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Artificial Intelligence Enabling Entrepreneurship Orientation——Opening Up to the Outside World and the Regulatory Mechanism of Industrial Structure

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ABSTRACT
In the context of a burgeoning digital economy, examining the impact of artificial intelligence (AI) output on firms' entrepreneurial orientation is of significant practical importance. Using panel data from Chinese A-share listed companies from 2011 to 2022 and estimating two-way fixed-effects models, this study empirically tests the effect and underlying mechanisms of AI (measured by Allpatents) on entrepreneurial orientation. The results indicate that (1) AI significantly enhances firms' entrepreneurial orientation, and this finding remains robust after excluding outliers and applying winsorization; and (2) both regional openness and industrial upgrading positively moderate the effect of AI on entrepreneurial orientation through technology spillovers and optimized factor allocation. These findings offer empirical guidance for firms optimizing their AI deployment and for policymakers crafting innovation-driven strategies, while also extending entrepreneurial orientation theory to the digital technology context.

KEYWORDS
Artificial intelligence; Entrepreneurship orientation; Regulation effect

1 Introduction

In the midst of rapid global economic growth and digital transformation, a firm's entrepreneurial orientation (EO) is pivotal for securing competitive advantage and achieving sustainable development in fierce market competition. As a strategic technology spearheading a new wave of technological revolution and industrial change, artificial intelligence (AI) is profoundly reshaping firms' operating models and innovation pathways. Although prior research has begun to explore the link between AI and EO, it has largely focused on digital technologies more broadly or on information systems, leaving a gap in our understanding of how AI output—measured strictly by AI patents—affects EO and how this relationship is moderated by regional openness and industrial upgrading.

Using the Chinese market as a case study, we observe that the number of AI patents has surged alongside varying trends in firms' entrepreneurial orientation. Preliminary time-series analysis suggests that regions with rapid AI development and high patent output tend to exhibit stronger entrepreneurial behaviors among firms. This raises two key questions: Is there an intrinsic causal relationship between AI output and corporate EO, and how do external environmental factors such as city openness and industrial structure upgrading moderate this effect?

This paper makes three primary contributions. First, by quantifying AI output, we provide precise empirical evidence on its direct impact on EO. Second, we uncover positive moderating roles of regional openness and industrial upgrading in the AI – EO relationship, thereby extending EO theory into the digital technology context. Third, through rigorous robustness checks and causal inference tests, we offer reliable guidance for firms optimizing their AI strategies and for policymakers crafting innovation-driven policies.

2 Theoretical Basis and Research Hypothesis

2.1 Proposing Core Assumptions

Based on the Resource-Based View (RBV), artificial intelligence (AI) capabilities constitute valuable, rare, inimitable, and non-substitutable (VRIN) knowledge assets that underpin sustained competitive advantage (Barney, 1991) [1]. Dynamic capabilities theory further posits that firms must continuously sense, seize, and reconfigure resources to adapt to turbulent environments (Teece et al., 1997)[2], and AI systems amplify these routines by externalizing tacit expertise and recombining explicit data into actionable insights (Nonaka & Takeuchi, 1996) [3]. Empirical evidence shows AI-driven predictive maintenance can reduce unplanned downtime by approximately 40%, freeing up resources for exploration and innovation—an indicator of enhanced sensing and reconfiguring capacity (T Adimulam et al., 2019) [4]. Moreover, AI-powered decision support tools accelerate opportunity seizing by improving decision speed and accuracy in small business settings (Nicholas Otis et al., 2019)[5]. Studies in South African SMEs reveal that higher AI adoption correlates with stronger entrepreneurial orientation (EO) dimensions—innovativeness, risk-taking, and proactiveness—mediated by enhanced organizational learning and innovation capacity, while configurational analyses highlight the joint role of AI and dynamic internationalization capabilities in shaping EO (Mostafiz M I et al., 2025)[6]. Systematic reviews confirm that AI serves as a core enabler of entrepreneurial processes—opportunity recognition, decision-making, performance improvement, and knowledge research—across contexts (Simonsson & Agarwal, 2021)[7]. Collectively, these theoretical and empirical insights support our core hypothesis:

H1. Enhancement of AI capabilities positively influences firm-level entrepreneurial orientation.

