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Future-Relevant Technologies for Switzerland: Technological Priority Signals and Cross-Industry Robustness Based on Job Postings Analysis

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Abstract: Foresight research constantly strives to identify and utilize new data sources for its technological 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 online job postings from Switzerland to identify technologies frequently mentioned in connection with future-related terms in job description texts. This novel approach provides a data-based perspective on the technology domains in which companies in Switzerland perceive future potential and actively recruit talent. Furthermore, we compare the recruiting dynamics for these technology fields across industries to identify robust technologies that are future-relevant in multiple sectors. Our methodology comprises text mining techniques – including keyword analysis and named entity recognition – and results in a data-driven trend study aimed at both innovation management researchers as well as business practitioners.

Keywords: Trend Analysis, Technology Foresight, Data-Driven Foresight, Robust Technologies, Industry Trends, Job Postings Analysis, Text Mining, Named Entity Recognition

Zukunftsrelevante Technologien für die Schweiz: Technologische Prioritätssignale und branchenübergreifende Robustheit basierend auf der Analyse von Stellenausschreibungen

Zusammenfassung: Die Foresight-Forschung ist ständig danach bestrebt, neue Datenquellen für ihre Technologietrendstudien zu identifizieren und zu nutzen. Zusätzlich zu den etablierten Datenquellen wie Patenten und wissenschaftlichen Publikationen haben sich auch Stellenausschreibungen als aussagekräftig für die Vorausschau erwiesen. In unserer Forschung nutzen wir Stellenausschreibungen aus der Schweiz, um Technologien zu identifizieren, die häufig im Zusammenhang mit zukunftsbezogenen Begriffen genannt werden. Dieser neuartige Ansatz liefert eine datenbasierte Perspektive auf Technologiebereiche, in denen Unternehmen in der Schweiz Zukunftspotenzial sehen und für welche sie aktiv Personal einstellen. Zusätzlich vergleichen wir die Einstellungsdynamiken für diese Technologiebereiche über Industrien hinweg, um robuste Technologien zu identifizieren, die in mehreren Sektoren zukunftsrelevant sind. Unsere Forschungsmethode umfasst verschiedene Text-Mining-Techniken und resultiert in einer datengetriebenen Trendstudie mit Wissenschafts- und Praxisrelevanz.

Stichwörter: Trendanalyse, Technologievorausschau, Data-Driven Foresight, Robuste Technologien, Industrietrends, Stellenausschreibungsanalyse, Text Mining, Named Entity Recognition

Legend

AI	Artificial Intelligence
AR	Augmented Reality
DDF	Data-Driven Foresight
FTE	Full-Time Equivalent
GPTs	General-Purpose Technologies
IoT	Internet of Things
LLM	Large Language Model
ML	Machine Learning
NAICS	North American Industry Classification System
NER	Named Entity Recognition
NLP	Natural Language Processing
TRL	Technology Readiness Level
VR	Virtual Reality

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 (Blind et al., 1999; Bassani et al., 2016; Kindras et al., 2019). Data-driven foresight (DDF), on the contrary, is a specialized stream within the foresight discipline that exploits quantitative data analyses 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, p. 2; Scheuffele et al., 2024, p. 132). With the latter, DDF pursues the same goal as strategic foresight, only that it is usually more focused on the identification of emerging technologies and innovation fields rather than on the organizational integration of futures thinking into strategic decision-making processes (Müller-Stewens & Müller, 2010, p. 245).

In terms of the data sources used, scientific publications and patents are the most established and extensively utilized in DDF, with many examples of successfully conducted trend studies in a variety of analysis contexts (Block et al., 2021; Han et al., 2021; Niknejad et al., 2021; Wider et al., 2023). Nevertheless, while these data sources provide valuable insights into emerging technologies and their early downstream maturing phases, the later development phases are not sufficiently covered by scientific publications or patents, as the focus shifts from technical to strategic and market-related factors. Especially scientific publications 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, p. 144). Also, science- and technology-heavy data sources alone do not contain all the information needed to anticipate an innovation's market success, nor can they single-handedly cover all aspects of a multi-perspective foresight (Mühlroth & Grottke, 2018, pp. 673–674; Cagnani et al., 2023). Finally, scientific publications and patents usually require considerable time before their information can be utilized effectively, due to lengthy application and publication processes, which can lead to a timely disconnection from real market needs (Gerken et al., 2015; Zhang et al., 2017).

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 priority signals for future-relevant 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 trend identification, reflecting the early business practice perspective of technology adoption and development efforts without major review or publication delays (Zhang et al., 2017; Goldfarb et al., 2023, p. 2; Scheuffele et al., 2025).

Based on the approach by Goldfarb et al. (2023), who analyze job postings across various industries to compare emerging technologies for their potential as general-purpose technologies (GPTs), we also examine the occurrence of our identified future-relevant technologies across industries. Our aim, however, is to assess 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, p. 159; 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 (NER) of technologies frequently mentioned in connection with future-related terms in job descriptions. Importantly, we do not conceptualize future-relevant technologies as innovations that are guaranteed to remain dominant in the long term. Instead, we use the term to describe technologies and innovation fields that exhibit early widespread and cross-industry relevance signals in labor market data. Specifically, we focus on technologies for which firms articulate forward-looking skill requirements and capability needs, as reflected in job postings. From a foresight perspective, such signals are commonly interpreted as proxies for future strategic importance, rather than as deterministic predictions of technological success (Gilmore et al., 2023, p. 1).

Proposing our 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-relevant for Switzerland based on job postings analysis and cross-industry robustness evaluation?

