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An Attempt at Data-Driven Validation of Early-Stage Technology Trends

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Abstract: Foresight of early-stage technology trends via bibliometrics is often criticized for its perceived limitations in articulating practical relevance or predicting application success. To address that gap, foresight researchers and practitioners usually rely on expert interviews to qualitatively validate their quantitative findings. This study introduces a novel, data-driven approach to validate the relevance of early-stage technology trends for businesses and to detect early implementation efforts by technology leaders. By combining a bibliometric analysis of scientific publications with trend insights from online job postings as an innovative foresight data source, we use the presumably most early-phased data sources of both perspectives – science and practice – for our assessment of future technology innovation fields. The presented research is part of a larger project which strives to deepen our understanding of the links between scientific advancements and business innovation efficiency, thereby providing a more comprehensive perspective on the commercial viability of emerging technologies.

Keywords: Emerging technologies; innovation fields; technology trend topics; technology foresight; technology trend analysis; data-driven foresight; bibliometrics; job postings data; innovation efficiency.

1 Introduction

Bibliometric analysis of scientific publications is a well-established method for data-driven foresight of emerging technology trends in various industries (Huang and Chang 2014; Stelzer et al. 2015; Woon et al. 2011). However, it is subject to the limitation that scientific success of a technology or research field does not necessarily lead to market success or innovation breakthroughs (Stelzer et al. 2015). To overcome this deficiency and to include contextual factors into the trend analyses, qualitative foresight methods such as expert interviews or scenario techniques are often combined with bibliometrics (Hanisch and Wald 2012; Niu 2014). In general, the literature strongly recommends combining two or more methods for effective foresight (Haegeman et al. 2013; Lüdeke 2013; Malanowski and Zweck 2007). Very popular in this regard, is the combination of quantitative methods such as bibliometrics or system dynamics with the qualitative scenario technique or roadmaps (Geum et al. 2014; Hirsch et al. 2013; Zhang et al. 2013). In our research, we take an alternative approach by combining two quantitative methods, respectively the quantitative analysis of two different textual data sources. We start off with a tool-based bibliometric analysis of 15,447 innovation-related research papers, that results in 37 different research frontiers. Afterwards, we match the top five TF-IDF terms (term frequency-inverse document frequency) of each frontier with the job descriptions of recent online job postings in the DACH region (Germany, Austria, Switzerland). By evaluating the hit rates per cluster, we can draw first conclusions about the practical relevance of each research frontier. With this we strive to answer the following research question: How can we use quantitative job postings analysis to assess the practical relevance of current technology trend topics from science?

While scientific publications are a long-established data source in academic foresight, job postings are just entering the field of future-oriented trend analysis. Nevertheless, both data sources are attributed with long foresight horizons (Goldfarb et al. 2023; Martino 2003; Segev et al. 2015). Researchers agree that an increase in scientific publications in a particular technology field can predict an increase in patents in the same field up to six years in advance. Moreover, scientific publications are even nine years ahead of marketable technologies (Segev et al. 2015). When it comes to job postings data, the argument prevails that technological innovations must be developed by employees before a company can file a patent – hence, job postings should reflect a company's intentions to engage with a certain technology earlier than patent data (Goldfarb et al. 2023). Referring to these findings, we combine the most forward-looking data source from the scientific perspective with the presumably most early phased data source from business practice. This as such represents a novel contribution to research. Additionally, we contribute a data-driven trend analysis of emerging technology topics together with a proposal on how to set these results into a practical context.

2 Research methodology

After a brief introductory literature review, the research design of our paper follows that of an academic trend study. First, a bibliometric analysis is applied to scientific publications from the Web of Science to derive early-stage technology trends. Second, the trend topics resulting from the bibliometric analysis are examined for their practical relevance by carrying out a keyword matching analysis with online job postings data. We thus cover the first four steps of a standard foresight process from preparation to interpretation (Keller and Gracht 2014; Reger 2001) without the involvement of time consuming expert interviews.

Bibliometrics is a method for analysing scientific and non-scientific papers, where data processing is based on mathematical and statistical calculation methods (Hood and Wilson 2001). For foresight purposes, bibliometrics is mainly applied to scientific databases to identify future developments in promising research areas and leading authors in a field (Stelzer et al. 2015). With the help of dedicated software solutions, connections between publications can be displayed graphically as networks. For this, two different approaches exist. The first approach to identify so-called research fronts focuses on bibliographic coupling. A bibliographic coupling exists when two publications cite the same third publication. The more such joint citations exist between two publications, the stronger the linkage. The second approach to bibliometric analysis identifies so-called knowledge bases. These can be derived from co-citations, whereby a co-citation is defined by the fact that two publications are jointly cited by a third publication. Knowledge bases thus suggest the scientific origins of a research area, while research fronts tend to serve as directional guides for future research (Persson 1994). Publications which are thematically similar due to bibliographic coupling or co-citation, lie closer together in the graphical network and form a cluster. By analysing the metadata provided for each publication, the thematic field of a given cluster can be defined more precisely, and research portfolios can be created to assess the relative importance of the individual clusters in a network (Stelzer et al. 2015). In our research, we use the NETCULATOR tool (Meyer-Brötz 2018) to perform the above mentioned analyses and to visualize the results. The tool's special strength lies in the combination of bibliographic coupling with lexical measures, which makes it also possible to compare the similarity of terms (Meyer-Brötz et al. 2018).

In a first step, we (1) extract scientific meta data from the Web of Science, and (2) calculate first-order similarity by a weighting factor, a term frequency-inverse document frequency (TF-IDF) score, for all terms in an article's abstract, title, and keywords and for all references of an article. Then, (3) transforming these similarities into grouped research fronts (clusters) based on their second-order similarities to determine the "Top TF-IDF Terms" for each cluster. The identified top TF-IDF terms are utilized for our keyword matching process, laying the groundwork for an in-depth analysis that follows.

