

Artificial Intelligence and Firm Internationalization: Evidence from Chinese Listed Companies

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Abstract

This study examines whether firm-level artificial intelligence (AI)-related strategic intensity is associated with the internationalization of Chinese listed companies - whether that association depends on complementary R&D resources and ownership structure. The research employs an unbalanced panel of data covering the period from 2017 to 2024 with a final regression sample comprised of 31,839 firm-years of data from a total of 5,211 firms in the sample. The level of internationalization is determined as the natural logarithm of 1 + the number of active foreign subsidiaries, thereby reflecting the organizational volume of an existing foreign presence by any company. The level of AI is taken as a natural logarithm of 1 + the frequency of AI-related phrases in management discussion and analysis and interpreted as a measure of AI-related textual or strategic intensity instead of actual monetary investments in AI. Firm and year fixed-effects models with firm-clustered standard errors show a positive AI-internationalization association (coefficient = 0.0179, SE = 0.0051, $p < 0.01$). As investment in domestic R&D grows, the association becomes stronger (AI $\times$ R&D coefficient equals 0.0096 (SE = 0.0037, $p = 0.0087$)). Ownership effect is more ambiguous – AI coefficient is positive for private enterprises and negligible for companies with state ownership, and the slope in terms of ownership variation is only marginally significant (at the 10% level, $p = 0.0821$). Stability of the positive correlation in different variations of outcome definitions, lagged AI variable, the sample with the omitted gap, fixed-effects Poisson estimation, the size of firms and extra controls is also important. Results conform with the interpretation of the findings referring to the dynamics of the development of contingencies since AI – internationalization connection is stronger if complementing internal R&D investments are larger. The research, being observational, provides evidence of correlation but not causes.

Keywords

Artificial Intelligence; Firm Internationalization; Dynamic Capabilities; R&D Investment; Ownership Structure; Chinese Listed Companies.

1. Introduction

Artificial intelligence (AI) is changing the conditions of information and organization that the companies take into account while making strategic decisions. The issue is especially important for the internationalization process because the companies need to analyze new markets, manage resources in an uncertain way, and coordinate activities. Digitalization is able to change the transferability and governance of company-specific resources (Banalieva and Dhanaraj, 2019[1]), but digitalization and internationalization strategies are still connected to local institutions (Meyer et al., 2023[2]). AI makes the situation even more complicated, as it transforms the information entryway to the decision-making process but remains dependent

on humans and institutions (Lindner et al., 2025[3]). Thus, from the Business Economics standpoint, the question is not whether AI has technological importance in the general sense but when the use of AI at the company level becomes economically significant for cross-border resource usage and expansion of the company.

One gap is related to construct and outcome specificity. Digital transformation and internationalization research covers a cross section of technologies, mechanisms and international outcomes (Feliciano-Cestero et al., 2023[4]). Broad digital transformation is associated with internationalization development and breadth, export survival and OFDI efficiency; the magnitudes of the relationships differ depending on the construct and the outcome of the studies (Chen and Li, 2023[5]; Wang et al., 2022[6]; Du et al., 2025[7]; Chang et al., 2025[8]). AI-specific studies progress towards the current question. Liu et al. (2024)[9] analyse the relationship between AI and overseas entry decision, Yang, Wu and Yue (2026)[10] investigate the link between AI-related patents and OFDI decision, breadth and depth and Yang and Peng (2026)[11] find that the application of AI is positively associated with the breadth and depth of international operations. These studies confirm that AI related firm activity can be relevant to international strategy, but not that AI patents, AI application, the wide-spread phenomenon of digitalization or broad digitization and AI related strategic intensity based on texts are interchangeable.

The aspect of the outcome in this case gains significance as various indicators illustrate different aspects of internationalization. According to Adarkwah et al. (2024)[12], the number of subsidiaries remains a significant outcome of foreign investment, while results from Wei and Nguyen (2020)[13] indicate that presence of foreign subsidiaries provides an extremely valuable measure of the multinational activity. The study in hand focuses on the measure of the firm-level active foreign presence, defined as $\ln(1 + \text{active foreign subsidiaries})$. The related AI-related literature does not give much insight into the ways in which text-based firm-level indicators of AI correlate with this specific outcome.

Another gap relates to the circumstances in which the association between AI and internationalization should be stronger. Dynamic capabilities research shows that technology not necessarily guarantees productivity because its effectiveness is based on complementary technological, human, organizational, and knowledge resources (Teece et al., 1997; Teece, 2007; Mikalef and Gupta, 2021[14-16]). Absorptive capacity research indicates that knowledge recognition, absorption, transformation, and utilization depend on prior knowledge and organizational processes (Cohen and Levinthal[17], 1990; Zahra and George, 2002[18]) and innovation studies argue that firm internal R&D can facilitate other types of knowledge acquisition (Cassiman and Veugelers, 2006[19]). Ownership constitutes a specific organizational boundary condition. State ownership can change the accessible resources and objectives of the corporation as well as incentives in the market (Cuervo-Cazurra et al., 2014[20], 2023[21]) whereas Chinese studies show that different ownership patterns relate to different forms of digitalization and internationalization (Wang et al., 2022[6]; Wang and Fu, 2023[22]). Thus, the literature necessitates the explanation based on the context rather than just technologies.

This study fills these gaps in a single firm level framework. It asks whether or not AI Level is associated with organizational level of foreign presence, if the investment in internal R&D exacerbates that association and if the association is different in state and private enterprises. AI Level is based on AI-related sentences in companies' management discussion and analysis (MD&A) statements. Internationalization is calculated from CSMAR data on overseas-affiliate operations. The R&D expenditure is considered as complementary internal stock of knowledge-investment and ownership is determined by a hard criterion: private versus state owned. The analysis will not equate AI attention with investment in or capability of AI, and not every

internationalization measure will be considered the same, as the meaning of each construct will be taken as given before testing the hypotheses.

The main theoretical contribution is that a contingent dynamic-capabilities explanation of AI-related internationalization is developed. Dynamic capabilities emphasize the company's potential to sense risks as well as opportunities, capitalize on certain opportunities, as well as reformulate, or rearrange assets and procedures in response to changes in the environment (Teece et al, 1997; Teece, 2007). Internationalization brings with it an increased need for these capacities, as it needs the ability to process various information and to constantly strive to spread and re-distribute resources across borders. The notion of AI-related strategic intensity has a strong correlation with the amount of information-processing and decision-support activities related to sensing, seizing, and reconfiguration activities. While R&D is used as an additional knowledge resource that can help to drive the conversion of information from AI into action, ownership modifies the context on resource configuration and incentives for action to be taken.

The empirical contribution comes from the correspondence between this framework and the research design. The study integrates an AI-based measure that employs the MD&A, a foreign activity score based on subsidiaries, an AI and R&D relation and determines the slope of difference between private firms and SOEs. The technique relies on unbalanced data from 2017 to 2024 in form of panel data, fixed effects, clustered standard errors and four controls that change over time. Different dependent variables, timing of AI, data handling, method of estimating and firm size were subject to checks of reliability. Going through the provided example contributes to the literature through specificity of concepts and explains conditionalities without violating inference rules.

The results provide three main pieces of evidence. In the final baseline specification, AI Level is positively associated with internationalization (coefficient = 0.0179, SE = 0.0051, $p < 0.01$). The AI $\times$ R&D interaction is also positive (0.0096, SE = 0.0037, $p = 0.0087$), indicating that the positive association becomes stronger as internal R&D investment increases. Ownership evidence is more tentative. The AI coefficient is positive and statistically significant among private firms (0.0186, SE = 0.0068) and negative but statistically insignificant among SOEs (-0.0045, SE = 0.0113), while the formal AI $\times$ SOE difference is -0.0230 (SE = 0.0132, $p = 0.0821$). The direction is consistent with the private-firm hypothesis, but the evidence is only marginal at the 10% level. Additional tests show no statistically significant AI-slope differences by firm size or leverage, and the positive baseline association remains stable across the reported robustness checks.

