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Exploring the patterns and influencing factors of emerging technology impact: a case study of digital medical technology

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Abstract

Introduction. Impact, as an intrinsic attribute of emerging technologies, plays a crucial role in their identification and understanding. Traditional citation metrics, while reflective of impact magnitude, fail to explain its nature.

Method. Addressing this deficiency, this study categorizes the impact of emerging technologies into internal and external field, as well as impacts on basic versus applied development. With a focus on digital medical technology, this research investigates these four distinct impact patterns and their determinants. Using ordinary least squares (OLS) regression analysis on patent records from the Derwent innovations index (DII), the study examines how temporal novelty, innovation novelty, growth, and uncertainty influence both the magnitude and patterns of technological impact.

Analysis. Analysis shows a U-shaped relationship between temporal novelty and impact, indicating that older technologies gain influence through cumulative effects, while emerging technologies attract attention early on due to their pronounced novelty. Additionally, innovation novelty positively correlates with impact, underscoring its critical role in the effectiveness of emerging technologies. In contrast, growth rates and uncertainty demonstrate inconsistent effects.

Conclusions. These insights offer valuable guidance for policymakers, investors, and R&D managers in strategically advancing the development and deployment of emerging technologies.

Introduction

In our rapidly evolving digital era, emerging technologies such as digital medical technology are not only reshaping the healthcare ecosystems but also the broader socio-economic structures in which they operate. This transformation is particularly pronounced in the age of 'AI-*algorithmic*' control, where the advancement of technologies like text mining and natural language processing (NLP) enhances our ability to identify and assess the impacts of emerging technologies more precisely and deeply. Understanding the impact patterns and influencing factors of these technologies becomes crucial, as they are often pivotal in driving innovation and boosting productivity (Rotolo et al., 2015). Given their potential to lead new industrial revolutions, reshape existing industry structures, optimize resource allocation, and propel economic and social advancement, it is essential, with the aid of text mining techniques, to conduct a comprehensive study of their impacts.

Existing studies predominantly focus on two areas: evaluating the impact of technologies and identifying the factors that drive these impacts. Methods such as bibliometrics and text mining have been extensively used to develop indices and models to assess technological influence (Gao et al., 2021). Citation metrics, widely regarded as appropriate indicators, suggest that a higher number of citations implies greater technological impact (Lee et al., 2012). However, these indicators merely quantify the extent of influence and fail to elucidate the nature of the impacts themselves. On the other hand, studies on factors impacting technology often focus on its role in the emergence of new industries or upgrades within existing ones, identifying key elements that yield significant technological impacts, typically using patent citations as metrics targeted towards enterprises or industries (Messeni Petruzzelli et al., 2015). While these studies offer valuable insights, they frequently overlook the nature of technological impacts and the diverse factors influencing various impact types. This oversight is critical as it limits our comprehension of how attributes of emerging technologies can lead to distinct patterns of influence, pivotal for shaping and transforming technological evolution paths.

The impacts of emerging technologies manifest in one or several domains and produce extensive cross-domain effects, influencing the entire system of technological innovation. Different types or patterns of influence have varied effects on technological innovation, necessitating targeted technological strategies by enterprises. This requires an analysis based on subdivided technological impact patterns to predict technological developments and mitigate R&D investment risks. However, current research has not systematically differentiated these technological impact patterns nor explored the factors influencing different patterns. Addressing these gaps, this study seeks to explore and resolve the following questions:

> Q1. How can we categorize technological impact patterns to consider the nature of their influences?
>
> Q2. Do attributes of emerging technologies affect different impact patterns in distinct ways?
>
> Q3. Which attributes significantly influence specific impact patterns, and what are the underlying mechanisms?

By exploring these questions, this study aims to enhance the impact of emerging technologies through innovative means, thus promoting their development and providing robust support for a deeper analysis of the intrinsic mechanisms influencing emerging technologies.

Method

Building upon prior studies, this research utilizes data from 15,116 patent records in the digital medical technology sector derived from the Derwent innovations index (DII). The abstracts of these patents were processed using natural language processing (NLP) to extract technological terminologies, detailed in Jiang et al. (2024). Based on these findings, 1016 emerging technology terms within the digital medical technology field were selected using threshold indices (https://github.com/jiangman29/Paper-Data_JOI_ETs-Identification.git). These terms, characterized by their ET-scores and attributes of novelty (including temporal and value novelty), growth, uncertainty, and impact, serve as the sample for this study. Given the innovative and interdisciplinary nature of digital medical technology—which intersects medical, AI, and telecommunication fields—the impact patterns of this technology represent crucial strategic information for technology management. Technological innovations in this context play a key role in enterprise performance and innovation management.