For the second phase of our study, we obtained an extensive set of online job postings from the commercial data provider LinkUp. LinkUp specializes in sourcing online job listings directly from employer websites worldwide daily. Since its foundation in 2007 the data provider has managed to index hundreds of millions of jobs from over 60,000 companies in 195 countries (LinkUp 2023). The data comes in different kinds of files, which can be merged depending on the focus of the analysis. For our analysis, only the job records files containing basic information on a job posting such as job title, company name, country, create date etc., as well as the job descriptions files are relevant. Each job posting is assigned with an individual job hash that serves as the unique identifier for merging the different files and for removing duplicates. To limit the scope of our analysis and to reduce the total size of the data set, we focus only on job postings from January 1 to January 31, 2024, in the DACH region. This leaves us with a total number of 106,912 job postings in English and German language.

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According to the literature, automated keyword matching with a predefined directory is a proven methodology for analysing job postings (Brancatelli et al. 2020; Brasse et al. 2023). In our case, the keyword directory is composed of the top five TF-IDF terms of each research frontier from the bibliometric analysis. To avoid that specific terms get lost in translation, we refrained from translating the TF-IDF terms to German. This has the disadvantage that job advertisements that are only available in German are not included in the analysis, but the advantage that job advertisements that are available in both languages are not recorded twice. In a first analysis step, we apply Python code to automatically scan the job descriptions for the occurrence of the TF-IDF terms. A hit is flagged if at least three out of the five keywords per cluster occur in a job description. In a second analysis step, every job posting with a hit is assigned to the corresponding cluster – an assignment to multiple clusters is possible – so that we receive an extensive Excel file with one tab sheet per keyword group. In further processing these results we create a heatmap that visualizes the hits per cluster and company. The final heatmap forms the basis for interpreting the practical relevance of the emerging technology topics and for evaluating our attempt at data-driven validation of early-stage technology trends.

3 Literature review

The following literature review provides a compact overview of academic trend studies and application fields in which scientific publications and job postings data have already been used as data sources for data-driven foresight studies.

A lot of foresight literature focuses on the identification and analysis of alternative data sources (Mikova and Sokolova 2019; Mühlroth and Grottke 2018; Segev et al. 2015; Wustmans et al. 2022) and on the optimization or combination of established foresight methods (Geurts et al. 2022; Lee et al. 2021; Stelzer et al. 2015; Zhang and Huang 2020). Contextual trend studies in which different data sources are analyzed for weak signals in specific technology fields (Chang et al. 2010; Daim et al. 2006; Kim et al. 2020) make up a large proportion of the literature, together with comparative analyses of data sources' content validities (Bonaccorsi et al. 2020; Laurell and Sandstrom 2022; Mikova and Sokolova 2019). A few studies also concentrate on the differences in temporal foresight horizons of established data sources (Cozzens et al. 2010; Mühlroth and Grottke 2018; Segev et al. 2015). From this and from the leading studies by Martino (2003) and Watts and Porter (1997) originates the statement that some data sources allow for a further look into the future than others and that foresight data sources can be characterized based on their individual strengths in lifecycle phase-specific expressiveness. The analysis of scientific publications as a foresight data source is particularly suitable to identify technology trends or technology-specific weak signals (Mühlroth and Grottke 2018). Emerging technologies can be identified that are still in their early lifecycle phases of basic research or beginning applied research (Martino 2003). Thus, scientific publications clearly represent the technology push side of innovation fields (Mikova and Sokolova 2019). In the literature, research-based data sources, such as scientific publications, are attributed with long foresight horizons and a high degree of forecasting accuracy (Segev et al. 2015). In Mikova and Sokolova's (2019) trend study, scientific publications deliver the best results for the identification of technology trends in the field of green energies. However, it must be repeated that trends derived from scientific publications are often at the very beginning of a new research stream and the development of market-ready technologies can still take several years (Mikova and Sokolova 2019).

When it comes to foresight with job postings data, the body of literature contains way less contributions. Most studies using this data source focus on the identification of future skills in specific countries, technology fields or job domains (Brasse et al. 2023; Firpo et al. 2021). Goldfarb et al. (2023) contribute a leading trend study which examines the potential of Artificial Intelligence (AI) to become a General-Purpose Technology (GPT) based on online job postings data. This study also forms the basis for our argument that job postings show a long foresight horizon and are well suited to represent the practice perspective in data-driven foresight. Overall, job postings data are not yet fully established in foresight research, which is why our research could make an important contribution to the scientific discourse. Table 1 briefly summarizes leading trend studies that exploit either scientific publications or job postings in different foresight contexts. So far, we are not aware of any studies that use both data sources in combination, which confirms our research gap and emphasizes the novelty of our attempt at data-driven validation of early-stage technology trends.

Table 1 Overview of trend studies using either scientific publications or job postings data

Focus of the trend study	*Data sources used*	*Authors*
Identification and measurement of emerging technologies and topic areas	Scientific publications, research proposals	Cozzens et al. 2010
Forecasting of emerging technologies in the fields of fuel cell, food safety and optical storage	Scientific publications, patents	Daim et al. 2006
Foresight study on the digital transformation in advanced manufacturing and engineering	Scientific publications	Lee et al. 2021
Trend analysis in the field of green energy based on a comparison of different foresight data sources	Scientific publications, patents, media etc.	Mikova and Sokolova 2019
Identification and analysis of technology trends based on diverse data sources	Academic articles, patents	Segev et al. 2015
Trend analysis in the field of personalized medicine with the method combination of bibliometrics and scenarios	Scientific publications	Stelzer et al. 2015
Identification of future skills for the manufacturing industry in Baden-Württemberg, Germany	Job advertisements	Brasse et al. 2023
Mapping the demand for (future) digital skills in the Tunisian labour market	Online job ads	Firpo et al. 2021
Determining the likelihood of emerging technologies to become General-Purpose Technologies	Online job ads	Goldfarb et al. 2023

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4 Bibliometric analysis of emerging technology trend topics

Our application of the NETCULATOR tool transcends conventional bibliometric analysis by integrating both lexical and bibliographic data to form a hybrid measure of similarity, as mentioned in chapter 2. This fusion, advocated by Thijs et al. (2013), allows for a more nuanced exploration of research fronts, leveraging the method to dissect the diversity within scientific fields. Glänzel and Thijs (2017) used this method to explore the diversity of research in astronomy and astrophysics. They showed that hybrid measure improves the identification of research fronts by accounting for lexical content, making synonyms and spelling variants less problematic. This reduces the issues caused by synonyms and various spelling differences (Zupic and Čater 2015). Therefore, this hybrid measurement approach can be used to analyse literature in the fields of technology and innovation management (Meyer-Brötz et al. 2018). The citation network created in this way, offers an organized overview of the numerous fields of study. The NETCULATOR tool surpasses previous limitations highlighted by Zupic and Čater (2015), especially regarding co-citations. A key advantage of bibliographic coupling lies in its ability to spotlight emerging areas of research without necessitating extensive citation knowledge. This feature is especially beneficial for incorporating the latest research developments. Meyer-Brötz (2019) created the NETCULATOR on this premise. Bayrle (2021) and Stein et al. (2019) outline Meyer-Brötz's (2019) methodology in four stages.