For Business Economics readers, this progress provides a clearer response to the inquiry of how new technologies attain economic significance. The results indicate that the indicator for AI-relevant firms determined by texts has to do with the level of the firm's foreign presence, that investing in knowledge internally significantly influences this correlation, and that ownership differences are not as strong as one might think based on the mere analysis of significance levels across the subgroups. The findings are related to cross-border resource management, foreign companies' resources complementing one another, and organizational diversity at the emerging markets' level of analysis but they do not provide the answers on cross-country applicability.

The rest of the paper is set up in the following manner. In section two, relevant literature is reviewed, the dynamic capabilities framework is created, and three hypotheses are established. In Section three, the data, formation of samples, creation of variables, control strategy, and empirical specifications are discussed. Section 4 presents the baseline results, R&D moderation, ownership and additional heterogeneity analyses, and robustness checks. Section 5 discusses the main findings, contributions, managerial and policy implications, limitations, and directions for future research.

2. Literature Review and Hypothesis Development

2.1. Theoretical Foundation: Dynamic Capabilities and Emerging-Market Internationalization

This paper relies on the idea of dynamic capabilities for presenting the theory it elaborates on. The term “dynamic capabilities” has been defined by Teece, Pisano and Shuen (1997)[14] as the firm’s ability to accumulate, enhance and alter its resource base in response to changes in the environment. In his work, Teece (2007)[15] insists on the correctness of this definition and explains the term in terms of identifying opportunities and threats and acting in respect to that. The proposed framework is useful for this study because just using technology does not assure getting the expected results owing to many other factors. The company’ economic potential depends on the interpretation of information, the usage of resources and the adjustment of performance. Organizations have to work in a global domain, so they raise their standards in terms of capabilities. Teece (2025) suggests that capability formation is the backbone of success within multinational firms in a digitalized global continuum. In a similar fashion, Yang and Stoian (2025) [23-24] reveal the correlations between general and managerial dynamic capabilities and some particular aspects of post-entry internationalization in organizations. The respective studies emphasize the notion of dynamic capabilities as a tool for transforming newly emerged information and resource conditions into an international business process, although it cannot be stated that the mentioned micro-level processes exist in practice at present.

The context of developing nations does not allow to treat internationalization as similar in all enterprises. As noticed by Gammeltoft and Cuervo-Cazurra (2021)[25] in their research, the process of internationalization in developing countries is conditioned by home country circumstances and the regulations while they are proposing models that capture different factors involved in the process. This is relevant in the case of China, where ownership and regulations influence the operations of resources of the firms abroad.

Digitalization alters the setting in which dynamic capabilities are used and still leads to coordination and governance problems. Banalieva and Dhanaraj (2019) demonstrate that the digital economy results in changes to the nature and transferability of firm-specific resources and the governance of international operations. Similar conclusions are made by Meyer et al. (2023), thus confirming the interaction and impact between digital strategies and internationalisation strategies in terms of influence of national institutions. That is, digital technologies have the potential to change economics of cross-border resource use but somehow leave companies to deal with organizing, controlling, and adjusting the resources.

According to Lindner et al. (2025), AI is clarifying the issue of capabilities through its impact on the information used in management decision-making. Lindner et al. (2025) investigate how AI is being utilized within enhanced decision-making in international business and emphasize that the situation as for the usage of AI by firms still depends on human factor and institutions. Dos Santos and Williamson (2024)[26] suggest some AI-related solutions of firms’ internationalization issue in order to clarify how learning through the interaction in digital environment is changing the informational basis for the company being adapted to the market. However, it has to be stated that the analysis of digital companies impedes the generalization of results of this study to the wide variety of companies. According to Mikalef and Gupta (2021)[16], AI capacity is understood as an organizational capability that has emerged from the use of complementary technical, human resources, and organizational resources. It is essential to emphasize the differentiation of the capacity categories defined here from the empirical measure used in the study. In the context of the present research, AI capability is closely related to a text-based measure of AI strategic intensity in the disclosures of MD&A. In this case, AI capability is not even connected to a survey-based measure of the achieved AI capability. The

dynamic capability theory thus provides a theoretical link between the observed strategic attention to AI and the organizations' mechanisms through which that attention can be translated into economic gains.

The same also applies to how we cannot take the internationalization process for granted, and assume that it is the same or similar in all contexts. According to the research by Gammeltoft and Cuervo-Cazurra (2021)[25], the internationalization process in emerging economies cannot be separated from home-country factors, including government involvement. This is especially important when we consider the case of the Chinese listed companies, where ownership structure and institutional factors matter as far as resource allocation in the international markets is concerned.

2.2. AI-related Strategic Intensity and Firm Internationalization

In the following, the relationship examined for AI is set in relation to the place of research on digital internationalization, which furnishes the wide-ranging empirical framework for that specific relationship. In a systematic review, Feliciano-Cestero et al. (2023) reveal that the integration of digital technologies into internationalization research is both multi-technological and multi-international, insofar that it involves various technologies, organizational mechanisms and international outcomes. This challenge provides the context for the relevance of digital change, but at the same time, evidence on broad digital change is not necessarily evidence on AI. The construction of discipline is particularly significant since the mechanisms surrounding generic digitalisation, AI, platforms and other technologies do not have to be the same.

Evidence from Chinese companies illustrates that digitalization is correlated with internationalization, and also reveals varying outcomes for different aspects of internationalization examined (Chang et al., 2025[8]; Du et al., 2025[7]; Wang et al., 2022[6]; Chen and Li, 2023[5]). Whilst this evidence attests to the digital background required, digital transformation and its outcomes are not synonymous with AI or are different types of internationalization outcomes equivalent?

In recent studies specifically related to AI, a bit more of an argument for the first hypothesis can be made. Liu et al. (2024) [9] link up AI and an overseas entry mode decision whilst taking ownership heterogeneity into account. Among these, Yang et al. (2026) find that AI technology is positively related to OFDI participation and extent and Yang and Peng (2026)[11] find that AI application is positively related to international operations. These studies reinforce the belief that the firm activity can be correlated with internationalization and finds there are different measures of AI firm activity and internationalization outcomes than the text-based AI Level and international measure of active-subsidary adopted in this study.

Our present dependent variable is measure of how organizational the presence of foreigners continues. Wei and Nguyen (2020)[13] offer a complimentary set of evidence that the presence of foreign subsidiaries is also an important component of a multinational's activity in China, and Adarkwah et al. (2024)[12] provide a good precedent for the number of foreign subsidiaries as a substantive measure of investment outcome. None of these two operationalizations were replicated: In the present research, firm observations at the firm-year level are operationalized by taking the natural log of the one plus the number of foreign subsidiaries with an active presence; and observations with no subsidiaries with active presence are retained.

A recent precedent from the literature reviewed in the form of a text-based example increases the legitimacy of the measurement of a variable regarding AI. Drawing on the text of the annual reports of Chinese listed companies, Wu et al. (2024)[27] build an index, called corporate AI-development measure, to reflect the degree of AI-development, for which they use the total AI-word frequency, but which they transform into $\log(1 + \text{frequency})$. While their outcome and

empirical design differ from the current study, which employs frequency of AI-related sentences in MD&A disclosures as a proxy to reflect firm-level AI-related corporate activity, the study reveals that text-frequency measures that have been logarithmically transformed can be used to reflect corporate activity. It is being interpreted with purpose of being more narrow and relating to strategic or textual intensity of your AI vs direct visibility of deployed AI systems. AI-related strategic intensity can be theoretically actually related to internationalization by multiple pathways, as seen from a dynamic-capabilities perspective. In the case of sensing, information processing aspects with AI can help expand or speed up the information used when detecting opportunities and threats in foreign countries. It can be used for capturing and informing the decisions of evaluation, forecast and resource allocation in seizing. It might even aid in reconfiguration, alerting adjust in routines or coordination as a company's foreign presence develops. These are facets to rate and not directly observed here in the data. However, there is no evidence suggesting that the machines and outcomes are moving in tandem, either in terms of AI Level or internationalization, after the firm and year fixed effects and controls are removed from the observational panel, which means that there is no relationship alone with AI that is causal per se.

