

**Analysing the Impact of Regulatory and Cultural Factors on Recent Graduates
Initiating AI Technology Startups in China's Urban Centers**

A Doctor of Management Thesis

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Abstract

This thesis examines the roles played by regulatory frameworks, technological infrastructure, cultural expectations, and educational background in shaping the entrepreneurial experiences of recent graduates who start artificial intelligence (AI) companies in urban centres in China. The research employed a sequential exploratory mixed-methods approach, collecting survey data from 150 AI startup founders and conducting in-depth interviews with 15 participants. Quantitative results indicate that perceived technology infrastructure and regulatory understanding are strongly associated with self-reported startup success within this sample, while educational background shows a weak or negative association. Qualitative analysis identifies six overlapping themes: regulatory complexity; funding access and strategic dependencies; cultural narratives and entrepreneurial identity; gaps in entrepreneurial education; infrastructure and digital inequality; and ecosystem navigation and strategic adaptation. The thesis proposes a Layered Ecosystem Pressures Model to interpret how institutional, ecosystem and founder-level pressures shape entrepreneurial agency. The study applies institutional theory, entrepreneurial ecosystem theory and resource-based perspectives to interpret how graduate founders experience layered pressures in early-stage AI venture formation. It concludes that AI entrepreneurship in China is shaped not only by technological opportunity, but also by perceived regulatory clarity, access to infrastructure, cultural legitimacy and the practical agency of recent graduate founders.

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1. Introduction

1.1. Overview of the Research Problem

The central problem addressed by this thesis is that recent graduates who try to create AI start-ups in China occupy a particularly exposed position: they enter a capital-intensive and tightly regulated sector with technical knowledge, but often without mature business networks, policy literacy, managerial experience, or the institutional legitimacy enjoyed by established firms and experienced entrepreneurs. The study therefore focuses less on AI entrepreneurship in general than on how this specific founder group interprets and navigates regulatory uncertainty, cultural expectations, resource constraints and ecosystem support in major Chinese urban centres.

The topic also emerged from the researcher's professional and educational exposure to engineering, innovation and management. This background shaped the practical orientation of the project: the thesis is concerned not only with explaining barriers, but also with identifying how universities, incubators, policymakers and founders can respond to the practical difficulties encountered by technically trained graduates attempting to commercialise AI-based ideas.

1.1.1. Introduction to AI Startups in China

The concept of Artificial Intelligence (AI) has brought about a massive change to economies and technology across the globe. China, like the rest of the world, is not left behind in the development of such technology. China has also actively advanced AI research, venture funding, and AI markets, the goal of which is to become a global AI powerhouse. The Chinese AI startup ecosystem has grown exponentially throughout the last ten years, owing to government backing and the rise in the use of AI solutions (Roundy, 2022). Ever since AI has entered the healthcare industry, finance, production, and smart cities, the need for innovation has been relatively high, creating many opportunities for start-up ventures. Nonetheless, it aligns with the high challenges of developing a successful AI start-up firm in the Chinese market, especially among young enthusiasts who sometimes are deficient in capital, experience, and legal regulations that are relevant to starting a business (Basole and Accenture, 2021). Despite ensuring inclusivity and innovation, policy rhetoric and institutional realities are conflicting on graduates in China, as they contend with ambiguous regulation, lack of guanxi, and inherent inaccessibility to capital, inhibiting meaningful entrepreneurial discretion (Zenglein and Holzmann, 2019).

The overall culture of startups in China has been changing alongside its economic and technological development, with Beijing, Shanghai, and Shenzhen being the strategic points of AI development. These cities boast of AI incubators, AI research labs, and government innovation districts to promote innovation and spur growth. Although the ecosystem of AI startups in China is growing, its competitive structure, concentration of platform resources, and policy-mediated access to support can create entry barriers for newcomers, particularly recent graduates with limited organisational legitimacy and business networks. Although these characteristics are typical of the tradition of Silicon Valley, namely large capital flows into funding high-risk and innovative startups, in China, AI entrepreneurship is heavily influenced by government policy, the law, and small monopolies.

1.1.2. Growth of AI Technology and Startup Culture in China

Government incentives, corporate support, and technological development have facilitated the growth of AI in China. AI startups are appearing across multiple sectors, with applications in areas such as machine learning, natural language processing, robotics, and computer vision (Hannigan et al., 2022). Startups in automation, fintech, and medical diagnostics have emerged because of the increased demand for intelligent systems that improve efficiency and the quality of decision-making. These developments have created new business opportunities and opened up possibilities for AI-based startups to evolve progressively (Schulte-Althoff et al., 2021).

The culture of AI startups in China has been greatly affected by government policies. The Made in China 2025 programme was initiated in 2015 as a ten-year plan to improve the country's manufacturing industry through artificial intelligence (AI), big data, and automation. In this context, AI startups have opportunities to use technological breakthroughs to achieve national goals through government-funded projects and research collaborations (Gueguen et al., 2021). This also reflects the Silicon Valley-like nature of China's AI startup ecosystem, as key market players include Alibaba, Tencent, and Baidu (Torres and Godinho, 2022). These firms lead the AI sector and hold dominant positions in major areas such as low-cost cloud computing, proprietary datasets, and machine learning software. They play an essential role in supplying technological inputs, but dependence on them creates a range of strategic interdependencies that do not necessarily enable AI startups to become self-sufficient. In addition, large players tend to acquire AI startups

while they are still young companies, and stand-alone ventures often have limited opportunities to grow without collaborating with a major firm (Rane et al., 2024). These dynamics therefore offer both opportunities and challenges to recent graduates who want to develop AI startups, as they must navigate an industry dominated by established firms.

1.1.3. Challenges Faced by Recent Graduates in the AI Startup Ecosystem

Nevertheless, recent graduates can struggle to establish AI startups in China despite the market's scale and rapid growth. Some of the current challenges include regulatory requirements, cultural barriers, resource scarcity, and market competition. Experienced business professionals often have extensive networks of contacts and open channels to multiple funding options. However, for young graduates, operating an AI firm comes with a set of challenges such as obtaining funding, complying with regulations and certification. The next issue is regulation as regulatory and legal requirements could pose challenges when Chinese firms co-operate with their foreign counterparts to set up a new AI company. AI startups need to follow data protection, cybersecurity and data governance regulations (van der Vlist et al., 2024). China's Data Security Law and relevant data governance regulations introduce procedures such as data classification, security assessment, data localisation (under certain circumstances), and personal information protection, making legal compliance more difficult for AI companies dealing with big data. Moreover, AI application startups in the areas of facial and vocal recognition, financial and medical analysis need to consider specific licensing and permission issues. The primary lack of legal awareness and human resource allocations among today's graduates does not enable them to skillfully navigate these regulations, and makes them less competitive than larger groups with professional legal advisors.

Second, there are also risk-averse perceptions among young graduates to start a business and be involved in risky entrepreneurship, due largely to insecurities, which could be contextualised with traditional Chinese culture where failure is not generally perceived as success. Even then, many graduates remain prepared to take on the entrepreneurial challenge. However, many of them are still driven by cultural demands to find employment opportunities instead of running their own start-up business (Arenal et al., 2020). Young entrepreneurs can raise funds to establish AI startups from their own savings, university funding or government grants, but their financial resources are usually limited without other sources of support (Lundvall and Rikap, 2022). Finally, there is also the issue of

market saturation, as China's AI market is already highly competitive and highly saturated by big companies and technology startups. Nascent startups may try to access the market with new markets, products, or business models, but will find it challenging without financial backing by capital-rich investors.

1.1.4. Importance of Study

Previous studies of the Chinese AI industry have mainly examined large enterprises, national innovation policy, AI governance, or the general development of entrepreneurial ecosystems (Arenal et al., 2020; Roberts et al., 2021; Lundvall and Rikap, 2022). Despite providing some important background information on the institutional environment related to AI entrepreneurship activities, these studies do not focus on the activities of the new generation of entrepreneurs, who face some challenges when they enter the market in the early stage. Such research is lacking in the existing literature, especially qualitative research on the challenges faced by young AI entrepreneurs in financing, regulation and cultural aspects. Such challenges must be addressed to build better policies and institutional settings to ensure more equal chances for AI entrepreneurship in China.

The current research is therefore significant as it provides primary data on the experiences of founders, with a postgraduate background, who has tried to set up AI firms in China. By studying young AI entrepreneurs, rather than established enterprises, this thesis aims to understand the particular challenges they face and how they resolve them (Knox, 2020). This research addresses a knowledge gap. Existing research is oriented towards more established AI firms, and relatively little has been said to the graduate-run startups and the different regulatory, funding and cultural issues that they can confront. As such, this represents a serious gap in the knowledge of the early phases of entrepreneurship. Hence, this research aims to bridge this gap by offering a more holistic view of opportunities and challenges facing emergent AI startups. This study, in turn, advances theory and provides insights to inform practice.

1.2. Research Aim, Objectives, and Questions

The research aims to analyse the challenges and opportunities faced by recent graduates starting AI technology startups in urban China. It seeks to fill this gap by employing a sequential exploratory mixed-methods design to understand how China's AI startup

ecosystem can be strengthened to support new graduate entrepreneurs. Consequently, the following three research objectives were developed:

- To identify and analyse the regulatory and cultural challenges of recent graduates in AI startups.
- To examine the support systems and growth opportunities in China's AI startup ecosystem.
- To formulate a strategic framework for new graduates to navigate the AI startup landscape.

The following are three research questions developed:

1. What are the key regulatory and cultural challenges faced by recent graduates starting AI startups?
2. What support structures exist, and how effective are they?
3. What strategies can be developed to help graduates overcome obstacles and succeed?

1.3. Importance and Significance of the Study

1.3.1. Academic Significance

The study is significant for multiple disciplines such as entrepreneurship, regulation, and innovation management (Hua and Huang, 2021). There is a gap in the literature regarding the new breed of AI graduates' entry into entrepreneurship (Yu, 2023). Existing research has largely centred on technical transformation, competition and AI economy activities, while little research has explored recent graduates' role in entrepreneurship in the AI economy. Consequently, this thesis brings new understanding of the issues of entrepreneurship, regulation, and AI solutions in the Chinese market. It provides valuable insights into how young entrepreneurs navigate legal, cultural and financial constraints in their efforts to promote innovation and establish a new enterprise in technology-based industries (Kitsara, 2022). The theoretical contributions of the study are based on the Resource-Based View (RBV), Entrepreneurial Ecosystem Theory and Institutional Theory to show how new-generation entrepreneurs obtain, utilise and mobilise resources as part of their operations in the formal market environment.

The other key contribution of this work is the discussion of regulatory frameworks influencing AI entrepreneurship (Xie et al., 2019). Laws regarding AI startups in China are complex and ever-evolving, particularly in areas of privacy, AI ownership, AI ethics and compliance. While similar legal frameworks have come to the fore, there has been a heavy focus on the fit between these legal arrangements and the policy goals and how they have impacted large companies, and little discussion about how startups, especially those in the initial stages of their operations, respond to compliance regulations (Zahra, 2021). Through this gap, this thesis provides an in-depth discussion of the regulatory challenges faced by AI entrepreneurs, and offers ways in which policy and entrepreneurship interact in a fast-changing AI startup ecosystem.

The research also sheds light on the sociocultural dynamics of AI entrepreneurship, in addition to entrepreneurial and regulatory factors. The sociocultural context of Chinese entrepreneurship includes long-standing concerns with hierarchy, relational trust and *guanxi*, while also changing rapidly as younger founders engage with digital innovation and global startup models. While most of the Western literature associated the term "startups" with individual innovation and opportunities to generate wealth, China has become a potential market for AI startups, which operate under different socio-political circumstances in which government regulatory power plays an important role (Farley et al., 2020). As a result, in addition to contributing to the body of knowledge on the impacts of culture and governance on AI startups' performance, this study proposes a framework applicable to similar socio-economic conditions in other risk-based economies.

1.3.2. Practical Significance

This study has several implications for stakeholders such as policy makers, investors, start-up incubators and educational institutions (Que et al., 2019). The findings of the study help stakeholders identify the challenges faced by recent graduates of setting up AI start-ups and how they can address these challenges. This may encourage them to explore new ways of supporting AI start-ups in the evolving economy. The study also assists policymakers in identifying policy frameworks that need to be changed to facilitate AI start-ups by recent graduates. China is proactive in tackling AI challenges in Made in

China 2025 and the Next Generation Artificial Intelligence Development Plan (Li and Branstetter, 2024).

The research also contributes to the knowledge of investors, incubators and accelerators who fund or work with AI startups. Venture capitalists and angel investors might be cautious about investing in organisations led by recent graduates due to concerns about inexperienced management, regulatory and financial risks (Ashta and Herrmann, 2021). Because the study collected and analysed data on the successes and challenges faced by AI startups, investors can better recognise the risks and opportunities that may apply to an AI startup. Similarly, start-up incubators and accelerators can tailor their practices to the specific needs of young organisations, particularly in terms of regulatory business practices, investment opportunities and market development strategies.

In the context of universities, the study provides recommendations on how universities can support students in AI entrepreneurship. While leading Chinese universities in AI are rated as the world's best in terms of AI research, they often lack exposure to business management, policy and financing to build AI startups (Gao et al., 2024). By analysing surveys of AI startup founders, the study identifies opportunities for skill development that may be met through entrepreneurship education, involvement in high-tech start-up incubation, and industry partnerships. This type of educational resources will also make academic AI programs more sustainable and give graduates the technical and business skills needed to develop a startup (Shamim et al., 2019).

1.3.3. Economic and Technological Significance

The economic and technological significance of this research is not just for individual startups, as AI entrepreneurship is now crucial for China's innovation-driven development and national competitiveness (Cantú-Ortiz et al., 2020). AI has become an important part of Chinese economic planning, as the country seeks to lead the world in AI by 2030. Greater participation by young people is needed because startups play a significant part in supplying innovative solutions, sector-specific AI tools and distinct AI-driven business models. However, there are some challenges such as the lack of specific intervention programs for recent graduates (Akgun and Greenhow, 2022).

This thesis is aimed at informing economic and industrial policy debates by examining the hardships facing recent graduates trying to become entrepreneurs in the AI field (Yu, 2023).

If regulations continue to stifle young AI startups, while they also face difficulties raising funds and competing with more established players, this could result in a few key corporations monopolising the AI market in China, thereby constraining market competition and innovation (Geetha et al., 2024). This paper's findings can help policy makers to create more balanced AI policies where young technology startups are considered as valuable assets in the growing AI market, rather than as threats.

This study also has global implications for investment in AI startups by recent graduates. While the innovation is largely happening in China, there is increasing international interest in international collaboration, investment and trade in AI (Adam et al., 2022). While many Chinese artificial intelligence start-ups have entered into global markets, regulatory compliance, limited capital mobility and disputes with international partners inhibit their development. Analysing the learning experience and views of recent graduate hires can give insight to international investors, policymakers, and technology firms in collaborating or investing in Chinese AI start-ups (Pedro et al., 2019). The worldwide AI market is fiercely competitive and Silicon Valley, the European Union and other technology clusters actively support the development of AI start-ups. To stay competitive, China needs to empower its emerging artificial intelligence start-ups to invent, patent, and export their innovative products and services. This research examines AI strategies in China and the new start-up environment in a comparative context in terms of the strength and weakness with respect to the international market, and offers recommendations on how the start-up ecosystem can be improved.

The purpose of the present study is therefore to offer insights into research, practice, financing and technology issues in AI entrepreneurship. It contributes to the literature by focusing on recent graduate founders and by examining how policy, culture and ecosystem support are perceived in early-stage AI venture formation. Thus, the findings of the study could highlight the influence of regulation, culture and financing on AI startups, and help the government, investors, and education institutions make suitable decisions for the future direction of AI startups.

1.4. Research Context: Artificial Intelligence and Startups in China

1.4.1. Government Policies and AI Development

China's dominance of the AI field is driven by government policy and support, investment, and regulation. But unlike many Western nations, where AI development is more influenced by the strategies of private enterprise and independent research facilities, in China, AI development is heavily motivated by government ambitions for economic and security. In support of the growth and application of AI, the Chinese government has issued policies that aim to improve AI research and AI entrepreneurship (Jorzik et al., 2024). These strategies have been beneficial as they permit AI startups to be created. However, they also incorporate bureaucratic structures that can be difficult to navigate due to the lack of legal advice and funds to adhere to bureaucratic processes among many startups (Tomy and Pardede, 2018).

One of the most important policies allowing AI development in China is the Next Generation Artificial Intelligence Development Plan, which was published in 2017. This plan outlines how China intends to become a world leader in AI by 2030 through investment in research, development and deployment. In addition, Made in China 2025 is relevant to the wider industrial upgrading context in which AI start-ups seek opportunities in smart manufacturing, logistics and supply-chain management. These policy signals have helped cultivate an AI start-up culture, but the extent to which such support reaches recent graduate founders remains uneven.

Another important aspect of the Chinese policy landscape is the policy incentives for AI entrepreneurs. In this regard, the government can serve as a co-investor in AI projects through direct funding, subsidies, or government-sponsored venture capital and facilitates the funding of AI start-ups (Bhutoria, 2022). Many AI start-ups can access subsidised loans and incentives such as tax benefits and discounts in rent in AI innovation zones such as Zhongguancun in Beijing, AI Valley in Shanghai, and science and technology parks in Shenzhen. Incubators at the university level and government-run AI-centred challenges help young entrepreneurs with start-ups in the area of AI-based projects by connecting them with potential funding and business opportunities (Arenal et al., 2020). These subsidies play a crucial role in funding, though they may be allocated based on alignment with these state priorities, which may not prioritise startups pursuing commercial, as opposed to public-distributive, objectives (Lambert and Stevens, 2024).

However, there are also opportunities and challenges for new startups in adhering to AI regulations. China has also intensified its data security, cybersecurity and AI oversight measures, such as the Data Security Law (DSL) in 2021 (Yu, 2023). These laws mandate domestic data storage, security assessments, and government oversight in the use of AI applications, such as facial recognition software and financial and critical infrastructure models (Wu et al., 2020). Regulatory requirements can also create additional obstacles for AI startups, as they demand significant resources in legal and technical manpower. Also, software that uses critical data and monitoring technologies, or enables cross-border movement of goods, requires government permission to operate, making it hard for startups to scale their business (Kasneci et al., 2023). For AI startups built by recent graduates these policies can be particularly challenging due to time, resource and know-how requirements in adapting to changing regulatory requirements.

While government grants and policies are helpful, startups may have to still meet compliance requirements with the support of professional lawyers or policymakers, or work with legacy organisations that have compliance capabilities (Lundvall and Rikap, 2022). Therefore, the key concerns are regulatory incentives and compliance risks, which typify the entrepreneurial ecosystems of AI startups in China.

1.4.2. The Role of Market Leaders and Incumbents

Market leaders Alibaba, Tencent and Baidu influence the start-ups' AI ecosystems in China in terms of innovation, data supply and technology use (Allen, 2019). These market leaders have built massive tech ecosystems in AI, cloud computing, natural language processing, and machine learning, as well as AI-based consumer-facing products, which create challenges for direct competitors to penetrate most of the mainstream AI markets. Despite the emergence of AI supporting start-ups and small and medium enterprises (SMEs), the success of these market leaders poses issues related to innovation, market competition and ease of entry (van der Vlist et al., 2024). Entry barriers include a lack of access to data and processing power, which is crucial for high-level AI model training (Muganyizi et al., 2022). Large firms like Alibaba and Tencent have access to vast amounts of corporate and user data, which enable them to better train and tune models, and adapt algorithms (Knox, 2020). In particular, startups often live in ecosystems of big firms, including Alibaba Cloud and Tencent Cloud, to access a range of services. This leads to a risk of "lock-in" as startups

might find it difficult to develop AI-specific services and products unrelated to existing companies' units, data or investments.