2. Theoretical background

Our research bridges the gaps between the scientific discourses on technology foresight in Switzerland, methodological advancements in DDF, and the utilization of job postings for anticipatory trend studies. 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 (Tsesmelis et al., 2022; Niggli & Rutzer, 2023). 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 of Engineering Sciences SATW (2023) as well as in a focused market study by Deloitte (2021). Although non-academic, both studies provide valuable insights into current technology trends for Switzerland and underscore the need for further technology foresight research within the country. Another literature stream in the Switzerland-related foresight discourse examines how foresight activities are implemented in different national business practice contexts (Peter, 2019; Baumgartner & Peter, 2022). 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 the latter research stream does not provide any insights into actual technology or innovation trends, the formerly mentioned trend studies do not only identify specific emerging technologies and innovation fields but also explain the data sources and analysis methods in use. Table 1 summarizes the findings of these studies and gives an overview of the relevant research methodologies and data sets.

Emerging technologies and innovation fields	*Data sources and analysis methods used*	*Authors*
Artificial intelligence, digital personalized health, robotics, advanced manufacturing, blockchain	Expert opinions (qualitative data) collected through interviews	Deloitte, 2021
5G, big data & machine learning, blockchain, contact tracing	Patent analysis of granted patents per technology field 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

Emerging technologies and innovation fields	*Data sources and analysis methods used*	*Authors*
Digitalization: 5G applications, blockchain, Internet of Things (IoT), 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 and storage, geothermal energy, mobility concepts Manufacturing processes and materials: low-carbon concrete, sustainable adhesives and sealants, bioplastics, thermal interface materials, fiber-optic sensors, antimicrobial surfaces	Technology Outlook 2021 reassessed through Technology Readiness Level (TRL) evaluation Expert opinions (qualitative data) collected through semi-structured interviews Economic importance 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 X accounts of Swiss universities	Swiss Academy of Engineering Sciences SATW, 2023

Table 1: Technologies and innovation fields identified in recent trend studies for Switzerland

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 perspective emerges when considering the foresight literature without regional limitations. In this context, the body of literature also contains trend studies that compare the content validity of different data sources (Mikova & Sokolova, 2019; Bonaccorsi et al., 2020; Laurell & Sandstrom, 2022) and examine their individual foresight horizons (Cozzens et al., 2010; Segev et al., 2015; Mühlroth & Grottke, 2018).

Much of this discourse builds on two leading studies that classify foresight data sources from different perspectives according to their technology lifecycle predictiveness (Watts & Porter, 1997; Martino, 2003). Orienting towards the observable sequence of technological change – from theoretical proposal to commercial introduction – it is possible to determine a technology's maturity and anticipate its transition to the next lifecycle phase based on publication peaks in specific types of data sources. 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 press, and popular press allow for trend insights regarding the daily application and social impacts of a technology (Martino, 2003, pp. 720–721). Specialized studies show that an increase in scientific publications within a specific technology field can predict a subsequent rise in patent activity in the same field by up to six years. With regard to marketability and application success of technologies, scientific publications can even be nine years ahead. This makes them the earliest-phased data source for foresight purposes but not necessarily the most practice-oriented (Segev et al., 2015, p. 7; Stelzer et al., 2015, p. 144; Block et al., 2021; Hsieh et al., 2024).

These findings, along with the argument that different data sources offer different foresight potential (Watts & Porter, 1997, p. 29), provide the rationale for using job postings data as an innovative foresight data source. Goldfarb et al. (2023, p. 2) argue that job postings should 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 forward-looking data source of the business practice perspective, reflecting exactly when a company or industry starts adopting emerging technologies or innovation fields.

Nevertheless, it is important to acknowledge that hiring activities may also be reactive in nature. Companies may start recruiting for certain technological capabilities only once these have already proven strategically important in the market. Prior research highlights that labor demand signals – particularly in technology-intensive contexts – often reflect a combination of anticipatory and responsive organizational behavior (Carnevale et al., 2014; Hershbein & Kahn, 2018). But rather than contradicting their value for foresight, this dual role of job postings strengthens their relevance as an anticipatory data source. Reactive job postings indicate that a technology has reached a level of maturity and organizational salience that necessitates dedicated human capital, whereas proactive job postings reflect early experimentation and capability-building (Bakhshi et al., 2017). In both cases, recruitment behavior provides timely and resource-backed evidence of technological importance within firms, complementing publication- or patent-based indicators that capture earlier stages of the innovation lifecycle but are less indicative of organizational commitment and market-driven relevance.

Despite this potential, job postings are not yet fully established in the foresight discipline. Most studies using this data source focus on the identification of future skills required in specific countries, technology fields, or job domains. For example, Brasse et al. (2024) analyze job advertisements to identify future skills for the manufacturing industry in Baden-Württemberg, Germany, while Firpo et al. (2021) reveal a skills mismatch in the labor market of Tunisia and highlight the demand for specific digital competencies based on online job ads. The seminal study by Goldfarb et al. (2023), which uses online job postings to assess the potential of different emerging technologies to become GPTs, illustrates that even the metadata of job postings can be leveraged for foresight purposes. In their study, the authors analyze the North American Industry Classification System (NAICS) codes associated with job postings for the various emerging technologies to derive their *widespread use* and *innovation in application industries* as part of the GPT assessment (Goldfarb et al., 2023, p. 4). This approach to measuring cross-industry robustness, combined with the text mining techniques described in the following chapter, forms the basis for our own identification and evaluation of priority signals for future-relevant technologies for Switzerland.

3. Research methodology

3.1 Data retrieval and preparation

Next to the brief literature 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 priority signals for future-relevant 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 315 million jobs from 80,000 companies across 195 countries (LinkUp, 2026). 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 utilized the 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 2 summarizes the contents and structures of the file types and gives an overview of the data preparation steps.