2.2 The Regulation of Urban Opening up to the Outside World

From an institutional-environment perspective, regional openness—manifested in robust property-rights regimes, transparent regulatory frameworks, and efficient administrative services—reduces the transaction costs of innovation (North, 1990; Porter, 1990)[8-9]. It facilitates the cross-border flow of capital and technology, thereby accelerating geographically localized knowledge spillovers (Jaffe, Trajtenberg, & Henderson, 1993)[10]. Open regions also attract and concentrate high-skill labor through liberalized migration and employment policies, amplifying the human-capital endowments essential for AI-driven entrepreneurial activities (Moretti, 2012)[11]. Moreover, policy-driven openness cultivates a diverse entrepreneurial ecosystem via targeted innovation policies and market-supportive regulations, reinforcing the translation of AI capabilities into entrepreneurial orientation (Acemoglu, Johnson, & Robinson, 2005)[12]. Therefore, we hypothesize:

H2. The higher the degree of regional openness, the stronger the positive effect of AI capabilities on firm-level entrepreneurial orientation.

2.3 The Regulatory Role of Industrial Structure Upgrading

According to the economic complexity framework, regions exhibiting higher industrial complexity—characterized by a greater share of high-technology sectors—demonstrate stronger capacities for innovation and knowledge creation, as complexity correlates positively with regional innovation performance (Hidalgo & Hausmann, 2009)[13]. The clustering of advanced industries and research institutions in upgraded industrial structures generates localized technology spillovers and collaborative ecosystems, providing firms with enhanced access to specialized inputs, research partners, and talent necessary for AI-driven entrepreneurial initiatives (Porter, 1998)[14]. Empirical evidence from China indicates that industrial upgrading significantly boosts regional total factor productivity through spatial spillover effects of technological innovation, indirectly reinforcing firms' capacity to leverage AI capabilities for opportunity recognition and strategic renewal (Yu, 2022)[15]. Consequently, in regions with more advanced industry structures, the translation of AI capabilities into entrepreneurial orientation is facilitated by richer ecosystems of resources, networks, and supportive institutions.

H3. The higher the level of industrial structure upgrading, the stronger the positive effect of AI capabilities on firm-level entrepreneurial orientation.

3 Research Design

3.1 Sample Selection and Data Source

This paper selects panel data at the A-share listed company level from 2011 to 2022. In terms of data processing, in order to ensure the rationality of the data and the reliability of the research results, this paper conducts the following screening processing: (1) Exclude financial industry samples and ST and *ST companies to avoid interference with the results by special financial situations; (2) Remove samples with missing data of key variables, and use multiple interpolation (MICE) to process the missing values of non-critical variables to ensure sample integrity.

3.2 Variable Definitions

3.2.1 Dependent Variable (Entrepreneurial Orientation, EO)

Following Yu (2024)[16] and based on the Chinese EO lexicon developed by Yu, Xiao & ZHANG(2022)[17], we employ Python web-scraping to extract the frequency of EO-related terms from the "Discussion and Analysis" sections of firms' annual reports. Specifically, we sum the counts of keywords reflecting the five EO dimensions and then take the natural logarithm of this total to construct each firm's EO score.

3.2.2 Core Explanatory Variable (AI Output)

In line with Yao (2024)[18], we use the number of AI-related patents filed by the firm in a given year—retrieved from the IRPDB database (including title, abstract, application date, assignee, and classification)—as a proxy for its AI capability.

Patents whose title or abstract contain predefined AI keywords are identified and tallied to measure the firm's annual AI output.

3.2.3 Control Variables

a) Firm Size (Size): Natural log of total assets at year-end. *b)* Leverage (Lev): Total liabilities divided by total assets. *c)* Return on Assets (ROA): Net profit divided by total assets. *d)* Fixed Asset Ratio (Fixed): Net fixed assets divided by total assets. *e)* Top-10 Shareholding (Top10): Combined shareholding ratio of the largest ten shareholders.

3.2.4 Moderating Variables

a) Regional Openness (Open): Measured as the ratio of total import–export volume to GDP.
b) Industrial Upgrading (Str): Measured as the ratio of tertiary-sector value added to secondary-sector value added.

