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Future-ready technologies for Switzerland: Trend insights from job postings analysis

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Abstract: Foresight research is constantly striving to identify and utilize new data sources for its technology trend analyses. In addition to long-established data sources such as patents and scientific publications, job postings data have recently proven to be an insightful data source for foresight purposes, reflecting the adoption of emerging technologies in practice without major time or publication delays. In our research we use current online job postings from Switzerland to identify technologies that are frequently mentioned in connection with future-related terms in job descriptions. This novel approach provides a data-based overview of the specific technology areas in which companies in Switzerland see future potential and are actively hiring for. Furthermore, we compare the hiring dynamics for these technology fields across industries to identify robust technologies that are future-relevant in many industries. Our methodology comprises text mining techniques, including keyword analysis and named-entity recognition, resulting in a data-driven scientific trend study.

Keywords: Trend analysis; technology foresight; robust technologies; industry trends; Switzerland; job postings analysis; text mining; keyword analysis; named-entity recognition.

1 Introduction

Technology trend studies with a regional focus and practical implications are widespread in the literature and show a high relevance for the scientific discourse on corporate and technology foresight. A lot of these studies, however, apply qualitative foresight methods such as scenario techniques, expert interviews, or the Delphi method to set trend signals into national or regional contexts (Bassani et al. 2016; Blind et al. 1999; Kindras et al. 2019). Data-driven foresight, on the contrary, is a specialized stream within the foresight discipline that exploits quantitative data analysis to derive weak signals from various data sources for potential future trend developments and helps companies in proactively identifying and seizing emerging competitive advantages (Rohrbeck et al. 2015; Scheuffele et al. 2024). In terms of the data sources used, scientific publications and patent data are the most established and utilized, with many examples of successfully conducted trend studies in a variety of analysis contexts (Block et al. 2021; Michelino et al. 2016; Stelzer et al. 2015). Especially scientific publications, however, lack the ability to represent practical relevance or anticipate application success because scientific success of a technology or research field does not necessarily lead to market success or innovation breakthroughs (Stelzer et al. 2015). This is why, in both foresight science and practice, constant efforts are being made to identify alternative data sources from various perspectives and to analyze them for weak signals on emerging innovation fields. Bonaccorsi et al. (2020), for example, use Wikipedia pages as a data source to identify emerging technologies and industrial leadership in the context of Industry 4.0. Laurell and Sandstrom (2022), moreover, present social media analytics of multiple platforms as an innovative foresight approach.

In our research, we use online job postings as an alternative data source to identify future-ready technologies for Switzerland. For this purpose, we examine over one million job postings from Switzerland from September to December 2024 for the technologies they mention in connection with future-related terms in their job description texts. Although job postings data are not yet fully established in the foresight discipline, they have recently proven to be an insightful data source for trends identification, reflecting the early business practice perspective of technology adoption and development efforts without any review or publication delays (Goldfarb et al. 2023; Zhang et al. 2017). Based on Goldfarb et al.'s (2023) approach to analyze job postings across various industries to compare emerging technologies for their potential to become a general-purpose technology (GPT), we also examine the emergence of our identified future-ready technologies across industries. Our aim, however, is to derive the technologies' potential robustness in terms of cross-industry future relevance. Robust technologies in foresight are usually characterized by the fact that they occur in various future scenarios and play a dominant role for future competitive advantages without being too sensitive to changes in future conditions (Maier et al. 2016; McPhail et al. 2020). Applied to our study, technologies are robust if they are identified as future-relevant technologies in many different industries through keyword analysis and named-entity recognition of technologies frequently mentioned in connection with future-related terms in job descriptions. Proposing this novel methodology for data-driven foresight to the scientific discourse and following the outlined approach, we strive to answer the following research question: Which technologies and innovation fields are future-ready and relevant for Switzerland based on job postings analysis and cross-industry robustness evaluation?

2 Research methodology

After a brief review of the theoretical background of technology trend analysis in Switzerland, its utilized data sources and methods, and the analysis of job postings data in general, our paper presents a data-driven trend study on future-ready technologies for Switzerland based on job postings analysis. For this purpose, we acquired an extensive set of online job postings from the commercial data provider LinkUp, which is updated daily and sourced directly from employer websites worldwide. The data provider has indexed hundreds of millions of jobs from over 60,000 companies across 195 countries (LinkUp 2025). Both numerical and textual data are available in different file types, which can be merged depending on the focus of the analysis. For our analysis, we utilize the so-called job record files, the job description files, as well as the company reference files. Each job posting is assigned an individual job hash that serves as the unique identifier for merging the different files and for removing duplicates. Table 1 summarizes the contained information and the structures of the files in use, giving an overview of how we compiled and cleansed the data for our analysis.