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 company_id: merge files (with company reference files) country: filter by CHE created: filter by analysis period delete_date: exclude inactive records
Descriptions	job_hash, description	job_hash: merge files, remove duplicates description: basis for text mining
Company PIT 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: basis for industry analysis

Table 2: Overview of LinkUp data files relevant for the analysis

3.2 Two-phase text mining approach

The cleansed data set of 1,079,079 job postings from Switzerland that were online between 1 September and 31 December 2024, forms the basis for our two-phase text mining analysis. In the first phase of the analysis, we use Python-based keyword analysis to automatically scan the job description texts for the co-occurrence of future-related terms and technology topics. In the second phase, we extract specific technologies mentioned in the relevant job descriptions by applying both a NER in Python and a ChatGPT-assisted technology identification approach. To illustrate how these steps operate on the original data, Figure 1 presents a representative, fully anonymized excerpt of a job posting from our data set. The example shows how future-related and technology-related terms trigger inclusion in the first analysis phase and how specific technologies can subsequently be detected in the second phase, with the relevant segments highlighted accordingly.

hash	98a54ff9f7634bc9be6ae450795244e5
title	**Technology** Strategy Consultant (all genders)
description (excerpt)	As a Strategy Consultant, you will work with us to develop strategies for a smarter, digital ***future*** and use your expertise and innovative ideas to convince potential clients to work with us. You will work closely with managers and our interdisciplinary teams to develop an agile operating model. Together, you will design integration/carve-out strategies as part of an M&A process, analyse IT cost optimisation potential using current benchmarks and design industry-specific **cloud** strategies to develop new business models. Based on sound qualitative and quantitative analyses, you will develop new solutions, taking expert and careful account of disruptive ***trends*** (e.g., **blockchain**, **artificial intelligence**, **IoT**).
company_id	1425
company_name	Anonymized
naics_code	541519
city	Zürich
state	Zürich
zip	8000
country	CHE
created	01.12.2024 04:09:00
last_checked	01.12.2024 04:09:00
last_updated	N/A
delete_date	N/A
unmapped_location	FALSE
url	Anonymized

Figure 1: Anonymized excerpt from a sample job posting from the original data set

3.3 Future-term filtering logic

The use of future-related terms in our first analysis phase serves to identify job postings that explicitly reference technologies in a forward-looking or strategic context. Without such a filter, the analysis would include a substantial number of job postings in which technologies are mentioned only incidentally, operationally, or without any strategic relevance (e.g., routine IT support, maintenance, or generic software use). Prior studies emphasize that distinguishing between strategic and operational technological skills is essential, as only the former provide meaningful insights into emerging innovation trajectories (Bakhshi et al., 2017; Carnevale et al., 2014). By requiring the co-occurrence of future-oriented terminology and technology-related terms, our approach intentionally narrows the focus to job postings in which firms articulate technological change, capability expansion, or innovation intentions. We acknowledge that this introduces a controlled sampling bias. However, this bias is theoretically motivated and strengthens the validity of our foresight perspective. Including all job postings that mention a technology – even if the reference is purely operational – would risk overwhelming weak signals with contextually irrelevant noise, thereby decreasing the precision of the resulting trend insights. Our analysis approach therefore follows established principles in text mining-based foresight, where identifying future-relevant narratives is a prerequisite for extracting meaningful trend signals (Laurell & Sandstrom, 2022, p. 566; Rohrbeck et al., 2015, p. 4).

In this sense, the future-term filter does not exclude strategically important technologies, instead it improves the signal-to-noise ratio by focusing the analysis on job postings where companies actively articulate technological development, transformation, or innovation-related intentions. At the same time, our methodological design incorporates an explicit future orientation by restricting the analysis to technologies that are mentioned in direct conjunction with future-related terminology in job postings. This co-occurrence filter serves as a first-order proxy for future-oriented intent in firms' recruitment communication and helps to reduce purely reactive hiring signals. By focusing on job postings in which companies explicitly articulate technological change, capability expansion, or innovation intentions, this design choice strengthens the foresight orientation of the analysis and further improves the signal-to-noise ratio. Nevertheless, the use of future-oriented language cannot fully eliminate the possibility that some postings reflect responses to already emerging or established technological needs. Accordingly, while this filter enhances the forward-looking perspective of our approach, it does not replace ex-post validation of future technological relevance.

3.4 Quantitative analysis and robustness assessment

Following the above analysis steps, we conduct in-depth analyses and result visualizations in Excel to determine how the identified technologies are represented in job postings

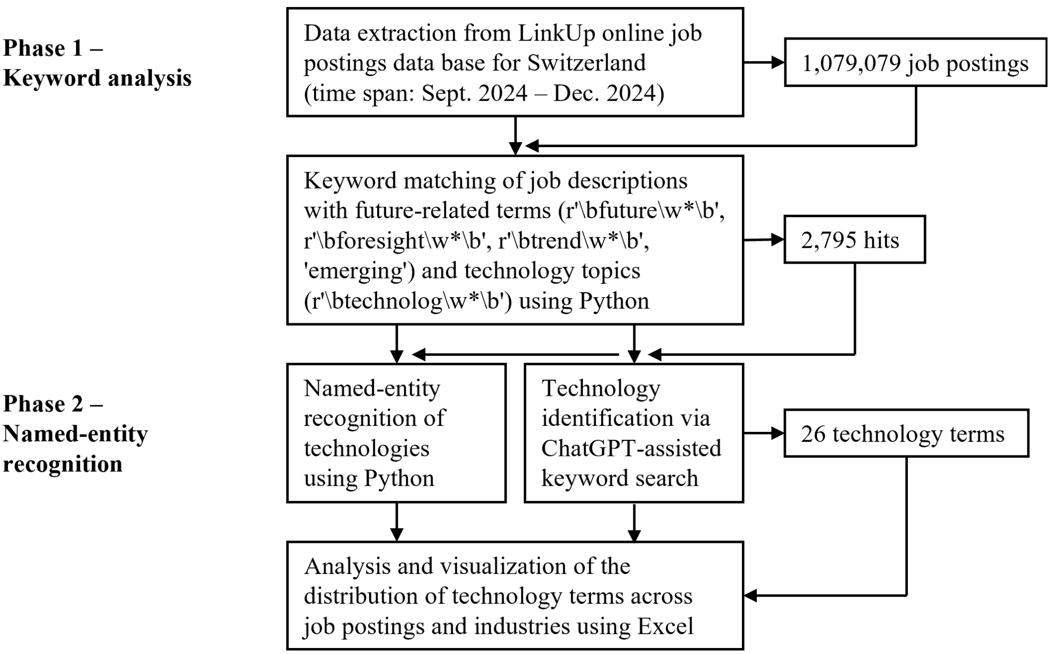


Figure 2: Flowchart of the two-phase research methodology

across industries. Finally, we calculate the entropy of this distribution to assess the technologies' potential futures robustness. Figure 2 visualizes the outlined approach in a methodology flowchart and shows how the analysis phases and individual steps are linked with each other.

