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An Interview Study of Artificial Intelligence Adoption and Sentiments in Chinese Enterprises

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Abstract

This study investigates Artificial Intelligence (AI) adoption patterns, employee perceptions, and the influence of organisational size within Chinese enterprises. Methodologically, it employs 20 unstructured qualitative interviews with employees in Hangzhou, China, which are analysed using qualitative content analysis. Key findings indicate overwhelmingly positive sentiments towards AI across all organisational sizes. Adoption strategies vary: large enterprises implement complex optimization systems, medium-sized firms focus on decision support, and small enterprises prioritise customer-facing applications. The study's original contribution is a novel flywheel model that explains China's high AI adoption rates despite significant implementation barriers. This model details how four organisational mechanisms (positive perception, barrier tolerance, training/competency, future planning), accelerated by China's unique cultural context and supportive policy environment, create self-reinforcing momentum against size-dependent friction. Managerial implications suggest large firms should leverage scale and policy alignment, investing in comprehensive training and long-term planning, while SMEs should strategically adapt to resource constraints and seek niche policy support, navigating the interplay of cultural optimism and practical challenges.

Keywords: Artificial Intelligence, China, Innovation Management, Organisational Size, Sentiments, Technology Adoption

Introduction

China has emerged as a leader in the global race for AI adoption, as this technology continues to transform economies and societies worldwide. A recent global industry survey of 1,600 decision-makers underscores China's dominance: 83% of Chinese respondents report the active use of generative AI–significantly higher than the average of 54% across the 16 surveyed countries and regions (Coleman Parkes & SAS, 2024). This leadership position comes at a time when AI is triggering intense international competition for technological supremacy, with far-reaching economic and social implications. Recent AI developments demonstrate this competition, as shown by the release of DeepSeek R1 model (DeepSeek-AI et al., 2025) and Janus Pro (Chen et al., 2025), which has lead to record market-cap losses in the American stock market (Carew, Cooper & Banerjee, 2025).

China's current leadership in AI adoption follows a long-term strategic vision. Since its "New Generation AI Development Plan" in 2017 (The State Council of the People´s Republic of China, 2017), China has been systematically pursuing a pioneering role in this field, with the declared goal of becoming one of the world's leading AI innovation centres by 2030 and using AI as the driving force behind its industrial and economic transformation (AlShebli, Memon, Evans & Rahwan, 2024). These ambitions are supported by substantial investments in research and development and the

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commercialisation of AI within China by its government (Khanal, Zhang & Taeihagh, 2025). The Chinese government's narrative portrays AI as an inevitable technological innovation and a necessity for global competitiveness, framing it as "the core driving force for a new round of industrial transformation" and a solution to societal challenges such as population ageing (Bareis & Katzenbach, 2022). Notably, this official enthusiasm appears to be mirrored in public discourse: an analysis of 140,000 AI-related articles on WeChat and People's Daily Online revealed that public discussion largely aligns with the government's positive narrative, focusing primarily on economic potential with minimal critical debate (Zeng, Chan & Schäfer, 2022).

This positive narrative is reflected in various domains of AI adoption research in China. Recent studies have examined different aspects of this technological transformation and Artificial Intelligence (AI) as an innovation: In the private sector, (Sun, Tohirovich Dedahanov, Li & Young Shin, 2024) examined how high-tech SMEs adapt to sanctions by leasing AI computing power, highlighting the importance of factors such as innovativeness, perceived risk, and task-technology fit in adoption decisions. Within the telecommunications industry, (H. Chen, Li & Chen, 2021) developed a framework integrating technological, organisational, and environmental factors to understand AI adoption success factors. The public sector has received attention as well, with Xiaoyan and Segumpan (2024) investigating AI implementation challenges in Chinese public services. Their findings emphasise barriers related to tools, competencies, and data management, while highlighting the supportive role of major technology companies like Alibaba, Tencent, and Baidu. At a broader urban level, (Wang, Zhao, Gangadhari, & Li, 2021) analysed challenges in AI adoption for smart city development, identifying infrastructure limitations, insufficient funding, and cybersecurity risks as key barriers. In the educational context, (Kumarasinghe & Jayarathna, 2024) explored AI adoption intentions among management students in Hangzhou, revealing the significance of perceived advantages and trialability, while emphasising the role of social and cultural contexts in shaping adoption attitudes.

