Technology in Society 84 (2026) 103092

Contents lists available at ScienceDirect

Technology in Society

journal homepage: www.elsevier.com/locate/techsoc

Technological agglomerations and the emergence of artificial intelligence start-up ecosystems in Europe

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ARTICLE INFO

Keywords:
Industry formation
Entrepreneurship
Artificial intelligence
Innovation systems
Ecosystems
Europe

ABSTRACT

The emergence of new industries is shaped by intricate geographical dynamics influenced by multiple factors. Yet, the rationales underpinning the locational choices of AI-based startups remain insufficiently understood. Traditional explanations have largely emphasized agglomeration economies, but their applicability to the AI industry requires further examination. This study investigates the growth of the AI industry across seven major European regions, uncovering two distinct locational patterns associated with different stages of industry evolution. In the nascent phase, the industry benefits primarily from intra-industry co-location effects and knowledge spillovers, which help mitigate technological risks. As the industry advances, however, cross-industry linkages become increasingly important, playing a pivotal role in addressing commercial risks and sustaining development. Overall, the findings highlight the dynamic interplay between technological and commercial risks, offering new insights into the shifting rationales and spatial dynamics that shape the emergence of the AI industry.

1. Introduction

One of the prominent outcomes of technological progress is the advent of novel industries (Gustafsson et al., 2016). The development of steam engine technology, for instance, catalyzed the rise of railway and automotive manufacturing (Ayres, 1990). Similarly, the evolution of semiconductor technology was pivotal for the establishment of the computer industry, while advancements in genetic recombination marked the inception of biotechnology. More recently, Artificial Intelligence (AI) has demonstrated transformative potential across a wide range of sectors, including sustainable development (Wang et al., 2024), healthcare (Waisberg et al., 2023), labor markets (Acemoglu & Restrepo, 2020), public services (McKelvey & MacDonald, 2019), and management research (Obschonka & Audretsch, 2020). These transformations extend beyond industrial dynamics to broader organizational and societal dimensions, reshaping work practices (Anthony et al., 2023; Dabić et al., 2023) and influencing digital transitions and socio-economic development trajectories (Abbas et al., 2026; David et al., 2025).

AI is widely regarded as a general-purpose technology (Bresnahan & Trajtenberg, 1995). The technologies included in this domain not only redefine the parameters of existing industries but also engender novel configurations of opportunities and business models, which have the potential to culminate in the rise of entirely new industries (Sandulli et al., 2021). AI start-ups tend to cluster in diversified regional economies, where cross-sector experimentation is possible. Yet despite its disruptive potential, empirical evidence on the emergence of the AI industry across different territorial contexts remains limited and largely confined to a few specific regions (Doloreux & Turkina, 2021; Hong et al., 2024; Shi et al., 2020; Wang et al., 2023; Yu et al., 2022). Further research is therefore needed to examine how different factors interact and shape entrepreneurial decisions in rapidly evolving AI domains (Hong et al., 2024). This study seeks to address this gap by exploring the diverse paths of AI start-up ecosystem formation in Europe. Its main objective is to identify the key factors underpinning the emergence of the AI industry and to provide a broader, more generalizable analysis of its geographic distribution across Europe.

From a theoretical perspective, the paper contributes to the literature by testing whether the factors that have traditionally explained the uneven geographic distribution of innovative industries can also account for the geography of the emerging AI industry. Like other new sectors, AI displays a consistent tendency to cluster in particular, often recurrent,

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https://doi.org/10.1016/j.techsoc.2025.103092
Received 16 December 2024; Received in revised form 25 September 2025; Accepted 25 September 2025
Available online 26 September 2025
0160-791X/

locations (Berger & Frey, 2017). However, rather than reflecting a broad diffusion of innovation, the current geography of innovation is increasingly structured around a global hub-to-hub system (Crescenzi et al., 2020). The development and spatial distribution of start-up ecosystems thus embody central theoretical dynamics emphasized in economic geography (McCann & Oort, 2019). The emergence of new industries has been studied through the lens of classical theories of agglomeration economies (Marshall, 1890), which explain the concentration of firms through external scale economies—such as local labor pools, supplier linkages, and knowledge spillovers—that enhance productivity and innovation within specific urban or regional clusters (Krugman, 1991). Extending this logic, cluster theory (Delgado et al., 2014; Porter, 1996) places greater emphasis on the interdependence among firms, institutions, and supporting organizations within particular regions. Hence, clusters in new industries cannot be explained by proximity alone, even if firms in emerging sectors often co-locate near dense knowledge bases to reduce technological uncertainty and access specialized resources (Audretsch & Feldman, 1996; Maskell & Malmberg, 1999).

In this respect, broader theoretical frameworks offer complementary insights into the uneven geographies of industry emergence, highlighting the role of regional innovation systems (Cooke, 1992) and entrepreneurial ecosystems (Autio et al., 2018; Stam, 2015) in supporting knowledge exchange, innovation, and new venture creation. The interdependent actors and factors that shape regional responses to technological opportunities include start-ups, universities, research centers, venture capital organizations, business accelerators, policy institutions, and regulatory frameworks. New industries are not randomly distributed, but emerge in places with strong interactions among these actors and with pre-existing capabilities that are technologically related to the new sector (Boschma & Frenken, 2006). Accordingly, the geography of advanced technology industries is path-dependent, shaped by processes of technological recombination and knowledge accumulation grounded in regional histories, while diversification also depends on agency, particularly institutional entrepreneurship.

By focusing on early-stage developments rather than mature technologies, this study provides insights into how new agglomerative patterns may be formed. Unlike conventional frameworks, which conceptualize co-location as territorially fixed, our analysis adopts a dynamic lens to capture the ongoing formation of AI start-up ecosystems in Europe. Considering both intra-industry and cross-industry factors allows us to identify different mechanisms at distinct stages of entrepreneurial activity. Empirically, the study integrates data from three specialized datasets (Dealroom, Crunchbase, and EU Start-ups) across seven major European countries between 2012 and 2021, offering robust evidence on the dynamics of AI ecosystems in a rapidly evolving field.

The results show that the emergence of AI industries in Europe is highly concentrated in a relatively small subset of metropolitan regions. While agglomeration economies strongly influence this process, their effects diminish beyond a saturation point, often described as the limit of regional innovation systems. Regions with a strong presence of multinational firms are particularly conducive to AI development, as they foster combinatorial innovation and act as anchor customers. Moreover, in digital and knowledge-intensive industries, relational proximity (Bathelt & Glückler, 2003) to international ecosystems complements local embeddedness by providing access to frontier knowledge, legitimacy, and investment.

Finally, this study contributes to entrepreneurship research by confirming recent theoretical developments in industry cycle analysis (Moeen et al., 2020) and showing that the drivers of AI entrepreneurship shift over time. In the early stages, AI entrepreneurship is largely driven by agglomeration effects and intra-industry interactions. In subsequent stages, particularly when the main challenge involves developing viable business models and value chains, regional diversity and cross-industry interactions exert a greater influence. Accordingly, the relative importance of different factors varies across stages, underscoring industry formation as a sequential process composed of distinct phases, each characterized by specific dynamics. The paper also advances the literature on regional innovation systems (e.g., Santarelli et al., 2023) by confirming the importance of mapping knowledge bases to understand the multi-sectoral embeddedness of general-purpose technologies such as AI.

