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Quantifying the Political Attributes of Technology for Potential Bottleneck Technologies Identification: Evidence from Chinese Integrated Circuits Industry

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Abstract

Technological innovations are becoming increasingly competitive among nations, as countries strive to gain a technological advantage to safeguard their national interests. This competition leads to technology suppression, supply disruption, and export controls, which can undermine the integrity of supply chains. Technologies supply disrupted by export controls from collaborating countries are referred to as bottleneck technologies, posing significant threats to national security. These technologies shall be identified promptly to inform effective technology and diplomacy policymaking. Existing studies have focused on the quantity and quality gaps or topic strength gaps of technologies, emphasizing their technological attributes. However, political attributes, particularly those driven by political competition, have received insufficient attention. We argue that bottleneck technologies are not only technological products but also political products, shaped by both technological and political factors. This paper introduces the concept of 'technological political distance' to identify bottleneck technologies, characterized by a country's subjective motivation to create a 'control.' By analyzing citation networks and calculating indices like PageRank as “be able to control”, we identify highly cited patents in key technology areas as 'worthwhile to control' in terms of value. Empirical research in the field of integrated circuits shows that China faces high risks in foundational semiconductor technologies, circuit integration methods, material science, and manufacturing processes, while the risks in sensor, imaging, and signal transmission technologies are relatively low.

Introduction

Science and technology (S&T) innovation has become a critical arena of national competition, with countries vying for emerging and advanced technologies to secure global competitive advantage(Schmid et al., 2025). This intense rivalry not only heightens technological competition but also disrupts international technological collaboration, posing significant threats to national security(Luo, 2022; Sun, 2019; Vivoda, 2023). Consequently, it is crucial to identify potential bottleneck technologies and assess the associated risks, so that policymakers can both leverage the dividends of global collaboration and safeguard S&T security. Drawing on historical instances of international technology competition—particularly the U.S.-China rivalry, this paper argues that bottleneck technologies are not merely a technical concern but also a political one, exhibiting intertwined attributes of technology and politics. We extend the literature on technology identification and bottleneck technologies (Guoxiong et al., 2021; Haiqiu et al., 2023; Jin et al., 2020; Zhiwei et al., 2021) by conceptualizing bottleneck technologies as those characterized by (1) the willingness to impose technology controls, (2) the capacity to impose such controls, and (3) the strategic value that motivates these controls. To quantitatively evaluate these attributes, we incorporate a Political Distance (PD) index—calculated from large-scale United Nations (U.N.) voting data—to quantify geopolitical risks encountered by technologies and construct a citation network to represent the overall technology system. We then apply the PageRank algorithm to identify key technologies which play key roles in maintain the function and integrity of the technology system, whose removals may cause the system dismantling and technology dysfunction. Combining patent-based and topic-based analyses, we propose that those bottleneck technologies are controlled by competitors who both desire and are able to halt supply to China, and which China cannot rapidly reproduce. An empirical study on integrated circuits demonstrates that China is highly vulnerable in foundational areas such as semiconductor devices, circuit integration methods, material science, and manufacturing processes, yet faces relatively lower risks in sensor technology, imaging technology, signal transmission, and other applications. These findings are validated by expert assessments and the U.S. technology control list, highlighting the practical utility of this method.

Methodology and Research Design

This study introduces a novel metric, **Technology Political Distance (TPD),** to quantify the political risks associated with various technologies. The metric is derived from extensive voting data sourced from the United Nations. Additionally, this research incorporates PageRank-based algorithms to identify technologies that are central to the overall technological ecosystem. By combining these approaches, the study highlights key bottleneck technologies at both the patent and topic levels. The proposed research framework is visually represented in Figure 1.

