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Modeling Early Diffusion of AI Patents: Institutional Roles, Compute Intensity, and Knowledge Diversity

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Abstract

Purpose: This study examines the factors that accelerate early citations in artificial intelligence (AI) patents and investigates how these determinants vary across countries. By integrating perspectives from innovation management and engineering management, the research aims to clarify how collaboration structures, technological attributes, and knowledge diversity influence the diffusion speed of AI-related inventions. **Design/methodology/approach:** This study utilizes a global patent dataset encompassing major countries to estimate the time to first citation for each AI patent using Cox proportional hazards models. We test five hypotheses: university collaboration, government research institution involvement, computational resource coherence, technological prominence, and knowledge diversity. **Findings:** The results above reveal that the initial citation speed of AI patents is explained by the development of AI computational resources (H3), the visibility of the technology (H4), the diversification of application domains (H5), and the nature of the research entities (H1, H2). **Research limitations/implications:** This study focuses on patent-level data and does not include other R&D outputs such as research papers. It also excludes firm-level strategic variables, such as R&D intensity. Future research could deepen causal inference by integrating firm characteristics and longitudinal collaborative networks. **Practical implications:** These findings provide practical insights for R&D managers and policymakers. Strengthening industry-academia-government collaboration and expanding R&D investment may accelerate the adoption of AI technologies. **Originality/value:** This study is among the

first to apply survival analysis to AI patents across multiple countries, combining claims-level text analytics with innovation management theory. It contributes to understanding how engineering and organizational factors jointly shape the diffusion dynamics of AI innovations.
Keywords: Artificial Intelligence Patents, Knowledge Diffusion, Cox Proportional Hazards Model, Triple Helix

Introduction

Artificial intelligence (AI) has emerged as a central driver of technological transformation across industries, influencing innovation processes and reshaping competitive dynamics. In this rapidly evolving landscape, patents serve as a critical indicator of technological progress and knowledge diffusion, particularly within AI-related research and development (R&D). However, the speed at which AI patents are cited—reflecting how quickly new knowledge is absorbed and built upon by subsequent innovations—varies considerably across countries and organizations. Understanding what accelerates early citation in AI patents is therefore essential for clarifying how knowledge flows through global innovation ecosystems.

Prior studies have primarily examined patent citations from the perspectives of technological significance or inventor collaboration (Hall et al., 2005; Nakaoka et al., 2025; Park et al., 2025). However, few have explored the temporal dynamics of early citation using survival analysis, especially within the context of AI technologies. Moreover, because AI innovation depends heavily on computational resources, interdisciplinary expertise, and institutional collaboration, the extent to which these factors shape citation speed remains insufficiently explored.

Building on the innovation diffusion and organizational collaboration literature (Abernathy & Utterback, 1978; Ancona & Caldwell, 1992; Pelled et al., 1999; Wong, 2004), this study integrates perspectives from the resource-based view and the Triple Helix model of university–industry–government relations (Etzkowitz & Leydesdorff, 2000). The Triple Helix framework emphasizes that innovation emerges from dynamic interactions among academic institutions, industry actors, and governmental bodies, creating hybrid organizations and networks that foster knowledge exchange and technological development. This theoretical lens provides a valuable foundation for examining collaborative dynamics in AI research, where cross-sector partnerships often play a pivotal role in accelerating knowledge diffusion. To empirically investigate these mechanisms, the present study applies a Cox proportional hazards model to a large-scale dataset of AI patents from major economies, including the United States, China, Japan, and South Korea. Five determinants are examined: university collaboration, government research institution involvement, computational resource alignment, technological prominence, and knowledge diversity. By integrating these dimensions, this research aims to reveal how organizational collaboration structures and technical attributes jointly influence the early diffusion of AI-related inventions, and how these mechanisms differ across national innovation systems (Lee & Lim, 2001; Zenglein & Holzmann, 2019).

Literature Review

Innovation research has long emphasized the role of collaboration and organizational learning in driving technological progress. Abernathy and Utterback (1978) proposed that industries evolve through patterns of incremental and radical innovation, where technological and organizational capabilities co-develop. Building on this, Tushman and O'Reilly (1996) introduced the concept of ambidextrous organizations, emphasizing the need to balance exploration and exploitation in innovation processes. Within this framework, collaboration among diverse actors—universities, firms, and government institutions—has been recognized as a critical source of innovation synergy (Etzkowitz & Leydesdorff, 2000). The Triple Helix model suggests that innovation increasingly arises from interactions across institutional boundaries, where universities provide scientific knowledge, industry contributes application expertise, and governments offer regulatory and financial support. Such collaborations are especially relevant in the field of artificial intelligence (AI), where innovation depends on both computational resources and interdisciplinary expertise (Etzkowitz, 2003).