Table 1 Overview of LinkUp data files relevant for the analysis

File name	*Information contained*	*Relevance for analysis*
Job records	hash, title, company_id, company_name, city, state, zip, country, created, last_checked, last_updated, delete_date, unmapped_location, url	hash: merge files, remove duplicates country: filter by CHE created: filter by analysis period delete_date: exclude inactive records
Job descriptions	job_hash, description	job hash: merge files, remove duplicates description: basis for text mining
Company reference	company_id, start_date, end_date, company_name, company_url, lei, open_perm_id, naics_code	company_id: merge files end_date: exclude inactive references naics_code: allocate industries

The cleansed data set of 1,079,079 job postings from Switzerland, being online between 01.09.2024 and 31.12.2024, forms the basis for our two-step text mining analysis. In the first analysis step, we automatically scan the job description texts for the simultaneous occurrence of future-related terms and technology topics via keyword analysis in Python. In the second analysis step, we extract the specific technologies mentioned in the relevant job descriptions by applying both a named-entity recognition in Python and a ChatGPT-supported technology identification. Following this, we perform in-depth analyses and result visualizations in Excel to determine how the technologies are represented in job postings across industries. Finally, we calculate the entropy for this distribution to derive statements about the technologies' potential futures robustness. Figure 1 visualizes the outlined approach in a methodology flowchart and shows how the analysis steps are linked with each other.

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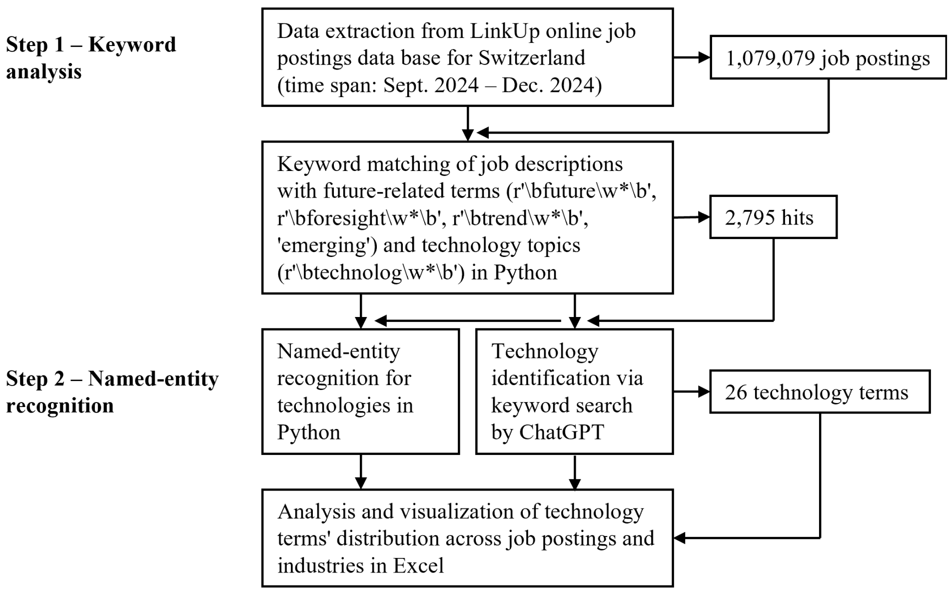


Figure 1 Flowchart of the two-step research methodology.