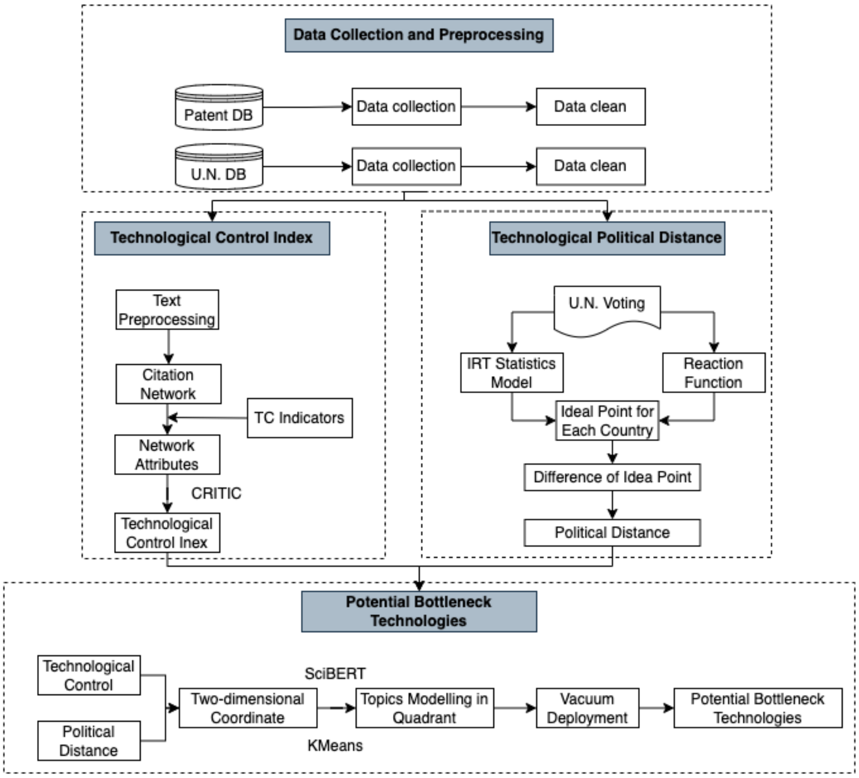

Figure 1. Research framework.

Quantifying the Political Attributes: Technology Political Distance

This paper introduces the concept of political distance to analyse the potential effects of international collaboration across different countries. Drawing on the idea proposed by Bailey et al. (2016), political distance is characterized using discrepancies in countries' voting behaviors at the United Nations on various issues. These voting differences act as proxies for the political distance between nations. A larger voting disparity between two countries typically reflects divergent national interests, increasing the likelihood of rivalry. In contrast, a smaller voting difference indicates closer alignment in interests, suggesting a higher probability of these countries being allies or partners. To enhance the accuracy of the political distance measure, we employ the Item Response Theory (IRT) statistical model, which constructs annual scale data representing each country's "ideal point"—a binary metric indicating the shifting similarity in political preferences between two countries. The IRT model, traditionally used to describe the relationship between a subject's latent traits (such as abilities) and their responses to test items, is adapted here to estimate the ideal point, which reflects a country's foreign policy orientation. This methodology provides a more nuanced and robust framework for measuring political distance in international relations.

$$\Pr(Y_{itv} = K) = \Phi(r_{kv} - \beta_v \theta_{itv}) - \Phi\left(r_{k-1,v} - \beta_v \theta_{itv}\right) \tag{1}$$

In the above equation, the left-hand side represents the probability distribution of country i's choice of approval (k=1), abstention (k=2), and negation (k=3) in the v-th vote, which can be obtained by observing the voting behavior. Where β represents the differentiation parameter of the item, r represents the difficulty parameter of the item, and θ represents the ideal point of the measured ability or trait, the posterior expectations of the parameters β, r, and θ can be estimated using Bayesian estimation with the help of MCMC (Markov Chain Monte Carlo) algorithm.

Further, following Davis et al. (2019), the absolute difference between the ideal points of China and its partner countries is employed as a proxy for bilateral political distance. This metric specifically quantifies the degree of divergence between China's foreign policy orientation and that of its trading partners, thereby providing an indicator of the political relationship between the two nations. This approach offers a more precise measure compared to traditional indices such as the voting similarity index, the affinity index, and the "S" index. So, we employ the divergence of ideal point distance to quantify the political distance between countries. By following these steps, the political distance between China and other countries can be calculated.