Research on patent citations provides a quantitative perspective on knowledge diffusion. Hall, Jaffe, and Trajtenberg (2005) demonstrated that patent citations serve as indicators of technological value and knowledge flow across organizational boundaries. Uzzi and Spiro (2005) extended this notion by linking the structure of collaborative networks to creativity, showing that small-world network properties enhance innovation diffusion. Subsequent studies applied survival analysis to patent data to examine the timing of knowledge diffusion, revealing that early citations reflect rapid recognition and absorption of novel ideas (Fleming et al. 2007). However, few studies have systematically applied survival models to AI-related patents, despite their distinct dependence on computational infrastructure and cross-disciplinary integration.

Organizational behavior and team diversity research also offer valuable insights for understanding patent-level collaboration. Ancona and Caldwell (1992) emphasized that external boundary-spanning activities enhance team performance by facilitating the exchange of diverse knowledge and expertise. Similarly, Pelled, Eisenhardt, and Xin (1999) and Wong (2004) showed that cognitive and functional diversity can generate both constructive conflict and learning benefits within R&D teams. These findings align with the perspective that diversity in inventor backgrounds or institutional affiliations contributes to the quality of innovation and its diffusion speed. In the AI sector, where technological convergence and hybrid knowledge are critical, such diversity may accelerate early citations by enhancing the applicability and visibility of new inventions.

At the national level, differences in innovation systems also influence the dissemination of AI knowledge. Lee and Lim (2001) argued that national innovation systems determine technological trajectories, influencing how firms catch up or leapfrog in emerging fields. Zenglein and Holzmann (2019) highlighted that industrial policies, such as China's *Made in China 2025*, play a vital role in fostering AI-related R&D through state–industry coordination. Integrating these perspectives suggests that cross-national variations in university–industry–government collaboration, computational resource availability, and industrial policy frameworks can create heterogeneous diffusion patterns for AI patents. In addition, recent work conceptualizes AI as a general-purpose technology whose impact depends critically on complementary assets and diffusion dynamics across sectors (Cockburn, Henderson, & Stern, 2018; McElheran et al., 2023).

Collectively, the existing literature underscores the multifaceted nature of innovation diffusion, integrating organizational, technological, and policy perspectives. Nevertheless, empirical studies that jointly examine collaboration structures, technological characteristics, and national differences in shaping early AI patent citations remain limited. Addressing this gap, the present study applies the Cox proportional hazards model to identify the determinants of early citation in AI patents, focusing on five key factors: university collaboration, government involvement, compute-resource alignment, technological hotness, and knowledge diversity.

Hypothesis Development

H1: University R&D

Prior research emphasizes that collaboration with universities enhances the novelty and applicability of inventions through access to scientific knowledge and exploratory research (Etzkowitz & Leydesdorff, 2000; Etzkowitz, 2003). In AI-related innovation, where algorithmic development and theoretical grounding are essential, such university involvement can increase the visibility and perceived quality of patents, leading to earlier recognition through citations.

Hypothesis 1 (H1): AI patents applied by universities are more likely to be cited early.

H2: Government research institution involvement

Government research institutes contribute to innovation diffusion by providing funding, infrastructure, and national strategic direction (Lee & Lim, 2001; Zenglein & Holzmann, 2019). Their participation may legitimize emerging technologies and reduce uncertainty, especially in regulated or strategic sectors such as AI, thereby encouraging earlier uptake and citation by other actors.

Hypothesis 2 (H2): AI patents applied by government research institutes are more likely to be cited early.

H3: Computational resource alignment

AI technologies are uniquely dependent on computational infrastructure such as GPUs, cloud platforms, and data pipelines. Patents closely aligned with prevailing hardware and computer architectures are more directly implementable and compatible with existing ecosystems, which can accelerate their adoption and early citation.

Hypothesis 3 (H3): AI patents with higher alignment to computational resources are more likely to receive early citations.

H4: Technological hotness (emerging field intensity)

In rapidly evolving sectors, patents positioned in “hot” technological clusters—those receiving high contemporary attention—are more visible and thus more rapidly cited (Hall, Jaffe, & Trajtenberg, 2005; Uzzi & Spiro, 2005). Given the dynamic nature of AI, patents located in fast-growing technological areas are especially likely to benefit from such momentum effects.

Hypothesis 4 (H4): AI patents in rapidly growing technological areas are more likely to receive early citations.

H5: Knowledge diversity

Diverse technological and disciplinary foundations facilitate recombination and knowledge spillover, which enhance the visibility and diffusion of new inventions (Ancona & Caldwell, 1992; Pelled, Eisenhardt, & Xin, 1999). In the AI domain, patents covering multiple

International Patent Classification (IPC) categories can appeal to broader technological communities and thereby attract earlier citations.
Hypothesis 5 (H5): AI patents encompassing a greater diversity of technological domains are more likely to receive early citations.

