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Anticipating Technology Convergence with Online Job Postings Data

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Abstract: Foresight and anticipation of technology convergence has been of interest to innovation management scholars and practitioners for almost three decades. Since then, the prevailing data source for analysing convergence movements and for delimiting them from fusion dynamics are patents. However, increasing criticism arose about the limited forecasting power of established analysis methods, insinuating they rather monitor technology convergence than anticipating it. Our ongoing research argues that the discipline is in need of a new data source for analysing technology convergence and thus proposes online job postings as more forward-looking and future-oriented data. This research-in-progress paper provides a brief literature review on the theoretical background of technology convergence and outlines the preliminary design of our ongoing research on anticipating fusion and/or convergence movements in the AI technology field. Next to describing our keyword-based job postings analysis we also introduce a novel interpretation approach for differentiating between technology fusion and convergence.

Keywords: Technology convergence; technology fusion; technology foresight; innovation management; trend study; artificial intelligence; AI technology skills; job postings analysis; keyword analysis.

1 Introduction

The phenomenon of technology convergence, whereby formerly distinct technology trajectories begin to overlap and merge into a joint offering (Greenstein and Khanna 1997), has been of interest to innovation management scholars and practitioners for almost three decades. And anticipating technology convergence as well as understanding the changing innovation patterns and industry structures that come with it, is a crucial component of strategic and technology foresight (Song et al. 2017). While patents are still the most frequently used data source for analyzing technology convergence (Lee et al. 2022; No and Park 2010), increasing criticism arose about the limited forecasting power of the underlying studies (Song et al. 2017). In many cases we see an undeniable degree of backward orientation in the methods of analysis, which tend to focus on monitoring converging technology fields rather than anticipating them (Brännback et al. 2002; Curran et al. 2010). Thus, we propose to use a more early-phased and future-oriented data source for the foresight of technology convergence – namely online job postings data. Our ongoing research tests and strives to validate the applicability of this alternative data source for anticipating technology convergence, by identifying and analyzing potential convergence dynamics around the technological field of artificial intelligence (AI).

Previous research shows that properly understanding and interpreting technology convergence can be a key factor for future growth and innovation. Businesses that manage to anticipate a possible convergence ahead of their competition are likely to gain an advantage in interacting with formerly separated industries and forming cross-industry alliances to develop innovative solutions and to proactively influence the changing value chain as a technological leader (Eselius et al. 2008; Nyström 2009; Song et al. 2017). Retrospectively, the literature agrees that digital technologies and especially the information and communication technologies (ICTs) formed the centerpiece of past technology convergence, as they profoundly impacted all types of industries (Von Tunzelmann 1999). With artificial intelligence standing at the front line of changing various industry landscapes again (Lee et al. 2022) the AI technology field has obviously been the center of attention for more and more foresight and convergence researchers lately. Some authors even argue that AI has the potential to become a general purpose technology (GPT), for which technological convergence can be a decisive factor (Brynjolfsson et al. 2017; Goldfarb et al. 2023). While trend studies on the GPT potential of AI already rely on job postings data (Goldfarb et al. 2023), the convergence of AI has only been analyzed using patent data so far (Lee et al. 2022). However, it is argued that job postings data is more forward-looking than patent data because human capital is an input into technology development and the inbound of specialized skills should reflect a company's intentions to engage with a new technology earlier than the resulting patents (Goldfarb et al. 2023).

2 Methodology

Providing a brief literature review on the theoretical background of technology convergence and outlining the preliminary research design of our ongoing research, this research-in-progress paper lays the foundation for answering the following research question: How can online job postings data be used to anticipate technology convergence and does the data show a convergence of AI technology with formerly separated industries?

The systematic literature review focuses on the scientific explanation of technology convergence and on the state of the art in technology convergence analysis. For the empirical part of our ongoing research, we acquired an extensive set of online job postings data from the data provider LinkUp, which is updated daily and sourced directly from employer websites worldwide (LinkUp 2024). In its basic functionality, the data analysis follows the approach of a simple keyword matching using Python code to get an overview of past and present hiring dynamics for AI technology skills. As keyword directory serves the AI keyword list by Baruffaldi et al. (2020), which contains over 200 AI-related keywords and was developed from scientific publications based on a two-step bibliometric approach including text mining techniques and expert validation. While the keyword analysis will merely reveal which job postings contain which AI keywords in their job descriptions, an in-depth analysis of the O*NET classifications given for each job posting will allow for first conclusions about the industries and occupations most impacted by AI. By comparing the hiring dynamics over a longer period of time, we strive to identify emerging convergence trends and directions of AI technology skills with formerly AI-independent industries and technology fields.