Market positioning and consumer acceptance are also key issues. Most AI startups focus on developing specific products and services within smart healthcare, industrial AI and finance. However, it is challenging to compete with well-known brands, many of which have already won over customers' trust (Chen et al., 2021). Tech giants acquire and absorb valuable AI startups at an early stage of development to mesh them with their own technology ecosystems. On the one hand, this offers an exit option for some startups, but on the other hand, it also restricts their opportunities for future growth (Pan et al., 2023).

However, there are still opportunities to differentiate: startups can focus on niches, compliance or ethical AI startup development. Startups can capitalise on these opportunities by recognising areas where the market leaders are not so active and then segmenting the market niches, like AI for sustainable practice, AI for ethical compliance and vertical AI solutions for SMEs (Tula et al., 2024). Thus, successful start-ups are defined by partnership and co-operation with incumbents and also by protecting their innovation areas.

1.4.3. Educational and Institutional Support for Startups

Universities, incubators and accelerators supply institutional resources, technical support, funding and other resources needed by young entrepreneurs to Chinese AI startups. The majority of leading Chinese universities, such as Tsinghua University, Peking University and Zhejiang University, established AI research institutes that work with startups to develop and implement AI algorithms and solutions (Zenglein and Holzmann, 2019). These institutions are a key source of knowledge, offering graduates with expertise to have access to the latest research in the field of AI, academic consulting services, technical services and relevant technologies.

University-based incubators can help AI startups by providing mentoring, workspace, networking and access to early-stage resources. In China, these initiatives often operate

alongside local-government innovation programmes, which means that they may provide policy-related opportunities as well as practical entrepreneurial support. However, not all initiatives are designed for small experimental AI start-ups at the earliest ideation stage. This distinction matters for recent graduates, who may need basic business, legal and investor-readiness support before they can benefit from more selective accelerator programmes.

The incubator programs provide many valuable opportunities, but these are not always successful in providing targeted support to novice entrepreneurs, especially graduates. Furthermore, not all AI entrepreneurship education in China focuses on training startups in business management, investment negotiation, and legal issues, which exposes many founder CEOs to entrepreneurial risks when setting up startups (Gao et al., 2024). Young AI teams could benefit from greater entrepreneurship training and mentoring as well as access to computing resources to better support AI entrepreneurship (Hua and Huang, 2021). Therefore, universities and incubators can do more to nurture new talent to navigate the challenging AI market in China.

1.5. Research Methodology Overview

1.5.1. Research Approach

In order to investigate the challenges and opportunities confronting recent graduates in China who set up AI startups, this research design adopts a mixed-methods approach - in which both qualitative and quantitative approaches are used in a pragmatic way. This research strategy is particularly applicable as AI entrepreneurship may be seen as multi-dimensional, with institutional regulations, cultural factors, structural factors, and individual agency intersecting in various ways. Holding to the principles of one methodological tradition may result in analytical insight or lack of depth.

The qualitative component is of an inductive nature and seeks to explain the experiential insights, perceptions and coping mechanisms of recent graduate entrepreneurs. Inductive qualitative inquiry is conducive to theory generation rather than hypothesis testing, which is essential in a rapidly changing policy and technological environment, like the one that encompasses China's AI industry (Greener and Martelli, 2015). Changing funding policies, unclear regulatory frameworks and shifting cultural norms requires flexibility in the

research design, so that patterns and meanings can be inductively described from the participants' experiences (Maylor et al., 2017).

The quantitative element of this research adds to this inductive learning by capturing larger patterns, relationships, and trends in a larger sample of AI entrepreneurs. The statistical analysis of the survey allows the study to explore hypotheses based on factors such as knowledge of regulations, access to infrastructure, education, and self-reported startup success. While the qualitative data illuminated how participants perceived and experienced challenges, the quantitative data provide an analytical approach to explore associations between the constructs and self-reported startup success.

Rather than privileging one method over another, the current study adopts a sequential exploratory mixed-methods design, and integrates the qualitative and quantitative findings at the analysis stage. This design enhances the analysis through triangulation, heightened validity and reduced methodological bias. As such, the mixed-methods design allows for contextual detail and interpretation as the empirical data are aligned with the purpose of the study, which is theory and practice development in the field of AI entrepreneurship.

1.5.2. Data Collection Method

Primary data were collected through two main data collection techniques: semi-structured interviews and a survey questionnaire. The qualitative part of the research is semi-structured interviews, which can yield contextualised and detailed stories of entrepreneurial decision-making, regulatory environment and cultural environment. These interviews allow respondents to speak in their own language, and enable the researcher to probe their experiences about key issues of regulators, financiers, educators, and ecosystem participation (Ang, 2013).

The interviewees were young founders of AI start-ups in major Chinese cities. This type of sampling offers an analytical focus because it targets founders who have a low degree of prior business knowledge and networks. They were therefore not corporate spin-offs or state-sponsored enterprises. Semi-structured interviewing was particularly useful for addressing delicate topics such as regulatory uncertainty, the use of *guanxi*, and legitimacy, as structured research tools can hinder disclosure (Evans, 2017).

The quantitative arm involves a questionnaire survey of a larger sample of AI startup founders. The questionnaire also measures demographic information, education, awareness of regulations, infrastructure capacity, and early outcomes of the ventures. The survey data provide a structured comparison with the qualitative themes of patterns found in the qualitative data analysis. Together, the two methods support methodological complementarity.

1.5.3. Data Analysis Method

The data from the qualitative interviews are analysed using thematic analysis that provides an approach to identifying patterns of meaning across diverse entrepreneurial stories. The analysis is conducted according to a structured approach involving familiarising oneself with the data, generating initial codes, developing themes, reviewing themes, defining and naming themes and producing the final analysis (Braun and Clarke, 2022). Coding is an iterative process that helps identify and minimise conceptual overlap while maximising coherence, and themes are refined in terms of the research aims and relevant theoretical understandings.

Quantitative survey data were analysed using descriptive and inferential statistical analyses with SPSS software. Reliability checks, correlation analysis and regression analysis were used to explore associations between the constructs and self-reported startup success. These analyses provide structured quantitative patterns to be interpreted alongside the qualitative themes.

Integration is done at discussion level where analysis of qualitative results is juxtaposed with quantitative trends to develop a more complete interpretation of AI entrepreneurship by recent graduates. These techniques bring the benefits of mixed-methods approaches into the analysis and increase contextual understanding, while keeping the findings empirically grounded and analytically cautious.

1.6. Structure of the Thesis

This study consists of six chapters which conceptualise the research problem and objectives, theoretical analysis, research design and methods, empirical analysis, discussion, and conclusion. This approach helps to establish a flow, enabling the reader to connect the development of the study in a logical way, and to keep a coherent line of

argument going through the thesis. In general, the chapters tackle the research questions and offer an in-depth understanding of the opportunities and challenges faced by graduates who have started AI start-ups in China.

- Chapter 1: Introduction - The introduction chapter establishes the research problem, its significance and describes the Chinese AI start-up ecosystem. This chapter provides an overview of government policy for AI entrepreneurship, the influence of large tech firms, and institutional resources for startups. It also identifies the major challenges in regulation, financing, and cultural challenges faced by recent graduates.
- Chapter 2: Literature Review - Chapter 2 examines literature about AI startups, Chinese entrepreneurship, regulation of AI, and culture and entrepreneurship. This chapter introduces relevant theoretical approaches, such as the Resource-Based View (RBV), Entrepreneurial Ecosystem Theory, and Institutional Theory. This chapter explores the legal and political environment of AI start-ups, competition in the Chinese technology industry, and cultural factors that might impact entrepreneurship. It also reviews gaps in the literature such as the lack of attention paid to virtually inexperienced graduates and their experiences in China's AI start-ups. The review thus forms the foundation for the research questions and lends justification for the analysis of the study.
- Chapter 3: Research Methodology - Chapter 3 describes the research methodology of this study. It introduces the mixed-method approach and provides an overview of how qualitative and quantitative data are integrated in the study to understand the experiences of young AI entrepreneurs. This chapter provides details of the data collection methods, which involve semi-structured interviews with young entrepreneurs who have created AI start-ups and a questionnaire for a larger cohort of AI start-up founders. It outlines the sampling, ethical considerations, and interviewing and recording methods used. Finally the analysis of data is discussed, which for the semi-structured interviews uses thematic analysis and for the survey questionnaire involves descriptive, correlation and regression analysis. These methods help eliminate bias and account for contextual and empirical observations respectively.
- Chapter 4: Data Analysis and Findings - Chapter 4 outlines the analysis and results of the quantitative survey and semi-structured interviews. For quantitative data, the chapter presents descriptive stats, reliability and validity test, correlation analysis and regression

analysis. The qualitative part explores the key themes that emerged from the thematic analysis and how recent graduate AI entrepreneurs view and deal with regulatory, financial, market, infrastructural, educational and cultural challenges. Potential opportunities, including government policies, engagement with industry and opportunities in the changing AI market scene, are also examined. The research findings are complemented by statistical data and quotes from participants, enabling the chapter to discuss quantitative patterns and qualitative insights.

- Chapter 5: Discussion - Chapter 5 translates the study's findings in the context of theoretical research on AI entrepreneurship, regulatory contexts, and cultural influences on startups. The discussion seeks to interpret how the results are consistent with, extend, or conflict with theoretical perspectives such as the Resource-Based View, Institutional Theory and the theory of Entrepreneurial Ecosystem. It also highlights the policy, investment, incubation and education implications of the study for fledgling AI entrepreneurs. This chapter outlines how the study adds to the body of knowledge, bridging theory and empirical findings.

- Chapter 6: Conclusion and Recommendations - Chapter 6 explores the key findings and explains the contribution to knowledge, as well as how the research findings contribute to AI entrepreneurship in China. The chapter explains how the study has answered the research questions using the mixed-methods approach. It then proposes the reforms to improve the governance of AI startups, funding support and entrepreneurship education for young AI entrepreneurs. Lastly, it provides suggestions for future studies, including longitudinal research, ecosystem comparisons with other global AI ecosystems, and research that explores gender and diversity issues in AI entrepreneurship. This chapter wraps up the thesis by summarising its contribution to academic research, policy development and the industry.

2. Literature Review

2.1. Introduction

The literature review is important for the thesis because it establishes the context for the research and places the study within the intellectual tradition. It begins by summarising the current state of knowledge to show that more research is necessary into the challenges and opportunities for postgraduate entrepreneurs in the early stage of AI startups in key Chinese cities. Given the rapidly changing nature of technology and regulatory environment, it is important to investigate how these two factors impact the new breed of graduates seeking to start a business. The literature review draws upon past research to explore how other external factors, such as the regulatory environment, culture, and financial and infrastructural factors, play a role in the success of AI startups in China. Then, based on this review, the chapter builds the theoretical and empirical foundation for the research questions and research methodology.

2.1.1. Purpose of the Literature Review

A literature review is used to discuss the relevant literature pertinent to the research topic. This includes the collection and integration of information from sources such as journals, government reports, policies and industry reports regarding the policies, culture and environment of startups for young Chinese graduates. The aim of the current review is to provide a theoretical framework for the topic. This review includes theories from the Resource-Based View (RBV), Institutional Theory and Entrepreneurial Ecosystem Theory.

The review of the literature is also concerned with various views and arguments. Some studies have argued that the Chinese government fosters the creation of startups through the provision of capital, tax incentives and incubation networks, while others have argued that legal policies, bureaucracy and political control are barriers for the establishment of startups. As such, this chapter examines government policies and recent graduates in the field of AI start-ups. In addition, through exploration of the commonalities and differences in the literature, the review is able to better understand startup ecosystems.

2.1.2. Scope of the Literature Review

The literature review is broad in its approach while also focusing on factors impacting artificial intelligence startups in China. This includes regulations, culture, funding and technology. The study addresses these factors in the context of Chinese macro-level

business policies, applications and global economic growth. Additionally, the review explores the development of AI startup ventures in China in comparison to other regions, such as Silicon Valley in the US and the European Union, to identify the distinctive challenges facing Chinese start-ups.

Due to the changing nature of business environments in China, which are influenced by technology and policy, the review draws on publications mainly from the past decade, and in particular since 2018. That means the review is relevant to a business environment where the economic environment is changing and new policies are emerging. But previous literature relating to key concepts, venture development, historical debates on economic opportunity and other pertinent theory is also included as necessary. The review thus creates a sound grasp of the research problem through the inclusion of recent empirical research and previous theoretical work.

2.1.3. Structure of the Literature Review

The literature is organised thematically in order to examine and introduce the factors that impact the success of AI startups of recent Chinese graduates. This structure is purposeful as it enables the study to examine the factors that help and hinder young entrepreneurs. In this chapter, the theoretical approaches of the study are discussed first. This includes the Resource-Based View (RBV), which explains how firms can build, obtain and develop internal and external resources to gain a competitive advantage. This is followed by the Institutional Theory, which looks at the impact of government and institutional policies on the business environment, and Entrepreneurial Ecosystem Theory, which looks at the external environment of entrepreneurial activities.

After this theoretical overview, the review of literature presents an overview of the overall regulatory landscape in China. The effects of policies such as AI governance policy, intellectual property law and licencing, on startups are also considered. The regulatory environment is examined to understand how policy affects AI entrepreneurship. Next, the review examines the availability of financing and funding opportunities, such as venture capital and funding from external parties, to support AI startups. It also reviews the problem of funding and the suitability of current financing strategies for young entrepreneurs. Lastly, the review highlights areas for future research. They relate to the need for further AI-based quantitative, and AI-based qualitative, research on young

graduates in AI entrepreneurship; insufficient understanding of how regulation and culture interact in entrepreneurial activity; and an absent research in regards to strategies adopted by young AI entrepreneurs to resolve structural issues.

2.2. Theoretical Frameworks

The theoretical framework is important to setting out the opportunities and risks faced by new generations of university graduates in China who want to found an AI company. The following theories explain how to interpret the influence of resource, policy, market and culture on entrepreneurship. The present study applies the Resource-Based View (RBV) Theory, the Entrepreneurial Ecosystem Theory and Institutional Theory to build a classification of internal and external factors that affect the success of startups.

The three theoretical lenses are used selectively rather than as parallel claims to broad theoretical contribution. Institutional theory is the primary lens because the study is centrally concerned with regulatory ambiguity, legitimacy and formal/informal rules.

Entrepreneurial ecosystem theory is used to explain the distribution of support, infrastructure and network access across urban innovation settings. RBV is used more cautiously: it is relevant where founders seek to assemble human, technical and relational resources, but it is less suited to explaining external regulatory constraints faced by very young ventures. This limitation is important because the thesis examines nascent firms rather than mature organisations with established strategic resource bundles.

This critical positioning addresses a risk of theoretical overextension. Rather than claiming equivalent contributions to RBV, ecosystem theory and institutional theory, the thesis uses these perspectives to frame an empirical investigation of graduate AI entrepreneurship and to interpret how founders perceive and respond to layered pressures.

2.2.1. Resource-Based View (RBV) Theory

Resource-based view (RBV) theory is one of the most commonly applied theories in modern strategic management and entrepreneurship (Adam et al., 2022). It suggests that the key source of competitive advantage for a firm is mainly derived from its resource ownership, creation and exploitation. First developed by Wernerfelt (1984) and further popularised by Barney (1991), RBV suggests that for a firm to gain competitive advantage, it must possess "valuable, rare, and inimitable" resources. This theory accounts for how new graduates can take advantage of capital, technical expertise, and industry partnerships to build competitive businesses. RBV has significant implications for AI startups as the

industry is knowledge-based. Unlike traditional manufacturing and retail businesses, AI firms are heavily reliant on people, such as machine learning experts, data scientists and programmers (Rane et al., 2024). A typical problem is that fresh graduates may have deep knowledge of technology but not business skills to deal with the challenges of startups. As a result, an empirical model that explains success of AI startups should also consider factors such as founders' industry-specific knowledge and readiness for available resources such as finance, alliances and mentoring.

The RBV model can also explain the relationships between internal resources and capabilities and external factors, such as the policies of government for supporting startups and the ability to provide venture capital to entrepreneurs (Zahra, 2021). One of the most basic resources in the RBV is financial capital. This resource is a matter of particular concern for new graduate AI entrepreneurs interested in founding start-ups. Seasoned entrepreneurs may boast of more experience and expertise but new graduates tend to struggle to secure venture capital and access funding. As mentioned by Murzacheva and Levie (2020), this shortcoming can force them to pursue other sources of finance, grants and angel investments. RBV is therefore helpful in showing that finance is a significant threat to AI startups and in recognising the need to find ways to do more with less. While RBV helps to show how resources can affect startup evolution, it does less to emphasise the influence of external factors. But AI startups also have to deal with the regulatory environment, market forces and new technology.

A limitation of RBV in this thesis is that it was developed primarily to explain firm-level competitive advantage in organisations that already possess resources and routines. Recent graduate AI start-ups often lack such accumulated resources. The theory is therefore used here as a sensitising lens for resource constraints rather than as the main explanation of start-up success.

2.2.2. Entrepreneurial Ecosystem Theory

Entrepreneurial Ecosystem Theory (EET) is the environment that enables startups to establish and grow. It demonstrates how the growth of startups is influenced by a variety of ecosystem factors, such as government intervention, incubator/accelerator support, competition and resource availability. According to Tomy and Pardede (2018), while the analysis of self-reported entrepreneurial success should primarily focus on firm-specific competencies, it is important to understand the broader entities and systems that form

entrepreneurial ecosystems. This theory is important in understanding the role of various actors in the Chinese AI startup ecosystem, particularly government, technology platforms and financial institutions. The Chinese government plays an important role in the market system, through policies and funding arrangements, and strategies (Byrd, 2019).

The Chinese government is highly active in innovation policy compared with more market-led systems. China leverages national plans, local funding mechanisms, technology parks and incubator programmes to encourage new technology firms, including AI-related ventures. These initiatives bring together both capital and infrastructure resources for entrepreneurs, addressing entrepreneurs' challenges in accessing finance, space and mentoring. Market and competition also play a role in the entrepreneurial ecosystem. Competition in AI startups in China is especially fierce due to the presence of existing internet and technology platforms such as Alibaba, Tencent and Baidu. These firms have dominant positions in the market and can control access to critical resources such as computing power, cloud computing, data and exclusive data sets (van der Vlist et al., 2024). This is a major threat to startups as larger, established firms already tightly control customers, funds and licenses.

There are some restrictions on what AI start-ups can do, but surveys and case studies on Entrepreneurial Ecosystem Theory recommend strategic alliances to deal with these issues (Cavallo et al., 2019). For profit-making AI startups, rather than providing services themselves, they would rather sell their products to large companies or co-evolve with other business models. This enables them to enter larger markets while avoiding competition. While EET highlights the role of ecosystem and market conditions for AI startups, it lacks a focus on institutional and legal factors of Chinese entrepreneurship. Therefore, it is important to include Institutional Theory to complement this.

Entrepreneurial ecosystem theory is valuable because it directs attention to incubators, funding, infrastructure, universities and policy support. Its limitation is that ecosystem accounts can become overly structural, treating entrepreneurs as recipients of support rather than active agents. This study therefore uses the theory alongside interview evidence about how founders interpret, negotiate and sometimes work around ecosystem constraints.

