Localization Management Challenges and Domain-Specific AI Empowerment Strategies for Chinese Manufacturing Enterprises Expanding to India

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ABSTRACT

Against the backdrop of global supply chain restructuring and increasingly complex Sino-Indian relations, Chinese manufacturing enterprises expanding to India face three systemic challenges: high compliance costs, cross-cultural management conflicts, and local skill gaps. This study combines Dunning's eclectic paradigm (OLI theory) with Kostova's institutional distance theory, systematically puts AI in specialized fields into the three-dimensional institutional distance framework, and puts forward the concept of "digital L advantage". We used mixed methods, including case study, system prototype development and benchmark testing, developed a BOM compliance RAG-AI prototype, and compared it with the general language model, and analyzed two cases, Transsion Holdings and Sany Heavy Industry. It is found that the core advantages of domain AI are professional evidence traceability, real-time regulation synchronization and audit accountability. Different industries should choose different AI entry points. Our AI solution, with a one-time investment of 80,000 to 150,000 RMB, can replace the traditional compliance scheme that costs 800,000 to 1 million RMB per year.

Keywords: Domain-specific AI; Manufacturing internationalization; Institutional distance; OLI theory; Cross-cultural management

1. INTRODUCTION

1.1 Research background

India is an exciting and challenging place for China manufacturing to go global. India's GDP is about $3.9 trillion (World Bank in 2024), and there are 1.4 billion people in India, almost 65% of whom are under 35 years old, and their Production Linked Incentive (PLI) plan covers 14 important industries. However, there is a big gap between those grand stories that sound great and the reality [1].

The first gap is between policy and implementation. India's manufacturing added value only accounts for about 12.5% of GDP, which is far from the 25% target set by "Make in India". The net FDI in fiscal year 2024-25 has even dropped to $353 million. The second gap is reflected in the political and economic aspects of Sino-Indian relations. After the implementation of PN3 in 2020, China's FDI in India plummeted to less than $100 million by 2023, but during the same period, the trade volume between our two sides exceeded $113.5 billion [2]. This differentiation phenomenon of "investment decline and trade growth" shows that the basic logic of the economy is still there, but the institutional obstacle has been upgraded to an access obstacle. The third gap is about the management ability after entering. China enterprises in India generally face compliance costs (traditional solutions cost 800,000 to 1 million RMB per year), cross-cultural conflicts and skills shortage. Since 2024, AI technology has changed from universal to vertical paradigm, which provides a new way to solve these pain points [3].

1.2 Research questions and significance

The core question is: To what extent can AI in specialized fields help China's manufacturing enterprises to meet those systematic management challenges in India? Theoretical significance: Expand the digital dimension of OLI theory, and build an algorithm-neutral framework for cross-cultural management. Practical significance: provide an operable solution, including working prototype and test data.

2. LITERATURE REVIEW

2.1 Theoretical foundations of multinational operations

According to Dunning's eclectic paradigm (1979, 2001), ownership, location, and internalization advantages drive FDI. Luo (2021) extended this with "New OLI Advantages," emphasizing digital integration capabilities. This study argues that in highly complex regulatory environments like India, traditional ownership advantages are evolving into "Algorithmic Ownership Advantages." Kostova (1999) identifies regulatory, normative, and cognitive dimensions of institutional distance, while Hofstede (2001) notes that despite similar power distance, China and India differ in power operation logic. Together, these theories underpin our proposed concept of "algorithmic neutrality."

2.2 Chinese enterprises in India and AI applications

The research on Indian China enterprises has gone through three stages: investment opportunity assessment (2014-2019), PN3 impact assessment (2020-2022) and solution exploration (2023-present). Although the academic circles have widely discussed the barriers to entry, few studies have started from the perspective of technical governance. LoRA fine-tuning [9] and RAG [10] have reduced the cost of customized AI to tens of thousands of RMB, among which RAG can ensure the factual accuracy of compliance recommendations. This paper is located at the intersection of these research gaps, and thinks that AI is not only an extension of the advantages of OLI, but also a buffer layer to deal with "liability of foreignness" [11].

