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The AI Patent Paradox in Healthcare: The Inhibitory Effect of Strategic Patent Applications on Corporate Digital Transformation

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Abstract

In the era of AI-driven healthcare digital transformation, patents are commonly perceived as indicators of a firm's innovative capability. However, based on 2021-2023 data of Chinese A-share listed healthcare companies, this study finds that an increase in AI patent applications does not significantly advance firms' digital transformation. On the contrary, when the share of patents in the highly abstract conceptual tier and the broad application tier is higher, the digitalization process is significantly inhibited. Mechanism tests reveal that this patent paradox stems from the resource-crowding-out effect of strategic patent filings, which is particularly pronounced in firms with stronger financing constraints. The study calls for a policy shift from "rewarding quantity" to "promoting practical implementation", guiding firms back to the essence of technology.

Keywords

Artificial Intelligence, Healthcare Industry, AI Patents, Digital Transformation, Patent Paradox, Resource Crowding-Out

1. Introduction

Under the global wave of digitalization, artificial intelligence (AI) is seen as a core engine for upgrading the healthcare industry, and its enormous potential has triggered an explosive growth in related patent applications. Existing research generally treats AI patents as positive signals: patents are a direct manifestation of technological innovation and should, in principle, promote firms' digital transformation (Dang & Motohashi, 2015; Lin et al., 2021). However, the reality is more complex: massive investments in cutting-edge technologies do not necessarily yield corresponding productivity improvements, echoing the digitalization paradox observed at the macro level (Vial, 2019). Similar paradoxes have been observed in other high-tech, cumulative-innovation industries (Hall & Ziedonis, 2001). This study focuses on this paradox at the firm level, challenging the traditional assumption that "AI patents foster digital transformation". We aim to answer a core question: when patenting shifts from being the natural crystallization of innovation outcomes to a strategic goal pursued by firms, might it actually inhibit their deep digital transformation?

In modern business competition, patents are no longer just tools for intellectual property protection; they have evolved into key strategic signals (Spence, 1973; Connelly et al., 2011). Especially in high-tech fields with information asymmetry, patents serve as a powerful signal to the capital market and partners of a firm's technological strength (Hsu & Ziedonis, 2008; Long, 2002). However, this signaling value can also generate opportunistic behavior: firms may strategically file a large number of low-value patents to cultivate an image of technological leadership or to obtain subsidies, leading to a patent bubble (Dang & Motohashi, 2015; Li, 2012). Moreover, firms' motives for patenting extend well beyond direct commercialization, encompassing strategic objectives such as blocking rivals, gaining leverage in negotiations, and pre-empting litigation (Cohen, Nelson, & Walsh, 2000). This phenomenon gives rise to what we term the patent paradox (Vial, 2019). Digital transformation is a systemic endeavor that requires long-term investment of substantial financial, human, and managerial capital. When a firm's strategic focus overly shifts toward producing patents for external display, it inevitably crowds out resources that would have otherwise been used for internal system upgrades, software development, data integration, and other substantive digital initiatives. Such a crowding-out effect causes patenting activities to become decoupled or even in conflict with digital transformation goals. Based on this reasoning, we propose our first hypothesis:

Hypothesis 1: All else equal, an increase in a firm's AI patent count does not significantly promote its level of digital transformation, and may even exert an inhibitory effect.

The resource-based view (RBV) holds that a firm's sustained competitive advantage comes from its possession and control of unique, valuable, inimitable, and non-substitutable resources and capabilities, including both tangible and intangible assets (Barney, 1991). Digital transformation is essentially the process by which firms build and deploy a series of new digital resources and capabilities (Bharadwaj, 2000). Different types of patents represent different directions of resource allocation within a firm, and thus have heterogeneous effects on digital transformation. In an innovative contribution, this paper introduces a three-tier taxonomy of AI patents—shown in **Table 1**—according to their level of technical abstraction and distance from end-use applications:

We argue that the resource-crowding-out effect driven by strategic motives is particularly severe under an "ideation-heavy" patent portfolio. When the portfolio is excessively skewed toward highly abstract conceptual patents and broad application patents, innovation becomes more like stockpiling ideas: it consumes large amounts of R&D resources but yields few usable digital assets (Fisch, Block, & Sandner, 2016). Therefore, the higher the share of such patents, the stronger the inhibitory effect on digital transformation. In contrast, R&D efforts directed toward technical-level patents align more closely with building the firm's digital infrastructure, and these investments are more likely to be complementary to digital transformation rather than competitive. Based on this reasoning, we propose the second and third hypotheses:

Table 1. Definitions of AI patent tiers.