Methodologies

Data Retrieval and Preprocessing

This study utilizes AI-related patent information filed between 2010 and 2024 to elucidate the factors behind citation lags based on the aforementioned H1-H5 hypotheses. Patents concerning “computing devices based on specific computational models,” broadly considered to represent core AI technologies, are assigned the IPC code G06N. Therefore, all patents assigned G06N (limited to English descriptions) were acquired. This study aims to clarify differences in citation lags across countries, which requires aligning applicant and country information. Given the dataset contains 29,193 applicants, accurately assigning country information to all is extremely difficult. Therefore, this study analyzes only applicants with 10 or more patent applications during the period and focuses on the top 10 countries by frequency, as shown in Table 1.

Table 1
Target Countries

United States	China	Japan	South Korea	Germany
United Kingdom	France	Israel	Canada	Taiwan

Calculation of H1 and H2 Scores

For H1 and H2, the proportions of university institutions and government research institutions among the applicants for each patent are utilized. Since the names of university institutions and government-affiliated institutions also require mapping similar to country information, university institutions were labeled based on keywords such as “大学”, “大學”, “学院”, “學院”, “大学校”, “UNIV”, “INSTITUTE OF TECHNOLOGY”, ‘POLYTECHNIC’, and “COLLEGE”. For government institutions, we used keywords such as “GOVERNMENT”, “METROPOLITAN GOVERNMENT”, “PREFECTURAL GOVERNMENT”, “CITY GOVERNMENT”, “MUNICIPAL GOVERNMENT”, “PEOPLE'S GOVERNMENT”, “STATE COUNCIL”, “MINISTRY OF”, and others. For representative research institutions in the AI industry, such as “Chinese Academy of Sciences” and “KOREA RESEARCH INSTITUTE OF STANDARDS AND SCIENCE”, we determined classification based on whether the text matched these specific names.

Calculation of H3 Score

In recent years, as sovereign AI has gained attention, it has become clear that AI inherently requires computational resources. This study extracts only patents concerning computational devices based on specific computational models assigned G06N in the IPC. By adopting the method described below, we derive a single indicator that represents the degree to which technical content corresponds to computational resources and computational methods.
Step 1: Define a total of 105 words, including those shown in Table 2, as words corresponding to AI and computation.
Step 2: Extract patents where the claims document contains one or more of these AI words during the target period.

Step 3: Calculate the frequency of these patents within their IPC information.
Step 4: Determine the most frequent IPCs. Confirm IPCs reaching 25% cumulative coverage as those corresponding to AI and computation. The list of these IPCs is shown in Table 3.
Step 5: Calculate the overlap rate between the IPC assigned to each patent and the aforementioned IPC list as the H3 score.

Table 2
Representative Terms for AI and Computing

Accelerator	GPU	TPU	NPU	ASIC	FPGA
DSP	SOC	Microcontroller	Matrix Engine	Tensor Core	Vector Unit
Processing Element	Matrix Multiplication	Compute Unit	Memory Controller	On-chip Memory	Energy Efficiency
Convolution	Kernel	Embedded	Vectorize	Parallelize	Chiplet

Table 3 IPC List for AI and Computing

G06N20/00	G06N3/08	G06N3/04	G06N5/04	G06K9/62
G06N5/02	G06N7/00	G06N99/00	G06N3/063	

Calculation of H4 Score
The AI industry has made remarkable progress in recent years, but differences exist depending on the characteristics of the technology. Therefore, we evaluate whether each patent belongs to a notable technology cluster.

Step 1: Identification of English sentences by FastText
In this study, we obtained all patents written in English under the conditions described in this section. However, patent information submitted to the World Intellectual Property Organization (WIPO) may contain descriptions in multiple languages, including English, the native languages of the companies and other countries' languages. Therefore, it is impossible to analyze the entire abstract, and it is necessary to extract only English sentences in advance. The fastest can estimate the language in which each sentence is written. In this study, one sentence is extracted from each abstract and loaded into Fasttext for language estimation. As a result, only sentences determined to be English are used for subsequent analysis.

Step 2: Vectorization of Patent Information by Sentence BERT
H4 requires clarifying technology clusters. However, since processing text data is not straightforward, the summary information of each patent is vectorized and converted into a format that is easy to handle as numerical data. In this research, we use Sentence BERT to vectorize patent information for the abstract sentences of patents spanning a total of four years, including the past three years. For the pre-training model, we use the commonly used all-MiniLM-L6-v2 model, which converts text information into a 384-dimensional embedding.

