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How do China and the United States fund artificial intelligence? Multi-dimensional characteristics analysis from the lifecycle perspective

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Abstract

Funding for artificial intelligence (AI) research and development has become a strategic priority in national research agendas worldwide. This study compares the multi-dimensional characteristics of AI-related funded projects in China and the United States (US), the two global leaders in AI development. Based on the incoPat and Sci-Fund databases, as well as text analysis and large language model techniques, we identified the AI technology lifecycle in these two countries and analyzed the characteristics of funding entities, types, and topics of AI-related projects. Results reveal that the US began funding AI projects earlier, while China followed a trajectory of catching up and eventually surpassing the US in the number of funded projects. Regarding funding entities, the US was led by the National Science Foundation, National Institutes of Health, and Department of Defense, while China has shifted from a pattern dominated by the National Natural Science Foundation of China to a more balanced and multi-agency layout. Regarding funding types, both countries prioritize applied research projects. However, the US increased its support for technology commercialization projects in the later stages of the lifecycle, while China placed greater emphasis on fundamental research projects with relatively less investment in commercialization. Regarding funding topics, the US prioritized national security and military applications, while China focused more on healthcare, education, and other areas closely tied to social needs. These findings contribute to a deeper understanding of the differentiated developmental stages and funding strategies between China and the US.

Keywords Research funding · Artificial intelligence · Technology life cycle · Large language model

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Introduction

Technological innovation has become a key driver of economic growth and competitiveness in the new wave of scientific and technological (S&T) revolution. Disruptive technologies and emerging technologies, which lead to breakthroughs at the technological frontier, transform industries and reshape the global competitive landscape (Rotolo et al., 2015). Among these, artificial intelligence (AI) stands out for its innovative capacity, transformative potential, and wide societal impact (Pavaloaia et al., 2023). As global leaders in AI development, China and the United States (US) play crucial roles in promoting AI research and innovation (Chen et al., 2025). Their funding strategies and policies are critical drivers of global progress in this field.

The development of disruptive technologies like AI is deeply dependent on the national funding landscape. Strategic financial support accelerates the emergence of these technologies, thereby catalyzing technological innovation, industrial transformation, and broader economic competitiveness (Zhang et al., 2022). As a key tool for supporting S&T innovation, grants promote technological progress and industrial development by funding research in priority areas and aligning with national plans and strategies. Due to the unique developmental trajectory of disruptive technologies (Liu et al., 2022), appropriate project layouts are needed to support different stages of their development. This requires a strong emphasis on fundamental research and its integration with technological innovation.

Current research on funding for technological innovation focuses on three main aspects: funding mechanisms and processes, the scope of funding domains, and the evaluation of funding impacts. Regarding funding mechanisms and processes, recent studies have critically examined the design of grant allocation systems to foster breakthrough innovations. A central debate revolves around the design of evaluation processes, as traditional peer review often penalizes highly novel or unconventional proposals due to cognitive biases against intellectual distance (Boudreau et al., 2016). To overcome these systemic barriers, scholars have investigated alternative funding mechanisms. For instance, Azoulay et al. (2011) demonstrated that funding models emphasizing "people over projects," which provide long-term flexibility and tolerate early failures, are significantly more effective in producing breakthrough, disruptive innovations than standard short-term grants. Furthermore, macro-level analyses of funding ecosystems suggest that structural factors in the funding process directly influence the disruptiveness of funded outcomes (Packalen et al., 2020). Huang et al. (2025) analyzed 10 representative disruptive technology funding programs worldwide. By focusing on the project life cycle, it systematically analyzed these funding programs across four stages. Zhao et al. (2022) analyzed the R&D and management funding systems for disruptive technology in the US, Europe, and Japan. Based on the funding practices of major countries, they have proposed recommendations. Regarding the scope of funding domains, current studies aim to map the technological landscape by identifying which specific research topics and emerging technologies receive financial support. To achieve this, scholars increasingly rely on advanced text mining and natural language processing techniques applied to grant databases and funding acknowledgments (Jin et al., 2022). For instance, Bai et al. (2020) integrated natural language processing, topic identification, and complex network analysis to uncover potential research frontiers. Kaur et al. (2026) utilized structural topic modeling to uncover the dynamic landscape of sustainable innovation funding, demonstrating how these models can dynamically identify emerging technological hotspots and track resource allocation across different innovation trajectories. Regarding the evaluation of funding impacts, research has primarily focused on the output of scientific research results (Gao et al., 2019; Thelwall et al., 2023). Some scholars have examined the indirect effects of scientific funding on technological innovation through patent citations of non-patent literature (Narin et al., 1985). For example, Du et al. (2019) studied the "funding-science-technology-innovation" chain in the pharmaceutical field, highlighting the critical role of public funding in pharmaceutical innovation. Fajardo-Ortiz et al. (2020) analyzed the funding landscape of major government agencies and organizations in the CRISPR. Abadi et al. (2020) compared AI funding in China and the US, while Sargent et al. (2019) analyzed the development of 3D printing technology and its primary drivers.

Existing studies have offered valuable insights into the performance and distribution of funding for technological innovation. However, they have paid limited attention to the potential differences in funding needs at various stages of technological development. These studies often fail to adequately integrate funding support with the different stages of the technological lifecycle. Therefore, this study aims to address this gap by examining the evolution of the multi-dimensional characteristics of funding agency grants in China and the US from a technology lifecycle perspective, using AI technology as a case study. We begin by constructing the lifecycle curves of AI technology in China and the US to identify the AI development stages in each country. Then, we integrate descriptive statistics and large language models to analyze the funding entities, project types, and research topics of funded projects at different stages. The study aims to provide a deeper understanding of the funding priorities, strategies, and evolutionary trends of AI projects in China and the US.

Research design

Given the potential differences in funding needs across different stages of technological development, this study applies the technology development lifecycle framework to examine the evolving characteristics of AI-funded projects in China and the US, with a focus on how funding strategies differ at different stages. This study employs a multi-dimensional analytical framework to systematically analyze project data, focusing on three key dimensions: funding entities, project types, and research topics. While metadata for project entities can be directly extracted, identifying project types and analyzing topics requires multi-stage data processing to obtain deeper insights. This section begins by presenting the study's analytical framework, followed by an introduction to the research data. Finally, it describes the methods used to identify project types and topics.

Analytic framework

To comprehensively examine the evolving funding characteristics of AI development at different stages in China and the US, we first construct the lifecycle of AI technologies based on the Logistic curve. Then, we analyze project characteristics across three dimensions: funding entities, project types, and research topics. From the perspective of funding entities, we analyze the distribution of funding agencies and identify the main sources of financial support at each stage, addressing the question of "who" drives innovation. In terms of project types, we analyze fundamental research, applied research, and commercialization, and illustrate how a country balances investments across these categories, thereby explaining "how" funding supports innovation. The analysis of research topics emphasizes topic focus and their shift across various stages, uncovering "what" issues are prioritized. These

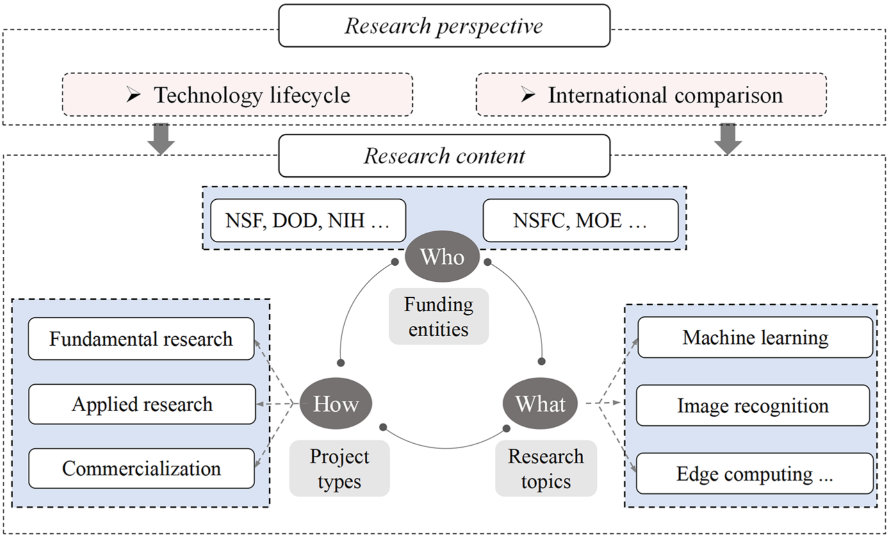


Fig. 1 Analytic framework

dimensions are interrelated and together provide a comprehensive perspective on resource allocation and strategic priorities within the technology lifecycle. This multidimensional framework not only reveals the funding characteristics and their evolution in AI development in China and the US but also offers systematic insights into the differences in their technological development trajectories. Figure 1 illustrates the research framework of this study.