Tier (Patent Level)	Definition
Conceptual Level	Patents on abstract algorithms or theoretical models. These are the furthest from the market and more akin to "idea placeholders" in frontier research areas.
Application Level	Patents on specific business scenarios or commercial methods. These are closer to the market but still require substantial development work before practical implementation.
Technical Level	Patents on foundational technologies or data processing methods. These are core technical modules used to build higher-level applications and are directly related to enhancing the firm's overall digital capabilities.

Hypothesis 2: The proportion of conceptual-level AI patents in a firm's patent portfolio negatively moderates the relationship between AI patent count and digital transformation. That is, for firms with a high share of conceptual patents, the inhibitory effect of AI patent count on digitalization is stronger.

Hypothesis 3: The proportion of application-level AI patents in a firm's patent portfolio negatively moderates the AI patent-digital transformation relationship; whereas the proportion of technical-level AI patents has no significant moderating effect.

By integrating strategic patent theory, signaling theory, and the resource-based view, this paper constructs a complete causal chain to explain the patent paradox: firms, motivated to transmit positive signals externally, engage in strategic behavior (filing many abstract, conceptual patents), which triggers the mechanism of crowding out finite financial, human, and managerial resources, leading to the consequence that substantive digital transformation is impeded. This framework offers a new perspective for understanding corporate innovation strategies amid the AI boom.

2. Research Design

2.1. Sample and Data

The study sample consists of all healthcare companies listed on China's A-share market during 2021–2023. We apply the following data treatments: 1) exclude firms labeled ST, *ST, or PT; 2) exclude any firm-year observations with serious missing values in key variables; 3) winsorize all continuous variables at the 1% and

99% percentiles. After screening, we obtain an unbalanced panel dataset with 1255 firm-year observations. Data are drawn from multiple authoritative sources: firms' textual disclosures on Generative AI (GAI) and financial data come from annual reports; AI patent data are obtained from the China National Intellectual Property Administration (CNIPA) patent database.

2.2. Variable Definitions

Table 2 lists the key variables used in the analysis.

2.3. Variable Definitions

We employ a firm-level fixed-effects panel regression model to control for

Table 2. Variable definitions.

Category	Symbol	Variable Name	Definition
Dependent variable	digi	Digitalization Level	The ratio of digitalization-related intangible assets to total intangible assets in the current year.
Explanatory variable	AI_patent1	AI Patent Count	Natural log of (1 + the number of AI invention patents applied for by the firm in the year).
Moderating variables	lndime1	GAI Basic Concept Disclosure	Degree to which the firm mentions basic terms and representative products of generative AI; natural log of (1 + frequency of related terms).
	lndime2	GAI Application Scenario Disclosure	Degree to which the firm describes specific business applications and implementation scenarios of generative AI; natural log of (1 + frequency of related terms).
	lndime3	GAI Underlying Technology Disclosure	Depth of explanation of generative AI's unique technical principles and implementation methods; natural log of (1 + frequency of related terms).
Control variables	Finlev	Financial Leverage	Total liabilities divided by total assets.
	lnSale	Firm Size	Natural log of total operating revenue.
	age	Firm Age	Number of years since the firm's stock market listing.
	cflow	Cash Flow	Net cash flow from operating activities divided by total assets.
	BoardScale_57	Board Size	Total number of board members.
	top1	Ownership Concentration	Shareholding percentage of the largest shareholder.
	INST	Institutional Ownership	Aggregate shareholding percentage held by institutional investors.
	Dual	CEO-Chairman Duality	Dummy variable equal to 1 if the firm's chairman and CEO are the same person; 0 otherwise.
	F101001A	State Ownership	Dummy variable equal to 1 if the firm is state-owned; 0 otherwise.
	SA_index	Analyst Coverage	Number of analysts covering the firm.
	Negshrcr1	Stock Crash Risk	Indicator measuring the firm's future stock price crash risk.

Note: t-statistics in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

unobserved time-invariant heterogeneity (e.g. corporate culture, location) and common annual macro shocks (e.g. policy changes, pandemic effects). The model is specified as follows:

$$\begin{aligned} digi_{it} &= \beta_0 + \beta_1 aicx1_{it} + \beta_2 lnweidu_{k,it} + \beta_3 \left(aicx1_{it} \times lnweidu_{k,it} \right) \\ &\quad + \gamma' Controls_{it} + \alpha_i + \delta_t + \epsilon_{it} \end{aligned} \tag{1}$$

where subscripts i and t denote firm and year, and k denotes patent tier (conceptual, application, or technical).

3. Empirical Results

3.1. Baseline Regression Analysis

3.1.1. Main Effect Test: AI Patent Count and Digital Transformation

We first examine the direct effect of AI patent count on digital transformation. In **Table 3** (Models 2, 4, and 6), the coefficient on the AI patent count (AI_patent1) is not statistically distinguishable from zero. This preliminary finding forms the starting point of our argument: after controlling for firm fixed effects and year fixed effects, simply accumulating more AI patents does not bring any measurable improvement to a firm's substantive digitalization level. This result directly supports Hypothesis 1—that there is no significant facilitating relationship between AI patent count and digital transformation—and reveals the core paradox of our study.