The aim of this study is to explore the patterns of technological impact of emerging technologies and to analyse how attributes of these technologies influence their impact under different impact patterns. To achieve this, we first categorize the impacts of emerging technologies based on their nature into impacts within the technological field and impacts beyond the technological field, as well as impacts on basic and applied research. We then employ ordinary least squares (OLS) regression analysis to examine how the attributes of novelty, growth, and uncertainty influence the impacts across these four patterns. The overall framework is depicted in Figure 1. The subsequent section will detail the procedures of each step.

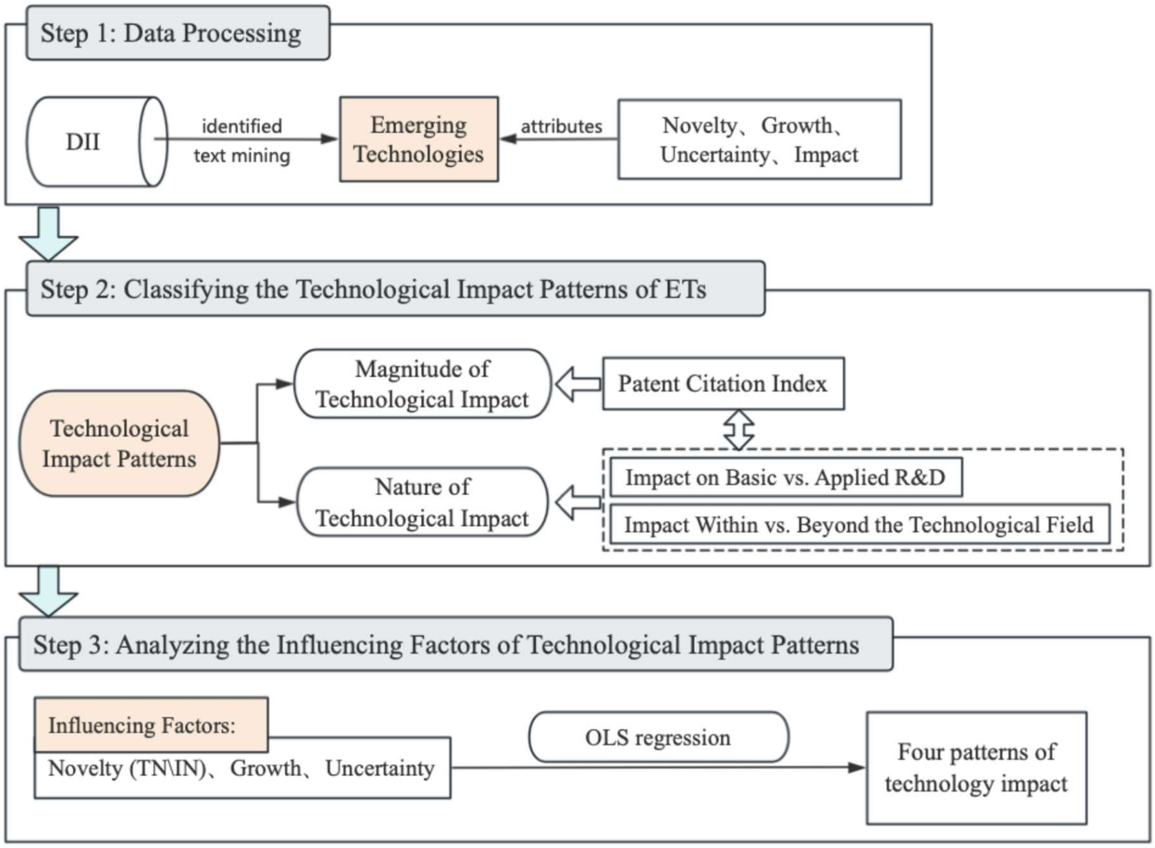

Figure 1. Research framework

Categorization of technological impact patterns

Magnitude of technological impact

Previous studies indicate that the frequency of direct patent citations is a viable metric for measuring technological impact (Glänzel & Thijs, 2012; Wang, 2018). The prominent impact of a term can be quantified by the standardized citation counts appearing in patent records. To account for variances in term representations across patents, normalized TF-IDF values are utilized to weight terms accordingly. The prominent impact (PI) of a term is calculated as follows:

$$\mathrm{PI} = \sum \alpha_i C_{i,t} \qquad (1)$$

where $C_{i,t}$represents citation counts, and α_i denotes the normalized TF-IDF values for the term in the i-th patent record, aggregating the values across all records to derive the term's PI index.