Step 3: Clustering by Mini-Batch K-means
Cluster patent documents from four years, including the target year. Since the dimensionality output in Step 2 is high, perform principal component analysis beforehand to reduce it to 50 dimensions. Additionally, due to the large volume of data handled in this study, Mini-Batch K-

means is adopted for its faster clustering speed. Furthermore, the silhouette method was used to determine K. Approximately 6-10 clusters were extracted for each year.

Step 4: Calculating the Hotness Score
For each cluster a patent belongs to, calculate the proportion of patents from the latter two years. Since the AI industry experiences significant fluctuations in patent volume, the overall patent count influences this proportion. Therefore, to eliminate this volume-related bias, multiply the aforementioned score by the reciprocal of the proportion of patents from the latter two years relative to the total patent count.

Calculation of H5 Score
AI holds value not only as information technology or an information infrastructure, but is also expected to have broad applications in fields such as healthcare, business, autonomous driving, and agriculture. Therefore, we calculate the diversity in the IPC (International Patent Classification) representing the technical fields of each patent. As indicated in 3), this study has obtained IPC classifications down to the subgroup level. For diversity calculation, we convert the data to a format including only subclasses and use their Shannon entropy as the diversity value.

Results
Number of Patents
Figure 1 shows the trend in patent applications during the study period. As mentioned above, companies filing fewer than 10 applications during this period were not assigned country labels; therefore, they are grouped as "Others," including countries not listed in the study's target country list. Furthermore, representative years were selected, and the frequency of appearances by university institutions and government agencies is shown in Tables 4 and 5. The results reveal an explosive increase in AI-related patent numbers, with the United States showing a particularly high proportion. This is likely influenced by the fact that this study focuses on English-language patents. Although a recent downward trend appears to exist, this is due to the time lag between patent application and publication. In addition, it is also evident that the number of patent applications filed by universities and government research institutions is increasing alongside the overall rise in applications.

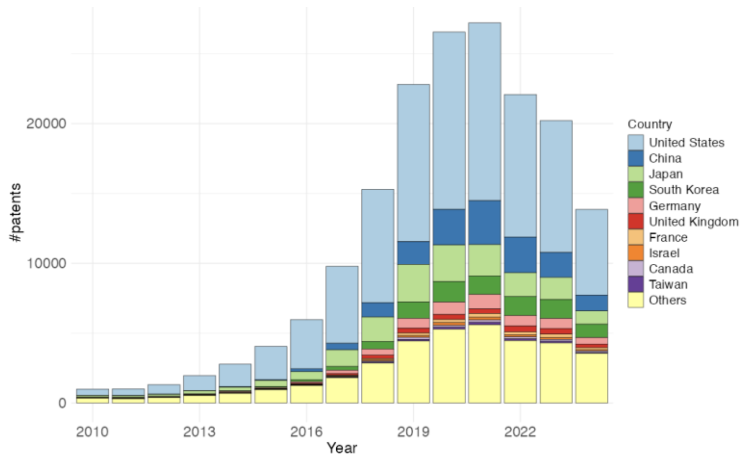


Figure 1 Trends in AI Patent Applications by Country

Table 4
Number of Patents Applied by Universities (Top 3 Institutions)

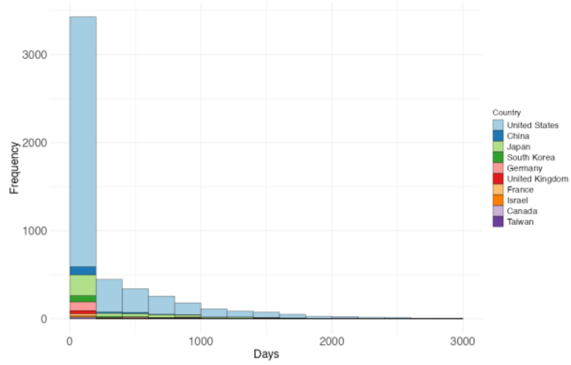
2010		2014		2018		2022	
Institution	Freq.	Institution	Freq.	Institution	Freq.	Institution	Freq.
NORTHWESTERN UNIVERSITY	3	PRESIDENT AND FELLOWS OF HARVARD COLLEGE	10	THE REGENTS OF THE UNIVERSITY OF CALIFORNIA	29	SEOUL NATIONAL UNIVERSITY R&DB FOUNDATION	65
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA	3	THE REGENTS OF THE UNIVERSITY OF CALIFORNIA	6	SEOUL NATIONAL UNIVERSITY R&DB FOUNDATION	18	THE REGENTS OF THE UNIVERSITY OF CALIFORNIA	53
THE UNIVERSITY OF UTAH RESEARCH FOUNDATION	3	UNIVERSITY OF TENNESSEE RESEARCH FOUNDATION	6	PRESIDENT AND FELLOWS OF HARVARD COLLEGE	14	ZHEJIANG UNIVERSITY	37