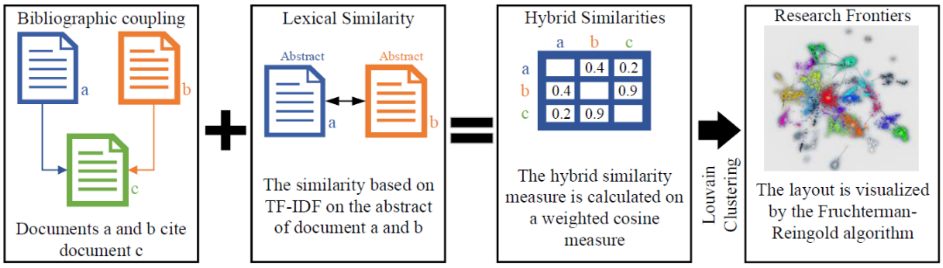

Figure 1 Four stage process to calculate research frontiers. Adapted from Bayrle et al. 2019

In bibliographic coupling, the strength of the connection or "coupling" between two articles increases with the number of references they have in common. Vogel and Güttel (2013) visually distinguish between bibliographic coupling and co-citation analysis in their study, highlighting the differences between these two methods.

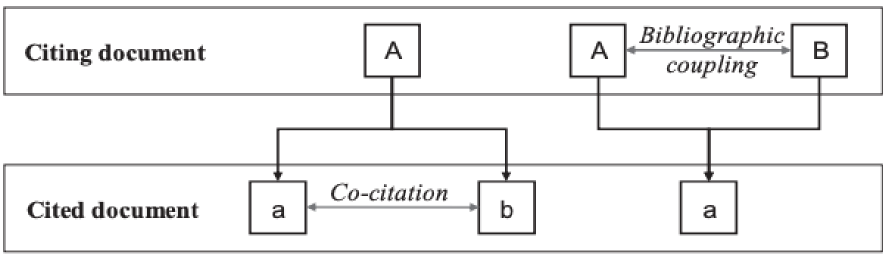

Figure 2 Co-citation and bibliographic coupling. Source: Vogel and Güttel 2013

The count of mutual references two articles share remains constant over time, which means bibliographic coupling is static, because the number of references within an article does not change. In contrast, co-citation patterns develop more pronouncedly over time. Since citation practices fluctuate, bibliographic coupling is most effective within a certain timeframe. In conclusion, to portray a current research front, bibliographic coupling might be used, whereas for older documents, co-citation might be preferable (Upham and Small 2010). Studies indicate bibliographic coupling's accuracy in depicting a research front is superior to that of co-citation analysis (Boyack and Klavans 2014).

Subsequently, "lexical similarities" are determined based on the weighted term measure "weighted term frequency-inverse document frequency" (TF-IDF). This method includes the reduction of words to their stems, the elimination of stop words, and the filtering out of special characters. f_{tm} denotes the frequency of occurrence of a phrase or word in a document *m*, and *n* is the total number of documents that contain the term *t* (Bayrle 2021; Meyer-Brötz et al. 2017):

$$w_{tm} = f_{tm} * \log(\frac{N}{n_t})$$

Thirdly, hybrid similarities calculations are followed. Meyer-Brötz et al. (2017) found that the hybrid similarity measure of second-order achieves better clustering results. This approach incorporates the lexical and bibliographic first-order similarities, which consist of textual similarities and bibliographic coupling. The weighting factor ranges from 0 to 1, with 0 representing solely text-based matching and 1 signifying exclusively bibliographic linkages. These computations are executed in the NETCULATOR through “weighted Cluster Centrality” and “cluster Centrality”, facilitating the ensuing allocation for each publication. Lastly, research fronts were grouped using Louvain Clustering based on their hybrid similarity (Blondel et al. 2008). Meyer-Brötz et al. (2017) define the second-order similarity $S_{2,mn}$ between two publications *m* and *n* as:

$$S_{2,mn} = \frac{\sum_{i=1}^{k} S_{im} * S_{in}}{\sqrt{\sum_{j=1}^{N} S_{jm}^2} * \sqrt{\sum_{j=1}^{N} S_{jn}^2}}$$

Lastly, research fronts were grouped using Louvain Clustering based on their hybrid similarity (Blondel et al. 2008). Finally, visualization is conducted based on the Fruchterman-Reingold algorithm (Fruchterman and Reingold 1991).

Data retrieval for our study was carried out using the Web of Science database – by its Web of Science Core Collection. Table 2 outlines the specifics of the conducted bibliometric analysis search query executed on 10th January 2024, with a data range from 2022 to 2024 focusing on the most recent publications. 15,447 results were obtained by applying a search string across titles and author keywords of scientific articles, books and proceeding papers. The search string encompasses a broad set of terms related to emerging or disruptive technologies and innovations, using operators to combine search terms indicative of newness, development, advancement, or uniqueness in both the fields of technology and innovation.