2.2.3. *Institutional Theory*

Another relevant critical theory for the business world is Institutional Theory, which examines the impact of institutional (formal and informal) pressures on organisations (Peters, 2022). This approach considers the regulatory environment, culture and bureaucratic challenges facing AI startups in China. Institutions are "the rules of the game" that govern economic and social interactions according to North (1990). These rules in China are largely determined by governance (including government and the state), and culture. Regulation is one of the major challenges facing AI startups (Roberts et al. 2021). China currently has some of the most stringent laws on data protection, information security and AI. While regulatory compliance is important globally, in the Chinese market regulatory compliance is more centralised and dynamic in nature than in the West.

These regulatory requirements can be costly for startups, in part because there is still a lack of clear interpretation of national security, ethical code of AI, and data localisation rules that regulate startups. The social pressures, policies and client expectations also pose major challenges for AI start-ups in China. This research builds on previous studies by drawing upon the Resource-Based View (RBV), Entrepreneurial Ecosystem Theory (EET) and Institutional Theory (IT) to explore how this group of recent university graduates in China view and interact with the current AI landscape. All theories have their merits and drawing on multiple theories offers key insights into both the internal and external development of organisations.

Institutional theory is especially relevant to this thesis because AI ventures in China operate in a setting shaped by formal regulation, local implementation practices, cultural expectations and legitimacy requirements. Its limitation is that it can underplay founder agency if institutions are treated as fixed constraints. The qualitative strand therefore examines how graduates make sense of institutional ambiguity and how they adapt their strategies in response.

2.3. Regulatory Environment for AI Startups in China

The regulatory environment in the Chinese market is another important factor impacting the emergence, growth and diversification of AI startups (Roberts et al., 2021). The Chinese government has recognised AI as a strategic sector, and has implemented a series of measures to promote the development of AI businesses. It has also introduced regulatory measures to govern development of the industry. The core components of China's

regulation of AI include the Made in China 2025 strategy, privacy regulations, AI governance and standards, regulations governing AI businesses and funding policies. These help China to strengthen its leading position in the field of AI technology competition, but these policies also create new challenges for recent graduates entering the AI industry (Wu et al, 2020). In this regulatory environment, regulatory problems may bring about compliancy issues, protection issues and resource constraint issues. Given the regulatory environment is continually evolving, AI startups need to understand current opportunities and risks impacted by state involvement and laws.

2.3.1. Government Policies and AI Regulation

The main reason behind the differences between AI regulation in China, and other G7 nations is China's approach to governance: the balance of fast innovation and strong control (Lundvall and Rikap, 2022). In contrast, in many Western markets, innovations are often initiated and led by markets rather than the government, while the AI industry in China is tightly connected with the government. This is due to the influence of China's national policies, such as Made in China 2025, cybersecurity policy, and compliance with ethical regulation, which impacts AI startups in China (Allen, 2019). The Chinese government is not only a regulator, but also an investor, talent developer and market controller, which results in a unique AI market compared to other markets.

2.3.2. Made in China 2025 and AI Governance

The Made in China 2025 strategy, released in 2015, is relevant to the broader Chinese policy environment for advanced manufacturing and AI-related industrial upgrading (Zenglein and Holzmann, 2019; Li and Branstetter, 2024). It was aimed at supporting the transition from export-driven manufacturing to advanced technological manufacturing, including artificial intelligence, robotics and high-tech manufacturing. For AI start-ups, such policy agendas may create opportunities to align with national priorities, but they may also increase the need to understand policy language, eligibility criteria and compliance expectations.

Therefore, China's form of AI governance is characterised by the fact that the government makes certain rules and regulations for AI market actors to follow. Unlike Silicon Valley AI start-ups, Chinese AI start-ups may not have the freedom to operate on their own and must rely on the state for resources, such as financial support and research grants, to operate (Zeng 2022). Hence, "Made in China 2025" is not without risk and challenges,

despite offering numerous benefits, such as bureaucratic backing and access to government resources. The strategy may also present risks such as procedural and policy barriers (Pan et al., 2023). Many start-up entrepreneurs, particularly those who are recent graduates, may not have the experience and financial resources to deal with complex government funding applications and other types of support. As a result, it may occur that government-embedded large companies enjoy preferential policy support for their business, while start-ups face a lot of regulatory hurdles.

2.3.3. Data Protection and Cybersecurity Laws

China has some of the most stringent laws on data protection and cybersecurity for AI startups in the world, as reported by He et al. (2019). New laws, including the Cybersecurity Law of 2017 and other data privacy laws, have had negative impacts on artificial intelligence (AI) industries that use large data to develop AI and automation. These regulations dictate that companies store user data in China and implement certain data processing and cybersecurity management regulations and policies (Knox, 2020). These are impacting the cash flow and business processes of AI startups. Compliance in preserving data, which involves information and data security, consumes time and money, which many young and emerging businesses cannot reach.

Further, compliance with laws taking care of data may be problematic and costly for many young entrepreneurs (Chen et al., 2021). Failure to comply with the regulations could result in fines, revoke of operating licenses, and, in the worst case scenario, closure of the business, making it a critical matter for an AI start-up. In addition, a second issue in China's data regulation is the amount of government intervention in AI data. Chinese law differs from data protection laws in the West, where the interests of the data subject are often prioritised, in favour of state supremacy (Allam et al., 2020). This presents greater challenges for artificial intelligence entrepreneurs, particularly in security-driven industries (such as facial recognition, autonomous transport and financial AI) since there are restrictions imposed by the state on how the data can be used (Allam et al., 2020). Data protection is especially relevant for recent graduates that are interested in AI entrepreneurship, as any data misuse can result in legal penalties.

2.3.4. AI Ethics and Compliance Challenges

The ethics of artificial intelligence has gained traction at the international level. In response, China has tried to establish an ethics framework of artificial intelligence systems to ensure AI is ethically used (Zenglein and Holzmann, 2019). The Chinese government has also published guidelines on ethical principles for the use of artificial intelligence - AI should be open, explainable to stakeholders and should not discriminate. These ethical principles are important for startups that leverage AI to support their decision-making processes, as concerns about discrimination and fairness may engender regulatory attention. However, it's still widely challenging for many AI startups to provide ethical norms for technologies and business operations. Notably, this is a problem for cash-strapped AI startups. Startups may not always have the funds to support ethical AI research or to employ experts to answer questions relating to ethics in AI.

Furthermore, it can be ambiguous for startups to understand how to adhere to ethical compliance measures. Ethics is a major concern for emerging AI-based startups by graduates, given they have little or no knowledge, or experience with the regulatory framework around fairness and transparency in AI (Feijóo et al., 2020). This places startups in an ethical compliance no-man's land. It also restrains them from hiring legal consultancy and makes it more expensive for them to set up and compete in the market.

2.3.5. Startup Regulations and Business Registration

Legal procedures offer a range of challenges to Chinese startups in the field of AI (Hua and Huang, 2021). In China, business licences come in various forms according to the type of business and corporate structure. Other AI startups may also need to seek special approval since they have special functions. If a business wants to develop and use AI for medical, financial or automation purposes, extra approval may be required from specialised industry regulators (Muganyi et al., 2022). While the Chinese government has been more proactive in strengthening its intellectual property rights in recent years, there are still concerns about enforcement of laws, patent infringement and theft (Gao et al., 2024). Some companies may not be very familiar with the patenting process of their products, despite the fact that the CEO of the AI company may be a technical expert.

According to Kitsara (2022), licensing and intellectual property are two key concepts that newly graduated entrepreneurs must know for inventing and innovating their product.

Acquiring permits can take time, which may limit the number of start-ups and entry into the industry (Kitsara, 2022). In addition, the cost of patents can be significant, so some players in the industry are limited, particularly start-ups with little access to funding.

2.3.6. *Funding and Financial Regulations*

Funding is a major challenge for start-ups in the area of artificial intelligence, and it is heavily influenced by the financial system established by the Chinese government (Allen, 2019). The Chinese government encourages various types of funding through state-owned venture capital funds, funding for new start-ups and research. However, funding from the government is often coming with major requirements and restrictions, making it challenging for new start-ups to meet these requirements. A further legal factor which may impact the establishment of AI start-ups in China is the restriction on international investment in its AI industry. The Chinese government has put in place legal provisions to regulate foreign investment in AI firms, particularly in critical sectors. As a result, start-ups could face challenges in finding international investment; as such, accessing foreign capital markets might be a challenge (Zeng, 2022).

But some emerging AI start-ups are still trying to solve these challenges by engaging in corporate collaborations and/or creating international business models. The financial and regulatory landscape is becoming more difficult for newly graduated professionals to secure funding for AI-based start-ups. Many young entrepreneurs are unfamiliar with the process of funding acquisition, and thus have limited access to capital for their business, especially if they don't have substantial business networks (Lundvall and Rikap, 2022). The argument is also made that many start-ups are dependent on government funding; therefore, they have to comply with government policies, and may have less control over their own business development.

2.4. Cultural Factors Influencing AI Startups in China

In addition, another factor that impacts on entrepreneurship is culture, particularly with regard to artificial intelligence start-ups. Culture plays a significant role in business operations, business relationship building and risk assessment (Arenal et al., 2020). But unlike Western countries, where independence and innovation are often considered key factors in the creation of new business enterprises, Chinese business culture remains steeped in Confucianism, a bureaucratic management system, and the network of personal

connections (or guanxi). Therefore, these cultural tropes impact business decisions and are as important for new graduates working in AI startups as economic or regulatory factors (ÓhÉigeartaigh et al., 2020).

2.4.1. Confucianism and Entrepreneurship

Confucianism has long been a dominant philosophy in China, which has influenced individual behaviour and work culture (Xie et al., 2019). As a hierarchical, age- and leader-oriented system, Confucianism holds values that favour stability. For AI startups, this cultural context can be seen in organisational design, leadership and management styles and decision-making. Given the nature of entrepreneurship, which requires creativity and adaptation, Confucian cultural legacies may encourage respect for hierarchy, stability and family expectations, but their relationship with entrepreneurship should be treated cautiously because cultural values are not uniform and are reworked by younger founders in practice.

The hierarchical nature of organisations in the Confucian culture is an advantage for AI entrepreneurs. In China, business management systems are frequently centralised, particularly at the institutional level, which is characterised by decision-making power in the hands of influential people (Ai and Tan, 2020). This can also be seen in start-ups that have hierarchical business structures, as regard for the superior may be seen as a sign of stability in the enterprise. However, Farley et al. (2020) also suggested that this might be challenging for recent college graduates, as many young entrepreneurs and novices may not be given respect due to lack of status, credibility or professional experience, especially for traditionally networked businesses. In Silicon Valley, disruptive ideas and innovations may help to undermine existing businesses and establish the young business. But the same cannot always be said for firms in China, where start-ups often need to "go with the flow" (Farley et al., 2020).

Additionally, risk-averse behaviour can influence entrepreneurial decision-making in China, which can be linked to Confucianism, as highlighted previously in this column. This is opposed to many industrialised countries, where failure can be viewed as a natural part of the entrepreneurial process. Chinese values tend to favour security, stable jobs and income (Pan et al., 2023). This social constraint puts many recent graduates who pursue AI start-ups in a dire situation because they might be pressured to find a job in traditional IT companies or state-owned enterprises rather than to build their own businesses. One of the

main issues encountered by young entrepreneurs when starting a business is that family may consider entrepreneurship to be unsafe and risky (Sayler, 2020). Business failure can be socially expensive, which leads to graduates' consideration of entrepreneurial opportunities, seeking government support, finding larger firms to partner with and risking losing capital.

2.4.2. *Role of Guanxi in Business Success*

Guanxi is one of many factors that influence the complexity of the Chinese business culture (Que et al., 2019). While in Western societies, business deals are often aided by legal rules (such as contracts and tenders) and regulated by government policies and laws, in China, business relationships are more dependent on personal interactions through word of mouth, and trust-building, when it comes to the signing of contracts; securing funding for investment; or obtaining official approvals. Guanxi can then play an important role in the operation of AI startups, as it impacts market access in the highly competitive industry.

The literature mentions the importance, recognition, mobilisation and diversity in the development of start up ventures (Emmanuel et al., 2022). Chinese consumers may tend to rely on referrals when buying products, rather than backing activities primarily based on the merits of business ideas. This could increase the chances of venture capitalists and angel investors investing in startups that are recommended to them instead of investing in startups with unknown owners (Emmanuel et al., 2022). Support from government can also come from funding sources for AI startups, but these may have a greater preference for candidates with relevant experience, education or institutional affiliations (Allam et al., 2020). This might seem contradictory because many graduates may have excellent start-up ideas, but may not have the same networking opportunities due to a lack of business experience, capital or connections to potential incubators.

In this case, graduates may lack guanxi, which could be a major local handicap. While young entrepreneurs may possess new ideas and entrepreneurial spirit, they may fail to have direct access to key business players, such as seasoned business professionals, collaborators or sponsors who can help with their start-up projects. This is particularly problematic for AI development, as larger firms and data are required to build AI models. This means that obtaining regulatory approval, forming contracts, and even attracting the attention of investors can all become key challenges for new players in the market, such as young entrepreneurs (Bhutoria, 2022).

However, it is crucial to note the significance of guanxi does not mean a recent graduate does not have a chance to succeed in AI entrepreneurship. Universities and start-up incubators can also serve as valuable information sources for young entrepreneurs to network with potential investors, consultants and others. Old-fashioned networking approaches are still significant, but newer platforms such as WeChat, LinkedIn and AI-specific business forums are increasingly gaining importance, allowing young entrepreneurs to build their networks beyond their immediate connections. As a result, with the shift in business operating environment, the development of guanxi no longer necessarily disadvantages young entrepreneurs in the AI startup industry.

2.4.3. Changing Entrepreneurial Mindset Among Younger Generations

While Confucianism and guanxi are still deeply rooted in Chinese business culture, there is a shift towards innovation, Western entrepreneurial culture and the potential opportunities in the new technology era among young generations (Froese et al., 2019). Globalisation, Silicon Valley and more government attention on start-up initiatives in China, all profoundly affect the way Chinese graduates value start-up opportunities. Unlike their parents' generation, who prized job security, the new generation of young professionals increasingly see entrepreneurship as a viable career option, particularly in the field of AI applications (Keane and Yu, 2019).

Young Chinese entrepreneurs' tendency towards flexibility, flat organisational structures, and risk-taking also echoes the values of Silicon Valley entrepreneurs. Inspired by companies such as Google, Amazon and Tesla, young Chinese graduates are prepared to better embrace risks when launching AI-based businesses (Zhao et al., 2022). Policies to promote entrepreneurship education in universities also play a part. Such measures as start-up funding, mentorship programs for entrepreneurs, and overseas business events have provided greater independence and creativity for graduates.

Recently, entrepreneurship-focused policies led to Chinese graduates' attitude towards risk-taking (Shamim et al., 2019). While cultural attitudes are changing, individual success is still emphasised. But a new wave of young entrepreneurs, failure is not the final destination but part of the journey to success. Pressure from social media debates on entrepreneurship among aspiring entrepreneurs has led to more discussions of the

challenges of business building. Young AI entrepreneurs do not see failure as a sign of personal failure but rather as an opportunity to learn and grow (Cuong and Tai, 2023).

This shift is also related to growing AI applications in various industries, and has affected the attitudes of today's entrepreneurs. AI is a priority in China's development strategy, and this has attracted many young graduates to try to make their investments in start-ups. The AI industry is unique in that mature organisational forms and traditional business models are not as prevalent as they are in other industries (Sayler, 2020). The development of artificial intelligence and government strategies aimed at technological self-sufficiency has had a significant impact on entrepreneurship by encouraging young entrepreneurs to be more innovative and adventurous.

That said, there are a number of challenges in developing new-generation AI startups. While young people may be willing to take risks, they are restrained by the cultural and legal environment for businesses. Established companies are more likely to be favoured by government policies and regulatory frameworks, and hierarchical corporate cultures can position young businesses as a disadvantage in the business environment. Thus, the challenge for AI startups is how to make new generations of graduates innovative while they conform to existing practices.

2.5. Challenges Faced by Recent Graduates in AI Startups

2.5.1. Graduate Entrepreneurship, Age and Entrepreneurial Agency

A central gap in the literature concerns the agency of recent graduates. Graduate founders are not simply 'young' versions of established entrepreneurs. They may possess advanced technical knowledge and strong motivation, while also facing weaker investor credibility, limited managerial experience, less developed guanxi networks and lower tolerance for prolonged financial uncertainty. Age and career stage therefore matter because they shape both the resources available to founders and the way external actors evaluate their legitimacy.

This thesis treats recent graduate entrepreneurs as active agents who interpret constraints, seek legitimacy, assemble resources and make strategic choices under uncertainty. The study therefore asks not only what regulatory and cultural factors exist, but how graduate AI founders perceive those factors and respond to them in practice.

The struggles of recent graduates to start AI startups are intertwined with China's economy, law, and competition (Borenstein and Howard, 2021). Despite China emerging as a new

player in the international artificial intelligence industry, its entrepreneurial opportunities are still limited by financial operations, organisational hurdles, competition and entrepreneurship education (Borenstein and Howard, 2021). It can be challenging for new players to join the industry due to the increasing competition from new and existing entrepreneurs and firms. They, therefore, may require support from big enterprises and face regulatory challenges (Cantú-Ortiz et al., 2020). These key challenges pose serious risks and make it more difficult for AI startups to thrive and grow.

2.5.2. Limited Access to Funding

The funding required for graduates who pursue AI projects is generally limited (Lauterbach, 2019). While established entrepreneurs may have experience and networks that convince investors to fund them, graduates may not have a financial track record or standing to secure substantial investment. The capital costs of AI startups are also very high, including research and development, data sets, IT and people costs. As a result, many AI startups are still in the initial and basic stages of development as they cannot raise funds to advance to the next level of growth (Prem, 2019).

Venture capital is among the most typical funding sources of startups globally. Yet, China's most recent college graduates experience some challenges getting venture capital. In addition, startups with artificial intelligence technology typically take a longer time to mature and deliver valuable returns on the investment, which may make them less appealing to the venture capital companies that focus on short-term profit. This forces many young people who are interested in business to find alternative funding sources which might not be sufficient to support business based on artificial intelligence (Kuleto et al., 2021). This funding gap might be partially solved by government funding, but, in turn, there are challenges in this respect. The Chinese government offers financial support with various funding programs, such as AI grants, research subsidies and venture incubation funds, which are supported by policy frameworks such as Made in China 2025 and the Next Generation Artificial Intelligence Development Plan (Brem et al., 2021). However, government funding is highly competitive and some of it is geared towards startups with links to universities, government institutions, and "important" people. The majority of graduates who don't have these connections, face challenges to access affordable funds from the government to develop AI-related technologies. What's more, entrepreneurial managers in need of state funding tend to encounter certain conditions that limit their room

for growth, forcing them to follow the state's strategies, rather than the market's potential, in their research and enterprise activities (Pedro, et al. 2019).

An alternative way of financing AI start-ups for new graduates is to seek funding from private investors, including angel investors, and venture capital funds. However, there is limited access to capital in the initial phase of building AI-related businesses, particularly if there are no celebrities associated with the products or services to promote or market the solutions (Benbya et al., 2020). This is difficult because many new start-ups have yet to demonstrate their ideas; to win customers; or to obtain patents, which are often demanded by private investors. It is said that "the entrance barrier of AI startups is very high and many possible innovations are never born or startups are relying on small capital (personal) investment and cannot survive in a new market place".