However, while these studies provide valuable insights into various institutional aspects of AI adoption in China and its innovation capabilities, they predominantly focus on organisational decision-making and systemic barriers, overlooking a critical perspective: that of the employees who directly interact with these technologies. This gap becomes particularly significant when considering Elish and Boyd´s (2018) warning that widespread technological optimism often obscures AI's limitations and methodological challenges. They argue that overconfidence in AI systems, coupled with insufficient critical examination, risks undermining their actual potential and effectiveness. Indeed, recent research by (Zirar, Ali & Islam, 2023) suggests that AI's impact on the people most affected by it–employees–is complex and multifaceted, simultaneously leading to enhanced efficiency and engagement while also generating increased insecurity and stress.

Given China's ambitious AI agenda and high adoption rates, understanding how employees across different organisational contexts perceive and experience AI implementation becomes crucial for evaluating the impact of the country's AI transformation. Therefore, this study addresses the following first research question:

(1) RQ: How do employees across different organisational contexts perceive AI adoption in Chinese enterprises?

Additionally, the relationship between organisational size and AI adoption merits particular attention in the Chinese context. While research indicates that larger companies generally have higher innovation adoption rates due to greater R&D resources (Shefer & Frenkel, 2005), and IT innovation specifically increases with organisational size (Lee & Xia, 2006), these patterns may manifest differently in China's unique institutional environment. Recent U.S. research shows AI adoption clustered in large companies and specific industries such as manufacturing and healthcare (McElheran et al., 2023). However, China's distinctive innovation ecosystem and policy environment could lead to different adoption patterns across organisational sizes. This leads to our second research question:

(2) RQ: How does organisational size influence AI adoption patterns and employee experiences in Chinese enterprises?

As the empirical basis for answering these questions, we conducted unstructured qualitative interviews. Our

analysis follows Mayring's (2000, 2014) qualitative content analysis methodology. Based on the results, as well as existing concepts from innovation and organisational research, we created a framework that combines employee perspectives, adoption patterns, organisational influencing factors and cultural contexts to depict the development of AI integration in Chinese companies. The concept of the flywheel is particularly suitable for visualising the dynamics and self-reinforcing effects of this transformation process (Collins, 2001), and was thus used as the basis.

The remainder of this paper is structured as follows: First, we detail the effect of AI on innovation as well as organisational and human dimensions of AI adoption. This is followed by the methodological approach and the data, followed by a comprehensive presentation of our content analysis. We then discuss our findings considering existing literature and suggest a flywheel for AI adoption in China, as well as describing theoretical and managerial implications. The paper concludes with a discussion of limitations and suggestions for future research.

Literature Review

Digital technologies are fundamentally transforming both innovation and its management practices. Through digital innovations, traditional industries are achieving unprecedented scalability, market reach, and strategic agility, while the innovation process itself undergoes complex and often ambiguous transformations (Appio, Frattini, Petruzzelli & Neirotti, 2021). These emerging technologies are extending product and service capabilities in multiple dimensions (Kohtamäki, Parida, Patel & Gebauer, 2020), though within an innovation landscape that has become increasingly chaotic and irregular (Pietronudo, Croidieu & Schiavone, 2022). The distinct characteristics of digital technology have enabled novel innovation processes that, while powerful, prove particularly challenging to control or predict (Nylén & Holmström, 2015).

In this context, AI has emerged as a particularly transformative force, offering the potential to rationalise innovation processes and reduce arbitrary decision-making (Pietronudo et al., 2022). Its influence extends beyond mere product and service enhancement; AI is increasingly integral to the innovation process itself, facilitating both incremental improvements and new product development (Hutchinson, 2021; Muhlroth & Grottke, 2022). This integration fundamentally challenges traditional assumptions about innovation processes and management (Benner & Tushman, 2015).

While innovation has historically been considered an inherently human domain (Amabile, 2019), the deepening integration between products and companies is reshaping this paradigm. The iPhone exemplifies this shift, establishing continuous data flows that provide detailed insights into user experiences. Moreover, embedded software enables bi-directional information exchange between companies and users, facilitating personalised solutions that continuously evolve in real-time (Verganti, Vendraminelli & Iansiti, 2020). Under these conditions, AI demonstrates the capacity to surpass human experts in terms of quality, efficiency, and overall results (Haefner, Wincent, Parida & Gassmann, 2021), pointing toward a fundamentally more effective and efficient innovation process (Füller, Hutter, Wahl, Bilgram & Tekic, 2022).

