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Business model strategies and venture financing of AI startups

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Abstract

Aim. To demonstrate the impact of different business model configurations on the effectiveness of venture capital fundraising by artificial intelligence (AI) startups, and to identify the types of business models most attractive to the capital market.

Objectives. To classify AI startup business models into three types: infrastructure-oriented, application-oriented, and hybrid; to empirically assess the relationship between business model type and the volume of raised capital; to develop strategic recommendations for early-stage AI startups regarding resource allocation and market positioning.

Methods. The study was based on an empirical analysis of a sample of 980 private AI startups. The methods included classification of companies by their key value propositions and analysis of historical fundraising data using statistical modeling to identify the relationship between business model choice and funding outcomes.

Results. The study finds that infrastructure-oriented companies are more likely to attract investment and demonstrate higher funding performance. Application-oriented companies tend to have weaker capital-raising capabilities compared to infrastructure-focused companies. Hybrid models carry a significant discount in terms of the volume of funding raised.

Conclusions. To enhance competitive advantages and fundraising success, companies should adhere to clearly defined business models rather than diversified hybrid models. Strategic focus proves to be more effective in gaining capital market support than resource-intensive integration.

Keywords: *business model, AI startups, venture financing, fundraising effectiveness, infrastructure-oriented model, application-oriented model, hybrid model, strategic positioning*

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Стратегии бизнес-моделей и венчурное финансирование ИИ-стартапов

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Аннотация

Цель. Показать влияние различных конфигураций бизнес-моделей на эффективность привлечения венчурного финансирования стартапами в сфере искусственного интеллекта (ИИ), а также выделить типы бизнес-моделей, наиболее привлекательные для рынка капитала.

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Задачи. Классифицировать бизнес-модели ИИ-стартапов на три типа: инфраструктурно-ориентированные, прикладно-ориентированные и гибридные; выполнить эмпирическую оценку связи между типом бизнес-модели и объемом привлеченного финансирования; разработать стратегические рекомендации для ИИ-стартапов ранних стадий в аспектах распределения ресурсов и рыночного позиционирования.

Методология. Исследование основано на эмпирическом анализе выборки из 980 непубличных ИИ-стартапов. Методология включает в себя классификацию компаний по их ключевым ценностным предложениям и анализ исторических данных о привлечении финансирования с использованием статистического моделирования для выявления взаимосвязи между выбором бизнес-модели и результатами финансирования.

Результаты. Установлено, что инфраструктурно-ориентированные компании с большей вероятностью привлекают инвестиции и демонстрируют более высокие показатели финансирования. Прикладно-ориентированные компании, как правило, обладают более слабыми возможностями по привлечению капитала, если сравнивать их с компаниями, нацеленными на инфраструктуру. Для гибридных моделей предусмотрен значительный дисконт по объему привлекаемого финансирования.

Выводы. Для повышения конкурентных преимуществ и успешности привлечения финансирования компаниям целесообразно придерживаться четко определенных бизнес-моделей, а не диверсифицированных гибридных моделей. Стратегическая фокусировка оказывается более эффективной для получения поддержки со стороны рынка капитала, чем ресурсоемкая интеграция.

Ключевые слова: бизнес-модель, ИИ-стартапы, венчурное финансирование, эффективность привлечения финансирования, инфраструктурно-ориентированная модель, прикладно-ориентированная модель, гибридная модель, стратегическое позиционирование

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Introduction

In recent years, generative AI has experienced rapid evolution, and large language models have emerged as a prominent technological paradigm, creating new opportunities for startups to develop AI-enabled products and services [1]. The McKinsey (2025) report points out that general model capabilities, open source components and cloud infrastructure make it increasingly easier to acquire AI capabilities¹. To develop a sustainable business advantage in the real market, companies increasingly rely on management innovation [2]. Specifically, it requires companies to have a precise business model positioning [3] and to build strong organizational delivery capabilities [4]. The business model is defined as the design of transaction content, structure, and governance. It can establish a systematic association with the performance of entrepreneurial firms through value creation drivers such as novelty and efficiency [5]. The technology itself has no intrinsic value until it is commercialized; therefore, how a

business model can transform technology into commercial returns is itself a key competitive issue [6].