Data acquisition & processing

This paper selected the incoPat and the Sci-Fund databases as the main sources for AI patent and project data. Patent data were used to construct the technological lifecycle, as they directly reflect the process and stages of technological innovation (Huang et al., 2022). Constructing a technology life cycle focuses on tracking R&D momentum and technological trajectories rather than commercial valuation, so we used each nation's domestic patent data to independently fit its technology life cycle. Furthermore, to ensure data quality and cross-national comparability, we strictly limited the dataset to invention patent applications, effectively filtering out utility models and designs. incoPat is a global patent database that provides comprehensive coverage of patent-related data, including data from the China National Intellectual Property Administration (CNIPA), the United States Patent and Trademark Office (USPTO), and relevant agencies. Sci-Fund is a project tracking database owned by Wanfang company that consolidates over 8 million projects from nearly 20 countries (according to the statistics on October 20, 2025), including China, the US, the United Kingdom, Japan, etc. It integrates funding data from about 200 government agencies, national research institutions, and non-profit organizations, with continuous updates dating back to 1900.[1] Crucially, this broad coverage captures a comprehensive, multi-tiered funding ecosystem, allowing for a holistic view of innovation landscapes beyond. The

[1] Sci-Fund Database. Retrieved from https://scifund.wanfangdata.com.cn/.

platform sources data from authoritative repositories, such as the National Natural Science Foundation of China (NSFC), National Science Foundation (NSF), and National Institutes of Health (NIH). For project data collection, a keyword search was conducted, covering project titles and keywords, with the project approval period limited to 2024.

The search strategy in this paper is as follows: (1) Use core keywords related to AI technologies, such as “Artific* Intelligen*” or “AI Technolog*,” as the basic search terms; (2) Conduct supplementary searches based on key subfields. The identification of these subfields and keywords refers to the core terms and field classifications from the AI index in PATENT-SCOPE provided by the World Intellectual Property Organization (WIPO) and the United States Patent and Trademark Office (USPTO). Details are shown in Table 1.

In determining the search strategy for this study, we evaluated various methodological approaches in the existing literature. Notably, Baruffaldi et al. (2020) proposed a highly rigorous dynamic search methodology in an OECD report that combines expert knowledge with machine learning and serves as a pioneering benchmark for micro-level text mining to identify AI-related patents. However, considering the specific objectives and data characteristics of our study, we opted for the two-step strategy described above. This decision was driven by two main considerations. First, our study involves processing heterogeneous text data from both patents and funded projects. By utilizing core AI terms alongside official macro-level subfield classifications derived from WIPO and USPTO, our strategy ensures better classification consistency across different data sources. Second, utilizing frameworks grounded in the official standards of the world’s leading intellectual property organizations ensures high reproducibility and allows our empirical findings to be directly comparable with other research.

The data processing process consists of two main steps:

Firstly, duplicate patents were removed, resulting in 13,429 US patent applications and 79,302 China’s patent applications. Based on the processed data, the cumulative annual patent applications were calculated to characterize the technology lifecycle. Secondly, duplicate projects were removed, and the titles, abstracts, and keywords of the projects were cleaned. Missing values were manually supplemented by consulting original data sources, such as the website of NSFC, and other available project information platforms, to ensure data completeness and reliability. After data processing, 21,941 projects funded by China and 17,283 projects funded by the US were obtained. Patent and project data were retrieved on October 20, 2025.

Method for dividing technology lifecycle stages

The technology lifecycle serves as the central temporal dimension for the multi-dimensional analysis in this study. To objectively delineate the development stages of AI technology in China and the US, we employ the S-curve model based on patent cumulative data. The S-curve, originally rooted in Verhulst’s logistic growth model, is a classical method for forecasting technology diffusion and maturity. Among the primary variants (Logistic and Gompertz), this study adopts the Logistic model due to its suitability for describing symmetrical growth patterns in technology accumulation.

Given the distinct research trajectories and technological maturity levels across the two nations, analyzing patent data separately enables precise identification of country-specific development phases. This separation is crucial for understanding how each country adjusts its funding strategies in response to its domestic technological innovation status. In this study, we employ the classic 3-parameter Logistic growth model to fit the cumulative

Table 1 AI technology fields and search keywords

Classification	Subfields	Search keywords
AI techniques	Fuzzy logic	fuzzy logic*
	Logic programming	logic* program*
	Machine learning	machine* learn*; robotic learn*; machine study*; generative AI; large language model*; general AI
	Ontology engineering	ontolog* engineer*
	Probabilistic reasoning	probabilistic reasoning
AI functional applications	Computer vision	compute* vision*; machine* vision*
	Control method	control* method*
	Distributed artificial intelligence	distribut* artific* intelligen*
	Knowledge representation and reasoning	knowledge representat* and reason*; knowledge process*; knowledge handl*
	Natural language processing	natur* language process*
	Planning and scheduling	plan* and schedul*; plan* and control*
	Predictive analytics	predict* analysis*; forecast* analysis*
	Robotics	intelligen* robot*; smart* robot*
	Speech processing	speech process*; vioce process*
	AI hardware	AI hardware*; artific* intelligen* hardware*
	Evolutionary computation	evolution* computation*; evolution* algorithm*

patent trajectories and identify the technology lifecycle stages. The model is defined mathematically as:

$$y = \frac{K}{1 + e^{-r(t-t0)}}$$

where y represents the cumulative number of patents at year t; K is the carrying capacity (the theoretical maximum limit of cumulative patents); r is the intrinsic growth rate; and $t0$ is the inflection point year (the midpoint where cumulative patents reach 50% of K). Based on this parameter, the technology lifecycle is segmented into four distinct stages: Introductory, Emerging, Growth, and Maturity, which are quantitatively defined by the cumulative patent volume reaching the critical thresholds of 1, 10, 50, and 90% of the fitted saturation level K, respectively. These quantitative thresholds provide a consistent framework for identifying the specific time windows of AI development for both China and the US.

Multi-dimensional characteristic identification based on LLM

After establishing the temporal framework, this study further constructs the content dimension by analyzing the characteristics of funded projects. Given the semantic complexity of project texts, we employ large language model (LLM) techniques to achieve fine-grained identification of project characteristics. We select DeepSeek-R1-7B-Distill as the base model due to its superior performance in natural language understanding. To optimize the model efficiently for specific tasks, we employ supervised fine-tuning (SFT) combined with low-rank adaptation (LoRA) techniques. This approach allows the model to learn specific semantic patterns from a small set of high-quality annotated samples while maintaining computational efficiency.

This study first categorizes AI funding projects into three distinct types: Fundamental Research, Applied Research, and Commercialization. The classification criteria and characteristics vocabulary are based on the definitions and classifications of projects in existing policies or literature, as shown in Table 2. According to UNESCO, research and development (R&D) activities can be divided into three categories: fundamental research, applied research, and experimental development. Similarly, the *Law of the People's Republic of China on Scientific and Technological Progress* emphasizes the principle of "encouraging fundamental research driven by applied research, and promoting the integrated development of fundamental research, applied research, and achievement transformation". In practice, funding projects are often categorized into four types—personnel training, fundamental research, applied research, and commercialization—or three types: fundamental research, applied research, and developmental research (Liang, 2023).