Following AI's impact, our understanding of AI adoption requires examining three key dimensions that emerge from our research questions and the existing literature. These dimensions—employee perspective, organisational context, and company size—create a framework for analysing AI implementation in organisations. The employee perspective focuses on how workers perceive and respond to AI technologies, with the Technology Acceptance Model (TAM) by Davis (1989) showing that employee acceptance depends on perceived usefulness, ease of use, and trust. This helps us analyse how employees respond to AI implementation and what factors encourage or discourage adoption. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2012) adds more factors to this model, particularly social influence and supporting conditions, which are especially relevant in Chinese organisations, where collective values and hierarchies can strengthen social aspects of technology decisions. Complementing these models, Psychological Contract Theory (Rousseau, 1995) helps explain how technological changes like AI affect the implicit expectations between employees and organisations; when new technologies are introduced, these unwritten agreements often need renegotiation, which can affect commitment and openness to innovation. The organisational context as a second dimension includes structures and cultural elements that shape AI adoption,

with Contingency Theory (Kotter, 1996) providing a framework for understanding how organisational factors influence AI implementation through steps like creating urgency, building leadership teams, developing vision, and involving employees. In Chinese organisations, hierarchical structures and long-term thinking can make decision-making more efficient but may limit innovation if employees are not properly engaged in the process. Company size as the third dimension significantly affects AI adoption patterns, with research showing larger companies have more resources and that smaller companies therefore face challenges with IT adoption (Lee & Xia, 2006) and IT strategy (Kling, Haugk & Gebauer, 2025).

Methodology

Given the qualitative character of the data collection, this study employs qualitative content analysis, a systematic method for analysing textual data that bridges qualitative and quantitative approaches to text interpretation (Mayring & Fenzl, 2022). Developed by Mayring (2000, 2014), the methodology enables researchers to process large volumes of text while maintaining the interpretative depth characteristic of qualitative methods. The approach is distinguished by its systematic, rule-based categorisation of text segments, allowing for both manifest and latent meaning to be captured through careful analysis. It operates through a category system that serves as the primary analytical instrument.

As the interviews conducted for this exploratory paper were unstructured, the researchers created the categories inductively. The coding unit was set as meaningful phrases or complete sentences from the interviews. This ensures that the researchers maintain the contextual meaning of statements rather than analysing isolated words. The context unit was established as the entire interview transcript.

Building on this analytical framework, the researchers employed summarising content analysis as the primary analytical technique, which is particularly suitable for exploratory studies where the goal is to reduce the material while preserving essential content. This approach was chosen because the unstructured interviews about AI adoption in Chinese companies required an open, exploratory analysis process without predetermined theoretical categories. The summarising technique allows the researchers to condense the interview material into core statements while maintaining the authentic meaning of the participants' responses.

To operationalise the qualitative content analysis framework, this study draws on 20 unstructured qualitative interviews conducted through a peer-to-peer research approach. The following section provides an overview of the data collected, including the participants' organisational contexts, industry sectors, and the structure of the interviews.

Data

The empirical foundation comprises 20 unstructured qualitative interviews conducted through a peer-to-peer research approach between September and November 2024 in Hangzhou, China. We employed bilingual (Chinese-German) students as co-researchers for the data collection. Understanding *guanxi* (personal connections) and *mianzi* (face or social dignity) are important concepts to understand when doing intercultural research in the Chinese field (Buckley, Clegg & Tan, 2006). Given that AI adoption is viewed favourably in China (Bareis & Katzenbach, 2022; Zeng et al., 2022), respondents might feel pressure to provide socially desirable answers to foreign researchers. By leveraging established *guanxi* networks and cultural understanding of *mianzi*, our co-researchers were able to access authentic perspectives beyond official narratives.

Each interview began with a core question about AI usage in the participant's workplace, followed by an exploration of reasons for adoption or non-adoption. This open-ended approach allowed participants to guide the conversation toward aspects of AI implementation most relevant to their daily work lives. The resulting data consists of interview transcripts and memory protocols, created in Chinese and subsequently translated into English. The sample represents diverse organisational contexts, with participants from large enterprises (44%), medium-sized companies (25%) and small enterprises (31%). Participants span multiple industries, including manufacturing, finance, healthcare, technology, and creative sectors, providing a broad perspective on AI adoption across different business contexts. For a detailed overview of the participants' characteristics and their organisational contexts, see Table 1.