Types of technological impact

Existing studies indicate that the manifestations of technological influence vary according to technological characteristics, application contexts, and knowledge dissemination pathways (Messeni Petruzzelli et al., 2015). To explore whether different modes of technological influence are affected by distinct factors, this paper categorizes technological influence into four patterns based on the scope and direction of impact: within the technological domain, outside the technological domain, basic research and development (R&D) influence, and applied R&D influence.

(1) Impact within vs. beyond the technological field

Emerging technologies in the digital medical sector often have extensive cross-disciplinary impacts. Analyzing how novelty, growth, and uncertainty influence different technology adoption paths aids in revealing the scope and trajectory of technology dissemination. It also helps determine whether a technology is more specialized or has interdisciplinary value. Therefore, we classify the impacts of emerging technologies based on their citations within or beyond their primary field. For instance, a technology is considered to have an internal field impact if it is cited by patents within the digital medical field and an external field impact if cited by patents in other fields. This categorization extends to calculating PI_In and PI_Out indices:

$$\mathrm{PI\_In} = \sum \alpha_i Cin_{i,t} \qquad (2)$$

$$\mathrm{PI\_Out} = \sum \alpha_i Cout_{i,t} \qquad (3)$$

where $Cin_{i,t}$ and $Cout_{i,t}$ denote the citation counts within and outside the digital medical technology field, respectively.

(2) Impact on basic vs. applied R&D

Existing research shows a propensity for companies to focus on applied research while universities lean towards basic research (Poege et al., 2019; Kwon et al., 2021). Therefore, we classify the impact based on the patent holder's type, such as a company or university. If the holder is a company, the impact is considered as applied R&D; if a university, then as basic R&D. The indices PI_Ba and PI_Ap are obtained as follows:

$$\mathrm{PI\_Ba} = \sum \alpha_i Cu_{i,t} \qquad (4)$$

$$\mathrm{PI\_Ap} = \sum \alpha_i Cc_{i,t} \qquad (5)$$

where $Cu_{i,t}$ and $Cc_{i,t}$ represent the citation counts by university and company patent holders within the digital medical technology field, respectively.

Factors influencing the impact patterns of emerging technologies

The attributes of emerging technologies co-evolve (Rotolo et al., 2015), and while quantitative evidence suggests that novelty is a significant factor influencing technological impact (Uzzi et al., 2013; Messeni Petruzzelli et al., 2015), qualitative evidence also points to growth and uncertainty as influential (Messeni Petruzzelli et al., 2011). However, a systematic quantitative study of how these intrinsic attributes affect technological impact is still lacking. Following the classification of technological impact patterns outlined earlier, this study employs regression analysis to explore the effects of temporal novelty, value novelty, and uncertainty on different technological impact patterns.

Dependent variables

The dependent variables in this study are the measures of technological impact of emerging technologies, including the overall impact (PI), impact within the technological field (PI_In), impact beyond the technological field (PI_Out), impact on basic development (PI_Ba), and impact on applied development (PI_Ap).

Independent variables

The independent variables are other attributes of emerging technologies, including temporal novelty, value novelty, growth, and uncertainty:

Temporal novelty (TN) measures the recency of technology emergence, suggesting newer technologies with later emergence dates. It is quantified by the mean filing year of patents associated with a given term, as follows:

$$TN = \sum_{i=1}^{n} t_i \,/n$$

Here, t_i denotes the filing year of the patent term, and n is the number of patents containing the term.

Innovation novelty (IN) measures the degree of technological innovation from the perspective of technical content. Breitzman and Thomas (2015) highlight that the recombination of technical knowledge is a key source of novelty (Fleming & Sorenson, 2001; Strumsky & Lobo, 2015). A broader range of knowledge absorbed during recombination indicates higher novelty (Jiang et al., 2024; Savino et al., 2017). Thus, the IN of a term is defined as the diversity of technical fields reflected in its backward citations:

$$IN = N\sum filed_{Bx}$$

Here, $\sum filed_{Bx}$ denotes the set of technology fields from backward patents where the term i appears in the patent x. The variable N signifies the total number of patents incorporating term i, and the IN denotes the cumulative technical fields from all backward citations in these patents. This classification of technological fields is based on the WIPO Technology Concordance Table, which defines 35 standard fields (WIPO35) (Jiang et al., 2024).