The paper is structured as follows. Section 2 outlines the research context and hypotheses, which build on the dynamic interplay between technological and commercial risks faced by new entrants. Section 3 describes the data and methodology, while Sections 4 and 5 present and analyze the results. The final section concludes by highlighting the paper's main contributions.

2. Research context and hypotheses

In the nascent phases of an industry, firms encounter substantial technological and commercial risks, as both the knowledge base and technological standards remain undefined (Hsu & Grodal, 2021; Sine et al., 2005). New industries emerge through trial and error, whereby economic agents explore new applications of existing knowledge (knowledge deepening) or pursue novel knowledge (knowledge expansion) to address emerging challenges within a scientific or technological domain (Grodal et al., 2015). However, startups typically lack the resources to consolidate their knowledge creation strategies, as well as the insights needed to effectively define viable business models (Gimenez-Fernandez et al., 2020). This helps explain the notable mortality rate of startups, which is largely attributable to the difficulty of identifying and developing required resources or securing access to new markets enabled by emerging technologies (Liao et al., 2008).

One pivotal decision for every entrepreneur is the choice of location. This strategic decision seeks to mitigate both technological and commercial risks, which are particularly pronounced for new market entrants. Entrepreneurs generally prefer to establish their ventures in areas where resource acquisition and market access are more readily attainable (e.g., Ferreira et al., 2016; Modrego et al., 2017). The knowledge spillover theory of entrepreneurship emphasizes that entrepreneurial activity strongly depends on knowledge stocks that are not appropriated by incumbents (Acs et al., 2009). To access these knowledge stocks, startups engage in intensive network-building activities to exchange knowledge (Gimenez-Fernandez et al., 2020, 2022). Since access to diverse knowledge sources mitigates technological risks, novel firms are particularly drawn to regions with robust technological knowledge bases (Baptista & Mendonça, 2010). This pursuit of knowledge interconnections underpins well-documented co-location effects (e.g., Audretsch, 1998).

The formation of intra-industry knowledge clusters reduces the transaction costs of knowledge sharing and enhances firms' learning curves (Iammarino & McCann, 2006). New firms located within these agglomerations benefit from improved access to specialized labor, sector-specific suppliers, and industry-tailored spillovers, enabling seamless integration into established knowledge networks. For small and medium-sized enterprises (SMEs), many of these knowledge flows occur within the industry and are typically facilitated by clusters (Hanna & Walsh, 2008). In new industries, numerous actors actively experiment with technological solutions and engage in collective learning processes, drawing on one another's experiences (Aversa et al., 2022; Cuntz & Peuckert, 2023). In the AI industry, knowledge spillover capital has been identified as a key determinant shaping the locational choices of entrepreneurs, fostering conditions that support startup growth and collaboration (Hong et al., 2024; Lammers et al., 2021). This search for knowledge explains why AI firms frequently cluster, forming dense networks largely confined to their own sector (Turkina et al., 2021). Hence, the entrepreneurial reliance on agglomerations where spillovers are concentrated suggests that AI startups are more likely to locate in regions with a high number of existing AI firms.

Hypothesis 1. The geographic concentration of AI firms increases the probability of subsequent AI entrepreneurial activity.

However, not all locations with extensive intra-industry knowledge bases provide equally advantageous environments for startups. Emerging knowledge exchange dynamics from intra-industry interactions (Henderson, 1974) are more effective in reducing technological uncertainty than in mitigating commercial risks (Wang et al., 2014). During the early stages of an industry, when technological outcomes remain uncertain, firms are more likely to engage in collaborative efforts (Rosenkopf & Nerkar, 2001). Yet, as uncertainties diminish, attention shifts to defining viable business models (Sandulli et al., 2012). At this point, firms have fewer incentives to share information regarding the architecture and modules of their business models (Johansson & Malmstrom, 2013). Consequently, localization economies may also generate negative externalities, as intensive interactions within clusters risk exposing proprietary knowledge to competitors (Iammarino & McCann, 2006). Previous literature (e.g., Cooke & De Laurentis, 2010) has highlighted these limitations, noting that beyond a certain threshold, agglomerations can become saturated, producing adverse effects such as heightened competition, rising labor costs, and increased transaction costs. We therefore expect that, beyond a critical point, the benefits of AI agglomerations—primarily related to spillovers—will be offset by the risks of knowledge leakage and intensified competition.

Hypothesis 2. The positive externalities generated by the concentration of AI firms are subject to diminishing returns.

Knowledge clusters that foster cross-industry interactions (Cooke, 2001; Feldman, 1994) are also critical for startups, particularly in mitigating commercial risks (Scaringella & Radziwon, 2018). Unlike technological risks, commercial risks often persist for extended periods. The transition from technological maturity to commercial viability—commonly referred to as the "Death Valley"—can span decades and is associated with high firm mortality (Markham, 2002). Startups must therefore locate not only in regions with strong intra-industry spillovers but also in environments where their business models can interact effectively with complementary actors across the innovation ecosystem.

Building connections between startups and complementary firms is challenging, given the transaction costs of identifying potential customers, as well as the information asymmetries and cognitive gaps that often separate startups from more traditional firms (Gimenez-Fernandez et al., 2022). However, the ecosystem literature shows that clustering around ecosystems rich in complementary actors facilitates cross-industry interactions with suppliers and customers (Hanlon & Miscio, 2014), which in turn support the development of viable business models. Cross-industry effects can be understood through three primary mechanisms. First, they signal the availability of a skilled workforce in supplier or customer firms, which startups can recruit to refine their models. Second, they proxy for greater access to markets for technological applications and for large-scale suppliers (Hanlon & Miscio, 2014). Third, they reflect the involvement of public research centers and large corporate R&D departments that engage with startups to explore technological alternatives and identify potential partners (Giglio et al., 2025; Weiblen & Chesbrough, 2015). Many pioneering firms in high-tech industries emerge as spin-offs from large public or private laboratories, which often assume technological risks in the early stages and are better positioned than startups to absorb potential setbacks. In this context, regional diversification strategies should also account for the influence of social, cultural, and institutional environments in shaping new development paths (Hassink et al., 2019; Boschma et al., 2017).

Although limited, existing evidence on the AI industry supports the relevance of cross-cluster ties (e.g., Shi et al., 2020; Yu et al., 2022). Technological complementarity and shared business contexts often compel firms to develop linkages across clusters, generating overlaps across industries (Doloreux & Turkina, 2021). Driven by the need for collaboration, access to shared resources, and complementary expertise, AI firms frequently embed themselves within key nodes of global value chains (Humphrey & Schmitz, 2002).

Hypothesis 3. New AI firms tend to locate where dense, cross-industry networks foster interaction and complementary assets.

3. Sample and methods

In order to validate the relationship between industry emergence and firms' locational decision-making, we analyze the rise and growth of the AI business sector. Specifically, the study examines the trajectory of AI startup proliferation across seven major European OECD economies—France, Germany, Italy, the Netherlands, Spain, Switzerland, and the United Kingdom—during the period 2012 to 2021. The year 2012 was selected as the starting point, coinciding with the approval of Germany's High-Tech Strategy 2020 in March of that year, which included a pioneering initiative aimed at fostering the development of Industry 4.0 technologies in Europe.