Table 1: Characteristics of Interview Participants

Interview	*Company Size*	*Industry Sector*
INT 1	Medium	Game development
INT 2	Large	Finance
INT 3	Medium	Medical Tech
INT 4	Small	E-Commerce
INT 5	Large	Manufacturing
INT 6	Small	E-Commerce
INT 7	Small	Not specified
INT 8	Large	Semiconductor
INT 9	Medium	Not specified
INT 10	Small	Creative
INT 11	Small	Media
INT 12	Large	Manufacturing
INT 13	Large	Automotive
INT 14	Medium	Healthcare
INT 15	Large	Big Tech
INT 16	Medium	Finance
INT 17	Small	Retail
INT 18	Large	Manufacturing
INT 19	Large	Manufacturing
INT 20	Large	Manufacturing

Results

Our analysis of the interview data reveals five distinct themes in how Chinese enterprises approach and experience AI adoption. These themes encompass the organisational contexts of implementation, general sentiments toward AI technology, technical and regulatory barriers, human-centred challenges (including training needs and employee concerns), and future AI implementation plans.

Implementation Context

The first theme we identified was distinct patterns in how Chinese enterprises implement AI technologies across different organisational sizes. The implementation contexts vary systematically, with organisations focusing their AI initiatives on different operational aspects depending on their scale and resources.

The data indicates that small enterprises primarily focus their AI implementations on enhancing customer experience and interaction. For instance, a retail sector representative (INT 17) described implementing "AI recommendation systems to recommend products to customers that they might like." This customer-centric focus appears consistent across small enterprises in our sample, though some face implementation challenges, as evidenced by INT 7's observation their "AI customer service has been a bit strange lately."

Medium-sized enterprises, in contrast, tend to concentrate their AI implementations on data analysis and decision-support capabilities. A game development company representative (INT 1) highlighted how "AI can directly help analyse our user questions," while a finance sector participant (INT 16) emphasised AI's role in analysing "market trends and predict risks so that we can make decisions with more confidence." Large enterprises demonstrate the most complex implementation patterns, utilising AI for sophisticated optimisation tasks across multiple business functions. In the financial sector, AI serves critical security functions, as noted by INT 2: "We use them to detect anomalies in transactions and identify potential cases of fraud." Similarly, in manufacturing, AI has become "an important aspect of supply chain optimisation" (INT 5).

Sentiments

A striking feature of our analysis is the predominantly positive sentiment toward AI across organisations of all sizes. This positive attitude manifests even in organisations that have not yet adopted AI technologies.

Interviewees consistently emphasise AI's operational benefits. INT 1 states matter-of-factly that "the use of AI can significantly increase our efficiency," while INT 2 highlights AI's data processing capabilities. INT 11's assessment that "AI makes the impossible possible" exemplifies the optimistic outlook prevalent among respondents. This positive sentiment even extends to organisations that have not yet implemented AI. For instance, INT 4, despite lacking resources for implementation, maintains an optimistic future outlook: "We would like to use AI to analyse our customers'

purchasing behaviour. If the business grows, we could reconsider the use of AI."

Among all interviews, only one expressed a neutral stance. INT 20 noted: "At the moment, I don't see much potential for the use of AI at my company. There are no clear use cases that show how AI could really make a significant contribution to improving supply chain management." Critical perspectives were minimal, with only two interviewees expressing concerns. INT 7 noted issues with AI customer service performance, while INT 10, despite initial scepticism about AI as "a simple imitation machine that just copies the style of images given to it," ultimately described positive personal experiences with the technology.

Technical and Organisational Barriers

Further, we identified different technical and organisational barriers to AI adoption that vary across organisational sizes. However, these barriers did not prevent the implementation, apart from in the case of INT 4.

Large enterprises primarily face three distinct types of technical and organisational challenges. First, regulatory compliance, particularly regarding data protection, emerges as a significant concern, as noted by INT 2 who highlighted "… challenges regarding data protection." Second, technical integration poses notable difficulties, exemplified by INT 5's experience where "the integration of AI systems with existing supply chain management systems was not entirely seamless." Third, data quality and reliability present operational challenges, as illustrated by INT 5's observation that "since AI accuracy heavily depends on data, it was problematic that data from some of our suppliers was not always timely or accurate enough, which negatively impacted AI predictions and decisions."

Medium-sized enterprises encounter a different set of challenges, primarily centered around resource constraints and regulatory compliance. INT 3 articulated this dual challenge, noting that "AI model training requires enormous amounts of data. Data protection and technical requirements are challenging here." The resource intensity of AI implementation appears particularly burdensome for medium-sized organisations, as evidenced by INT 1's statement that "implementing AI systems can be costly and resource-intensive for us."