3 Theoretical background

Recent academic foresight studies and technology trend analyses for Switzerland identify digital technologies as further emerging and highly relevant for the Swiss economy and its core industries (Niggli and Rutzer 2023; Tsesmelis et al. 2022). In their data-driven trend study on cybersecurity technologies in Switzerland and abroad, Tsesmelis et al. (2022) evaluate 5G, big data, machine learning, blockchain, and contact-tracing methods as emerging technologies based on job openings, patents, and publications analysis. Most of these technologies are also mentioned in a national trend study by the Swiss Academy for Engineering Sciences SATW (2023) as well as in a focused market study by Deloitte (2021). Despite being non-academic, these two studies provide valuable insights into the state of the art of current technology trends for Switzerland while highlighting the need for further Swiss technology foresight research. Another literature stream in the Switzerland-related foresight discourse examines how foresight activities are implemented in different national business practice contexts (Baumgartner and Peter 2022; Peter 2019). Baumgartner and Peter (2022), for example, analyze how international Swiss banks incorporate strategic foresight into their innovation activities and develop a new framework for enhanced innovation activity through collaborative foresight. While this research stream does not provide any insights into actual technology or innovation trends, the above-mentioned trend studies do not only identify specific emerging technologies and innovation fields but also explain the data sources and analysis methods in use, as summarized in Table 2.

Table 2 Summary of technologies and innovation fields identified in trend studies for Switzerland

Emerging technologies and innovation fields	*Data sources and analysis methods used*	*Authors*
5G, big data and machine learning, blockchain, contact tracing	Patent analysis of granted patents per technology in Switzerland Publication analysis of scientific publications uploaded to arXiv Analysis of Google search history for technologies and insights from Google Trends	Tsesmelis et al. 2022
Digitalization: 5G applications, blockchain, internet of things, extended reality, connected machines, quantum computing, quantum and post-quantum cryptography, autonomous vehicles, photonic integrated circuits, digital twins Energy and environment: photovoltaics, sustainable food production, artificial photosynthesis, carbon capture storage, geothermal energy, mobility concepts Manufacturing processes and materials: low-carbon concrete, sustainable adhesives and sealants, bioplastics, thermal interface materials, fibre-optic sensors, antimicrobial surfaces	Technology Outlook 2021 reassessed through Technology Readiness Level evaluation Expert opinions (qualitative data) collected through semi-structured interviews Economic significance for Switzerland evaluated by sales revenue data of companies based in Switzerland Research competence in Switzerland evaluated through publications of academic and industrial research in Switzerland plus monitoring of Swiss universities' X accounts	Swiss Academy for Engineering Sciences SATW 2023
Artificial intelligence, digital personalized health, robotics, advanced manufacturing, blockchain	Expert opinions (qualitative data) collected through interviews	Deloitte 2021

The brief review of trend studies for Switzerland already shows a variety of data sources and analysis methods used for technology foresight purposes. An even broader overview of foresight data sources and methods can be gained by looking at the foresight literature without a regional focus. In this regard, the body of literature also contains trend studies that compare the content validities of different data sources (Bonaccorsi et al. 2020; Laurell and Sandstrom 2022; Mikova and Sokolova 2019) and examine their varying temporal foresight horizons (Cozzens et al. 2010; Mühlroth and Grottke 2018; Segev et al. 2015). These considerations are based on two leading studies that categorize foresight data sources from different perspectives according to their technology lifecycle predictiveness (Martino 2003; Watts and Porter 1997). Orienting towards the observable sequence of technological change – from theoretical proposal to commercial introduction – it is, therefore, possible to determine the maturity of a technology and anticipate its advancement into the next lifecycle phase based on peaks in publications of a specific type of data source. Scientific publications, for example, are best suited to represent emerging technologies in their basic research phase. Patents, on the other hand, reflect technologies that are already in the development stage, and newspapers, business, and popular press allow for trend insights regarding the daily application and social impacts of a technology (Martino 2003). Recent studies show 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. Regarding marketability and application success of technologies, scientific publications can be even nine years ahead, which makes them the most early-phased data source for foresight purposes but not necessarily the most practice-oriented (Block et al. 2021; Hsieh et al. 2024; Segev et al. 2015; Stelzer et al. 2015).