Growth (R) is measured using the average growth rate. To mitigate random fluctuations in the annual number of patents, we follow the approach of Q. Wang (2018) by applying a smoothing technique, where the number of patents for a given year is calculated as the average over the preceding three years. The growth rate of a term is then defined as its average annual increase.:

$$\mathrm{R} = \mathrm{A}ve \sum_{i} \frac{p_t}{p_{t+1}}$$

Here, p_t denotes the number of ET term appears in patents records at time t.

Uncertainty (H) is measured using the H-index, originally proposed by Brillouin (1956) as a measure of uncertainty based on the principle of information entropy. This study applies the H-index to evaluate the uncertainty surrounding the future applications of emerging technologies (ETs) (Jiang et al., 2024). A higher H-index for a term reflects greater ambiguity in its functional definition and substantial inherent uncertainty in its potential applications.

$$H = \frac{lgN! - \sum(lgN_i!)}{N}$$

Here, N_i represents the occurrence frequency of a term within technical field i, and N represents the aggregate frequency of the term across all technical fields.

The theoretical basis and detailed explanation of these metrics are further elaborated in Jiang et al. (2024). Despite the linear relationships among dependent variables, such as the correlation between growth and novelty discussed in related work (Messeni Petruzzelli et al., 2015), these relationships do not compromise the investigation of technological impact as these attributes are inherent to emerging technologies and are likely interconnected (Rotolo et al., 2015).

Control variables

Several control variables were incorporated to account for variations in technical impact. Firstly, we controlled for the *number of patents* associated with emerging technology, as the volume of patents can influence the technological impact. Secondly, the size of the team involved in technology development was included as a control variable because economies of specialization, a larger and more diverse knowledge base, and a broader and more heterogeneous external network can influence the impact of the technology (Messeni Petruzzelli et al., 2015). Thus, the number of inventors involved in the emerging technology (*TeamSize*) was included (Messeni Petruzzelli et al., 2015). Thirdly, the *patent family size* was controlled for, as a larger patent family typically has a higher technological impact (Corredoira & Banerjee, 2015). Fourthly, we controlled for the distribution of patents across different *countries* (Kwon et al., 2021).

For the regression analysis, we fit our data to an OLS regression model using robust standard errors to take into account probable violation of the homoskedasticity assumption in estimation.

Analysis and results

Descriptive analysis

Table 1 displays the correlations among the key variables. All correlation coefficients are below 0.4, indicating that multicollinearity is not a significant concern in the regression analysis (Kwon et al., 2021). Furthermore, the examination of the variance inflation factor (VIF) associated with each regression coefficient, ranging from 1.02 to 1.16, confirms the absence of collinearity concerns, as values less than 10 suggest negligible collinearity (Messeni Petruzzelli et al., 2011). Below is a representation of the correlation matrix and VIF values extracted from the data:

	TN	IN	R	H	PI	VIF
TN	1					1.02
IN	-0.012	1				1.15
R	0.150	0.014	1			1.03
H	0.016	0.363	0.061	1		1.16
PI	-0.008	0.181	0.007	0.100	1	/

Table 1. Correlation between variables

Regression results

Table 2 displays the OLS estimation results for different types of technological impact. Model 1 provides an analysis of overall patent impact (Y_PI), while Models 2-5 test the technological impacts categorized by internal vs. external technological fields (PI_In vs. PI_Out) and by basic vs. applied R&D (PI_Ba vs. PI_Ap).

Model 1 highlights a U-shaped relationship between temporal novelty (TN) and technological impact. This nonlinear relationship is significant and robust, with a correlation coefficient as high as 0.6, indicating that although older technologies might generate greater impact due to the cumulative effect of time, newer technologies are more likely to be identified by innovators to highlight technological progress. This is particularly true in emerging technology fields where newer technologies can achieve higher impacts. Innovation novelty (IN) consistently shows a positive relationship with technological impact, reinforcing the notion that more innovative technologies are likely to evolve into high-impact technologies. This finding aligns with prior research that posits innovation as a driver of technological impact (Corredoira & Banerjee, 2015; Kwon et al., 2021). However, the growth rate (R) and uncertainty (H) did not exhibit significant effects in most models, suggesting that the simple annual patent growth rate may not be a strong predictor of technological impact within this dataset.

The significant results for technological novelty are clear, while the non-significant effects of growth and uncertainty on technological impact are expected. Growth does not always positively influence impact. In early-stage technologies, small bases amplify base effects, leading to potentially negative correlations (Porter et al., 2019). High growth rates often reflect proportional accumulation rather than enhanced influence and may result from novelty-driven growth (Castaldi et al., 2015; Rosiello & Maleki, 2021). However, rapid growth can over-concentrate resources, intensify competition, and diminish impact in later stages due to resource constraints or market saturation (Corredoira & Banerjee, 2015).