4. Job postings analysis

4.1 Keyword-based filtering of job postings

Since automated keyword matching with a predefined directory is a proven methodology for analyzing job postings data (Brancatelli et al., 2020, p. 12; Brasse et al., 2024, p. 482), we also employed a keyword-based text mining approach in the first phase of our analysis. Rather than restricting the search to a fixed list of terms, we developed the following custom search query using logical operators to minimize bias in the detection of technologies:

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 the files from the LinkUp server. Without additional preprocessing, the monthly job description texts could be matched against the search query from above 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. Only job offers published and active in Switzerland between 01.09.2024 and 31.12.2024 were retained for the further analysis. In doing so, we did not impose any language restrictions on the description texts, as job advertisements in Switzerland are often multilingual due to the country's linguistic diversity, and as our defined keywords can appear across different languages. Nevertheless, given the English-language search string, the majority of job postings in the resulting data set were written in English, with fewer postings in German, French, and Italian. In total, 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 phase.

4.2 Named entity recognition for technology extraction

Since the aim of the second analysis phase was to extract the specific technologies and innovation fields targeted in these job postings, we applied the following NER analysis to their job description texts using spaCy's standard model for natural language processing (NLP) in Python via 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)
```

4.3 LLM-assisted technology consolidation

To complement the NER-based extraction, we applied a ChatGPT-assisted technology identification step. Importantly, ChatGPT was not used to generate new data or to define technologies a priori, but rather to systematically filter and consolidate the large set of several thousand named entities extracted in the previous step. Specifically, the unfiltered list of named entities obtained through NER was provided to ChatGPT-4o with a structured prompt instructing the model to identify technologies and innovation fields relevant in a business and technology foresight context. The model was asked to exclude generic terms, company names, and non-technological entities and to return a consolidated list of distinct technology domains. To ensure transparency and reproducibility, the prompt used for the ChatGPT-assisted step is provided in Appendix A. While the use of an LLM introduces an element of algorithmic interpretation, this approach aligns with recent methodological advances in text-based foresight and labor market analysis, where LLMs are increasingly used as supplementary tools for extracting and consolidating structured concepts from unstructured text, supporting downstream analysis steps rather than replacing researcher-defined decisions (Li et al., 2025; Norouzi et al., 2025; Sioziou et al., 2024). Accordingly, this step served as a supportive classification and aggregation mechanism, enabling us to reduce noise and to derive a manageable and interpretable set of future-relevant technology topics for Switzerland from the NER results, which are presented below in alphabetical order along with 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

4.4 Verification of LLM results

To assess the robustness of the LLM-assisted technology consolidation step, we conducted an additional verification using alternative LLMs. Specifically, the original list of named entities extracted through the NER procedure was processed using the same prompt with three additional models, namely ChatGPT Auto, Gemini 3, and Claude Sonnet 4.6. The resulting technology domains were then compared with the domains obtained in the original ChatGPT-4o-based analysis. The comparison showed that all technology and innovation fields included in our original analysis were consistently identified by the alternative models as well. While the additional models suggested some further candidate technologies and synonyms for existing domains, the core set of technology fields remained stable across models. This indicates that the technology topics shown above are not driven by a single model choice but reflect robust patterns in the underlying entity list. Addressing further potential prompt-induced bias in the LLM-assisted technology consolidation step, we additionally tested several alternative prompt formulations that differed in how technological relevance and exclusion criteria were specified. Across these prompt variants, the resulting technology domains showed a high degree of overlap with the domains obtained using the original prompt formulation. In particular, all technology and innovation fields shown above were consistently identified across the prompt variants. Differences between prompts were limited to minor variations in terminology or additional candidate technologies suggested by some prompts. However, all identified technology domains were manually reviewed and validated by the authors to ensure conceptual coherence and analytical relevance before inclusion in the final analysis. Overall, these results indicate that the technology consolidation step is robust to moderate variations in prompt wording and model choice.

4.5 Recall-oriented technology screening and final data set construction

To further increase the completeness of the technology identification, we applied an additional complementary screening step using ChatGPT-4o. This step was not intended to independently define or classify emerging technologies but to flag potentially relevant technology-related concepts that may not have been consistently captured by the spaCy standard NER model due to linguistic variation, context dependence, or domain-specific phrasing. For this purpose, ChatGPT-4o was prompted to support a recall-oriented screening of the job description texts of all 2,795 postings identified in the first analysis phase and to highlight technology-related terms and innovation fields mentioned therein. The model was explicitly instructed to operate in a supportive, recall-oriented manner, returning candidate technologies without performing any ranking or evaluative judgement. To ensure transparency and reproducibility, the exact prompt used for this recall-oriented screening step is provided in Appendix B. All suggested concepts were subsequently manually reviewed, consolidated, and validated by the authors and cross-checked against the NER-based results. Through this complementary screening, ChatGPT-4o flagged several additional technology domains that were underrepresented or not consistently detected in the initial NER output. After removing overlaps with previously identified technologies and excluding concepts that did not meet our analytical criteria (e.g., overly broad terms such as data science), the following technology domains were added to the final list of future-relevant technology topics for Switzerland:

- 5G
- Augmented Reality (AR)
- Blockchain
- Cloud Computing
- Cryptography
- Drones
- Nanotechnology
- Smart Devices
- Virtual Reality (VR)

As this step was designed to increase recall rather than to determine the final set of technologies, minor variations in extracted candidate terms do not affect the final analysis, which is based on manually validated and consolidated technology domains. Importantly, the ChatGPT-assisted steps described did not determine whether a technology is emerging or future-relevant. Instead, the identification of future-relevant technologies and innovation fields in our study is based on the co-occurrence of technology-related terms with future-oriented terminologies in job postings, followed by an assessment of cross-industry dispersion using an entropy-based measure. ChatGPT was used solely to support the consolidation and recall of technology-related concepts extracted via NER, thereby reducing noise and linguistic variation. All decisions regarding which technology domains are included in the final analysis were made by the authors based on predefined criteria. Consequently, the role of ChatGPT is supportive rather than decision-making and does not define the core construct of future relevance.

4.6 Quantitative analysis and entropy-based robustness assessment

After successfully identifying the above technologies and innovation fields as co-occurring with future-related terms in Swiss job postings using a combination of query analysis, NER, and ChatGPT-assisted technology extraction, we proceeded with a two-step quantitative hit evaluation in Excel. First, we conducted a descriptive frequency analysis to assess how often each technology appeared in the job description texts. Using conditional Excel formulas (e.g., IF, SEARCH, ISNUMBER, SUM, and IFERROR), we marked which job postings mentioned which technologies and counted the total number of occurrences per technology or innovation field. Second, we performed an industry-level comparison by leveraging the six-digit NAICS codes assigned to each job posting. These were aggregated at the two-digit level to determine how frequently each technology or innovation field appeared across different industries. When interpreting industry-level job postings frequency, it is important to acknowledge that industries differ substantially in size, employment levels, and overall hiring intensity. Larger industries may naturally generate more job postings, which could influence the absolute frequency counts of technology mentions. To address this structural effect, our analysis does not only rely on absolute frequencies alone but focuses on the distribution of future- and technology-related job postings across industries, operationalized through an entropy-based measure. Entropy captures how evenly the technology mentions are spread across industries and is therefore largely independent of the absolute industry size. A technology that appears across many industries – even if each industry contributes relatively few job postings – will yield a higher entropy value than a technology concentrated in a single large industry. By emphasizing dispersion rather than volume, our approach mitigates size-related bias and aligns with prior labor market-based foresight research that assesses cross-industry relevance instead of raw hiring intensity (Goldfarb et al., 2023, p. 2). Consequently, our robustness assessment reflects cross-industry technological relevance rather than the dominance of large industries in the labor market.

Our outlined approach was inspired by Goldfarb et al. (2023), who used Gini coefficients to evaluate the distribution of enabling technologies in job postings. In their study, the authors calculated Gini values across industry sectors to assess both the *widespread use* of a technology (based on all job postings) as well as its *innovation in application industries* (based on research-related job postings). Similar to the Gini coefficient, entropy also serves as a measure of dispersion or concentration within a distribution. To calculate the entropy of technology occurrence across industries in our data set, we applied the following formula:

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

where p_i denotes the proportion 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 entropy value H reaches its maximum, $\log_2(n)$, when the distribution of hits is perfectly uniform, indicating equal representation of a technology field across all industries. Based on the entropy values calculated for each technology or innovation field, we were finally able to draw data-driven conclusions regarding the cross-industry relevance and potential futures robustness of our future-relevant technologies for Switzerland. These insights, along with the results of the preceding analysis steps, are presented in the following chapter.

5. Results and discussion

The descriptive evaluation of job posting hits per innovation field provides a clear indication of which technologies are most frequently mentioned in connection with future-related terms in our data set. Artificial intelligence – along with its common abbreviation, AI – generates by far the most keyword matching hits, followed by automation, machine learning (and its abbreviation ML), cybersecurity, and robotics. Other innovation fields such as drones, cryptography, smart devices, or nanotechnology generate only a few hits. This does not necessarily imply that these technologies are not future-relevant, but it indicates that they are currently less established in everyday business practice or that they are highly specialized niche technologies which are subject to other modes of capability acquisition, such as outsourcing or strategic partnerships. Figure 3 shows for all technologies and innovation fields identified above in how many job postings from our data set they are mentioned in connection with future-related terms in the job description texts. For that, the frequency of a specific keyword within a single job posting is not considered, however, a single posting may be assigned to multiple innovation fields if it includes more than one relevant term. In addition to displaying the total number of matching job postings per technology across the full analysis period, Figure 3 also provides a breakdown of monthly occurrences, capturing potential seasonal dynamics in recruitment activity.