Small enterprises face the most fundamental challenge: resource constraints that can completely prevent AI adoption. This is clearly illustrated by INT 4's experience: "We have thought about it [adoption of AI], but to be honest it is financially difficult. We would like to use AI to analyse our customers' purchasing behaviour, but we lack the data volumes for that." This suggests that for small enterprises, resource limitations can create an insurmountable barrier to AI adoption, despite the recognised potential benefits.

Human-Centered Barriers

Beyond technical and organisational barriers, we identified human-centered challenges in AI adoption that manifest differently across organisational sizes. These challenges primarily relate to employee competencies and attitudes toward AI implementation.

In large enterprises, resistance to change emerges as a significant challenge, particularly among experienced employees. As INT 5 describes: "Especially the experienced older employees, who were more familiar with manual management methods, had reservations about introducing AI. They feared that AI could replace their jobs." This required substantial organisational investment in change management, with the company needing to "invest considerable time in training employees and showing them how AI can support rather than replace their work" (INT 5). Additionally, large enterprises face challenges related to AI competency development, as evidenced by INT 18's observation that "AI is still new to us, and we need to learn to use these tools better."

Medium-sized enterprises primarily struggle with training and competency development. INT 9 articulates this challenge clearly: "I do not think we have the AI training and do not know where to start." This challenge is compounded by resource constraints, particularly time limitations, as the same interviewee notes: "Besides, our time is occupied with daily work, so how can we have time to study AI?"

Notably, small enterprises in our sample did not explicitly mention human-centred challenges. Nor did they refer to specific future planning, as discussed in the next sub-chapter.

Future Planning

Future plans encompass both technical advancement and organisational development. Large enterprises demonstrate comprehensive planning for AI expansion. INT 5 outlines a multi-faceted approach: "There are plans to further optimise the data collection and processing process and strengthen communication with employees. Training will help employees better understand the benefits of AI. The company is also considering hiring more experts to solve technical integration problems and accelerate AI application." The future vision extends to specific operational applications. INT 18 describes potential AI applications in procurement: "AI could be increasingly used to determine whether the right time has come to purchase demand and how many materials need to be bought at the best costs." Similarly, INT 19 emphasizes efficiency gains: "In my opinion, AI could contribute to further improving efficiency and time savings in the future."

Optimism about the use of AI was observed across the board, independent of the adoption of AI (although all companies in the sample adopted AI in some way, apart from INT 4).

Discussion

Our analysis reveals distinct patterns in Chinese organisations' AI adoption that can be conceptualised through a flywheel framework, explaining the notably high implementation rates despite various barriers. Collins (2001) originally developed the flywheel as a metaphor for organisational transformation, emphasising that successful change is not the result of a single defining action or breakthrough, but rather a process of consistent effort that builds momentum over time. Accordingly, we propose that AI adoption in Chinese enterprises operates as a self-reinforcing system where four interconnected spokes (positive perception, barrier-tolerance implementation, training and competency development, and future planning) create momentum through their interactions, while two forces (the Chinese cultural context, China's policy environment) accelerate the wheel. Lastly, there is friction (technical, organisational, and human-centred barriers) that slows down the wheel and is determined by company size. The conceptual framework is presented in Fig. 1.