Since a single patent may belong to multiple patent families registered across different countries, it is essential to consider the patent family structure. We argue that expanding a patent family across multiple nations generates substantial technology spillover effects in the current market (Frakes & Wasserman, 2021; Lee, 2021; Taichen et al., 2022). This expansion can accelerate technology transfer and foster local technological development (Xue, 2022), driving technological advancement and industry upgrading. Building on this, we hypothesize that when countries with significant political distance from China register patents either within China or in countries with close technological proximity to China, the resulting technology spillover can stimulate local technological growth and upgrading. This, in turn, reduces the likelihood of these technologies becoming bottlenecks for China. On the other hand, if countries with considerable political distance from China register patents in other nations that also maintain substantial political distance from China, these countries are more likely to form technological alliances and establish barriers, which could restrict China’s access to these technologies. Based on this framework, we define TPD as the average political distance between the countries where the patent family is registered and China, denoted as:

$$TPD_n = \frac{\sum_{i=1}^{m} PD_i}{m} \tag{2}$$

Technology Control Capability

Motivated by technology system theory as proposed by Arthur (2009), we conceptualize the entire technological landscape as a complex system. Building on prior studies that employ complex networks to model such systems (Han et al., 2021), we construct a citation network to capture the interconnections and structural composition of the technology ecosystem. In the context of technology competition, the control over certain key technologies has been observed to disrupt the proper functioning of an entire technological field. To further explore this phenomenon, we introduce the concept of network dismantling, which involves the strategic removal of specific nodes (i.e., technologies) to fragment the citation network and induce dysfunction within the broader technology field (Fan et al., 2020). The identified nodes represent potentially risky technologies, whose removal could critically impair technological continuity and development.

Building on this concept, we introduce a network-based algorithmic approach to identify critical technologies—those essential to maintaining the integrity of the technology system. Given that different algorithms assess node importance from varying perspectives, we integrate multiple algorithms to create a complementary framework for identifying key technologies more effectively. To achieve this, we employ degree centrality (DC), betweenness centrality (BC), and structural hole (SH) analysis (S. Burt, 1992), along with HITS and PageRank (PR) (Tongliang et al., 2023). These measures collectively capture different dimensions of a technology's influence within the network: (1) Degree centrality (DC) identifies technologies with the highest number of direct connections. (2) Betweenness centrality (BC) detects technologies that serve as critical bridges between different subfields. (3) Structural hole (SH) highlights technologies that control access to otherwise disconnected technological domains(S.Burt, 1992). (4) HITS (Hyperlink-Induced Topic Search) distinguish between hub technologies (those that connect to many authoritative technologies) and authority technologies (those that are referenced by influential hubs). (5) PageRank (PR) assigns importance based on the recursive influence of a technology within the citation network (Tongliang et al., 2023). By leveraging this multi-perspective approach, we enhance the robustness of our analysis, ensuring a more comprehensive identification of crucial technologies within the system.

To comprehensively assess the weight of each indicator, we employ the Criteria Importance Through Intercriteria Correlation (CRITIC) algorithm, a well-established method for determining indicator importance (Danae et al., 1995). The CRITIC algorithm evaluates the significance of each indicator by analyzing both its comparative strength and its degree of conflict with other indicators. Through this approach, the weight of each indicator is systematically determined based on its intrinsic information content and its correlation with other indicators. The calculation of indicator weights follows the methodology outlined below:

$$W_j = \delta_j \sum_{j=1}^{n} \left(1 - R_{kj}\right), j \neq k, j = 1,2, \ldots, n \tag{3}$$

W_j denotes the weight for indicator j, and R_{kj} represents the correlation between the k-th indicator and the j-th indicator.

Based on the weight and value of each indicator, the TC for each technology can be calculated by:

$$\begin{aligned} TC_i = W_{DC\_norm} * DC\_norm(i) + W_{BC\_norm} * BC\_norm(i) + W_{SH\_norm} * SH\_norm(i) \\ + W_{HITS\_norm} * HITS\_norm(i) + W_{PR\_norm} * PR\_norm(i) \end{aligned} \tag{4}$$

The TC_i denote the technology control capability of i th technology, and W_{DC_norm}, W_{BC_norm}, W_{SH_norm}, W_{HITS_norm}, W_{PR_norm} denote the weight of DC, BC, SH, HITS, PR respectively which have been normalized and the weight is calculated by CRITIC.

Technologies classification based on dual perspective of politics and technology

According to the dual properties of technologies in TC and PD perspectives, we categorize technologies into four types as Type A (high TC and high PD), indicating risky technologies due to those highly-impact technologies which are important to technology system are held by rival countries who have great PD with our country. Type B (high TC and low PD) is friendly sophisticated technologies held by our country and friendly countries. Type C and Type D are low-impact technologies, which exert limited impact on the technology system, so, whether those technologies held by our country, friendly countries or rivals will not significantly influence the normal operation of technology system, so, they are difficult to be the bottleneck technologies.