The business models of AI startups can be characterized as either directly embedding the capabilities of trained models into product and service delivery to generate tangible value for specific business scenarios, or facilitating customers' AI development through interfaces, tools, and platform capabilities, providing a foundation upon which external innovators can build complementary products and services [7]. In terms of delivery models, this difference is often reflected in the application-based implementation of Software as a Service (SaaS) and the platform-based empowerment of Platform as a Service (PaaS) [8]. Based on these differences, this paper classifies AI startup business models into two types: infrastructure-oriented and application-oriented. Such differences may lead to different expectations of the capital market regarding its growth potential and risk structure, which will be reflected in the financing results. At the same time, many

¹ Open source technology in the age of AI: Report // McKinsey & Company. April. 2025. URL: <https://www.mckinsey.com/capabilities/quantumblack/our-insights/open-source-technology-in-the-age-of-ai> (accessed on 17.03.2026).

companies are adopting cross-layer combinations. Whether this hybrid positioning will bring synergistic premiums or lead to external discounts due to resource dispersion and unclear positioning is also worth examining.

In the existing literature on AI startups, a question highly relevant to industry practice but lacking systematic empirical evidence is: how does the tiered positioning of AI startup business models affect their fundraising performance? The paper utilizes a large sample of Crunchbase data on AI startups, combining textual descriptions and structured information to identify the characteristics of their infrastructure and application layers, and measures fundraising performance using the logarithmic transformation of cumulative funding amounts. Given the information asymmetry in venture capital financing, investors often rely on observable signals to form judgments [9; 10]. The paper further incorporates organizational characteristics such as firm size to characterize the impact of execution capability and degree of organization on financing performance. This paper's contribution lies in its empirical examination of the correlation between the characteristics of the infrastructure and application layers of AI startups and their financing performance, based on a hierarchical positioning perspective of business models, thus providing empirical evidence for related discussions.

The article is structured as follows: Section 2 reviews relevant literature and proposes theoretical mechanisms and research hypotheses; Section 3 introduces data sources, variable construction, and research methods; Section 4 reports empirical results; and Section 5 summarizes the entire article and proposes future research directions.

Theory and Hypothesis

Business Model and Capital Market Pricing

Research on business model innovation redefines the source of value creation as a company's ability to structure its activity system and transaction structure, rather than simply relying on technology or the product itself. Such structuring ability that establishes a competitive advantage based on efficiency, complementarity, lock-in, and novelty [3; 11]. Teece's classic framework for profiting from

innovation points out that whether technological innovation can be transformed into economic returns fundamentally depends on the configuration of appropriability regulations and complementary assets [12]. In the modern industrial environment of rapid technological diffusion and reduced barriers to imitation, business model design has become the decisive mechanism for capturing value from innovation [13]. Business model innovation is often constrained by existing knowledge and asset paths, therefore new entrants need to restructure their business models to overcome the value transfer brought about by the commoditization of technology [6].

In the context of AI entrepreneurship, the capital market's evaluation of companies and its resource allocation reflect expectations of the companies' future expansion paths, sustainable advantages, and organizational capabilities¹. Under conditions of information asymmetry, an external party often finds it difficult to directly confirm the quality of another party and therefore relies on externally observable signals to form a judgment [9]. Information related to a company's disclosed business model can serve as such signals and is considered to have informational value by market participants [14].