3.3 Model Construction

In order to explore the impact of artificial intelligence technology on the entrepreneurial orientation of enterprises, the following two-way fixed effect model(TFEM) is constructed:

$$\text{Incy}_{it}=\beta_0+\beta_1\text{Allpatents}_{it}+\sum\beta_{it}X_{it}+\alpha_i+\varepsilon_t+\varepsilon_{it} \tag{1}$$

Among them, Allpatents_{it}represents the number of artificial intelligence patents of enterprise *i* in year*t*, which measures the level of artificial intelligence, Incy_{it} represents the innovation and entrepreneurship orientation of the enterprise *i* in year *t*, and X_{it} is a set of control variables (including 5 indicators). Finally, ε_{it} is the error term, α_i,ε_t represent the parts that are not explained by the model. These are year fixed effects and enterprise fixed effects respectively.

3.4 Descriptive Statistics

The descriptive statistics (Table 1) reveal that Incy exhibits a mean of 5.640 with a limited standard deviation, indicating a clustering of entrepreneurial orientation scores . The distribution of Incy suggests most firms maintain a moderately high level of entrepreneurial orientation, with outliers offering insights into particularly conservative or innovative practices. Allpatents shows substantial variability, as evidenced by its high standard deviation relative to the mean, reflecting heterogeneous AI engagement across the sample. Control variables such as Size, Lev, and ROA display distributions consistent with previous corporate finance studies, ensuring alignment with extant literature . The relatively narrow range of Size implies a sample centered on small to medium–sized enterprises, facilitating generalizability within this cohort. Leverage (Lev) and profitability (ROA) metrics fall within typical bounds, supporting the model's internal validity and echoing industry benchmarks . Asset structure indicators, such as FIXED, reveal balanced capital allocations, further affirming the sample's representativeness. Shareholding concentration, measured by TOP10, presents sufficient dispersion to capture governance effects without extreme bias.

Table 1 Descriptive Statistics

Variable	N	Mean	SD	Min	Max	Variable	N
Incy	2700	5.640102	0.3713516	3.713572	6.72022	Incy	2700
Allpatents	2700	0.2911111	1.650579	0	31	Allpatents	2700
Size	2700	22.3308	1.173045	19.58496	26.37597	Size	2700
Lev	2700	0.4567297	0.1855208	.0298116	.9078884	Lev	2700
ROA	2700	0.0391989	0.0603511	-.3730353	.2473081	ROA	2700

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4 Empirical Analysis and Results

4.1 Benchmark Regression Model

In the baseline regressions, we examine the effect of firm-level AI innovation on entrepreneurial orientation. Table X presents two sets of results: Column (1) reports estimates without firm and year fixed effects, while Column (2) includes both firm and year fixed effects.

First, in Column (1), without fixed effects, AI innovation (measured by Allpatents) exerts a significant positive impact on entrepreneurial orientation (measured by Incy), with a coefficient of 0.0118 ($p < 0.01$). This indicates that a firm's innovation activities actively promote its entrepreneurial orientation. Firm size (Size), return on assets (ROA), and the shareholding ratio of the largest ten shareholders (TOP10) also show significant positive effects—coefficients of 0.0207, 0.343, and 0.00298 respectively (all $p < 0.01$). In contrast, leverage (Lev) and the fixed-asset ratio (FIXED) both have significant negative effects on entrepreneurial orientation ($p < 0.01$).

Second, after adding firm and year fixed effects in Column (2), AI innovation remains positively and significantly associated with entrepreneurial orientation, with a coefficient of 0.00837 ($p < 0.05$). The positive impacts of Size, ROA, and TOP10 not only persist but also strengthen in significance. Conversely, the effect of FIXED becomes insignificant, while Lev continues to exert a significant negative influence on entrepreneurial orientation.

Table 2 Benchmark Regression Test

Project	(1)	(2)
VARIABLES	Incy	Incy
Allpatents	0.0118***	0.00837**
	(0.00419)	(0.00399)
Size	0.0207***	0.108***
	(0.00667)	(0.0138)
Lev	-0.214***	-0.274***
	(0.0446)	(0.0583)
ROA	0.343***	0.480***
	(0.129)	(0.111)
FIXED	-0.635***	-0.134*
	(0.0470)	(0.0748)
TOP10	0.00298***	0.00475***
	(0.000506)	(0.000708)
Constant	5.263***	3.114***
	(0.137)	(0.297)
Enterprise fixed effect	No	Yes
Year fixed effect	No	Yes
Observations	2,700	2,700
R-squared	0.109	0.674

4.2 Identify the Headings

In Models (1) and (2), we examine the relationship between entrepreneurial orientation (Incy) and AI output (Allpatents), as well as the moderating roles of regional openness (open)—measured by the ratio of total import–export value to GDP—and industrial upgrading (Str)—measured by the ratio of tertiary to secondary industry output.