Based on this classification (Figure 2), those technologies exist in Type A but do not appear in Type B are those sophisticated technologies held by rivals but not held by us and our friends, which can be taken as highly risky potential technologies, which is our general idea on bottleneck technologies identification.

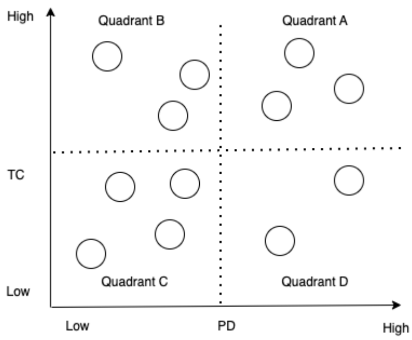

Figure 2. Four types of technologies classified by PD and TC.

Potential bottleneck technologies identification

Based on quantifying the PD and TC, we identify potential bottleneck technologies on patent and topic level respectively to complement the micro and macro information. In micro level, we propose the bottleneck index as K index which is defined as:

$$K_i = TC_i * TPD_i \tag{5}$$

K index describes whether those highly impact technologies are held by rival countries, to reflect the risk of be controlled in both technological and political perspective.

Furthermore, given that technology export control lists typically reference clusters of technologies rather than isolated patents, we conceptualize these clusters as "technology topics." To extract these topics, we first obtain the abstract text from each patent and employ SciBERT which is proposed by Beltagy et al. (2019) to convert the text into semantic vectors, ensuring that words with similar meanings are positioned closely in the semantic space. Next, we apply the K-means clustering algorithm to group semantically similar words, thereby forming coherent technology topics. Finally, we compare the semantic similarity between topics in Type A and Type B—using a threshold of 0.8 to indicate identical topics. Technologies associated with topics that appear in Type A but not in Type B are classified as potential bottleneck technologies, whereas those found in Type B but absent from Type A are identified as strategic advantage technologies that could inform the implementation of technology sanctions.

Empirical Study: Initial Results on Chinese Integrated Circuits Fields

Data Source and Preprocessing

Integrated circuits (IC) are at the heart of modern information technology and the electronics industry. As core technologies, they are pivotal for building national competitive advantages in the digital age and have become a central arena in the U.S.-China technology competition. Accurately identifying potential bottleneck technologies in the IC domain is therefore essential for maintaining national security. Furthermore, recent U.S. export controls on various IC technologies have intensified bottleneck effects. The methodology proposed in this study, which does not rely on pre-tested information and can be validated through an actual list of bottleneck technologies, offers timely insights into these challenges. For these reasons, the IC sector was selected for our empirical analysis. Patent data were retrieved from the Derwent Innovation Index (DII) database using the manual coding system developed by Derwent experts. We employed the retrieval formula "U13-*" on 30 November 2023, which returned a total of 290,743 patents. Recognizing that bottleneck technologies are often characterized by high-value patents—as reflected in their citation counts—we filtered the dataset to retain only those patents with at least five citations, resulting in a subset of 83,211 patents. Finally, comprehensive data cleaning and preprocessing procedures were applied to ensure the dataset's readiness for further analysis.

Political Distance Calculation

According to the Equation 1, we utilize the IRT reaction function to calculate the ideal point for each country respectively, and calculate the absolute difference of ideal point between each country pairs. Notably, for organizations such as the European Patent Office (EP) and the World Intellectual Property Organization (WO), we calculate their TPD as the average PD between China and the participating countries within each organization. Further we extract the country (organization) of each patent holder and have 32 countries in total, and list those 5 countries with largest and closest political distance from China as shown in Table 1:

Table 1. The five countries with the largest and closest political distance from China.

Country	PD
US	3.116
IL	2.952
GB	2.179
CA	2.082
FR	1.962
BR	0.318
MY	0.266
SG	0.242
ZA	0.203
IN	0.161

Technology Control Capability

Based on the patent citation network, we apply the five network-based algorithms to calculate the PR index and other indicators for each patent, and apply the Equation 3 for evaluating the weight for each indicator as shown in Table 4 and calculate the TC for each patent by Equation 4. We list the 5 patents which have the highest TC as shown in Table 3.

$$W_j = \delta_j \sum_{j=1}^{n} \left(1 - R_{kj}\right), j \neq k, j = 1,2, \dots, n \tag{5}$$

Table 2. Weight for each indicator calculated by CRITIC.