2.5.3. Regulatory Compliance and Bureaucratic Barriers

Another concern of the Chinese market is related to the regulatory framework for AI startups, particularly for those with a recent degree who may not be aware of the regulatory and bureaucratic processes (Akgun and Greenhow, 2022). The AI industry is regulated under the regulatory framework of AI standards, data governance regulations, licences and cybersecurity. These guidelines help to ensure potentially unsafe AI systems are used in a safe environment in the short term and national security is guaranteed. But they also add additional barriers to the establishment of newcomers who do not have the legal knowledge or financial capacity to adhere to regulatory requirements.

The bureaucracy associated with approval regimes can be time-consuming, and therefore a nascent AI startup may take time to begin its operations. Some sectors, such as medical, financial and security-related AI, are highly scrutinised, and startups in these sectors may need special permits or licences before commencing their services. Artificial intelligence goods and services must also comply with Chinese data security and cybersecurity requirements, particularly if they process personal, sensitive or government-related data (Roberts et al., 2021; Muganyi et al., 2022). Young graduates may not have the legal, financial or managerial resources needed to navigate these requirements easily.

AI startups are also under the governance of a multi-layer system, which includes national laws, of course, but also local (municipal and provincial) rules and regulations, which differ between China's regions (Mou, 2019). On one hand, China offers legal support for AI

development; on the other hand, there are wide variations in urban regulations of AI. Cities such as Beijing and Shenzhen, for instance, could have more advanced regulatory frameworks and government support programs for startups, but they could also have more rigorous approval procedures and AI-specific regulations (Giannini, 2023). China's regulatory fragmentation therefore poses a challenge for CEOs of AI startups to keep up with regulatory developments and plan current regulations according to future needs.

2.5.4. Competitive Market Landscape

Market competition is increasing with Chinese technology giants, such as Alibaba, Tencent, Baidu and Huawei, already well entrenched in the Chinese AI market (Furman and Seamans, 2019). These firms have strong economic and technical resources and they can benefit from government funding programs, research grants and big data. The impact of this competition is differently perceived by founders of new AI startups, particularly with regards to marketing positioning and customer acquisition.

These companies also dominate access to required resources and platforms, such as computing power, AI datasets, and product distribution (Haleem et al., 2022). Many AI startups gain support from companies like Alibaba Cloud and Tencent AI Lab, creating a power inequality between these companies and startups, and allows these companies to control startups in more ways. And these companies often acquire potential AI teams before they have developed their full potential, which means that many independent AI-based companies have limited chances to grow unless they are partner or being acquired by large enterprises.

Innovation and differentiation will be critical for survival as the number of AI-based startups increases, particularly if they are equipped by youths and have limited work experience (Arakpogun et al, 2021). Start-ups are not well-established businesses, so they cannot leverage brand and market power; they need to innovate and deliver unique AI solutions with value propositions. But they face the challenges of high costs to conduct research and develop AI products, acquire customers and differentiate themselves. This may be very difficult for young entrepreneurs with potentially low marketing budgets and limited development assistance from large firms (Flores-Viva and García-Peñalvo, 2023).

2.5.5. Skills and Knowledge Gaps

A key issue for startups in AI entrepreneurship is the lack of a strong transformation of technical skills into business competencies. Many university graduates are familiar with AI development, but the majority don't have the necessary management skills for the Chinese market (Rudolph et al., 2023). The core entrepreneurial skills to manage the business include finance, communication with investors, marketing and regulatory considerations in the business processes. Some young AI entrepreneurs might be unfamiliar with these skills.

Historically, higher education in China is institutionalised to train technically-focused students, whereas graduates with start-up management skills are not the focus of their training. As a consequence, undergraduates are less prepared to manage a start-up (Dasawat and Sharma, 2023). In contrast, western university education systems tend to have more mature entrepreneurship courses and start-up incubators, while business education in the Chinese AI or engineering disciplines is still in its infancy. This "system gap" compels start-up entrepreneurs to "learn-by-doing" in practising business strategies, which often involves inefficient trial and error, leading to slower growth.

Moreover, there is a lack of graduates with experience in the modern start-up innovation system (Geetha et al., 2024). Most university-based incubators for start-ups in China are research oriented. For many AI start-ups, a lack of early experience leaves the challenge of developing product marketing strategies (Kasneci et al., 2023). The failure rates of AI start-ups without real-life experience in attracting investment, market & competitor analysis, networking and engaging with industry professionals will be higher.

2.6. Opportunities for Recent Graduates in AI Startups

While these factors are present and recent graduates may face some challenges to found AI startups in China, there are also opportunities (Filiari et al., 2021) in the AI landscape. Young people can set up and succeed in business owing to the government's support, new market opportunities, technological advances and globalisation. Given that AI is now a vital component of China's strategy, the development of the legal framework, investments and infrastructure building has promoted innovation among AI startups. Further, AI's deployment in various sectors opens up new business opportunities, increases trans-borders collaboration and global opportunities for startups (Lambert and Stevens, 2024). This could

help build successful businesses for new graduates looking to make use of their technological and entrepreneurial capabilities.

2.6.1. Government Support and Policy Incentives

China's government recognises AI as the crucial part of China's economy, technological innovation, and national development (Mishra et al., 2020). This has seen the development of more projects and investments in early-stage support for AI start-ups. Granting, start-up incubators and AI development parks have helped lower the financial barriers and help graduates directly participate in the AI start-up scene.

The most notable government policy intervention in AI has been through funding grants to develop artificial intelligence. Regional governments have also set up financial schemes to support start-up's early-stage development, with a wide range of activities covered, including research and development, product commercialisation and market expansion (Allen, 2019). These support schemes can be focused on areas of AI that are crucial in the country's economy and regional requirements, including health, financial, and smart manufacturing, as outlined in the national plan for technological development. These schemes provide support to young graduates who may not have the capital to access funding to develop AI technologies. This type of funding does not require organisations to surrender part of their business, as is often the case when seeking venture capital funding.

This also comes from accelerators that want to support start-ups in the artificial intelligence industry (Benbya et al., 2020). University-based incubators, government research centres and privately-owned technology parks offer knowledge, premises, facilities and funding. The incubators assist young companies to develop and adopt the right business models, attract potential investors and familiarise themselves with local and national policies. Pestel analysis of the external environment shows incubators can have a positive impact on the companies they incubate and make them more attractive to investors and partners in the future (Cantú-Ortiz et al., 2020). These schemes are especially significant for post-graduate students who choose to startup their business right after they graduate and have little business knowledge.

The emergence is also enabled by the establishment of AI development zones and policies to create a more positive operating environment for AI's entrant firms in China as mentioned by Gray and Suri (2019). Promoting AI startups, big cities such as Beijing,

Shanghai and Shenzhen offer tax benefits, government-funded research and business incubators. These AI clusters are explicitly designed to build links between startups and high-tech firms and universities to facilitate knowledge and collaboration. These tech zones help entrepreneurs start their own businesses with access to advanced AI technologies such as computing devices, tech parks and related regulatory support (Furman and Seamans, 2019). These policies help them cut costs and increase the chance of survival in AI for young entrepreneurs.

2.6.2. Emerging Market Trends and Technological Advancements

The increasing adoption of AI has a sound foundation for startups to develop AI-based applications (Pedro et al., 2019). With cost savings, increased efficiency and better decision making, the business community's use of AI is also growing. New graduates of AI and machine learning are well positioned to capitalise on this and offer those industries solutions that address their needs. As noted above, health care is an industry in which AI startups can grow. Currently, China is experiencing an ageing population, and a growing need for quality medical care. As a result, healthcare has emerged as a key area for AI, including applications in medical diagnosis, surgical robots and medical imaging. This has led the government to promote the application of artificial intelligence in healthcare through regulatory measures and investments in medical AI research (Qin and Chiang, 2019). Young AI entrepreneurs can build solutions in this field which not only have a positive impact on society, but also open the door to a new and exciting industry.

Another industry where AI can enhance the work of various organisations and start-up ideas is fintech. Banks, insurers, and financial investment firms have embraced AI technologies to limit fraud, answer customers' questions and enhance their portfolio performance (Giuggioli and Pellegrini, 2023). And with China being one of highest growth and digital payment markets globally, fintech startups utilising AI, blockchain, risk management services and personal financial advice are likely to have a great deal of potential. An increasing number of young IT graduates and computational finance professionals are tapping into AI- and data science-based investment management services through the creation of new services for institutional investors and retail investors (Brem et al, 2021).

Another significant area for AI innovation is smart manufacturing or Industry 4.0. These include smart robotics and computer vision, which are likely to flourish as China makes the transition from labour-intensive manufacturing to smart and AI-based manufacturing (Huang et al., 2022). Government AI programs in the industry provide funding to startups to develop automation technologies to enhance productivity (Kopalle et al., 2022). New graduates in AI engineering and robotics can work with manufacturing firms to develop new technologies for the factory floor by utilising industry partnerships and policies.

AI entrepreneurship also offers start-ups the opportunity to develop new business models to commercialise AI. Traditionally, models were primarily centred on software licences and consulting. But recently AI as a Service (AIaaS) has been gaining popularity. Such middle products enable companies to pay for access to AI solutions, instead of training new staff. Many fresh graduates are increasingly building AIaaS startups to provide specialised machine learning cloud APIs (application programming interfaces), data analytics solutions and smart automation platforms, suitable for SMEs (Tschang and Almirall, 2021).

2.6.3. International Collaboration and Expansion

The Chinese AI market is rapidly growing and becoming more connected to the world, enabling Chinese AI startups to quickly expand into new markets (Lauterbach, 2019). This globalisation process allows AI enterprises to engage in cross-border operations, collaborate with experts from other countries and attract global investment. Given the global nature of the AI industry, startups that expand their technologies and services to the rest of the world can test different business environments, opportunities, acquisitions and investment strategies, and learn from other markets. It is estimated that cooperation in AI is likely to take place in sectors with which China signed technology cooperation deals (Soni et al., 2019). Belt and Road Initiative (BRI) members are looking for AI technologies on smart infrastructure, smart logistics and smart governance. When Chinese AI-based startups dedicate some of their commercialisation activities to the markets of the BRI, they may be able to win contracts and attract international investments (new markets).

What's more, global markets and funding for AI startups are expanding. While Chinese venture funding is developed, international investors are increasingly interested in promising Chinese AI startups. AI startups based in China can receive some consultation,

exposure and funding opportunities from AI funding platforms, accelerators and technology incubators around the globe (Whalen and Mouza, 2023). New graduates starting AI startups are more and more open to working internationally and competing in startups, conferences and international accelerators about AI to build their brand and raise capital.

Going international may also help AI startups mitigate their regulatory risk in China by generating revenue from multiple sources. AI startups tend to target the Chinese market before expanding to the broader market (Ashta and Herrmann, 2021). Students who prioritise developing scalable businesses from the beginning may have a higher chance of success than others and may be able to have multiple income streams.

2.7. Comparison with Other AI Startup Ecosystems

Chinese AI startups have significant potential and are part of the most vibrant entrepreneurial ecosystem, influenced by government opportunities, fierce competition, and unique regulations. There are a number of unique features present in the AI startup ecosystem in China compared with more mature AI ecosystems based in Silicon Valley, the US market, and the European Union (EU). These relate to government policies, funding options, regulation, and culture of innovation (Roundy, 2022). Another aspect of the development of the Chinese AI ecosystem is the build-up of infrastructure and the application of AI across various industries (Weber et al., 2022). Lessons from these comparisons can also highlight the strengths and weaknesses characterising China's AI startup scene and suggest potential improvements.

2.7.1. Comparison with Silicon Valley and the US AI Industry

Silicon Valley, the world's most renowned hub for start-up establishment, investment, innovation and technological development (Rocha et al., 2019), is well known for its role in AI development. Nonetheless, China's government provides substantial support and China's AI industry is well developed. Silicon Valley relies more on market forces, competition and venture capital for driving innovation. A key element in the US AI startup ecosystem is the willingness to take risks, and accept that sometimes experiments fail. This risk-taking culture can be contrasted with the AI culture in China where many startups align with government-driven corporate strategies or partnerships with business partners to minimise risk (Basole and Accenture, 2021).

Another key component of Silicon Valley's AI startup ecosystem is venture capital. The United States has a strong pool of existing and potential investors (such as angel investors, corporate venture funds and institutional investors) for AI startups. Silicon Valley venture capital investors frequently encourage disruptive innovation (Tula et al, 2024). This may mean disruptive and new AI ideas and technologies may have more opportunities for early-stage investment. However, in China, venture capital is more driven by government guidance and concentrated in the hands of investors who invest in startups that are in alignment with the Chinese government agenda or obtain funding from the government. This may have an impact on the volume and nature of early financing provided, as Silicon Valley startups may be more likely to develop risky AI concepts, while AI startups in China are more likely to be focused on key areas of AI development, such as manufacturing, surveillance, or financial technologies (Cetindamar et al., 2020).

A further aspect of the Silicon Valley and China comparison concerns regulatory process. The United States has historically been associated with a more market-led innovation environment, although data privacy, platform governance and AI accountability have become more prominent regulatory concerns. The point of comparison is not that one model is simply less regulated than the other, but that Chinese graduate founders may encounter a more state-coordinated policy environment when seeking legitimacy, data access and market entry.

However, China may have an edge over Silicon Valley in terms of the application of AI technologies in the manufacturing sector, public services and products (Jacobides et al., 2021). The Chinese government has been significantly engaged in the deployment of AI in service provision, smart city and e-government programs, offering startups a rich environment for the use of AI. Silicon Valley, on the other hand, may find it trickier to implement some of the technologies due to its corporate orientation and business strategies (Battisti et al., 2022). This implies that even though the US has many opportunities for disruptive AI solutions, China has become a key "live lab" for AI startups to build and delivery large-scale AI solutions.

2.7.2. Comparison with the EU AI Startup Environment

There are some unique features of the European Union startup ecosystem compared to China in terms of regulation, ethics and funding. According to Hannigan et al. (2022), the

European Union has taken a more "deliberative" approach to the responsible use of AI so that individuals' privacy and rights are not infringed upon. This has led to policies regulating AI and its usage, such as the General Data Protection Regulation and the EU Artificial Intelligence Act. These laws are quite restrictive, impacting the collection, processing, and use of data by AI startups, which may sometimes make business life harder for the latter.

Chinese AI startups can learn a lot from the EU approach (Burström et al., 2021). China's regulations of AI tend to maintain national security and enhance government control, while the EU regulations tend to be more privy to personal rights. Chinese entrepreneurs focusing on developing business enterprises in Europe should be informed about Europe's GDPR, among other artificial intelligence ethics guidelines. But, startups that can meet these guidelines might see this as an opportunity to grow their business, as the European market welcomes integrable and ethical AI solutions.

EU AI start-ups have their own particularities and challenges as compared with those in California and China. For instance, while the EU predominantly attracts research grants and funding schemes, the USA uses more private venture funding and China more state funding. These EU funding schemes include the Horizon Europe programme that funds AI research and development. But they can also be slower to award funding than private forms of capital financing (Schulte-Althoff et al., 2021).

The fourth characteristic is AI research, partnerships and integration. The EU has formed alliances with academic institutions, business and agencies for research and development on AI. This is a good system because it allows for the development of AI-related solutions at different levels, with an integration of ethics, innovation and market needs (Singh et al., 2020). A further known difference is that Chinese AI start-ups are more centralised, although they are not entirely different to those in the US. Their innovation efforts may not be less robust in terms of quality, but their innovation goals are more focused on meeting the demands and objectives of the Chinese government. While the Chinese model helps businesses get AI technological solutions, it does not provide business with AI technological solutions in the relations with academia to the same level as in the European model, which is more centred on education and research (Xu et al., 2019).

2.7.3. Lessons China Can Learn from Other Markets

China's AI start-up market is also growing and it exhibits many differences from California and the European Union (Gueguen et al., 2021). One lesson from Silicon Valley concerns greater tolerance of entrepreneurial risk. This reflects the risk tolerance associated with some forms of AI innovation in the US, where many companies begin with high-risk, high-reward experimentation. China's AI market is highly entrepreneurial and is often positioned as a leading market. It is, however, also a controlled and regulated market, which can limit innovation in certain contexts.

By learning from the EU, China can recognise the advantages of having a policy on the ethical use of AI and the importance of collaborating with other countries (Raneri et al., 2023). Currently, China's approach to AI governance is mainly concerned with national security and regulatory frameworks. But it often fails to consider the ethical considerations that can serve the interest of users. Strengthening AI regulation may help China to "reposition" and make Chinese AI start-ups more appealing to foreign investors and buyers (Torres and Godinho, 2022).

The distinct funding model is one of the consistent lessons from comparisons with Silicon Valley and the EU. China's state-supported approach can provide resources, but it can also make start-ups dependent on policy priorities and official eligibility requirements. A broader mix of private venture funding, angel investment and international collaboration may improve the financing environment for AI-based businesses. These comparative reflections should be read as practical implications rather than as a full evaluation of national innovation systems.

2.8. Identified Research Gaps

There is a range of research literature on AI startups and the ecosystem (Ashta and Herrmann, 2021). However, there is still a need for studies on threats and opportunities for new entrants to AI. There have been studies on regulation and startups in relation to AI innovation but very few have addressed the perspectives of start-ups founded by graduate students. In addition, there's little research on the impact of regulatory and cultural factors on AI innovation in China. These highlights a need for an investigation into how student entrepreneurs start AI businesses in the growingly regulated and competitive business environment in China.

2.8.1. Lack of Research on Recent Graduates in the AI Startup Sector

A large part of the literature on entrepreneurship associated with artificial intelligence has been related to big businesses, government-funded projects, or startups by experienced entrepreneurs (Tschang and Almirall, 2021). While these papers offer insights into the types of AI business models and technologies, the views of AI start-ups by new graduates have been overlooked. New graduates do not have the same level of support in terms of capital, networks and government support as other business professionals. But little research has paid attention to these factors. This study identifies this gap as a vital area of research since young entrepreneurs in the field of AI lack a structure and a strong set of principles.

Another challenge faced by younger entrepreneurs is that they can't afford to stay in business for a long time without making money whereas more experienced entrepreneurs may stay in business and still not make enough money in the first 12 months of operation (Brem et al., 2021). They also often have little or no relevant work experience, making it difficult for them to raise funds, gain interested investors, and build a profile in the highly competitive artificial intelligence sector. While there is research on AI funding, most deals with corporate strategies for AI funding and government support, instead of issues young AI start-ups might encounter. There is a gap in the literature on startup funding, credibility and business development among new graduates in a field dominated by tech giants, restricting our ability to understand how the sector can be made more accessible to recent graduates (Lambert and Stevens, 2024).

Moreover, little is known about the performance of AI start-up founders with and without such experiences. This is particularly relevant to the business skills of new university graduates who may have considerable technical skills but lack commercial skills. AI is an emerging field with many research findings, and it is crucial to explore how young entrepreneurs translate research findings into action and assess the methods which are successful. This may guide future policies and initiatives (Kasneci et al., 2023). Research could explore the contributions of young entrepreneurs in product development, market research, and fund-raising in the AI industry.

2.8.2. Limited Exploration of the Intersection Between Regulation and Culture

There have been several studies on accountability and control in artificial intelligence (Dasawat and Sharma, 2023). However, a large part of this research relates to regulation in terms of compliance, data and intellectual property laws. Other research on business culture has addressed guanxi (persona networks and relationships), Confucianism and hierarchy in China. So far, there has been little research on the relationship between regulations and cultural aspects of AI start-ups. This is significant as contemporary bureaucratic practices and cultural values are barriers for young graduates interested in starting a business (Flores-Viva and García-Peñalvo, 2023).