Table 2 Characteristic words for the classification of funded projects

Project type	Project characteristics
Fundamental research projects	Focusing on in-depth exploration and study of scientific theories, principles, and concepts.
Applied research projects	Focusing on research on the application of scientific theories and research results in solving practical problems.
Commercialization projects	Focusing on advancing research outcomes toward practical applications, trials, demonstrations, or commercialization.

The identification of project types involves three major steps:

1. *Prompt design and vocabulary construction.* We construct a vocabulary of classification keywords and design prompts for the model. For instance, fundamental research projects often include keywords such as "theory," "mechanism," and "principle"; applied research projects often contain "application," "system design," and "platform"; while commercialization projects are typically associated with "translation," "commercialization," and "product". Based on the characteristics of the projects and vocabulary, prompt is designed with explicit classification rules: if commercialization research keywords appear, the project is directly classified into this category; if both fundamental research and applied research keywords are present, the dominant type is determined based on keyword frequency and contextual semantics; if only a single category of keywords is present, the project is classified accordingly.
2. *Model fine-tuning and prompt optimization.* To achieve efficient fine-tuning, we apply the LoRA technique to the DeepSeek model. By training the model on high-quality samples obtained through manual annotation, we enable it to learn specific semantic patterns required for project classification tasks. At the same time, we iteratively refine the prompt rules to further improve classification accuracy.
3. *Project classification.* During the classification process, the model analyzes the semantic information in project titles, keywords, and abstracts, and applies the classification vocabulary to achieve precise categorization. For projects that cannot be assigned to specific categories, we label them as "unclassified" and exclude them from subsequent analyses.

Specifically, we have randomly selected 300 project samples from a dataset of 39,224 AI-related projects funded by China and the US for manual annotation to construct high-quality training data. The annotated data were split into a training set and a test set in an 8:2 ratio, with 240 samples used for model fine-tuning and 60 samples for performance evaluation. Experimental results on the test set demonstrated that the model achieved a classification accuracy of 91.7%, a recall of 88.5%, and an F1 score of 90.1%, indicating excellent performance in the classification task. Using the fine-tuned model, the remaining project data were automatically classified. Through the classification process, 15.7% of the records were categorized as "unclassified" and excluded from the subsequent funding type analysis. Projects fell into this category primarily because their textual descriptions did not align with predefined keyword vocabularies or lacked sufficient semantic context to determine a dominant research type under our classification rules. The proportions of unclassified rates were comparable between the two countries, suggesting that their exclusion is unlikely to introduce a systematic bias into the cross-national comparison of the three core research types.

In addition to project types, this study further extracts and analyzes the core research topics of the funded projects to capture the granular content of innovation. Similar to the project type classification, the DeepSeek-R1-7B-Distill model was fine-tuned for topic extraction.

To ensure the precision and granularity of the extracted topics, specific emphasis was placed on prompt engineering. The prompts were designed to guide the model to focus on substantive technical concepts, such as specific algorithms, model architectures, and application scenarios, while explicitly excluding general academic terminology (e.g., "study," "analysis," "method") that lacks distinctive information. Furthermore, we instructed the model to synthesize semantic information from both project titles and abstracts to ensure the extracted keywords accurately reflect the core innovation of each project.

During the data processing, we construct a high-quality training dataset with 80% used for training and 20% for testing. The results show that the fine-tuned DeepSeek-R1-7B-Distill model achieves an accuracy of 87.5%, a recall of 84.2%, and an F1 score of 85.7% on the project research topic identification task. These results demonstrate the model's high accuracy and its effectiveness in identifying core research topics.

Results

Evolution of AI technology lifecycle stages

Based on the Logistic model, the cumulative patent data for both countries were fitted to identify their respective lifecycle stages. The fitting window for our empirical data spans from 1998 to 2024. The parameters were estimated using the non-linear least squares (NLS) procedure, implemented via the SciPy optimization library in Python, which allows for robust boundary constraints and high-precision iterative fitting. The fitting results are illustrated in Table 3 and Fig. 2.

Applying the milestone formulas, the lifecycle stages are precisely identified. For the US, the technology transitioned through the Emerging, Growth, and Maturity stages in the years 2013, 2017, and 2021, respectively. In contrast, China's trajectory shows a later start but a steeper acceleration, with the corresponding milestones occurring in 2015, 2019, and 2022.

To test the symmetry assumption, we introduced the asymmetric Gompertz model as a robustness check. As presented in Fig. 3, both models achieve an exceptionally high goodness-of-fit ($R^2 > 0.99$). However, the Logistic model consistently yields a higher fitting accuracy (0.9998 for China, 0.9961 for the US) than the Gompertz model (0.9989 for China, 0.9931 for the US). Given that the near-perfect R^2 values in cumulative time-series data can sometimes obscure model distinction, we further evaluated the models using the akaike information criterion (AIC), which compares model quality by balancing goodness-of-fit against model complexity (Ganguly et al., 2010), and the model with the lowest AIC value is generally considered the optimal fit (Hinge et al., 2021). The results demonstrate that the Logistic model yields strictly lower AIC values for both the US (310.5) and China (312.0) compared to the Gompertz model (325.9 and 360.9, respectively). This dual confirmation indicates that the Logistic model precisely captures the actual growth rhythm and offers a more parsimonious fit. The near-perfect R^2 of the logistic model for both China and the US is largely driven by the strictly monotonic nature of cumulative data and the macro-scale smoothing effect of large economies. This suggests that while AI may experience multi-wave dynamics at the micro-technological level, these fluctuations are smoothed

Table 3 Results and parameters of the logistic fitting

Country	K	r	t0	R^2	1% K	10% K	50% K
China	100,460.51 (865.12)	0.6808 (0.0075)	2021.97 (0.08)	0.9998	2015.22	2018.75	2021.97
The US	18,070.75 (450.30)	0.5639 (0.0261)	2020.84 (0.35)	0.9961	2012.69	2016.94	2020.84

Note: Standard errors of the estimates are reported in parentheses

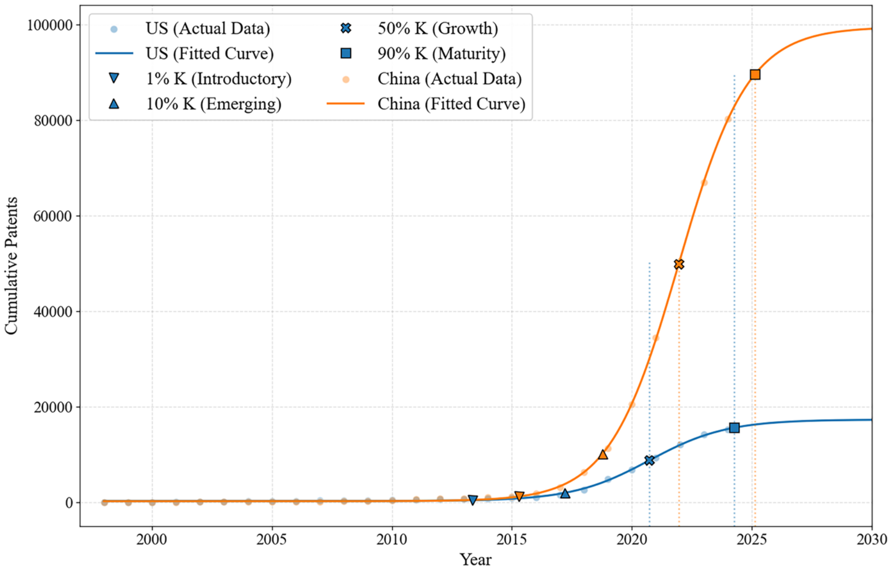
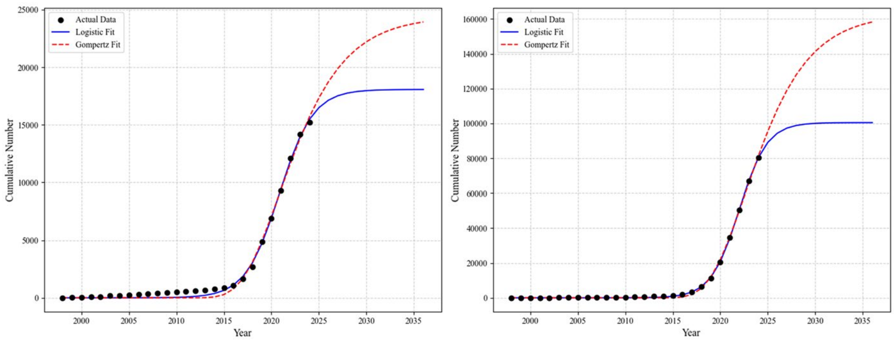