Hypothesis 1. The firm's AI level is positively related with the firm's internationalization.2.3. Complementary knowledge resources and the moderating role of R&D

Dynamic capability suggests that the value of technology is not only dependent on itself but also on the additional knowledge and skills possessed by a firm. This is especially true in the case of AI, as information, forecasts, and analysis do not turn into a strategic action on their own.

Companies need technical knowledge and skills to analyze such information, link it to their current operations, and try out potential applications of that information. Internal R&D investments serve as a useful source of knowledge investment in this respect.

Research on absorptive capacity offers the knowledge mechanism behind the argument. Cohen and Levinthal (1990)[17] stress the importance of prior knowledge in identifying, comprehending, and using new information. Zahra and George (2002)[18] differentiate between potential absorptive capacity, associated with acquisition and understanding, and achieved absorptive capacity, associated with modification and utilization. These concepts answer the question of why access to AI-related information presents a different economic value than capability to analyze and apply such information. The research conducted does not equate R&D costs with absorptive capacity; it treats R&D expenses as a measurable internal knowledge resource which provides the learning and experimenting infrastructure necessary for capability development.

Research on innovation has provided evidence of interactions rather than simple additivity. According to Cassiman and Veugelers (2006)[19], internal R&D could form complements as opposed to just being included in other activities of learning, while the same has been found in the other study by Adomako et al. (2021)[28-29] which shows that the resources related to R&D and the processes of knowledge creation could be interrelated. None of these studies has tested the current relationship between AI and R&D, but both studies support the concept of complementary internal resources with regard to inputs related to knowledge.

Internationalization research provides a similar capability example. Fredrich et al. (2022) point out that R&D-related capability conditions are significant for internationalization and growth, while Yang and Peng (2026)[11] relate the formation of R&D-related capability with the international implications of AI use. Yang, Wu, and Yue (2026) also find dynamic capabilities important for AI-related OFDI. Although the studies do not present the actual AI $\times$ R&D test, they confirm the theoretical significance of internal knowledge resources for transforming AI-related activity into international results.

New evidence from China shows that innovative practices of a company correlate with its international expansions. Therefore, even though we use this study for comparative purposes, it employs a different unit of analysis and different constructs.

R&D has the potential to enhance all three dynamic capabilities in the existing framework. For example, R&D contributes to sensing by increasing the level of technical expertise required to interpret AI-related data; it contributes to the seizing function by assisting firms in their experimentation with various options; and it contributes to reconfiguration by adding to firms' reservoir of knowledge for incorporating new information into existing routines and technical systems. As a result, the relationship is positive; any increase in the intensity of AI-related strategies should be strongly linked to the extent to which companies operate internationally and that is especially the case in companies that have greater internal investments in this area. Hypothesis 2. R&D investment positively moderates the relationship between firm AI Level and internationalization.

2.3. Ownership Heterogeneity as an Organizational Boundary Condition

In a theoretical sense, having ownership constitutes an important boundary condition in the case of China since the presence of government ownership modifies both what the resources of the environment are and what the goals are with respect to international strategy formulation. Cuervo-Cazurra et al. (2014)[20] demonstrate that state-owned multinationals practice business under particular conditions associated with the principles of state ownership. Furthermore, Cuervo-Cazurra et al. (2023)[21] state that state-owned firms can take advantage of state ownership-related benefits and face several drawbacks while pursuing non-business goals related to the involvement of the government. These statements suggest that ownership does not mean that SOEs are inherently more or less successful internationalizers; however, they imply that ownership is responsible for changing the context in which resources are used to make international strategies.

The Chinese institutional context provides an ideal opportunity to use boundary condition theory. Ma et al. (2026) propose a framework for understanding how strategic knowledge management in Chinese MNEs depends on state-market interactions and classify different state-driven and market-driven logics applied in acquiring knowledge, transferring it, and creating global knowledge. Similarly, Gammeltoft and Cuervo-Cazurra (2021)[25] show that government intervention can facilitate the process of internationalization of firms from emerging markets by mitigating certain types of risks and constraints in terms of resources. At the same time, government assistance does not eliminate market incentives, capability restraints, and organizational disparities. Therefore, type of ownership alters the environment, where strategic insights derived from AI technologies are put into practice.

According to the Chinese literature, ownership heterogeneity is not uniformly recognized in relation to internationalization outcomes. Wang et al. (2022) establish that there is a stronger relationship with digital transformation for private firms with one of the internationalization margins, while Wang and Fu (2023)[22] find a stronger relationship for state-owned enterprises with regard to another. Also, Liu et al. (2024)[9] consider government ownership to be a moderating variable in the case of AI-based internationalization settings. This combination of findings serves to show that ownership constitutes a significant limit to economy but does not offer a universal pattern that could be applied in the present study.

Therefore, there are two possible ways to address this phenomenon. One way is the "state-resource" approach which posits that a government's ownership and institutional support can help accomplish the application of expensive technology and adoption of foreign practices. If on the other hand one uses the "market-incentive" approach, the conclusion will differ, since the incentives might enhance the market-oriented behaviors and depending on this the flexibility regarding the international changes in terms of AI usage. Wei and Nguyen (2020)[13]

show that state-owned resources and limitations caused by capabilities simultaneously exist in terms of internationalization.

H3 adheres to the framework of the market-incentive paradigm but is aware of the counterbalance of the state-resource paradigm. The prediction seems to be precise: commercialization incentives render the shifts in AI strategy more endogenous to decisions about how to allocate foreign resources. The result would indicate the need for a straightforward comparison of regression slopes. A difference between the two groups in terms of the existence of statistically significant coefficient in one group and non-significant results in another group cannot prove that two groups are significantly different.

Hypothesis 3. The positive correlation between artificial intelligence level in a firm and globalization is more significant in private companies than in public companies. 2.5. Research framework, novelty, and contribution to Business Economics

The literature has revealed two related shortcomings. First of all, existing research looks into all-encompassing digital transformation, AI patents, AI application, AI-related decision making, exports, OFDI engagement and its scope, entry strategy, and investment of subsidiaries, although two concepts are not the same. By contrast, the research in question is concentrating on a more detailed combination of terms - text-based measure of AI-related strategic intensity combined with how widespread the active network of foreign subsidiaries is. Secondly, the literature demonstrates that technological outcomes depend on the combination of resources and organizational context, but lacks in an ability to demonstrate the connection between whether the internal R&D make this specific relation of AI-globalization stronger or if the slopes of AI for state-owned and private companies differ in terms of statistical significance.

The concept of theoretical progress involves combining direct relationships, complementarity in R&D, and ownership diversity within a single dynamic capabilities framework. The framework rejects the premise that strategic focus on AI automatically leads to international growth but sees AI information as having economic significance only when companies recognize, exploit opportunities through investments in resources, and reorganize their structures, relying on R&D for supplementary knowledge and ownership patterns affecting the institutional and incentive environment. As a result, boundary-condition results that are insignificant or not significant provide useful information rather than being problematic since, if the moderator does not create a different slope statistically, it indicates a lack of evidence for the boundary condition.