These findings and the resulting argument that different data sources hold different foresight potentials (Watts and Porter 1997) also form the basis for utilizing job postings data as a foresight data source. Goldfarb et al. (2023) argue that job postings reflect a company's intentions to engage with a new technology or innovation field earlier than patent data because human capital is an input into technology development, and technological innovations must be developed by employees before a company can file a patent. Hence, job postings data can be seen as the most early-phased data source of the business practice perspective, reflecting exactly when a company or industry starts adopting emerging technologies or innovation fields. Nevertheless, job postings data are not yet fully established in the foresight discipline. Most studies using this data source focus on the identification of future skills in specific countries, technology fields, or job domains. Such as Brasse et al. (2024), who analyze job advertisements to identify future skills for the manufacturing industry in Baden-Württemberg in Germany, or Firpo et al. (2021), who map the demand for future digital skills in the Tunisian labor market based on online job ads. From the leading trend study by Goldfarb et al. (2023), who use online job postings data to examine the potential of artificial intelligence (AI) to become a general-purpose technology (GPT), it can be deduced that also the metadata of job postings are exploitable for foresight purposes. In their study, the authors analyze North American Industry Classification System (NAICS) codes of job postings associated with various emerging technologies to derive the "widespread use" and "innovation in application industries" of these technologies for their GPT assessment (Goldfarb et al. 2023). This approach to measuring cross-industry robustness, together with the text mining techniques described in the following chapter, forms the basis for our own identification and evaluation of future-ready technologies for Switzerland.

4 Job postings analysis

Since automated keyword matching with a predefined directory is a proven methodology for analysing job postings data (Brancatelli et al. 2020; Brasse et al. 2024), we also made use of a keyword-based text mining approach in our first analysis step. But instead of limiting the search terms to fixed words, we developed the following self-defined search query, including appropriate operators to avoid any bias in the technology detection:

future* OR foresight* OR trend* OR emerging AND technolog*

The initial data set of 1,079,079 job postings from September to December 2024 in Switzerland was available in .xlsx format after downloading from the LinkUp server, and without further preprocessing of the data, the job description texts could be matched with the above search query using the following Python code in Google Colab:

```
future_terms_patterns = [r'\bfuture\w*\b', r'\bforesight\w*\b',
r'\btrend\w*\b', 'emerging']
technology_term_pattern = r'\btechnolog\w*\b'

df['description'] = df['description'].fillna('')
def find_future_terms_with_technology(text):
    found_terms = []
    text_lower = text.lower()

    if re.search(technology_term_pattern, text_lower):
        for pattern in future_terms_patterns:
            if re.search(pattern, text_lower):
                found_terms.append(re.search(pattern, text_lower).group()
    return found_terms

df['future_terms'] =
df['description'].apply(find_future_terms_with_technology)
filtered_df = df[df['future_terms'].str.len() > 0]
filtered_df['future_term'] = filtered_df['future_terms'].apply(lambda x:
x[0] if x else None)
output_df = filtered_df.copy()
output_df.to_excel('', index=False)
```

After this analysis step, the remaining data set was manually cleansed of duplicates and outdated or inactive job postings in Excel, ensuring only job offers posted and active between 01.09.2024 and 31.12.2024 in Switzerland are included in the subsequent analysis. In doing so, we did not impose any language restrictions on description texts, as job advertisements in Switzerland can be multilingual due to the country's language diversity, and our defined keywords can certainly be used in different linguistic contexts. Nevertheless, because of the English search string, most job postings in the results data set are published in English, accompanied by fewer job postings in German, French, and Italian. Finally, a total of 2,795 unique job postings were identified as simultaneously containing technology and future-related terms in their job descriptions and qualifying for the second analysis step.

Since the aim of the second analysis step is to extract the specific technologies and innovation fields these job postings are hiring for, we applied a named-entity recognition (NER) analysis based on the spaCy standard model for natural language processing (NLP) on their job description texts using the following Python code in Google Colab:

```
import spacy
nlp = spacy.load("en_core_web_sm")

descriptions = df['description'].dropna().tolist()

entities = []
for desc in descriptions:
    doc = nlp(desc)
    for ent in doc.ents:
        if ent.label_ in ["ORG", "PRODUCT", "TECHNOLOGY"]:
            entities.append(ent.text.lower())
```

```
from collections import Counter
entity_counts = Counter(entities)

import pandas as pd
tech_df = pd.DataFrame(entity_counts.most_common(), columns=["Technology",
"Count"])
tech_df.head(20)
tech_df.to_excel('', index=False)
```

Encompassing several thousand hits for named entities in the job description texts, we uploaded the unfiltered results of the NER analysis to ChatGPT-4o and prompted it to extract only emerging technologies and innovation fields from the identified entities. This resulted in the following future-relevant technology topics for Switzerland in alphabetical order, including their common abbreviations:

- Artificial intelligence/AI
- Automation
- Big data
- Biotechnology
- Cybersecurity
- Digital twins
- Fintech
- Internet of Things/IoT
- Machine learning/ML
- Natural language processing/NLP
- Robotics

To ensure that no technologies are missed that may not be recognised by the spaCy standard model, we complemented the NER analysis with a technology keyword analysis using ChatGPT-4o. The Large Language Model (LLM) was provided with the job descriptions of all 2,795 job postings from analysis step 1 and automatically matched them with the following keywords: artificial intelligence, machine learning, blockchain, cloud computing, cybersecurity, big data, Internet of Things, 5G, robotics, automation, data science, quantum computing, augmented reality, virtual reality, biotechnology, nanotechnology, wearable technology, drones, smart devices, and cryptography.