Table 5
Number of Patents Applied by Government Research Institution

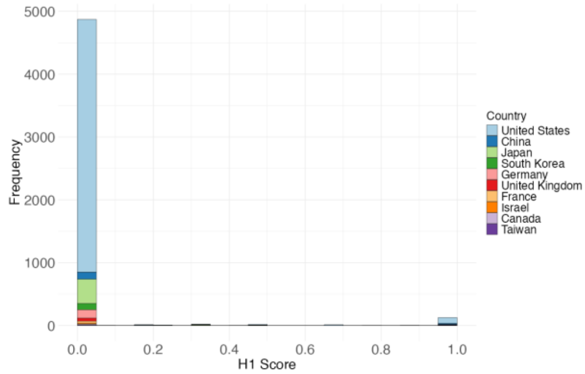
2010		2014		2018		2022	
Institution	Freq.	Institution	Freq.	Institution	Freq.	Institution	Freq.
AGENCY FOR SCIENCE TECHNOLOGY AND RESEARCH	1	GOVERNING COUNCIL OF THE UNIV OF TORONTO THE	2	AGENCY FOR SCIENCE TECHNOLOGY AND RESEARCH	3	INSURANCE SERVICES OFFICE INC	13
		JAPAN SCIENCE AND TECHNOLOGY AGENCY	2	AGENCY FOR DEFENSE DEVELOPMENT	3	GOVERNMENT OF THE UNITED STATES OF AMERICA AS REPRESENTED BY THE SECRETARY OF COMMERCE	7
		THE GOVERNING COUNCIL OF THE UNIVERSITY OF TORONTO	2	GOVERNMENT OF THE UNITED STATES OF AMERICA AS REPRESENTED BY THE SECRETARY OF COMMERCE	2	JAPAN SCIENCE AND TECHNOLOGY AGENCY	6

Score Distribution of each Hypothesis

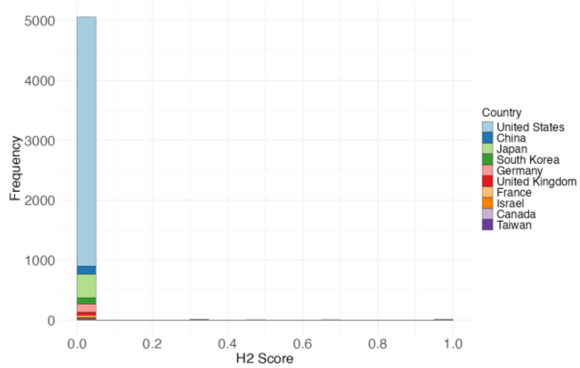
Figure 2 shows the citation delay scores between each patent and the first cited patent, along with the histograms of each patent's scores from H1 to H5. This graph focuses solely on patents cited by AI patents, yet it still shows that the United States holds a very high proportion. Furthermore, the majority of high scores in H4's hotness score are from the United States, highlighting its outstanding leadership in this industry.