Models 2 and 3 provide evidence that several impact factors differ significantly between technological impacts within the digital medical technology field and impacts outside of it. Specifically, it appears that TN, IN, R, and H show no significant effects within the technological field (PI_In), whereas for the technological impact outside of the field (PI_Out), TN exhibits a positive U-shaped relationship, and IN shows a positive linear relationship, as shown in Figure 2. This indicates that new technologies might initially struggle to make an impact within their primary fields but gain significant traction and influence over time in external fields. This may suggest that while a technology's direct field may be slow to recognize its utility or potential, auxiliary fields might quickly discover new applications or value.

Models 4 and 5 indicate that both TN2 and IN have a significant positive impact on applied research, with technological innovation novelty positively influencing both basic and applied research impacts, albeit more pronounced in applied research, as shown in Figure 3. This suggests that in the context of applied development, newer and more innovative technologies may have a greater impact. Here, the temporal novelty reflects a preference for actual applications, indicating a favour for newer innovative solutions.

These contrasts between internal vs. external impacts and basic vs. applied research impacts provide valuable insights into how different sectors and types of research within the digital medical technology field perceive and value technological innovations. The significant differences in how temporal and innovation novelties are valued across these models suggest that varying strategies may be necessary to maximize technology adoption and impact according to the specific target domain or research focus.

Variables	(1) Y_PI	(2) PI_In	(3) PI_Out	(4) PI_Ba	(5) PI_Ap
TN	-0.248***	-0.008	-0.240***	-0.236***	-0.018*
	(0.080)	(0.007)	(0.077)	(0.075)	(0.010)
TN2	0.615***	0.020	0.594***	0.585***	0.044*
	(0.199)	(0.018)	(0.191)	(0.187)	(0.026)
IN	0.072***	0.001	0.071***	0.067***	0.005**
	(0.019)	(0.002)	(0.019)	(0.018)	(0.003)
R	-0.004	-0.000	-0.004	-0.004	-0.001
	(0.009)	(0.001)	(0.009)	(0.009)	(0.001)
H	0.500	-0.131*	0.632	0.555	-0.130
	(0.789)	(0.071)	(0.758)	(0.742)	(0.103)
Patent_Num	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Team_Num	-0.016	0.001	-0.017*	-0.012	-0.002*
	(0.010)	(0.001)	(0.010)	(0.010)	(0.001)
PatentFamily_Num	0.113***	0.004**	0.109***	0.108***	0.005**
	(0.020)	(0.002)	(0.019)	(0.019)	(0.003)
Country_Num	-0.003***	-0.000***	-0.003***	-0.003***	-0.000**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
_cons	2.5e+06***	8.3e+04	2.4e+06***	2.4e+06***	1.8e+05*
	(8.1e+05)	(7.3e+04)	(7.8e+05)	(7.6e+05)	(1.1e+05)
r2_a	0.065	0.006	0.069	0.069	0.009
N	1016	1016	1016	1016	1016