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Table 2 Data set for the bibliometric analysis

Title	*Description*
Date	10^{th} Jan. 2024
Data Range	2022 - 2024
Results	15,447
Search Criteria	Title AND Author Keywords
Search String	((emerg* OR innovat* OR new OR disrupt* OR develop* OR unfold OR reveal OR improv* OR revol* OR latest OR ground braking OR "state of the art" OR recent OR advanc* OR experimental OR modern OR cutting edge OR novel OR unique OR non traditional OR unconventional) (Title)) AND ((technolog* OR innovation) (Title)) AND ((technolog* OR innovat*) (Author Keywords))

In the next step, the hybrid similarities between the 15,477 papers were calculated and resulted in 37 total clusters. The identified top TF-IDF terms from the determined clusters are used to name each research frontier. The associated publications of each cluster are checked for semantic coherence through sampling based on individual document properties like title, abstract, keywords, and Web of Science Categories. Here, the identified TF-IDF terms constitute the largest possible quantifiable factor allowing for topic-specific naming conclusions, shown in Table 3.

Table 3 Results of the bibliometric analysis: Emerging technology topics (2022-2024)

Cluster	*Results*	*Research frontier*	*Top TF-IDF terms*
1	1482	Sustainable Technological Advancements	technology, systematic, design, sustainability, economy
2	1392	Entrepreneurial Business Innovations	firm, business, knowledge, capability, entrepreneurial
3	1035	Healthcare Innovation and Technology	health, healthcare, care, surgery, clinical
4	1009	Environmental Innovation & Green Tech	green, environment, regulatory, enterprises, chinas
5	949	Educational Innovations & (e)Learning Tech	education, teachers, students, teaching, learning
6	760	Network-Driven Performance Innovation & Open Innovation	open, networks, collaboration, project, knowledge
7	751	Energy Innovations for Environmental Mgmt.	emissions, carbon, energy, co2, renewal
8	743	Digital Transformation and Green Innovation	digital, transform, green, enterprises, digitalization

9	630	Corporate Sustainability and Green Perf.	green, csr, environment, sustainability, corporate
10	622	Innovation Dynamics in Corporate Ent.	corporate, enterprises, patents, firm, uncertainty
11	575	Leadership and Organizational Innovation	leadership, team, cultural, organization, employees
12	557	Innovation in Agricultural Tech & Food Production	agricultural, food, farmers, farming, product
13	499	Rural Innovation and Social Research	social, rural, communities, brand, users
14	425	Systematic Innovation in Energy & Technology	energy, renewal, climate, hydro, technology
15	424	Regional Industry Development and Innovation	region, efficiency, spatial, industry, agglomeration
16	421	Urban Technological Innovation and Development	cities, urbanization, smart, lowcarbon, green
17	397	Supply Chain Innovation & Technological Study	chain, supply, blockchain, disruptive, supplement
18	391	Ecosystem Innovation & Platform Development	ecosystem, platform, startups, helix, digital
19	315	Public Service Innovation & Customer Studies	services, public, customer, lab, procurement
20	241	Eco-Innovation and Economic Circles	ecoinnovation, circles, waste, environment, economy
21	196	Fintech Innovation and Banking Technology	bank, fintech, finally, corruption, credit
22	193	Governmental Impact on Innovation	subsidies, taxes, government, vehicle, enterprises
23	187	Innovation Adoption and Diffusion	intention, diffusion, adoption, consumer, acceptance
24	174	Tourism and Industry Innovation	tourism, hotels, hospitality, destined, industry
25	164	Water and Oil Process Technologies	water, oil, treatment, wastewater, membrane
26	143	Intellectual Capital in Innovation	capital, library, intellectual, employment, human
27	132	AI Ethics and Intelligent Innovation	intelligence, artificial, ethics, technology, emerging
28	123	Diversity and Governance in Firm Innovation	board, gender, directors, diversity, women
29	94	Family Business & Wealth Management	family, firm, socioemotional, wealth, nonfamily
30	88	Internationalization and Firm Performance	exports, internationalization, firm, performance, enterprises
31	75	Advanced Algorithms in Innovation	filters, algorithm, estimated, multiinnovation, kalman

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32	66	Frugal Innovation for Sustainable Development	frugal, sustainability, leadership, entrepreneurial, knowledge
33	54	ICT and Inequality in Innovation	ict, inequality, income, communication, countries
34	51	Corporate Governance and ESG Performance	esg, green, corporate, performance, governance
35	40	Nursing Practice Innovation	nursing, students, practice, clinical, education
36	36	Sports Innovation and Analytical Research	sport, athletic, multientity, psychological, rfet
37	13	Quantum Communication and Patent Innovation	quantum, computing, entangling, qubits, options

In the rapidly evolving landscape of modern research, it becomes paramount to recognize patterns and emerging trends across a multitude of disciplines, seen here as research frontiers. To summarize our findings from the calculation, we distinguish three domains that share synergistic relationships between each other:

[1] Business and Entrepreneurship
[2] Sustainability and Environmental Management
[3] Digital Transformation and Information Technologies

Within the domain of [1] Business and Entrepreneurship, clusters such as Entrepreneurial Business Innovations (Cluster 2) emphasize the creation and implementation of new business models and strategies that stimulate growth and competitiveness. Innovation Dynamics in Corporate Entities (Cluster 10) explores how firms develop and sustain innovation processes within the corporate framework, while Leadership and Organizational Innovation (Cluster 11) focuses on the impact of leadership and management practices on fostering a culture of innovation within organizations. [2] The Sustainability and Environmental Management domain encompasses clusters like Sustainable Technological Advancements (Cluster 1), which deals with the development of technologies that are environmentally sustainable and economically viable. Environmental Innovation & Green Tech (Cluster 4) focuses on technological solutions to environmental problems, aiming to create a greener economy. Energy Innovations for Environmental Management (Cluster 7) delves into the creation of new energy technologies and management practices that contribute to environmental sustainability. In the realm of [3] Digital Transformation and Information Technologies, Educational Innovations & (e)Learning Tech (Cluster 5) represents a pivotal shift towards digital learning platforms and educational technologies that enhance learning experiences. The cluster of Network-Driven Performance Innovation & Open Innovation (Cluster 6) investigates how digital networks foster collaborative innovation, while Digital Transformation and Green Innovation (Cluster 8) examines the convergence of digitalization and sustainability efforts within the business sector.