3. THEORETICAL FRAMEWORK AND CONCEPTUAL MODEL

3.1 Core concepts and model

Domain-Specific AI (DSAI) refers to an intelligent system that is deeply customized for a specific industry. This paper divides DSAI into RegTech AI (regulatory compliance), Management AI (organizational management) and Industrial AI (production empowerment). Based on the procedural justice theory (Thibaut & Walker, 1975) [12], the Algorithmic Neutrality transforms the subjective game in cross-border management into objective rules through impersonal logical instructions. The core framework constructs an "AI-mediated institutional distance resolution model": regulatory distance corresponds to RegTech AI, regulatory distance corresponds to Management AI, and cognitive distance corresponds to Industrial AI, thus forming a dynamic "Digital L-Advantage".

3.2 Research propositions

P1: RegTech AI based on RAG is much more powerful than those general models in terms of completeness and accuracy of evidence, and can reduce compliance costs by more than 80%. P2 (This is theoretical speculation, because we don't have the data of employees' feelings, so there is no actual test in this study): The decision feedback made by the algorithm can make local employees feel that the process is fairer. P3: Industrial AI has reduced its dependence on those dispatched technicians through knowledge distillation. P4: Whether the effect brought by industry AI is good or not will be influenced by the level of industry standardization [4][7].

4. RESEARCH DESIGN AND METHODS

4.1 Research methods

This research adopts a mixed-method approach combining case study, system prototype development, and benchmark testing [13]. Based on Yin's (2018) theoretical sampling principles, Transsion Holdings (B2C consumer electronics, primarily facing regulatory distance) and Sany Heavy Industry (B2B heavy machinery, primarily facing cognitive distance) are selected as polar-type dual cases. Data are obtained through triangulated secondary sources including annual reports, broker research, and Indian government statistics. The absence of primary field interviews constitutes this study's main limitation.

4.2 System prototype design

In order to verify P1, we developed a lightweight RegTech prototype based on RAG architecture: a Milvus vector database stores India's GST bill, PLI guide and HS coding manual; Hybrid search combines keyword matching and semantic retrieval; Qwen2.5-7B is used as the basic model and fine-tuned by LoRA. The boundary test case uses a smart home controller (HS 8537.10), and its calculated DVA is 53.0%, which is only 3 percentage points higher than the 50% threshold required by PLI. This product is chosen as the benchmark because its multi-source component structure (combining domestic purchased and imported components under several HS subheadings) represents the BOM complexity that our electronics manufacturers in China usually encounter under India's PLI plan [9].

5. TECHNICAL SOLUTION AND IMPLEMENTATION

5.1 Architecture and RegTech module

This system uses three separate layers: the basic layer (Milvus vector database plus RPA engine), the model layer (Qwen2.5-7B, with LoRA fine-tuning, only 0.1% of the 7 billion parameters of the basic large model), and the application layer (RegTech, Industrial AI and Management AI function clusters, which can be plugged and played). RegTech module uses LoRA to train on consumer GPU, saving more than 95% money; The RAG supervision knowledge base is searched by Top-K to avoid talking nonsense; The RPA engine can connect the ERP of the enterprise and the ICEGATE customs platform in India for real-time verification [9] [10].

5.2 Industrial AI and Management AI

Industrial AI leverages IIoT platforms to automatically convert Chinese operating manuals into Hindi voice instructions and 3D visual disassembly guides. Management AI generates explainable AI audit logs, attaching objective data evidence chains to every management decision [8] [12].

5.3 Prototype test results

The BOM-Audit RAG-AI prototype achieves: DVA calculation accuracy of 53.0% with less than 0.1% deviation from manual review at 1/50th the processing time; 12/12 perfect accuracy in HS code blind testing; legal citation accuracy of 98% (versus 62% for general-purpose models); DVA calculation correctness of 100% (versus 75%); and deployment cost of 80,000–150,000 RMB as a one-time investment [9].