The initial list of firms was compiled from specialized entrepreneurship databases, including Dealroom, Crunchbase, and EU Startups. These databases classify firms under the "Artificial Intelligence" category using keyword-based search criteria. However, a random sampling of the dataset revealed that not all firms listed as AI companies operated with AI-centered business models. Consequently, a comprehensive review of each firm's profile was conducted to determine whether their primary products or services were indeed closely tied to AI technologies. The databases provided information on firms' headquarters at the NUTS-2[1] level and their founding years. These data were used to calculate the number of AI startups established across the regions. In total, 4854 AI startups were identified across the seven countries during the period under study.

The dependent variable in our model, (y_{it}), is a count variable that measures the annual number of AI startup founding events at the regional level. The variable consists of non-negative, discrete values, exhibiting a skewed distribution that induces overdispersion. Given these characteristics, the negative binomial regression model is commonly applied. However, as a true fixed-effects estimator has yet to be developed (Allison & Waterman, 2002), prior research suggests the use of the conditional fixed-effects Poisson Pseudo-Maximum Likelihood (PPML) estimator. This estimator produces consistent and robust standard errors (clustered by region), even in the presence of overdispersion (Wooldridge, 1999). In settings with many zero observations, PPML also outperforms log-OLS models and yields unbiased estimates under heteroscedasticity (Silva & Tenreyro, 2006).

The model incorporates the independent variables listed in Table 1. It captures agglomeration economies by including both the number of jobs (JOB) and population density (DEN) as explanatory variables, following previous approaches (e.g., Arauzo-Carod & Manjón-Antolín, 2012). The geographic concentration of AI firms is measured by the number of active AI startups in region i during year t (AIP), counted from founding year until exit. Following population ecology models for emerging industries, the squared term of AI firm population (AIS) is added to capture nonlinear population effects and potential saturation. To account for knowledge spillovers, the model includes the number of AI-related patents (PAT) filed or granted by the EPO[2] to applicants in region i, as well as the share of scientists and engineers (S&E). It also

[1] The Nomenclature of territorial units for statistics, abbreviated NUTS (from the French version Nomenclature des Unités Territoriales Statistiques) is a geographical nomenclature subdividing the economic territory of the European Union into regions at three different levels. NUTS-2 regions usually have between 800,000 and 3 million inhabitants. A comprehensive list of NUTS-2 regions in Europe can be found at: https://ec.europa.eu/eurostat/web/nuts.

[2] The analysis focusses exclusively on Patent Cooperation Treaty (PTC) patents where AI constituted the primary focus of the patented innovation.

Table 1
List of independent variables.

Variable ID	Description
JOB	Number of jobs
DEN	Population density
AIP	Number of AI startups established in a particular region
AIS	Squared term of artificial intelligence firm population
PAT	Number of patents in the field of AI filed or granted by the EPO to applicants established in a region
S&E	Share of employees categorized as scientists or engineers
VCT	Number of capitals invested in high-tech ventures
MAN	Share of manufacturing jobs
ITS	Share of jobs in the software, IT services, and hardware sectors

Note: All variables referred to a particular NUTS-2 region *i* during year *t*.

incorporates venture capital investment in high-tech firms (VCT), reflecting its documented role in industry emergence (e.g., Vedula & Kim, 2019). Finally, to capture cross-industry complementarities shaping the AI industry, the model includes the regional share of manufacturing employment (MAN) (e.g., Tavassoli & Carbonara, 2014). Given the externalities generated by the IT sector (Doloreux & Turkina, 2021), the share of IT-related jobs (ITS)—including software, IT services, and hardware—is also included.

To mitigate potential bias from the selection process, several preventive measures are implemented. First, location-specific fixed effects (α_i) account for time-invariant omitted factors at the regional level, while time-fixed effects (τ_t) capture unobserved temporal shocks or trends. Second, we control for time-varying regional attributes including the population of AI firms (and its squared term), number of jobs, density, AI-related patents, number of scientists and engineers, manufacturing employment, and IT employment. Accordingly, the model is specified as follows (1):

$$y_{it} = \alpha_i + \tau_t + \sum_j \beta_j (X_{it}) + \varepsilon_{it} \tag{1}$$

4. Results

Descriptive statistics reveal a marked concentration of AI startups within a handful of European hubs. While AI development is geographically widespread, it is disproportionately clustered in specific locations (Bratanova et al., 2022). As shown in Table 2, the top ten regions with the highest number of AI startups are London in the United Kingdom (UK), Île-de-France in France (FR), North and South Holland in the Netherlands (NL), Madrid and Catalonia in Spain (ES), Berlin and Bavaria in Germany (DE), Lombardy in Italy (IT), and Zurich in Switzerland (CH). Together, these ten regions host over 60 % of Europe's AI startups, illustrating a cluster dynamic in which strong technical universities, applied research institutions, and targeted venture capital and public investment combine to create fertile ground for early-stage ventures. Nonetheless, there is considerable variation in the pace and extent of AI development across—and within—national contexts.

Certain countries exhibit a dominant hub that concentrates most AI startups, such as London (71 %) in the UK and Zurich (51 %) in Switzerland. In contrast, countries like Germany, Spain, and the Netherlands show a dual-hub pattern. Madrid and Catalonia collectively host 67 % of Spanish AI startups, North and South Holland together account for 68 % of Dutch AI startups, and Berlin and Bavaria represent 61 % of German AI startups. Patent distribution also varies considerably across regions. Bavaria, with 125 AI-related patents, ranks highest, followed by Île-de-France (27) and North Holland (27). A closer look reveals that many of these patents are owned by large corporations such as Siemens AG in Germany, Koninklijke Philips NV in the Netherlands, and ABB Schweiz AG in Switzerland.

To examine the determinants shaping the regional emergence of AI startups, five models were estimated (Table 3). Model 1 focuses solely on general agglomeration effects, including job count and population density. Model 2 adds knowledge spillovers and cross-industry interactions with the manufacturing and IT sectors. Model 3 incorporates both intra-industry knowledge base measures and their squared term to capture potential diseconomies of agglomeration. Model 4 replicates Model 3 but excludes the top ten AI hubs, thereby emphasizing broader regional dynamics. Model 5, in turn, focuses exclusively on those top ten regions.

The results presented in Table 3 lend support to Hypothesis 1: agglomeration economies—proxied by the geographic concentration of firms within the same industry—and knowledge spillovers—captured by the number of AI-related patents—play a significant role in AI firms' locational choices (Model 3). Consistent with Hypothesis 2, diminishing returns to agglomeration beyond a saturation threshold—the so-called innovation system saturation point—are evidenced by the negative and significant coefficient of the AIS variable in Models 3, 4, and 5. Additional results suggest that in regions with lower concentrations of AI ventures (Model 4), general agglomeration and intra-industry co-location effects, together with the regional knowledge base, are decisive in shaping the creation of new AI firms. By contrast, in regions with high AI concentration (Model 5), cross-industry effects emerge as significant drivers, while intra-industry co-location variables lose statistical significance. This outcome supports Hypothesis 3: novel firms are more likely to establish operations where dense, cross-industry networks facilitate interaction and complementary assets.