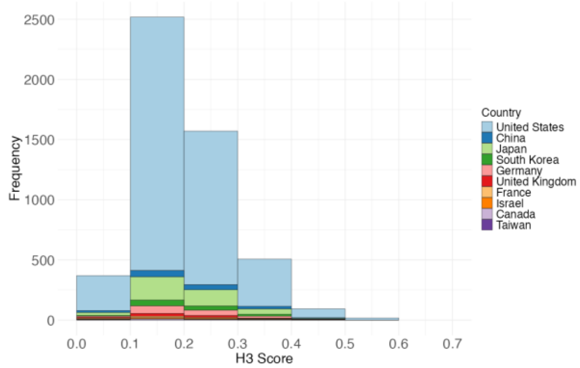
(a) Citation Lag



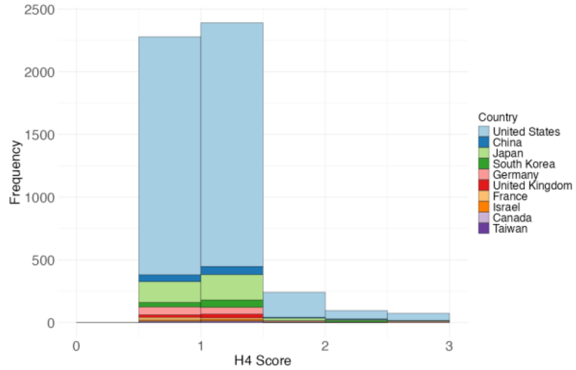
(b) H1



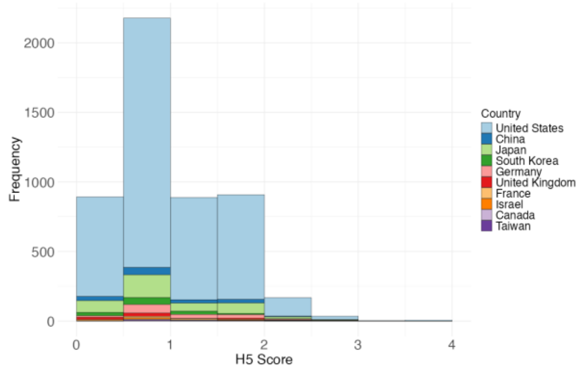
(c) H2



(d) H3



(e) H4



(f) H5

Figure 2 Score Distribution

Result of Cox Proportional Hazards Model

This study employed a Cox proportional hazards model analysis, using the number of days until the first citation of AI-related patents as the dependent variable and applicant composition (H1: university ratio, H2: government agency ratio) and technological characteristics (H3: AI computational resource compatibility, H4: technological attention, H5: technological diversification) as independent variables.

First, we estimated the overall static effects. The results are shown in Table 6. In addition, the Kaplan-Meier plot for each country is shown in Figure 3.

Table 6
Results of the Cox Proportional Hazards Model on Time to First Citation
(n = 12,010; Events = 5,077)

Variable	Coef. (β)	Hazard Ratio exp(β)	Std. Error	z-value	p-value	95% CI [Lower, Upper]	Interpretation
H1: University R&D	−0.295	0.744	0.086	−3.44	0.0006 ***	[0.629, 0.881]	Higher university involvement slows down first citation (basic research orientation)
H2: Government research institution involvement	0.730	2.075	0.325	2.24	0.0248 *	[1.097, 3.925]	Government participation accelerates early citation
H3: Computational resource alignment	3.562	35.246	0.131	27.12	$< 2 \times 10^{-16}$ ***	[27.245, 45.597]	Strong positive impact: compute capability drastically shortens citation lag
H4: Technological hotness	0.442	1.556	0.039	11.34	$< 2 \times 10^{-16}$ ***	[1.442, 1.680]	Highly visible patents are cited earlier
H5: Knowledge diversity	0.214	1.239	0.022	9.93	$< 2 \times 10^{-16}$ ***	[1.188, 1.293]	Broader application scope leads to earlier citation

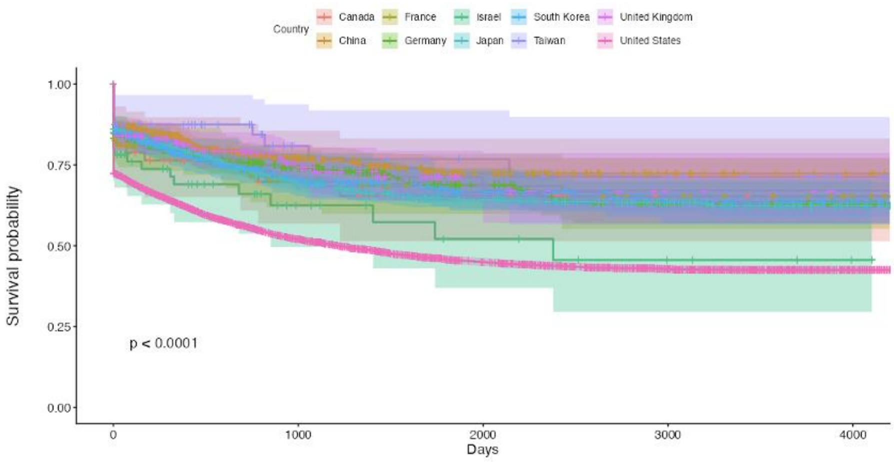


Figure 3 Survival curve in target countries

First, we estimated a basic model assuming the effects of all variables were time-invariant. The analysis covered 12,010 AI-related patents, of which 5,077 were cited during the observation period. The model fit was Concordance = 0.65 (se = 0.004), with high overall significance (LRT = 1001, df = 5, $p < 2\times10^{-16}$). As a result, H3 (AI computational resources), H4 (attention), and H5 (diversification) were all significantly positive, confirming their contribution to increased citation rates. Notably, the effect size for H3 was particularly prominent, indicating that addressing computational infrastructure strongly promotes the knowledge diffusion of patents. Conversely, applications originating from universities (H1) showed a significantly negative effect, confirming that university-led applications tend to have longer periods until first citation, indicating slower diffusion. Figure 3 also shows that the initial citation rate of U.S. patents is outstanding, while Chinese patents, which ranked second in terms of volume, do not hold an advantage in citation speed. To verify the proportional-hazard (PH) assumption, the Schoenfeld residual test was applied. The test results are shown in Table 7. The results show that H3 and H5 violate the PH assumption, while H1, H2, and H4 do not.

