climate Action), Dec. 27, 2020 (the official start of the Covid vaccination campaign in Germany), and Nov. 1, 2022 (the month in which ChatGPT was first released). Note that T3, T4, and T6 are robotics/AI topics, T9 is a real-world lab topic and T3 is a bridge topic. Across time we see a shift of the dominating topic from RAI to RWL.

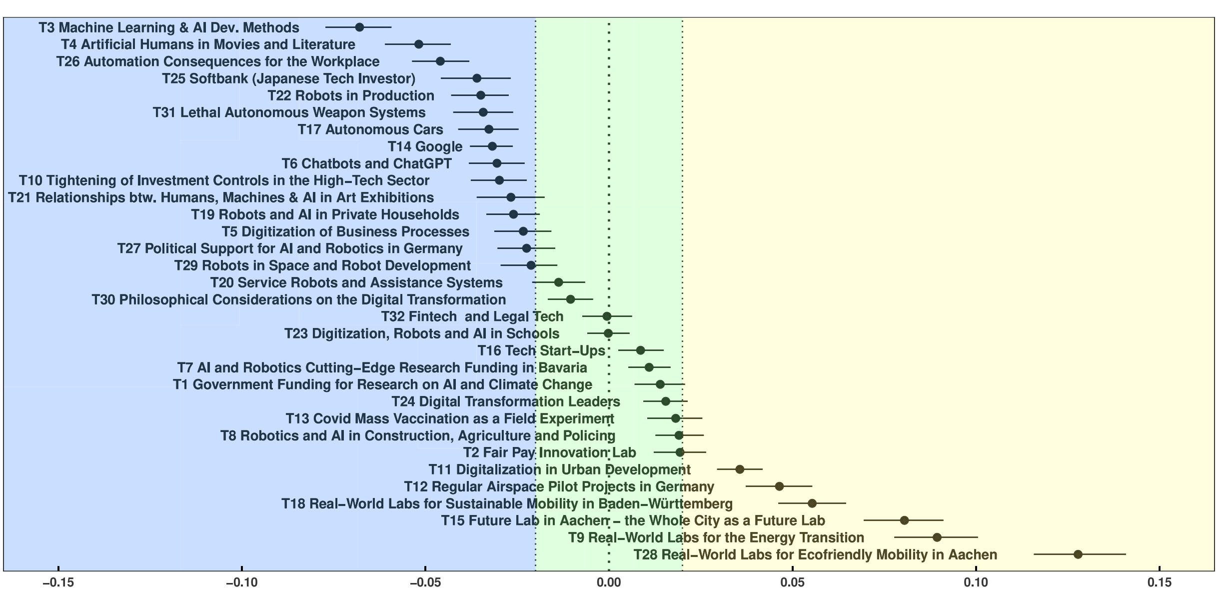

Fig. 6. Topical prevalence contrast reflecting the variability of topic coverage conditional on the sub-corpus. The dots denote the means and the lines denote the 95% confidence intervals of the estimates. Topics in the blue area are predominantly based on the Robotics/AI corpus, topics in the yellow area are mostly based on the Real-World Lab corpus and topics in the green area are bridge topics that link the two domains.

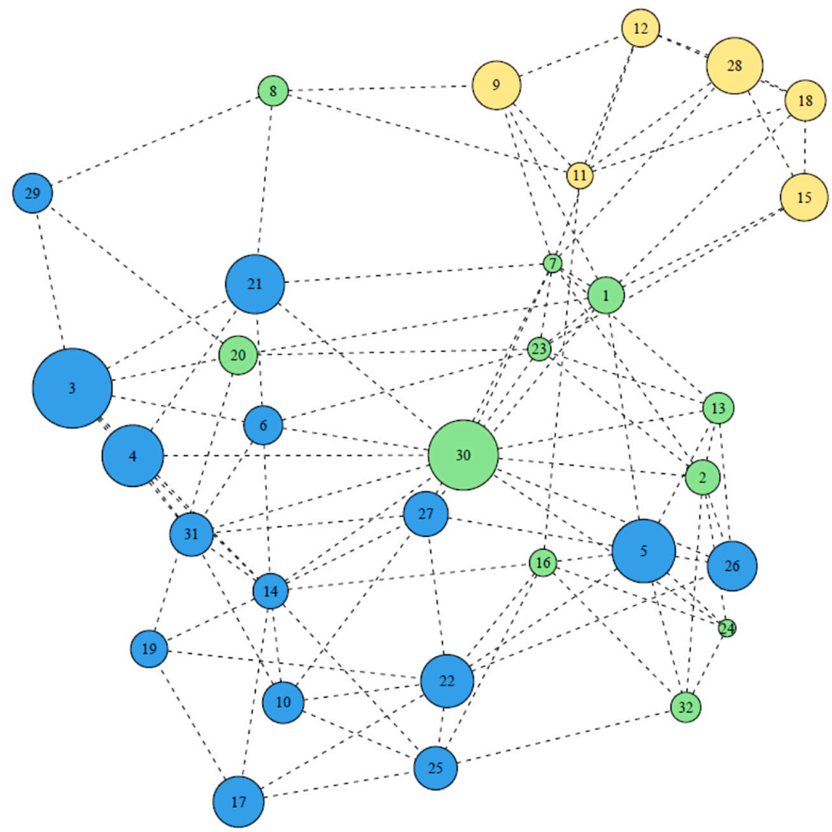

Fig. 7. Correlation network. The edges display a positive correlation between two topics and indicate that the two topics are likely to be discussed in the same articles. The threshold value for drawing edges is 0.01. The sizes of the vertices represent the proportions of the topics disregarding the timeline. Blue vertices represent topics mainly based on the Robotics/AI corpus, yellow vertices represent topics mainly based the Real-World Lab corpus and green vertices represent bridge topics that link the two domains.

We are particularly interested in the topics that are equally based on both sub-corpora. They are the bridge topics that link the domains of robotics/AI and real-world labs and are marked green in Figs. 6 and 7. The bridge topics at the interface of robotics/AI and real-world labs include "Service Robots and Assistance Systems" (T20), "Philosophical Considerations on the Digital Transformation" (T30), "Fintech and Legal Tech" (T32), "Digitization, Robots and AI in Schools" (T23), "Tech Start-Ups" (T16), "AI and Robotics Cutting-Edge Research Funding in Bavaria" (T7), "Government Funding for Research on AI and Climate Change" (T1), "Digital Transformation Leaders" (T24), "Covid Mass Vaccination as a Field Experiment" (T13), "Robotics and AI in Construction, Agriculture and Policing" (T8), and "Fair Pay Innovation Lab"[16] (T2).

4.4. Correlation network

In addition to topics and their proportions, the STM algorithm outputs information on the structure of the relationships between the topics. The correlation network offers a visual representation of this relationship structure. The vertices denote topics and the edges represent positive correlations, that indicate that the two topics are likely discussed within the same articles. The correlation network of our model is given in Fig. 7. Note that the size of the vertices represent the proportions of the topics disregarding the timeline.

We colored the vertices according to the three types of topics identified by the topical prevalence contrast analysis in the section above: blue vertices represent topics that are predominantly based on articles in the Robotics/AI corpus, yellow vertices represent topics that are mainly based on articles in the Real-World Lab corpus and green vertices represent bridge topics that link the two domains.

We observe by visual inspection that the correlation network has two main clusters that neatly divide the 32 topics into real-world labs topics (marked yellow) and non-real-world lab topics (marked blue and green). There are some edges between the two clusters.[17] Notably, these edges connect vertices that represent real-world lab topics with vertices that represent bridge topics, specifically the application topic "Robotics and AI in Construction, Agriculture and Policing" (T8) and the three funding topics "Government Funding for Research on AI and Climate Change" (T1), "Tech Start-Ups" (T6), and "AI and Cutting-Edge Research Funding in Bavaria" (T7). Three of these four topics (T1, T7, T8) are located at the margin of the non-real-world lab cluster and have the smallest distance to the real-world lab cluster.

Community detection can be used to detect topics with similar properties and extract sub-groups based on various specifications. We have tried various cluster (or community) detection algorithms that are commonly used in network analysis.[18] We analyzed the resulting clusters for several of threshold values for correlation and saw some similarities to our approach of the bridge topics. E.g. T1 acts as a link between a variety of clusters for several threshold values.

Regarding the importance or the "prestige" of a topic within a network, Eigenvector centrality is an indicator that is frequently applied. Eigenvector centrality is an important concept in graph theory to measure the influence of a node in a connected network. Connections to

[16] Based in Berlin, the Fair Pay Innovation Lab is an advocacy group for fair pay and equal opportunity at the work place.

[17] Note that the appearance of an edge is conditional on the chosen threshold value which we have set to 0.01. If we reduced (increased) the threshold, more (less) edges appeared.

[18] We used the Louvain algorithm of the igraph library of R.