With our research design we orient towards Song et al. (2017), who argue that patterns of technological convergence can best be identified at the intersection of distinct disciplines and who analyze knowledge flows based on International Patent Classification (IPC) codes to anticipate convergence. Due to the similar functionality and structure of IPC and O*NET codes we see the potential to tailor this proven methodology and reasoning to our alternative data source. A detailed description and structured argumentation for our approach is given in chapter 4 of this work.

3 Literature review

The following literature review is limited to a theory-based explanation of technology convergence and the necessary delimitation from technology fusion as well as to a consolidated overview of established convergence research methodologies. While the scientific discourse on technology convergence also includes a strong research stream on the drivers of convergence, we exclude this from the scope of our paper by merely summarizing that technological developments, regulatory measures, customer preferences, and social change are the most important reasons and determinants for the occurrence of convergence (Song et al. 2017). When talking about convergence, the literature usually incorporates different properties such as know-how, technologies, markets or industries (Athreye and Keeble 2000). Although our paper dwells on the terminology of technology convergence, we do not want to neglect the interdependencies between those properties, which is why the following paragraph concentrates on convergence in general.

In orientation towards Curran and Leker (2011) who define convergence as “the blurring of boundaries between at least two hitherto disjoint areas of science, technology, markets or industries” and further explain that “through this convergence, a new segment is being created in a new spot as a merger of the old segments” the procedural character of convergence becomes clear. To illustrate this process and to differentiate convergence from fusion (Bierly and Chakrabarti 2001) the use of overlapping circles has become established in the literature. Figure 1 depicts the processes of fusion and convergence in a simplified manner and highlights the main difference between them, which lies in the distinction between unilateral and reciprocal approximation.

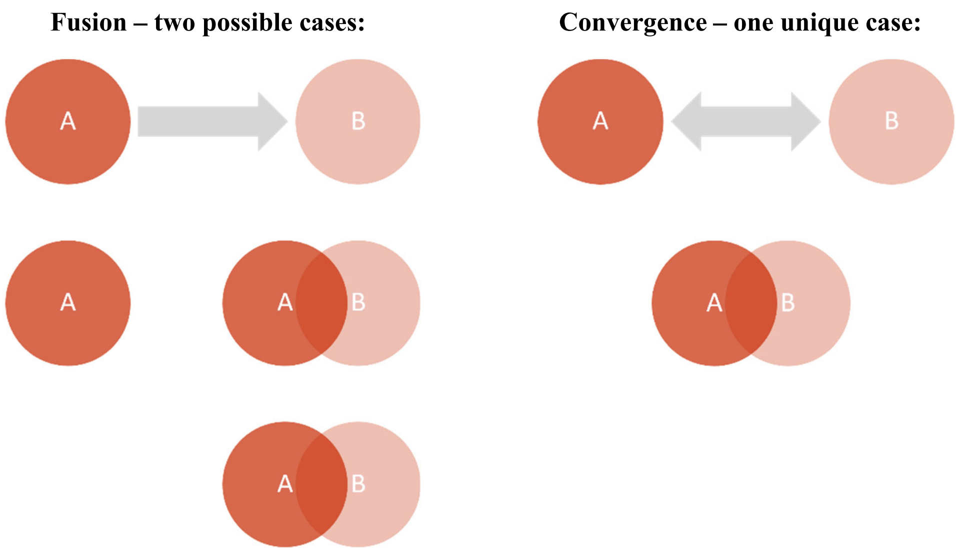

Figure 1 Illustration of the processes and distinctions of fusion and convergence. Modified from Curran (2013) and Song et al. (2017)

For the more common phenomenon of technology or market fusion two different cases are possible. In both cases the process starts with two disjoint areas A and B, whereby A begins to move towards B and a merged segment is created at the former spot of segment B. In the first case, however, segment A remains as an independent area, that can be part of new fusions in the future. In the second case, segment A disappears after the fusion and only the merged segment remains marketable. The process of convergence differs significantly from this in that it shows a mutual movement of A and B towards each other (Curran and Leker 2011). As both segments leave their former spots here, a new application domain is created, which is impossible in the case of fusion (Song et al. 2017).

When it comes to the analysis or attempted anticipation of technology convergence, the use of patent data as a data source prevails. Regarding the methods of analysis, most of the studies rely on at least one of the four approaches displayed in Table 1.