The study is original not only in terms of theoretical framework, but also in the accuracy of measures established for testing hypotheses. It employs the sentence-frequency-based MD&A measure of strategic intensity in the field of AI, the firm discipline-related indicator showing the presence of foreign subsidiaries around the world, the interaction of formal AI and R&D amounts, and the combined slope-difference method comparing private firms and State-owned enterprises. Unlike other studies that employed similar measures, the method proposed in this work varies from others with the specific meaning of each of the examined concepts. The study demonstrates how new methods can enrich the current debate on the role of AI in internationalization of companies.

In terms of the scope of business economics, the model provides insights into current discussions in the area of technology, resource allocation, and the resource constraints of companies. It shows whether variations in AI-related strategic effort correlate with an increased global position of companies and whether investments in relevant technological knowledge are needed in order to create a stronger connection. The case of Chinese firms that are publicly listed is rather informative due to the fact that the market and governmental logics coexist here, but it should be noted that the findings cannot be readily assumed to be applicable to other contexts.

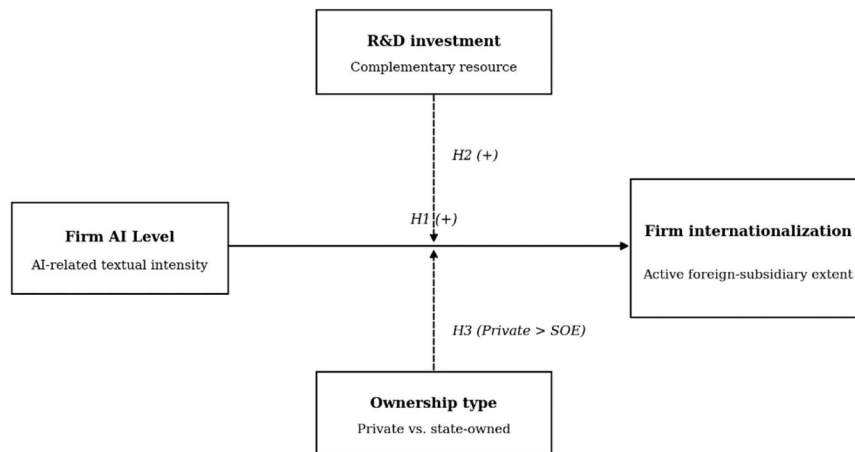


Figure 1. Research framework.

3. Research Design

3.1. Data, Panel Structure, and Sample Formation

The study conducted utilizes an unbalanced firm-year panel of Chinese-listed firms from the years of 2017 to 2024. The complete financial dataset has data on 36596 firm-year cases drawn from 5629 companies. The internationalization index is available for all 36596 cases. Requiring the usage of the AI index will lower the sample to 35347 cases drawn from 5487 firms. The variables of leverage, ROA, and the size of the firm do not lead to any further reduction of the AI necessary sample. Adding the R&D variables needed in the analysis gives rise to the final sample of 31839 firm-year cases from 5211 firms.

The concluding regression sample is employed in the principal descriptive stats, correlation study, as well as in the base fixed-effects models, and R&D moderation test. The ownership survey makes use of a smaller strict sample due to the fact that only companies that remain unambiguously and reliably classified as private or state-owned across their monitoring years are retained. Robustness specifications differ by the number of observations since other data requirements apply, including lagged AI, the outcome without gaps, fixed-effects Poisson estimation, or revenue-based company size.

The key information sources are CSMAR company's accounts, foreign affiliate information, AI text data, research and development information, and ownership records. The R&D information used for the main analysis comes from periodic reports and consolidated statements (Source = 0, StateTypeCode = 1). The current construction eliminates parent company and IPO fallback's R&D information from the primary analytical sample.

3.2. Variable Measurement and Operationalization

3.2.1. Firm Internationalization

The term dependent variable references the measure of the firm's active foreign presence. Specifically, it refers to the number of active foreign affiliates of firm "i" in year "t" listed in the database CSMAR OFDI_AFFCOMPINFO. When the criteria of RelationshipID = 1 and IsExit = 0 are met, the subsidiary's records are logged in the database. Active subsidiaries are those that must be managed as corporate overseas entities. So this concept differs from other overseas business measures like export value or OFDI decisions because it measures ongoing activity.

The dependent variable in the primary regression is $\text{Internationalization_it} = \ln(1 + \text{ForeignSubsidiaries_it})$. The inclusion of one ensures that firms with no foreign subsidiaries are

kept in the model, while the logarithmic transformation makes the count variable's distribution symmetric and limits the impact of big international business. The simple count variable and the dummy variable equal to one whenever the count is greater than zero are alternative dependent variables in the robustness checks.

The operationalization has well-defined antecedents, albeit not a direct copy. Adarkwah et al. (2024[12]) use the number of subsidiaries as an actual host country investment result, while Wei and Nguyen (2020) [13] use the foreign subsidiary criterion to define Chinese service multinationals. The current measure in this study is different from both and therefore this study defines operationalization to mean organizational scope.

3.2.2. Firm AI Level

The explanatory variable of the study constitutes AI Level. Accordingly, in the CSMAR AI_WordFreSta database, the MDAAIAISentenceFre variable signifies the frequency of sentences in a company's management discussion and analysis (MD&A) sections that are AI-related. Thus, the empirical measure of calculating AI Level is described as follows: $AI\ Level_it = \ln(1 + MDAAIAISentenceFre_it)$. This particular transformation maintains zero-frequency observations while limiting the impact of excessive sentence frequency values.

From an economic standpoint, AI Level refers to a text-based metric that reflects how strongly executives have focused on the importance of AI in the disclosure of management. AI Level should not be understood as the monetary representation of AI investments, number of patents granted, adoption of robots, actual number of systems that have been deployed, or any other measure of actual realization of the AI capabilities. Such a cautious interpretation acts in line with the distinction made by Mikalef and Gupta (2021)[16], who understand AI capability as a larger combination of technological, human, and organizational factors.

Wu et al. (2024)[27] have a closely related precedent in text with the measure, which utilizes annual report AI word frequencies to create a corporate AI development indicator and applies a $\log(1 + \text{frequency})$ transformation. Unlike the cited study, the current measure uses AI-related sentence frequency instead of word frequency while also being confined to MD&A disclosure. While the cited study validates the overall application of transformed AI textual intensity, it does not confirm that the current measure of sentence frequency is a universal standard AI metric.

3.2.3. R&D, Ownership, and Baseline Controls

R&D comes into play in empirical analysis in two different methods. The H2 moderator is annual R&D expenditure, RDSpendSum, transformed as $\ln(1 + RDSpendSum)$ and mean-centered before interacting with AI Level. This measure illustrates the scope of internal knowledge investment. Separately, R&D intensity is measured as RDSpendSum divided by total assets and winsorized at the first and ninety-ninth percentiles. R&D intensity is a base control rather than the H2 moderator. Thus, the distinction keeps the theoretical moderation test from being mistaken for the base control for research commitment as related to firm size.

The data on ownership is taken from CSMAR EN_EquityNatureAll. According to EquityNatureID, 1 corresponds to state-owned enterprises, 2 is used for private enterprises, 3 includes foreign-owned enterprises and 4 refers to other kinds of enterprises. The strict H3 sample includes only state-owned and private enterprises. Ownership switchers and the observations that are classified as foreign, other, mixed, or missing classification are no longer taken into account in the strict comparison. The pooled formal difference specification uses private enterprises as the reference group, which is why a negative AI x SOE coefficient is the prediction given by H3. The initial model consists of four time-changing company level controls. Firm size is measured as $\ln(1 + \text{TotalAssets})$. Leverage is CSMAR AssetLiabilityRatio, which is the total liability divided by total assets. ROA is calculated with the aid of CSMAR ROAA, which means return on average assets. R&D intensity is the sum of R&D spending divided by total assets. Firm fixed effects

eliminate firm characteristics that do not change over time while year fixed effects eliminate events affecting all firms at that time.