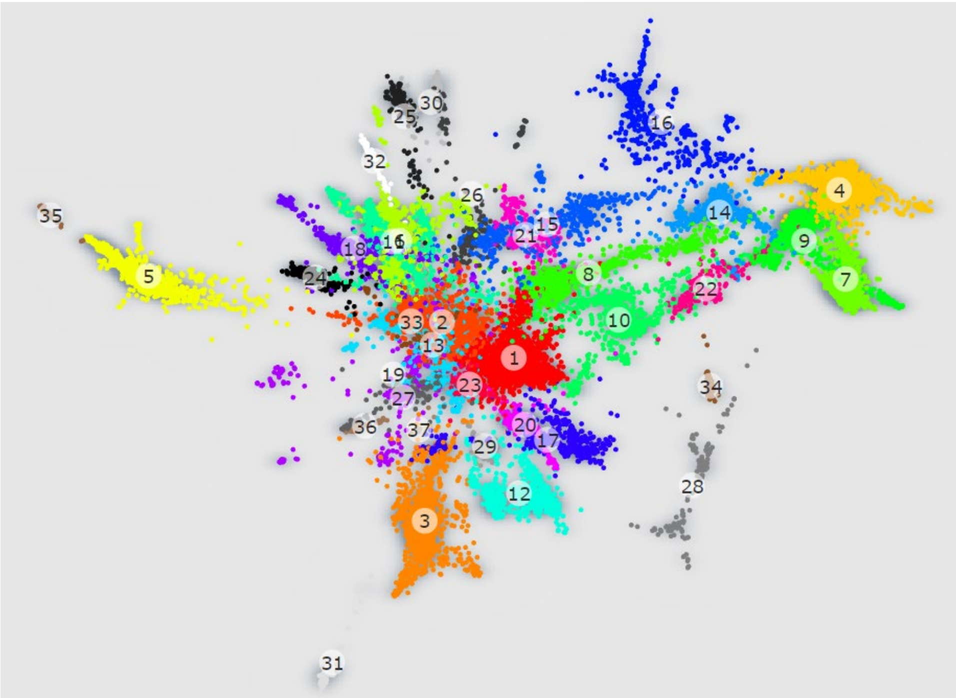

Figure 3 Visualization of the bibliometric analysis: Emerging technologies (2022-2024)

In Figure 3, each dot on the graph corresponds to an individual publication. By employing the Louvain clustering algorithm, an X/Y coordinate is determined for each publication. This positioning within the graph is derived from computing the hybrid similarity between publications, as well as measuring the relative distance of each publication to others, which in turn influences their spatial location on the graph. The central outcome of this visualization reveals that most publications are concentrated at the centre, indicating that these works share a high degree of bibliographic and lexical similarities, in contrast to those positioned on the periphery. Specifically, the clusters located in the middle are predominantly focused on themes of innovation. Clusters such as 4, 7, and 9, on the other hand, are distinctly aligned with themes of the domain [2] Sustainability and Environmental Management regarding energy, sustainability, and environmental topics on the upper right edge of the graph. While clusters such as 28, 31, 34, and 35, which are positioned in a somewhat isolated manner on the graph's edge, potentially indicating novel trends in research. Therefore, isolated clusters like (31) Advanced Algorithms in Innovation might contain emerging research which doesn’t share similarities with others.

5 Matching technology trend topics with online job postings

As already described in chapter 2, the top TF-IDF terms identified above form the directory for our automated keyword matching. Applied to the pre-filtered data set of 106,912 job postings from January 2024 in the DACH region, the keyword matching results in a total of 29,071 hits. This means that 29,071 job postings contain at least three out of five TF-IDF terms from any one of the topic clusters in their job descriptions. Job Postings that contain at least three out of five keywords from several clusters also count multiple times. Table 4 shows how the hits are distributed across the 37 topic clusters including the percentage share of the cluster number of hits over the total number of hits.

Table 4 Distribution of keyword matching hits across topic clusters incl. percentage share

Cluster number and top TF-IDF terms	*Number of hits*	*%*
1 – technology, systematic, design, sustainability, economy	504	1.734
2 – firm, business, knowledge, capability, entrepreneurial	2,389	8.218
3 – health, healthcare, care, surgery, clinical	2,097	7.213
4 – green, environment, regulatory, enterprises, chinas	91	0.313
5 – education, teachers, students, teaching, learning	176	0.605
6 – open, networks, collaboration, project, knowledge	4,702	16.174
7 – emissions, carbon, energy, co2, renewal	200	0.688
8 – digital, transform, green, enterprises, digitalization	1,037	3.567
9 – green, csr, environment, sustainability, corporate	862	2.965
10 – corporate, enterprises, patents, firm, uncertainty	53	0.182
11 – leadership, team, cultural, organization, employees	7,003	24.089
12 – agricultural, food, farmers, farming, product	88	0.303
13 – social, rural, communities, brand, users	204	0.702
14 – energy, renewal, climate, hydro, technology	456	1.569
15 – region, efficiency, spatial, industry, agglomeration	204	0.702
16 – cities, urbanization, smart, lowcarbon, green	33	0.114
17 – chain, supply, blockchain, disruptive, supplement	76	0.261
18 – ecosystem, platform, startups, helix, digital	275	0.946
19 – services, public, customer, lab, procurement	5,207	17.911
20 – ecoinnovation, circles, waste, environment, economy	29	0.1000
21 – bank, fintech, finally, corruption, credit	71	0.244
22 – subsidies, taxes, government, vehicle, enterprises	1	0.003
23 – intention, diffusion, adoption, consumer, acceptance	2	0.007
24 – tourism, hotels, hospitality, destined, industry	91	0.313
25 – water, oil, treatment, wastewater, membrane	20	0.069
26 – capital, library, intellectual, employment, human	112	0.385
27 – intelligence, artificial, ethics, technology, emerging	339	1.166
28 – board, gender, directors, diversity, women	983	3.381
29 – family, firm, socioemotional, wealth, nonfamily	58	0.200
30 – exports, internationalization, firm, performance, enterprises	96	0.330
31 – filters, algorithm, estimated, multiinnovation, kalman	0	0.000
32 – frugal, sustainability, leadership, entrepreneurial, knowledge	475	1.634

33 – ict, inequality, income, communication, countries	470	1.617
34 – esg, green, corporate, performance, governance	502	1.727
35 – nursing, students, practice, clinical, education	161	0.554
36 – sport, athletic, multientity, psychological, rfet	0	0.000
37 – quantum, computing, entangling, qubits, options	4	0.014