Indicator	Weight
ω_{DC}	0.0562
ω_{BC}	0.0371
ω_{HITS}	0.0265
ω_{PR}	0.0258
ω_{SH}	0.0543

Table 3. Patents with top 5 TC.

PN	TC
US2006007612-A1	0.133
WO9907000-A2	0.126
EP1746645-A2	0.118
US2007196982-A1	0.112
EP738010-A2	0.105
…	…

Potential Bottleneck Technologies Identification: patent and topic level

According to the definition and method for quantifying the bottleneck technologies (Equation 5), we first calculate the K index for each patent and list those patents with top 5 K index as shown in Table 4.

By reading the abstract of those five patents, we find that they are in the technology field of: (1) circuit design for protecting nonvolatile read-only memories; (2) programming methods for nonvolatile memory cells; (3) reverse read-programmed EEPROMs and ROMs; (4) process and structural optimization of nonvolatile memory arrays; (5) construction of imaging sensors.

Table 4. Patents with top 5 K Index.

Rank	PN	K Index
1	US2006007612-A1	0.133
2	WO9907000-A2	0.126
3	EP1746645-A2	0.118
4	US2007196982-A1	0.112
5	EP738010-A2	0.105
…	…	

To classify the technologies into four distinct categories, we use two threshold criteria: the median value of TPD and the 80th percentile of TC. These thresholds, indicated by the red dashed lines in Figure 3, divide the dataset into four quadrants, with each quadrant representing a unique category of technology.

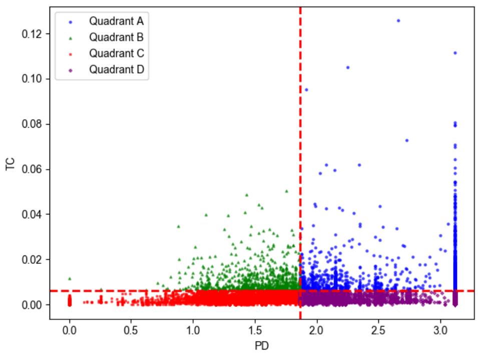

Figure 3. The distribution of four types of technologies.

To evaluate the topic distribution within Quadrant A (Type A technologies) and Quadrant B (Type B technologies), we employ a two-step approach. First, we use the SciBERT-Kmeans method to extract technology topics. However, since the number of topics for each technology type must be determined manually, we then apply Latent Dirichlet Allocation (LDA) for topic modeling to determine the proper number of topics. For each technology type, we calculate the coherence score to assess model quality and select the number of topics that yields the highest coherence score. Based on this analysis, we define 14 topics for Type A technologies and 20 topics for Type B technologies. The resulting topic distributions are presented in Figure 4.

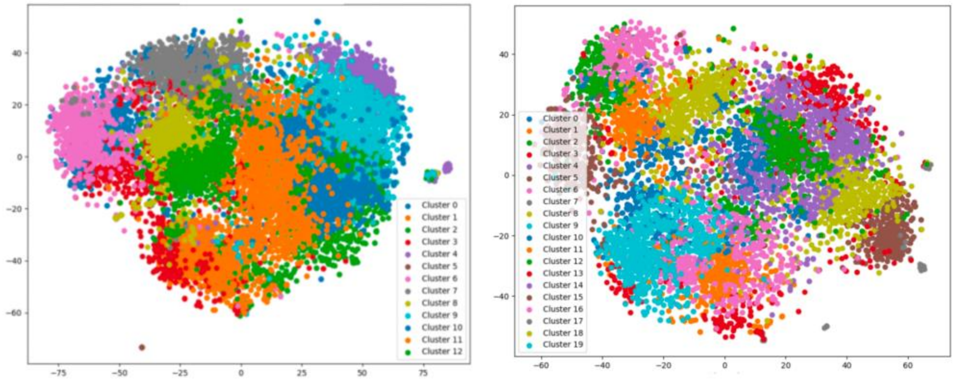

Figure 4. Topic distribution for Quadrant A(left) and Quadrant B(right).