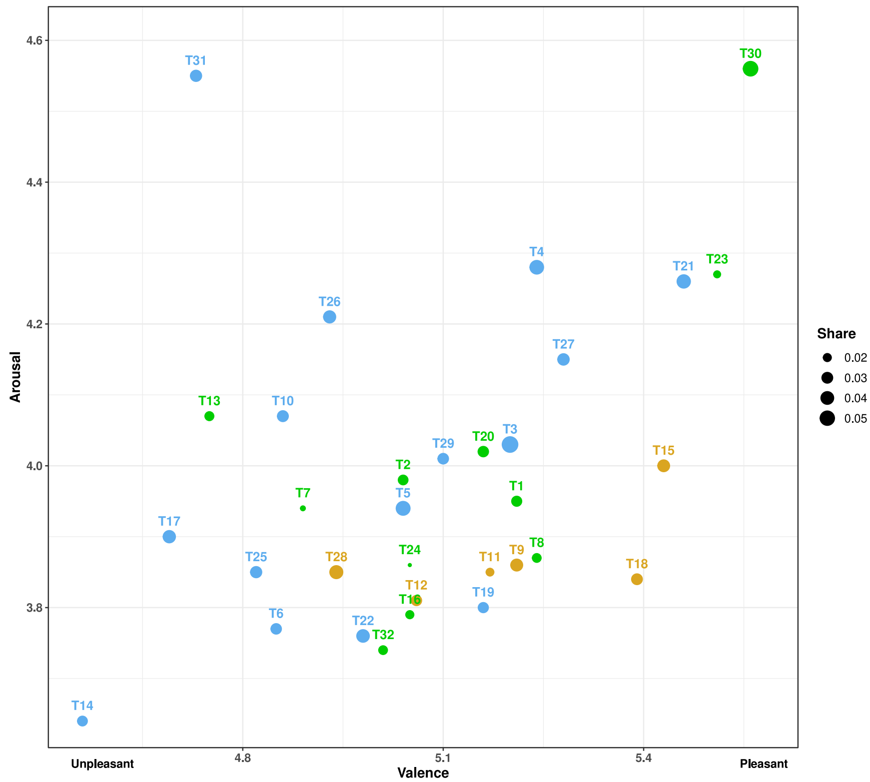

Fig. 8. Topic valence and arousal. The size of the dots represent the proportions of the topics disregarding the timeline. Blue vertices represent topics based on the Robotics/AI corpus, yellow vertices represent topics mainly based the Real-World Lab corpus and green vertices represent bridge topics that link the two domains.

high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. A high eigenvector score thus means that a node is connected to many nodes who themselves have high scores. Sometimes, eigenvector centrality is also used to measure the "prestige" of a node in a network. Interestingly, the topics with the highest Eigenvector centrality are "Philosophical Considerations" (T30) and "Political support for AI in Germany" (T27) (compare Table 4 in the Appendix).

4.5. Sentiment analysis based on four psycholinguistic attributes

Another avenue of text analysis is the study of the emotional content of a text. Topic sentiment analyses allow to assess even large datasets. The results exploit information based on unsupervised methods and can be applied with minimal a-priori assumptions and at low costs (compare Quinn, Monroe, Colaresi, Crespin, & Radev, 2010). To analyze texts in German, SentiWS, a comprehensive sentiment lexicon with more than 3,000 words, can be applied (Remus, Quasthoff, & Heyer, 2010). However, only one dimension is covered. In contrast, our sentiment analysis is based on a specialist dictionary for the German language which provides for four psycholinguistic attributes for roughly 340,000 German lemmas (compare Köper & Schulte im Walde, 2016). The attributes include valence, arousal, abstractness and imageability and values ranging from 0 to 10.

Valence refers to the pleasantness of a word (unpleasant vs. pleasant), arousal rates the intensity of emotional activation inherent in a word (calm vs. alert), abstractness determines the level of sensory perceptibility (abstract vs. concrete), and imageability describes the visibility of the meaning of a word (invisible vs. visible).

We define the topic score for these four attributes as follows:

$$s_a = \sum_{w \in V} \gamma_{w,t}\, \sigma_{w,a}.$$

Here V refers to the vocabulary of the entire corpus, $\gamma_{w,t}$ denotes the estimated frequency of a word w in a topic t, and $\sigma_{w,a}$ represents the score for attribute a of word w in the dictionary. The topic scores are given in Table 4 in Appendix F.

The articles in the corpus report on both, abstract topics (e.g. T30) and more concrete topics (e.g. T20). We address the psycholinguistic dimensions of abstractness and imageability in Section 4.6.

We studied the attributes valence and arousal in more detail. Fig. 8 displays the topic scores of these two attributes. Like in Section 4.4 above, the colors represent the topic types (Robotics/AI topics vs. bridge topics vs. Real-World Lab topics), and the size of the dots denote the topic shares disregarding the timeline as reported by their proportions in Table 3.

As expected, the topic about lethal autonomous weapon systems (T31) has a low valence score and one of the highest arousal scores. This topic is based on articles reporting on progress in the development of lethal robots and AI that activates high levels of emotions and is generally unpleasant. Its opposite is T30 ("Philosophical Considerations on the Digital Transformation") that has the highest scores for both, valence and arousal, and is based on articles discussing the potential of the digital transformation, with high frequencies for words that evoke hope in a better future.

Other topics with high valence scores include T23 ("Digitization, Robots and AI in Schools"), T21 ("Relationships between Humans, Machines and AI in Art Exhibitions"), T15 ("Future Lab Aachen - the Whole City as a Future Lab"), and T18 ("Real-World Labs for Sustainable Mobility in Baden-Württemberg"). These are the most pleasant topics. T26 ("Digitalization and Automation Consequences for the Workplace") ranks second regarding arousal.

The most unpleasant topics on the other end of the spectrum, include T17 ("Autonomous Cars"), T13 ("Covid Mass Vaccination as a Field Experiment"), and T14 ("Google"). T17 draws from reporting on the dangers of autonomous mobility and T13 is based on discussions of the high mortality rates of the Covid pandemic, so the low valence scores of these topics are easily comprehensible. However, the low valence score of T14 comes as a surprise and needs further investigation.

4.6. Discussion

In Section 4.2 we have shown how the focus of the reporting on RAI and RWL in German broadsheet newspapers has changed over time. For more than three years from the start of our time frame, the topic “Machine Learning and AI Development Methods” (T3) was most reported on. It is remarkable that this topic held such prominence for such a long time, given that the readers of the newspaper articles were not experts in the field, but the general public. This demonstrates that the German public was intrigued by technical details of machine learning and AI development and attentive to emerging developments.

The topic “Artificial Humans in Movies and Literature” (T4) was one of the top two topics for the first four years of our time frame. In this period it was the most important topic next to the topic about machine learning and AI development methods (T3). While T3 kept the public abreast of technical details, T4 captured and nurtured their imagination, demonstrating the implications of living with advanced technologies through fictional stories. The comparatively high valence and arousal values (see Fig. 8) indicate that these stories were mostly inspiring and hopeful.

The topic “Covid Mass Vaccination as a Field Experiment” (T13) was prominent for ten months in 2020 and 2021, the period when strategies to contain the Covid-19 pandemic were hotly debated and mass vaccinations against the virus were perceived as a field experiment. This topic is one of the bridge topics that link the two domains under consideration and it stands out as one of the topics with the lowest valence values (see Fig. 8), easily explainable on the grounds that Covid had initially such high mortality rates.

The topic “Real-World Labs for the Energy Transition” (T9) began gaining attention mid 2018 and from the start of 2020 to October 2022 this topic remained one of the two top topics. This ranking reflects the significance of the real-world labs for the energy transition, a new project type established by the Federal Ministry for Economic Affairs with the publication of the 7th Program for Energy Research in September 2018. These guidelines for energy research policy introduced real-world labs for the energy transition as test spaces for innovation and regulation, designed to accelerate the maturation process of innovative energy technologies. Table 2 lists the milestones in the development of this new project and funding format.

Finally, the shares of topic “Chatbots and ChatGP” (T6) increased rapidly towards the end of the evaluation period and became the dominant topic in October 2022. The reason for this astonishing rise is the release of the generative AI ChatGPT in November 2022, the media attention it garnered and the hype it entailed. However, this topic has a low valence value (see Fig. 8), indicating that it was predominantly discussed in negative terms, though unemotionally, as suggested by its low arousal value.

In Section 4.3 we have identified the topics that are evenly based on both sub-corpora and have introduced the term “bridge topics” for them, since they link the domains of robotics/AI and real-word labs, as depicted in Fig. 6. Note that the two bridge topics with strong links to research activities, “Government Funding for Research on AI and Climate Change” (T1) and “AI and Robotics Cutting-Edge Research Funding in Bavaria” (T7), belong to the broader theme “Public and Private Funding”. As shown in Section 4.4, both topics are among the few topics from the non-real-world lab cluster that have edges to the real-world lab cluster in the correlation network (see Fig. 7). We conclude that these topics are essential for linking the two domains. Further, the bridge topics “Service Robots and Assistance Systems” (T20), and “Robotics and AI in Construction, Agriculture and Policing” (T8) belong to the broader theme “Robots and AI Applications in Professional Contexts”. In the correlation network, T20 also serves as a topic that links the real-world lab cluster to the non-real-world lab cluster, indicating that it is particularly suited to act as a linkage between the two domains robotics/AI and real-world labs.

We also observed that some overarching themes are discussed in very different ways. For example, there are two topics about mobility: the topic on autonomous cars (T17) is part of the RAI domain and is viewed rather critically and the topic on sustainable mobility (T18) is part of the RWL domain and viewed very positively. T19 and T20 relate to robotic assistance systems, both of which appear with high valence and somewhat different arousal scores.

Note that the network in Fig. 7 does not display three distinct clusters that correspond to the three types of topics identified in Fig. 6. Rather, the network reveals a structure that may be grouped to clusters in various ways and that needs further analysis which we postpone to follow-up work. However, our focus on prevalence contrast is novel and provides additional insights that could not be gained from standard network metrics.

As argued before, the topics with the highest Eigenvector centrality are “Philosophical Considerations” (T30) and “Political Support for AI in Germany” (T27) (compare Table 4 in the Appendix).

We also applied a correlation analysis covering the dimensions of topic proportion, Eigenvector centrality, topical contrast and the four psycholinguistic attributes disregarding the timeline. The results are shown in Fig. 14 in Appendix G. Clearly, the size of the topic proportion has almost no impact on the other dimensions discussed (with the exception of arousal that weakly correlates with size (0.367*)).

The correlation plot in Fig. 14 confirms the intuition that more abstract and less imageable topics are less prestigious (as reflected by low Eigenvector centrality values) and thus negatively correlated with Eigenvector centrality (−0.590** for imageability and −0.569*** for abstractness). In contrast, arousal and Eigenvector centrality are positively correlated (0.394*).

The negative correlation between topical prevalence contrast and the Eigenvector centrality (−0.560***) highlights that mostly topics from the RAI subcorpus are linked to other prestigious topics.[19] Finally, topics originating more from the RWL sub-corpus trigger less arousal.