Government rules for the development of AI start-ups in China present opportunities and challenges in terms of legislative and regulatory frameworks for data security, internet security and national AI product testing. While these regulations are helpful in developing a framework for ethical AI use and national security, they also introduce new problems which are hard for young and/or economically disadvantaged entrepreneurs. Formal systems create unequal outcomes for these entrepreneurs by creating a risk-averse stance, emphasis on business stability, favouring established corporations, and relying on status networks (Haleem et al., 2022). As such, current research does not take into account the cross-cultural and regulatory dynamics.

In this sense, young Chinese AI entrepreneurs may suffer from a lack of funds as they do not have connections to suitable mentors and benchmark firms. Another reason is business culture. Contracts may be bureaucratic, and this may present those who are new to business (recent graduates) with challenges. Also, the need for approval may slow down the adoption of AI in the firm that is not familiar with bureaucratic processes (Giannini, 2023). So, it is crucial to better understand the interaction of these cultural and regulatory factors and how young entrepreneurs can benefit from AI entrepreneurship.

2.8.3. Gaps in Understanding Startup Strategies for Overcoming Barriers

Even though the literature discusses challenges in AI entrepreneurship, less is known about how recent graduate founders manage these challenges in practice. While previous work on barriers and enablers highlight issues of funding, regulation and competition as being significant barriers, it does not detail how SMEs or startups navigate these challenges. This is particularly evident for new graduates as there is limited literature describing how they

overcome the lack of resources, plan their market entry strategy, and adapt to market positioning in markets that are already dominated by market leaders. The young AI entrepreneurs need to be innovative in raising capital for their business ideas, as venture capitalists often invest in new firms with a stable of founders they know. Some may obtain funds from grants, university connected incubators, or crowdfunding, but research is needed on how effective these funding streams are for AI startups (Akgun and Greenhow, 2022). From the case studies of young entrepreneurs, it would be useful to study how young entrepreneurs secure funding and what investment models and funding sources are useful to support AI startups.

Two more areas that warrant further research concern the strategies used to compete against the tech giants (Alibaba, Tencent and Baidu). Some startups aim to position themselves in niches, while others seek to position themselves by meeting the needs of established companies. However, little is known about the viability of these strategies for startups owned and managed by recent graduates (Kuleto et al., 2021). Knowledge of this type would help to identify successful differentiation strategies as it would inform us about the types of strategies new firms can pursue when attempting to achieve a niche.

2.8.4. Insufficient Focus on AI-Specific Entrepreneurial Challenges

While plenty of research has been conducted on entrepreneurship in general, some of the issues that may arise in AI startups are less well understood (Yu 2023). New artificial intelligence (AI) startups are distinct from tech startups in many aspects, with the first being that they need to command large amounts of data, computing power, and human capital. Recent graduates also require resources like good data sets, as well as computing resources to build models, which are often in limited supply. Continuing in this vein, there has been little discussion so far about how, at the startup level, individual AI firms can successfully deal with such technical risks and uncertainties without the investment of massive amounts of capital or interaction with existing corporate players (Borenstein and Howard, 2021).

Another challenge faced by AI startups is finding talent, as there is a shortage of global machine learning engineers and AI researchers. Most new grads fail to attract top AI talent for hiring due to the issue of compensation and the competition from large tech giants. Studies regarding solutions to nurture human talent development in upcoming AI startups,

such as team structure of equity sharing or talent cohort setting, are welcome (Cuong and Tai, 2023).

The ethical issues of AI startups have also received little research, particularly regarding bias issues, opacity of AI and appropriate regulation of AI. Some recent work has centred on the ethical regulation of the application of artificial intelligence between startups, but less research has asked questions about the ethical development of artificial intelligence for experimental startups (Bhutoria, 2022). There is a need for studies on how emerging AI startups can implement ethical considerations in their business and monetization strategies that will help academic and business research. As such, three research questions have been developed as follows:

1. What are the key regulatory and cultural challenges faced by recent graduates starting AI startups?
2. What support structures exist, and how effective are they?
3. What strategies can be developed to help graduates overcome obstacles and succeed?

2.9. Synthesis of the Literature and Remaining Gap

The literature reviewed above shows that AI entrepreneurship is commonly examined through three broad emphases: the growth of national AI strategies and regulation, the development of entrepreneurial ecosystems, and the capabilities needed by technology ventures. These studies are useful for explaining why AI start-ups matter and why China provides an important context. However, much of this literature remains weighted towards established firms, platform companies, mature start-ups, national policy frameworks or ecosystem-level conditions. It therefore does not fully explain how recent graduate founders, who often enter the market with technical knowledge but limited business experience and weak institutional legitimacy, interpret and navigate the early formation of AI ventures.

A second limitation is theoretical. Institutional theory explains how formal rules, informal norms and legitimacy pressures shape organisational action, while entrepreneurial ecosystem theory explains how finance, incubators, universities, infrastructure and networks are distributed across places. RBV helps identify the importance of resources and capabilities. Yet these perspectives tend to explain structural conditions more readily than founder agency. They say less about how recent graduates make sense of regulatory

ambiguity, how they adjust their claims to different audiences, how they compensate for weak guanxi or business experience, and how they experience support systems as both enabling and restrictive.

This matters because the research questions in this thesis are not simply asking whether regulation, culture or infrastructure exist. They ask how these factors are perceived, experienced and acted upon by recent graduates initiating AI technology start-ups in China's urban centres. Existing theory can sensitise the analysis, but it cannot by itself answer these questions because the empirical intersection of graduate career stage, AI-specific regulatory uncertainty, urban ecosystem dependence and founder-level agency remains underdeveloped.

The remaining gap is therefore located at the intersection of perception, agency, regulatory ambiguity and early-stage AI entrepreneurship. This thesis responds to that gap by using interviews to explore founders' lived navigation of constraints and a survey to examine patterns in perceived regulatory, cultural, infrastructural, educational and ecosystem conditions. The contribution is not that it replaces existing theories, but that it uses them critically to interpret a founder group and empirical setting that existing studies have not adequately connected.

2.10. Conceptual Framework for the Study

The model of this research is designed to incorporate regulatory enablers, cultural antecedents and entrepreneurial variables to ascertain the entry and new venture creation barriers among new graduates in the Chinese AI industry (Emmanuel et al., 2022). Given the variables primarily interact with each other, the framework offers a way to rigorously explore the dynamics of public policy, cultural impact, and business environment that shape the opportunities and risks of new AI entrepreneurship in China. In seeking to answer these questions, the framework adopts information on regulatory compliance, Chinese culture and the business environment, and aims to provide a more holistic understanding of the regulation and antecedent variables in the Chinese AI start-ups.

The first and most obvious variable in the conceptual framework is the regulatory framework, which is treated as a perceived condition associated with self-reported success of AI start-ups. Government policy affects the development of Chinese AI, with key issues including data policy, copyright and financing policy, all in line with the government's agenda (Pan et al., 2023).

The second dimension of the framework is made up of cultural aspects that affect entrepreneurial decisions, including family expectations, hierarchical norms, risk attitudes and business relationships such as guanxi. In contrast to Western cultures, which are often seen to be free and more entrepreneurial, Chinese business cultures are more risk-averse, bureaucratic, loyal to long-term partners and pro-government. In this situation, young entrepreneurs tend to raise funds and conduct required trading through social networking. This is important when seeking investments and establishing business networks, and having an understanding of the approval processes required by various management bodies. Moreover, the framework addresses cultural attitudes towards risk and failure management, and their impact on young entrepreneurs' decision-making. Although there are new trends and a new generation of young people who are more willing to set up a business, conventional cultural considerations still play a role in the choice of profession and in entrepreneurship (Kitsara, 2022).

The third component of the framework relates to how graduates respond to the issue of finance, regulations and competition. Recently arrived startups face financial restrictions in terms of research and development costs, data and cloud infrastructure. It also considers state-funded venture capital, angel capital, and global capital to comprehend young entrepreneurs' access to capital (Gao et al., 2024). Market entry approaches include focusing on specific AI applications, partnerships with established enterprises, and AI innovation zones. In this competitive environment, with KOLs (key opinion leaders) like Alibaba, Tencent, and Baidu still dominating the market, this framework can be used to assess strategies adopted by young AI companies. The conceptual framework is founded in the notion that the dynamic between the regulatory regime, culture and knowledge of new graduates drives AI startups. Additionally, it explains the dilemmas and opportunities facing them, offering data that is key to policy-making, funding, innovation and entrepreneurship education (Muganyi et al., 2022). The conceptual framework resolves current misconceptions of the development of AI startups in China, enhances theoretical insights, and provides data-based recommendations to future AI startups.

The concepts underlying the design of the research framework and hypotheses used in this survey are an extension of the conceptual theory that underpins the Resource-Based View (RBV) and the Entrepreneurial Ecosystems framework. These approaches offer multiple aspects of understanding the development of AI technology startups established by

first-time entrepreneurs (First-generation entrepreneurs) in major Chinese cities (Hua & Huang, 2021). The framework in the figure above is based on the hypothesis that elements such as Startup Success are the dependent variable, driven by Regulatory Environment, Access to Funding, Cultural Attitudes towards Entrepreneurship, Educational Background and Technology Infrastructure, as illustrated in Figure 1.

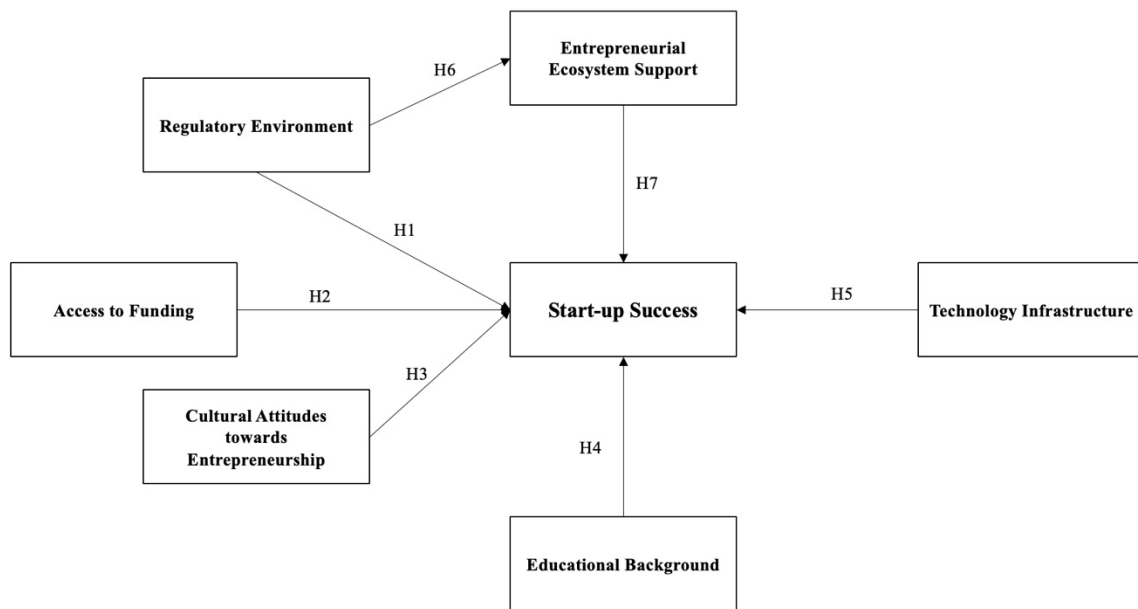


Figure 1 Conceptual Framework

The intermediary role of entrepreneurial ecosystem support is a logical way of incorporating the RBV focus on the internal qualities and resources of the firm while also recognising the importance of external conditions that enable startups to access opportunities and resources (Wang et al., 2021). In this manner, the combination of theories allows this research to examine the relationship between tangible and intangible resources and self-reported start-up success, as well as the role of entrepreneurial ecosystem support. The following are six hypotheses developed for this research study:

H1: Founders' perceived favourability and clarity of the regulatory environment is significantly associated with self-reported AI start-up success in China.

H2: Founders' perceived access to funding is significantly associated with self-reported AI start-up success in China.

H3: Founders' perceptions of cultural attitudes towards entrepreneurship are significantly associated with self-reported AI start-up success in China.

H4: Founders' educational background and perceived entrepreneurial preparedness are significantly associated with self-reported AI start-up success in China.

H5: Founders' perceived access to AI-related technological infrastructure is significantly associated with self-reported AI start-up success in China.

H6: Founders' perceived entrepreneurial ecosystem support is significantly associated with self-reported AI start-up success in China.

2.11. Summary of Chapter

This chapter has examined the literature on regulatory, cultural and entrepreneurial challenges faced by recent graduates in establishing AI start-ups in China. It has also examined the Resource-Based View (RBV), Entrepreneurial Ecosystem Theory (EET) and Institutional Theory that offer theoretical lenses into the external and internal dynamics that may impact the AI industry and the preconditions for self-reported entrepreneurial success. Theories show the availability of resources, governmental policy, regulatory environment and culture play an important role in participants' accounts of startups. Previous studies show that, while there is much innovation opportunity in the AI sector, China has a highly competitive environment characterised by government regulation, top-down business models and competition with large platforms.

Regulation requirements are one of the key sub-factors that influence the regulatory environment, particularly in the case of government policies. Many policies have facilitated the entrepreneurship in AI, such as Made in China 2025 and the overall AI regulation framework; however, they also lead to bureaucracy. Legal responsibilities such as data protection laws, cybersecurity and AI ethics are among the legal requirements entrepreneurs face in using customer data. These requirements are particularly financial and legal burdens for inexperienced entrepreneurs. IP and licensing is another important regulatory concern since many AI startups may not secure their technologies or get patents for them. The level of financing of independent start-ups through government schemes, state-led initiatives and government incubators is often tied to state priorities and may limit independent start-ups' access to resources.

Cultural considerations are also important in self-reported business outcomes in China, particularly AI startups. The literature examines the role of Confucianism, hierarchical organisation and the avoidance of risk in entrepreneurship. Compared to Western-style entrepreneurship, which tends to be more independent and innovative, Chinese business culture and government administration is more conservative. Guanxi (social connections)

continue to play a key role in accessing finances, affiliations, licences and authorisations. Students have relatively few business networks, and often they cannot connect with these networks in the market. However, there is evidence that younger people's attitudes towards entrepreneurial opportunities have shifted, given the rise of international startups and the importance of government policies to promote entrepreneurial culture. While risk-averse and conventional business culture still prevails, there is also evidence of increased readiness to take risks and try new things in AI startups, showing that the business culture in China is changing.

The data provided in this chapter delivers insights into the four key problems that recent graduates have when attempting to start a business in AI: funding, regulatory, competition and talent issues. Lack of capital remains a challenge since most venture capitalists evaluate startups based on the team's experience and capabilities, and are reluctant to provide early-stage funding. Alternatives such as grants and incubators are also possible, but may come with political considerations and bureaucratic red tape. There are also regulatory concerns, such as data abuse, ethics of AI and copyright. Young entrepreneurs may not fully comprehend these laws. They may also not have suitable resources to address legal issues and comply with these regulations, which can affect enterprise operation or lead to non-compliance. The domination of the world's largest technology enterprises, such as Alibaba, Tencent, Baidu, and others, make it hard for small startups to enter the market, particularly when they are trying to secure the first opportunity in the market, or to develop relationships with big enterprises or organisations. There is also a lack of business learning and training that is linked with business management, such as entrepreneurship, investment relationships, and commercialisation.

3. Research Methodology

3.1. Introduction

This chapter explains why, and through what structure, the research objectives were investigated (Imran et al., 2024). It evaluates and justifies the methodological choices used to explore the relationship between regulatory and cultural factors and the experiences of recent graduates initiating AI technology start-ups in China's urban centres.

The overarching aim of this research is to examine the regulatory and cultural barriers facing recent graduates in China seeking to launch AI startups in the key cities of innovation: Beijing, Shanghai and Shenzhen. Even with China's reputation as a global leader in artificial intelligence and tech entrepreneurship, regulatory and social structures pose a complex barrier to entrepreneurship (Gupta, 2024). The study is founded on three key objectives: (1) to identify and explore the regulatory and cultural challenges that recent graduates face when starting an AI startup; (2) to evaluate the effectiveness of support systems and growth potential for AI startups in China; and (3) to develop a strategy that can assist graduates in addressing the barriers. To this end, the study is informed by three questions: What are the main regulatory and cultural barriers to setting up an AI startup faced by graduates? Which support structures are available and how effective are they? What support mechanisms can support graduates to overcome challenges and thrive?

In this research, a mixed-method research design, which uses both qualitative and quantitative data collection and analysis methods, is implemented to address those multifaceted questions. The qualitative method includes in-depth interviews with 15 recent graduates running AI start-ups in China's urban areas. This approach yields detailed narratives of experiential, regulatory and cultural perspectives. This is complemented by a quantitative questionnaire survey with a broader sample of 150 founders of AI startups, allowing the researcher to detect overarching trends, and statistically test the relationship between the constituent variables of regulatory stress, cultural distinctiveness, educational level and business success.

This mixed-methods approach is critical to the multi-faceted nature of study. Saunders et al. (2009) note that a solely quantitative study design may lack context for the regulatory and cultural issues faced, while a solely qualitative design may suffer from a lack of external validity and reduced ability to test theories about causes and effects. As such, by adopting

a combination of quantitative and qualitative approaches, this study is able to focus on the contextual factors while also providing empirical testing, effectively utilising pragmatism to strengthen the research (Nagpal et al., 2021). At the same time, multiple sources of data can be triangulated to allow for more valid analysis.

The philosophy of this study is pragmatic epistemology because the research is more concerned with the practicality of the research methods in answering the research questions, rather than following a specific philosophical system. The study is pragmatic by focusing on practical issues and ways to humanely support young entrepreneurs and policymakers (Brister, 2024). It also draws upon some aspects of an interpretivist tradition, particularly in the interview strand of the study, where interpretation is crucial to understanding meaning-making and social constructs. Conversely, the quantitative component has elements of the positivist tradition, particularly with the objective nature of data and hypotheses testing. So, the research is epistemologically inclusive in that both sides of the philosophical divide are brought together and in line with the complexities of AI entrepreneurship in the Chinese socio-political environment.

Finally, the decision on a mixed methods approach is related to research gaps from the literature review. By using insights from interviews and data from surveys, this research will feed into policy-making, entrepreneurship education and innovation systems theory in transition economics.

3.2. Research Philosophy and Paradigm

Philosophical foundations and theory are needed for the validity of interpretations, congruence of theories, and methodological integrity in research (Duberley and Johnson, 2015). Mackey (2016) suggests that philosophical conceits impact not only the design and choice of methods, but also the actions of the researcher in using data to make sense and how they integrate their research with current literature. The questioning of ontological, epistemological and axiological views is an important consideration in the current context of scaling up an urban inauguration of recent university graduates' AI technology startups in China. The next section will explain these assumptions, as well as the suitability of a pragmatic paradigm (there are several) to the complexity and practical use of the current study.

3.2.1. Ontological and Epistemological Assumptions

Ontology is the branch of philosophy that deals with the nature of reality, things, what they are and what can be known or understood, while epistemology has to do with how we know things (Al-Saadi, 2014). This study's ontological position does not rule out the possibility of multiple realities that reflect the perspective and background of the individual, the cultural background, and institutional context. For instance, graduate views of regulatory issues may be divergent in Beijing from those of another graduate in Shenzhen. Likewise, the value of *guanxi* (connections or relationship networks), for instance, may differ among people with different educational and social backgrounds. Different perspectives suggest that reality can be socially constructed and relative, and thus an interpretivist ontology.