Infrastructure-oriented Business Model

AI technology is impacting the identification of entrepreneurial opportunities, decision-making, and resource allocation for startups, altering the logic of value creation and the mechanisms for forming competitive barriers. These changes influence external investors' assessments of startups' growth potential, risks, and valuations [15]. According to the Resource-Based View (RBV), a firm's ability to develop a sustainable competitive advantage depends on whether the resources it controls possess the characteristics of being valuable, scarce, difficult to imitate, and irreplaceable [16]. High capital intensity, strong technological complexity, and long-term accumulated resources are more likely to form the basis of a sustainable competitive advantage. Transaction cost economics (TCE) laid the theoretical foundation for asset specificity. Williamson pointed out that when firms make highly specialized investments, such assets are difficult to redeploy without losing

¹ Rocio Wu. RIP Old VC Playbook: How Investors Are Rethinking AI Startups' Diligence // Forbes. June 17, 2025. URL: <https://www.forbes.com/sites/rociowu/2025/06/17/rip-old-vc-playbook-how-investors-are-rethinking-ai-startups-diligence/> (accessed on 17.03.2026).

value, resulting in a lock-in effect for both parties in the transaction [17].

As AI evolves towards a generative paradigm, the AI industry ecosystem exhibits significant stratification. Business model innovation often revolves around a company's strategic choices within its niche. Infrastructure-oriented companies typically build AI factories, closed-loop systems consisting of data pipelines, algorithm development platforms, experimental systems, and software infrastructure to accumulate scalable learning and competitive capabilities [18]. Such startups focus on delivering fundamental and general-purpose capabilities like large-scale models, computing infrastructure, and machine learning operations, as opposed to application-layer solutions. By positioning themselves at the core of the AI value chain, they provide indispensable technological input to downstream developers and application providers, thereby deeply integrating into the AI ecosystem [18; 19]. AI startups focused on infrastructure benefit from strong economies of scale and cumulative learning effects. AI systems continuously improve through iterative data accumulation, model improvement, and deployment feedback, building a virtuous cycle of data-algorithm-user. Feedback data from actual deployments enables predictive machines to learn continuously during use, allowing enterprises to continuously improve performance and operational efficiency as usage increases [18; 20].

From investor's perspective, these characteristics mean that AI startups focused on infrastructure require a unique evaluation logic. Building the underlying infrastructure and computing clusters requires a huge initial capital investment, but the extremely highly competitive barriers and customer lock-in effect established by this business model reduce the risk of being replaced [11]. The accumulation of data and the potential for model iteration accompanying actual deployments create powerful data network effects [21]. In theory, occupying a bottleneck or core node in an ecosystem can enhance a company's bargaining power in value creation and capture [22], and is seen as having greater profit potential and strategic importance in the capital market. Therefore, investors are often willing to invest more capital in such companies and accept higher valuations. Based on the above, we propose the following hypothesis:

H1: Infrastructure-oriented business models are positively correlated with the funding performance of AI startups.

Application-oriented Business Model

In the AI ecosystem, application-oriented startups primarily occupy the downstream layer of the value chain. These companies deeply integrate general-purpose functionalities into specific business use cases, production workflows, or industry verticals by invoking or fine-tuning upstream foundation models [19; 23]. With the proliferation of related tools and infrastructure, more companies are adopting AI in various application scenarios, thus intensifying competition in the field and shortening the duration of technological advantages. Application-layer firms typically operate as supplementary players within platform-based ecosystems, heavily reliant on upstream models and infrastructure providers. It limits their bargaining power and ability to capture value [20; 24].