Table 7
Proportional Hazards Test Using Schoenfeld Residuals

Variable	χ^2	df	p-value	Result
H1	1.534	1	0.216	No violation
H2	0.671	1	0.413	No violation
H3	9.455	1	0.002	Violation
H4	1.052	1	0.305	No violation
H5	5.587	1	0.018	Violation
Global	16.373	5	0.0059	PH violated

The significant p-values for H3 and H5 ($p < 0.01$, $p < 0.05$) indicate that the effects of computer readiness and diversification vary over time. This finding justifies the use of time-dependent Cox models with interaction terms involving log(time). Based on these results, we introduced an interaction term between H3 and H5 multiplied by log(time) and estimated a time-dependent Cox model. The estimation results are shown in Table 8. Both H3 and H5 showed negative time coefficients, and a clear trend of diminishing effects over time was confirmed for both.

Table 8
Results of the Time-dependent Cox Proportional Hazard Model

Variable	Coef. (β)	Hazard Ratio exp(β)	Std. Error	z-value	p-value	95% CI [Lower, Upper]	Interpretation
H1: University R&D	–0.294	0.745	0.086	–3.42	0.0006 ***	[0.630, 0.882]	Negative effect: university involvement slows citation speed.
H2: Government research institution involvement	0.730	2.076	0.326	2.24	0.0249 *	[1.097, 3.929]	Positive effect: government-affiliated applicants accelerate diffusion.
H3: Computational resource alignment	3.853	47.144	0.166	23.22	$< 2 \times 10^{-16}$ ***	[34.056, 65.261]	Strong positive effect: compute-intensive patents diffuse rapidly.
H4: Technological hotness	0.440	1.553	0.039	11.31	$< 2 \times 10^{-16}$ ***	[1.439, 1.677]	Positive effect: patents in trending clusters receive faster citations.

Variable	Coef. (β)	Hazard Ratio exp(β)	Std. Error	z-value	p-value	95% CI [Lower, Upper]	Interpretation
H5: Knowledge diversity	0.251	1.286	0.029	8.80	$< 2 \times 10^{-16}$ ***	[1.216, 1.360]	Positive effect: diversified patents have broader citation reach.
tt(H3) – Time interaction of computational resource alignment	−0.125	0.882	0.044	−2.88	0.0040 **	[0.810, 0.961]	Time-decreasing effect: compute advantage weakens over time.
tt(H5) – Time interaction of knowledge diversity	−0.015	0.985	0.007	−2.09	0.0368 *	[0.972, 0.999]	Time-decreasing effect: diversification impact slightly declines.

Findings

The results above reveal that the initial citation speed of AI patents is explained by the development of AI computational resources (H3), the visibility of the technology (H4), the diversification of application domains (H5), and the nature of the research entities (H1, H2).
The detection of time-dependent effects in H3 and H5 is particularly significant. This demonstrates the temporal dynamics of knowledge diffusion in AI technology, empirically showing that access to computational resources significantly influences early-stage knowledge propagation, while technological diversification attracts temporary attention but lacks sustained impact. These findings are crucial for understanding technology diffusion and standardization processes in the AI field. Policy-wise, they suggest that "investment in computational resource infrastructure", "visualization support in the initial phase," and "appropriate role division among industry, academia, and government" are key to optimizing the speed of knowledge diffusion.

Discussion and Conclusion

The results of the Cox proportional hazards analysis provide important insights into the determinants of early citation in AI-related patents. Overall, the findings confirm that institutional collaboration, technological positioning, and knowledge structure significantly shape the pace of knowledge diffusion within emerging innovation ecosystems. However, the direction and magnitude of these effects vary considerably across the five hypothesized factors.

First, contrary to Hypothesis 1, university collaboration was found to delay early citation. Although prior research emphasizes that university involvement increases the scientific novelty and exploratory character of inventions (Etzkowitz & Leydesdorff, 2000; Etzkowitz, 2003), the current result suggests that academic partnerships may initially focus on upstream knowledge creation rather than immediate industrial application. University-based patents often embody high originality and theoretical complexity, which require time to be absorbed and recontextualized in applied technological domains. This finding suggests that universities play a crucial role in deepening and diversifying innovation, but their contributions may have a greater long-term impact than immediate recognition. In contrast, the significant positive effect of government research institution involvement (H2) supports the notion that public R&D participation facilitates early diffusion. Co-developed patents with government institutes were approximately twice as likely to receive early citations, indicating that the legitimacy, funding stability, and infrastructural support provided by public institutions reduce uncertainty and enhance visibility in the AI innovation space. This finding resonates with national innovation system theories (Lee & Lim, 2001), emphasizing the catalytic role of state institutions in legitimizing emerging technologies and accelerating their diffusion.