Furthermore, we employ the Term Frequency-Inverse Document Frequency (TF-IDF) method to extract the top 30 keywords representing each topic, subsequently inviting domain experts to label each topic based on these keywords. Our analysis reveals that the topics in Quadrant A primarily pertain to semiconductor devices, circuit integration, logic devices, insulation technology, electrode engineering, imaging and sensing, logic circuits, electrode integration, oxidation technology, electrical signals, electrode dynamics, imaging integration, as well as insulation and electrode-related fields. This indicates that the technologies in Quadrant A predominantly focus on the manufacturing and design of semiconductor devices. Similarly, the topics in Quadrant B encompass areas such as imaging processors, insulated circuits, signal imaging, semiconductor devices, line transmission, storage arrays, selective thin films, photoelectric imaging, signal films, circuit components, voltage thin films, sensing imaging, insulated storage, imaging thin films, insulating films, sensing transistors, signal gates, semiconductor surface engineering, insulated circuits, and voltage equipment.

To compare the topic similarity between topics in two category, we apply the cosine similarity calculation on topics' semantic vector which can be found in Figure 5.

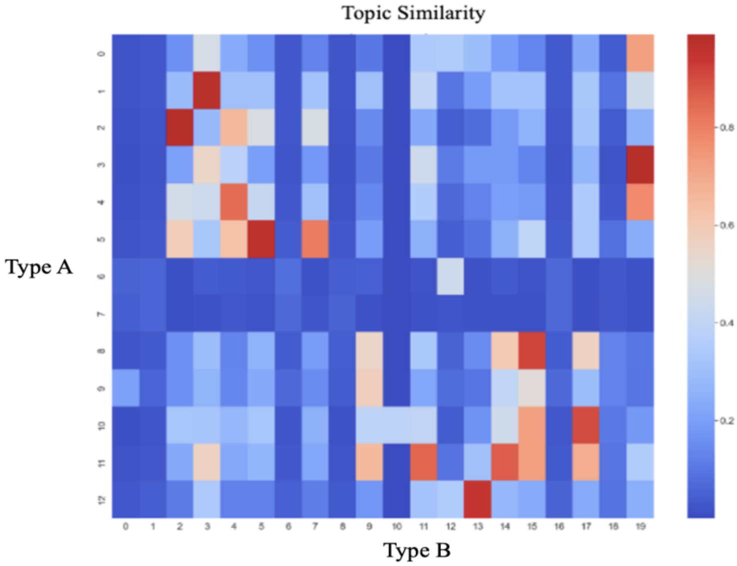

Figure 5. The topic similarity between Quadrant A(y axis, Type A) and Quadrant B(x axis, Type B).

As illustrated in Figure 5, our analysis reveals that in our (our country and friendly country with small TPD) Topic 0, 1, 6, and 7 (Type B in Figure 5), rivals who have large TPD (Type A in Figure 5) have not made any significant deployments in these technological areas. This absence of rival engagement provides us with a strategic advantage, which can be used as diplomatic tools. These technologies primarily encompass advanced sensors, novel materials, and energy storage and conversion technologies, including microelectromechanical systems, optoelectronic sensors, photovoltaic conversion technologies, solar photovoltaic cells, 3D imaging, and nanomaterials, as determined through the distribution of topic keywords.
Conversely, in the case of topics dominated by competitors—specifically Topics 6, 7, and 9 (Topic A in Figure 5), our country and those friendly nations (Topic B in Figure 5) have few deployments on those topics. If competitors impose export restrictions on these technologies, we may face significant vulnerabilities, potentially leading to supply chain disruptions. These technologies can therefore be identified as high-risk bottleneck technologies with the potential to pose critical challenges to technological and economic security. By reading the keywords identified by TF-IDF algorithm in those topics, it can be found that potential bottleneck technologies are mainly distributed in: **(1) basic electronic components**, including the application of traditional materials such as silicon-based semiconductors and compound semiconductors, **(2) Circuit manufacturing and design**, encompassing ASIC design, chip manufacturing, and packaging technologies, **(3) Signal processing and voltage control**, including analog and digital signal processing technologies used in communications and data processing.