A look at the top six clusters with several thousand hits (Clusters 2, 3, 6, 8, 11, 19) reveals that the associated trend topics focus strongly on organizational, processual, and business model innovation. Technology-heavier clusters such as clusters 1, 7, 14 and 27 tend to be midfield in terms of hit numbers. Clusters, which focus on a very specific technology have low hit numbers between zero and single-digit values (see Clusters 31 and 37). Generally, it can be noticed that the highest hit rates tend to occur in the first 19 clusters. This is consistent with the basic functionality of the bibliometric analysis, according to which the lower cluster numbers are those with the most scientific publications assigned to. Orienting towards the previous chapter, these clusters are also the ones that are more established in scientific research than the higher cluster numbers, which are only emerging. The job postings analysis seems to generally confirm this from a practice perspective. However, the percentage share of the individual clusters differs considerably in some cases between the scientific and the practical perspective. To get a deeper understanding of the hiring dynamics per topic cluster we created an extensive heatmap, by identifying all companies hiring within the topic clusters and analysing how many hits each of them produces within the clusters. Our automated in-depth analysis identified 1,432 distinct companies and assigned each the exact number of unique hits per cluster. According to this, in January 2024, 1,432 different companies had job postings online for the DACH region that match at least one of our topic clusters.

6 Results and discussion

While the extensive results heatmap offers room for various kinds of discussions, we consider it insightful to focus on the topic clusters with most hits, fewest hits and the specific companies that are hiring in many clusters.

Figure 4 shows for the six topic clusters with the most total hits (in descending order) which companies have the most job postings assigned to the respective clusters. We focus on the top ten companies, except for cases in which several companies have the same amount of hits – as shown by the numbers given in Figure 4.

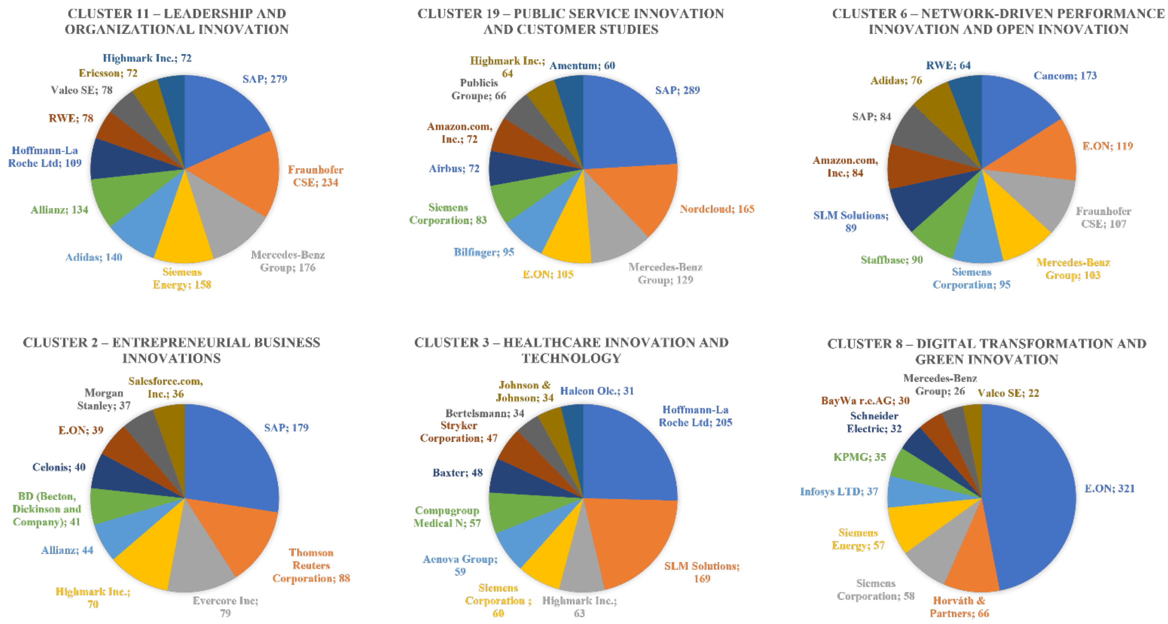

Figure 4 Companies with most job postings in topic clusters with most total hits.

A closer look at the top companies in these clusters reveals no clear industry focus, except for Cluster 3, which is obviously dominated by medical and pharmaceutical companies. What the analysis shows is that mainly large multinational corporations are responsible for the majority of hits in these rather generic innovation fields. This should be no surprise as the above trend topics are broad enough to be tackled by many different companies and multinationals naturally advertise a lot of jobs, which makes it easy for them to gain the upper hand in terms of quantity. Nevertheless, picking out individual companies allows for a direct comparison across the clusters. In the case of SAP, for example, our analysis leads to the assumption that leadership and organizational innovation is currently of higher priority than network-driven performance innovation and open innovation. For E.ON, on the other hand, digital transformation and green innovation seems to be the top priority, whilst RWE from the same industry is not among the top ten companies in this cluster. Of course, our analysis is limited to a very short period of time and represents only a snapshot of the hiring dynamics, but in an attempt to better understand practice's interest in the most recent trend topics we had to refrain from looking at past job postings too.

As indicated in the previous chapter and based on the way our bibliometric analysis works, we already assumed that the lower cluster numbers tend to reflect rather established trend topics. The job postings analysis and the discussion above confirm this from a practice perspective, which makes it even more interesting to look at the higher cluster numbers, respectively those clusters that got none to only a few hits.

The keyword matching analysis produced no hits for Cluster 31 (Advanced Algorithms in Innovation) and Cluster 36 (Sports Innovation and Analytical Research). This could be an indicator that the underlying technologies and innovation fields are still emerging and that they are still too early phased to be of commercial interest. However, especially for Cluster 36, we cannot rule out the possibility that it might be too niche-specific to be captured by LinkUp data. For this reason, we focus our further analysis on the clusters with the fewest hits, zero hits excluded.