5. Policy implications, critical reflection, and future perspectives

In times of multiple challenges and in an increasingly complex world, technological innovations and the associated institutional settings must be consistently jointly evaluated and jointly further developed. This is the only way to shape current future challenges in a targeted manner and to successfully master them.

Embedded in the theoretical framework of Technical Innovation Systems (TIS) and based on a quantitative text analysis, this paper identifies the dominant topics that are addressed in the broad media discourse at the intersection of RAI and RWL and shows their dynamics. Using psycholinguistic attributes, it is possible to carry out differentiated sentiment analyses. It is also worthwhile, especially in times of tight budgets, to identify interfaces between the two currently important funding priorities of RAI and RWL. Our approach provides valuable information for a regulatory authority that aims to develop flexible and targeted policy instruments.

The proposed data-driven approach also contributes to fulfill the promise of real-world labs to be transparent and accessible for evaluation. One of the aims of RWLs is to alleviate a recognized weakness of innovation systems, namely the frequent lack of quantifiability of considerations. The development of suitable indicators contributes to a solution. Society plays an important role in successfully mastering the current challenges of the future, however, assessing the societal perspective in particular is not trivial. Regulatory policy makers must have a solid understanding of the assessment of the population of

[19] Recall, that the values for topical prevalence contrast result from the analysis in Fig. 6. A positive contrast value implies that the topic originates more from the RWL sub-corpus whereas a negative contrast value implies that the topic is more closely related to the RAI sub-corpus.

the relevant issues. This is the only way to develop and continuously improve suitable policy instruments and adapt them to changing conditions.

While R&D processes at the beginning of the innovation process are already well understood and underpinned by suitable indicators (see OECD/Eurostat, 2018), the evaluation of the diffusion of innovations and the potentially necessary adjustments to the legal framework conditions at the end of the innovation process are still not sufficiently underpinned by quantitative indicators. However, they are absolutely necessary in order to do justice to the claim of evidence-based policy-making. At the same time, a regulatory authority also needs neutral signals that it can use as a guide when designing policy instruments.

Based on this study, we suggest two ways in which political decision making and design of instruments can be improved.

First, the successful implementation of new policies depends on effective communication and a positive reception of the proposed policies by the constituencies that are most affected. The method outlined in this study can be used to elicit the potential reception of new policy instruments while they are being designed and continuously further adjusted and developed. Regulatory sandboxes by definition create restricted spaces that experiment with various boundary conditions and deliberately break legal constraints to explore which configuration of conditions best promote innovation. By design, regulatory sandboxes are particularly suited for developing, testing and adjusting new policy instruments.

Second, creating a budget always implies tough choices regarding competing funding priorities. Both robotics and regulatory sandboxes are important current funding lines in Germany. Politicians often face budgetary constraints and are called to prioritize funding. Especially in times of increasingly tight budgets, it is therefore all the more important to identify links between different funding contents and to promote complementarities. When developing bases for political funding decisions, the method showcased in this study may be used to identify areas that link two competing funding priorities. Investing in these bridge areas will generate synergies by serving both priorities simultaneously.

Regarding content, our aim was to identify unifying elements in complex media reports as well as idiosyncratic topics. Such a comprehensive approach is particularly important in times of overlapping challenges.

As with all scientific analyses, a classification of the results requires a close examination of the data used. The data set consists of two sub-corpora, which are based on well-founded search terms. These were carefully determined in advance and a broader perspective was chosen in the case of the relatively new concept of real-world laboratories, which are not yet clearly defined and which include a wide range of English-language terms even though the language of the newspapers was German.

We chose as data sources big German broadsheet newspapers that cover a broad political spectrum, expecting as a result a comprehensive and undistorted picture of reporting in the fields of RAI and RWL. These newspapers were selectively supplemented by regional newspapers from cities with a variety of real-world laboratory activities. We made sure that only one regional newspaper was used per federal state (e.g. in Baden-Württemberg the *Stuttgarter Zeitung*, but not the *BNN* from Karlsruhe). Furthermore, not all federal states were covered.

As a result, we compiled a combined text corpus where the RAI sub-corpus is twice as large as the RWL sub-corpus. This imbalance appears to be harmless for the analysis. We find that over time there is a shift in the dominant topics towards RWL-related topics (cf. the topic diffusion curve for T9 in Fig. 5).[20] We interpret this shift as evidence that the increasing importance of institutional innovation is reflected in the public media. The analysis does not include user generated content on social media, although this would be possible from a methodological point of view. Reference is made here to future work.

The results obtained by applying the STM and the interpretations derived from these results strongly depend on the preprocessing of the data, which should only be partially automated. The outcome has to be carefully evaluated and individual process steps may have to be adapted in order to obtain valid analysis bases. In particular, compiling the custom stop word list requires careful consideration.[21] One advantage of the German language is the creation of a comprehensive sentiment analysis along four dimensions of psycholinguistic attributes, which goes far beyond commonly used sentiment analyses.

The selection of the number of topics and the topic labeling are particularly critical for the outcome. While the selection of the best possible number of topics can be supported by the algorithm, this is not feasible for topic labeling. In order to obtain accurate labels, we have chosen a combined view of the top terms and the top articles from which the topic originates. This text corpus also shows that not all topics can be conclusively assessed and consistently included in the overall context (here, for example, this applies to T14 “Google”).

In addition, Grimmer and Stewart (2013) highlighted that automated methods cannot replace careful manual validation of the results and cannot wholly avoid manual assessment. Domain knowledge helps to link the results to policy analyses and to interpret the findings. These interpretations also need to take into account that newspaper articles may be biased regarding sentiment since media more frequently report about problems or concerns than about opportunities.

To show that our core idea of bridge topics delivers meaningful results not only in the context of RAI/RWL, we applied the concept to another text corpus (the GEL corpus; details below). This text corpus also includes broadsheet newspaper articles for reasons of comparability and focuses on the interface between geothermal energy/geothermal heat and lithium. Details of the analysis can be found in Appendix H. For a model with 34 topics, we determine the TPC (i.e. mean difference and confidence interval), present the topic correlation network and roughly classify the results in the context of the content of GEL.[22]

Once again, bridge topics are defined as the topics with a mean difference close to zero and a confidence interval sufficiently close to the mean difference. The bridge range for the RAI/RWL corpus is represented by the boundary of the green area in Fig. 6. It can only be determined in the interaction between the mean difference and the associated confidence intervals of the bridge topics and depends on various factors. These include the research question, delimitation of the topic area, identification of relevant data, data volume and text preprocessing.

A comparison of the results of the TPC for the RAI/RWL corpus and the GEL corpus shows that the width of the confidence interval is topic-specific. The topics in the RAI/RWL model have narrow confidence intervals. This simplifies the definition of the bridge range and it is straightforward to identify the bridge topics. However, the topics in the GEL model have wider confidence intervals. We suggest to further subdivide the bridge topics in the GEL model as follows: “strong bridge topics” are bridge topics where both, the mean difference and the confidence interval, lie in the green bridge area, whereas “weak bridge topics” have the mean in the green area, but the confidence interval extends into the area of the covariates, i.e. either the blue area or the yellow area.

This robustness analysis confirms that the considerations for the RAI/RWL corpus also work methodically for the GEL corpus and provide meaningful interpretable results. The extent to which a refined

[20] Other studies with comparable unbalanced datasets also show that this is harmless for the interpretation of the results, e.g. geothermal energy.

[21] As the German language includes many compound nouns, *n*grams do not play a significant role. This is different in English and other languages. Working with text data in these languages, *n*grams must be chosen carefully.

[22] In the context of this paper, a detailed discussion of the content is not necessary for the justification of the methodological approach.

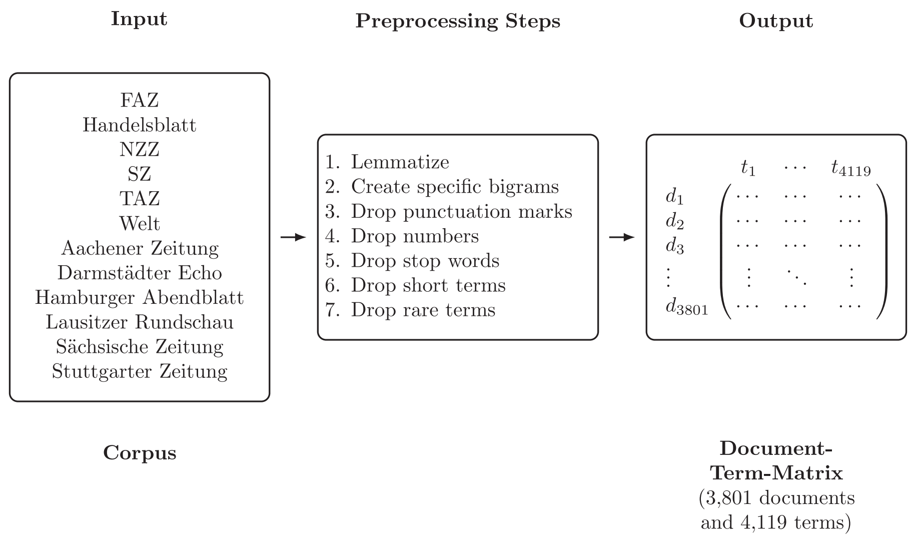

Fig. 9. The preprocessing steps that take the collection of newspaper articles (corpus) and facilitate mapping it to a mathematical representation, the document-term matrix. Compare (Loewe et al., 2024) for a similar presentation.

subdivision into strong and weak bridge topics is necessary depends on the respective research question. The fine-tuning of the bridge range in particular must be carefully set individually for each text corpus, critically scrutinized and justified in terms of content. In addition to methodological competence, this also requires subject-specific domain knowledge.

The following strengths of the chosen approach are particularly obvious. STMs facilitate the analysis of large volumes of text that cannot be analyzed manually in this depth. For example, using this method, we found a shift in importance from technological to institutional innovations in the fields of RAI and RWL.