3.2.4. Control-set Comparability and Additional Controls

Table 1. Definitions, measurement, data sources, and expected roles of variables

Variable	Definition	Measurement	Data source	Expected role/sign
Internationalization	Organizational extent of active foreign presence	$\ln(1 + \text{active foreign subsidiaries});$ RelationshipID=1, IsExit=0	CSMAR OFDI_AFFCOMPINFO	Dependent variable
AI Level	Firm-level AI-related strategic/textual intensity	$\ln(1 + \text{MDAAIASentenceFre})$	CSMAR AI_WordFreSta	+ in H1
R&D expenditure	Scale of internal knowledge investment	$\ln(1 + \text{RDSpendSum});$ mean-centered for H2	CSMAR PT_LCRDSPENDING (Source=0; StateTypeCode=1)	Moderator; AI $\times$ R&D: + in H2
AI $\times$ R&D	Interaction of AI Level and internal R&D investment	AI Level $\times$ centered $\ln(1 + \text{RDSpendSum})$	Derived from CSMAR AI_WordFreSta + PT_LCRDSPENDING	+ in H2
Ownership	Stable state versus private ownership	EquityNatureID: 1=SOE, 2=private; strict H3 retains stable SOE/private firms only	CSMAR EN_EquityNatureAll	Boundary condition
AI $\times$ SOE	Private-SOE difference in the AI slope	AI Level $\times$ SOE; private is reference	Derived from CSMAR AI_WordFreSta + EN_EquityNatureAll	- in H3
Firm size	Firm scale	$\ln(1 + \text{TotalAssets})$	CSMAR AIQ_LCFIndexY	Baseline control
Leverage	Financial leverage	Total liabilities / total assets	CSMAR AIQ_LCFIndexY	Baseline control
ROA	Profitability	CSMAR ROAA (return on average assets)	CSMAR AIQ_LCFIndexY	Baseline control
R&D intensity	R&D commitment relative to assets	RDSpendSum / total assets; winsorized at 1st/99th percentiles	CSMAR PT_LCRDSPENDING + AIQ_LCFIndexY	Baseline control

Notes: The table is restricted to the focal variables, moderators, ownership boundary condition, and baseline controls used in the main empirical specifications. AI Level is a text-based MD&A measure and is not monetary AI investment or a direct measure of realized AI capability. R&D expenditure and R&D intensity are distinct: logged R&D expenditure is the H2 moderator, whereas R&D intensity is a baseline control. Expected signs are reported only for the focal hypotheses.

According to Liu et al. (2024)[9], Yang et al. (2026), and Yang and Peng (2026)[11], the findings, samples, and methodologies implemented in AI and internationalization studies differ from each other. This means that different methodologies cannot be compared, hence, this paper does not apply a mechanical counting technique for controls, which is why the control group is

termed minimal rather than sophisticated. It states the baseline control variables relevant to the present design and subject to changes over time while testing the stability of AI variables with the help of other two available control variables.

The current baseline is deliberately cautious in its approach: it takes into consideration the time-varying firm size, financial structures, profits, and the degree of R&D intensity, as well as utilizes firm fixed and year fixed effects. The analysis has a goal of being more precise rather than mechanically adding variables on the sample of 30,376 and taking advantage of CSMAR InsInvestorProp to determine institutional ownership, or what percentage of total shares are owned by the institutional investors. Also, the measurement of transparency was obtained from CSMAR CompanyOpacity where grades are defined as follows A=excellent, B=good, C=strong, and D=weak; D serves as the reference category. Additionally, the lack of changes in AI coefficient when these factors are taken into consideration shows a good robustness test for the method used for establishing the control.

3.3. Empirical Specifications'

H1 is estimated with firm and year fixed effects. The coefficient of interest is β_1 , which captures the within-firm association between AI Level and internationalization after controlling for time-varying firm characteristics and common year shocks. Standard errors are clustered at the firm level.

$$INTL_{it} = \beta_1 AI_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where $INTL_{it}$ is $\ln(1 + \text{active foreign subsidiaries})$, AI_{it} is AI Level, X_{it} contains firm size, leverage, ROA, and R&D intensity, μ_i denotes firm fixed effects, and λ_t denotes year fixed effects.

H2 adds mean-centered log R&D expenditure and its interaction with AI Level. The formal test of the moderation hypothesis is the interaction coefficient β_3 , not the standalone R&D coefficient.

$$INTL_{it} = \beta_1 AI_{it} + \beta_2 c_lnRD_{it} + \beta_3 (AI_{it} \times c_lnRD_{it}) + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

H3 is first illustrated with separate regressions for stable private firms and SOEs and then tested formally in a pooled slope-difference model. Private firms are the reference category. The final formal-difference specification interacts AI, the baseline controls, and year indicators with SOE, while firm fixed effects absorb the time-invariant ownership main effect.

$$INTL_{it} = \beta_1 AI_{it} + \beta_2 (AI_{it} \times SOE_i) + \gamma' X_{it} + \delta' (X_{it} \times SOE_i) + \lambda_t + \kappa_t (SOE_i \times Year_t) + \mu_i + \varepsilon_{it} \quad (3)$$

Under H3, β_2 is expected to be negative because it measures the SOE slope difference relative to private firms. The ownership hypothesis is supported only if the formal difference is statistically distinguishable in the predicted direction; different significance levels in separate subsamples are not sufficient evidence of a slope difference.

3.4. Descriptive Statistics and Multicollinearity Diagnostics

Table 2 reports descriptive statistics for the final regression sample. Total assets are presented in RMB billion and R&D expenditure in RMB million, so the large monetary variables are shown in actual economic units. Leverage, ROA, and R&D intensity are reported as ratios. Internationalization and AI Level are reported on the transformed scales used in the empirical analysis, with their exact transformations stated in Table 1 and the table note.

Table 2. Descriptive statistics

Variable	N	Mean	SD	Min	Max
Internationalization	31,839	0.8494	0.9252	0.0000	5.4116
AI Level	31,839	1.0532	1.1916	0.0000	4.3041
Total assets (RMB billion)	31,839	16.7760	57.6710	0.2341	697.5963
Leverage	31,839	0.4094	0.2072	0.0558	0.9658
ROA	31,839	0.0280	0.0813	-0.3827	0.2112
R&D expenditure (RMB million)	31,839	304.0845	1393.5938	0.0000	54160.9640
R&D intensity	31,839	0.0268	0.0238	0.0001	0.1357

Notes: Final regression sample: 31,839 firm-year observations from 5,211 firms. R&D intensity is winsorized at the 1st and 99th percentiles. Internationalization is $\ln(1 + \text{active foreign subsidiaries})$, and AI Level is $\ln(1 + \text{AI-related MD\&A sentence frequency})$. Total assets and R&D expenditure are presented in actual economic units.

The mean Internationalization index is 0.8494 and the mean AI Level is 1.0532. The sample is heterogeneous in firm scale: mean total assets are RMB 16.776 billion, with a standard deviation of RMB 57.671 billion. Average R&D expenditure is RMB 304.085 million, again with substantial dispersion. The average leverage ratio is 0.4094, average ROA is 0.0280, and average R&D intensity is 0.0268.

Table 3. Pearson correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1.000						
(2)	0.135	1.000					
(3)	0.360	0.216	1.000				
(4)	0.374	-0.025	0.549	1.000			
(5)	0.170	-0.061	0.149	0.444	1.000		
(6)	-0.005	-0.071	0.098	0.055	-0.370	1.000	
(7)	0.091	0.370	0.449	-0.213	-0.195	0.019	1.000

Notes: (1) Internationalization; (2) AI Level; (3) Log R&D expenditure; (4) Firm size; (5) Leverage; (6) ROA; (7) R&D intensity. N = 31,839. Moderation-model mean VIF = 2.09; maximum VIF = 2.98.