Fig. 2 Lifecycle curve of AI technology in the US and China



(a) The US

(b) China

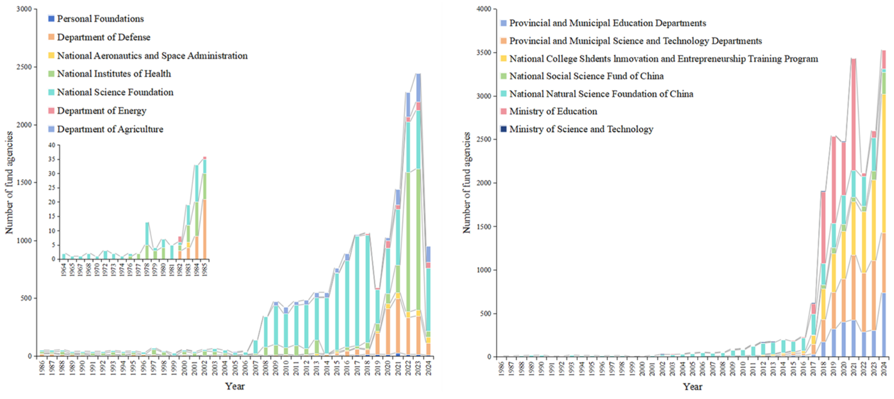
Fig. 3 Logistic and Gompertz curve fitting of cumulative patents in the US (panel (**a**)) and China (panel (**b**))

into a continuous, overarching macro-trajectory at the national patent accumulation level. Consequently, we adopt the Logistic model as the baseline for identifying the evolutionary stages in the subsequent analysis.

Involvement of funding entities across AI development stages

The study analyzes the evaluation of funding entities of the two countries, as shown in Fig. 4.

In the US, AI-related funding primarily comes from the NSF, the NIH, and the Department of Defense (DoD), which funded about 86.9% of AI projects. NSF mainly supports



(a) The US

(b) China

Fig. 4 The evolution of funding agencies funding AI-related projects in the US (panel (**a**)) and China (panel (**b**))

applied research and fundamental research, with universities and academic alliances as its primary funding recipients, accounting for 75–80% of total funding. Funded projects include Standard Awards, which provide full funding for the entire research period within one fiscal year, and Continuing Awards, which distribute funding incrementally over multiple years, with an average project duration of three years (NSF, 2024). Since 1990, NSF has implemented SGER for small-scale exploratory research, which was redefined in 2009 as EAGER projects, focusing on "high-risk, high-reward" research (Wagner et al., 2013). NIH is the second largest funding agency, with its funding divided into Research Grants (R-Series Funds), Career Development Awards (K-Series Funds), and Fellowships (F-Series Funds). Among these, the R21 program under the R-Series specifically supports exploratory research, encouraging early-stage and conceptual project development. The DoD, through its Defense Advanced Research Projects Agency (DARPA), has established a unique funding model that consistently prioritizes high-risk, high-reward projects to drive major breakthroughs and disruptive innovations (Bonvillian, 2018; Fuchs, 2010).

In China, AI-related funding is mainly provided by the National College Students Innovation and Entrepreneurship Training Program (NCSIETP),[2] the NSFC, and the Ministry of Education (MoE), which collectively funded 57.8% of AI-related projects. NCSIETP primarily supports undergraduate students in conducting innovative and entrepreneurial projects, aiming to cultivate practical skills and innovative thinking among young talent. Given the substantial proportion of NCSIETP and the potential comparability issues, we conducted a rigorous robustness check by excluding these projects. The results, detailed in Appendix 1, confirm that the macro-level structure and evolutionary trends of China's AI funding remain highly consistent. NSFC, as a national scientific research fund in the field of natural sciences, plays a key role in the development of China's innovation system. In recent years, the MoE has implemented initiatives to promote cooperation among

[2] The National College Students Innovation and Entrepreneurship Training Program (NCSIETP) is a national-level initiative led by the Ministry of Education, coordinated by provincial education authorities, and implemented by colleges. Designed as a training-oriented program, it is primarily undertaken by college students under the guidance of mentors, aiming to cultivate innovation and entrepreneurship skills while addressing economic, social, and national strategic needs.

universities, enterprises, and research institutes. The Department of Science, Technology and Informatization, under the MoE, has played a significant role in advancing technological development and talent cultivation through the establishment of laboratories, research institutes, and innovation practice bases.

Considering the different stages of AI development, the funding patterns of the US and China exhibit distinctive characteristics.

In the US, AI-related funding began as early as 1964, the US began funding AI technology earlier and led during the early stages of development. The first funded project was supported by NSF at the University of Kentucky Research Foundation and Case Western Reserve University Institute of Technology. During the introductory stage, the number of funding entities was relatively small, primarily dominated by the NSF, NIH, and DoD. By 2007, the number of funded projects began to increase. As the AI entered the emerging stage, the number of funding entities further expanded, with NSF gradually becoming the leading funder, while the US Department of Energy and NIH also increased their share of funded projects. This shift may be attributed to three key factors. First, significant advancements in AI applications in biomedicine played a pivotal role. For instance, the development of AlphaFold by DeepMind (DeepMind, 2022), which resolved the decades-old challenge of protein structure prediction, marked a groundbreaking achievement that garnered widespread attention. Second, policy initiatives from the US government further promoted AI adoption in life sciences and healthcare. Since 2019, a series of policies have been introduced to encourage the application of AI in these domains (National Science & Technology Council, 2019). Notably, in 2022, the NIH released "NIH-Wide Strategic Plan" highlighting the potential of AI in health (NIH, 2022b), and launched the "Bridge2AI" initiative to integrate multi-modal biomedical data through AI (NIH, 2022a). Finally, the COVID-19 pandemic significantly increased the demand for biomedical research and public health technologies, accelerating the adoption of AI in healthcare.

In China, AI-related funding began with steady growth during the introductory stage, with the NSFC serving as the primary funding agency. China's funding began in 1986, and the first five institutions to receive funding included Fudan University, Beihang University, Tsinghua University, Zhejiang University, and the University of Science and Technology of China. Since then, the number of funded projects in China has gradually increased, particularly after 2003, although at a slower rate compared to the US. By 2016, as AI technology entered the emerging stage and was identified as a new engine for national development, the number of funding agencies and projects experienced explosive growth, surpassing that of the US, with provincial and municipal funded projects rising. The MOE and the NCSI-ETP gradually increased their share, reaching a peak in 2021. This shift aligns closely with China's policy direction. In 2018, MOE launched the "Action Plan for AI Innovation in Higher Education" (MOE, 2018) to strengthen AI disciplines and promote collaboration among industry, academia, and research institutions. This initiative likely contributed to the rise in projects funded by MOE. However, a decline in funding was observed in 2022 and 2023, which may be attributed to changes in the overall economic environment and adjustments in resource allocation during the later stages of the pandemic.

In summary, both countries transitioned from a few dominant national agencies in the early stages to a more diversified funding structure as AI developed. Specifically, the US emphasizes sectoral diversification with specialized agencies expanding their roles, while China follows a model led by national agencies with regional institutions playing a collaborative role.