In terms of the study's epistemology, the study is both interpretivist and positivist, and has a pluralistic approach to knowledge creation (Suri, 2013). On one hand, the interpretivist element of the study, through in-depth interviews, attempts to capture the reasoning of the participants with their entrepreneurial stories (Elbardan and Kholeif, 2017). This knowledge is individualistic, emergent and discursive, as it emerges from narratives. Conversely, the quantitative strand of the research, based on questionnaire administration, tends to align with the positivist view of knowledge and provides structured patterns within the sample. The focus on testing associations such as the link between regulatory environments and the success of startups, can be seen as a more irreversible knowledge that is impersonal and quantitative. Letherby et al. (2012) wrote that this double stance recognises the need to investigate depth and breadth, subjectivity and objectivity, and specificity and generality, tensions that are important to social research. In this regard, one philosophical worldview would be insufficient for such a study.

3.2.2. Rationalisation of Pragmatic Worldview

The interplay between the interpretivist and the positivist traditions is overcome by adopting pragmatism as philosophical paradigm for this study. Pragmatism is based on what works for the purpose and can be defined as an interest in the efficacy of a phenomenon for addressing a particular research question (Kaushik and Walsh, 2019). It is not a method-focused paradigm and thus supports methodological pluralism. Pragmatism has gained popularity as a paradigm underpinning mixed-methods designs, particularly

those that are complex, interdisciplinary or practice-based (Dingyloudi and Strijbos, 2018). Pragmatism is relevant for this study for the following reasons:

1. Fitting with the research aim: The study does not only have the purpose to understand the status quo of AI-related startup conditions for new graduates, but also to make strategic suggestions to improve the status quo. This pragmatic tendency can also be seen as having affinity with pragmatism, which values usefulness and verifiable knowledge - and seeks to avoid excessively neat theory.
2. Multifaceted approach: The interplay of regulatory frameworks (institutional and objective) and cultural conditions (subjective and symbolic), requires a paradigm that facilitates multiple epistemological positions. Pragmatism allows the incorporation of interpretivist and positivist orientations by recognising the value of both in-depth experience and empirical rigour (Sim et al., 2024).
3. Addressing the research gaps: While previous research has centred on macroeconomic policy frameworks or broad overviews of the startup ecosystem, very few have explored the microeconomic level of understanding of new entrepreneurs in the field of AI, especially those who are recent graduates. The choice of a pragmatic paradigm is justified because it helps enable flexibility in addressing these research gaps.
4. Flexibility in the sequential design: The sequential exploratory design of mixed-methods research used in this study involves a qualitative exploratory component where interviews are used to guide the design and analysis of the quantitative survey. This calls for flexibility supported by pragmatism. Pragmatism enables this reasoning process, in which the researcher follows the evolving understanding of the phenomenon, ensuring consistency across the research aim, methods, and results.

Further, the pragmatist approach acknowledges that the researcher is immersed in the research setting while enabling some objectivity in statistical quantification. It does not demand philosophical purity, as other more wholly critical realist or constructivist approaches might, it focuses on congruence between methods, questions and aims addressed.

3.2.3. Axiology and the Researcher

Axiology relates to the role of values in research. The researcher in a pragmatic inquiry is not external to the subject, as in positivism, nor is the researcher completely embedded in the subject, as in critical ethnography. Rather, the researcher is conscious of the interplay between subjectivity and objectivity (Morgan, 2014). In this project, the researcher, who is an objective observer and narrator in the Chinese AI industry, is aware of their role in the interpretation and coding of the qualitative data and need to ensure some degree of openness and objectivity in quantitative research. This thesis acknowledges that value-laden choices may occur in interpretation, for instance, decisions on what constitutes supportive regulation and an entrepreneurial culture. Morgan (2014) argues that pragmatic research does not eliminate values but treats them reflexively within the research process. This matters here because culture plays an important role in the interpretation of findings. This is especially important in the context of the diverse ideologies and political perspectives on AI governance in China.

3.2.4. Connecting the Philosophy and the Research Gap

The literature review identified three gaps addressed through the pragmatic research design: (1) limited qualitative insights into recent graduates working in the field of AI startups; (2) the lack of an integrated regulatory and cultural analysis; and (3) the absence of evidence-based models to assist young entrepreneurs in Chinese cities. The existing literature is often framed through a macroeconomic perspective or based on major government surveys on policy initiatives. This study therefore employs a pragmatic research design that reflects lived experiences and offers cautious policy and practice recommendations.

3.3. Research Approach and Design

This section introduces the broader research approach and design, bridging the philosophical underpinning to the operationalisation of activities in the research process. It provides an explanation for the reasoning approach, rationale for a mixed-methods approach and qualitative-quantitative order and rationale. The consideration of an exploratory sequential design follows the research paradigm and knowledge framework of the study, where it is important to explore the experiences of recent founders of AI startups in China before quantifying them, and gaining limited analytical insight and cautious policy implications from the results.

3.3.1. Deductive and Inductive Reasoning

The study draws on a rational juxtaposition of deductive and inductive reasoning to address the study objectives because it is a mixed-methods study. Inductive reasoning underpins the qualitative component of the study and facilitates developments of theories and themes from the bottom up by interpreting semi-structured interviews (Frost, 2021). This is essential in exploratory research such as this one, as entrepreneurship experiences of recent graduates are relatively under-explored in the literature. Braun and Clarke (2022) explain that through the process of thematic coding of interview data, the study can identify patterns of themes, which can then be used as a source of conceptual knowledge about regulation, culture and entrepreneurship.

The quantitative component, however, employs deductive reasoning, where hypotheses that attempt to explain connections among variables are tested through survey questions (based on in part, the literature and the qualitative themes) (Casula et al., 2021). These are tested to assess the relationships between the key concepts: regulation, culture, educational readiness and success. For example, one hypothesis looks at the contribution of access to government funding toward perceived startup success. In this way, it can become possible to combine inductive analyses of meaning formation with deductive analyses of relationships, producing well-analysed and well-contextualised findings.

3.3.2. Mixed-Methods Approach

As the research problem is complex and demands an integrated understanding of impact with an in-depth appreciation of individual experiences, with a general view of trends, the study takes a mixed-methods approach, in particular an exploratory sequential design. This design has two phases:

1. Phase 1: Qualitative phase - semi-structured interviews with recent graduates who had set up, or were closely involved in setting up, AI startups in major Chinese cities. This phase explored how participants interpreted regulatory, cultural, market and resource-related pressures. The themes generated from these interviews informed the wording and emphasis of the subsequent questionnaire.
2. Phase 2: Quantitative phase - a structured questionnaire administered to 150 AI startup founders or co-founders from the same broad demographic and industry context. The aim

was not to measure the objective regulatory environment itself, but to examine patterns in founders' perceptions of regulation, culture, infrastructure, funding and ecosystem support, and how those perceptions were associated with self-reported startup success.

The design was sequential exploratory: qualitative interviews were conducted first, followed by the questionnaire survey and then an integrated interpretation of both strands. The interviews were conducted between January and mid-February 2025, and the survey was administered between 1 July and 15 August 2025. The time gap between the qualitative and quantitative stages allowed the interview themes to be reviewed, translated into survey items and piloted before wider distribution. This sequence is important because it clarifies that the questionnaire was informed by the qualitative themes rather than being independent of them.

3.3.3. Coherence with Research Questions and Objectives

The research approach is well aligned with the three sets of questions driving the research objectives:

1. To understand and examine the regulatory/cultural issues of young graduates in AI startups
→ Researched through interviews, and thematically analysed stories, on policy, culture and organisational legitimacy issues
2. To identify ecosystem support and business development in China's AI startups
→ Addressed in interview questions, as well as survey items focusing on mentoring, incubators, funding and access to resources.
3. To develop a strategy for new graduates to approach AI startup ecosystem
→ Integrated across the two phases and based on the conceptual framework of an integration of RBV, EET and Institutional Theory.

These are because the qualitative stage is exploratory; something unanticipated might be discovered; it is also applicable in its larger scale due to the explanatory ability of the survey (Kalu and Bwalya, 2017). The two stages are then repeated to ensure conceptual clarity and rigour in data. Further, the two-fold nature of the research design assured that the recommendations for policy and educational changes the study made were driven by experience, and not trivial. This makes the study credible and relevant to the target audience such as the policymakers, university incubators, and venture capitalists.

3.3.4. *Validity of Design and Adaptability*

A major advantage of this research design was its capacity to combine exploratory depth with a structured follow-up survey. The semi-structured interview style in the qualitative phase allowed interviewees to explain issues that might not have been captured in a direct questionnaire (Blandford, 2013). The survey then provided a way to examine whether themes such as perceived regulatory clarity, infrastructure access and ecosystem support appeared across a wider sample. However, this flexibility did not remove the limitations of self-report data, non-probability sampling or the modest survey size. The quantitative findings are therefore interpreted as evidence of associations within the sample, not as proof of causal relationships or generalisable measurements of the external environment.

3.4. Qualitative Method: Semi-Structured Interviews

A mixed-methods approach is used in this study; the first phase is a qualitative phase that includes semi-structured interviews. Here, data were gathered about the lived experience of recent graduates who established AI start-ups in Chinese cities. The use of semi-structured interviews gave rich insight into regulatory and cultural processes as participants were able to share their practical expertise via their own voices. This section outlines the justification for interviews, sample, decision making on participant selection, development of the interview instrument, methods of data collection, ethical issues and limitations of the process.

3.4.1. *Justification of Semi-Structured Interviews*

Semi-structured interviews were used in this thesis, under the interpretivist-theory view of the philosophical context. As highlighted by Ruslin et al. (2022), semi structured interviews can be used to explore entrepreneurship related experiences, attitudes or ideas in a way that cannot be done with a structured survey. It also aligns with the pragmatic paradigm adopted for this research - involving deploying appropriate tools to tackle problems encountered in the real world.

Semi-structured interviews are applicable in China as the AI startup ecosystem there is heavily regulated and culture-specific. It's therefore appropriate for the interview process to be relatively unstructured while simultaneously keeping to several key themes for each interviewee (Ruslin et al., 2022). This is particularly important in dealing with issues that are sensitive and hard to discuss, such as licensing red tape, guanxi-building, or the risk of not sticking to a business-as-usual culture. Lim (2025) noted that this approach allows the

researcher to interact with the interviewee to their responses, dig deeper into a range of unanticipated issues, and re-arrange the questions to fit with the narrative. The second point is that the quantitative part of the second stage research is grounded in semi-structured interviews. Interview interpretations can guide survey questions' design and formulation and ensure these questions are conceptually and culturally appropriate.

3.4.2. Participant Selection and Sampling Strategy

The research participants are purposively sampled and the inclusion criteria are well defined in terms of the research aim. These criteria are:

- Recent graduate: Entrepreneurs should be recent graduates (within the past five years).
- Entrepreneurial experience: The entrepreneurs should be first-time entrepreneurs in AI technology, not engaged in developing other startups.
- Location: The startups should be based in cities with considerable AI activities in China, such as Beijing, Shanghai, Shenzhen, or other cities.
- Industry relevance: The startups should specialise in AI-based technologies (for instance, machine learning, natural language processing, and computer vision) as their primary business.

At the first stage of the study, participants were identified through alumni associations, university incubator networks and entrepreneurship support organisations. The study also uses the snowball approach to supplement the sample with referrals from participants who may be aware of other members of their community who fit the inclusion criteria (Valerio et al., 2016). This maximises access to a guarded and competitive entrepreneurial community, which may be resistant to general marketing efforts. A total of 15 participants were interviewed, consistent with Guest et al. (2020), who recommend that saturation is most likely to occur between 12 and 20 interviews in expert-focused qualitative studies. This sample size is sufficient given that the population being studied consists of a relatively identifiable and focused group of new AI startup founders and open-ended interviewing is needed for thematic saturation while maintaining manageability and rigour (Guest et al., 2020). This sample size is in line with the sample size of qualitative research that explores and describes a specialised phenomenon and an expert population.

3.4.3. *Thematic Structure and Interview Guide*

The interview questions were created deductively to address the research questions and theories such as the Resource-Based View, Institutional Theory and Entrepreneurial Ecosystem Theory, to learn about the regulatory, cultural and strategic aspects of student-led AI startups. They were semi-structured, enabling respondents to provide insights on their experiences with regulatory, guanxi, capital, and entrepreneurship. Themes were then inductively identified using Braun and Clarke (2022) six-stage method of thematic analysis, which includes: familiarising, initial coding, searching for themes, creating themes, defining and naming themes and writing up results, per the table below..

Table: Application of Braun and Clarke’s Six Stages of Thematic Analysis in This Study

Stage	Braun and Clarke’s Description	Application in This Research Study
Stage 1: Familiarisation with the data	Immersion in the data through repeated reading and initial noting of ideas	Interview transcripts from recent AI startup founders were read multiple times to gain an in-depth understanding of participants’ experiences related to regulation, culture, infrastructure, and entrepreneurial decision-making. Initial analytic notes were recorded to capture early impressions and recurring issues emerging from founders’ narratives.
Stage 2: Generating initial codes	Systematic coding of meaningful features across the entire dataset	Transcripts were coded line by line using an inductive approach, focusing on segments relating to regulatory ambiguity, access to funding, guanxi, educational preparedness, infrastructural inequality, and ecosystem navigation. Coding remained open and flexible to allow new concepts to emerge from the data rather than being constrained by predefined categories.
Stage 3: Searching for themes	Collating codes into potential themes and gathering relevant data for each	Related codes were clustered into broader candidate themes, such as regulatory complexity, cultural identity tensions, experiential education gaps, and strategic adaptation. These preliminary themes captured patterned responses across participants while preserving contextual nuance.
Stage 4: Reviewing themes	Refining themes by checking coherence within themes and distinction between themes	Candidate themes were reviewed against the full dataset to ensure internal consistency and conceptual clarity. Overlapping or weak themes were merged, refined, or discarded, ensuring that each theme was analytically distinct and meaningfully represented founders’ lived experiences.
Stage 5: Defining and naming themes	Ongoing analysis to refine the essence of each theme and develop clear definitions	Final themes were clearly defined to articulate their analytical focus and theoretical relevance. For example, regulatory ambiguity was defined as founders’ perceptions of inconsistent policy interpretation and enforcement, while ecosystem navigation captured strategic reliance on platforms, incumbents, and informal networks.
Stage 6: Producing the report	Selecting vivid extracts and linking analysis to research questions and theory	Representative quotations were selected to illustrate each theme and were analytically interpreted in relation to the research questions and theoretical frameworks, including Institutional Theory, Entrepreneurial Ecosystem Theory, and the Resource-Based View. The findings were integrated into the discussion chapter to support theoretical contribution and policy implications.

Initial open codes captured recurring patterns from participant narratives, which were later grouped into higher-order categories such as regulatory ambiguity, infrastructural inequality, and cultural identity tension. These emergent themes were refined through cross-case comparison to ensure saturation, coherence, and theoretical alignment with the study's mixed-methods design. The interview protocol, as shown in the Appendix, was developed based on the literature review, conceptual framework, and ethical approval documents. It is organised around four thematic areas:

- Theme 1: The difficulties of establishing AI startups
 - o Participants recall the issues they experienced during the initiation of their ventures, focusing on regulatory requirements, compliance burdens, legal expertise, and cultural barriers, such as social risk aversion or attitudes toward youth entrepreneurship.
- Theme 2: Support Systems and Competitive Landscape
 - o This section discusses funding, mentorship, networks, and access to incubators. Participants share their views on the effectiveness and drawbacks of government-driven programmes, as well as the tactics used to compete with technology giants such as Alibaba or Tencent.
- Theme 3: Resource Accessibility and Government Influence
 - o The interviewees discuss their relationships with government programmes, such as Made in China 2025, public procurement schemes, and start-up subsidies. They also consider infrastructural access, such as AI computing platforms or proprietary datasets, and strategic reliance on other ecosystem actors.
- Theme 4: Reflections and Future Strategies
 - o The interview concludes by asking participants to share their long-term plans, sustainability strategies, and advice for new graduates. This helps identify success factors and perceived enablers within the ecosystem.

3.4.4. Data Collection and Interview Procedures

The interviews were held online via secure virtual platforms, such as Zoom or Microsoft Teams, which provide secure and adaptable options in the post-pandemic era. The digital platform was also appropriate for the generation of digital natives, some of whom may prefer the use of digital platforms (Dingli and Seychell, 2015). Interviews ranged from

45-60 minutes, and were conducted at the interviewee's convenience. Participants could choose the language they were most comfortable speaking in for the interview (Mandarin or English); 9 interviews were held in Mandarin, while six were held in English. When Mandarin was spoken, the researcher confirmed the transcription and translation.

Interviews were recorded with participants' permission and secure interview recording software. They also stored the recordings in encrypted cloud storage. None of the video or audio recordings of the interviews was identified to maintain participant confidentiality. Descriptive information about the length, location, language, interview platform, and participant code was documented for each interview, with each participant code obfuscated (e.g., P01). Transcripts were supported by interview field notes, which included context and non-verbal interactions that could inform the coding process (Pratomo et al., 2023).

The transcripts were manually coded, which allowed them to be compared with each other to identify common themes (Braun and Clarke, 2022). The themes were identified through open coding and later grouped together into axial codes that signalled patterns. After some refinement, codes were condensed into themes, such as regulatory ambiguity and cultural tension.

3.4.5. *Ethical Considerations*

Ethical approval for data collection for the research project was sought and gained from the University of Stirling Research Ethics Committee at the outset. Participants received a Participant Information Sheet and Electronic Consent Form, at least 48 hours prior to the interview. This provided information about the study's purpose, privacy and security of data management, data use, and the option of withdrawing before analysis. Consent and participation were voluntary and there were no financial incentives (Pratomo et al., 2023). The results are not published or shared with personal information. The researcher was also mindful of the potential sensitivities of the participants when they spoke about state regulations or restrictions in their workplace. As a result the interviews were not political and solely discussed professional encounters and relationships with institutions.

3.4.6. *Limitations of the Interview Method*

While semi-structured interviews are useful in collecting rich and informative data, there are some limitations to using the technique. For one thing, the sampling is non-probabilistic, so the research findings have limited transferability. The views of

individuals sampled, while informative, might not represent the views of all founders of AI startups in Chinese cities and provinces. Second, there may be a bias from social desirability, particularly in the responses relating to the relationships with government or funding organisations. Participants may downplay negative experiences and emphasise positive ones to demonstrate their entrepreneurial abilities.

Third, there are language issues. While the option of Mandarin language interview increases inclusivity, the language dynamics between the interviewees and interviewer could affect the interpretation of language expressions and words. This is minimised, but not eliminated, by using certified transcribers. Finally, the online nature of the interviewing precludes the researcher from being able to visualise body movements and other non-verbal indicators. However, this can be somewhat mitigated by the videos and through probing questions, respondents have the opportunity to explain in more detail.

3.5. Quantitative Method: Survey Questionnaire

The second phase of this study used a quantitative survey questionnaire to complement and extend the results from qualitative interviews. The aim of this phase was to gather standardised perception data from a larger sample of recent founders of AI startups in urban China. The survey therefore supported descriptive analysis, correlation and cautious regression modelling. It did not provide a direct objective measure of regulation, culture, infrastructure or startup performance.