STMs allow mapping the text data to a mathematical representation and thus to link it with other analysis methods including network analyses, eigenvector centrality and sentiment analyses based on a dictionary with psycholinguistic attributes. This combination of methods and indicators facilitates a comprehensive analysis of the corpus and there are a number of extensions that go far beyond what is described here.

The present approach is only a first step that could be followed by many other analyses. These include a much more comprehensive network analysis, the comparison of standard community detection with the idea of bridge topics developed here, as well as the additional consideration of the strength of topic correlation, which varies between the topics. We experimented with the Louvain method for community detection as implemented in the algorithm of the R package "igraph". However, none of the detected communities could be applied 1:1 to our network-cluster perspective and especially the bridge topics that we propose. We are therefore confident that our perspective of the bridge topics and their embedding in the network brings additional insights that go beyond the application of already established cluster perspectives. In addition, a particular challenge is to explore the interfaces with other established indicators. Furthermore, it is possible to search for specific terms in topics and to view the text corpus from this perspective. Contentwise, such a targeted analysis is basically possible in all directions and depends very much on the chosen research question. We see great potential here. Another avenue for future research would be the creation and analysis of a knowledge graph.

Links between the theory of innovation systems and the RWL exist in particular in the functions mentioned in Section 2: guidance of the search that considers societal embedding, preferences and expectations, the creation of legitimacy and the importance of protected niches where learning can occur. RWLs extend this learning perspective from firms to governments. Regulatory learning in the context of real-world labs refers to the process of developing, testing, and refining regulations, policies, and governance structures within a controlled, experimental setting that closely mimics real-life conditions. Real-world labs provide a space for stakeholders — such as researchers, policymakers, businesses, and the public — to collaborate on innovative solutions to societal challenges. However, the tools and indicators proposed so far are mostly backward-looking. In the future it would be particularly interesting to apply the setup also to forward-looking perspectives. One idea could be to bridge the perspectives of innovation systems, RWLs and the discipline of Future Studies. In particular, the aim is to make decisions not only on the basis of so-called "strong signals", i.e. information that is available at an early stage and is specific enough to allow for adequate responses. Instead, modern methods of analysis could be used to identify "weak signals" and take them into account as an impulse, for example for the design of policy instruments.

Ansoff (1975), one of the earliest contributors to the study of weak signals, referred to them as symptoms of possible future change. Hiltunen (2008) described weak signals along three dimensions: signal, issue and interpretation. The signal denotes the visibility of the weak signal as reflected by the frequency of occurrence, the issue captures the extent to which the weak signal diffuses across different events, and the interpretation reflects the understanding of the receiver and feedback on the signal. This paper already uses newspaper articles to assess the concept, although it does not rely on a large amount of data to motivate the dimensions. Hiltunen (2010) examines weak signals and related concepts and tests a tool for using weak signals to improve organizational future learning. Holopainen and Toivonen (2012) provide a summary of weak signal studies where they highlight how they contribute to a variety of futures studies.

More recently, Griol-Barres, Milla, Cebrián, Fan, and Millet (2020) attempted to quantify the three dimensions of weak signals proposed by Hiltunen (2008) and explained them as a novel analytical framework to assess visibility, diffusion, and influence. However, emerging issues were not addressed in their study. Newspaper articles were also considered as a source for identifying weak signals. Recently, El Akrouchi, Benbrahim, and Kassou (2021) made a first step in this direction; the title of their paper highlights this: "End-to-end LDA-based automatic weak signal detection in web news". More information can be found in van Veen and Ortt (2021), or Ha, Yang, and Hong (2023).

In addition, a combination of STM and a changepoint analysis would be conceivable in order to quantitatively map the determinants of temporal dynamics. To date, only a few studies have pursued this approach of combining time series analyses and topic models. Dehler-Holland, Schumacher, and Fichtner (2021) and Dehler-Holland et al. (2021) showed that such an approach can be used for German wind energy to trace the coincidence between changepoints and changes in the underlying policies.

The combination of established theories and modern analytical methods has the potential to make an important contribution to the creation of indicators that will help policymakers develop suitable regulatory instruments in the future. However, we leave these ideas for future research.

6. Conclusion

Modern robots that operate outside well-structured environments and interact with humans are among the most promising technologies for future applications. Concrete requirements for the machines are still unclear, as are the framework conditions for testing the machines. The framework needs to be set up in such a way that it allows for continuous testing, while at the same time providing legal certainty for innovators and meeting the needs of potential customers. Regulatory sandboxes are a modern tool of innovation policy to enable precisely this and to involve the state as a learning actor. But how does society view these two phenomena together? Newspapers are a traditional and long-standing medium for conveying information to the public, including scientific and technological developments, and placing them in a larger context.

Both RAI and RWL are current topics in innovation promotion, but they are mostly treated in isolation. This paper uses quantitative text analysis to examine 3,800 German newspaper articles in the period 2016–2023. We were particularly interested in the interface between RAI and RWL. We show that in our combined corpus, the dominant topic has changed over time from "Machine Learning and AI Development Methods" to "Real-World Labs for the Energy Transition". The connecting themes are diverse and include philosophical and legal considerations, specific application areas for robots and public funding.

A particular focus was placed on a quantitative analysis and the linking of these two perspectives that are otherwise considered in isolation. Fostering technology adoption is a pivotal step in the innovation process and represents a well known bottleneck for the successful deployment of a new technology from research and development to the market and end user (Grubb et al., 2021).

Ideally, by bridging traditional and new perspectives, the role of regulatory sandboxes in innovation system research can be further substantiated, findings from regulatory sandbox research can be scaled and transferred to other contexts, and the impact of regulatory sandbox research can be better evaluated and scaled. To conclude, the potential of regulatory sandboxes should be exploited to a greater extent by using them in a wide variety of contexts. Sustainability transformation and technology development at the interface with society are two examples that can be expanded. However, regulatory sandboxes need to be complemented by other theories and methods that are well established in order to gain deeper insights. This way regulatory sandboxes have the potential to gain societal and scientific impact.

Smooth co-evolution of technological development and the institutional environment are essential to enhance aggregate productivity and international competitiveness and to continuously increase social welfare.

CRediT authorship contribution statement

Martha Loewe: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ingrid Ott:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL and DeepL Write in order to improve the linguistic quality of the article. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

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

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Appendix A. Excerpt from the custom stop words list for illustration

"Roboter", "Robotik", "Robotics", "Robot", "Roboterauto", "Industrieroboter", "Roboterarm", "Sexroboter", "Robotaxi", "Roboterhersteller", "Pflegeroboter", "Roboterwagen", "Killerroboter", "Roboterhund", "Robotic", "Robotertechnik", "Serviceroboter", "Saugroboter", "Robotiker", . . . , "Dabei", "Dadurch", "Dafür", "Dagegen", "Daher", "Dahinter", "Damals", "Damit", "Danach", "Daneben", "Daniel", "Dann", "Daran", "Darauf", "Daraus", "Darin", "Darum", "Darunter", "Darüber", "Dass", "David", . . . , "voneinander", "vorab", "voran", "voraus", "voraussichtlich", "vorbei", "vorerst", "vorhanden", "vorhandenen", "vorher", "vorigen", "vorn", "vorne", "vorrangig", . . .

Appendix B. Preprocessing text data

The preprocessing steps are shown in Fig. 9.

Appendix C. Model specification

The model specification can be found in Fig. 10.

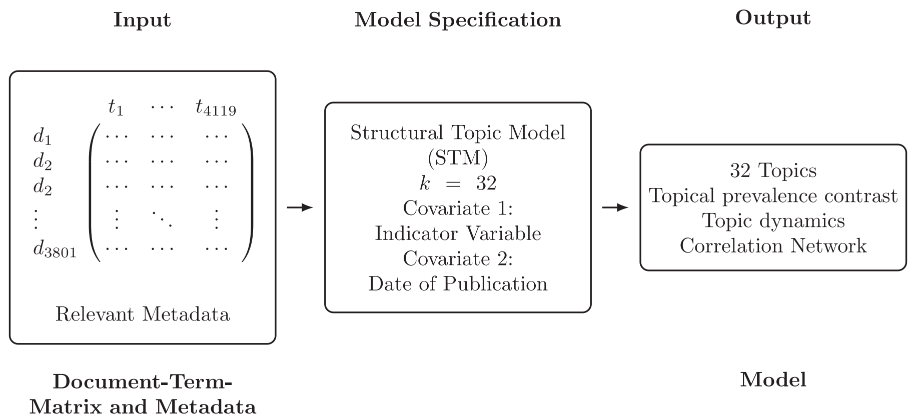


Fig. 10. The Structural Topic Model (STM) is specified by the number of topics k and the definition of covariates. It takes as input the document-term matrix and relevant metadata and outputs k topics and an estimate of the relationship between the topics and the covariates. Compare (Loewe et al., 2024) for a similar representation.

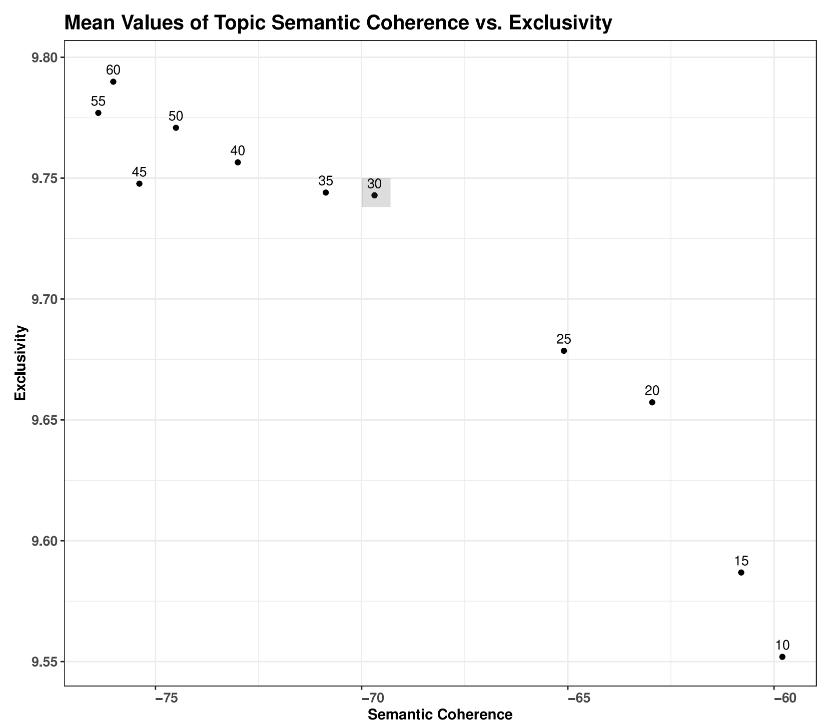


Fig. 11. Finding the optimal k. Mean values of topic semantic coherence and exclusivity for the first candidate model set. The labels denote the values of k.