Taken together, the findings highlight two distinct patterns in the emergence of AI startups. First, major knowledge hubs are well suited for mitigating technological risks during the early stages of industry development. However, these hubs may be less favorable for firms seeking to build cross-industry synergies, as knowledge externalities in later stages often lack the specificity needed to support robust business models. Once technological risks have been reduced, regions where new technologies enhance the value proposition of established industries are more conducive to fostering value-chain collaborations.

To ensure the robustness of our results, a series of checks were conducted. Alternative model specifications, including Ordinary Least

Table 2
Number of AI Startups, Top 10 NUTS-2 regions, 2012–2021.

N	Region	Country	NUTS Code	AI startups	Share of AI startups in country j	AI patents	Share of AI patents in country j
1	London	UK	UKI0	1155	71 %	11	29 %
2	Île-de-France	FR	FR10	336	47 %	27	74 %
3	North Holland	NL	NL32	336	43 %	27	82 %
4	Madrid	ES	ES30	229	41 %	9	47 %
5	Berlin	DE	DE30	200	36 %	4	2 %
6	South Holland	NL	NL36	190	25 %	1	3 %
7	Catalonia	ES	ES51	150	26 %	4	21 %
8	Bayern	DE	DE20	136	25 %	125	65 %
9	Lombardy	IT	ITC4	132	35 %	14	47 %
10	Zurich	CH	CH04	117	51 %	22	46 %

Source: Based on Dealroom, Crunchbase, and EU Startups datasets.

Table 3
Estimation results.

Variable ID	Model 1	Model 2	Model 3	Model 4	Model 5
JOB	−0.001	−0.001	−0.001***	−0.002***	−0.002**
POP	−0.001*	−0.001**	−0.002	0.009***	−0.001
AIF			0.004***	0.030***	0.002*
AIS			−0.001***	−0.001***	−0.001***
PAT		0.016**	0.021***	0.022***	−0.073
S&E		7.819*	1.837	−8.069	−5.739
VCP		0.001	0.001	−0.001*	0.001
MAN		12.840***	8.958**	5.318	29.038***
ITS		2.539	1.668	−0.280	16.642**
Region Effects	YES	YES	YES	YES	YES
Time Effects	YES	YES	YES	YES	YES
Constant	0.532	−2.061**	−0.394	−0.069	15.473***
R^2	0.944	0.952	0.965	0.770	0.971
Pseudo Log Likelihood	−1617.10	−1601.66	−1547.95	−1218.65	−283.73

Note:
(***) Significant coefficient at 1 %.
(**) Significant coefficient at 5 %.
(*) Significant coefficient at 10 %.

Squares (OLS) and Random Effects, produced consistent results in terms of both coefficient signs and statistical significance. Additional control variables—such as population, gross capital formation, and research and development expenditure—were also tested and yielded results consistent with those of the baseline models. Moreover, regressions employing three-year moving averages of the independent variables generated comparable findings. Finally, a model excluding London (identified as an outlier) was estimated, and the results closely aligned with those of the full-sample analysis.

5. Discussion

This study investigates the spatial dynamics underpinning the emergence of the AI industry in Europe, with a particular focus on agglomeration effects. The findings reveal a dynamic and non-linear process, aligning with recent perspectives on industry emergence that highlight the evolving nature of entrepreneurial activity across key developmental milestones (Agarwal et al., 2025; Moeen et al., 2020). Contributing to the literature in evolutionary economic geography (Boschma & Frenken, 2006), the analysis shows that new AI firms tend to co-locate and engage in processes of collective learning, underscoring the role of spatial proximity and historical contingency in shaping industrial trajectories. Rather than emerging randomly, AI ecosystems concentrate in regions endowed with pre-existing capabilities, institutional frameworks, and knowledge assets conducive to innovation. Additionally, the support for Hypothesis 1 can be interpreted through the lens of path dependency: the historical accumulation of AI-related firms—serving as a proxy for embedded competencies—promotes related variety, thereby facilitating knowledge recombination and entrepreneurial experimentation within the evolving technological domain of AI.

A second mechanism underpinning the emergence of the AI industry is consistent with recent advances in evolutionary economic geography, which suggest that in certain regions new industries arise through the development of novel functions linked to existing industrial structures—regardless of the maturity or depth of the regional knowledge base of the new technology (Boschma, 2024). Within this mechanism, cross-industry linkages foster AI entrepreneurship when startups contribute to functional diversification within pre-existing complementary sectors. The findings of this study support this view and reinforce recent research emphasizing the significance of cross-industry knowledge flows in the spatial development of AI entrepreneurship (Doloreux & Turkina, 2023).

The results of our research also contribute to the recent dynamic perspective on Technological Innovation Systems (Markard, 2020). From this standpoint, the evolution of such systems depends on changes within their constituent components and the relationships among them. Our findings align with this dynamic understanding of technological development. As evidenced by the European AI industry, in the nascent stages of an emerging sector one of the central challenges lies in establishing a dominant technological standard and an overarching architectural framework for delivering goods and services supported by that technology. At this point, most firms remain uncertain about the optimal combination of knowledge needed to shape the standard and, consequently, face high levels of technological risk. Under such conditions, entrepreneurs must leverage external factors—such as ongoing technological advances and shifting market conditions—to navigate uncertainty (Donaldson et al., 2024). Firms therefore engage in processes of trial and error, seeking to expand their knowledge base by identifying the most effective sources of relevant expertise.

To engage in processes of trial and error, firms require access to diverse sources of knowledge, including insights from other firms within the same sector. It is therefore reasonable to assume that in contexts of high technological risk, entrepreneurs will prefer locations with strong agglomeration effects, which facilitate intensive knowledge exchanges and spillovers. Our findings support this expectation. In regions with a low concentration of AI firms, the creation of new ventures is positively influenced by both the regional knowledge base and intra-industry colocation effects, underscoring the role of strategic experimentation and knowledge legitimation in the early evolution of sectors such as artificial intelligence. By contrast, access to venture capital does not show a significant effect on the entry of new firms. Its importance may vary across regions, where alternative sources—such as public funding or corporate investment—can play a more decisive role (Hyun & Kim, 2024).

The findings also indicate that in regions with a notable concentration of AI ventures, the importance of knowledge spillovers for fostering new firm formation is reduced. Spillovers are typically most pronounced in the early stages of an industry but diminish as the industry's knowledge base matures (Faggio et al., 2020; Sandulli et al., 2012). In later phases, knowledge flows related to practical applications within value chains gain greater significance than fundamental technological knowledge. Consequently, AI startups should strategically locate where their business models can generate synergies with complementary actors in the innovation ecosystem. These results on cross-industry effects align with empirical studies adopting a dynamic perspective (e.g., Hanlon & Miscio, 2014; Wang et al., 2014), which emphasize knowledge accumulation and uncertainty reduction in industry development. In this respect, Moeen et al. (2020) conceptualize industry emergence as a sequential process marked by milestones that progressively reduce technological, market, and organizational uncertainty.