The simple correlation between Internationalization and AI Level is 0.135. Log R&D expenditure is correlated 0.360 with Internationalization and 0.216 with AI Level, while firm size is correlated 0.374 with Internationalization. The largest reported pairwise correlation among the listed explanatory variables is 0.549 between firm size and leverage. In the moderation specification, the mean VIF is 2.09 and the maximum VIF is 2.98, which does not indicate severe multicollinearity.

4. Empirical Results

4.1. Baseline Fixed-effects Estimates

Table 4. Baseline fixed-effects estimates

	(1)	(2)	(3)	(4)
AI Level	0.0341*** (0.0052)	0.0190*** (0.0051)	0.0190*** (0.0051)	0.0179*** (0.0051)
Firm size		0.2446*** (0.0142)	0.2434*** (0.0143)	0.2515*** (0.0142)
Leverage			0.1258*** (0.0405)	0.1230*** (0.0405)
ROA			-0.2492*** (0.0448)	-0.2446*** (0.0451)
R&D intensity				1.7101*** (0.3737)
Observations	31,839	31,839	31,839	31,839
Within R-squared	0.0796	0.1362	0.1407	0.1426

Notes: Dependent variable: Internationalization = $\ln(1 + \text{active foreign subsidiaries})$. Firm fixed effects: Yes. Year fixed effects: Yes. Standard errors are clustered at the firm level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 provides sequential baseline estimates. The first column contains the coefficient of AI Level together with the fixed effects for firm and year. The coefficient of AI is equal to 0.0341 (SE = 0.0052, $p < 0.01$). When size of the firm is added in the second column, the coefficient is reduced to 0.0190 (SE = 0.0051, $p < 0.01$). Even after the inclusion of leverage and ROA in the third column, the coefficient remains unchanged at 0.0190. Finally, in the last column representing the full baseline specification with control for R&D intensity, the coefficient risen to 0.0179 (SE = 0.0051, $p < 0.01$).

In column (1), the within R-squared value is 0.0796, while in column (4), it is 0.1426. The coefficients of the control variables are not what the hypotheses are based on, but a comprehensive baseline shows that the coefficient of size is positive, the coefficient of leverage is positive, the coefficient of ROA is negative and the coefficient of R&D intensity is positive. Most importantly for H1, the relationship of AI Level and internationalization is not explained away by including the observed dynamic characteristics of firms. Thus, the hypothesis H1 is supported as an association.

4.2. R&D Moderation

Table five assesses Hypothesis Two (H2). The second column contains centered logarithm of researchand development in the base model and the third column demonstrates the interaction between artificial intelligence level and centered log of R&D. The interaction coefficient is 0.0096 with a standard error of 0.0037 and a precise p-value of 0.0087. This positive interaction is the formal test of H2 and implies that coefficients of the positive relation between AI and internationalization are becoming stronger with higher levels of internal R&D.

The primary coefficient for AI in the interaction model stays positively at 0.0155 (SE = 0.0049, $p < 0.01$). The negative coefficient of centered log R&D only applies at AI Level = 0, and is not the hypothesis of interest. Therefore, moderation results will be interpreted as an interaction instead of a claim for an unconditional negative effect of R&D expenditure on

internationalization. The found evidence is supportive of H2 and is in line with the statement that investments in internal knowledge support AI-related strategic intensity.

Table 5. R&D moderation

	(1)	(2)	(3)
AI Level	0.0179*** (0.0051)	0.0179*** (0.0051)	0.0155*** (0.0049)
Centered log R&D		-0.0089* (0.0054)	-0.0122** (0.0055)
AI × R&D			0.0096*** (0.0037)
Firm size	0.2515*** (0.0142)	0.2601*** (0.0154)	0.2535*** (0.0155)
Leverage	0.1230*** (0.0405)	0.1209*** (0.0405)	0.1265*** (0.0405)
ROA	-0.2446*** (0.0451)	-0.2427*** (0.0451)	-0.2390*** (0.0451)
R&D intensity	1.7101*** (0.3737)	1.9847*** (0.4101)	1.7581*** (0.4139)
Observations	31,839	31,839	31,839
Within R-squared	0.1426	0.1428	0.1438

Notes: Column (3) is the formal H2 specification. Centered log R&D is $\ln(1 + \text{RDSpendSum})$ demeaned over the final regression sample. Firm and year fixed effects are included. Standard errors are clustered at the firm level. Exact p-value for AI × R&D = 0.0087. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Ownership Heterogeneity

Table 6. Ownership heterogeneity

	Private	SOE	Formal difference
AI Level	0.0186*** (0.0068)	-0.0045 (0.0113)	0.0186*** (0.0068)
AI × SOE			-0.0230* (0.0132)
Firm size	0.2664*** (0.0181)	0.1648*** (0.0377)	0.2664*** (0.0181)
Leverage	0.0465 (0.0505)	0.2372* (0.1415)	0.0465 (0.0505)
ROA	-0.2253*** (0.0501)	0.0135 (0.2269)	-0.2253*** (0.0501)
R&D intensity	2.4633*** (0.4291)	-1.2097 (1.2765)	2.4633*** (0.4292)
Observations	18,150	7,097	25,247
Within R-squared	0.2015	0.0511	0.1668

Notes: Ownership classification is based on tight stable firm ownership over the years observed. The reference category of the formal-difference model is private. SOE is formally coupled with AI, baseline controls and year indicators. Fixed effects are included and are assumed to be fixed. Standard errors are in parentheses and are firm-clustered. Exact p-value for AI × SOE = 0.0821. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The ownership results are presented in Table 6. In the private-firm subsample, the AI coefficient is 0.0186 (SE = 0.0068, $p < 0.01$). In this subsample of SOE, the coefficient is -0.0045 (SE = 0.0113) and is not statistically significant. Each of these regressions are informative descriptively, but fail alone to provide a statistically significant difference between ownership. Pooled formal-difference model is the proper H3 model. The AI $\times$ SOE coefficient is -0.0230 (SE = 0.0132), with $p = 0.0821$. The negative sign is in the direction predicted by H3: the AI slope is lower for SOEs than for private firms, as the category of private firms is the reference. But the difference is only marginally significant at 10% level and not significant at 5% level. As such, evidence is limited or provides marginal support for H3, not strong confirmation. This distinction is of substantive nature as it prevents overstating the ownership conclusion based on a separate level of significance in each of the subgroups.

4.4. Additional Heterogeneity by Firm Size and Leverage

Table 7. Additional heterogeneity analyses

	Smaller firms	Larger firms	Lower leverage	Higher leverage
AI Level	0.0165** (0.0064)	0.0181** (0.0077)	0.0186*** (0.0066)	0.0166** (0.0074)
Firm size	0.1999*** (0.0173)	0.2925*** (0.0210)	0.2701*** (0.0218)	0.2399*** (0.0181)
Leverage	0.1534*** (0.0508)	0.0458 (0.0661)	0.0704 (0.0625)	0.1510*** (0.0542)
ROA	-0.2326*** (0.0485)	-0.2604*** (0.0840)	-0.2625*** (0.0563)	-0.2091*** (0.0665)
R&D intensity	1.9539*** (0.4422)	1.0296 (0.6576)	2.6495*** (0.4413)	0.5249 (0.6421)
Observations	14,549	17,290	14,772	17,067
Within R-squared	0.1562	0.1408	0.1796	0.1233

Notes: Groups are based on firm-level mean size and mean leverage and median splits in the main sample. There is no significant difference in mean formal AI-slope values between the firm sizes ($p = 0.8665$). Another result: Formal difference between AI-slope and leverage is $p = 0.8335$. Firm and year fixed effects have been added and standard errors clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The AI coefficient is still positive and statistically significant for each of the four subsamples. However, there is no statistically significant heterogeneity in the formal comparisons of slopes: $p = 0.8665$ for the size comparison and $p = 0.8335$ for the leverage comparison. It should therefore not be concluded that the AI relationship is stronger in one size or leverage group, but that there is no statistically distinguishable AI slopes along these two dimensions.