As we had already identified many of these technologies through the NER analysis, and quantum computing as well as wearable technology did not occur in any of the job descriptions, and data science as a discipline is too broad, only the following innovation fields in alphabetical order were added to our list, including their common abbreviations:

- Augmented reality/AR
- Blockchain
- Cloud computing
- Cryptography

- Drones
- Nanotechnology
- Smart devices
- Virtual reality/VR
- 5G

After successfully identifying the above technologies and innovation fields as appearing simultaneously with future-related terms in Swiss job postings through the combination of keyword analysis, NER analysis, and ChatGPT-supported technology identification, we continued first with a descriptive hit evaluation and then with the industry comparison in Excel. For the former, we used conditional formulas in Excel, combining IF, SEARCH/FIND, ISNUMBER/SUM, and IFERROR functions to mark which job postings contain which of the technology keywords and to count the total number of hits for each technology or innovation field. For the latter, we exploited the six-digit NAICS codes assigned to each job posting at their two-digit level to count how many job postings per industry contain the technologies and innovation fields from our previous analysis. These results were finally subject to an entropy calculation that determines how evenly or unevenly the hits are distributed across the industries and allows for statements about the potential futures robustness of our identified technologies and innovation fields. Here, we oriented towards Goldfarb et al. (2023), who calculated Gini coefficients for job postings referencing enabling technologies across industry sectors to evaluate widespread use and for research job postings referencing enabling technologies across industry sectors to evaluate innovation in application industries as part of their GPT study. Similar to the Gini coefficient, entropy also measures the degree of disorder or dispersion in a distribution. For our purpose of calculating the entropy of job posting hits per technology field across industries, we applied the following formula:

$$H = -\sum_{i=1}^{n} p_i * \log_2 (p_i)$$

where p_i specifies the share of hits in industry i relative to the total number of hits for a given technology field and n represents the total number of industries included in our analysis. The value of H reaches its maximum, $\log_2$ (n) when the distribution is perfectly uniform, indicating equal representation across all industries. Depending on the entropy value of each technology or innovation field, we could finally draw data-based conclusions about the cross-industry relevance and robustness of our future-ready technologies for Switzerland, which we outline in the following chapter together with the results of the preceding analysis steps.

5 Results and discussion

The descriptive evaluation of job posting hits per innovation field reveals a clear picture regarding the most frequently mentioned technologies in connection with future-related terms in our data set. Artificial intelligence, together with its abbreviation AI, generates by far the most keyword matching hits with job descriptions from Switzerland, followed by automation, machine learning/ML, cybersecurity, and robotics. Other innovation fields such as cryptography, drones, nanotechnology, or smart devices generate only a few hits, which does not necessarily mean that they are future-unready but certainly less established in business practice to date. Figure 2 shows for all technologies and innovation fields identified above in how many job postings from our data set they are mentioned in the job description texts. For that, it is irrelevant how often a particular keyword appears in a job description, but multiple assignments to different technologies are possible if a job description contains more than one of our innovation topics. In addition to displaying the total number of matching job postings per technology for the whole analysis period, Figure 2 also breaks down the monthly hits to account for any seasonal recruitment dynamics in the labour market.