Validation

To validate our findings, we first engaged domain experts in the integrated circuit (IC) industry who hold Ph.D. degrees in semiconductor-related fields and possess both academic and industrial experience. Their combined expertise enables them to make well-informed judgments on the technological landscape. The experts concurred with our conclusions that basic electronic components, circuit manufacturing and design, and signal processing and voltage control constitute China's current bottleneck technologies, primarily controlled by the United States and Japan. These constraints have significantly disrupted China's ability to manufacture advanced chips. However, the experts also noted that due to the vast scope of the IC industry, it is challenging for any single expert to maintain a comprehensive and systematic understanding of the entire technological landscape. As a result, they recommended an additional validation step—comparing our findings with the export control policies of major countries. Following this recommendation, we referenced the U.S. Commercial Control List and its annotation system from the Export Control Database of the National Science Library of Chinese Academy of Sciences (Fang et al., 2022). By analyzing controlled technologies in the integrated circuits sector, we identified the five most highly regulated technologies on the control list: (1) Semiconductor device testing, (2) Electronic testing, (3) Electronic sensors, (4) Communication testing equipment, (5) Wafer inspection-related technologies. All five of these technologies were successfully identified through our methodology. Notably, the electronic sensor technology listed in the control database includes the optoelectronic sensor technology identified in our study. Although subject to export controls, this technology remains an area where China currently holds a competitive advantage, making it less susceptible to becoming a critical bottleneck. In contrast, the other technologies on the control list represent key bottleneck areas that could significantly impact China's technological and industrial security. These results further validate the scientific rigor and practical value of the methodology proposed in this study.

Conclusion and Discussion

In this paper, we propose a novel approach to quantifying the political attributes of technology within the context of global competition. By introducing the concept of political distance, we aim to identify potential bottleneck technologies that may pose risks to national security and highlight technological vulnerabilities. First, we define political distance by considering the countries of patent assignees and conceptualize the Technology Political Distance Indicator as a measure of a country's preference for conducting technology exports. Second, we treat technology as a complex system represented by a citation-based network. Utilizing PageRank and other network-related indicators, we identify critical nodes (patent sets) whose removal could fragment the network and disrupt technological systems, thereby assessing the impact of technology export controls. Third, leveraging both technology political distance and technology control, we categorize technologies into four distinct types and identify potential bottleneck technologies at both the patent and topic levels. Through an empirical study on integrated circuit technologies, our findings indicate that China holds a leading advantage in cutting-edge applications such as advanced sensors, novel materials, and energy conversion technologies. However, foundational technologies—including basic electronic components, advanced semiconductor materials, and circuit manufacturing and design—are predominantly controlled by countries with which China has distant political relations. Notably, key areas such as logic circuits and electrode integration remain largely underdeveloped domestically. If access to these foundational technologies were restricted, it could severely disrupt China's industrial and supply chains. As such, these fundamental technologies represent critical bottlenecks that China must address. Our results are validated through expert assessments and cross-referenced with the U.S. Commercial Control List, demonstrating the robustness and practical relevance of our proposed method.

Meanwhile, we acknowledge the potential limitations of our research and propose future directions that warrant further investigation. While our study introduces a novel method for quantifying the political attributes of technologies, thereby enhancing the understanding of the nature and implications of bottleneck technologies, it is important to recognize that bottleneck technologies are inherently complex. Their formation is influenced by multiple interrelated factors, including the foundational scientific knowledge, the structure of the technology supply chain, and the positioning of a given technology within the global value chain. These factors interact in intricate ways and collectively shape the emergence of bottleneck technologies. Therefore, we suggest that future research on bottleneck technology theory should focus on developing a rigorous logical framework and modeling approaches to better explain the dynamic mechanisms underlying the formation of bottleneck technologies. From a practical perspective, researchers should also explore strategies for integrating multi-source data to construct a comprehensive and systematic depiction of the technological landscape, enabling more precise identification of critical bottleneck points.

References

Arthur, W. B. (2009). *The nature of technology: what it is and how it evolves*. Simon and Schuster.

Bailey, M. A., Strezhnev, A., & Voeten, E. (2016). Estimating Dynamic State Preferences from United Nations Voting Data. *Journal of Conflict Resolution*, *61*(2), 430-456. https://doi.org/10.1177/0022002715595700

Beltagy, I., Lo, K., & Cohan, A. (2019). *SCIBERT: A Pretrained Language Model for Scientific Text*. Arxiv. Retrieved 2024-6-17 from https://arxiv.org/pdf/1903.10676

Danae, D., Georges, M., & Lefteris, P. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers & Operation Research*, *22*(7), 763-770.