From a financing and valuation perspective, such structural position is of great significance. When evaluating startup projects, venture capitalists and early investors focus on their short-term market performance and long-term defensive and value-capturing capabilities [12]. The low barrier to entry for the application layer means that it is very easy for the capital market to quickly commoditize it. Since these startups are essentially just repackaging third-party application programming interfaces (API), they cannot possess the scarce and inimitable resources needed to maintain a sustainable competitive advantage [16]. Investors believe they are highly vulnerable to substitution and margin compression, which aligns with broader economic observations that downstream application providers are increasingly less capable of capturing long-term value compared to core infrastructure owners [25]. Application layer startups face the threat of platform swallowing or functional assimilation. Upstream infrastructure providers natively integrate downstream application functions into their core products, stifling independent application developers and limiting their development potential [26]. Therefore, the capital market underestimates the valuation of application-oriented AI startups. When allocating capital and structuring investments, venture capitalists explicitly prioritize scalable business models, defensible

competitive advantages, and long-term value capture potential [27]. Companies lacking control points over underlying technologies or ecosystems, like application-layer startups, are inherently disadvantaged in capturing value within the digital ecosystem [28]. In the field of AI, this structural vulnerability and high degree of uncertainty have led to a systematic underestimation of funding for related projects [29]. Based on this, we propose the following hypothesis:

H2: Application-oriented business models are negatively correlated with the funding performance of AI startups.

Hybrid Business Model

In AI business practice, many startups are trying to adopt a hybrid business model that combines infrastructure and application layers. These companies aim to empower developers by providing underlying APIs or basic models, while also building vertical SaaS applications for end users. On the surface, such a strategy seems to balance long-term platform potential with short-term monetization. Research in the field of strategic management has long pointed out that when different strategic positioning relies on incompatible value creation logics and activity systems, companies often face the risk of being stuck in the middle [30; 31]. The risk is particularly pronounced in startups with highly limited resources and unstable organizational boundaries. For AI startups, the infrastructure layer and the application layer differ significantly in their core business logic.

From a resource-based perspective, key resources that can support a competitive advantage need to be scarce and not entirely substitutable for startups, high-quality capital and technical talent often meet these characteristics [16; 32]. Hybrid business models require companies to invest significant resources simultaneously in both underlying model development and upper-level product market expansion. It can easily lead to key resources being dispersed across multiple competitive dimensions, making it difficult to establish a competitive advantage that is hard to imitate on any one path [16]. It is difficult for enterprises to compete with highly focused platform vendors at the infrastructure layer, and at the application layer; they cannot match solution providers focused on a single vertical industry. It is logically consistent with the “stuck

in the middle” dilemma described by Porter [30]. Because it covers both the infrastructure and application layers, hybrid business models may weaken the clarity of a company’s core competitive advantages and make its long-term value capture path less clear. This resulting ambiguity in strategic signals often increases investors’ perception of potential risks, thereby reducing the company’s attractiveness during the fundraising process. Therefore, we propose the hypothesis:

H3: Hybrid business models are negatively correlated with the funding performance of AI startups.

Methodology

Data Source and Sample Selection

The empirical data in the study comes from Crunchbase, a globally widely used database of startups and venture capital firms. This database systematically collects key information about companies at different stages of development. To focus on AI startups, we implemented a rigorous data retrieval and cleaning process. Companies with industry tags containing “Artificial Intelligence”, “Machine Learning”, or “Generative AI” were extracted, with the time window ending in early 2026. Given the fundamental differences between public market valuation logic and early-stage venture capital, this study excluded all observations labeled IPO, Post-IPO, or Secondary Market based on the “Last Funding Type” and “Funding Status” fields to ensure the sample consisted purely of privately held startups not publicly traded. Furthermore, observations lacking key variables were also excluded. After the above cleaning process, a valid sample of 980 AI startups was finally obtained. Among the 980 AI startups, 133 firms are classified as infrastructure-oriented only, 372 as application-oriented only, 69 as hybrid models, while the remaining 406 firms constitute the baseline group.

Variable Measurement

The total funding amount in USD since the company’s inception is used as a proxy variable for the financing performance. Since the distribution of venture capital amount is typically right skewed, this study follows the conventional practice in the field of venture finance [29] and applies a natural logarithmic transformation to one plus the cumulative funding amount.