Table 1 Overview of established methods for analysing technology convergence with patent data

Patent analysis method	*Functionality and limitations*	*Authors*
Citation analysis	Recording of bibliographic coupling by analysing forward and backward citations of patent and non-patent literature Difficulties in taking latest patent applications into account Bias towards US patents	Choi and Park 2009; Karvonen and Kässi 2011; Karvonen and Kässi 2013; Ko et al. 2014; No and Park 2010

Classification analysis	Calculation of the ratio between co-classified patents and the total number of patents in a technological field based on IPC codes Distinction between fusion and convergence depending on unilateral or bilateral co-classification Classification systems as static constructs with difficulties in mapping emerging technologies Imprecise delineation of technology fields with a bias towards clearly labelled (established) technologies	Curran et al. 2010; Curran and Leker 2011; Gauch and Blind 2015; Lee et al. 2015; Lee et al. 2022; Luan et al. 2013; Song et al. 2017; Wang et al. 2019
Semantic analysis	Analysis of jointly contained textual elements using similarity measures Extraction of relevant terms per technology field Superior approach when only a few patent documents are available (e.g., in an emerging technology field) Creation of analysable patent sets relies on IPC codes and is subject to classification-specific limitations	Lee et al. 2022; Passing 2017; Preschitschek et al. 2012; Preschitschek et al. 2013
Patent maps	Visual exploration and analysis of patent similarities based on different proximity measures Different appearance and clustering of the map after every analysis run due to necessary reduction of data dimensions in the matrix Inconsistency in perception and valuation by analysts	Curran and Leker 2011; Leydesdorff et al. 2014; Passing 2017

As mentioned before, the above methods and their associated studies are increasingly criticized for monitoring the convergence of preselected technology fields rather than anticipating it (Song et al. 2017). After reviewing the literature and highlighting the state of the art in convergence analysis, we would like to argue that the problem is likely to lie less in the methods than in the data source itself. To our current understanding, little to no research has been conducted on the use of alternative data sources for anticipating technology convergence. Curran et al. (2010) are among the few who have worked with a combination of data sources by analysing patents and scientific publications for early signs of convergence in the cosmeceuticals as well as nutraceuticals and functional foods industries.

Recent trend studies on the identification of future skills in specific countries, technology fields, or job domains (Brasse et al. 2023; Firpo et al. 2021) together with Goldfarb et al.'s (2023) examination of AI's potential to become a GPT have convinced us of the forecasting power and long foresight horizon of online job postings data – especially in the field of artificial intelligence. Thus, our ongoing research aims to contribute a first feasibility study on the foresight of technology convergence with online job postings data in this very technology area and the subsequent chapters strive to introduce our newly developed analysis and reasoning approach to the scientific discourse.

4 Description of the data set and the ongoing analysis

The LinkUp (2024) online job postings data set that we use for our ongoing research consists of different kinds of files, which can be compiled depending on the focus of the analysis. For our convergence study only the so-called "Job Records", "Descriptions" and "ONet 2019 Taxonomy" files are relevant. Table 2 shows the information contained in each of these files.

Table 2 Overview of relevant LinkUp data files and the information they contain

File name	*Information contained*
Job Records	hash, title, company_id, company_name, city, state, zip, country, created, last_checked, last_updated, delete_date, unmapped_location, url
Descriptions	job_hash, description
ONet 2019 Taxonomy	job_hash, onet_occupation_code

Source: LinkUp 2024.

Each job posting in the data set is assigned with an individual job hash that serves as the unique identifier for merging the different files and for removing duplicates. In the course of our analysis, we create monthly data sets from the files above over a period of several years. The total time span of our analysis has not yet been determined, as established job postings researchers recommend analysis periods between three (Brasse et al. 2023) and nine (Goldfarb et al. 2023) years and we still need to test the best time span for our research context. Due to the currently perceived rapid spread of AI technology, however, we tend towards a shorter analysis period of one to two years.

After data clearing, the first analysis step will be to automatically scan the job descriptions for the occurrence of AI-related keywords using simple Python code. According to the literature, automated keyword matching with a predefined directory is a proven methodology for analysing job postings (Brancatelli et al. 2020; Brasse et al. 2023). By using the scientifically derived AI keywords list from Baruffaldi et al. (2020) as our keyword directory, we increase the validity and transparency of our approach. To ensure that we can distinguish between the various sub-areas of AI technology in the further steps of our analysis, we already grouped the keywords into the following eight clusters using ChatGPT and manual assignment:

- Machine Learning Algorithms
- Data Mining
- Natural Language Processing
- Computer Vision
- Robotics and Automation
- Optimization and Metaheuristic Algorithms
- Cyber-Physical Systems and IoT
- Human-Computer Interaction

The automated keyword analysis recognises job postings that contain at least one of the AI keywords in their job descriptions and assigns them to the corresponding keyword and its superordinate cluster. Based on this, we can carry out the in-depth analyses of potential convergence or fusion dynamics with specific industries and occupational groups. To identify and delineate the industries in which AI technology skills are being sought, we make use of the Global Industry Classification Standard (GICS) by MSCI and S&P Global (MSCI 2023). Each job posting with a keyword match will be assigned to its appropriate GICS sector – and possibly also to the subordinate industry groups, industries, and sub-industries – based on the company that posted the job posting. To identify and delineate the occupational groups from which AI technology skills are being expected, we make use of the Occupational Information Network-Standard Occupational Classification (O*NET-SOC) by the U.S. Department of Labour and the Office of Management and Budget (U.S. Department of Labour 2024), which is already given for each job posting in the LinkUp (2024) data set. The analysis steps described above will be performed for all monthly data sets and their results will be visualised in two different two-dimensional bar charts, showing the AI technology sub-areas on the x-axis, the total amount of job postings on the y-axis and the distribution across industries and occupational groups in color-coded bars. More detailed visualisation options are currently being tested and depend partly on the final results. How the interpretation and aspired forecasting of technology convergence and/or fusion will work based on the results of our data analysis and based on the theoretical constructs from our literature review is described in the subsequent chapter.