*p < 0.10; **p < 0.05; ***p < 0.01; Standard errors in parentheses

Table 2. OLS regression results for different types of technological impact

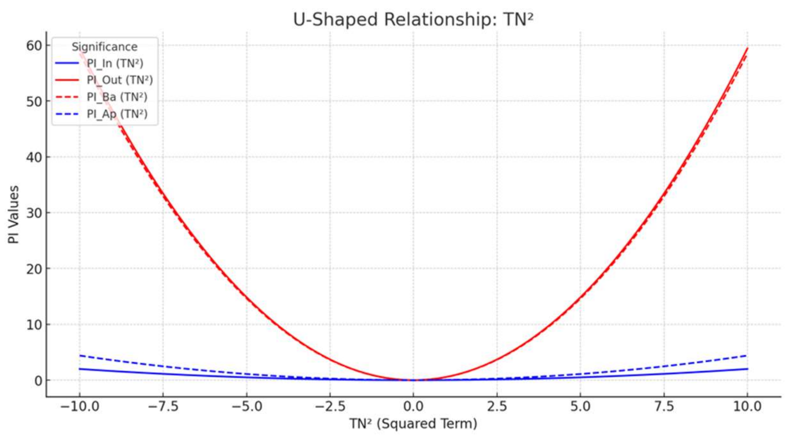

Figure 2. The U-shaped relationship between TN² and PI

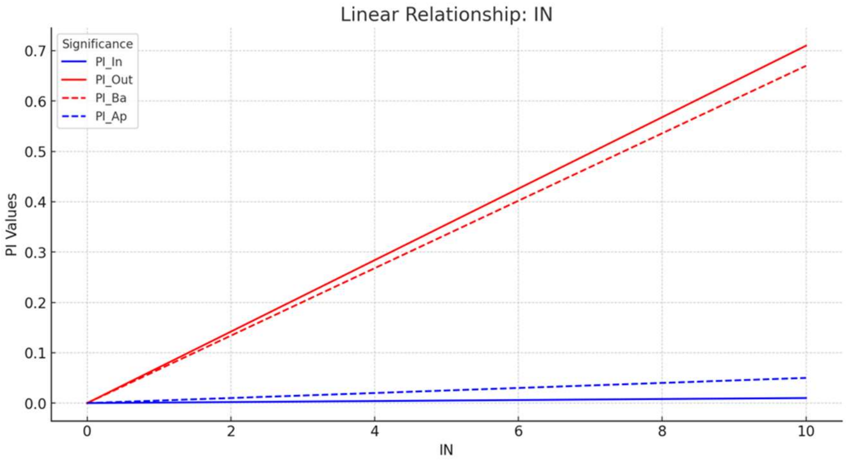

Figure 3. The linear relationship between IN and PI

Robustness testing

We performed robustness testing on the OLS results by applying a log transformation to the dependent variables. The results, consistent with Table 2. Additionally, fractional response regression models were used for further validation. Table 3 reports the outcomes, providing additional evidence for the relationship between technological novelty and technological impact.

Variables	lnY_PI	lnPI_In	lnPI_Out	lnPI_Ba	lnPI_Ap
TN	-1.4606***	-0.8811	-1.4903***	-1.3979*	-1.4910***
	(0.515)	(0.777)	(0.523)	(0.791)	(0.536)
TN2	1.6329***	0.9658	1.6636***	1.3845*	1.6739***
	(0.482)	(0.774)	(0.495)	(0.804)	(0.501)
IN	0.5540***	0.1343	0.5805***	0.4322**	0.5688***
	(0.147)	(0.210)	(0.146)	(0.217)	(0.154)
R5	-0.0793	0.1447	-0.0915	-0.4588	-0.0419
	(0.362)	(0.332)	(0.368)	(0.489)	(0.350)
H	0.1183	-0.3606*	0.1602	-0.1948	0.1520
	(0.147)	(0.196)	(0.149)	(0.187)	(0.156)
Patent_Num	0.1632	0.2582	0.1501	-0.0126	0.1871
	(0.198)	(0.246)	(0.209)	(0.444)	(0.189)
Team_Num	-0.2442*	0.2805	-0.2832**	-0.5846**	-0.2178
	(0.132)	(0.202)	(0.134)	(0.250)	(0.133)
PatentFamily_Num	0.9274***	0.5117**	0.9437***	0.5346**	0.9511***
	(0.184)	(0.237)	(0.185)	(0.263)	(0.188)
Country_Num	-0.3843***	-0.4985***	-0.3674***	-0.3793**	-0.3740***
	(0.129)	(0.184)	(0.131)	(0.175)	(0.134)
Constant	-1.7588***	-1.5630***	-1.8152***	-1.3767***	-1.8382***
	(0.135)	(0.183)	(0.139)	(0.175)	(0.142)
Obs.	1016	1016	1016	1016	1016

*p < 0.10; **p < 0.05; ***p < 0.01; Standard errors in parentheses

Table 3. Robustness testing results

Conclusions

This study has systematically explored the impact patterns and influencing factors of emerging technologies, with a specific focus on digital medical technology. The analysis employed an extensive dataset comprising 15,116 patent records to scrutinize the influence of various attributes of emerging technologies—namely temporal and innovation novelty, growth, and uncertainty—on their technological impact across different patterns.