Distribution of project types across AI development stages

After text analysis and type matching, the funded projects in China and the US are classified into three categories: fundamental research, applied research, and commercialization projects. The number and distribution of each type of project in the two countries are shown in Table 4 below.

In the US, applied research projects dominates (79.3%), with a relatively low proportion of fundamental research projects (13.2%) and a modest share of commercialization projects (7.5%), reflecting a "application-oriented" structure. In contrast, while China also focuses primarily on applied research projects (64.2%), it allocates a significantly higher proportion to fundamental research projects (31.5%) and a slightly lower share to commercialization projects (4.4%). China is also primarily focused on applied research projects (64.2%), but the proportion of fundamental research projects is significantly higher (31.5%), while the share of achievement transformation is slightly lower (4.4%). This indicates that China places greater emphasis on fundamental exploration, while translation into practical applications remains limited.

To further analyze the characteristics of project types in China and the US at different stages of AI development, this paper examines the proportions of various funded project types based on the AI development stages, as shown in Fig. 5.

As shown in Fig. 5, the project types at different stages of AI show significant differences between the US and China. The US consistently prioritizes applied research projects, with its share exceeding 70% at all stages. As AI develops into the growth stage, the US gradually increases its investment in commercialization projects, which account for 11.3% by the maturity stage. This reflects a strategic shift from "application" to "commercialization" and demonstrates a dynamic adjustment in funding priorities.

In contrast, while China also emphasizes applied research projects, which constitute the majority of its funding, the share of fundamental research projects (27.9–34.8%) is significantly higher than that of the US throughout the lifecycle. Notably, as AI advances into the growth stage, China increases its investment in fundamental research. However, commercialization projects remain underfunded, accounting for only 4.4% of total funding by the maturity stage. This reflects China's strong emphasis on applied research while simultaneously building a solid foundation in fundamental research, but with limited progress in technology transfer and commercialization.

Overall, the US places a strong emphasis on applied research and dynamically adjusts its funding strategies as AI develops, significantly increasing investment in commercialization projects during the maturity stage. In contrast, China's funding structure remains relatively stable, with a strong focus on steady support for fundamental research while continuing to advance applied research. However, commercialization and technology transfer remain relatively underdeveloped. This difference may arise from variations in policy orientation and innovation systems between the two countries. To address these challenges, China needs to improve its efforts in commercialization. This includes establishing a more

Table 4 Distribution of funded project types in the US and China

Classifications	The US (%)	China (%)
Fundamental research projects	13.2	31.5
Applied research projects	79.3	64.2
Commercialization projects	7.5	4.4

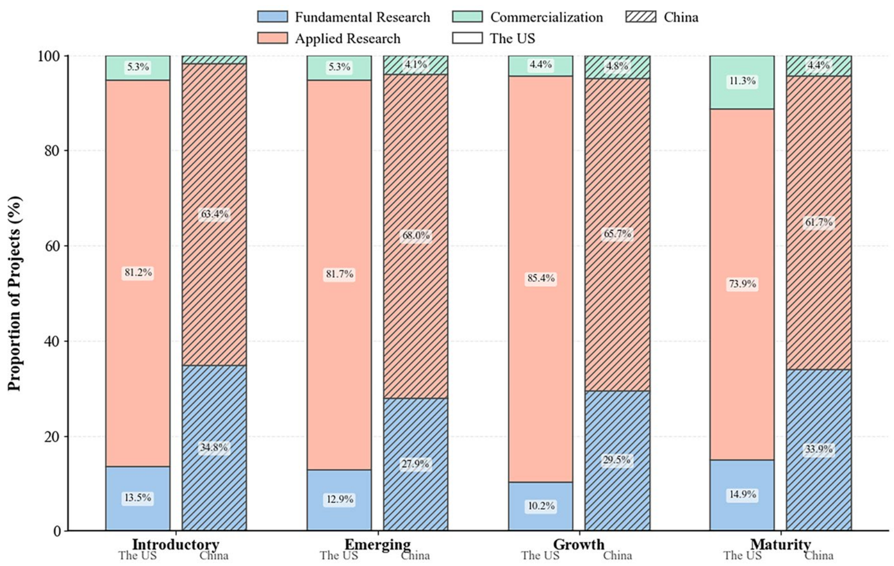


Fig. 5 Distribution of funded project types at different development stages in the US and China

comprehensive institutional framework to facilitate a strategic shift from "application" to "commercialization".

Evolution of research topics across AI development stages

The study analyzes the word frequency of the identified topic words and extracts the top 30 most frequent words for both countries to construct the topic word co-occurrence network, as shown in Fig. 6.

As shown in Fig. 6a, the co-occurrence network of research topics funded in the US reveals a focus on core technological research, biomedicine, and national security. For example, core technology topics such as "Machine Learning," "Deep Learning," and "Neural Networks"; biomedical directions such as "Biological Markers" and "Clinical Trials"; and military-related applications including "Autonomous Systems," "Cybersecurity," and "Naval Operations" are prominently featured. This highlights the US's significant emphasis on advancing AI in the fields of healthcare and military technology.

Figure 6b illustrates the co-occurrence network of technology topics funded by China, which emphasizes both core theoretical topics, such as "Machine Learning" and "Deep Learning," and the practical applications of AI to drive socioeconomic development. For example, the extensive focus on areas such as "Disease Diagnosis" and "Smart Agriculture" reflects China's policy orientation toward modernizing social governance through AI. Moreover, China's funded topics specifically highlight AI ethics and legal risks, indicating a strong focus on addressing the potential societal issues arising from technological applications.

Despite differences in focus, China and the US share significant commonalities in AI-funded projects. Both countries place great importance on core theoretical AI technologies, such as "Machine Learning," "Deep Learning," and "Neural Networks," which serve as key

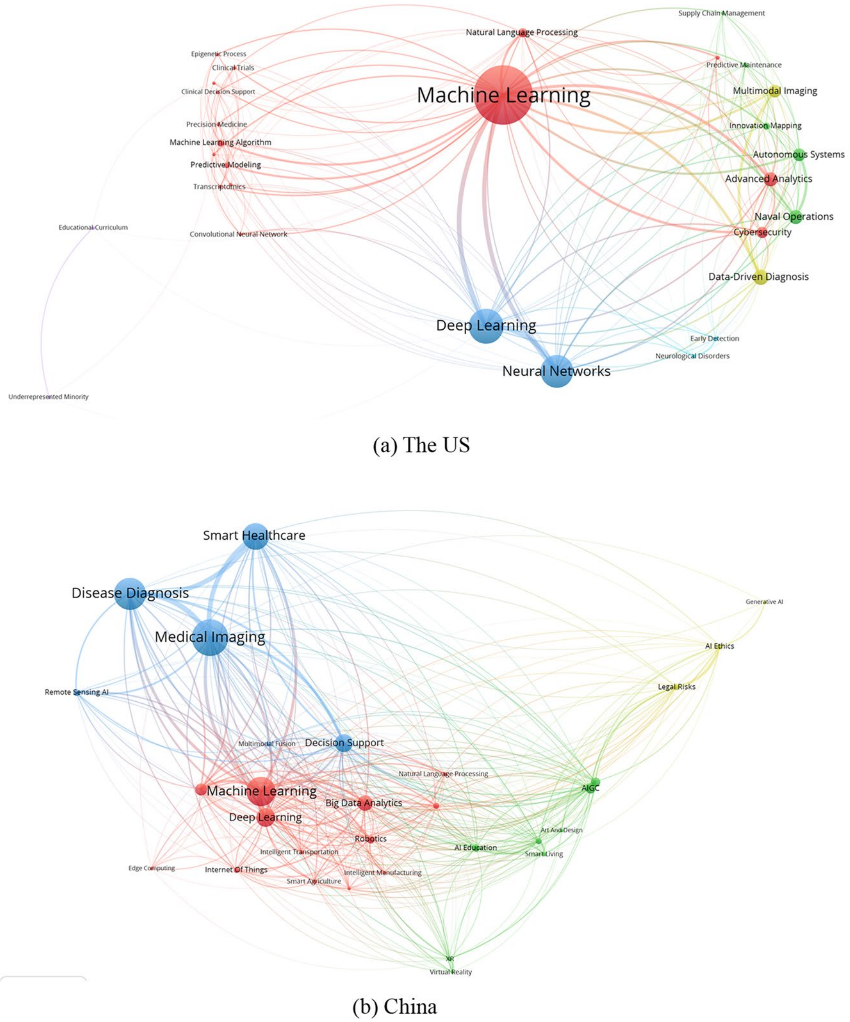


Fig. 6 Topic distribution of funded projects in the US (panel (**a**)) and China (panel (**b**))

driving forces behind AI development. Additionally, the healthcare sector is a key funding priority, underscoring the vast potential of AI in improving human health and advancing biomedical research. In particular, China's "Healthy China 2030" explicitly emphasizes the "development of internet-based health services" (Central People's Government, 2016). Furthermore, multimodal technologies and generative AI, due to their vast application potential, have become hot topics of mutual interest.