3.5.1. Rationale for Using Surveys

A structured survey contributes to the pragmatic mixed-methods approaches of this study. The interviews in this study provide a deep understanding of the various levels of complexity, but do not provide an opportunity to assess aggregate trends or relationships between variables. Nardi (2018) notes that surveys can assist researchers in assessing perceptions and behaviours in a large and diverse sample and, therefore, increase the external validity of their research. The survey approach is also well matched to studies that explore relationships between constructs, such as perceived regulatory favourability and startup performance, or access to funding and entrepreneurial confidence. Using a Likert scale, latent constructs can be measured on an ordinal scale and statistical techniques such as correlation and regression analysis can be used (Park, 2023) Moreover, the survey is consistent with the deductive nature of the study because the theories developed from the literature and themes from the qualitative research are tested. The survey also serves as an

instrumental function in this study: it translates the knowledge from the exploratory study. It provides a structured path from individual qualitative insights to standardised survey patterns that can inform researchers, policymakers and ecosystem actors.

3.5.2. *Questionnaire Design*

The survey instrument is structured into two main sections:

- Demographic and Startup Profile
- Thematic Construct Items (using 5-point Likert scales)

The first part contained categorical and ordinal information on participants' age, gender, education, startup location and time in operation. The second section included six thematic constructs, each comprised of five items rated on a five-point Likert scale. The constructs were developed from three sources: the literature reviewed in Chapter 2, the themes emerging from the qualitative interviews, and established survey-design principles for measuring perceptions and self-reported entrepreneurial outcomes. Items were adapted conceptually to the specific context of graduate AI start-ups in China, rather than transferred unchanged from a single existing scale.

The main constructs were operationalised as follows. Regulatory Environment measured perceived clarity, favourability and navigability of rules affecting AI ventures. Access to Funding measured perceived availability of venture capital, grants and early-stage finance. Cultural Attitudes captured perceived risk tolerance, family/social expectations and legitimacy of entrepreneurship. Educational Background measured perceived preparedness generated by formal education and entrepreneurial training. Technology Infrastructure measured perceived access to cloud services, data, technical platforms and AI development resources. Entrepreneurial Ecosystem Support measured perceived usefulness of incubators, mentors, university support and local innovation networks. Startup Success was measured subjectively through founders' self-reported progress towards financial, strategic and sustainability goals.

This operationalisation has an important limitation: the survey measures founders' perceptions and self-reports, not independently verified policy conditions or audited venture performance. The constructs are therefore suitable for examining how perceived environmental conditions are associated with reported outcomes, but they should not be read as direct measurements of the objective regulatory environment or as causal tests of venture success.

Table 1a Construct Sources, Adaptation Logic and Conceptual Limitations

Construct	Original literature or conceptual source	Adapted items	Why adapted for Chinese AI graduate founders	Conceptual limitation
Regulatory Environment	Institutional theory and AI governance literature; interview themes on licensing, local implementation and policy ambiguity.	Items on regulatory favourability, clarity, compliance burden and policy support.	AI founders face sector-specific data, cybersecurity and licensing uncertainty; recent graduates may have less policy literacy.	Measures perceived regulatory clarity/favourability, not the objective regulatory environment.
Access to Funding	Entrepreneurial finance and ecosystem literature; interview themes on grants, venture capital and guanxi-mediated access.	Items on venture capital access, grant access, investor openness and early-stage funding difficulty.	AI start-ups require costly compute, talent and data; graduate founders often lack investor track record and networks.	Captures perceived funding access, not verified investment amounts or funding outcomes.
Cultural Attitudes	Entrepreneurship culture, legitimacy and social capital literature; interview themes on family expectations, risk and guanxi.	Items on fear of failure, social approval, family pressure and relational legitimacy.	Cultural expectations may affect whether graduates treat start-up formation as legitimate or risky.	Culture is heterogeneous and cannot be reduced to a single national attitude score.
Educational Background	Human capital and entrepreneurship education literature; interview themes on technical training versus business readiness.	Items on university preparation, entrepreneurial skills, business knowledge and practical exposure.	Recent graduates may have strong AI skills but weaker finance, legal, management and market-testing experience.	Measures perceived preparedness, not objective educational quality or curriculum content.
Technology Infrastructure	AI ecosystem and digital infrastructure literature; interview themes on cloud, data, platforms and compute access.	Items on availability, affordability and reliability of AI development infrastructure.	AI ventures depend on cloud services, data access and platform ecosystems more heavily than many non-AI start-ups.	Measures perceived access and usability, not audited infrastructure provision.
Entrepreneurial Ecosystem Support	Entrepreneurial ecosystem literature; interview themes on incubators, mentors, universities and local support.	Items on incubator usefulness, mentoring, university support and local innovation networks.	Graduate founders often depend on institutional intermediaries for legitimacy, knowledge and resources.	Does not independently evaluate the quality of each support organisation.
Startup Success	Entrepreneurship performance literature adapted	Items on self-reported financial progress,	Many early AI ventures lack stable audited	Subjective self-report measure; not equivalent to

Construct	Original literature or conceptual source	Adapted items	Why adapted for Chinese AI graduate founders	Conceptual limitation
	to early-stage ventures; interview themes on survival, traction and goal progress.	goal achievement, sustainability and perceived growth.	performance data, so perceived progress is more feasible to collect.	objective financial performance, survival or audited growth.

Table 1 Constructs and Sample Items

Construct	Sample Survey Item
Regulatory Environment	"The regulatory environment in China is favourable for launching AI startups."
Access to Funding	"Accessing venture capital for AI startups is easy in urban China."
Cultural Attitudes	"Fear of failure affects my decision-making in the startup environment."
Educational Background	"My academic training adequately prepared me to start and run an AI venture."
Technology Infrastructure	"China's AI infrastructure is accessible and beneficial for startups like mine."
Entrepreneurial Ecosystem Support	"Incubators and accelerators in my city offer valuable resources for startups."

The items were scored on 5-point Likert scales, Strongly Disagree (1) to Strongly Agree (5), from which composite measurements can be derived for the constructs. These types of items allow for descriptive and inferential statistics to be undertaken, as well as reliability tests such as Cronbach's alpha. The questionnaire also contains a dependent construct called Startup Success, which is measured using items such as financial success, goal achievement and startups perceived sustainability (Anderson et al., 2020). We develop the survey in English, and translate it into Simplified Chinese for convenience. The back-translation method is used to make sure the concepts are the same across languages.

3.5.3. Sampling Strategy

The sampling approach of this phase is non-probability purposive, and the focus of the sample is recent AI entrepreneurs who fulfill the following requirements:

- Was a founder or co-founder of an AI-based technology company in China.
- Had started the business within five years of graduating from a university or technical institution.
- The startup needs to be located in a metropolitan center of innovation, e.g., Beijing, Shanghai, Shenzhen, Hangzhou, Nanjing, etc.
- A startup has to exist in the AI or machine learning environment, in general.

The final survey sample comprised 150 participants. This sample size was appropriate for descriptive analysis and for exploratory correlation/regression with a limited number of predictors, but it remains modest for subgroup analysis. The gender distribution was also uneven, reflecting both the sampling channels used and broader gender imbalance in technology entrepreneurship. For this reason, the analysis does not claim to represent all Chinese AI founders and treats gender-related patterns cautiously.

- Mother institutions, Startup incubators and tech accelerators (e.g., Tsinghua x-lab, TusStar, XNode)
- Alumni networks and university entrepreneurship centres.
- Online communities: WeChat groups, LinkedIn forums, and Zhihu discussions about AI startups.
- Referrals by participants of the interview (snowball sampling).

A short description of the study, eligibility criteria, and a link to the survey are already presented in an invitation message, and this survey is available on Qualtrics or Wenjuanxing, which serves as the most popular domestic survey site in China.

3.5.4. Data Collection Procedures

The JISC platform was used to administer the survey for six weeks (1 July - 15 August 2025). The survey was reviewed weekly to monitor response quality and demographic balance. Every participant was presented with information about the research on the first page, followed by an implied consent statement for anonymous questionnaire participation. No names, IP addresses or direct identifiers were collected. The survey generally took 10-12 minutes to complete.

3.5.5. Instrument Validity and Reliability

The instrument development process sought to enhance content validity and construct reliability (Zamanzadeh et al., 2015). Content validity was addressed by matching items to the literature, interview themes and the research questions. In the pilot stage ($n = 10$), wording, clarity and layout were amended. Face validity was supported through informal feedback from entrepreneurship academics and stakeholders in the entrepreneurship ecosystem. Construct reliability was assessed using Cronbach's alpha, with 0.70 used as the indicative threshold for internal consistency (Izah et al., 2023). Because the constructs were adapted to a specific context, the thesis treats the instrument as fit for exploratory analysis rather than as a fully validated universal scale.

3.5.6. *Ethical Considerations*

The quantitative phase adheres to the same ethical principles outlined in Section 4 and complies with the University of Stirling's ethics approval. Specific ethical procedures for the survey include:

- Anonymity: No names, IP addresses, or contact details are collected. Participation is entirely anonymous.
- Voluntariness: Participants may quit the survey at any point before submitting, with no penalty or consequences.
- Informed consent: A clear consent form is displayed on the opening page.
- Data security: All data are stored on encrypted, GDPR-compliant servers. Survey platforms are selected based on data privacy policies that are acceptable in both China and the UK.
- Cultural sensitivity: The survey avoids politically sensitive terminology and ensures questions are framed in a neutral, professional tone.
- No personal or commercial benefit is derived from the collected data. The primary objective is to enhance scholarly and policy understanding of the AI startup landscape in China.

3.5.7. *Limitations of the Survey Method*

Although the survey method allows for breadth, it introduces several limitations:

1. Sampling bias: The reliance on purposive and snowball sampling may result in overrepresentation of well-networked or resource-rich entrepreneurs, excluding more marginalised founders.
2. Self-reporting bias: Respondents may exaggerate their startup's success or underreport regulatory difficulties due to social desirability or fear of reputational risk.
3. Cross-sectional design: Data are collected at a single point in time, which limits the ability to infer causality or track temporal changes.
4. Platform accessibility: Some international survey platforms (e.g., Qualtrics) are less accessible within China's firewall, necessitating the use of domestic platforms that may have less robust analytics capabilities.

Despite these constraints, the survey offers a useful quantitative lens for examining patterns and relationships that complement the qualitative findings.

3.6. Data Analysis Techniques

This section explains how the qualitative and quantitative data collected through the sequential exploratory mixed-methods design was analysed. It explains how the thematic analysis of semi-structured interviews and statistical analysis of survey questions were carried out. It also justifies why using the two data sets adds to the analysis of the study and cites methodological literature to describe the methodological choice. Being a pragmatic paradigm study, the work on developing analytical strategies is centred on those that are theoretically and practically sound for the study.

3.6.1. Interview Interpretation: Thematic Analysis

Thematic analysis is used to interpret the qualitative data obtained from semi-structured interviews. It is a widely recognised method based on the identification, analysis and reporting of patterns in the data (Bell et al., 2022). This approach is particularly appropriate for the interpretivist aspect of this study because it assists with understanding how the interviewees perceive the regulatory, cultural and entrepreneurial practices. Clarke and Braun (2014) highlighted that thematic analysis can be used both to describe the data and develop theory, and this is consistent with the inductive nature of this phase of the study.

This analysis was conducted according to the six-stage model of thematic analysis described by Clarke and Braun (2014). During the first step, the researcher became familiar with the transcript data through repeated reading and analytic memoing (Kowal and O'Connell, 2014). The researcher then assigned preliminary codes by manually interpreting significant aspects of the data in relation to regulation, culture, support and coping strategies. Codes were grouped into more abstract themes; for example, duplicative bureaucracy, unclear licensing and policy inconsistency were clustered under regulatory complexity. Themes were then reviewed against the coded data and refined to ensure that they represented the research questions.

Table 2 Qualitative Data Coding and Theme Development

Stage	Example Codes	Sub-Themes	Final Themes	Analysis Approach	Description of Process
1. Familiarisation	–	–	–	Manual	Repeated reading of transcripts and memoing to capture first impressions and contextual nuances.

Stage	Example Codes	Sub-Themes	Final Themes	Analysis Approach	Description of Process
2. Initial Coding	<i>Duplicative bureaucracy, intransparent licensing, policy irregularity</i>	Regulatory barriers	Regulatory Ambiguity and Complexity	Manual	Codes were derived manually but categorised in manually for cross-case comparison and query generation.
3. Pattern Identification	<i>Unequal access to digital tools, regional disparity, cloud cost dependency</i>	Infrastructure gaps	Infrastructural Inequality	Manual	Pattern coding clustered similar experiences.
4. Theme Searching	<i>Respect for hierarchy, guanxi reliance, risk aversion</i>	Cultural barriers	Cultural Identity Tensions	Manual	Manual interpretation ensured contextual accuracy
5. Theme Refinement	<i>Lack of entrepreneurial exposure, limited business training, education-industry gap</i>	Skill and education deficit	Experiential Education Gaps	Manual	Overlapping codes were merged
6. Review and Finalisation	<i>Strategic adaptation, policy alignment, partnership dependency</i>	Coping and strategic mechanisms	Ecosystem Navigation and Strategic Adaptation	Manual	Final themes reviewed iteratively against transcripts and theoretical framework (RBV, IT, EET).

At stage five, the researcher named and described the final themes and checked that they represented facets of the research question (Vaismoradi et al., 2016). Subthemes were also developed to offer more specific subsections of each core theme. The last stage was reporting the results through participant quotations to express the meaning of the themes. This approach added descriptive detail and allowed iterative clarification of categories throughout the analysis process.

3.6.2. Survey Data Analysis

The survey responses are analysed using Statistical Package for the Social Sciences (SPSS). This starts with data preparation, which includes screening for incomplete responses, contradictory answers and outliers (Sharifnia et al., 2025). Next, descriptive statistics, such as measures of location and spread are used to summarise the characteristics of the respondents and their startups. The primary objective of the statistical analysis, as Okoye

and Hosseini (2024) note, is to explore the relationships between the dependent variable (start-up success) and independent variables including regulatory favourability, funding and cultural support. To achieve this objective, the study employs bivariate correlation tests which determine the degree and direction of the linear association between the variables measured using Likert type scales.

This was followed by multiple linear regression, which assessed the association between the independent variables and self-reported startup success. The 150 responses were sufficient for an exploratory model with a limited number of predictors under common rules of thumb (Hair et al., 2020), but the results should be interpreted cautiously because the sample was purposive and non-probability based. The model therefore explores associations between perceived regulatory knowledge, access to financial and support infrastructure, cultural attitudes and founders' self-reported success; it does not establish causality or support population-level analytical insight.

Cronbach's alpha tests the reliability of the Likert-scale items for each construct of interest (Nemec II et al., 2018). The minimum reliability is set at 0.70. Jung (2013) suggests that confirmatory analysis of construct validity can include exploratory factor analysis, but this analysis is contingent on a representative sample size. These analyses are used to assess whether the survey instrument is reliable and whether the constructs are sensitive to the ideas being studied. Through quantitative analysis, the researcher can measure the core themes and patterns identified during the interview phase, examine how these patterns appear within the study sample, and identify whether statistically significant associations are present and how they may inform the interpretation of the phenomenon under investigation.

3.7. Credibility and Reliability

The rigour of a methodology should also bear in mind the validity and quality of academic work. In mixed-methods studies, different measures of rigour in the qualitative and quantitative components of the study need to be applied to ensure consistency and methodological rigour in each component (Matović and Ovesni, 2023). This section sets out the relationship between rigour and traditional markers of quality in qualitative research - trustworthiness, in quantitative research - validity and reliability or, in mixed-methods research - integrative coherence. This is to demonstrate the credibility,

transferability and reliability of the findings, and the statistical and analytical rigour of the study.

3.7.1. *Credibility in Qualitative Research*

The trustworthiness of the qualitative phase is assessed through four conditions: credibility, transferability, dependability and confirmability (Haq et al., 2023). These conditions are used to ensure that all the data and meanings are adequate, have transferability, are relevant, and consider researcher biases. According to Janis (2022), credibility is achieved by spending an extended time with the data, repeatedly reading and reflecting on the interview transcript, and reflexive description in a thematic analysis. Through peer debriefing, the researcher can discuss interpretations with colleagues, confirm and test interpretations, challenge biases and remove any uncertainties. Furthermore, member checking is undertaken with a few respondents, in which they are asked to react to the summary of themes and how they believe their views have been captured. This confirms the empirical plausibility and power of the interpretation.

The transferable nature of a study's findings is termed transferability (Drisko, 2025). While this study does not attempt to transfer in a statistical fashion, thick descriptions promote transferability. The analysis of the interviews takes into account the geographical location of the interviewee, their industry and their sectoral specialisation. The study offers rich, descriptive accounts which guide the reader to make judgements about the transferability of the research to other settings. Dependability is enhanced by building an audit trail that documents decision-making processes in relation to data gathering and analysis (Carcary, 2020). This involves decisions about data coding, memoing and documentation of theme development, as well as documenting contradictions and revisions. This facilitates transparency and traceability in the process, although this may not always lead to the same outcome if replicated with different samples or settings.

Confirmability relies on minimising researcher bias and developing interpretations that are rooted in the data (Ahmed, 2024). While interpretivist research cannot be said to be, and perhaps should not be, totally neutral, the researcher nevertheless gains reflexive awareness during the process by acknowledging their positionality and any biases or prejudices they might bring to interpretations. In the findings chapter, all direct quotations are chosen for their representative nature - not their anecdotal interest.

3.7.2. Testing Reliability and Validity in Quantitative Research

The quantitative survey part ensures the rigour of the analytical framework via the application of the classical requirements of reliability and validity. According to Hajjar (2018), the reliability (internal consistency) of each thematic question is measured as Cronbach's alpha. A minimum Cronbach's alpha of 0.70 should be present for an acceptable level of reliability. However, item-total correlations are also checked, and items exhibiting low correlations are removed or revised. Survey items are developed to demonstrate content validity through a combination of literature and the researcher's qualitative findings. The items are founded on key concepts attributes that are identified in the entrepreneurship and institutional theory literature, as well as on situated insights generated from the interviews. This dual source approach also aids topical specificity and situational congruence. Academic colleagues and domain experts review the survey instrument to assess its face validity in terms of clarity, format and logical flow (Elangovan and Sundaravel, 2021). This results in minor revisions of some answers and order of blocks of questions.

A pilot test with 10 participants was conducted to test the clarity, reliability and appropriateness of the main survey. Respondents pointed out some unclear phraseology and redundancy, which was eliminated. A pilot test demonstrated the possibility of obtaining estimates of Cronbach's alpha and that reliability of level 0.70 and above was acceptable. Pilot testing improved the validity, question order and comprehension of the test, leading to a higher level of data accuracy and construct reliability for full implementation (Hajjar, 2018; Elangovan and Sundaravel, 2021).

To determine construct validity, exploratory factor analysis (EFA) can be used, but this also requires a large sample. When EFA is used, it is possible to see if the items load onto the constructs as expected. Where there is a mismatch between the predicted constructs and items, the model is redefined. Thus it's possible to confirm that the constructs capture unique, and conceptually relevant constructs. The statistical validity of the regression and correlation tests is enhanced by testing the assumptions of regression and correlation, including assumptions of linearity, multicollinearity and residual normality. The researcher also evaluates the power of the statistical tests and discusses the magnitudes of significant findings. These tests contribute to the data analysis strategy by ensuring the documented

relationships are statistically meaningful, not spurious and resulting from misspecification and/or sample variance.

3.7.3. *Mixed-Methods Integration Rigour*

Alongside the separate tests of rigour of the qualitative and quantitative phases, this study also examines mixed-methods rigour in terms of integration coherence, interpretive consistency and design transparency. Integration coherence relates to the logical and methodological coherence of the two phases of the study. First, in this study, the category themes identified from the qualitative study are directly applied to the design of the survey instrument, thus giving rise to conceptual coherence. Secondly, the qualitative data is also used to interpret the survey results, thus adding to the triangulation of data in a significant way.