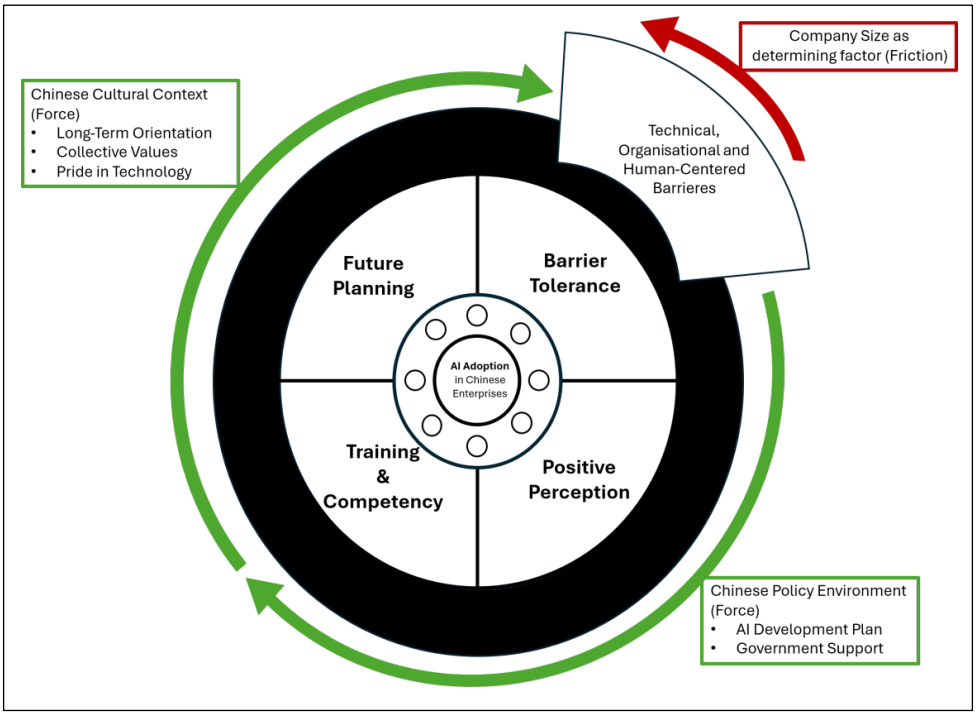

Fig. 1: Conceptual Flywheel of AI Adoption in China

Accelerating Forces

The first accelerating force is the Chinese cultural context, characterised by high power distance, long-term orientation, collective values, and technological pride. Pride serves as a key emotion in China's AI narrative, alongside hope and fear (van Noort, 2024). This pride cascades from national discourse down to organisational behaviour, which helps to explain why even resource-constrained companies maintain positive attitudes toward AI adoption. Chinese cultural dimensions create an environment where hierarchical implementation of new technologies faces less resistance than in Western contexts (Hofstede, 2011). Chinese organisations readily implement AI systems through clear command chains, focusing on organisational objectives rather than individual concerns. Further, China's AI narrative involves self-inflation which shapes the experience of pride, (van Noort, 2024) suggesting that AI adoption becomes an expected behaviour for Chinese companies. This cultural pressure creates a powerful momentum that appears to override typical adoption barriers, resulting in organisations pursuing AI implementation as part of a broader narrative about technological leadership and organisational identity. As Li and Shapiro (2020) note, Chinese organisational culture tends toward hierarchical and task-oriented structures, which helps facilitate faster AI adoption through clear command chains. This aligns with (Kelly, Kaye, & Oviedo-Trespalacios, 2023) observation that cultural factors significantly influence AI acceptance in the workplace. In the Chinese context, our interview data reflects these cultural influences through a consistent emphasis on operational and business outcomes.

The second accelerating force is China's distinct policy environment. The government's "New Generation AI Development Plan" launched in 2017 (The State Council of the People´s Republic of China, 2017) functions not merely as a strategic document but as an active accelerant for organisational adoption. What emerges from our interview data is telling: not a single respondent cited regulatory or legal barriers to AI implementation—a contrast to Western empirical findings where regulatory frameworks are frequently cited as significant impediments (e.g. Booyse & Scheepers, 2024). This absence of regulatory concern, combined with substantial government support through subsidies, tax reimbursements, and R&D grants (Johansson, 2022), transforms what might be friction in other contexts into positive momentum. The policy environment creates a symbiotic relationship between enterprises and government, where close collaboration helps forge strong relationships and secure future opportunities (Johansson, 2022). This policy-driven acceleration manifests in our data through the consistent emphasis on future AI expansion, particularly among large enterprises (INT 5, INT 18, INT 19).

Decelerating Friction

The friction within our AI adoption flywheel manifests differentially across organisational scales, directly aligning with established technology adoption frameworks. Large enterprises encounter sophisticated friction characterised by regulatory compliance demands, technical integration challenges, and employee resistance—reflecting what Psychological Contract Theory would classify as disruptions to implicit workplace agreements when AI threatens established roles (Rousseau, 1995). Medium-sized organisations experience what the UTAUT model terms "facilitating conditions" deficiencies, where limited resources for training and development create implementation bottlenecks despite positive adoption intentions (Venkatesh, Thong & Xu, 2012). For small enterprises, friction appears most acutely as fundamental resource limitations that can entirely halt implementation, consistent with the findings of (Lee & Xia, 2006), which show that resource availability significantly determines innovation capacity. To overcome such resistance, strong leadership is necessary (Kotter, 1996). The apparent heightened effectiveness of this approach in China suggests that the success of such change leadership strategies is, as broader contingency theories of leadership propose, dependent on the specific cultural context. This explains why, despite these varied friction forces, Chinese organisations maintain high AI implementation rates and positive sentiments, which are the first of four spokes.