The study further examines the evolution of funding research topics. We use the ItgInsight text mining tool to cluster funding topics, identify core concepts and topics of each group, and slice project topic data by year based on a time series, enabling deeper analysis of topic changes within each time period. First, extract key topic words or phrases from each time slice; then perform word frequency statistics on the extracted topic words or phrases; next, select the top 15 topic words by frequency for each year and rank them in

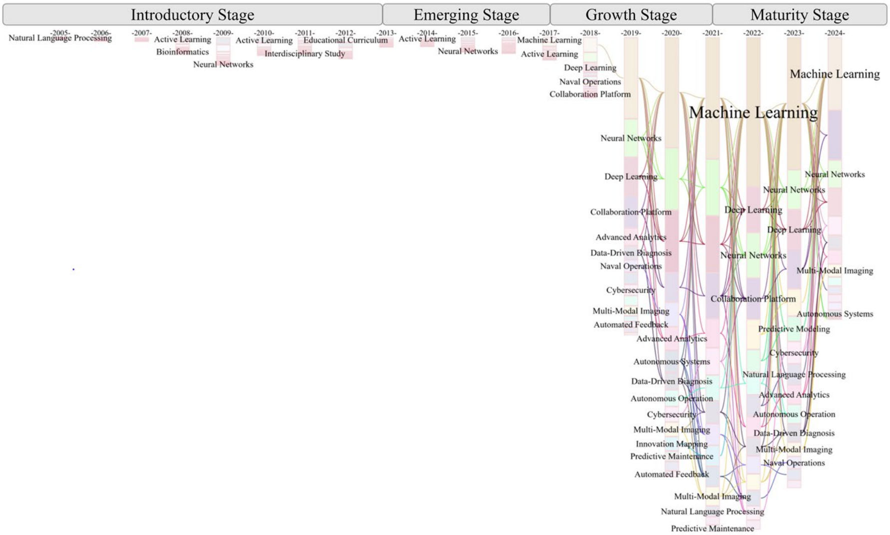


Fig. 7 Evolution of topics in the US funding for AI-related projects

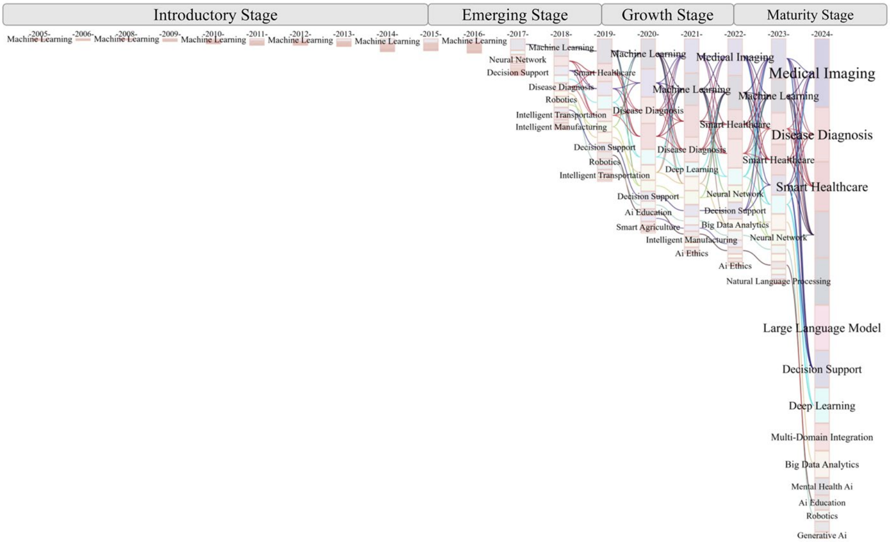


Fig. 8 Evolution of topics in China funding for AI-related projects

descending order. Figure 7 and Fig. 8 illustrate the evolution of funding topics in the US and China, respectively. It is worth noting that due to the longer duration of the introductory stage and the limited number of topics in the early stages of AI development, the topic evolution graphs focus on the period from 2005 to 2024, covering the introduction, emergence, growth, and maturity stages of AI.

During the early stages of AI development, including the introductory and emerging stages, funding topics in the US showed limited growth in both quantity and diversity. Early investments primarily targeted the advancement of core AI technologies and the exploration of interdisciplinary applications. For instance, topics like "Machine Learning," "Deep Learning," and "Neural Networks" highlight the focus on algorithm and model research, while areas such as "Bioinformatics," "Genomics," and "Magnetic Resonance Imaging" reflect early efforts to explore AI applications in life sciences and medicine. During this period, the overall scope of funding remained relatively stable, with few significant changes in topic focus.

As AI entered the growth stage, funding priorities shifted from foundational research to large-scale expansion into specific application areas, accompanied by a notable increase in funding intensity. Investments in national security and high-tech domains saw substantial growth, as reflected in keywords such as "Cybersecurity," "Naval Operations," and "Autonomous Systems," which highlight the extensive application of AI in military, cybersecurity, and autonomous systems. At the same time, funding increasingly emphasized practical applications, with topics like "Data-driven Diagnosis," "Predictive Maintenance," and "Advanced Analytics" showcasing efforts to translate AI advancements into real-world solutions and economic value.

In the maturity stage, the US funding topics demonstrated a shift toward technological optimization and multi-domain integration. For example, topics such as "Collaboration Platform," "Advanced Analytics," and "Multi-modal Imaging" underscore the deep integration of AI into areas like healthcare and data analytics, reflecting the evolution of AI from isolated innovations to comprehensive, cross-disciplinary solutions.

In the case of China, during the introductory stage of AI development, both the number of funding topics and funded projects showed a steady upward trend. Early funding primarily focused on core theoretical topics related to theories and algorithms, such as "Machine Learning," "Deep Learning," and "Neural Networks," establishing the theoretical and algorithmic foundations necessary for subsequent technological breakthroughs and providing robust support for driving innovation.

As AI entered the emerging and growth stage, the number of funding topics and projects grew rapidly. During this period, China's funding priorities gradually shifted from core research to specific application areas. On the one hand, core theoretical AI technologies remained funding priorities. On the other hand, application-oriented topics, such as "Medical Imaging" and "Smart Healthcare" began to dominate. Furthermore, funding topics started to address the societal impacts of AI, with areas like "AI Ethics" and "AI Education" gaining prominence. This period also saw a deepening of research in both theoretical technologies and their practical applications, reflecting a balanced approach to advancing both theoretical innovation and real-world deployment.

As AI entered the maturity stage, research topics further evolved toward multi-domain integration and social governance. Emerging technologies and application directions became key areas of focus, with topics such as "Generative AI," "AIGC," and "LLMs," receiving significant attention. This strategic focus highlights China's forward-looking approach, aiming to utilize cutting-edge technologies to foster innovation while proactively addressing societal challenges.