First, in Model (1), the interaction between Allpatents and open is positive and significant (coefficient=0.594), indicating that higher levels of trade openness strengthen the positive impact of AI output on entrepreneurial orientation. This suggests that firms leveraging AI technologies can more effectively enhance their innovation and entrepreneurial orientation in an internationalized market environment.

Second, in Model (2), the interaction between Allpatents and Str is also significantly positive (coefficient=0.0706), implying that industrial upgrading further amplifies AI's positive effect on entrepreneurial orientation. Additionally, Str itself exerts a negative effect on Incy (coefficient=-0.296), suggesting that structural shifts toward higher-value industries may, in isolation, exert some dampening effect on entrepreneurial orientation.

4.3 Robustness Test

4.3.1 Sample-Period Adjustment

Excluding the 2022 observations to avoid potential distortions from COVID-19 policy interventions, the coefficient on Allpatents remains positive and significant at 0.0094 ($p < 0.01$), closely matching the baseline estimate of 0.00837. This consistency indicates that our core finding is not driven by anomalies in a single year.

4.3.2 Outlier Treatment

After applying two-sided 1% winsorization to all continuous variables, the adjusted AI variable (Allpatents_w) yields a coefficient of 0.0147 ($p < 0.05$). Control variables retain both their original signs and significance levels, and the model's explanatory power (R^2=0.676) remains virtually unchanged from the baseline ($R^2 = 0.674$).

Together, these tests confirm that our results are robust to both sample-period adjustments and extreme-value controls, affirming the reliability of AI's positive effect on firms' entrepreneurial orientation.

Table 3 Regulation Effect

Project	(1)	(2)
VARIABLES	*lncy*	*lncy*
Allpatents* open	0.594*	
	(0.340)	
Str* Allpatents		0.0706*
		(0.0407)
Allpatents	-0.00436	-0.0308
	(0.00817)	(0.0230)
open	-1.849***	
	(0.470)	
Size	0.111***	0.105***
	(0.0137)	(0.0138)
Lev	-0.272***	-0.266***
	(0.0581)	(0.0583)
ROA	0.468***	0.476***
	(0.111)	(0.111)
FIXED	-0.137*	-0.137*
	(0.0746)	(0.0748)
TOP10	0.00484***	0.00473***
	(0.000707)	(0.000709)
str		-0.296**
		(0.139)
Constant	3.096***	3.321***
	(0.296)	(0.309)
Enterprise fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	2,700	2,700
R-squared	0.676	0.675

Table 4 Robustness Test

Project	(2)	(3)
VARIABLES	*Lncy(Reduce samples)*	*lncy_w(shrink the tail)*
Allpatents	0.00940**	
	(0.00405)	
Size	0.115***	
	(0.0142)	
Lev	-0.279***	
	(0.0604)	
ROA	0.383***	
	(0.116)	
FIXED	-0.122	
	(0.0770)	
TOP10	0.00488***	
	(0.000740)	
Allpatents_w		0.0147**
		(0.00595)
Size_w		0.105***
		(0.0134)
Lev_w		-0.271***
		(0.0564)
ROA_w		0.471***
		(0.119)
FIXED_w		-0.140*
		(0.0728)
TOP10_w		0.00476***
		(0.000690)
Constant	2.939***	3.185***
	(0.306)	(0.289)
Enterprise fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	2,512	2,700
R-squared	0.674	0.676

5 Conclusion

Based on data from China's A-share listed companies from 2011 to 2022, this paper studies the impact of artificial intelligence on corporate entrepreneurship orientation. Through benchmark regression, regulation effect, heterogeneity analysis, robustness testing and other methods, the following conclusions are drawn: the output of artificial intelligence technology has a positive impact on corporate entrepreneurship orientation, and this impact is stronger in an environment with a high degree of openness to the outside world and an advanced industrial structure. Enterprise size, profitability and equity concentration promote entrepreneurial orientation, while debt-to-asset ratio and fixed asset proportion have a inhibitory effect on entrepreneurial orientation. The research results provide a theoretical basis for enterprises to reasonably allocate artificial intelligence resources and improve their entrepreneurial orientation, and also provide a reference for policy makers to optimize the innovation environment.

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