Appendix D. Iterative process for selecting the value of k

In structural topic models (STMs), the number of topics k is given by the modeler. We selected k based on semantic coherence and exclusivity and proceeded as follows. We first generated a set of candidate models for all values $k \in [10, 60]$ in steps of 5. We computed the means of topic exclusivity and semantic coherence for each value of k and visualized the result, see Fig. 11. We observed that in this set of models the model with $k = 30$ performed best.

In the second step we generated another set of candidate models with values of k in the vicinity of 30, namely $k \in [25, 40]$ in steps of 1. We compared the distribution of topic semantic coherence and exclusivity of each model, not just their mean values. We observed that the model with $k = 32$ performed best, the respective distribution is given in Fig. 12.

Appendix E. Word clouds for selected topics: Top 50 words

See Fig. 13.

Appendix F. Topic scores

Table 4 lists the topic scores for the four psycholinguistic attributes and Eigenvector centrality.

Appendix G. Correlations between four psycholinguistic attributes, topical prevalence contrast, and eigenvector centrality

Fig. 14 highlights the correlations between four psycholinguistic attributes, topical prevalence contrast, and Eigenvector centrality.

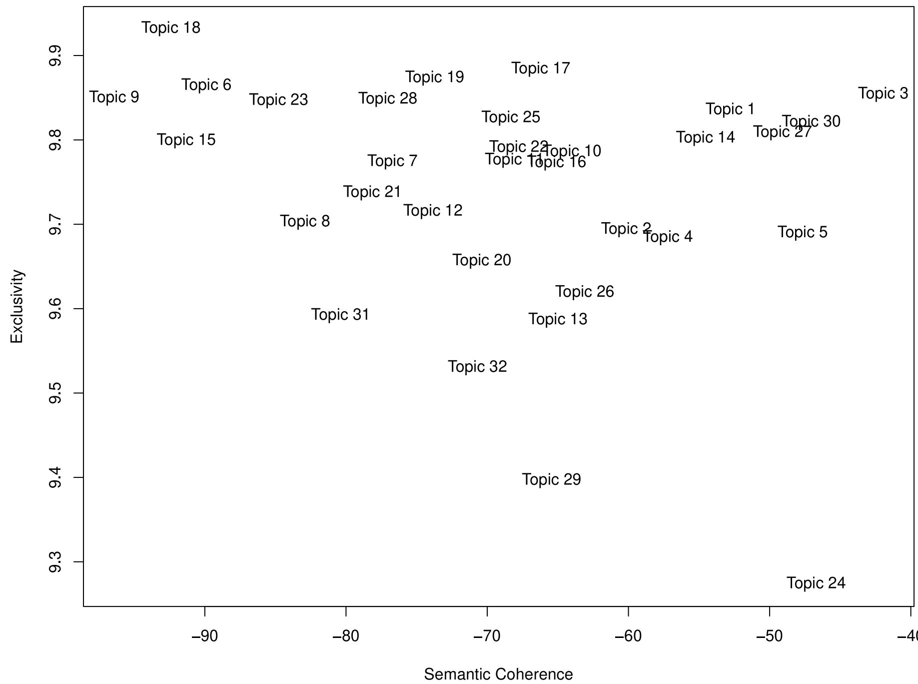


Fig. 12. The distribution of the values for semantic coherence and exclusivity for all topics in the model with $k = 32$.

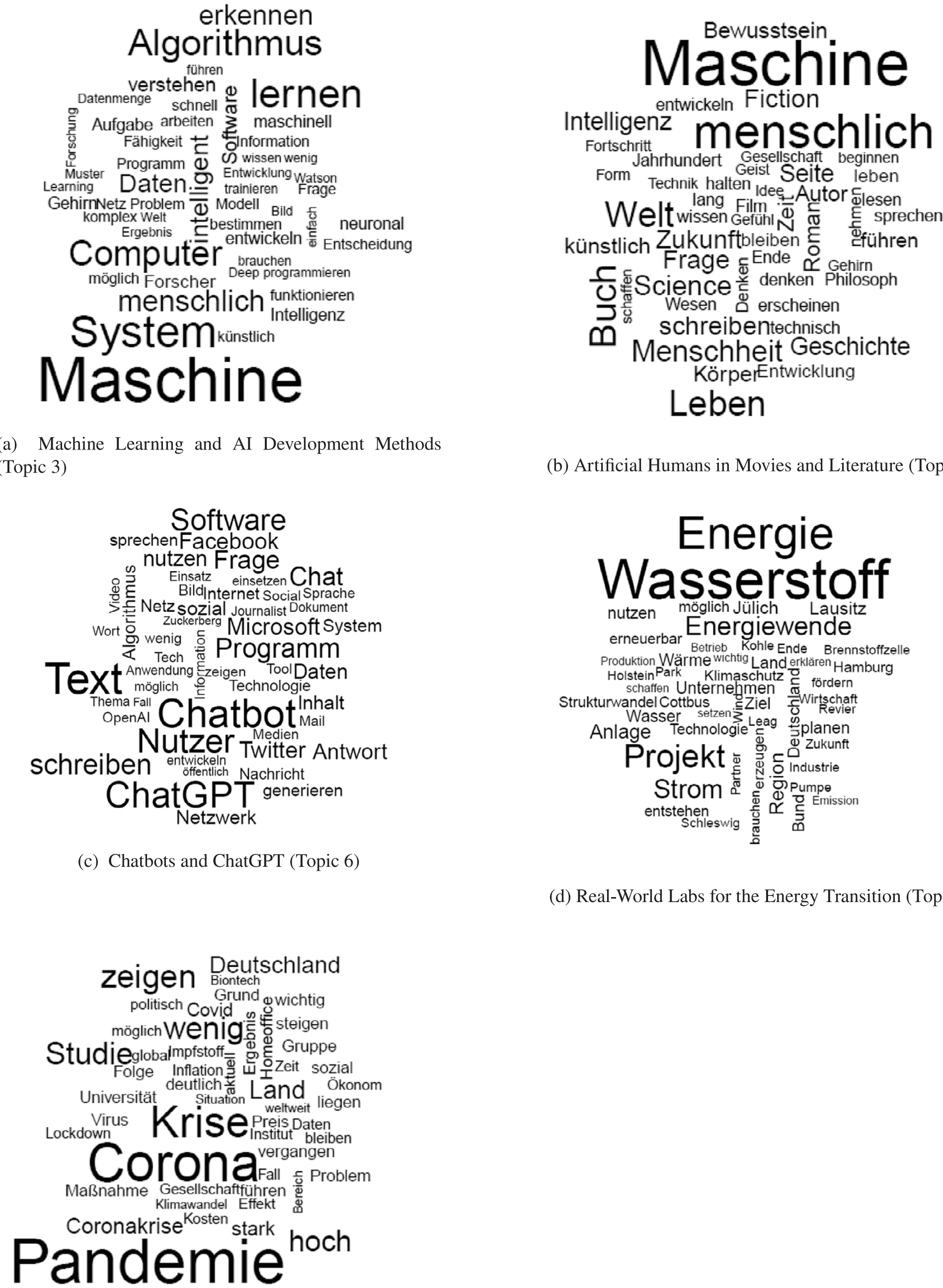
Table 4
Topic scores for four psycholinguistic attributes ($\in [0, 10]$), topical prevalence contrast ($\in [-0.07, 0.13]$), and eigenvector centrality ($\in [0, 1]$). Own calculation based on the full text corpus and disregarding the timeline.

Topic label		Valence	Arousal	Abstr.ness	Imag.blty	Contrast	Evt
Government Funding for Research on AI and Climate Change	1	5.206	3.955	4.065	4.205	0.013	0.633
Fair Pay Innovation Lab	2	5.044	3.977	3.827	3.917	0.020	0.621
Machine Learning and AI Development Methods	3	5.203	4.025	3.615	3.779	−0.068	0.539
Artificial Humans in Movies and Literature	4	5.236	4.284	3.564	4.080	−0.051	0.449
Digitization of Business Processes	5	5.036	3.942	3.616	3.626	−0.024	0.617
Chatbots and ChatGP T	6	4.851	3.769	3.699	3.627	−0.031	0.623
AI and Robotics Cutting-Edge Research Funding in Bavaria	7	4.885	3.943	3.957	4.137	0.011	0.704
Robotics and AI in Construction, Agriculture and Policing	8	5.239	3.872	4.195	4.428	0.019	0.000
Real-World Labs for the Energy Transition	9	5.209	3.860	3.983	4.088	0.089	0.000
Tightening of Investment Controls in the High-Tech Sector (USA, EU, Germany)	10	4.857	4.069	3.922	3.983	−0.029	0.436
Digitalization in Urban Development	11	5.171	3.846	4.217	4.511	0.037	0.059
Regular Airspace Pilot Projects in Germany	12	5.059	3.813	3.971	4.085	0.047	0.014
Covid Mass Vaccination as a Field Experiment	13	4.753	4.069	3.421	3.669	0.018	0.476
Google	14	4.557	3.636	3.974	3.862	−0.032	0.786
Future Lab in Aachen - the Whole City as a Future Lab	15	5.429	4.000	4.225	4.504	0.080	0.000
Tech Start-Ups	16	5.049	3.791	3.967	3.983	0.008	0.436
Autonomous Cars	17	4.691	3.901	4.261	4.335	−0.032	0.313
Real-World Labs for Sustainable Mobility in Baden-Württemberg	18	5.394	3.840	4.053	4.227	0.055	0.178
Robots and AI in Private Households	19	5.162	3.797	4.396	4.408	−0.027	0.187
Service Robots and Assistance Systems	20	5.162	4.024	3.877	4.100	−0.014	0.279
Relationships between Humans, Machines and AI in Art Exhibitions	21	5.463	4.258	4.155	4.668	−0.027	0.345
Robots in Production	22	4.983	3.757	4.115	4.112	−0.035	0.527
Digitization, Robots and AI in Schools	23	5.514	4.273	4.205	4.480	0.000	0.650
Digital Transformation Leaders	24	5.052	3.859	3.775	3.864	0.016	0.388
Softbank (Japanese Tech Investor)	25	4.820	3.847	3.903	3.941	−0.035	0.344
Digitalization and Automation Consequences for the Workplace	26	4.930	4.209	3.668	3.913	−0.046	0.646
Political Support for AI and in Germany	27	5.279	4.152	3.684	3.928	−0.021	0.847
Real-World Labs for Ecofriendly Mobility in Aachen	28	4.942	3.851	3.924	4.154	0.126	0.057
Robots in Space and Robot Development	29	5.095	4.010	4.144	4.288	−0.022	0.128
Philosophical Considerations on the Digital Transformation	30	5.558	4.561	3.458	4.067	−0.010	1.000
Lethal Autonomous Weapon Systems	31	4.726	4.545	3.553	3.845	−0.034	0.641
Fintech and Legal Tech	32	5.007	3.745	3.848	3.813	−0.001	0.573