Overall, China and the United States both emphasize core theoretical topics like "Machine Learning" and "Deep Learning," while staying highly sensitive to emerging fields such as "Generative AI," "LLMs," and healthcare-related topics. However, their funding strategies differ: China focuses on "application-oriented topics" aligned with national priorities, such as "Intelligent Manufacturing" and "Smart Agriculture," to drive social development, while the US places greater emphasis on areas related to national security and military applications, reflecting its strategic priorities.

Integration of multidimensional characteristics in AI-related funded projects

This study further analyzes the three dimensions of project entities, types, and topics to comprehensively reveal the overall characteristics and development strategies of AI funding in the US and China, as shown in Fig. 9. Considering that funding entities play a central role in shaping the development of AI through their strategic decisions on project types and research topics, we primarily focus on the relationships between funding entities and the other two dimensions to provide deeper insights into their impact on AI development.

From Fig. 9a, the US funding system establishes clearly defined roles among funding entities. This specialization enables comprehensive coverage of AI research topics and ensures that diverse areas of innovation receive targeted support. For example, NSF focuses on theoretical innovation, funding core research topics such as machine learning and deep learning. NIH emphasizes healthcare, supporting the application of AI, like predictive modeling, in medical scenarios. DoD prioritizes military technologies, with funding topics centered on autonomous systems, naval warfare technologies, and other defense-related applications. Additionally, the Department of Agriculture plays a significant role in agriculture-related AI, supporting the application and adaptation of AI technologies in this field. In addition to the diversity in topic coverage, the US funding system demonstrates a

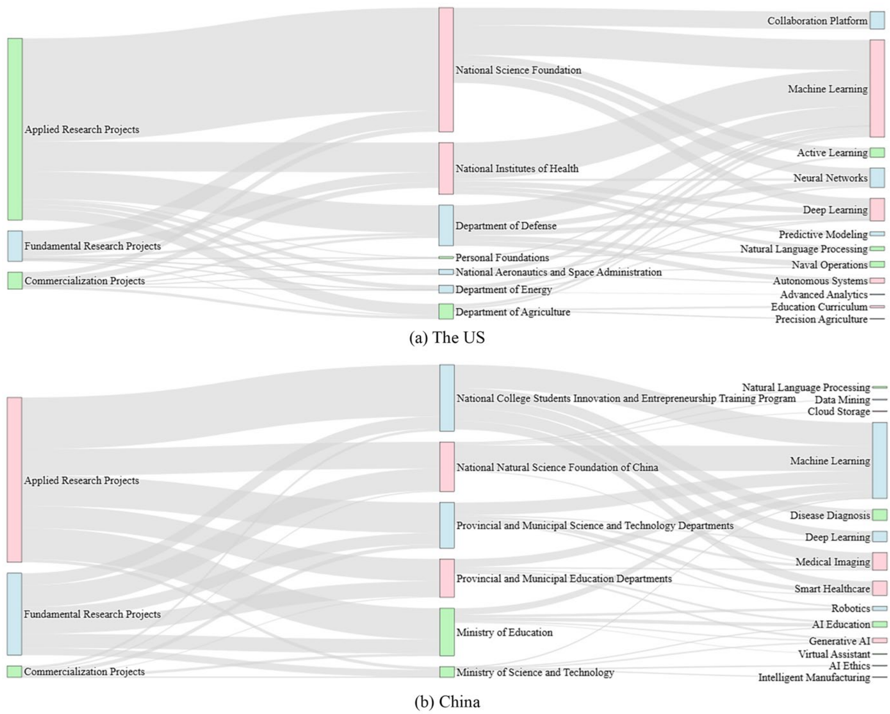


Fig. 9 Three-Dimensional Characteristics of AI-related Funded Projects in the US (panel (**a**)) and China (panel (**b**))

strong concentration on applied research and commercialization projects. The US funding system places significant emphasis on applied research, with NSF, NIH, and DoD serving as the primary contributors. For the commercialization stage, NSF, NIH, and DoD collectively account for nearly 80% of the funding, reflecting a strong national focus on advancing AI from research to real-world deployment.

From Fig. 9b, China's AI funding system is centered on a "national leadership" with "local collaboration" model, ensuring comprehensive coverage of various project types and topics through joint funding efforts. National agencies (e.g., NSFC and MoE) take the lead, while local governments (e.g., Provincial and Municipal Science and Technology Departments) provide coordinated support, forming an integrated network that spans fundamental research, applied research, and commercialization projects. For fundamental research, NSFC and Provincial and Municipal Education Departments jointly fund 45.5% of projects, primarily focusing on core technologies such as machine learning. In applied research, the MoE, NCSIETP, and Provincial and Municipal Science and Technology Departments collectively fund 68.6% of projects, targeting critical societal topics about healthcare and education. Although commercialization projects are relatively few, they are still funded through the coordinated efforts of national and local agencies. Notably, given its substantial proportion in the overall funding volume, the NCSIETP exhibits unique multidimensional characteristics. Structurally, NCSIETP functions as a massive incubator for practical AI applications rather than traditional theoretical exploration. In terms of funding types, it is overwhelmingly concentrated in Applied Research, accounting for nearly 78.0% of its total portfolio, far exceeding its fundamental and commercialization initiatives. Thematically, NCSIETP's funded topics skew heavily toward scenario-driven applications. Its top priorities are deeply integrated with the medical and health sectors, including "Medical Imaging," "Disease Diagnosis," and "Smart Healthcare." This distinct profile highlights NCSIETP's unique role in the broader ecosystem: driving early-stage talent to bridge the gap between AI technologies and real-world societal needs.

In summary, the US funding system establishes clearly defined roles among funding entities, with each focusing on topics aligned with their expertise and responsibilities. This specialization fosters both theoretical innovation and practical applications of AI, while promoting the commercialization of AI technologies across diverse domains. In contrast, China adopts a centralized approach led by national initiatives, complemented by the active participation of local governments, effectively integrating national and local resources to drive the comprehensive development of AI projects.

Conclusions and discussion

This study examines AI funding strategies and characteristics in China and the US across the technology lifecycle and receives following conclusions:

In the introductory stage of AI development, US funding is predominantly led by the NSF, with an emphasis on applied research. The number of funded topics shows a fluctuating upward trend, mainly focusing on exploratory research and applied technologies. In contrast, funding in China is primarily provided by the NSFC, with a focus on applied research projects, which accounts for 63.4%, while fundamental research projects accounts for 34.8%, a proportion significantly higher than that of the US. The number of funded topics steadily increases, with research content mainly revolving around theories and algorithms.

In the emerging stage of AI development, US funding remains primarily driven by the NSF, but the support from the DoD and NIH grows significantly. The number of funded topics experiences an explosive increase, with a focus on new research methods and social value. In China, the Ministry of Education has increased funding for AI technologies, particularly in applied research and talent development, with funding topics gradually shifting from fundamental research to special application domains.

In the growth stage of AI development, NIH funding in the US further intensifies. In 2019, the number of funded institutions and projects has sharply declined, with a shift in focus towards technology applications related to public health and disease prevention. Meanwhile, in China, the distribution of funding agencies becomes more diversified, with funding increasingly directed towards applied research and the practical application of AI technologies.

In the maturity stage of AI development, the US focuses on technological optimization and multi-domain integration, with increased investments in commercialization projects. Key topics include "Collaboration Platform" and "Multi-modal Imaging," highlighting AI's deep integration into healthcare and data analysis. However, the number of funding entities and projects decreases during this stage. China emphasizes multi-domain integration and social governance, with a strong focus on emerging technologies like "Generative AI" and "LLMs," showcasing its prioritization of cutting-edge innovations and societal applications. However, the proportion of funding for commercialization projects remains relatively low.