3.1.2. Moderating Effects I: Negative Moderation by Conceptual and Application-Level Patents

Since patent count itself is not the key, the key to the "patent paradox" lies in the strategic composition of the patent portfolio. Model (2) provides decisive evidence for this. The interaction term between AI patent count and the share of conceptual-level patents (AI_patent1\times lndime1) has a coefficient of −0.540, significant at the 1% level. Similarly, Model (4) shows that the interaction between AI patent count and the share of application-level patents (AI_patent1\times lndime2) is −0.432, also significant at 1%. These two significantly negative interaction coefficients clearly indicate that as a firm's patent portfolio becomes increasingly skewed toward the abstract "conceptual" tier and the broad "application" tier, the inhibitory effect of patenting on digital transformation significantly strengthens. This strongly supports Hypotheses 2 and the first part of Hypothesis 3: an innovation strategy biased toward "ideation" comes at the direct cost of sacrificing the firm's concrete digital transformation progress.

3.1.3. Moderating Effect II: Non-Significant Influence of Technical-Level Patents

In contrast, Model (6) (**Table 3**) provides a starkly different result. The interaction term for technical-level patents (AI_patent1 \times lndime3) is dropped from the model due to multicollinearity and is statistically indistinguishable from zero. This result precisely confirms our logic: when patenting activity returns to focusing on core technical modules (the "technical" tier), the conflict with digital transformation disappears. This finding provides evidence for the latter part of Hypothesis 3 and pinpoints the boundary condition of the inhibitory effect—it is not inherent in all patenting activity, but specific to patent strategies that diverge from core technology fundamentals and lean toward strategic signaling. In summary, the baseline regression results, through the progression of main effects and moderating effects, not only confirm the existence of the "patent paradox", but also reveal its underlying mechanism: the key driver of the inhibitory effect is not the number of patents per se, but the degree of "ideation-ism" in the firm's patent portfolio.

Table 3. Baseline regression results for ai patents, patent portfolio strategy, and corporate digital transformation.

Dependent variable: digi	(1)	(2)	(3)	(4)	(5)	(6)
AI_patent1	−0.012 (−0.34)	−0.009 (−0.28)	−0.022 (−0.63)			
lndime1	0.516 (0.62)	2.366*** (2.59)				
AI_patent1 × lndime1		−0.540*** (−4.51)				
lndime2			−1.714* (−1.66)	2.292 (1.64)		
AI_patent1 × lndime2				−0.432*** (−4.22)		
lndime3					−3.923 (−0.45)	−3.890 (−0.44)
AI_patent1 × lndime3						0.000 (.)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1255	1255	1255	1255	1255	1255
Adjusted R^2	−0.560	−0.523	−0.555	−0.524	−0.560	−0.561

Note: t-statistics in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.2. Robustness and Endogeneity Checks

To ensure the reliability of our findings and the robustness of causal inference, we perform a series of stringent checks. First, we replace the dependent variable with alternative measures—specifically, the firm's digitalization investment amount and a composite digitalization index constructed via text analysis of annual reports—and also lag the core explanatory variable by one period. The results consistently support the baseline findings, indicating that our conclusions are not driven by specific variable definitions and partially alleviating reverse-causality concerns. Second, to address the core endogeneity challenge, we implement an instrumental variable two-stage least squares (IV-2SLS) approach, using the annual average number of AI patent applications of other firms in the same industry as an instrument. The 2SLS results show that after correcting for endogeneity bias, the direct inhibitory effect of AI patents on digital transformation becomes highly significant, further strengthening our main argument. Finally, we adopt a more stringent high-dimensional fixed-effects model that controls for firm fixed effects and joint "industry × year" fixed effects, thus ruling out unobservable factors that vary jointly by industry and time. The core conclusions remain unchanged. These complementary checks jointly confirm that the "patent paradox" finding is highly robust.

We also conduct a series of supplementary tests. First, we change the winsorization threshold of continuous variables from 1% to 5% to examine the sensitivity of our results to outlier treatment. Second, we replace the dependent variable with the firm's digitalization investment and the text-based composite index. Third, to address potential heteroskedasticity and clustering issues, we use the Wild Cluster Bootstrap method for more robust standard error estimation. All these checks consistently affirm the reliability of our results.