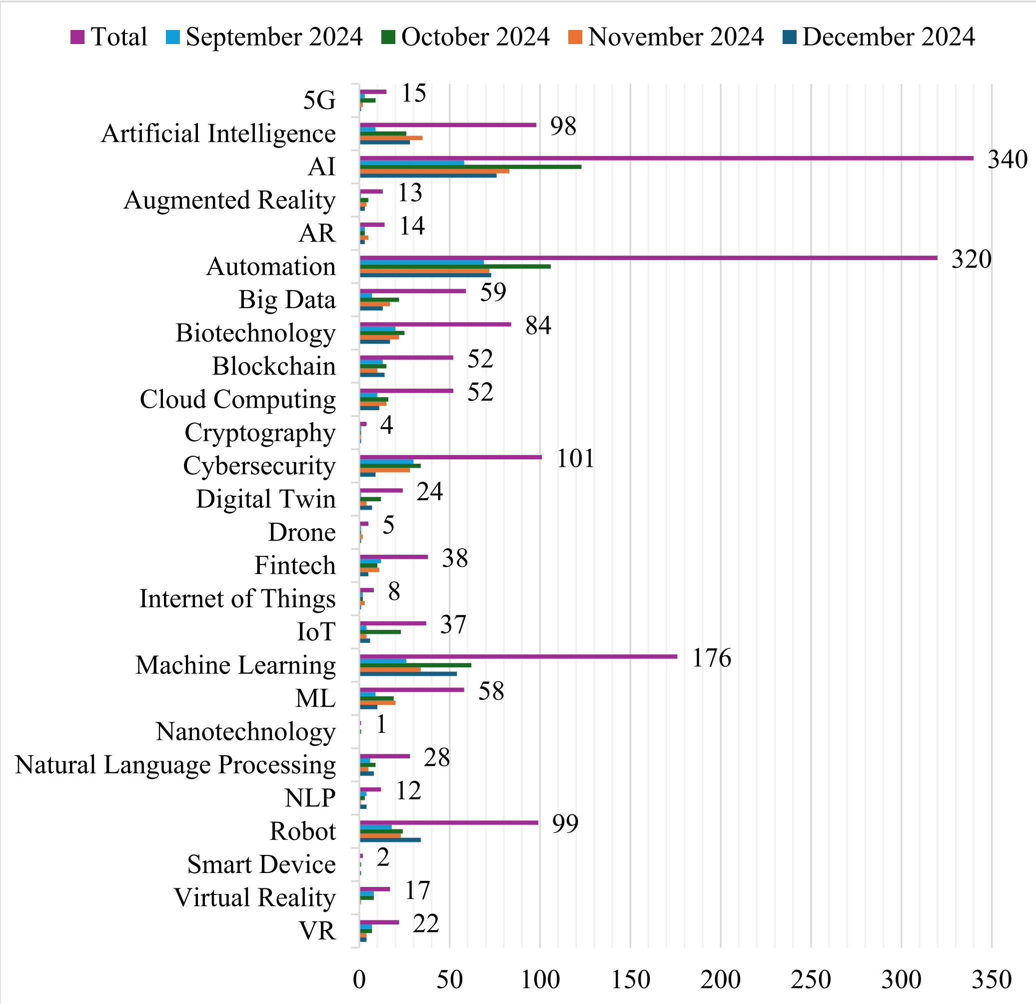
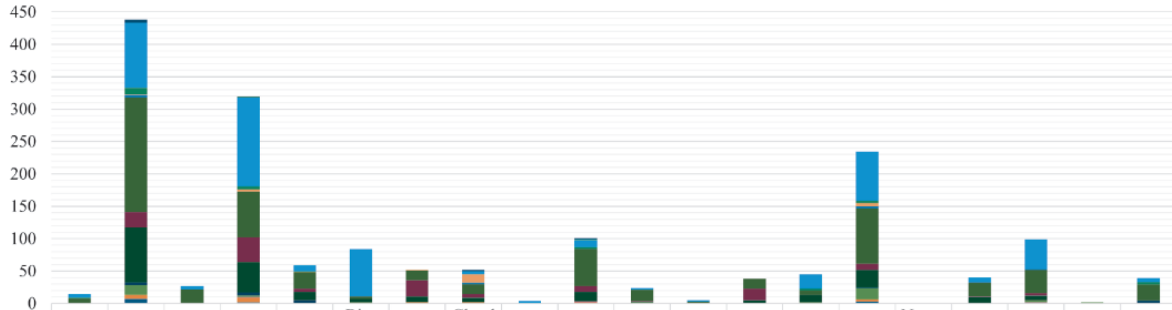


Figure 3: Descriptive evaluation of job posting hits per technology field

Regarding the technologies' general recruiting or adoption intensity, Figure 3 reveals some striking disparities. The combined mentions of artificial intelligence and its abbreviation, AI, add up to 438 hits, outpacing automation (320 hits) and machine learning, including ML (234 hits), by a significant margin. This dominance suggests that AI is not only a central topic in the current technological and public discourse but also actively drives recruitment efforts across Swiss companies. In contrast, technology fields such as cybersecurity, robotics, biotechnology, blockchain, and cloud computing (around 50–100 job posting hits) show only moderate levels of demand, pointing to their more selective, domain-specific adoption. The long tail of technologies and innovation fields (e.g., drones, cryptography, smart devices, and nanotechnology) illustrates that many emerging technologies have not yet reached widespread application in the Swiss labor market or are too specific to be hired for and are therefore rather outsourced. Interestingly, the monthly breakdown shows relatively stable demand for the leading technologies across the observation period. Except for the occasional peaks in October 2024, there are no strong seasonal spikes, implying that the predominance of these technologies is not driven by short-term campaign effects but by structural demand.

While Figure 3 provides a useful overview of which technologies and innovation fields from our analysis context are currently in high demand on the Swiss labor market, it does not offer insights into their cross-industry relevance or potential futures robustness. These aspects can only be assessed by examining how job postings referencing specific technologies are distributed across different industries, as illustrated in Figure 4.

To enhance the readability and clarity of the industry-specific analysis, technologies with commonly used abbreviations – such as AI or ML – are consolidated into a single technology category, and their respective hits from Figure 3 are combined accordingly. The industry labels shown in Figure 4 are based on NAICS, using the broader two-digit level rather than the more detailed six-digit classification typically available in the LinkUp data set. Also from Figure 4, we can easily determine the technology fields that are most frequently mentioned in connection with future-related terms in Swiss job postings from September to December 2024. The top three in descending order are AI, automation, and ML. With these findings 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. We do, however, add contextual depth to the trend results, such as the industry-specific insights from Figure 4.



	5G	AI	AR	Auto-mation	Big Data	Bio-tech-nology	Block-chain	Cloud Com-puting	Crypto graphy	Cybers ecurity	Digital Twin	Drone	Fintech	IoT	ML	Nano-tech-nology	NLP	Robot	Smart Device	VR
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	6	100	5	137	9	73		5	3	11	3	2		22	75		7	46		6
42 - Wholesale Trade	1	10		5	1					3				3	4					4
44-45 - Retail Trade		1		3	1		1	13							5					
48-49 - Transportation and Warehousing		4						2							3		1	1		
51 - Information	7	177	22	71	25	4	15	15	1	57	17	3	15	7	86		21	36		24
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	1	15		2		1					2			1	18	1		3	2	
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 4: Distribution of job posting hits per technology field across industries

A first look at the distribution of the job posting hits across industries reveals that especially in the top three technology fields, the hits extend across many sectors. The same impression applies to cloud computing and cybersecurity but not to biotechnology, blockchain, or NLP. Unsurprisingly, technology fields with only a few total 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. Definitive statements about the dispersion of the job posting hits – and thus the potential futures robustness of individual technologies – can only be drawn after calculating the entropy for each innovation field. Table 3 presents the results of these calculations based on the previously defined formula, along with a corresponding robustness rating ranging from low to high.

Technology field	*Entropy score*	*Robustness rating*
5G	1.56	Medium
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

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

Given that the maximum possible entropy for the 20 industries under consideration is

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

and the highest observed entropy score in our data is 2.67 for cloud computing, the robustness ratings must be defined in relation to the empirical data distribution. Accordingly, we classify robustness as high for entropy scores ≥ 2.3, medium for scores between 1.5 and 2.29, and low for scores < 1.5.

As shown in Table 3, the technologies and innovation fields with the highest entropy scores in our analysis are cloud computing, AI, ML, and automation. This indicates that job postings referencing these technologies are spread across a broad range of industries, suggesting the highest cross-industry relevance for these innovation topics within the scope of our study. For AI, ML, and automation, the high entropy scores and corresponding robustness ratings could be expected, given their overall high number of job posting hits. In contrast, cloud computing ranks only mid-range in terms of total job posting hits, yet it achieves the highest entropy score and indicates the broadest cross-industry relevance among all innovation fields in our analysis. The moderate number of job posting hits suggests that cloud computing currently lacks recruitment momentum compared to AI, automation, and ML – either because it is not yet fully established in business practice or because companies perceive less need to hire specialized staff in this area. Nevertheless, its broad cross-industry relevance indicates that it is of strategic interest across all industries examined. From a technology foresight perspective, these findings highlight the importance of closely monitoring developments in the cloud computing field and encourage further trend studies on this innovation topic using diverse data sources and applying complementary foresight methods. Just below the threshold for a high robustness rating are big data and cybersecurity, whose job posting hits show a notable concentration in a limited number of industries – especially in the Information industry and the Professional, Scientific, and Technical Services sector in the case of big data, and in the Information industry in the case of cybersecurity.