There are some key findings. ***Firstly***, temporal novelty and impact dynamics: The relationship between temporal novelty and technological impact exhibits a pronounced U-shaped curve. This pattern highlights the distinct characteristics of emerging technologies, which diverge from traditional technologies whose influence typically grows incrementally over time. Instead, emerging technologies demonstrate a strong impact early in their development cycle, underscoring the rapid initial uptake and the potential for early significant influence within their respective fields. ***Secondly***, innovation novelty as a driver of impact. Innovation novelty consistently exhibits a positive influence on technological impact, corroborating the hypothesis that more innovative technologies are more likely to evolve into high-impact innovations. This relationship holds true across different contexts of technological application, from internal to external fields and from basic to applied research. ***Thirdly***, the study differentiates the impacts within versus beyond the technological field and between basic and applied research. Findings reveal that newer technologies find it challenging to make an immediate impact within their primary domain but often gain substantial traction externally. Furthermore, applied research shows a greater receptiveness to innovative and novel technologies compared to basic research, which may have longer gestation periods for impact realization. ***Finally***, limited role of growth and uncertainty. Contrary to initial expectations, growth rates and uncertainty did not consistently influence technological impact, suggesting that these factors alone may not be reliable predictors of impact within the dataset explored. However, the nature of uncertainty and the challenges in accurately measuring this variable warrant further exploration. This area has seldom been comprehensively addressed in existing studies, pointing to a significant gap in the current understanding and measurement of technological uncertainty (Jiang et al., 2024; Xu et al., 2021).

In conclusion, this study enhances our understanding of how different attributes of emerging technologies influence their patterns of impact, providing critical insights that can help guide future technological developments, strategic industry positioning, and policy formulations in the rapidly evolving landscape of digital medical technology. Further research could expand these insights into other fields of emerging technology to validate the generalizability of the findings and refine our understanding of innovation dynamics across sectors.

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References

Carley, S. F., Newman, N. C., Porter, A. L., & Garner, J. G. (2018). An indicator of technical emergence. Scientometrics, 115(1), 35–49. https://doi.org/10.1007/s11192-018-2654-5

Cattani, G. (2005). Preadaptation, Firm Heterogeneity, and Technological Performance: A Study on the Evolution of Fiber Optics, 1970–1995. Organization Science, 16(6), 563–580. https://doi.org/10.1287/orsc.1050.0145

Corredoira, R. A., & Banerjee, P. M. (2015). Measuring patent's influence on technological evolution: A study of knowledge spanning and subsequent inventive activity. Research Policy, 44(2), 508–521. https://doi.org/10.1016/j.respol.2014.10.003

Corrocher, N., Malerba, F., & Montobbio, F. (2003). The emergence of new technologies in the ict field: Main actors, geographical distribution and knowledge sources. 33.

Day, G. S., & H, P. J. (2000). Wharton On Managing Emerging Technologies. Wiley.

Fortunato, S., Bergstrom, C. T., Börner, K., Evans, J. A., Helbing, D., Milojević, S., Petersen, A. M., Radicchi, F., Sinatra, R., Uzzi, B., Vespignani, A., Waltman, L., Wang, D., & Barabási, A.-L. (2018). Science of science. Science, 359(6379), eaao0185. https://doi.org/10.1126/science.aao0185

Furukawa, T., Mori, K., Arino, K., Hayashi, K., & Shirakawa, N. (2015). Identifying the evolutionary process of emerging technologies: A chronological network analysis of World Wide Web conference sessions. Technological Forecasting and Social Change, 91, 280–294. https://doi.org/10.1016/j.techfore.2014.03.013

Gao, Q., Liang, Z., Wang, P., Hou, J., Chen, X., & Liu, M. (2021). Potential index: Revealing the future impact of research topics based on current knowledge networks. Journal of Informetrics, 15(3), 101165. https://doi.org/10.1016/j.joi.2021.101165

Glänzel, W., & Thijs, B. (2012). Using 'core documents' for detecting and labelling new emerging topics. Scientometrics, 91(2), 399–416. https://doi.org/10.1007/s11192-011-0591-7

Huang, H. (2020). The effect of the small-firm dominated ecology on regional innovation. The Annals of Regional Science, 65(3), 703–725. https://doi.org/10.1007/s00168-020-01000-7

Jiang, M., Yang, S., & Gao, Q. (2024). Multidimensional indicators to identify emerging technologies: Perspective of technological knowledge flow. Journal of Informetrics, 18(1), 101483. https://doi.org/10.1016/j.joi.2023.101483

Kwon, S., Youtie, J., & Porter, A. L. (2021). Interdisciplinary knowledge combinations and emerging technological topics: Implications for reducing uncertainties in research evaluation. Research Evaluation, 30(1), 127–140. https://doi.org/10.1093/reseval/rvaa029

Larivière, V., Gingras, Y., Sugimoto, C. R., & Tsou, A. (2015). Team size matters: Collaboration and scientific impact since 1900. Journal of the Association for Information Science and Technology, 66(7), 1323–1332. https://doi.org/10.1002/asi.23266