Flywheel Spokes

The flywheel of AI adoption in Chinese enterprises gains its initial push from overwhelmingly positive

sentiments toward AI found across all organisational sizes, confirming Zeng et al.'s (2022) analysis of public AI discourse in China. This positive sentiment centres decisively on perceived relative advantage (Chen et al., 2021), particularly regarding efficiency gains." Unlike Western frameworks that often emphasise human-centred AI design focused on fairness, accountability, and transparency (Mosqueira-Rey, Hernández-Pereira, Alonso-Ríos, Bobes-Bascarán, & Fernández-Leal, 2023), Chinese organisations demonstrate a distinctly pragmatic approach, viewing AI primarily as an autonomous operational tool. This pragmatic orientation aligns with innovation as a driver of economic development, where Chinese organisations appear to view AI as a tool for creative destruction (Schumpeter, 1942) aimed at improving existing business processes rather than pursuing solely disruptive transformation. These findings strongly support the TAMs core premise that perceived usefulness is a primary driver of technology adoption (Davis, 1989). This overwhelming positive perception, grounded in anticipated pragmatic benefits (Davis, 1989), serves as the initial catalyst, overcoming inertia and setting the AI adoption flywheel in motion.

The second critical spoke—barrier tolerance—represents Chinese organisations' willingness to pursue AI implementation despite acknowledged obstacles, ensuring the flywheel continues to turn even when encountering resistance. This tolerance manifests differently across organisational sizes as mentioned in the explanation of frictions, but demonstrates a consistent pattern of persistence. Crucially, this remarkable willingness to push through barriers appears significantly bolstered by the accelerating forces discussed previously: a supportive policy environment actively encouraging adoption through various incentives (Johansson, 2022; The State Council of the People´s Republic of China, 2017) and a cultural context valuing technological leadership and national pride (van Noort, 2024; Hofstede, 2011). Our data show that, despite facing regulatory compliance issues, technical integration challenges, and data quality concerns, large enterprises continue their AI initiatives, as illustrated by INT 5's experience with supply chain integration difficulties that did not halt implementation. Medium-sized enterprises similarly press forward despite resource constraints. The evidence from our interviews demonstrates that organisations across size categories exhibit what Nelson and Winter (1982) describe as organisational routines that prioritise technological advancement even when faced with implementation challenges. This culturally and policy-supported persistence explains why barriers often slow, rather than stop, the flywheel. Only in extreme cases, such as INT 4's small enterprise did fundamental resource limitations completely prevent adoption—consistent with the (Lee & Xia, 2006) findings regarding resource constraints acting as critical friction points, particularly in smaller organisations, which are also found in other countries (Kling et al., 2025). This spoke highlights how external accelerators can directly influence an organisation's internal persistence, enabling the flywheel to maintain momentum against significant friction.

The third spoke—training and competency—serves as both a challenge amplifying friction and a crucial mechanism for sustaining momentum within the flywheel. Large enterprises recognise this critical component. This approach directly addresses the "facilitating conditions" component of the UTAUT model (Venkatesh et al., 2012), where organisational support for skill development is vital for technology acceptance and effective use. Successfully addressing this spoke, as seen in INT 5, reduces human-centred friction and enhances operational efficiency, thereby adding energy to the flywheel. This investment is particularly relevant in managing the disruptions to implicit workplace expectations that AI implementation creates, aligning with Psychological Contract Theory (Rousseau, 1995); training therefore becomes a key tool for renegotiating these expectations and mitigating resistance stemming from fears of job replacement. The importance of such support resonates with our theoretical framework's force effects, i.e. that collective values and hierarchies can strengthen social aspects of technology decisions in China, potentially making centrally managed training initiatives effective when resourced. However, medium-sized enterprises demonstrate awareness of this spoke's importance yet struggle with its implementation due to resource constraints. This training gap, compounded by time constraints, creates significant friction within the flywheel, acting as a bottleneck that slows adoption and limits the realisation of AI's potential benefits.