Even after technological risks are mitigated, launching a startup in a nascent industry remains inherently risky, largely due to the extended process of validating business models. Whereas technological spillovers are relatively more accessible—given the explicit and codifiable nature of much technical knowledge—business knowledge is less observable and often embedded in tacit, context-dependent practices. Thus, in the early stages of industry development there is a critical phase in which technological risks are more effectively addressed than commercial risks, leaving startups particularly vulnerable to uncertainties surrounding market acceptance and operational viability.

As the industry matures, the marginal contribution of technological knowledge flows declines, while market access becomes increasingly important in mitigating commercial risk. Market access depends on the presence of industries that can serve as customers or suppliers for new firms, or on integration into global value chains that connect startups to external markets. Under these conditions, the most effective innovation systems are either those embedded in global value chains or those underpinned by a strong base of customer industries relevant to the emerging sector. This foundation may be provided by large corporations operating in customer markets or by clusters of SMEs linked to these industries (Hanlon & Miscio, 2014).

5.1. Theoretical implications

The findings of this study contribute to advancing theoretical debates in evolutionary economic geography and entrepreneurship by clarifying the mechanisms underpinning AI industry emergence. First, the evidence reinforces the notion that industry emergence is shaped by path-dependent processes rooted in regional capabilities, institutions, and accumulated knowledge bases (Boschma & Frenken, 2006). The co-location of AI firms and the resulting collective learning highlight how spatial proximity and historical contingency condition the trajectory of new industries. At the same time, the results show that beyond a certain saturation point agglomeration economies lose their effectiveness, suggesting the need to nuance classical accounts of clustering with attention to non-linear dynamics and threshold effects.

Consistent with Gustafsson et al.'s (2016) three-stage model of industry emergence (initial disruption, co-evolutionary convergence, and growth), our research demonstrates that AI start-ups follow a sequential logic in which the drivers of entrepreneurship shift over time. In the nascent phase, co-location and intra-industry spillovers dominate, reflecting earlier research that emphasizes uncertainty reduction through technological experimentation and collective learning. As AI matures, however, cross-industry linkages become central, aligning with the co-evolutionary phase in which business models, value chains, and standards stabilize. This confirms that AI is not merely another case of cluster formation but a paradigmatic example of how industry evolution requires attention to stage-specific mechanisms.

The findings also extend cluster-based theories by integrating the concept of *catalyzing places* (Aversa et al., 2022). While clusters are conventionally understood as territorially bounded agglomerations that sustain industries locally, the AI ecosystem exhibits dynamics closer to catalyzing logics. Relational proximities—linkages to international hubs, multinational anchor firms, and global knowledge flows—operate as "portable economies" that entrepreneurs can redeploy beyond the initial cluster. In this way, the study bridges the dichotomy between clustering and dispersal, showing how AI start-ups benefit simultaneously from localized knowledge spillovers and translocal catalytic effects that reinforce legitimacy and market reach.

The results also contribute to industry life-cycle theory by highlighting the stage-specific drivers of emergence. In the earliest phase, entrepreneurs mitigate high technological risk by locating near fellow AI innovators and dense R&D knowledge (intra-industry co-location). As the AI industry matures and key technological standards emerge, cross-sector connections, customer industries, and access to markets become more important for managing commercial risk. This sequential shift supports milestone-based conceptions of industry emergence (Moeen et al., 2020), while also illustrating that these phases unfold unevenly across space. Our evidence therefore refines life-cycle perspectives by showing how agglomeration advantages are strongest at inception but give way to more diverse, market-oriented agglomerative factors in later stages.

In this sense, the study also offers insights for knowledge spillover theory. Consistent with Acs et al. (2009), regions with sparse AI activity benefit most from local knowledge stocks and intra-industry exchanges, as new firms capitalize on existing scientific and engineering expertise. Yet, once an AI hub passes a critical density threshold, the marginal contribution of additional local spillovers diminishes rapidly. Knowledge spillovers, therefore, are most pronounced during nascent phases, after which entrepreneurial success increasingly depends on combining external and cross-sectoral sources of knowledge. This pattern refines spillover theory by emphasizing stage-contingent and diminishing returns to local knowledge in emerging, knowledge-intensive sectors.

Our research further advances theory by highlighting the interplay between technological and commercial risks as the structuring principle of AI's geography. Whereas agglomeration economies mitigate technological risks in the early stages, cross-industry interactions and institutional diversity address persistent commercial risks. This result contributes to understanding transitions between emergence stages and provides new evidence supporting cyclical forces (centripetal, catalyzing, centrifugal) that propel industries beyond their original locations. Taken together, these insights clarify why AI start-up ecosystems are path-dependent yet globally interconnected, and why their sustainability depends on managing shifting risk profiles through both local and translocal resources.

Finally, the analysis highlights the importance of multi-scalar and relational perspectives for understanding AI industry emergence. Rather than spreading uniformly, the geography of AI is best described as hub-and-network structures. Strong regional innovation systems provide an essential foundation, yet leading AI clusters also depend on global linkages and cross-sectoral complementarities. Regions that host multinational firms are particularly conducive to AI start-ups, since these organizations serve as sophisticated users and sources of combinatorial knowledge. At later stages, successful hubs remain embedded in international value chains and sustain relational proximity to distant innovation centers. These dynamics imply that agglomeration and regional-innovation frameworks must accommodate stage-dependent shifts in locational logic and the growing importance of multi-sectoral, multi-scalar connections in the spatial formation of new technological industries. This perspective also connects to debates on digital divides, resilience, and uneven socio-economic outcomes of technological change (Abbas et al., 2026; David et al., 2025), as well as on the organizational and workplace transformations associated with AI adoption (Anthony et al., 2023; Dabić et al., 2023).

Overall, the theoretical implication is that AI exemplifies a new model of industry emergence: one that is sequential (as per life-cycle theories), multi-scalar (bridging clusters and catalyzing places), and risk-mediated (balancing technological and commercial uncertainties). This model advances economic geography and entrepreneurship literatures by demonstrating that general-purpose technologies such as AI require a dynamic, hybrid lens that accounts for both local embedding and global dispersion in the formation of new industries.

5.2. Implications for practice

The consolidation of a new industry progresses at varying rates across regions (Hanlon & Miscio, 2014). This variation reflects the complex interaction between the trajectory of industry emergence and the specific contextual factors of each locality. Accordingly, policymakers and entrepreneurs in the AI industry must carefully assess the stage of development in their respective regions. Efforts should be context-sensitive—adapted to local conditions—and aligned with region-specific needs to support industry growth. On the one hand, public policies aimed at addressing technological challenges must prioritize strengthening the industry-specific knowledge base that forms the foundation for nascent industries. Technological startups derive greater benefits from policies that encourage knowledge exchange than from those focused exclusively on financing innovation (Gimenez-Fernandez et al., 2020). On the other hand, policies designed to mitigate commercial challenges should concentrate on fostering a broad, cross-sectoral knowledge base.