Appendix H. Robustness check based on a different text corpus

H.1. Bridge topics: Application and extension

This robustness test evaluates whether the bridge topics approach yields reliable results beyond the RAI/RWL dataset. To this end, we apply the method to a newly compiled dataset, the GEL corpus (details of this corpus are given below). We find that (i) bridge topics can be identified in the GEL corpus and that (ii) specific features require further consideration as bridge topics may vary in strength. While this variation is present in the RAI/RWL dataset, it is less pronounced and



(a) Machine Learning and AI Development Methods (Topic 3)

(b) Artificial Humans in Movies and Literature (Topic 4)

(c) Chatbots and ChatGPT (Topic 6)

(d) Real-World Labs for the Energy Transition (Topic 9)

(e) Chatbots and ChatGPT (Topic 13)

Fig. 13. Word clouds for topics that were dominating the discourse (compare Fig. 5). These topics are discussed in more detail in Sections 4.2 and 4.6. The size of the words is an indicator of their proportions (shares) in the topic. Recall that a topic is defined as a distribution of words.

therefore not discussed in that context. Additionally, we highlight the necessity of normatively defining the bridge range while demonstrating that confidence intervals provide critical guidance whereas sole reliance on mean differences proves insufficient. We also find slight differences between the GEL corpus and the RAI/RWL corpus in their topic correlation networks, especially regarding the positioning of the (strong) bridge topics.

Bridge topics exploit the Topical Prevalence Contrast (TPC) facility of the STM method developed by Roberts et al. (2019). The TPC was originally designed to identify the topics that can be statistically significantly assigned to a covariate; bridge topics are their complement set. Rather than identifying topic-specific features, the method detects connections between topics based on two covariates. These interfaces are often not obvious and emerge through Topical Prevalence Contrast using mean differences and confidence intervals at the topic level. Covariate selection is content-driven, depending on the research question, as illustrated by prior studies: political affiliation (Roberts et al., 2019), patents and trademarks in a variety of high and low technology fields (Scheu, 2023), and patent data on remote sensing (Ott & Vannuccini, 2023). In each case, focusing on non-significant rather than significant affiliations reveals bridge topics.

The concept of bridge topics is inextricably linked to the STM method. The central innovation of our work is that bridge topics are explicitly insignificant according to the Topical Prevalence Contrast. As explained in the core text above, in purely technical terms, bridge topics are all the topics with confidence intervals that cross the value

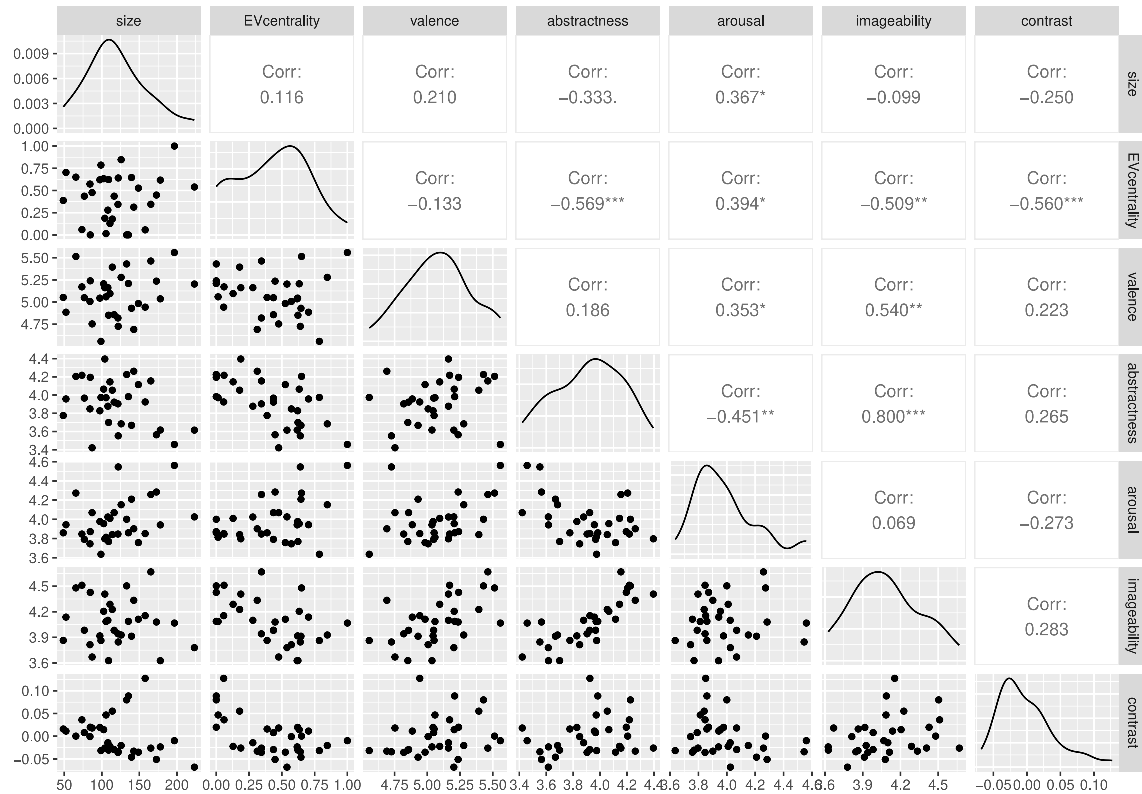


Fig. 14. Correlations between key variables; own calculation based on the full text corpus and disregarding timeline.

zero. A graphical representation of the TPC for the GEL corpus is given in Fig. 16.

We argue that the approach is broadly applicable, and further research could explore its validity across even more diverse datasets and languages. Here, however, our focus is to assess whether the bridge topics approach can also identify content interfaces in another text corpus beyond RAI/RWL.

Key results of this robustness test are that we can confirm the method's applicability beyond RAI/RWL. However, differentiating bridge topics by their bridging strength appears necessary. Further, methodological and content perspectives must be integrated — methodologically through TPC (mean difference and CI) and content-wise via the bridge range, which should be normatively defined but could be informed by the extent of the confidence intervals.

In this appendix, we show that the concept of "bridge topics" is not limited to the (combined) text corpus of RAI/RWL. For this purpose, we compiled a completely new text corpus, which, for the sake of comparability with the RAI/RWL topic, is again based on media coverage in German-language broadsheet newspaper articles. The new data set is based on the two categorical variables "geothermal (Geothermie/Erdwärme)" and "lithium (Lithium)". We call this dataset the *GEL* corpus, and motivate the choice of the covariates below. For the robustness check, we kept the analytical structure of our procedure similar to the RAI/RWL analysis.

Throughout the robustness check, we refine the concept of bridge topics. Such a refinement distinguishes between two cases: (i) "strong" bridge topics, where both, the mean differences and the confidence intervals, are within the green range, and (ii) "weak" bridge topics, where only the mean differences are within the green range, but the confidence intervals reach beyond this range to the right or to the left. Such a sophisticated distinction did not seem necessary in the context of the RAI/RWL corpus, since five of the eleven bridge topics identified there are "strong" according to our definition (compare Fig. 6). In the *GEL* corpus, the ratio of strong to weak bridge topics is somewhat different, and the definition of the bridge range is also more demanding, as we will show below.

We chose the GEL context for the following reasons: (i) "Geothermie/Erdwärme" or "geothermal water" is a key element of the energy transition and provides a CO_2-neutral heat supply. It is based on the use of regional resources and has the potential to increase Germany's energy resilience through diversification as it represents an additional energy source. However, early geothermal projects have experienced technical failures that have caused structural damage to buildings and led to long-lasting public skepticism, particularly in southern Germany and the border regions with Switzerland. (ii) Lithium is a scarce raw material, crucial for battery and storage technologies. It is mostly mined outside Europe, often under ethically questionable conditions. Such foreign sourcing makes Germany dependent on foreign suppliers and subject to intense international competition. Again, strengthening resilience and self-reliance are key motivations for using more regional (preferably mostly European) lithium deposits.