The most striking result emerged for computational resource alignment (H3), which exhibited a powerful positive effect on early citation (HR ≈ 35). This underscores the centrality of technological implementability in AI innovation, where advances are tightly coupled with computational infrastructure. Patents that align closely with hardware, data pipelines, or cloud architectures are rapidly adopted because they can be directly integrated into existing technological ecosystems. This reflects an “engineering-driven diffusion” mechanism distinct from traditional knowledge-based spill-overs, highlighting how physical and digital infrastructures jointly govern innovation speed.

Similarly, technological hotness (H4) and knowledge diversity (H5) were both positively associated with early citation. Patents embedded in fast-growing or “hot” technological clusters tend to be more visible and receive attention earlier, confirming the presence of network momentum effects (Uzzi & Spiro, 2005; Hall et al., 2005). Meanwhile, knowledge diversity accelerates diffusion by broadening the cognitive and disciplinary reach of a patent. Multidomain inventions that bridge AI with other technologies (e.g., robotics, sensors, materials) appeal to a broader range of inventors and are cited across multiple technological communities. Based on an analysis incorporating findings from prior research, this supports the view that both technological connections and cognitive diversity are essential for the early recognition of AI-related innovations. From a broader perspective, these findings contribute to the literature on innovation diffusion by revealing that AI’s unique characteristics—its dependence on computational infrastructure and cross-domain knowledge integration—reshape the traditional determinants of citation dynamics. Institutional collaboration exerts asymmetric effects: while government involvement accelerates diffusion, university collaboration decelerates it, suggesting a fundamental trade-off between scientific exploration and technological exploitation. This asymmetry illustrates how different types of collaboration shape the temporal trajectory of AI knowledge dissemination.

Theoretical Implications

This study advances theoretical understanding of knowledge diffusion and innovation management in several ways. First, it extends the Triple Helix model (Etzkowitz & Leydesdorff, 2000) by revealing asymmetrical diffusion effects between university and government collaboration. While university partnerships enhance exploratory and theoretical depth, government participation strengthens institutional legitimacy and accelerates the early diffusion of AI inventions. This suggests that the institutional type of collaboration—rather than collaboration per se—determines the temporal dynamics of technological diffusion. Second, the strong influence of computational resource alignment highlights the need to integrate infrastructural and architectural factors into innovation diffusion theory. Traditional models have emphasized cognitive or relational proximity (e.g., Fleming, 2001; Wong, 2004), yet the AI domain demonstrates that alignment with digital and physical infrastructures constitutes a new form of “implementation proximity” that governs diffusion speed. Third, the positive effects of technological hotness and knowledge diversity confirm the importance of network momentum and cognitive variety in shaping diffusion. These findings extend small-world and recombination theories (Uzzi & Spiro, 2005; Pelled et al., 1999) by showing how both structural connectedness and cognitive diversity jointly drive visibility and early recognition. Together, these results indicate that diffusion in AI is governed by the interaction between institutional configuration and technological embeddedness, enriching theory at the intersection of the Triple Helix, resource-based, and innovation diffusion frameworks.

Practical and Social Implications

The findings offer clear guidance for innovation management and policy.

For policymakers, the positive effect of government research involvement suggests that targeted public participation and infrastructure investment can accelerate the diffusion of strategic AI technologies. Universities should strengthen translational linkages with industry—such as joint R&D and technology transfer—to shorten the gap between academic discovery and application. For firms, aligning AI development with existing computational infrastructures and fostering cross-domain knowledge diversity can enhance patent visibility and diffusion speed. At a societal level, the configuration of AI R&D networks—who collaborate and how technologies align—shapes not only competitive advantage but also the broader pace and inclusiveness of digital transformation.

Limitations and Suggestions for Future Research

Several limitations should be acknowledged. First, while this study utilizes a large-scale global patent dataset, citations measure technical interest rather than actual adoption. Future research integrating market data, publication data, and product data will enable capturing the entire diffusion trajectory from invention to commercialization. Second, while this analysis models initial citations using a single-event Cox model, citation dynamics are iterative and interdependent. Future research could apply recursive event models or fragility models to capture temporal heterogeneity and inter-patent correlations. Third, although this study includes international comparative data, it does not explicitly examine differences in national systems. Comparative analysis of the US, China, Japan, and South Korea could elucidate the impact of national innovation systems on AI diffusion. Fourth, measuring concepts like computational coherence and technological prominence has limitations. These rely on proxies from patent text and collaborative classification, suggesting potential refinement through advances in semantic embedding, machine learning, and network analysis. Finally, future research could extend this framework to emerging technologies like quantum computing and biotechnology to verify whether infrastructure coherence and institutional imbalances represent universal diffusion mechanisms or are specific to the AI domain.

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