6. EMPIRICAL ANALYSIS

6.1 Domain AI versus general-purpose models

The core finding is that domain AI's competitive advantage lies not in "calculating more accurately" but in four dimensions that general models cannot replicate: professional evidence capability (citing customs rulings versus providing conclusions without precedent), real-time regulatory synchronization (indexing the latest notifications versus relying on outdated policies), batch engineering processing, and full audit traceability. In boundary cases, a 1–2% DVA deviation can determine compliance status [9] [10].

6.2 Case 1: Transsion Holdings

Transsion Holdings (688036.SH) achieved approximately 8.6% global smartphone shipment share in 2024 and faces "soft challenges": 22 official languages, a post-2020 structural trust deficit for Chinese brands, and GST state-level fragmentation requiring 5–7 days for monthly reconciliation. AI solutions include: integration of DeepSeek for multilingual content generation across six or more languages (cultural adaptation rather than machine translation); and RPA-enabled GST filing automation (processing time compressed to hours, discrepancy rate reduced to below 0.5%). The core finding is that AI transforms cultural difference from a "liability of foreignness" into a "data-driven localization advantage" [6][8] [11].

6.3 Case 2: Sany Heavy Industry

Sany Heavy Industry (600031.SH) has operated in India for over twenty years and faces "hard challenges": severe shortages of locally certified welders, CNC operators, and NDT inspectors, with welding first-pass rates 15–25 percentage points below domestic levels. AI solutions deploy four sub-modules: remote fault diagnosis identifying over 200 failure modes; preventive maintenance at 1/3 to 1/5 the cost of reactive repair; AI training systems converting expert knowledge into knowledge graphs for mother-tongue learning; and visual quality inspection reducing missed defect rates to below 1%. The core finding is that Industrial AI constitutes a new type of "knowledge infrastructure advantage"—when expatriates depart, knowledge remains on the platform [4][6].

6.4 Cross-case analysis and cost-benefit assessment

Common findings include: the "technological solubility" of institutional distance; shared incremental "most painful point first" deployment strategies; data flywheel effects; and cost affordability. Differential findings validate P4: consumer electronics should prioritize Marketing/Management AI for normative distance, while heavy industry should prioritize Industrial AI for cognitive distance; RegTech AI represents a shared need. Traditional solutions cost 800,000–1,000,000 RMB annually, whereas the AI solution requires 80,000–150,000 RMB one-time plus minimal maintenance, with estimated ROI exceeding 10x and a payback period of 6–12 months [2][3].

7. CONCLUSION

7.1 Main findings

First of all, the combination scheme of LoRA+RAG+RPA can replace the traditional scheme that used to cost 800,000 to 1 million RMB per year, and now it only needs to invest 80,000 to 150,000 RMB at one time. Secondly, the core advantages of domain AI are professional evidence traceability, real-time regulatory synchronization and audit accountability. Third, the empowerment path of AI should be differentiated according to different industries. Fourth, institutional distance is "technically solvable", but AI builds a buffer layer instead of eliminating institutional distance itself [4][5][7].

7.2 Theoretical contributions and practical implications

Theoretically, this work extends OLI's digital dimension, constructs an algorithmic neutrality framework for cross-cultural management, and proposes the "technological solubility of institutional distance" thesis. Practically, enterprises can initiate deployment with 80,000–150,000 RMB; should diagnose pain point distribution before selecting AI modules; should prioritize Chinese open-source model ecosystems; and must synchronize AI deployment with management transformation [6] [12].

7.3 Limitations and future directions

This study mainly uses second-hand data; The prototype of the system has not been put into use on a large scale; The fairness of the algorithm has not been actually tested; The risk of hallucinating LLM has not been discussed enough. Future research should collect first-hand data to verify small details, expand the scope of comparison to Vietnam and Indonesia for transnational analysis, and upgrade to SEM model that can analyze interaction [13].

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