In addition, recent findings indicate that some geothermal reservoirs contain significant lithium deposits, raising the question of whether heat supply and raw material extraction can be combined. Seen through this lens, the GEL corpus combines two so far mostly isolated themes ("geothermal energy/geothermal heat" and "lithium"), which are increasingly discussed together in the light of current political developments and technological opportunities. For example, Stringfellow and Dobson (2021, p8) argued that "Geothermal brines are expected to be an important source of domestic lithium production in the future". They also provided an overview of the significant geothermal lithium resources that have been identified in Europe (Stringfellow & Dobson, 2021, Figure 8). How was lithium and geothermal energy reported on in German-language newspapers so far? What are the specific topics from a geothermal energy perspective? What are the specific topics from the perspective of lithium? Is it possible to detect any connection between the information presented and the audience?

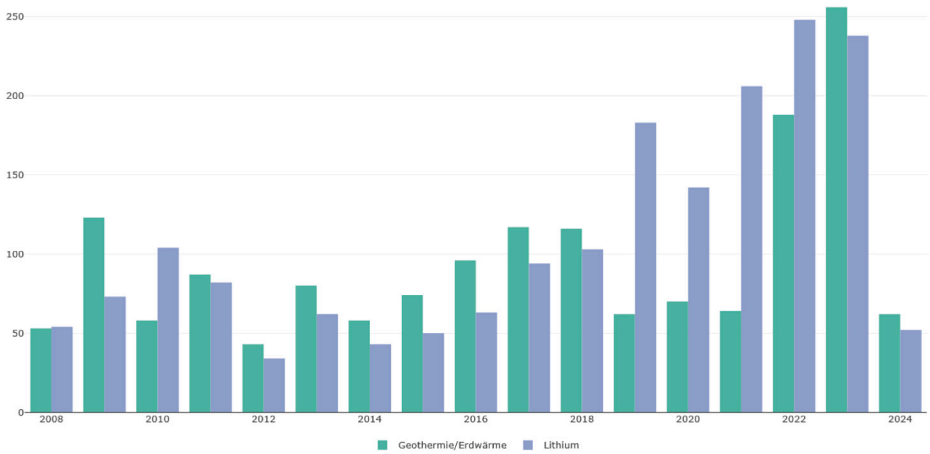


Fig. 15. Evolution of the number of articles on "Geothermie/Erdwärme" and "Lithium" in six German-language newspapers by search term for the period January 2018–May 2024. Both themes have increasingly gained attention in the last decade. Overall we see some fluctuation of the numbers for both sub-corpora and a shift of reporting from "Geothermie/Erdwärme" to "Lithium" in the period 2019–2022.

H.2. The GEL dataset

Unlike the RAI/RWL corpus, we restricted the GEL corpus to national German-language newspapers, specifically *FAZ*, *TAZ*, *NZZ*, *SZ*, *Handelsblatt*, and *Die Welt*, excluding regional publications and thus focusing on Germany as a whole. The analysis covers the period from January 2018 to May 2024. Using the search terms *Geothermie/Erdwärme* and *Lithium*, we initially identified approximately 14,500 articles. The final dataset was obtained by careful data cleaning and text preprocessing. Irrelevant articles (e.g., articles written in the Swiss dialect), comments and opinion pieces were removed and parts of broader overview articles, such as "topics of the day", were excluded if they were unrelated to our search terms.

The final GEL dataset has 3,439 articles: 1,831 identified via the term *Lithium* and 1,607 via *Geothermie/Erdwärme*. After removing duplicates, 3,299 unique texts remained, i.e. 70 (=140/2) articles appeared in both searches. Fig. 15 illustrates the distribution of articles over time by search term.

H.3. Analysis and key insights of the GEL corpus

We chose an STM model with 34 topics based on the best values of the measures semantic coherence and exclusivity. Table 5 lists the topic proportion and the top 7 keywords for each of these 34 topics. These keywords and the full texts of the most important articles of a topic have been the basis for the topic labels in Table 6. Note that we only provide labels for the topics that are important for gaining an understanding of the methodically motivated robustness section. We explicitly do not delve into the full substantive discussion of the content, although the joint perspective on GEL is an important research field gaining increasing attention.

Fig. 16 presents the Topical Prevalence Contrast results for the 34 topics of the GEL model. Mean differences are represented by dots and their corresponding confidence intervals by horizontal lines. Statistical significance of topic assignment to either field is inferred when the confidence intervals do not intersect the zero vertical line. Bridge topics are topics with mean differences in the green area. We suggest it seems

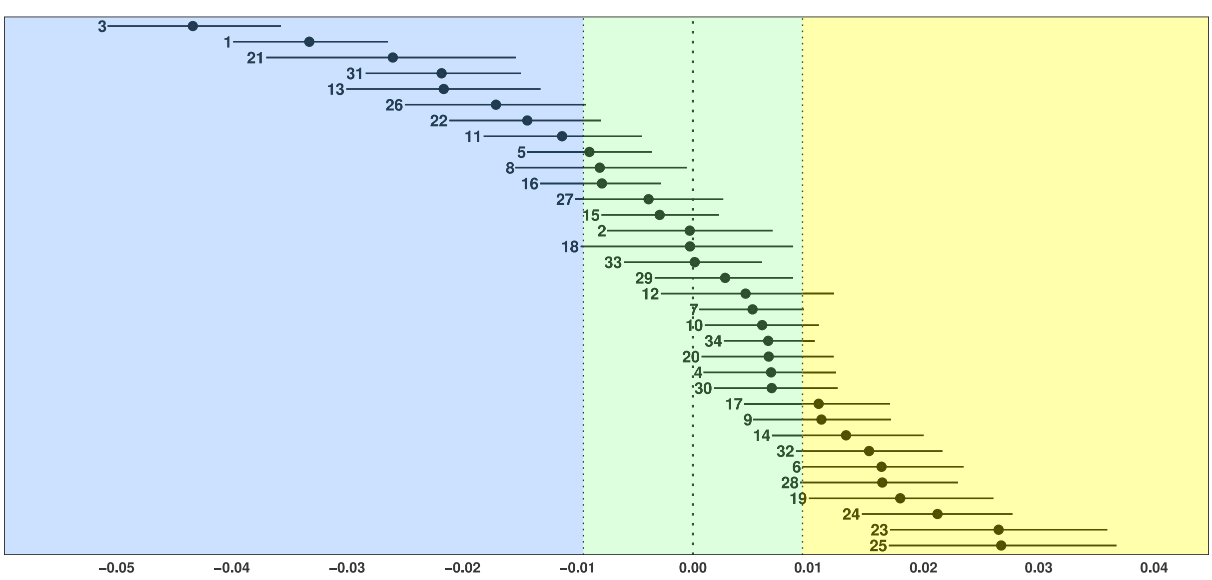


Fig. 16. Topical prevalence contrast reflecting the variability of topic coverage conditional on the sub-corpus. The dots denote the means and the lines denote the 90% confidence intervals of the estimates. Topics in the blue area are predominantly based on the Geothermal Corpus, topics in the yellow area are mostly based on the Lithium Corpus and topics in the green area are bridge topics that link the two domains. Strong bridge topics have both, means and confidence intervals, in the green area. Weak bridge topics have only the means in the green area whereas parts of the confidence intervals overlap with the blue or the yellow area. Weak bridge topics with confidence intervals reaching into the blue area are topics of the type "bridge-geo" in Table 6 and weak bridge topics with confidence intervals reaching into the yellow area are topics of the type "bridge-lit" in Table 6.

Table 5
Topic number, expected topic proportion ('prop.', in descending order) and top 7 terms for the GEL model with 34 topics. The topic proportions represent the overall weights of the topics within the entire corpus.

Topic	Prop.	Top 7 terms
21	0.064	Gemeinde, Projekt, Gemeinderat, Jahr, Bürgermeister, Vaterstetten, Bohrung
13	0.056	Erdwärme, Tiefe, Wasser, Bohrung, Wärme, Anlage, nutzen
25	0.052	Batterie, Akku, Ion, Elektrode, Elektrolyt, Forscher, Energiedichte
26	0.045	München, Stadtwerk, Erdwärme, Grünwald, Geschäftsführer, Landkreis, Unterhaching
20	0.043	Euro, Million, Jahr, Prozent, Milliarde, steigen, Preis
23	0.043	Kilometer, Euro, Akku, elektrisch, PS, Reichweite, Motor
18	0.040	Akku, Batterie, Gerät, Ion, Brand, Airbus, Smartphone
19	0.038	Tesla, Batterie, Ion, Jahr, Varta, Elektroauto, Bosch
11	0.034	Energie, Prozent, Strom, erneuerbar, Jahr, Deutschland, Anlage
6	0.033	Kobalt, Batterie, Nickel, Jahr, Prozent, Recycling, Rohstoff
31	0.032	Fernwärme, Bayern, Kommune, Ausbau, Jahr, Stadt, grün
24	0.031	Volkswagen, BMW, Europa, Batteriezelle, Batterie, Jahr, Konzern
8	0.031	Erdbeben, Beben, Staufen, Schaden, Riss, Haus, Stadt
3	0.030	Projekt, Basel, Untergrund, StGallen, Bohrung, Wasser, Million
9	0.030	Elektroauto, Fahrzeug, Auto, Batterie, fahren, Elektrofahrzeug, Verbrennungsmotor
4	0.029	Mensch, gut, Zeit, mal, Frage, Jahr, tun
27	0.029	Berlin, Stadt, SPD, Thema, CDU, Bürgermeister, grün
22	0.028	Wärmepumpe, Wärme, Zürich, Gebäude, Grad, Haus, Heizung
32	0.028	Rohstoff, China, Erde, Europa, Deutschland, wichtig, kritisch
12	0.027	Bolivien, Jahr, gewinnen, Tonne, Batterie, Morales, Rohstoff
17	0.026	Unternehmen, Jahr, Firma, Produkt, entwickeln, Deutschland, Technologie
2	0.026	Unternehmen, BASF, Deutschland, Standort, Brandenburg, RockTech, planen
1	0.023	Schweiz, Jahr, grossen, Frage, Franken, Kanton, Baustelle
14	0.022	China, USA, Land, Dollar, Russland, Regierung, Amerika
28	0.022	Aktie, Unternehmen, Vulcan, Anleger, Jahr, VulcanEnergy, Prozent
33	0.018	Forscher, Jahr, Studie, Universität, Element, Stern, zeigen
10	0.018	Batterie, Speicher, Strom, Energie, Netz, Jahr, Technologie
29	0.018	Chile, Jahr, Land, Mine, Region, Regierung, Unternehmen
16	0.017	Island, Wasser, Jahr, Insel, Kilometer, groß, Tag
5	0.016	Fracking, Gestein, Technik, Gas, Wasser, Untergrund, Deutschland
15	0.016	Energie, Japan, Deutschland, Jahr, Gas, CO2, Wasserstoff
7	0.015	europäischeUnion, Europa, Kommission, europäischen, Brüssel, EUKommission, Ziel
34	0.011	französisch, Paris, Bus, Jahr, Bahn, Frankreich, Renault
30	0.010	Wasserstoff, Energie, Jahr, Brennstoffzelle, Wasser, groß, erzeugen