To objectively quantify the business models of AI startups, the study employs dictionary-based text mining. We used Python regular expressions to scan the “Full Description” field in Crunchbase, constructing the following binary dummy variables:

Application oriented Model: Measures whether an enterprise uses general AI capabilities for vertical applications targeting end users. A value of 1 is assigned if the enterprise description contains keywords related to subscription-based software business models or vertical industry applications; otherwise, a value of 0.

Infrastructure oriented Model: Measures whether an enterprise provides underlying technology or empowers its developer ecosystem. To ensure the rigor of the definition, the study adopts strict underlying technology standards: A value of 1 is assigned if the company description indicates the provision of underlying AI infrastructure or developer-oriented capabilities. It includes keywords related to developer interfaces, open-source infrastructure, or core generative AI system components, throughput, or latency; otherwise, a value of 0.

Hybrid Model: Constructs interaction items between the infrastructure layer and the application layer. If an enterprise exhibits characteristics of both above modes, it represents a hybrid strategy of providing both underlying empowerment and end-user applications.

In the regression model, companies that are neither infrastructure-oriented nor application-oriented constitute an omitted reference group (baseline category), and all estimated coefficients are interpreted relative to this group. The relatively large size of the baseline group reflects the conservatism of the keyword-based classification method, which prioritizes the precise identification of explicit business model characteristics while excluding companies with ambiguous textual signals.

To eliminate the interference of other potential factors on financing performance, we controlled for the following key variables:

Firm Age: Measures the time span from the year the firm was founded to the time of data collection. Earlier-established firms typically have a longer window for fundraising.

Firm Size: Measured as the natural logarithm of the number of employees. Firm size

reflects organizational capacity and operational scale, which may influence investors' funding decisions.

Human Capital: Measured by the number of co-founders. The size of the founding team is generally considered an important indicator of a startup's human resource endowment and technological capabilities.

Funding Status: Due to the order-of-magnitude differences in funding amounts across different rounds, we transformed the funding status in Crunchbase into a series of fixed effects and incorporated them into the model to control for the impact of the firm's lifecycle stage.

To verify the three hypotheses, we constructed the following multivariate ordinary least squares (OLS) regression model:

$$\ln(1 + Funding)_i = \beta_0 + \beta_1 Infra_Layer_i + \beta_2 App_Layer_i + \beta_3 (Infra_Layer_i \times App_Layer_i) + \sum \gamma Control_Variables_i + \epsilon_i.$$

Considering the heteroskedasticity prevalent in cross-sectional data, the study employs HC3 heteroskedasticity-consistent robust standard errors correction in all regression models to ensure the reliability and rigor of statistical inference.

Empirical Results and Analysis

Descriptive Statistics and Model Fit

The study ultimately included 980 non-listed AI startups as a valid empirical sample. Before conducting regression analysis, we performed multicollinearity diagnostics on all continuous explanatory and control variables. The results showed that the variance inflation factor (VIF) of all variables was well below the conventional empirical threshold of 10, indicating that the model did not have a serious multicollinearity problem.

In the multiple OLS regression model, we used technology keywords to define the infrastructure layer and controlled for fixed effects related to firm age, firm size, human capital, and funding status. To eliminate the interference of heteroscedasticity, a common problem in cross-sectional data, on statistical inference, all regression models used HC3 robust standard errors. The overall regression results show that the model has an excellent goodness of fit ($R^2 = 0.441$, adjusted $R^2 = 0.434$), and the F test is highly signifi-

cant at the 1 % level ($F = 95,11$, $p < 0,001$), indicating that the model specification has a very strong explanatory power.

Main effect test

To examine the independent impact of different business models on the fundraising performance of AI startups, the study first examines the regression coefficients of individual business models and their total effect obtained through the Wald test.