Davis, C. L., Fuchs, A., & Johnson., K. (2019). State Control and the Effects of Foreign Relations on Bilateral Trade. *Journal of Conflict Resolution*, *63*(2), 405-438. https://doi.org/10.11588/heidok.00017673

Fan, C., Zeng, L., Sun, Y., & Liu, Y. Y. (2020). Finding key players in complex networks through deep reinforcement learning. *Nat Mach Intell*, *2*(6), 317-324. https://doi.org/10.1038/s42256-020-0177-2

Fang, C., Xuezhao, W., Xiwen, L., Yanpeng, W., & Ming, W. (2022). Research on Classification of Scientific Instruments and Technologies in The Commerce Control List of US Export Control. *World Sci-Tech R&D*, *44*(3), 287-298.
Frakes, M. D., & Wasserman, M. F. (2021). Knowledge spillovers, peer effects, and telecommuting: Evidence from the U.S. Patent Office. *Journal of Public Economics*, *198*. https://doi.org/10.1016/j.jpubeco.2021.104425
Guoxiong, Z., Wei, L., Gai, L., & Guanhua, L. (2021). A Research Based on Careful and Thorough Selection of "Neck-jamming"Technologies Using Delphi Method and AHP: a Case Study in Biomedical Field*. *World Sci-Tech R&D*, *43*(3), 331-343.
Haiqiu, Z., Xiaolin, H., Weisi, L., Guilong, L., & Tingyu, W. (2023). Research on the Selection Method of Key and Core Technology Task Based on MD-AHP. *Journal of Intelligence*, *42*(9), 149-154.
Han, X., Zhu, D., Wang, X., Li, J., & Qiao, Y. (2021). Technology Opportunity Analysis: Combining SAO Networks and Link Prediction. *IEEE Transactions on Engineering Management*, *68*(5), 1288-1298. https://doi.org/10.1109/tem.2019.2939175
Jin, C., Zhen, Y., & Zi-qin, Z. (2020). The Solution of"Neck Sticking" Technology During the14th Five- Year Plan Period: Identification Framework, Strategic Change and Breakthrough Path. *Reform*(12), 5-15.
Lee, P.-C. (2021). Investigating the Knowledge Spillover and Externality of Technology Standards Based on Patent Data. *IEEE Transactions on Engineering Management*, *68*(4), 1027-1041. https://doi.org/10.1109/tem.2019.2911636
Luo, Y. (2022). Illusions of techno-nationalism. *J Int Bus Stud*, *53*(3), 550-567. https://doi.org/10.1057/s41267-021-00468-5
S.Burt, R. (1992). *Strutural Holes: The Social Strcuture of Competition*. Havard University Press.
Schmid, S., Lambach, D., Diehl, C., & Reuter, C. (2025). Arms Race or Innovation Race? Geopolitical AI Development.
Geopolitics, 1-30. https://doi.org/10.1080/14650045.2025.2456019
Sun, H. (2019). US-China tech war: Impacts and prospects. *China Quarterly of International Strategic Studies*, *5*(02), 197-212.
Taichen, W., Minrong, L., & Zhenbiao, C. (2022). An Empirical Study on Influencing Factors of the Value of University Patent Technology Transfer and Transformation: Based on the Patent Transfer and Transformation Data from 11 First-Class Universities. *Library and Information Service*, *66*(9), 103-116. https://doi.org/10.13266/j.issn.0252-3116.2022.09.011
Tongliang, A., Ge, J., & Dazhong, W. (2023). Measurement of Critical Technologies in China's High-tech Manufacturing and the Catch-up Path: Lithium Battery Industry as an Example. *Economic Research Journal*, *58*(01), 192-209.
Vivoda, V. (2023). Friend-shoring and critical minerals: Exploring the role of the Minerals Security Partnership.
Energy Research & Social Science, *100*. https://doi.org/10.1016/j.erss.2023.103085
Xue, W. (2022). *Study on the Impact of Business Sophistication on National Innovation Output from the Perspective of Knowledge* Huazhong University of Science and Technology]. Wuhan.
Zhiwei, T., Yuxuan, L., & Longpeng, Z. (2021). Identification Method and Breakthrough Path of" Neck-jamming" Technologies under the Background of Sino-US Trade Friction: a Case of the Electronic Information Industry. *Science & Technology Progress and Policy*, *38*(1), 1-9.