In summary, China and the US differ in the pace of AI technology development. The US started earlier and took the lead in funding earlier. NSF, NIH, and DoD played leading roles in the US in the development of technology. Meanwhile, the US has always focused on applied research, with emphasis on multiple parallel topics. With the development of AI technology, funding for the commercialization projects has increased. In comparison, China followed a "catch-up and surpass" path and has gradually surpassed the US, especially since 2016, with accelerated growth in funding scale. China's funding system has shifted from being primarily dominated by the NSFC to a more diversified structure with multiple agencies. Meanwhile, China places more emphasis on both applied research and basic research, while the intensity of funding for technology transfer remains relatively low.

The AI technology funding strategies of China and the US reflect the strategic goals and policy orientations of both countries. The US has consistently maintained a leading position in applied research projects. As AI technology continues to advance, the US has increased funding for commercialization-focused projects. In contrast, China emphasizes the parallel development of fundamental research and applied research, but commercialization projects remain relatively low. This disparity may stem from differences in the policy orientation, innovation systems, and stages of technological development between China and the US. As a latecomer in AI development, China needs to maintain stable investment in key theoretical research areas, such as algorithms and chip architectures, while increasing funding for technology commercialization to promote the comprehensive development of artificial intelligence technology from theoretical research to practical applications. In contrast, the US, while maintaining its leading position in AI applied research, can focus more on driving innovation in frontier fields. By further optimizing the structural coordination among fundamental research, applied research, and technology commercialization, and dynamically adjusting funding strategies to adapt to the rapid evolution of AI technologies, the US ensures its leadership in global technological competition. Although the funding priorities of the two countries are different, their respective strategies and focus adjustments reflect their deep understanding of the development of scientific and technological innovation and their forward-looking layout.

This study acknowledges several limitations. Firstly, the data sources used in this study are not exhaustive, as the database does not comprehensively cover all enterprise funding data, potentially leading to biases and limiting the generalizability of the findings. Expanding data coverage to include private sector investments, international collaborations, and non-traditional funding sources would enhance representativeness. Secondly, using patent data to define the lifecycle of technologies may not fully capture the development trajectories of AI development. Future studies could expand lifecycle analysis by incorporating additional indicators, such as industry adoption and commercialization outcomes, to better capture the multifaceted nature of technological evolution. Lastly, the current indicators and analytical framework may not fully reflect the broader landscape of funding strategies. Future studies could incorporate new analytical perspectives, such as collaboration network analysis, including institutional collaboration, international cooperation, and interdisciplinary analysis, etc., to provide a more comprehensive understanding of the dynamics and evolution of funded projects. Furthermore, for the projects that did not fit the predefined categories of fundamental, applied, or commercialization research, future research could expand the classification taxonomy to investigate these "unclassified" projects. Exploring this subset may reveal other distinct funding activities.

Appendix 1: Robustness check on the impact of NCSIETP

Data reconstitution

To address potential concerns regarding the unique scale and educational nature of China's undergraduate innovation training projects (NCSIETP), we conducted a robustness check by excluding NCSIETP data. Out of the original 21,941 AI-related projects funded in China, 5376 NCSIETP projects were removed, leaving a filtered dataset of 16,565 projects. We re-analyzed the funding entities, types, and topics to verify the stability of our main conclusions.

Robustness of funding entities

The exclusion of NCSIETP does not alter the fundamental structure of China's funding ecosystem. Before the exclusion, the top funding entities (NCSIETP, NSFC, MoE, Provincial and Municipal Science and Technology Departments, and Provincial and Municipal Education Departments) accounted for 87.4% of the total. After excluding NCSIETP, the remaining top entities (NSFC, MoE, Provincial and Municipal Science and Technology Departments, and Provincial and Municipal Education Departments) still dominate, accounting for a highly concentrated 83.5%.

The core finding remains robust: China follows a model led by national agencies with regional institutions playing a collaborative role.

Robustness of funding types

To verify the stability of China's funding structure, we compared the overall distribution and evolutionary stages of funding types before and after excluding NCSIETP.

As shown in Table 5, the overall quantitative structure remains highly consistent. The exclusion of undergraduate projects slightly increased the proportion of fundamental research (from 31.5% to 35.5%) and slightly decreased applied research, while commercialization remained stable at a low level (around 4.5%).

Furthermore, Fig. 10 illustrates the evolutionary trends across four developmental stages. The chart demonstrates that the macro-level evolutionary patterns are perfectly preserved. Notably, after removing NCSIETP, the steady growth of fundamental research becomes even more pronounced, peaking at 40.6% in the Maturity Stage.

The original conclusion holds true and is further strengthened: China's funding structure remains relatively stable, with a strong focus on steady support for fundamental research while continuing to advance applied research. However, commercialization and technology transfer remain relatively underdeveloped.

Table 5 Overall distribution of funding types (before vs. after exclusion NCSIETP)

Project type	Before exclusion (%)	After exclusion (%)
Fundamental research	31.5	35.5
Applied research	64.2	60.0
Commercialization	4.4	4.5

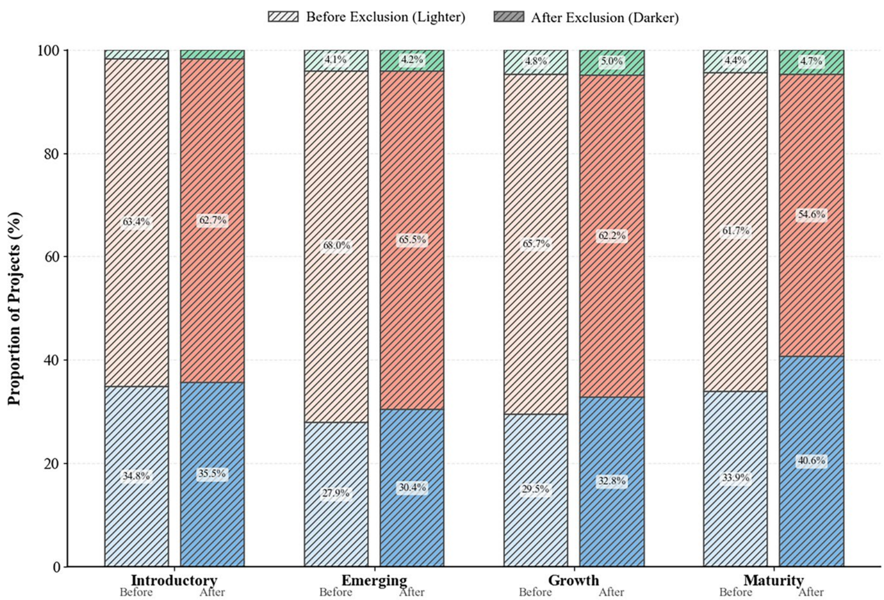


Fig. 10 Evolutionary **trends** of AI **funding types** in China (**before** vs. **after excluding** NCSIETP)

Robustness of funding topics

By comparing the statistical rankings of the top 30 funded topics before and after excluding NCSIETP, we found that the core thematic structure remains highly consistent with our main findings, while the focus on frontier technologies becomes even more pronounced.

The fundamental orientation of China's AI funding remains unchanged. Core theoretical topics such as "Machine Learning" and "Deep Learning" consistently rank at the top. Furthermore, practical application fields aimed at societal development, particularly "Smart Healthcare" and "Medical Imaging," continue to receive significant attention. This perfectly aligns with our main conclusion that China emphasizes both foundational AI theories and practical socioeconomic applications.

The primary difference after excluding undergraduate projects lies in the increased concentration of cutting-edge and industrial topics. Frontier fields such as "Generative AI" saw a significant increase in their rankings.

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Author contributions Hui Zhang developed the framework and research design, acquired and analyzed the data, and drafted the manuscript. Zhe Cao contributed to the construction of framework diagrams and participated in revising and reviewing the manuscript. Ying Huang supervised the research, provided funding support, and reviewed and edited the manuscript. Lin Zhang provided research guidance, assisted in manuscript revision, and contributed to the overall improvement of the study. All authors reviewed and approved the final manuscript.

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Data availability The data used in this study were obtained from the incoPat and Sci-Fund databases, which served as the main sources for AI patent and project data. Access to these databases may require a subscription. Processed data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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