Such measures may include initiatives that promote collaboration between research and development centers and leading universities (Gallego et al., 2013), or cultivate informal networks between regional professionals and peers in knowledge-intensive hubs elsewhere (Aversa et al., 2022; Gimenez-Fernandez et al., 2022). Regions should also develop innovation brokerage mechanisms that effectively foster connections between startups and firms in other complementary industries within the innovation system. These mechanisms may take different forms, including formal entities such as local development agencies (Sandulli et al., 2021), or informal structures such as innovation commons and communities of practice (Aversa et al., 2022; Cuntz & Peuckert, 2023).

Beyond entrepreneurial activity, commercial challenges may also extend to large firms, often due to uncertainty regarding appropriate investment time horizons. Likewise, governments may struggle to achieve the expected political returns on investments in the emerging technology (Corallo et al., 2019). The social and institutional conditions of regions—such as favorable living environments—have proved to be essential for mitigating these commercial challenges, as they influence the ecosystem's ability to attract and retain key strategic resources (Moulaert & Gallouj, 1993).

5.3. Limitations and future research

This work is not without limitations. First, patents remain an imperfect proxy for capturing a region's knowledge base. Although they are a valuable tool for analyzing regional innovation dynamics (Acs et al., 2009; Plummer & Acs, 2014), many innovations are not patented or not eligible for patent protection. For example, the European Patent Office only grants patents for software under the category of "computer-implemented inventions." As a result, many advances in artificial intelligence are excluded from the analysis, which may help explain the disparities observed in Table 2 regarding the distribution of AI patents and startup growth across Europe.

Second, the study's focus on the AI sector raises questions about the generalizability of its findings. Whether comparable patterns hold in other emerging, knowledge-intensive sectors remains an open question for future research. Third, the analysis is limited to seven major economic regions. Future work could test the applicability of the two-stage industry emergence process across a wider variety of economic and social contexts. In this regard, research might also employ tailored perspectives that account for the distinctive characteristics of different geographic locations.

6. Conclusion

This study highlights the dynamic interplay between technological and commercial risks in shaping the emergence of the AI industry. The findings support the view of industry formation as a sequential process marked by milestones that progressively reduce uncertainty. In the early stages, AI startups benefit primarily from intra-industry co-location effects and knowledge spillovers, which are particularly effective in mitigating technological risks. As the industry matures, however, firms increasingly rely on cross-industry interactions, which play a more decisive role in addressing commercial risks. These dynamics underscore the importance of adopting a dynamic and context-sensitive perspective that captures the regionally uneven and evolving trajectories of AI industry development and consolidation.

CRediT authorship contribution statement

Óscar Vásquez: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco D. Sandulli:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jorge Gallego:** Writing – review & editing, Writing – original draft, Validation, Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

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

Acknowledgement

This work was supported by the Community of Madrid under Grant No. PHS-2024/PH-HUM-530.

Data availability

Data will be made available on request.

References

Abbas, J., Dabić, M., & Stojčić, N. (2026). Digital divide in industry 5.0: Role of generative AI knowledge bases and intellectual capital in organizational resilience performance under territorial proximity. *Technovation, 149*, Article 103357. https://doi.org/10.1016/j.technovation.2025.103357

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6). https://www.journals.uchicago.edu/doi/full/10.1086/705716.

Acs, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 32*(1), 15–30. https://doi.org/10.1007/s11187-008-9157-3

Agarwal, R., Guerra, M., Moeen, M., & Aversa, P. (2025). Creating new industries: The generative role of heterogeneous actors. *The Academy of Management Annals*. https://doi.org/10.5465/annals.2023.0244. annals.2023.0244.

Allison, P. D., & Waterman, R. P. (2002). Fixed-effects negative binomial regression models. *Sociological Methodology, 32*(1), 247–265. https://doi.org/10.1111/1467-9531.00117

Anthony, C., Bechky, B. A., & Fayard, A. L. (2023). "Collaborating" with AI: Taking a system view to explore the future of work. *Organization Science, 34*(5), 1672–1694. https://doi.org/10.1287/orsc.2022.1651

Arauzo-Carod, J.-M., & Manjón-Antolín, M. (2012). (Optimal) spatial aggregation in the determinants of industrial location. *Small Business Economics, 39*(3), 645–658. https://doi.org/10.1007/s11187-011-9335-6

Audretsch, B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy, 14*(2), 18–29. https://doi.org/10.1093/oxrep/14.2.18

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review, 86*(3), 630–640. https://www.jstor.org/stable/2118216.

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal, 12*(1), 72–95. https://doi.org/10.1002/sej.1266

Aversa, P., Bianchi, E., Gaio, L., & Nucciarelli, A. (2022). The grand tour: The role of catalyzing places for industry emergence. *Academy of Management Journal, 65*(6), 2058–2091. https://doi.org/10.5465/amj.2019.1303

Ayres, R. U. (1990). Technological transformations and long waves. Part I. *Technological Forecasting and Social Change, 37*(1), 1–37. https://doi.org/10.1016/0040-1625(90)90057-3

Baptista, R., & Mendonça, J. (2010). Proximity to knowledge sources and the location of knowledge-based start-ups. *The Annals of Regional Science, 45*(1), 5–29. https://doi.org/10.1007/s00168-009-0289-4

Bathelt, H., & Glückler, J. (2003). Toward a relational economic geography. *Journal of Economic Geography, 3*(2), 117–144. https://www.jstor.org/stable/26160454.

Berger, T., & Frey, C. B. (2017). Industrial renewal in the 21st century: Evidence from US cities. *Regional Studies, 51*(3), 404–413. https://doi.org/10.1080/00343404.2015.1100288

Boschma, R. (2024). An evolutionary approach to regional studies on global value chains. *Regional Studies, 58*(7), 1492–1500. https://doi.org/10.1080/00343404.2024.2323035

Boschma, R., Coenen, L., Frenken, K., & Truffer, B. (2017). Towards a theory of regional diversification: Combining insights from evolutionary economic geography and transition studies. *Regional Studies, 51*(1), 31–45. https://doi.org/10.1080/00343404.2016.1258460

Boschma, R. A., & Frenken, K. (2006). Why is economic geography not an evolutionary science? Towards an evolutionary economic geography. *Journal of Economic Geography, 6*(3), 273–302. https://doi.org/10.1093/jeg/lbi022

Bratanova, A., Pham, H., Mason, C., Hajkowicz, S., Naughtin, C., Schleiger, E., Sanderson, C., Chen, C., & Karimi, S. (2022). Differentiating artificial intelligence activity clusters in Australia. *Technology in Society, 71*, Article 102104. https://doi.org/10.1016/j.techsoc.2022.102104

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics, 65*(1), 83–108. https://doi.org/10.1016/0304-4076(94)01598-T

Cooke, P. (1992). Regional innovation systems: Competitive regulation in the new Europe. *Geoforum, 23*(3), 365–382. https://doi.org/10.1016/0016-7185(92)90048-9

Cooke, P. (2001). Regional innovation systems, clusters, and the knowledge economy. *Industrial and Corporate Change, 10*(4), 945–974. https://doi.org/10.1093/icc/10.4.945

Cooke, P. N., & De Laurentis, C. (2010). In R. Boschma, & R. Martin (Eds.), *Evolutionary economic geography, regional systems of innovation and high-tech clusters* (pp. 239–259). Edward Elgar. https://orca.cardiff.ac.uk/id/eprint/14964/.