4. Mechanism Test and Further Analysis

4.1. Resource Crowding-Out Mechanism

The mechanism analysis aims to reveal the causal chain behind the patent paradox, focusing on verifying the resource-crowding-out theory (Klingebiel & Rammer, 2014). This theory posits that strategic patent filings for the sake of external signaling will crowd out the limited resources that could have been used for internal digital development. To test this, we examine the moderating role of financial constraints, using the SA index and equity pledge ratio as measures. The IV-2SLS results show that firms with higher pledge ratios have significantly lower digitalization levels. This directly confirms the resource-crowding logic: when a firm faces greater financial pressure, fewer resources are available for digital transformation, which in turn impedes substantive digital progress. In addition, we explore the oversight role of corporate governance, particularly institutional investors (Aghion et al., 2013; Bushee, 1998). Although the coefficient on institutional ownership is not statistically significant, its magnitude in the IV model is about seven times larger than in the baseline model, and its sign is consistent with expectations. This provides directional support for the idea that institutional investors, through effective monitoring, can guide firms to allocate resources to long-term value-creating digital activities, thereby weakening opportunistic patent behavior, instead, it may actually foster innovation (Kochhar & David, 1996; Kim, Park, & Song, 2019).

4.2. Heterogeneity Analysis

The heterogeneity analysis by firm characteristics—shown in **Table 4**—reveals that the patent paradox effect is not uniform, but concentrated among specific types of firms. First, in terms of ownership structure, the negative moderating effect of the patent portfolio is almost entirely driven by non-state-owned enterprises (non-SOEs). The interaction coefficient is highly significant (at the 1% level) in the non-SOE sample, but is not significant in the SOE sample. This suggests that market competition pressure and incentive mechanisms in non-SOEs may be key conditions that foster strategic patent behavior and resource crowding. Second, financial status serves as an important differentiator: we find that in firms with lower financing constraints, conceptual-level patents have an extremely strong inhibitory effect on digital transformation (Liu et al., 2024), whereas this effect is not apparent in highly constrained firms. This indicates that only when a firm's resources are relatively abundant does it have the motivation and capacity to pursue "ideational" patent strategies that crowd out substantive digital initiatives. Finally, firm size matters: the negative moderating effect is mainly observed in large firms, and is insignificant in small firms. This suggests that the complex interaction between an AI patent strategy and digital transformation requires the resource base, data volume, and diverse application scenarios typically found in large firms. In summary, the inhibitory effect is primarily present in large, resource-rich, non-state-owned firms operating in highly market-driven environments.

Table 4. Heterogeneity analysis by ownership, financial constraints, and firm size.

Variable	State-owned Firms	Non-state-owned Firms	Low Financial Constraint	High Financial Constraint	Small Firms	Large Firms
lndime1	2.541* (1.79)	2.440** (2.39)	2.850*** (3.40)	1.649 (1.00)	−0.680 (−0.19)	2.872*** (3.13)
AI_patent1	0.0677 (1.51)	−0.0177 (−0.46)	−0.0429 (−0.93)	0.00611 (0.10)	0.0271 (0.17)	−0.0211 (−0.64)
AI_patent1 × lndime1	0.000 (.)	−0.543*** (−4.16)	−0.623*** (−7.52)	0.0391 (0.09)	−0.179 (−0.18)	−0.578*** (−5.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	206	1049	654	601	474	781
Adjusted R^2	−0.263	−0.530	−0.370	−0.733	−0.824	−0.544
Variable	State-owned Firms	Non-state-owned Firms	Low Financial Constraint	High Financial Constraint	Small Firms	Large Firms

Note: t-statistics in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

5. Conclusion and Outlook

This study examines A-share listed healthcare companies from 2021 to 2023 and uncovers a patent paradox: the more AI patents a firm has, the slower its digital transformation progresses. The root cause lies not in the sheer number of patents, but in an excessively high share of "ideation-driven" patents. When firms massively apply for concept-level and broad application-level patents that are far from practical use, innovation becomes a symbolic game that significantly drags on digitalization. In contrast, patents focused on algorithms, data processing, and other technical-level contributions align with the goal of building long-term digital capabilities, and we find no inhibitory effect for such patents (Fisch, Block, & Sandner, 2016). The deeper mechanism is resource crowding: strategic patent filings made to signal external advantages consume financial, human, and managerial resources that could have been used for internal system upgrades (Laursen & Salter, 2006). This negative impact is especially acute in firms facing tighter financing constraints.

These findings have important implications for policy and management. Policymakers should shift the focus of incentives from rewarding patent counts to encouraging practical applications, insulating R&D and digital-transformation initiatives from the short-term pressures exerted by analysts and capital markets (He & Tian, 2013; Laverty, 1996), guiding firms from "innovating for patents" toward "innovating for application". Corporate managers should adopt a long-term innovation strategy that prioritizes quality over quantity, avoids getting caught in patent races, and concentrates resources on substantive R&D that can be translated into core competitiveness.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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