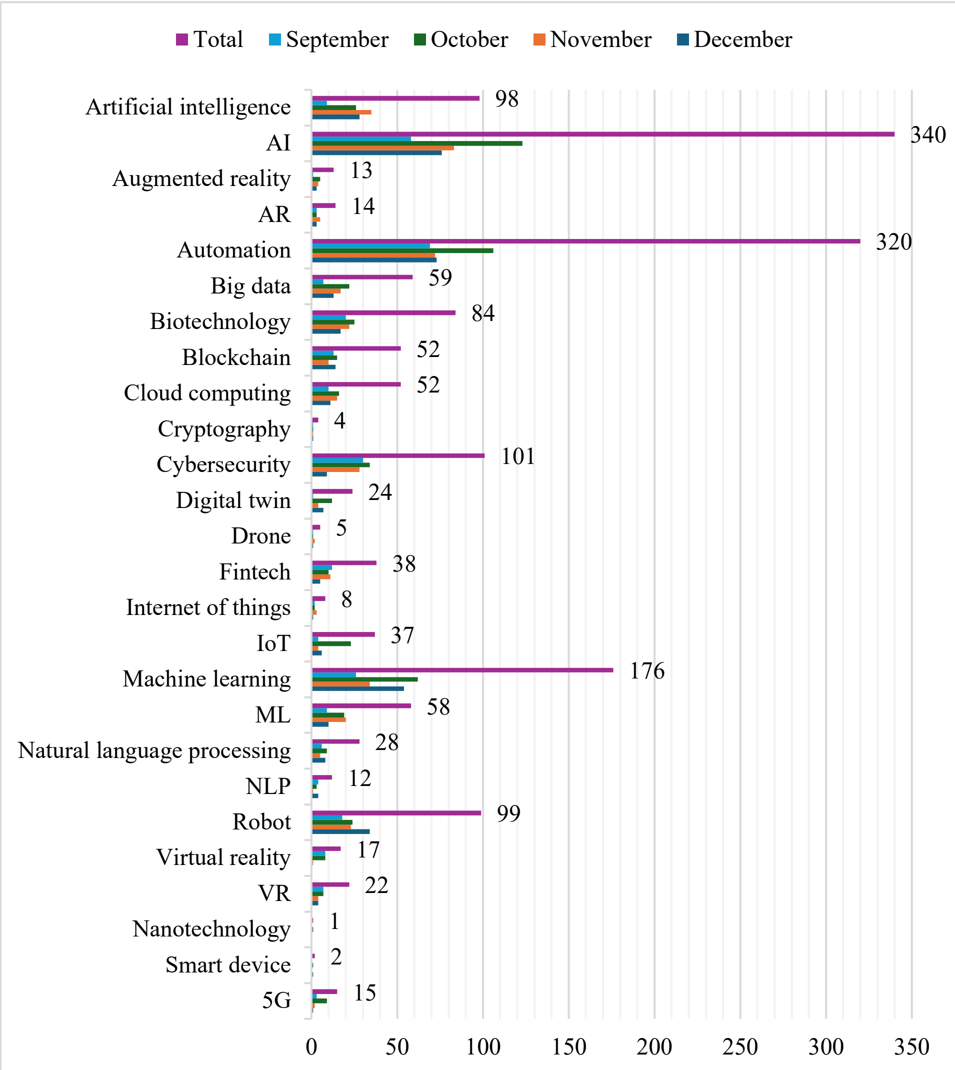
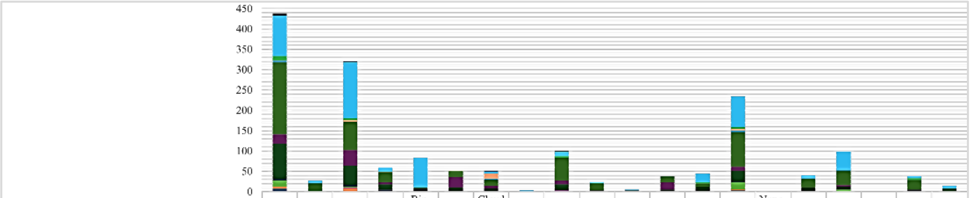


Figure 2 Descriptive evaluation of job posting hits per technology field.

While Figure 2 gives a good impression of which technologies and innovation fields from our analysis context are currently in frequent demand on the Swiss labour market, it does not allow for any conclusions about cross-industry relevance or potential futures robustness. These questions can only be answered by allocating the technology-specific job posting hits to their associated industries, as Figure 3 does.