An entropy value of zero occurs when all job posting hits for a technology or innovation field stem from a single industry, as is the case with nanotechnology and smart devices. For these and other innovation fields with low robustness ratings in Table 3, we find little to no cross-industry relevance within our analysis and argue that also their futures potential may remain confined to the associated industries from Figure 4.

In this context, it is important to note that our robustness criterion is intentionally defined in terms of cross-industry relevance. As a result, technologies that may be indispensable for the future of a single industry but remain highly specialized are not prioritized as robust within our analytical framework. Such industry-specific technologies may be critical for sectoral competitiveness and long-term viability, yet they do not exhibit the cross-sectoral diffusion that is central to our robustness concept. Accordingly, our findings should be interpreted as identifying technologies and innovation fields with broad, economy-wide future relevance signals, rather than technologies that are future-critical within individual industries.

In relation to our research question, the results of our job postings analysis can be summarized in three key findings: First, we successfully identified twenty technology and innovation fields that are frequently mentioned in connection with future-related terms in recent job postings from Switzerland. Second, we provided an overview of the industries that are actively recruiting for these fields. Third, we conducted a futures robustness assessment for the identified technologies and innovation fields, based on a statistical evaluation of their cross-industry relevance. Referring back to the definition of robust technologies within the context of strategic foresight and our analysis, we conclude that cloud computing, AI, ML, and automation emerge as the most relevant innovation fields across all industries represented in our data. Accordingly, these technologies can be considered future-relevant for Switzerland in the context of our study. Nevertheless, our findings do not claim to identify technologies that are inherently future-relevant in a deterministic sense. Rather, they reveal current technological priorities and capability signals across Swiss industries based on firms' articulated demand for future-oriented skills. By analyzing these priorities across industries and assessing their dispersion, our approach provides an indicator-based assessment of technologies that are robustly positioned across the Swiss economy, which is a central concern in business-oriented foresight research.

Overall, our findings align with those of previous trend studies for Switzerland, which also highlight digital technologies as further emerging and highly relevant for the Swiss economy (Deloitte, 2021; Tsesmelis et al., 2022; Niggli & Rutzer, 2023; Swiss Academy of Engineering Sciences SATW, 2023). In contrast to these studies, however, our findings are derived from a purely quantitative data analysis and reflect the early-stage business practice perspective of companies engaging with emerging technologies and innovation fields, free from expert opinion bias. Furthermore, the cross-industry relevance and resulting futures potential of cloud computing for Switzerland have, to our knowledge, not been highlighted to this extent in previous research. With these findings and our proposed analytical approach, we contribute to the scientific foresight discourse by presenting a data-driven trend study for Switzerland and demonstrating the feasibility of using online job postings data for this purpose. In addition to foresight scholars and trend researchers, also business practitioners from various fields can gain insights into future-relevant technologies for Switzerland as well as into the quantitative utilization of job postings data based on our study. This includes technology and innovation managers, foresight professionals, and human resources specialists, highlighting not only the academic but also the practical relevance of our research.

6. Limitations and future research

Our study adopts a novel approach by analyzing online job postings from Switzerland to identify priority signals for future-relevant technologies for the Swiss economy. Specifically, we examine the co-occurrence of technologies and future-related terms in job description texts and assess cross-industry relevance, using a combination of keyword analysis, NER, and entropy-based evaluation. As one of the first trend studies 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 certain limitations.

One of these limitations is the relatively short analysis period of four months. A longer observation window would allow for more detailed insights into shifts in demand for future-relevant technologies and facilitate the monitoring of newly emerging innovation topics over time. Another limitation concerns the evaluation of the NER results, which we conducted using a ChatGPT-based prompt. This step introduces an additional layer of algorithmic interpretation, as LLMs may apply implicit classification patterns based on their training data. Recent research highlights that outputs of LLMs may vary across models and prompt formulations (Camuffo et al., 2026). Although we conducted additional robustness checks using alternative models and prompt variations and manually validated the resulting technology and innovation domains, some degree of model-dependent interpretation cannot be fully excluded. Accordingly, while the ChatGPT-assisted step was used solely to support the consolidation of NER results and not to generate or rank technologies, full reproducibility cannot be guaranteed. Future research could compare LLM-assisted extraction with manual expert coding or alternative NLP-based classification approaches.

Further limitations arise in the industry-level analysis. These include the restriction to two-digit NAICS codes, which limits sectoral granularity, and the exclusive focus on hit frequencies without deeper insights into the companies posting the jobs or the occupational groups associated with them. Additionally, we acknowledge that differences in industry sizes and employment structures may influence the observed number of hit-generating job postings. While our entropy-based approach reduces size-related effects by focusing on cross-industry dispersion rather than absolute frequencies, future research could further normalize job postings data using industry-level employment or full-time equivalent (FTE) statistics to refine robustness assessments. Consequently, our approach also does not capture industry-specific technologies whose future importance may be high within a single sector but limited in cross-industry scope. Such technologies may be critical for sectoral competitiveness and long-term viability, yet they fall outside the scope of our robustness concept, which is intentionally oriented toward identifying technologies with broad, economy-wide future relevance signals.