Figure 5 shows for the six topic clusters with the fewest total hits (in descending order) which companies have the most job postings assigned to the respective clusters. A focus on the top ten companies was not necessary in this case, as fewer than ten companies produced hits for each of these clusters.

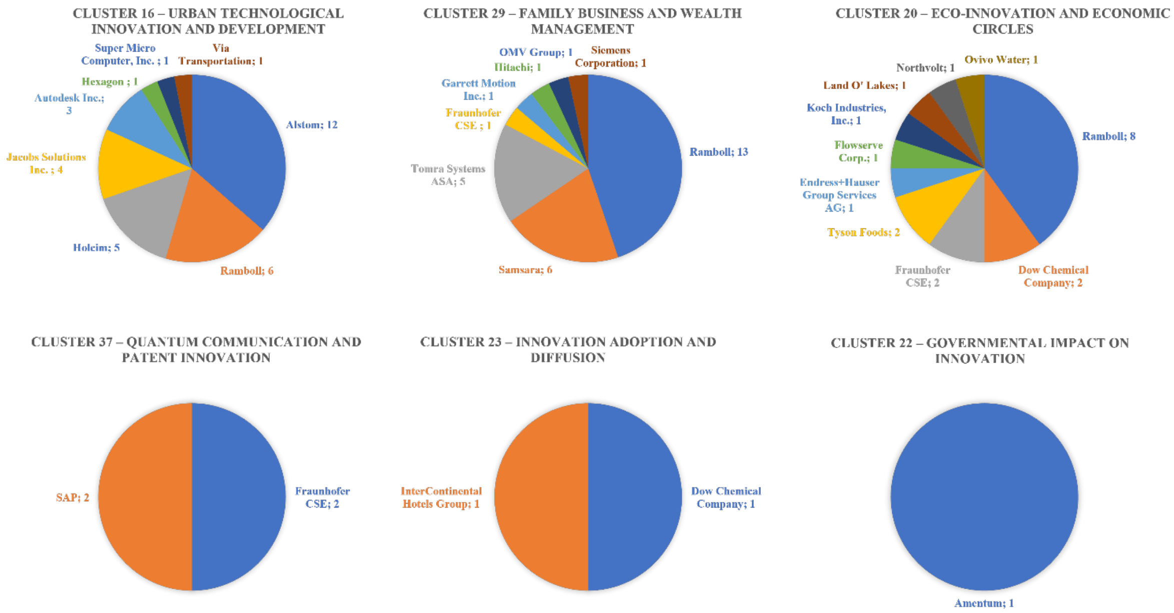

Figure 5 Companies with most job postings in topic clusters with fewest total hits.

Also, for the clusters with low hit numbers there is no clear industry focus evident. Except for Cluster 16, which with Alstom, Holcim and Jacobs Solutions displays some interesting players in the field of urban technological innovation and development. What is striking here is that, apart from Holcim, only companies headquartered outside the DACH region are represented in this cluster. This observation also applies to Clusters 29 and 20. Obviously, all these firms advertised jobs in Germany, Austria, or Switzerland – otherwise they would not be part of the analysis – but from a regional perspective they are foreign companies. Given the assumption that the above topic clusters and innovation fields are less established and more early phased than the ones from Figure 4, our snapshot analysis indicates that DACH companies are underrepresented in these emerging innovation fields. The opposite is true for Cluster 37 on quantum communication and patent innovation. SAP and Fraunhofer CSE appear, within the limited scope of our analysis, as technology leaders or at least early adopters of this technology field.

To put the previously discussed results into context, it is helpful to take the total number of hit-generating job postings per individual company into account. Therefore, Figure 6 shows an excerpt from the results heatmap, filtered by companies that generated more than 100 hits in the keyword matching analysis. On the y-axis, Figure 6 lists all these companies in an alphabetical order and on the x-axis, it shows the topic clusters from 1 to 37 including the total number of hit-generating job postings per company in the last column.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	
ABB LTD	3	1	2		1	41		17	5		17			1	7			2	45									5						2	1			150
Accenture	9	2				23	3	3	4		20				1		1		16								8					9		8				107
Adidas	6	23			1	76		2	10		140		4		11				39								2	5				9	5	4	1			338
Airbus	5				1	29		1			51							2	72							3	3	41				4		2				214
Alibaba Group LTD		33				28					39								59																			159
Allianz	6	44	28	7	2	60		8	17	25	134				2			2	52							2	2	53	2	25		8	6	14				499
Amazon.com, Inc.	4	14			2	84		1	7		65								72								1	2				7	5	2	2			268
BASF	2	1				36		14	4		16	7			5				47								1	27				1	1		1			163
BD (Becton, Dickinson and Company)	1	41	25			12		2	1		17						1		11							2	2	1				1	3	2	2			124
BayWa r.e. AG						45		30	30		49			17					7									35						15				228
BearingPoint	1	1						3	24		6										8							57	1					40				141
Bilfinger	1	7	2			14		1	3		47				2				95								3			26		1		3				205
CSL Behring LTD		7	20			21					55				2				12								2					2	7		1			129
Cancom						173					2							9	35																			219
Celonis		40	1			24	3				11							9	26							2	2	57					1					176
Continental	12	15			1	61		1	6		61				5				29								10					5	5	2				213
Department of the Air Force		24			1	46					35								49							30	1		2				1		1			190
Deutsche Bank	1	21	16			25			24		24		1		1				23								2	8					4	12				162
E.ON	19	39	2	12	7	119	9	321	75		61			53				14	105								22					3	3	24				888
ETH Zürich	4	1	2		43	37					9			1			1	2	11								3					1	1		6			122
Ericsson	1	27				5			1		72								25														44					175
Essity Aktiebolag (publ)	1	3	22			28		1			16		1						18									18					1					109
Forto	8	1				2		1	9		33			10					3													33	1					101
Fraunhofer CSE	25	15	19		1	107	7	6	4		234	1		22			5		53	1					2		20	15							1		2	540
General Electric	9	6	1			10	1		12		27			1					34													3						104
HP Inc		7	2			31					25								25									9						8				107
Hellmann Worldwide Logistics SE		40	3		1	9		1	1		24								31							2						1						113
Highmark Inc.	6	70	63		2	14					72		2						64							3	2	18				2			18			336
Hoffmann-La Roche Ltd	2	12	205	4		47			7		109							1	51							1	5	8				17	21		2			492
Horváth & Partners		24				19		66	12		7																					6		6				140
Infosys LTD	4	7		2		15		37	8	1	31							8	29											2		1	4					149
JLL		14				6			14		22		15						26					2										2				101
Johnson & Johnson	2	5	34			10		2			39				2			1	17															1	2			115
KPMG	4	19	7	1		9		35	9		28				1			5	7								8					3		3				139
KWS		5				41		1			53	25							12								1					1	8					147
Leidos Holdings Inc.		8	7			22					31								37									7					24					136
Mendix		5				5		9			41								9										41	9								119
Mercedes-Benz Group	5	28				103		26	5		176							1	129								5					3	7	4				492
Microsoft Corporation	2	4	3			22					62				2			4	34							7							1					141
Nordcloud		7				14					49								165																			235
Northvolt				20	1	52	2	3	6		36								12						1							1	2	7				143
PUBLICIS GROUPE	5	16	2			6					63								66									2				1						161
Palo Alto Networks Inc.		1	11			29					54							6	24								4	11					3					143
RWE	2	11	1	2	1	64	8	19	15		78			43	1				8									36				5	4	14				312
Ramboll	8			3		25	8		20		1			17	5	6			3	13					8							8						125
Robert Bosch Tool Corporation	4	20	8		2	34	2	2	2		11			5			2	2	9													6			1			110
SAP	11	179			17	84		9	5	3	279		10	1	1			9	289							2	9	1		2		10			3		2	926
SLM Solutions			169			89					68																15	15										356
Schaeffler AG	2	31				15		9	3		27								5								2		1			13		1				109
ServiceNow	1	1				12					43				1			4	41																			103
Siemens Corporation	7	12	60			95	7	58	11		70			4	1			1	83	1							9	4	3			2	3	4				435
Siemens Energy		16		2	1	30	39	57	6		158			154	15				36									8				7	7	2				538
Staffbase		4			1	90					47		2						1																			145
Syncreon	11	3	4			3			15		52						16		21							1		1				2	2					131
TK Elevator	15	3	25			19			2		16								23													1	1					105
Thomson Reuters Corporation	6	88	3			7				1	32								21							2	3	13				1	1	3				181
UNICEF	7	13	2			12			4		10		6				1		21							1	2	12				5	28	4				128
Valeo SE	1					18		22	78		78																						1	23				221
Viessmann	1	5				6	58				19			13	2				4																			108
Westwing Home & Living		2				32			5		21		1						46														5	1				113