	AI	AR	Automation	Big Data	Biotechnology	Blockchain	Cloud Computing	Cryptography	Cybersecurity	Digital Twin	Drone	Fintech	IoT	ML	Nanotechnology	NLP	Robot	Smart Device	VR	5G
11 - Agriculture, Forestry, Fishing, and Hunting																				
21 - Mining, Quarrying, and Oil and Gas Extraction	5		1				2		2											
22 - Utilities			1						1											
23 - Construction																				
31-33 - Manufacturing	100	5	137	9	73		5	3	11	3	2		22	75		7	46		6	6
42 - Wholesale Trade	10		5	1					3				3	4					4	1
44-45 - Retail Trade	1		3	1		1	13							5						
48-49 - Transportation and Warehousing	4						2							3		1	1			
51 - Information	177	22	71	25	4	15	15	1	57	17	3	15	7	86		21	36		24	7
52 - Finance and Insurance	23		38	5		25	6		9	1		18		9		1	4			
53 - Real Estate and Rental Leasing																				
54 - Professional, Scientific, and Technical Services	86		47	13	5	9	7		15	1		4	11	27		9	7		1	
55 - Mangement of Companies and Enterprises																				
56 - Administrative Support and Waste Management	4		5	4										1					4	
61 - Educational Services	15		2		1					2			1	18	1		3	2		1
62 - Health Care and Social Assistance			1						1				1				2			
71 - Arts, Entertainment, and Recreation																				
72 - Accommodation and Food Services																				
81 - Other Services (except Public Administration)	6		7			2	1		2			1		3						
92 - Public Administration	7		2	1	1		1							3		1				

Figure 3 Distribution of job posting hits per technology field across industries.

To improve the readability and clarity of the industry-specific analysis, we accumulate technologies with common abbreviations, such as artificial intelligence/AI or machine learning/ML, into one technology topic, adding up their total number of hits from Figure 2. The industry names displayed in Figure 3 are derived from the North American Industry Classification System, focusing on its two-digit level instead of the six-digit granularity that is generally feasible with the LinkUp data set.

From Figure 3 too, we can easily determine the technology fields that are most frequently mentioned in connection with future-related terms in the job description texts of recent job postings from Switzerland. The top three are artificial intelligence, automation, and machine learning in descending order. With these results and our identified technologies and innovation fields in general, we do not deviate from previous trend studies discussed in the theoretical background of this paper, but we do enrich them with contextual information such as the industry analysis in Figure 3. A first glance at the distribution of job posting hits reveals that especially in the top three technology fields, the hits extend across many industries. The same impression applies to cloud computing and cybersecurity but not to biotechnology, blockchain, or natural language processing. Unsurprisingly, technology fields with very few hits, such as cryptography, drones, or smart devices, do not show a broad distribution of hits across industries, depicting them as less robust in our foresight context. Final statements about the dispersion of the job posting hits and the resulting futures robustness of technologies, however, can only be made after calculating the entropy for each innovation field. Table 3 shows the results of the entropy calculations based on the previously defined formula in its second column, including a robustness rating from low to high in its third column.

Table 3 Entropy of job posting hits distribution per technology field including robustness rating

Technology	*Entropy score*	*Robustness*
Artificial intelligence/AI	2.39	High
Augmented reality/AR	0.69	Low
Automation	2.32	High
Big data	2.28	Medium
Biotechnology	0.78	Low
Blockchain	1.75	Medium
Cloud computing	2.67	High
Cryptography	0.81	Low
Cybersecurity	2.04	Medium
Digital twin	1.41	Low
Drone	0.97	Low
Fintech	1.52	Medium
Internet of Things/IoT	1.92	Medium
Machine learning/ML	2.38	High
Nanotechnology	0	Low
Natural language processing/NLP	1.81	Medium
Robot	1.84	Medium
Smart device	0	Low
Virtual reality/VR	1.66	Medium
5G	1.56	Medium

Since the maximum possible entropy for the twenty industries under consideration is

$$H_{max} = \log_2(20) \approx 4.32$$

and the highest entropy score in our data is 2.67 for cloud computing, we must define the robustness rating relative to the actual data dispersion. Accordingly, we evaluate high robustness for entropy scores ≥ 2.3, medium robustness for entropy scores of 1.5 – 2.29, and low robustness for entropy scores < 1.5.