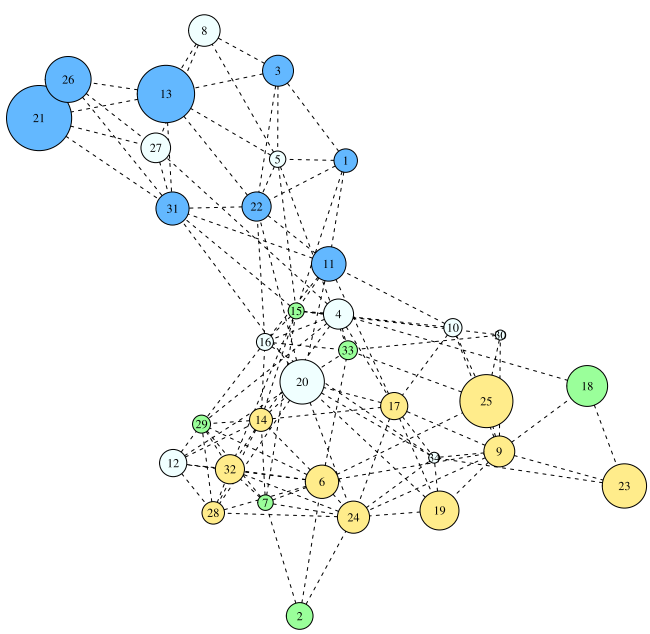


Fig. 17. Correlation Network. Edges represent positive correlations between topics, indicating co-occurrence in the same articles. The threshold for edge inclusion is 0.01. Vertex size reflects topic proportions, as detailed in Table 5 (e.g., topic 21 is the largest, while topics 34 and 30 are the smallest). Vertex colors indicate corpus affiliation: *blue* for "geothermal", *yellow* for "lithium". *Green* denotes strong bridge topics, where both the means and confidence intervals fall within the bridge range. *Azure* represents weak bridge topics, with mean differences in the bridge range but confidence intervals overlapping with either "lithium" or "geothermal".

promising to undertake further investigations of the GEL corpus, as there are many bridge topics with confidence intervals beyond the bridge range.

The topics 1, 3, 13, 21, 31 are predominantly associated with geothermal energy (blue shaded area), while the topics 19, 23, 24, 25 are significantly linked to lithium (yellow shaded area). Bridge topics are located between these extremes. They are related to the green bridge area and are further classified as *"strong"* or *"weak"* according to the following logic. Strong bridge topics are topics where both, the mean differences and the confidence intervals, fall within the green area (topics 2, 7, 15, 18, 29, 33). They represent intersections between the two sub-corpora. Weak bridge topics are topics where only the mean differences fall in the green area, whereas the confidence intervals reach into either the geothermal or lithium zones. They include topics 5, 8, 16, and 27 (overlapping with the geothermal area) and topics 4, 10, 12, 20, 34 (overlapping with the lithium area).

Overall, the combined analysis of Fig. 16 and Tables 5 and 6 indicates the following. (i) Strong bridge topics reflect a common interest in the convergence of advanced energy technologies with sustainability, safety, and environmental challenges. (ii) Geothermal-related bridge topics focus on transforming traditional energy and mobility paradigms through innovation and strategic resource management. (iii) Lithium-related bridge topics offer insights into natural resource utilization, reflecting both cultural appreciation and challenges associated with technological exploitation.

In addition, Fig. 17 presents a network of 34 nodes, structured into two clusters and categorized by four color codes. *Yellow nodes*: Lithium-related topics, the mean differences fall within the lithium range, with confidence intervals potentially overlapping the bridge range. Topics: 6, 9, 14, 17, 19, 23, 24, 25, 28, 32. *Blue nodes*: Geothermal-related topics, the mean differences fall within the geothermal range, with confidence intervals potentially overlapping the bridge range. Topics: 1, 3, 11, 13, 21, 22, 26, 31. Bridge topics (linking both fields) are

Table 6
Topic labels for the topics crucial for understanding the GEL contents, based on the most important articles of each topic. The variable "type" lists the classification type of the topics. There are seven types: (i) "geo": both, mean difference and CI, lie in the blue area in Fig. 16, (ii) "bridge": both, mean difference and CI, lie in the green area in Fig. 16 (strong bridge topics), (iii) "lit": both, mean difference and CI, lie in the yellow area in Fig. 16, (iv) "bridge-geo": the mean difference lies in the green area and the CI at the left-hand side reaches into the blue area in Fig. 16 (weak bridge topics related to geothermal energy), (v) "bridge-lit": the mean difference lies in the green area and the CI at the right-hand side reaches into the yellow area in Fig. 16 (weak bridge topics related to lithium), (vi) 'geo-bridge": the mean difference lies in the blue area and the CI at the right-hand side reaches into the green area in Fig. 16, and finally, (vii) "lit-bridge": the mean difference lies in the blue area and the CI at the left-hand side reaches into the green area in Fig. 16.

Topic	Type	Label
1	geo	Switzerland accelerates expansion of renewable energies
2	bridge	Site selection, especially in the context of lithium refineries, batteries and Tesla model production
3	geo	Geothermal utilization in Switzerland
4	bridge-lit	Lithium as a medicine
5	bridge-geo	Fracking in Germany and world wide
6	lit-bridge	Volatile nickel market and rising demand due to energy transition
7	bridge	EU Green Deal, places and actors in the context of lithium extraction
8	bridge-geo	Geothermal energy causes soil damage in Staufen
9	lit-bridge	Not yet labeled
10	bridge-lit	Second-life battery storage for a sustainable energy supply
11	geo-bridge	Not yet labeled
12	bridge-lit	German-Bolivian lithium joint ventures
13	geo	Not yet labeled
14	lit-bridge	Not yet labeled
15	bridge	Secure conversion of energy systems
16	bridge-geo	Icelandic bathing culture and nature experiences
17	lit-bridge	Not yet labeled
18	bridge	Hazards of lithium batteries
19	lit	Collaboration and competition in battery production
20	bridge-lit	Energy market developments and corporate strategies
21	geo	Not yet labeled
22	geo-bridge	Not yet labeled
23	lit	Not yet labeled
24	lit	Volkswagen and the European battery production
25	lit	Next generation energy storage
26	geo-bridge	Not yet labeled
27	bridge-geo	Citizen's dialogue geothermal
28	lit-bridge	Perspectives and controversies surrounding Vulcan Energy
29	bridge	Concerns and criticism of lithium mining
30	bridge-lit	The future of nuclear fusion energy
31	geo	Not yet labeled
32	lit-bridge	Not yet labeled
33	bridge	Basic research
34	bridge-lit	The future of mobility: autonomy and alternative drives

further distinguished. *Green nodes*: Strong bridge topics, where both the mean differences and confidence intervals fall within the bridge range. Topics: 2, 7, 15, 18, 29, 33. *Azure nodes*: Weak bridge topics, where only the means fall within the bridge range, but the confidence intervals overlap with either lithium or geothermal. Topics: 4, 5, 7, 8, 10, 12, 16, 20, 27, 30, 34.

The topic correlation network shows that there are two clusters with the majority of strong bridge topics being closely related to the (yellow) Lithium Corpus. Regarding the "Geothermal cluster", we see in addition to the significant blue-coded topics also the strong bridge topic "Citizen's dialogue" (T27) and the weak bridge topics "Geothermal energy causes soil damage in Staufen" (T8) and "Fracking in Germany and world wide" (T5). At the intersection between the two clusters are the non-technical topics "Lithium as medicine" (T4) and "Icelandic bathing culture and nature experiences" (T16), and the strong bridge topic "Secure conversion of energy systems" (T15).

A comparison of the network analyses of the two text corpora, RAI and GEL, shows that in the GEL corpus, in contrast to the RAI corpus, the strong bridge topics are mostly not located between the topics, but rather on the periphery of the network within the two clusters "geothermal" and "lithium". This demonstrates that the concept of bridge topics is not identical to the position of a topic within a network. Instead, the topic correlation network and the topical prevalence contrast are complementary perspectives that should be jointly considered when looking at content overlaps.

H.4. Summarizing and critical reflection

The robustness analysis highlights that the bridge topics approach may require refinements depending on the dataset and research question, enhancing its explanatory power (e.g., improved criteria for data selection). The quality of source data is critical: filtering misclassified texts (e.g., opinion pieces, comments, dialect) and applying rigorous text preprocessing (e.g., n-gram identification, lemmatization, domain-specific terms) significantly reduces confidence interval size.

Confidence intervals should guide interpretation: it is advisable to distinguish between strong and weak bridge topics if confidence intervals are large. The bridge range must be well-justified by content and research objectives. The mean differences define the core of the bridge range and the range of the confidence intervals refines its boundaries.

Common features of the RAI/RWL and GEL corpora include replicable topic prevalence contrasts and network structures. In both cases, two distinct clusters (blue and yellow) emerge. However, bridge topics show domain-specific tendencies: in RAI/RWL, they are more closely linked to RAI, while in GEL, they are more related to lithium. As stated before, the approach of bridge topics is broadly applicable, and further research could explore its validity across diverse datasets and also for different languages. This effort is left for future research.

Data availability

Data will be made available on request.

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