Figure 6 Heatmap of companies with more than 100 hits across all topic clusters.

First of all, this excerpt from the heatmap confirms what has already been mentioned several times in the previous analysis. The majority of keyword matching hits was generated in the first 19 topic clusters. Again, we can conclude that the underlying trend topics are well established and of high relevance in business practice. For Clusters 26 to 30 and 32 to 35 we received fewer hits in total. As these hits are still rather evenly distributed across the different companies, we can rule out any industry concentration and may assume that the underlying trend topics are not fully established yet, but they are certainly relevant. For clusters with very few hits, it can be argued that the hit-generating companies are technology leaders or at least early adopters of an emerging innovation field. To confirm this, however, in-depth case analyses of the companies concerned would be necessary. Since our research presented in this paper is limited to testing the sheer validation of trend topics from scientific publications with online job postings data, we will reserve this in-depth analysis for future research. What the results heatmap in general and the excerpt above allows us to do anyhow, is to get an impression about the current engagement of an individual company in a specific trend topic at a certain point of time. Taking BASF as an example, we can easily determine for each topic cluster, if the company is currently expanding its human resources or not and deduce from this whether the respective topic is currently a high priority in practice. These are questions that trend researchers usually ask the company representatives in qualitative interviews, and we can answer them now based on quantitative data.

Of course, our analysis is subject to timely and regional constraints and shows only a very brief snapshot of the actual hiring dynamics. But the purpose of our study was to introduce our novel attempt at data-driven validation of early-stage technology trends and to test the feasibility of combining bibliometrics with online job postings analysis. With regard to the research question and to the outlined difficulty of putting scientific trend studies into business contexts, we can finally defend our approach and conclude that it is worth pursuing.

7 Limitations and future research

As our study takes on the novel approach of combining a bibliometric trend analysis with the quantitative analysis of online job postings data and is merely testing the feasibility of this method combination, the work is naturally subject to some limitations. Concerning the job postings analysis, the very short analysis period of one month as well as the regional focus on the DACH region have already been mentioned as limitations. However, these restrictions were necessary to limit the amount of data for our test runs. Once the method is more sophisticated, the scope of the analysis will gradually be extended in our own future research.

Another limitation, that is rooted in the bibliometric analysis, is the imprecision of the TF-IDF terms. Without further processing the NETCULATOR results, the TF-IDF terms alone are not able to represent the technology-level of the trend topics. The core objective and intention of the NETCULATOR is to calculate the hybrid similarities and afterwards identify the top five TF-IDF terms. Consequently, this naturally leads to the creation of broad and generic terminologies, if we use a broad and a generic search strategy based around emerging innovations and technologies, which may not be as suitable for representing specific technological phenomena. However, the current analysis highlights the trends that the scientific community is exploring in the field of innovation and technologies in terms of research fronts. Additionally, it should be assessed to what extent the search string can be limited to the keyword "technology" in the second parenthesis and in the keywords for determining the datasets, to address technological trends more specifically. To achieve further depth, it is suggested that each technology cluster with its respective publications be recalculated and analysed in a sub-research front analysis using the NETCULATOR, thereby attaining the desired level of specific detail, which possibly describes more accurate technological phenomena in the top TF-IDF terms. Therefore, further bibliometric analysis approaches should be conceived and tested. Future research could add this sub-research frontier analysis as an intermediate step to our approach, which penetrates to the technology-level of bibliometric topic clusters and refines the terms for subsequent keyword matching. Alternatively, future research can concentrate on applying and further developing our proposed approach to validate technology trends in specific application areas, which should also eliminate the superficiality of the analysis.

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