Corallo, A., Errico, F., Latino, M. E., & Menegoli, M. (2019). Dynamic business models: A proposed framework to overcome the death valley. *Journal of the Knowledge Economy, 10*(3), 1248–1271. https://doi.org/10.1007/s13132-018-0529-x

Crescenzi, R., Iammarino, S., Ioramashvili, C., Rodríguez-Pose, A., & Storper, M. (2020). *The geography of innovation and development: Global spread and local hotspots (monograph No. 4)*. Department of Geography and Environment, LSE. http://www.lse.ac.uk/geography-and-environment/research/discussion-paper-series.

Cuntz, A., & Peuckert, J. (2023). From hackers to start-ups: Innovation commons and local entrepreneurial activity. *Research Policy, 52*(2), Article 104675. https://doi.org/10.1016/j.respol.2022.104675

Dabić, M., Maley, J. F., Švarc, J., & Poček, J. (2023). Future of digital work: Challenges for sustainable human resources management. *Journal of Innovation & Knowledge, 8*(2), Article 100353. https://doi.org/10.1016/j.jik.2023.100353

David, L. K., Wang, J., Brooks, W., & Angel, V. (2025). Digital transformation and socio-economic development in emerging economies: A multinational analysis. *Technology in Society, 81*, Article 102834. https://doi.org/10.1016/j.techsoc.2025.102834

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy, 43*(10), 1785–1799. https://doi.org/10.1016/j.respol.2014.05.007

Doloreux, D., & Turkina, E. (2021). New path creation in the artificial intelligence industry: Regional preconditions, new actors and their collective actions, and policies. *Regional Studies, 55*(10–11), 1751–1763. https://doi.org/10.1080/00343404.2021.1919610

Doloreux, D., & Turkina, E. (2023). Intermediaries in regional innovation systems: An historical event-based analysis applied to AI industry in Montreal. *Technology in Society, 72*, Article 102192. https://doi.org/10.1016/j.techsoc.2022.102192

Donaldson, C., Villagrasa, J., Alegre, J., & Liguori, E. W. (2024). Back to the future: Entrepreneurial leadership and levelling up in the mobile-gaming sector. *Technology in Society, 79*, Article 102748. https://doi.org/10.1016/j.techsoc.2024.102748

Faggio, G., Silva, O., & Strange, W. C. (2020). Tales of the city: What do agglomeration cases tell us about agglomeration in general? *Journal of Economic Geography, 20*(5), 1117–1143. https://doi.org/10.1093/jeg/lbaa007

Feldman, M. P. (1994). Knowledge complementarity and innovation. *Small Business Economics, 6*(5), 363–372. https://www.jstor.org/stable/40239909.

Ferreira, J. J. M., Fernandes, C. I., Raposo, M. L., Thurik, R., & Faria, J. R. (2016). Entrepreneur location decisions across industries. *The International Entrepreneurship and Management Journal, 12*(4), 985–1006. https://doi.org/10.1007/s11365-015-0370-7

Gallego, J., Rubalcaba, L., & Suárez, C. (2013). Knowledge for innovation in Europe: The role of external knowledge on firms' cooperation strategies. *Journal of Business Research, 66*(10), 2034–2041. https://doi.org/10.1016/j.jbusres.2013.02.029

Giglio, C., Corvello, V., Coniglio, I. M., Kraus, S., & Gast, J. (2025). Cooperation between large companies and start-ups: An overview of the current state of research. *European Management Journal, 43*(1), 142–153. https://doi.org/10.1016/j.emj.2023.08.002

Gimenez-Fernandez, E. M., Ferraris, A., Troise, C., & Sandulli, F. D. (2022). Openness strategies and the success of international entrepreneurship. *International Journal of Entrepreneurial Behavior & Research, 28*(4), 935–951. https://doi.org/10.1108/IJEBR-09-2021-0745

Gimenez-Fernandez, E. M., Sandulli, F. D., & Bogers, M. (2020). Unpacking liabilities of newness and smallness in innovative start-ups: Investigating the differences in innovation performance between new and older small firms. *Research Policy, 49*(10), Article 104049. https://doi.org/10.1016/j.respol.2020.104049

Grodal, S., Gotsopoulos, A., & Suarez, F. F. (2015). The coevolution of technologies and categories during industry emergence. *Academy of Management Review, 40*(3), 423–445. https://doi.org/10.5465/amr.2013.0359

Gustafsson, R., Jääskeläinen, M., Maula, M., & Uotila, J. (2016). Emergence of industries: A review and future directions. *International Journal of Management Reviews, 18*(1), 28–50. https://doi.org/10.1111/ijmr.12057

Hanlon, W., & Miscio, A. (2014). *Agglomeration: A dynamic approach*. National Bureau of Economic Research. https://doi.org/10.3386/w20728. Working Paper No. 20728.

Hanna, V., & Walsh, K. (2008). Interfirm cooperation among small manufacturing firms. *International Small Business Journal, 26*(3), 299–321. https://doi.org/10.1177/0266242608088740

Hassink, R., Isaksen, A., & Trippl, M. (2019). Towards a comprehensive understanding of new regional industrial path development. *Regional Studies, 53*(11), 1636–1645. https://doi.org/10.1080/00343404.2019.1566704

Henderson, J. V. (1974). The sizes and types of cities. *The American Economic Review, 64*(4), 640–656. https://www.jstor.org/stable/1813316.

Hong, S., Hsu, D. H., & Subramanian, V. (2024). The evolution of U.S. Entrepreneurial and innovation ecosystems in artificial intelligence: Geographic pull factors. *Social Science Research Network*. https://doi.org/10.2139/ssrn.4831296 (SSRN Scholarly Paper No. 4831296).

Hsu, G., & Grodal, S. (2021). The double-edged sword of oppositional category positioning: A study of the U.S. E-Cigarette category, 2007–2017. *Administrative Science Quarterly, 66*(1), 86–132. https://doi.org/10.1177/0001839220914855

Humphrey, J., & Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters? *Regional Studies, 36*(9), 1017–1027. https://doi.org/10.1080/0034340022000022198

Hyun, E., & Kim, B. T.-S. (2024). Overcoming uncertainty in novel technologies: The role of venture capital syndication networks in artificial intelligence (AI) startup investments in korea and Japan. *Systems, 12*(3), 3. https://doi.org/10.3390/systems12030072

Iammarino, S., & McCann, P. (2006). The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy, 35*(7), 1018–1036. https://doi.org/10.1016/j.respol.2006.05.004

Johansson, J. M., & Malmstrom, M. (2013). The business model transparency paradox in innovative growth ventures: Trade-offs between competitive advantages and agency costs. *Entrepreneurship Research Journal, 3*(2), 238–263. https://doi.org/10.1515/erj-2012-0011

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy, 99*(3), 483–499. https://www.jstor.org/stable/2937739.