5 Expected results and interpretation approach

We expect our results to show which sectors, industries, and companies are increasingly hiring which AI technology skills and we expect to better understand from which occupational groups these skills are required. Our approach to interpreting these results orients towards the basic reasoning from classification analyses of patents, where the indicator for technological convergence is an increase in the number of patents that are indexed in multiple subject areas (Song et al. 2017). We argue that an increase in job postings that are seeking AI technology skills and were posted by previously AI-independent companies may be a weak signal for proximity movements. The distinction whether these skills are expected from AI-typical or -atypical occupational groups further enables us to differentiate between fusion and convergence. Figure 2 visualises this interpretation approach with reference to the theoretical explanation and distinction of fusion and convergence.

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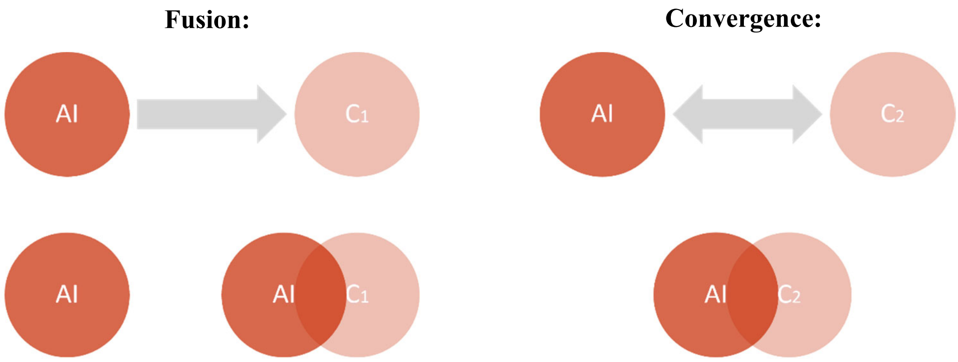

AI = AI technology skills
C_1 = AI-independent company (previously) requires AI skills from AI-typical occupational groups

AI = AI technology skills
C_2 = AI-independent company (previously) requires AI skills from AI-atypical occupational groups

Figure 2 Job postings data-specific interpretation approach of fusion and convergence.

To recognize whether a company was previously AI-independent or not, we refer back to the Global Industry Classification Standard and for determining AI-typical and -atypical occupational groups we rely on the O*NET codes. Interpreting our results in the context of the above framework should enable us to identify potential trends regarding the presence and directions of fusion and/or convergence movements in the AI technology field.

6 Outlook on future research and expected contribution

We expect our ongoing research to demonstrate the feasibility of anticipating technology convergence and/or fusion with online job postings data. As part of this, we are already working on a scientific trend study that examines the ongoing fusion and convergence dynamics in the AI technology field and attempts to anticipate future directions of one-sided or reciprocal proximity movements. The trend study is expected to contain insights into the hiring dynamics for AI technology skills by showing which industries hire which types of skills from what occupational groups and how the need for these technology skills has changed over time. Presumably, we will identify certain sub-areas of AI technology to be converging, which allows for a benchmarking with previous studies and for the further establishment of online job postings as a foresight data source. The use of online job postings to anticipate technological convergence can enrich the scientific discourse in that it proposes them as a more forward-looking alternative to patents and as a valid data source for technology foresight in general. Furthermore, our trend study will provide data-driven insights into the fusion and/or convergence dynamics of AI technology, which is not only relevant for research but also for practice. The practical implications arise mainly from the expected findings of our trend study. Knowing where AI technologies and skills might migrate in the future can not only benefit Technology and Innovation Managers but also HR experts and foresight practitioners. For the latter, our proposed method can also serve as guidance for incorporating job postings analysis into corporate foresight activities.

7 Areas for feedback and development

Feedback is friendly requested on the research question, the research design and, on the following aspects:

- What time span should our analysis of online job postings cover? (One year, two years, more or less?)
- Do you have any experience in working with online job postings data? Which data set or data provider did you use?
- Which other analysis method(s) would you recommend for our purpose?
- Can you recommend further literature or leading authors in the field?

Additional feedback that goes beyond these points is also highly welcome.

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