Another limitation of our approach relates to the distinction between internal hiring and external sourcing of technological capabilities. For certain highly specialized or niche technologies, firms may deliberately refrain from recruiting dedicated in-house staff and instead rely on external service providers, consultants, or technology partners. As a result, these technologies may appear never or rarely in job postings, despite being strategically important for specific firms or industries. This sourcing behavior is particularly relevant for technologies that require rare expertise, exhibit high fixed costs, or are only intermittently needed. Consequently, a low number of mentions in job postings does not necessarily imply low strategic relevance but may reflect alternative organizational strategies for accessing technological capabilities.

We also acknowledge that job postings may capture both proactive and reactive recruiting activities. While they can reflect forward-looking skill requirements and anticipated capability needs, they may equally represent reactive hiring responses to already emerging or established technological demands. As a result, our approach cannot fully disentangle future-oriented technology anticipation from responses to manifested skill gaps, nor can it empirically verify to what extent the identified technology signals anticipate future technological developments as opposed to reflecting current labor market needs. This limitation is inherent to labor market-based foresight approaches and underscores that our findings should be interpreted as indicator-based priority signals, rather than as validated predictions of future technological dominance. Nevertheless, both proactive and reactive recruitment activities indicate organizational recognition of technological importance and therefore provide valuable foresight-relevant signals. Future research could address this limitation by combining job postings data with longitudinal innovation indicators or ex-post validation analyses.

Another limitation of our approach is that the use of future-related terminology as a filtering criterion may exclude job postings that reference strategically relevant technologies without framing them explicitly in a future-oriented context. This constitutes a deliberate, theoretically motivated bias intended to distinguish strategic technological signals from routine operational references and to mitigate the aforementioned limitation. Future research could relax or vary this filtering requirement to examine how different levels of future-orientation affect the identification of technology trends.

Looking ahead, we also encourage future research to build upon our proposed approach by incorporating additional analysis steps that enable a more fine-grained examination of technologies and by applying the methodology to other national or regional contexts. For forthcoming trend studies and foresight research in general, we recommend fully acknowledging the potential of job postings data as a valuable foresight data source and continuing to enhance existing analysis methods or develop new ones. Beyond these methodology-related recommendations, we also propose comparing the trend insights derived from job postings with those obtained from other semi-structured data sources, particularly scientific publications and patents. Future research could investigate whether these data sources reveal overlapping or distinct thematic trends and how the temporal dynamics of trend emergence differ across them. In this context, it would be especially valuable to explore potential time lags between the different data sources, shedding light on how trend topics evolve with respect to their maturity and position within the technology lifecycle.

Finally, we encourage future research to examine the relationship between data-driven foresight, innovation efficiency, and firm performance. In particular, it would be worthwhile to investigate whether and how a company's financial and innovation-related performance is linked to its recruitment behavior concerning emerging technology domains or innovation fields, and whether firms that hire experts in emerging fields at an early stage achieve superior performance.

Appendix

Appendix A: Prompt used for the ChatGPT-assisted technology consolidation of NER results

The following prompt was used to support the identification and consolidation of technology-related concepts mentioned in the unfiltered NER output derived from job description texts:

> *"You are provided with a list of named entities extracted from job descriptions using a Named Entity Recognition (NER) model.*
> *Please identify and extract only technology and innovation fields relevant in a business and technology foresight context.*
> *Exclude company names, job titles, software tools with purely operational relevance, and generic terms.*
> *Consolidate closely related concepts under a common technology domain (e.g., "AI" and "Artificial Intelligence").*
> *Return a concise list of distinct technology and innovation fields.*
> *Do not rank, evaluate, or assess the future importance of the identified technologies."*

Appendix B: Prompt used for the ChatGPT-assisted technology screening of job descriptions

The following prompt was used to support the identification of additional technology-related concepts directly from job description texts in a recall-oriented manner:

> *"You are provided with job description texts that have already been filtered to include both future-related and technology-related terminology.*
> *Your task is to identify and extract any explicitly mentioned technology-related concepts, innovation fields, or technological domains.*
> *Include only technologies that are directly mentioned in the text.*
> *Exclude company names, job titles, soft skills, generic business or management terms.*
> *Return a list of candidate technology and innovation fields mentioned in the text.*
> *Do not rank, evaluate, or assess the importance of the technologies and do not infer technologies that are not explicitly mentioned in the text."*

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