4.5. Robustness Checks and Additional Controls

Table five assesses Hypothesis Two (H2). The second column contains centered logarithm of research and development in the base model and the third column demonstrates the interaction between artificial intelligence level and centered log of R&D. The interaction coefficient is 0.0096 with a standard error of 0.0037 and a precise p-value of 0.0087. This positive interaction is the formal test of H2 and implies that coefficients of the positive relation between AI and internationalization are becoming stronger with higher levels of internal R&D. The primary coefficient for AI in the interaction model stays positively at 0.0155 (SE = 0.0049, $p < 0.01$). The negative coefficient of centered log R&D only applies at AI Level = 0, and is not

the hypothesis of interest. Therefore, moderation results will be interpreted as an interaction instead of a claim for an unconditional negative effect of R&D expenditure on internationalization. The found evidence is supportive of H2 and is in line with the statement that investments in internal knowledge support AI-related strategic intensity.

Table 8. Robustness checks

	Raw count	Dummy	Gap excluded	Lagged AI	FE Poisson	Revenue size
AI Level	0.1705*** (0.0554)	0.0082** (0.0033)	0.0179*** (0.0051)		0.0314** (0.0126)	0.0237*** (0.0050)
Lagged AI Level				0.0173*** (0.0051)		
Firm size	1.5707*** (0.1505)	0.0920*** (0.0088)	0.2526*** (0.0142)	0.2346*** (0.0158)	0.4922*** (0.0343)	
Revenue size						0.1766*** (0.0107)
Leverage	0.2496 (0.3720)	0.0701*** (0.0266)	0.1239*** (0.0404)	0.0743* (0.0423)	0.5135*** (0.1161)	0.1359*** (0.0398)
ROA	-1.1833*** (0.3590)	-0.1256*** (0.0276)	-0.2369*** (0.0445)	-0.2094*** (0.0488)	-0.3729*** (0.1086)	-0.4252*** (0.0480)
R&D intensity	8.1088** (3.1525)	0.8823*** (0.2457)	1.7754*** (0.3725)	1.1609*** (0.4199)	2.8004*** (0.9125)	-0.6017 (0.3847)
Observations	31,839	31,839	31,733	27,004	21,757	31,834

Notes: Columns differ in the dependent variable or focal specification as indicated. Column (1) uses the raw active-subsidary count; column (2) an internationalization dummy; column (3) excludes internal-gap observations; column (4) uses one-year-lagged AI; column (5) estimates a fixed-effects Poisson model for the count; column (6) replaces asset-based firm size with revenue size, defined as $\ln(1 + \text{TotalRevenue})$. FE Poisson conditions out firms with all-zero counts or insufficient within-firm outcome variation. All applicable models include firm and year fixed effects with firm-clustered/robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion and Conclusion

5.1. Main Findings

This study examines the relationship between AI-related strategic intensity and the extent of foreign presence in the organization of Chinese publicly listed companies, and investigates whether such a relationship is conditioned on R&D spending, and ownership. The study has a number of conclusions. First, firms with a higher AI-related strategic intensity have higher rates of internationalization than firms with a lower AI-related strategic intensity, and this pattern remains positive when we conduct a variety of alternative specifications. The result highlights the consistency of the results with the latest AI based research which linked AI technology/application with internationalization.

Secondly, the association of AI with globalization is augmented by the effect of R&D expenditures. The positive and statistically meaningful interaction of AI with R&D corresponds well to the thinking that information about AI has a greater utility if the organization has a strong base of investing in knowledge from within. This reasoning corresponds with the concept of complementary resources in the area of AI capabilities proposed by Mikalef and Gupta (2021), as well as the theory of absorptive capacity. According to this theory, the prior

knowledge base and internal R&D activities allow firms to leverage new information. Additionally, this finding supports the findings of the internationalization stream of research where R&D-related resources and dynamic capabilities are treated as well as enablers of the internationalization process.

Thirdly, the diversification of ownership is more complex than just a simple comparison of subsamples would imply. The AI coefficient is positive for private companies and insignificant for state-owned enterprises, however the formal difference in slopes in private versus SOEs is statistically significant narrowly at the 10% threshold. This phenomenon agrees with the other findings provided by Wang et al. (2022) that address the scope of digitalization and international positioning and coincides with the data concerning the effect of ownership on enterprises from Wu et al. and Zhang and Li. At the same time, Wang and Fu suggest a more intense digitalization effect on the scope of internationalization for state-owned companies. Thus, the gathered evidence allows us to conclude that ownership matter in a context- and outcome-dependent way, rather than producing any universal differentiation between private and public companies.

5.2. Contributions

The initial contribution is theoretical. This research proposes a contingent dynamic-capabilities interpretation for AI-related internationalization. Dynamic capabilities have usually been employed as mechanisms for explaining firms' reactions to environmental changes by means of sensing, seizing, and reconfiguration. Recent literature has been discussing these capability processes as being at the center of multinational adaptation to digitalization and uncertainty. This framework gives a definition of the term 'contingent' in relation to the sphere of AI-related internationalization: strategic intensity in terms of AI is not viewed as self-implementing, but rather its relationship with the presence of foreign organization is strengthened with the growing investment in internal R&D, while ownership can affect the institutional and motivational environment in which capabilities turn into cross-border involvement.

The second contribution is regarding digital transformation and internationalization in the field of AI. Previous studies have shown the connection between digital transformation, AI technology and its application to different internationalization outcomes. The present research adds construct specification by using a text-based AI indicator and an organizational outcome for a daughter company, thus helping to have a clear understanding of the means. A company can be exporting goods or investing abroad without being necessary to have an equivalent degree of foreign activity, thus similar to AI measure based on patents and measure based on MD&A text being different for the purpose of research. For this reason, the contribution of the present work does not concern the fact that previous studies did not recognize AI or subsidiaries but rather that the connection exists.

The third contribution refers to complementarity. The research finding extends the debate regarding whether AI-input activity is positively linked with internationalization by specifying a firm-level condition under which this link is stronger. This discovery connects AI-resource orchestration reasoning to research on absorptive capacity and innovation complementarity. This is important in Business Economics because it moves the unit of analysis from mere technology adoption to the bundle of resources that enables a technology to create business value.

The methodological and explanatory contribution comes next. Ownership analysis rather compares formal significance rather than drawing inference from various levels of significance; additionally, size and leverage analyses rest upon the same principle. In accordance with this procedure, interpretation of results becomes more systematic: evidence for H3 is weak, while size and leverage do not generate statistically distinguishable AI slopes. The empirical approach also employs firm and year fixed effects, firm-clustered inference, alternative dependent

variables, lagged AI, fixed-effects Poisson estimation, different size proxies, and further controls, establishing results' stability while keeping difference between robustness of association and importance of causal identification.

In conclusion, the research adds to the conversation about internationalization in emerging markets. According to Gammeltoft and Cuervo-Cazurra, emerging market internationalization is determined by context, which encompasses several factors, including government factors. In relation to this, the current evidence provides a technological perspective at the firm level in the case of China, showing that companies with advanced AI technologies achieve higher levels of foreign presence. However, the strength of this link between foreign presence and intensity in AI technologies depends on the relative strength of companies' research and development capacities.