As shown in Table 3, the technologies and innovation fields with the highest entropies in our analysis are cloud computing, artificial intelligence/AI, machine learning/ML, and automation. This means that the job posting hits for these innovation topics are most widely distributed across the different industries, attributing them with the highest cross-industry relevance in our analysis context. For the innovation fields of AI, ML, and automation, the high entropy scores and robustness ratings are less surprising than for cloud computing, due to their overall high job posting hit rates. While cloud computing, with its 52 job posting hits, only ranks in the middle of the total hits evaluation, it shows the highest entropy score and thus the greatest cross-industry relevance in the context of our study. The medium total job posting hits together with the highest futures robustness rating could indicate that cloud computing is not yet fully established in business practice and has not yet gained as much momentum as AI, automation, or ML, but is certainly of interest to all industries under consideration. From a technology foresight perspective, these insights would suggest to closely monitor developments in the cloud computing field and to conduct further trend studies on this innovation topic by analysing diverse data sources and applying multiple foresight methods. Just missing out on the highest robustness rating are big data and cybersecurity, which is a result of their job posting hits concentration on the information industry plus the professional, scientific and technical services industry for big data, and on the information industry for cybersecurity. An entropy of zero results for technologies whose job posting hits come from a single industry, as is the case with nanotechnology and smart devices. For these and the other innovation fields with a low robustness rating in Table 3, we derive no to low cross-industry relevance in our analysis context and argue that also their futures potential might only be concentrated in the associated industries from Figure 3.

With regard to our research question, the results of all analysis steps can be summarized as, first, twenty successfully identified technology and innovation fields that are frequently mentioned in connection with future-related terms in recent job postings from Switzerland. Second, an overview of the industries that are actively hiring for these disciplines, and third, a futures robustness evaluation for the identified technologies and innovations fields based on statistically calculated cross-industry relevance. Referring back to the definition of robust technologies in the context of strategic foresight and our analysis, we can, thus, conclude that cloud computing, artificial intelligence/AI, machine learning/ML, and automation appear as the most relevant innovation fields across all represented industries and can be identified as future-ready technologies for Switzerland in our study. With this, our results resemble the findings of previous trend studies for Switzerland in that they also identify digital technologies as further emerging and highly relevant for the Swiss economy (Deloitte 2021; Niggli and Rutzer 2023; Swiss Academy for Engineering Sciences SATW 2023; Tsesmelis et al. 2022). In contrast to those studies, however, our results are based on a purely quantitative data analysis and reflect the early business practice perspective of companies engaging with emerging technologies and innovation fields without any expert opinion bias. Also, the cross-industry relevance and the resulting futures potential of cloud computing for Switzerland have not yet been recognized to this extent before. With these findings and our proposed analysis approach, we enrich the scientific foresight discourse with a data-driven trend study for Switzerland and successfully demonstrate the feasibility of using online job postings data for this purpose. Next to foresight academics and trends researchers, also business practitioners from various fields can gain insights into future-ready technologies for Switzerland as well as in the quantitative exploitation of job postings data based on our study. This includes technology and innovation managers, foresight experts, and HR professionals, which makes our research not only academically relevant but also practice-oriented.

6 Limitations and future research

Our study takes on the novel approach of analysing online job postings data from Switzerland for the co-occurrence of technologies with future-related terms in job description texts to identify future-ready technologies for the Swiss economy and to evaluate their cross-industry relevance based on keyword analysis, named-entity recognition, and entropy calculations. As we are among the first researchers to test this method combination in a technology foresight context by applying and expanding previous job posting analysis efforts from different application fields, our work is naturally subject to some limitations. The short analysis period of four months represents such a limitation, as possible changes in demand for the future-ready technologies and innovation fields could be better observed over a longer period of time, and the emergence of new innovation topics in the data set could be better monitored. Another limitation lies in the simplified evaluation of the NER results since we prompted ChatGPT to do it. A manual assessment of the recognized entities could enable us to identify further innovation fields at a deeper technical level and to include more specialized technologies in the subsequent analysis steps, which are possibly unknown to the LLM. Also, for the industry analysis some limitations arise, such as the restriction on the two-digit NAICS codes and the mere evaluation of hit numbers without further insights on the hit-generating companies or the associated occupation groups. Nevertheless, all these restrictions were necessary to limit the scope of our analysis and to test the feasibility of this novel data-driven foresight approach. Once the method is more sophisticated, we will gradually extend the scope of the analysis in our own future research.

Finally, we encourage future research to complement our proposed approach with further analysis steps to refine the results at deeper technological levels and to apply our methodology to other national or regional contexts. For future trend studies and foresight research in general, we recommend to fully recognize and further examine the potential of job postings data as a foresight data source and to improve existing analysis methods or to develop new ones.

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