Lee, C., Cho, Y., Seol, H., & Park, Y. (2012). A stochastic patent citation analysis approach to assessing future technological impacts. Technological Forecasting and Social Change, 79(1), 16–29. https://doi.org/10.1016/j.techfore.2011.06.009

Lee, C., Kwon, O., Kim, M., & Kwon, D. (2018). Early identification of emerging technologies: A machine learning approach using multiple patent indicators. Technological Forecasting and Social Change, 127, 291–303. https://doi.org/10.1016/j.techfore.2017.10.002

Lee, H., Lee, S., & Yoon, B. (2011). Technology clustering based on evolutionary patterns: The case of information and communications technologies. Technological Forecasting and Social Change, 78(6), 953–967. https://doi.org/10.1016/j.techfore.2011.02.002

Lee, W. H. (2008). How to identify emerging research fields using scientometrics: An example in the field of Information Security. Scientometrics, 76(3), 503–525. https://doi.org/10.1007/s11192-007-1898-2

Li, M., Porter, A. L., & Suominen, A. (2018). Insights into relationships between disruptive technology/innovation and emerging technology: A bibliometric perspective. Technological Forecasting and Social Change, 129, 285–296. https://doi.org/10.1016/j.techfore.2017.09.032

Litvinski, O. (2018). Emerging Technology: Toward a Conceptual Definition. International Journal of Trade, Economics and Finance, 9, 257–263. https://doi.org/10.18178/ijtef.2018.9.6.625

Messeni Petruzzelli, A., Maria Dangelico, R., Rotolo, D., & Albino, V. (2011). Organizational factors and technological features in the development of green innovations: Evidence from patent analysis. Innovation, 13(3), 291–310. https://doi.org/10.5172/impp.2011.13.3.291

Messeni Petruzzelli, A., Rotolo, D., & Albino, V. (2015). Determinants of patent citations in biotechnology: An analysis of patent influence across the industrial and organizational boundaries. Technological Forecasting and Social Change, 91, 208–221. https://doi.org/10.1016/j.techfore.2014.02.018

Nemet, G. F., & Johnson, E. (2012). Do important inventions benefit from knowledge originating in other technological domains? Research Policy, 41(1), 190–200. https://doi.org/10.1016/j.respol.2011.08.009

Noh, H., Song, Y.-K., & Lee, S. (2016). Identifying emerging core technologies for the future: Case study of patents published by leading telecommunication organizations. Telecommunications Policy, 40(10), 956–970. https://doi.org/10.1016/j.telpol.2016.04.003

Phene, A., Fladmoe-Lindquist, K., & Marsh, L. (2006). Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space and geographic origin. Strategic Management Journal, 27(4), 369–388. https://doi.org/10.1002/smj.522

Porter, A. L., Garner, J., Carley, S. F., & Newman, N. C. (2019). Emergence scoring to identify frontier R&D topics and key players. Technological Forecasting and Social Change, 146, 628–643. https://doi.org/10.1016/j.techfore.2018.04.016

Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology? Research Policy, 44(10), 1827–1843. https://doi.org/10.1016/j.respol.2015.06.006

Small, H., Boyack, K. W., & Klavans, R. (2014). Identifying emerging topics in science and technology. Research Policy, 43(8), 1450–1467. https://doi.org/10.1016/j.respol.2014.02.005

Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical Combinations and Scientific Impact. Science, 342(6157), 468–472. https://doi.org/10.1126/science.1240474

Wang, Q. (2018). A bibliometric model for identifying emerging research topics. Journal of the Association for Information Science and Technology, 69(2), 290–304. https://doi.org/10.1002/asi.23930

Xu, H., Winnink, J., Yue, Z., Zhang, H., & Pang, H. (2021). Multidimensional Scientometric indicators for the detection of emerging research topics. Technological Forecasting and Social Change, 163, 120490. https://doi.org/10.1016/j.techfore.2020.120490

Xu, S., Hao, L., An, X., Yang, G., & Wang, F. (2019). Emerging research topics detection with multiple machine learning models. Journal of Informetrics, 13(4), 100983. https://doi.org/10.1016/j.joi.2019.100983

Xu, S., Hao, L., Yang, G., Lu, K., & An, X. (2021). A topic models based framework for detecting and forecasting emerging technologies. Technological Forecasting and Social Change, 162, 120366. https://doi.org/10.1016/j.techfore.2020.120366

Zhou, Y. (2019). A novel method to identify emerging technologies using a semi-supervised topic clustering model: A case of 3D printing industry. Scientometrics, 120, 167–185.