The fourth spoke—future planning—completes the flywheel cycle by converting current implementation

experiences and perceived benefits into strategic forward momentum. This spoke is particularly pronounced in large enterprises, which demonstrate comprehensive planning for AI expansion, thus ensuring the flywheel continues spinning and potentially accelerates. INT 5 outlines a multi-faceted approach encompassing data optimisation, communication, training, and expert hiring. This strategic orientation aligns with Kotter's (1996) change management principles, where embedding changes and creating a vision for the future generates sustaining momentum. The future planning spoke connects directly to Chinese cultural tendencies toward long-term orientation (Hofstede, 2011) which, as our theoretical framework notes, can influence strategic decision-making. The specific operational applications envisioned, such as using AI for procurement optimisation, exemplify what Rogers (1962) would classify as activities within the "confirmation" stage of the innovation-decision process. In this stage, organisations seek reinforcement of their adoption decisions by integrating innovations further and exploring expanded applications to maximise benefits. This future planning spoke thus closes the self-reinforcing loop: by outlining tangible future benefits and integration steps (Rogers, 1962), it reinforces the initial positive perception (TAM), justifies continued investment and barrier tolerance, and provides sustained energy to keep the adoption flywheel turning powerfully into the next cycle. Notably, this explicit future planning was less evident in the data from small enterprises, potentially reflecting their more constrained resources and impacting strategic foresight, which has been seen in other empirical studies regarding IT strategy (e.g. Kling et al., 2025).

Limitations

However, several limitations warrant consideration. First, the translation of interviews from Chinese to English introduces potential interpretative challenges, particularly regarding culturally specific concepts like data protection and privacy. The sentiment analysis, based on the translated text, may not fully capture the nuanced emotional content of the original Chinese responses. Second, while our peer-to-peer research approach helped mitigate cultural barriers, it relied heavily on student co-researchers, potentially introducing sampling biases. Furthermore, the relatively small sample size of 20 interviews and the regional context of Hangzhou limit the generalisability of the findings across all of China. Third, our flywheel model is developed from qualitative data analysis, identifying patterns and relationships between factors influencing AI adoption. As such, it describes observed dynamics and associations rather than establishing definitive causal links between the framework components. Finally, this study provides a cross-sectional snapshot of AI adoption. Given the incredibly rapid pace of change in AI capabilities and their organisational integration—often described as 'AI eating the world'—a longitudinal study would be crucial to track how these flywheel dynamics evolve over time, how adoption barriers shift, and how organisational strategies adapt to ongoing technological advancements.

Summary

Our analysis of the 20 interviews, conducted with careful attention to Guanxi and Mianzi, reveals distinct patterns in AI adoption perceptions and implementation across different organisational contexts in China. Addressing our first research question about employee perceptions, we found predominantly positive sentiments toward AI adoption across all organisational contexts, with employees emphasising operational benefits and efficiency gains. This positive outlook persists even in organisations facing significant implementation challenges, suggesting a broader cultural acceptance of AI technology that transcends individual organisational contexts.

Regarding our second research question about the influence of organisational size, influence, we identified clear patterns in both adoption approaches and implementation challenges. Large enterprises demonstrate comprehensive AI integration across multiple business functions, particularly in the manufacturing and finance sectors, while medium-sized enterprises focus on specific applications like data analysis and decision support. Small enterprises, despite resource constraints, primarily target customer-facing AI applications. Our suggested flywheel model contributes to understanding China's high AI adoption rates while acknowledging the complex interplay between technological optimism and practical implementation challenges. This research underscores the critical need for technology adoption frameworks to incorporate contextual sensitivity, demonstrating how national

cultural and policy environments can fundamentally alter organisational responses to innovation barriers and shape adoption pathways, exemplified here by the pragmatic, efficiency-focused approach to AI observed across our sample.

For managers leading large enterprises, the key is leveraging organisational scale and resources to fully harness these accelerators. This involves actively aligning with national AI strategies to secure funding and partnerships, and utilising hierarchical structures common in the cultural context to drive implementation efficiently. Managing the flywheel spokes means focusing positive perceptions on complex, high-impact applications that demonstrating strategic value; cultivating barrier tolerance by planning for and investing in overcoming significant technical integration and data quality challenges (key friction points); making substantial investments in training and competency not just for skills but crucially for managing employee resistance and adapting roles (addressing human-centred friction); and developing robust, long-term future planning to guide continuous integration and maintain strategic momentum.

Conversely, for managers in SMEs, the approach must be adapted to resource constraints, which constitute the primary friction. While still benefiting from culturally grounded optimism towards technology, SMEs should strategically tap into niche or regional policy support. Future research could address the limitations of this study through larger samples, structured interviews or comparative case studies using Qualitative Comparative Analysis. Engaged scholarship might also reveal interesting results. Cross-cultural studies comparing AI adoption patterns between China and other regions, such as Germany, could illuminate how cultural and institutional factors influence adoption rates of AI.

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