5.3. Managerial and Policy Implications

For managers, the key takeaway is that the attention on AI strategies should not be considered on its own as an indicator of readiness internationally. The positive interaction between the AI and R&D suggests that the strength of the AI-internationalization association is greater when the investment in internal R&D is higher. Thus, managers who are interested in cross-border expansion should review the AI-based strategic plans in conjunction with the R&D foundation and capacity to interpret and incorporate new information. This implication falls along the same lines as in AI capability research that is complementary overall.

The subsidiary-based outcomes have also a pragmatic aspect. Maintaining a larger foreign-subsidiary network has more to do with ongoing coordination to maintain rather than simply an international transaction. Investigating AI is therefore a worthwhile effort for managers to understand if information and support routines of AI are included in the processes that govern overseas units, resource allocation and adaptation across locations. This outcome does not necessarily mean that the more subsidiaries the better (or that AI should mechanically improve foreign presence). Instead, it proposes that the strategic intensity of AI is relevant economically on the organizational level of cross-border activity when complemented by other capabilities.

The results indicate that, for policy makers, capability building needs to be addressed in addition to technology promotion. The positive interaction with R&D suggests that the AI-internationalization association is stronger if firms at the same time have a larger internal knowledge-investment base. Complementarity between the salience of AI development and firm R&D can be taken into account when designing policies, which means that policies should not automatically assume that a higher salience of AI development on its own is correlated with higher internationalization.

Special care must be taken with regard to ownership results. The difference between the private and formal firm slopes is formal and only marginally significant at the 10% level. So it would seem wrong to make policy based on the assumption that private companies on average gain more from AI-related activity or that SOEs are systematically less able to internationalize. The less risky suggestion is that policy and managerial systems need to be sensitive to variations in incentives, resources, and governance, and assess the capability configurations. This finding aligns with the state-market view of Chinese MNEs and the overall trend of government ownership potentially introducing both opportunities and boundaries.

5.4. Limitations and Future Research

The first restriction is regarding the evaluation of AI. AI Level essentially uses the rate of AI-related sentences in management discussion and analysis (MD&A) disclosures. Because of that, it's not a measure of true AI capacity, but rather of strategy or "textual density," and disclosure practices can influence this measure. A similar precedent in terms of measuring frequency is offered by Wu et al. (2024); and Mikalef and Gupta (2021)[16] also contend that AI capacity

includes broader organizational phenomena. In the future, another study should be conducted using other independent measures of AI capacity to conclude the degree of sensitivity of the internationalization relationship to the measure of AI.

The second constraint is related to the dependent variable concept. Though the number of active foreign subsidiaries reflects the organizational level of foreign presence, it does not reflect all the aspects of economic internationalization. Examples set by Adarkwah et al. (2024) and Wei and Nguyen (2020) show that subsidiary presence can be assessed together with other important aspects of multinational activities. This means that future studies should be conducted to see if the results are valid in the case of combined evaluation of the active-subsidiary extent and other measures of internationalization.

The next drawback is the issue of identification of causal effects. The inclusion of fixed effects of firms and years, using lagged AI as well as the use of another estimator improves the robustness of the correlation of the conducted survey, but does not remove problems related to omitted time-varying factors, reverse causality, or simultaneity. Moving forward, researchers should utilize a proper quasi-experimental design or use instrumental regression with exogenous variable for establishing causal links.

A fourth limitation is regarding the moderation process. The positive AI and R&D interaction complies with the complementary-knowledge approach; however, it cannot be said that the empirical model observes the absorptive capacity or the processes of capabilities, sensing, seizing, and reconfiguration. The expenditures on research and development indicate the size of internal knowledge investments but not in terms of actual capabilities. Further research should be undertaken in order to investigate this mechanism rather than rely only on R&D moderation that has been studied.

The fifth constraint deals with ownership heterogeneity. Adopting the stable private/SOE approach simplifies interpretation, though ownership swappers and firms outside these two types are not taken into account as a result. Still, the observed private/SOE slope differential is only marginally significant at the 10% level, meaning one should refrain from making generalizations beyond the results of the study. Future studies should examine ownership mechanisms by employing designs that would allow for determining the reasons for differences in slopes according to ownership types in place of utilizing ownership labels alone.

The sixth limitation pertains to external validity. The data used in this study involves companies that are listed in China for the years from 2017 to 2024. The importance of context in internationalization in emerging markets is highlighted by Gammeltoft and Cuervo-Cazurra (2021), while Meyer et al. (2023) pointed out the continuing importance of national institutions in conducting digital international business. The evidence presented above should be generalized carefully, and future comparative studies should examine to what extent similar AI-R&D-ownership relationships exist in different institutional contexts.

Changes of various types occurred during the time period 2017-2024, including changes in AI technology and business conditions around the world. Fixed effects in years account for certain shocks that affect all companies in the same way, but it is still impossible to say whether or not the effect is constant throughout the time period studied. More research is needed to look for the stability of the effect explicitly when new data is collected.

5.5. Conclusion

The research indicates that the degree of AI-related strategic intensity positively correlates with the level of active foreign presence among Chinese listed companies and that this link is even more pronounced as R&D spending increases. The influence of ownership diversity on the preceding relationship tends to be positive just as it was predicted for private companies, but the significance of this correlation is rather marginal. On the other hand, ownership features such as company size and leverage are not meaningful. These results confirm the dynamic-

capabilities framework indicating that the relationship between AI use and the level of internationalization is stronger when adequate complementarity exists in terms of R&D investment.

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Appendix

Appendix Table A1. Additional controls on a common sample

	Baseline common sample	+ Institutional ownership	+ Transparency	+ Both
AI Level	0.0167*** (0.0053)	0.0167*** (0.0054)	0.0166*** (0.0053)	0.0166*** (0.0053)
Firm size	0.2465*** (0.0153)	0.2482*** (0.0151)	0.2445*** (0.0154)	0.2462*** (0.0152)
Leverage	0.1186*** (0.0436)	0.1147*** (0.0436)	0.1239*** (0.0438)	0.1201*** (0.0437)
ROA	-0.2392*** (0.0478)	-0.2361*** (0.0477)	-0.2522*** (0.0473)	-0.2494*** (0.0472)
R&D intensity	1.4505*** (0.4183)	1.4735*** (0.4182)	1.4303*** (0.4174)	1.4537*** (0.4174)
Institutional ownership		-0.0006 (0.0005)		-0.0007 (0.0005)
Transparency: C			0.0188 (0.0164)	0.0193 (0.0164)
Transparency: B			0.0259 (0.0179)	0.0267 (0.0179)
Transparency: A			0.0367* (0.0200)	0.0378* (0.0200)
Observations	30,376	30,376	30,376	30,376
Within R-squared	0.1344	0.1346	0.1346	0.1348

Notes: Transparency category D is the reference group. Firm and year fixed effects are included. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A1 evaluates whether the focal association is sensitive to a richer control set. On the same 30,376-observation sample, the AI coefficient is 0.0167 in the common-sample baseline, 0.0167 after institutional ownership is added, 0.0166 after transparency is added, and 0.0166 when both are included. The near invariance of the focal coefficient provides direct evidence that the main association is not driven by these additional ownership and information-environment controls.

Appendix Table A2. Sample flow

Sample construction step	Observations	Firms
Full financial panel	36,596	5,629
Internationalization measure available	36,596	5,629
Plus AI Level available	35,347	5,487
Plus firm size, leverage, and ROA	35,347	5,487
Plus R&D expenditure and intensity: final regression sample	31,839	5,211

Note: The final regression sample is the common basis for the main descriptive statistics, correlation matrix, baseline fixed-effects estimates, and R&D moderation analysis.