The regression results (Table 1) show that the regression coefficient for the single infrastructure layer model (Infra_Layer) is significantly positive ($\beta = 0,286$, $p = 0,012 < 0,05$). Further Wald tests indicate that the total effect of the single infrastructure model relative to the baseline group is $+0,286$ ($p = 0,0117$). It suggests that, after controlling for other firm characteristics and funding rounds, startups focusing on providing underlying core algorithms, API services, or open-source frameworks can obtain a significant valuation premium of approximately 28,6 % in the venture capital market. The result supports H1, confirming that firms with control over underlying technology and the potential for platform network effects are systematically favored by capital.

The regression coefficient for the single application layer model (App_Layer) is significantly negative ($\beta = -0,238$, $p = 0,006 < 0,01$). The Wald test confirms its total effect as $-0,238$ ($p = 0,0061$). It means that relying solely on calling upon upstream general-purpose large-scale model capabilities and using them as vertical terminal applications will lead to a systemic funding discount of approximately 23,8 % for startups. The finding supports H2, demonstrating that application layer companies lacking a strong technological moat and highly susceptible to feature subsumption by underlying model providers face high structural disadvantages in the capital market.

Interaction and joint effects test

The interaction between the infrastructure layer and the application layer (Infra_Layer $\times$ App_Layer) aims to capture the impact of enterprises adopting a Hybrid Model that both provides underlying enablement and develops end-user applications on their financing performance. The results in Table 1 show that the regression coefficient of this interaction term is extremely significant and negative

($\beta = -0,404$, $p = 0,020 < 0,05$). It initially indicates that the simultaneous combination of the two business models failed to produce the expected organizational synergy, leading to serious internal friction. To precisely quantify the ultimate economic consequences of this hybrid strategy, the study performed the Wald joint test (Table 2).

Wald's test results reveal that the total effect of the hybrid model relative to the baseline group is as high as $-0,356$ ($p = 0,0075 < 0,01$). Notably, the funding penalty suffered by the hybrid business model ($-35,6$ %) is significantly greater in absolute value than that of the single application-oriented business model ($-23,8$ %). Therefore, Hypothesis 3 is confirmed. The results show that AI startups with hybrid business models are caught in the stuck in the middle strategic trap, where the double burden sends unfavorable market signals, leading to valuation discounts for these companies in venture capital investments.

Control variable analysis

The empirical results align with classic findings in the field of venture finance. Human capital (number of founders) exhibits a significant negative impact on fundraising performance ($\beta = -0,080$, $p < 0,001$). It suggests that in the highly uncertain early stages of AI startups, an overly large co-founder team may send negative signals to investors regarding excessive equity dilution, lengthy decision-making chains, or potential internal friction. Firm age shows a marginally significant positive impact ($\beta = 0,053$, $p < 0,1$). Furthermore, the regression coefficients and significance directions of the fixed effects at each fundraising stage are highly consistent with real-world business logic, further validating the robustness of the model in this study.

Conclusions and Discussion

In the current market environment, how AI startups can innovate their business models amidst technological and market uncertainties is a crucial issue. The paper based on a sample of data from 980 unlisted AI startups worldwide, uses text mining to deconstruct their business models and empirically examines the differentiated impact of different strategic positioning on venture capital performance.

The research results show that the infrastructure-oriented model, which masters

Table 1

Regression results (OLS) of business models on the funding performance of AI startups
 Результаты МНК-регрессии влияния бизнес-моделей на эффективность привлечения финансирования ИИ-стартапами

Variables	Expected symbol	Ln(Funding) regression coefficient	Robust Std. Err.
Independent variable			
Infrastructure-oriented Business Model (Infra_Layer)	+	0,286*	(0,114)
Application-oriented Business Model (App_Layer)	–	–0,238**	(0,087)
Hybrid Business Model (Infra_Layer × App_Layer)	–	–0,404*	(0,173)
Control Variables			
Human Capital		–0,080***	(0,016)
Firm Age		0,053 [†]	(0,031)
Funding Stage Fixed Effects		Yes	–
Constant		16,340***	(0,218)
Model Statistics			
Observations (<i>N</i>)		980	
Adjusted <i>R</i> ²		0,434	
<i>F</i> -statistic		95,11***	

Note: Dependent variable is Ln(1 + Funding)_{*i*}. Robust standard errors (HC3) are in parentheses.