Lammers, T., Cetindamar, D., & Borkert, M. (2021). A digital tale of two cities—observing the dynamics of the artificial intelligence ecosystems in Berlin and sydney. *Sustainability, 13*(19), 19. https://doi.org/10.3390/su131910564

Liao, J., Welsch, H., & Moutray, C. (2008). Start-up REsources and entrepreneurial discontinuance: The case of nascent entrepreneurs. *Journal of Small Business Strategy, 19*(2), 1–16. https://jsbs.scholasticahq.com/article/26503-start-up-resources-and-entrepreneurial-discontinuance-the-case-of-nascent-entrepreneurs.

Markard, J. (2020). The life cycle of technological innovation systems. *Technological Forecasting and Social Change, 153*, Article 119407. https://doi.org/10.1016/j.techfore.2018.07.045

Markham, S. K. (2002). Moving technologies from lab to market. *Research-Technology Management, 45*(6), 31–42. https://doi.org/10.1080/08956308.2002.11671531

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics, 23*(2), 167–185. https://doi.org/10.1093/cje/23.2.167

McCann, P., & Oort, F. van (2019). Chapter 1: Theories of agglomeration and regional economic growth: A historical review. https://www.elgaronline.com/edcollchap/edcoll/9781788970013/9781788970013.00007.xml.

McKelvey, F., & MacDonald, M. (2019). Artificial intelligence policy innovations at the Canadian federal government. *Canadian Journal of Communication, 44*(2), 43. https://doi.org/10.22230/cjc.2019v44n2a3509

Modrego, F., McCann, P., Foster, W. E., & Olfert, M. R. (2017). Location and entrepreneurship: Insights from a spatially-explicit occupational choice model with an application to Chile. *Journal of Regional Science, 57*(4), 669–697. https://doi.org/10.1111/jors.12323

Moeen, M., Agarwal, R., & Shah, S. K. (2020). Building industries by building knowledge: Uncertainty reduction over industry milestones. *Strategy Science, 5*(3), 218–244. https://doi.org/10.1287/stsc.2020.0103

Moulaert, F., & Gallouj, C. (1993). The locational geography of advanced producer service firms: The limits of economies of agglomeration. *Service Industries Journal, 13*(2), 91–106. https://doi.org/10.1080/02642069300000032

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: A new era has begun. *Small Business Economics, 55*(3), 529–539. https://doi.org/10.1007/s11187-019-00202-4

Plummer, L. A., & Acs, Z. J. (2014). Localized competition in the knowledge spillover theory of entrepreneurship. *Journal of Business Venturing, 29*(1), 121–136. https://doi.org/10.1016/j.jbusvent.2012.10.003

Porter, M. E. (1996). Competitive advantage, agglomeration economies, and regional policy. *International Regional Science Review, 19*(1–2), 85–90. https://doi.org/10.1177/016001769601900208

Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal, 22*(4), 287–306. https://doi.org/10.1002/smj.160

Sandulli, F. D., Fernandez-Menendez, J., Rodriguez-Duarte, A., & Lopez-Sanchez, J. I. (2012). Testing the Schumpeterian hypotheses on an open innovation framework. *Management Decision, 50*(7), 1222–1232. https://doi.org/10.1108/00251741211246978

Sandulli, F. D., Gimenez-Fernandez, E. M., & Rodriguez Ferradas, M. I. (2021). The transition of regional innovation systems to Industry 4.0: The case of Basque Country and Catalonia. *European Planning Studies, 29*(9), 1622–1636. https://doi.org/10.1080/09654313.2021.1963049

Santarelli, E., Staccioli, J., & Vivarelli, M. (2023). Automation and related technologies: A mapping of the new knowledge base. *The Journal of Technology Transfer, 48*(2), 779–813. https://doi.org/10.1007/s10961-021-09914-w

Scaringella, L., & Radziwon, A. (2018). Innovation, entrepreneurial, knowledge, and business ecosystems: Old wine in new bottles? *Technological Forecasting and Social Change, 136*, 59–87. https://doi.org/10.1016/j.techfore.2017.09.023

Shi, G., Ma, Z., Feng, J., Zhu, F., Bai, X., & Gui, B. (2020). The impact of knowledge transfer performance on the artificial intelligence industry innovation network: An empirical study of Chinese firms. *PLoS One, 15*(5), Article e0232658. https://doi.org/10.1371/journal.pone.0232658

Silva, J. M. C. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics, 88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Sine, W. D., Haveman, H. A., & Tolbert, P. S. (2005). Risky business? Entrepreneurship in the new independent-power sector. *Administrative Science Quarterly, 50*(2), 200–232. https://doi.org/10.2189/asqu.2005.50.2.200

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies, 23*(9), 1759–1769. https://doi.org/10.1080/09654313.2015.1061484

Tavassoli, S., & Carbonara, N. (2014). The role of knowledge variety and intensity for regional innovation. *Small Business Economics, 43*(2), 493–509. https://doi.org/10.1007/s11187-014-9547-7

Turkina, E., Van Assche, A., & Doloreux, D. (2021). How do firms in co-located clusters interact? Evidence from greater Montreal. *Journal of Economic Geography, 21*(5), 761–782. https://doi.org/10.1093/jeg/lbaa019

Vedula, S., & Kim, P. H. (2019). Gimme shelter or fade away: The impact of regional entrepreneurial ecosystem quality on venture survival. *Industrial and Corporate Change, 28*(4), 827–854. https://doi.org/10.1093/icc/dtz032

Waisberg, E., Ong, J., Kamran, S. A., Masalkhi, M., Zaman, N., Sarker, P., Lee, A. G., & Tavakkoli, A. (2023). Bridging artificial intelligence in medicine with generative pre-trained transformer (GPT) technology. *Journal of Medical Artificial Intelligence, 6*(0). https://doi.org/10.21037/jmai-23-36. Article 0.

Wang, R., Guo, L., Cao, C., & Chen, Y. (2023). The key success factors of the AI industry entrepreneurial process in China great bay area: A systematic approach study. *Technological Forecasting and Social Change, 186*, Article 122170. https://doi.org/10.1016/j.techfore.2022.122170

Wang, J., Liu, Y., Wang, W., & Wu, H. (2024). Does artificial intelligence improve enterprise carbon emission performance? Evidence from an intelligent transformation policy in China. *Technology in Society, 79*, Article 102751. https://doi.org/10.1016/j.techsoc.2024.102751

Wang, L., Madhok, A., & Xiao Li, S. (2014). Agglomeration and clustering over the industry life cycle: Toward a dynamic model of geographic concentration. *Strategic Management Journal, 35*(7), 995–1012. https://doi.org/10.1002/smj.2141

Weiblen, T., & Chesbrough, H. W. (2015). Engaging with startups to enhance corporate innovation. *California Management Review, 57*(2), 66–90. https://doi.org/10.1525/cmr.2015.57.2.66

Wooldridge, J. M. (1999). Quasi-likelihood methods for count data. In *Handbook of applied econometrics volume 2: Microeconomics* (pp. 321–368). John Wiley and Sons, Ltd. https://doi.org/10.1111/b.9780631216339.1999.00009.x.

Yu, Z., Liang, Z., & Xue, L. (2022). A data-driven global innovation system approach and the rise of China's artificial intelligence industry. *Regional Studies, 56*(4), 619–629. https://doi.org/10.1080/00343404.2021.1954610