*** $p < 0,001$, ** $p < 0,01$, * $p < 0,05$, [†] $p < 0,1$.

Source: Author's compilation (Yufan Sun).

Table 2

A comparison of the total financing effect of different business model positioning
 (Wald Joint Test)

Сравнение совокупного эффекта финансирования различных вариантов позиционирования бизнес-моделей
 (совместный тест Вальда)

Strategic Position	Variable Conditions	Estimated Total Effect	Z-Statistic
Infrastructure-oriented Business Model	$Infra = 1, App = 0$	+0,286	2,520
Application-oriented Business Model	$Infra = 0, App = 1$	–0,238	–2,740
Hybrid Business Model	$Infra = 1, App = 1$	–0,356	–2,675

Source: Author's compilation (Yufan Sun).

Note: The total effect represents the marginal change in log funding for each specific model compared to the baseline group, which consists of AI startups classified as neither infrastructure-oriented nor application-oriented under the keyword-based coding procedure. The total effect for the Hybrid Business Model is tested as the linear combination of $\beta_{Infra} + \beta_{App} + \beta_{Interaction}$.

the underlying core technologies, has a significant innovation premium, reflecting capital's systematic preference for technological moats and potential platform network effects; the application-oriented model, which relies on calling third-party models, is trapped in a value trap and is easily swallowed up by the functions of upstream suppliers in homogeneous competition; the hybrid model that attempts to simultaneously take into account both underlying R&D and end-user

applications triggers the most severe penalty of being stuck in the middle. It indicates that vertical integration strategy has failed to generate organizational synergy and have erased the original technology premium due to resource dilution and channel conflicts within the ecosystem.

The paper deepens the theory of business model innovation in the digital economy era. Previous literature largely treats startup business models as static.

This paper, considering the characteristics of the AI industry architecture, deconstructs it into infrastructure, application layer, and hybrid models. Using quantitative data, it reveals how technological capabilities shape the business loop and influence capital valuation, providing clear micro-level empirical evidence for the commercialization path of emerging technologies.

It expands the applicability of Michael Porter's competitive strategy theory in environments of extreme uncertainty. In the wave of rapid AI development, many companies blindly pursue full-stack integration. This paper, by revealing the financing problems faced by hybrid models, confirms the existence of Michael Porter's "stuck in the middle" trap in the AI startup field. In the early stages when computing power and talent are extremely scarce, it can lead to strategic misalignment, providing a new application scenario and empirical support for the RBV perspective.

The findings of this study offer guidance for AI industry practice. AI startups need to avoid overextending themselves strategically too quickly. In the resource-constrained early stages, companies must make clear strategic trade-offs: either focus on building underlying infrastructure or deeply cultivate a vertical industry, building barriers based on

proprietary data. Attempting a hybrid strategy that simultaneously targets both infrastructure and application layers often carries high risks; companies need to be wary of the competitive pressure from overexpansion of strategic boundaries and the resulting valuation discounts in the capital market.

Venture capital firms need to optimize their valuation logic for AI startups. During the investment evaluation process, investors should pay more attention to the company's position within the AI industry ecosystem and its potential ecosystem conflicts. Capital should be prioritized for companies with a clear business model in a single strategic dimension.

However, this paper also has certain limitations. We used cross-sectional data for empirical testing. Future research could construct panel data as the industry matures to capture the evolution of financing performance before and after the dynamic transformation of startup business models. While dictionary-based text mining can objectively handle large samples, it is difficult to fully capture the implicit strategic intentions in company prospectuses or in-depth interviews. Future research could combine multi-case grounded theory to further explore the deep organizational behavioral mechanisms of hybrid strategy failures.

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