Interpretive utility is enabled by the use of the same conceptual frameworks in the interpretation of both types of data (Resource-Based View (RBV) Theory, Entrepreneurial Ecosystem Theory and Institutional Theory). This approach avoids the survey and interview results being interpreted in isolation; rather, they are considered as complementing each other. Where they converge, the research adds to previous innovation literature. Where findings diverge, the research critically assesses these differences and considers potential explanations with regard to context, sampling and scope of measurement.

Transparency in design is achieved through a clear description of the order, purpose and processes of each methodological step (Hevner et al., 2024). The thesis outlines a well-documented approach that describes the relationship between the research questions, methods and findings. The research meets best practice standards for the reporting of mixed-methods research where relationships between the stages are described and the relationships between data types are well outlined. At the same time, the thesis recognises that issues of paradigm incompatibilities may still occur.

3.8. Methodological Limitations

While the current study uses a sound mixed-methods approach based on a pragmatic research paradigm, it also clarifies some of its limitations that can influence the range, the quality, and transferability of the data. The recognition of these limitations also contributes

to the transparency and confirmability of the study and the cautious interpretation of the results within reasonable bounds. Khan (2020) suggests that limited transferability is a major limitation when using purposive and snowball sampling in the qualitative and quantitative parts of a study, since the samples were selected non-randomly. The respondents and sample inclusion criteria are based on the research question, which in the current study is recent university graduates who are founders of AI startups in Chinese cities. This makes it relevant and rich for the study, but potentially biased and not readily transferable to the entire population of AI entrepreneurs in China. Those who are captured may be better connected, more educated and more formally rooted in entrepreneurial networks than those who are not.

The other limitation is the cultural interpretation of the qualitative interviews. While the interviews were undertaken in preference either in English or Mandarin, there is a risk of semantic loss during the transcription, translation and analysis processes. Certain words, like *guanxi*, face or regulatory legitimacy, may have tacit culture-specific meanings that are hard to communicate. Despite the use of a back-translation approach, and the discussion with bilingual academics, there may be subtle nuances of meaning, such as in the understanding of culture-specific norms or rhetorical differences. This could influence code inter-rater reliability and validity.

There are also issues of using self-report data, particularly in the survey phase of the research. The scales are measured by participants' perceptions of regulatory favourability, success, and cultural factors. Self-reporting can lead to social desirability bias, with participants potentially overstating their success and understating their challenges, in an attempt to appear more positive. The culture of competition in China may also create pressure for respondents to look positive, successful and stable, even in difficult times (discussing issues such as government support or failure). While respondents are assured of anonymity and confidentiality, these biases cannot be eliminated.

Second, the study has a cross-sectional design (with data collected at one time). As Chirico (2023) noted, it could limit the scope of examining the variation of the participants' opinions, business operations, or responses from the organisations over time. For instance, an entrepreneur's attitude towards regulatory issues may vary over time from the early to a more mature stage of a startup. Likewise, distinct structural changes, including policy reform or social change attitudes towards AI may not be captured in a cross-sectional study.

A panel design would enable more in-depth investigation of the temporal factor, but such complexity lies beyond the scope of this study.

However, the methodology is suitable for the exploratory nature of the study. Adopting purposive sampling, semi-structured interviews, and standardised survey scales ensures consistency and conceptual fit, but limits limited transferability given the lack of longitudinal analysis.

3.9. Conclusion

This chapter outlines the research approach used to study the regulatory and cultural barriers encountered by recent artificial intelligence (AI) graduates starting their ventures in large cities in China. It started with a discussion of the philosophical position of the study as one of pragmatism, which enables both interpretivist and positivist elements. Next, the chapter detailed the use of a sequential exploratory mixed-methods approach whereby semi-structured interviews were conducted before the structured survey questionnaire. This is because both conceptual and empirical validation is needed for this study.

The first phase involved thematic analysis to explore patterns in entrepreneurs' perceptions and strategies for overcoming regulatory, cultural and infrastructural challenges. This was complemented by the second quantitative phase, which statistically explored relationships between the key constructs, including access to funding, regulatory favourability and perceptions of self-reported entrepreneurial success. Sampling, coding and adherence to standards of trustworthiness and validity reflect the study's rigour. Ethics were also addressed in the chapter.

4. Research Findings

4.1. Quantitative Analysis

4.1.1. Introduction

This chapter reports the result of the quantitative phase of the study, which explores institutional, cultural and infrastructural problems faced by recent graduates in China who have set up AI start-ups in cities. The start-ups undertake AI products and services. Building on the information obtained during the qualitative interviews, the objective of this phase is to verify the results, and, to some extent, expand the findings to a larger sample size through statistical analysis. The chapter plays a vital role in answering the research question of how regulatory, financial, cultural and educational factors influence the experiences and perceived success of nascent AI entrepreneurs in China's innovation clusters.

The six key constructs measured via the quantitative survey are identified via the literature review and qualitative phase of this study. They are: (1) Regulatory Environment (RE), which assesses the transparency, favourability, and consistency of government regulations; (2) Access to Funding (AF), which includes the accessibility and ease of obtaining venture capital investment or grants; (3) Cultural Attitudes towards Entrepreneurship (CAE), which assesses societal values related to risk, failure, and entrepreneurial legitimacy; (4) Educational Background (EB), which assesses perceptions of how well academic institutions prepared respondents to become entrepreneurs; and (5) Technology Infrastructure (TI), which assesses the accessibility and adequacy of technological resources; (6) Entrepreneurial Ecosystem Support (EES), which assesses the availability and effectiveness of broader ecosystem resources, including incubators, accelerators, mentorship, networking opportunities, and institutional support for startup development.

These constructs are directly related to the three research questions of the paper, which explore: (1) the main regulatory and cultural challenges faced by AI startup founders, (2) the purpose and impact of support systems and external enablers, and (3) the influence of these circumstances on perceived success. Quantitative results help examine the relevance of the trends and themes identified in the qualitative data analysis and their patterns within the sample.

4.1.2. Descriptive Statistics

4.1.2.1. Sample Characteristics

A total of 150 recent graduates who were engaged in AI startup projects in the innovation hubs of China were surveyed. The background information reveals that the survey was conducted with a relatively young, gender-skewed and highly educated group, which was the primary focus of the study. The sample of entrepreneurs was also comparatively young, with most of the entrepreneurs in the 21-25 years old (46.0%) age group, followed by the 26-30 years old (26.67%) age group. This large proportion of young entrepreneurs suggests that this research examined graduate startups: something that the government has been pushing for to foster youth entrepreneurship in the technology industry.

Table 3 Demographic Background of Sample

Variable	Item	Frequency	Percentage (%)
Age	18–20	15	10.00
	21–25	69	46.00
	26–30	40	26.67
	31–35	26	17.33
Gender	Female	121	80.67
	Male	26	17.33
	Prefer Not to Say	3	2.00
Highest Education	Bachelors	49	32.67
	Masters	85	56.67
	PhD	10	6.67
	Prefer Not to Say	6	4.00
Startup Experience	< 1 year	11	7.33
	1–2 years	31	20.67
	2–3 years	79	52.67
	3+ years	23	15.33
	Prefer Not to Say	6	4.00
Startup Location	Beijing	34	22.67
	Shanghai	51	34.00
	Shenzhen	29	19.33
	Nanjing	22	14.67
	Prefer Not to Say	14	9.33

In terms of gender, the data show that a large proportion of respondents are women (80.67%). This is an important feature of the sample, but it should be interpreted cautiously because the purposive sampling strategy does not allow the thesis to infer the gender composition of AI entrepreneurship in China as a whole.

Regardless, 56.67% have a degree and 32.67% have a Bachelor's degree, showing that AI entrepreneurship in China is mainly driven by highly educated graduates with advanced degrees. The proportion with a PhD is 6.67% of respondents, suggesting that entrepreneurs are in the early stages of their careers.

In terms of startup age, 52.67% of startups have been established between 2-3 years, which indicates a post-pandemic level of maturity in AI innovation, while 28% have been established for less than 2 years, suggesting the inflow of new startups. This indicates sustained growth in entrepreneurship, but there is a potential risk of attrition due to regulatory or funding constraints.

The gender distribution reveals a large proportion of female respondents (80.67%), a smaller proportion of male respondents (17.33%), and a small proportion of participants who did not disclose gender (2.00%). The gender skew is a defining feature of the sample and should be explicitly accounted for in the discussion of results. It should not be treated as evidence of the wider gender composition of AI entrepreneurship in China; it may reflect the sampling channels used and the willingness of particular groups to respond. This limitation is noted in Section 6.5.

The sample is heavily concentrated in Shanghai (34%), Beijing (22.67%) and Shenzhen (19.33%), corroborating these as the most important AI innovation cities in China. The lower number from Nanjing (14.67%) suggests the emergence of a second-tier ecosystem. In summary, the sample examines a highly educated, tech-focused, gender diverse entrepreneurial population, concentrated in China's Tier-1 cities of innovation, offering a reliable but unrepresentative sample and providing valuable insights into the relationship between regulatory and cultural factors and youth AI entrepreneurship.

4.1.2.2. Central Tendencies of Key Constructs

Seven theoretical constructs are examined in the quantitative study, in line with the literature review and qualitative study. These include: Regulatory Environment (RE), Access to Funding (AF), Cultural Attitudes toward Entrepreneurship (CAE), Educational Background (EB), Technology Infrastructure (TI), Entrepreneurial Ecosystem Support (EES) and Startup Success (SS). All of these constructs are scored using 5-point Likert scales where higher numbers reflect greater agreement or better market conditions.

In the descriptive statistics, the Mean of Regulatory Environment (RE) is approximately 3.68, with a Standard Deviation of 1.08, implying moderate agreement (but some variance) with regard to supportive regulatory environment. This implies varied attitudes about the AI regulatory environment in China among young entrepreneurs.

The mean score for Access to Funding (AF) is 4.06, suggesting relatively positive views on the ability to raise funds. This is supported by the low dispersion ($SD = 0.77$) and slight skewness towards the left (i.e., a few reported negative views), meaning that while most respondents felt positive about AF, there may be some sense of relative gloom among those outside major incubators and/or who have weaker connections.

The highest mean (4.07) can be found in the Cultural Attitudes toward Entrepreneurship (CAE), suggesting strong positive social attitudes toward entrepreneurship. This suggests that social attitudes for entrepreneurship have improved, particularly in cities which strongly emphasise innovation. The low negative skew implies increasing acceptance among a greater number of respondents, which is consistent with their increased acceptance of innovation and their role in innovation-based entrepreneurial initiatives in China.

The mean score for Educational Background (EB) is 3.05, which indicates that respondents found their educational background dealt only moderately well with AI entrepreneurship. The standard deviation suggests some variation and possibly different experiences (such as that engineering is more relevant than business studies).

Technology Infrastructure (TI) has a mean score of 3.68 suggests moderate coverage of AI-related platforms, tools and infrastructure. Differences may reflect infrastructure opportunities across regions or access to expensive private platforms.

The constructor of Entrepreneurial Ecosystem Support (EES) has a score of 3.22, reflecting moderate satisfaction with incubator programs, mentoring programs and institutional support. Again, this may be due to variation in regional infrastructure.

The dependent variable, Startup Success (SS), has a mean score of 3.86, suggesting moderately to high levels of perceived success. The slight positive skewness and high kurtosis indicate that the distribution of responses is centred on relatively positive assessments, with few reporting very low success (or high failure) or very high success. In general, the majority of respondents felt their startups were going well.

These summary statistics suggest a number of advantages and perceived disadvantages of China's AI entrepreneurship ecosystem as reported by recent university graduates. Cultural environment and funding appear relatively positive, whereas education and ecosystem

support are at more moderate levels. The policy environment and technological environment are also moderately supportive, but the study can see considerable differences in respondent views. The statistical modelling of these constructs underpins the subsequent inferential tests and analyses, examining their associations and their predictive power for startup performance.

Table 4 Descriptive Statistics of Key Constructs

Construct	Mean	Std. Dev.	Min	25%	Median	75%	Max	Skewness	Kurtosis
Regulatory Environment (RE)	3.68	1.08	1.20	3.00	4.00	4.60	5.00	-0.53	-0.74
Access to Funding (AF)	4.06	0.77	2.00	3.60	4.20	4.60	5.00	-0.58	-0.44
Cultural Attitudes toward Entrepreneurship (CAE)	4.07	0.83	1.40	3.60	4.40	4.60	5.00	-1.09	0.51
Educational Background (EB)	3.05	0.95	2.40	2.40	2.40	4.00	5.00	0.97	-0.87
Technology Infrastructure (TI)	3.68	0.61	3.00	3.00	3.80	4.20	5.00	0.17	-1.44
Entrepreneurial Ecosystem Support (EES)	3.22	0.42	2.60	2.80	3.20	3.40	5.00	1.30	3.14
Startup Success (SS)	3.86	0.69	2.60	3.40	3.80	4.40	5.00	0.14	-0.93

4.1.3. Reliability and Validity Checks

In order to increase the validity of the findings from the quantitative data it is necessary to assess the internal consistency and construct reliability of the questionnaire. This section examines the reliability of the multi-item constructs using Cronbach's alpha and considers the results. While it would be preferred to assess construct validity by conducting exploratory factor analysis, reliability is an important diagnostic test of internal consistency in the present study. Cronbach's alpha is widely recognised as a reliable measure of internal consistency and indicates the extent to which the items in a construct consistently measure the same construct. The cut-off criteria for the scales is typically 0.70 or greater is considered acceptable, 0.80 and above is desirable and 0.90 and above is excellent (Nunnally and Bernstein, 1994).

Cronbach's alpha is used to examine the relationship between the items that comprise a construct and the level of reliability of the items as a measure of the latent construct. Any score greater than 0.70 is acceptable, while alpha scores over 0.80 and 0.90 can be considered as good and excellent respectively (Nunnally and Bernstein, 1994). The results are as follows:

The alpha coefficient for the Regulatory Environment (RE) is 0.899, which is satisfactory. This suggests that the six items, representing perceptions of government policy clarity, government regulatory favourability and government legal stability, also form a strong unidimensional scale. In other words, participants interpreted and responded to these items consistently, suggesting that this scale reliably measures this government and institutional condition.

Access to Funding (AF) has a Cronbach's alpha of 0.824, which is quite high. These items were statements about access to venture capital, access to grants and competition for funding. This suggests that these items accurately represent the funding levels available to AI startups in China.

The alpha for Cultural Attitudes towards Entrepreneurship (CAE) is 0.895, again suggesting high reliability. The individual items measure respondents' views on societal acceptance of risk-taking, fear of failure and cultural encouragement of innovation. This suggests a high degree of agreement among respondents about cultural support and barriers in entrepreneurial activities.

Educational Background (EB) alpha is 0.956, this is a very high alpha confirming a high level of internal consistency for the items measuring the level of perceived adequacy of Universities in providing training, skills and entrepreneurial culture to individuals. Though this may imply some overlap between items, it also reflects the high degree of overlap in perceptions around the role of the education system in shaping entrepreneurial skills.

Technology Infrastructure (TI) has a Cronbach's alpha of 0.705, which is considered acceptable for internal consistency. This suggests that the items in TI, such as the availability of AI computing power, data, and helpful digital platforms, are coherent, while some improvement in scale could increase its overall accuracy.

The Cronbach's alpha scores for Entrepreneurial Ecosystem Support (0.737) and Startup Success (0.704) exceed the acceptable limit of 0.70, indicating high internal consistency for the measurement items within these constructs (Hajjar, 2018). This suggests they are meaningful and consistent, and have little random variance. This provides diagnostic support for the reliability of the measurement scales, since participants appeared to understand the questions in a similar manner. Hence, these constructs can be used in the following correlation and regression analyses of the impact of the entrepreneur's perceived ecosystem support on the performance of a startup.

Hence, these constructs are reliable for use in correlation and regression analysis. The Cronbach's alpha scores for each construct suggests that the items in each scale are all measuring the same construct, giving greater confidence in the interpretability of the survey items..

Table 5 Cronbach`s Alpha Analysis

Construct	Cronbach's Alpha (α)
Regulatory Environment (RE)	0.899
Access to Funding (AF)	0.824
Cultural Attitudes (CAE)	0.895
Educational Background (EB)	0.956
Technology Infrastructure (TI)	0.705
Entrepreneurial Ecosystem Support (EES)	0.737
Startup Success (SS)	0.704

This section indicates that all seven constructs met the minimum threshold for acceptable internal reliability and therefore could be used for inferential analysis.

4.1.4. Correlation Analysis

Correlation analysis provides initial insight into the inter-variables relationships of the most important variables in this study, particularly the strength of the correlation (if any) between institutional, cultural, educational and infrastructural variables and perceptions of startup success. Pearson's correlation coefficient (r), which will have values between -1 and +1, is used to assess the linear relationship between the constructs. Values greater than +0.5 can be interpreted as a strong positive relationship, values between +0.3 and +0.5 as a moderate positive relationship and values less than +0.3 as a weak positive relationship. The significance of each correlation is tested using a two-tailed test, $n = 150$.

4.1.4.1. Relationship Between Independent Constructs

There are several significant intercorrelations between the independent variables. In particular, the Regulatory Environment (RE) is strongly related with Access to Funding (AF) ($r = 0.683$) and moderately related with Cultural Attitudes toward Entrepreneurship (CAE) ($r = 0.483$). This suggests that respondents who report a positive view of regulatory regimes are also more likely to see funding availability as more accessible, and a supportive cultural environment. This makes sense in the context of entrepreneurial ecosystems, where favourable regulatory policies can lead to greater inflows of investment and less culture bias against entrepreneurial risk-taking.

Funding Availability also has a strong correlation with Cultural Attitudes ($r = 0.644$), but this does not imply a causal link. It suggests that cultural support is positively associated with the entrepreneurs' ability or willingness to access financial support. On the other hand, EB has moderate relationships with both AF ($r = 0.288$) and RE ($r = 0.258$), suggesting that there is a weaker association between academic readiness and support within the system.

The strongest correlation between the independent constructs is between Educational Background (EB) and Technology Infrastructure (TI) ($r = 0.706$), which implies that when people think there is high infrastructural support, they tend to also think that educational support is strong. This may mean more support is focused in top-level institutional-level startup ecosystems, such as Tsinghua Science Park or the Shanghai Jiao Tong University (SJTU) innovation ecosystems, in which education and access to digital infrastructure is more intense.

4.1.4.2. Correlation with Startup Success

The main focus of this section is the relationship between the independent constructs and the dependent variable - Startup Success (SS). The correlation analysis shows positive associations between constructs. The largest correlations with Startup Success are for Technology Infrastructure ($r = 0.750$) and Regulatory Environment ($r = 0.653$), indicating that perceived digital capacity and perceived regulatory clarity are the strongest constructs associated with self-reported AI start-up success in this sample.

By contrast, age has a low positive relationship with Startup Success ($r = 0.248$), which may indicate that older startup founders perceive greater success in China's AI entrepreneurial ecosystem. In contrast, the correlations between Support for Entrepreneurial Ecosystem ($r = 0.253$) and Cultural Endorsement for Entrepreneurship ($r = 0.282$) with Startup Success are weaker, which suggests that the effects of ecosystem maturity and entrepreneurship culture might be more contextual. In sum, these results indicate that ecosystem attributes, particularly technological infrastructure, regulatory frameworks, education and financing are more (strongly) related to early stage AI startup performance than individual personal demographic attributes.

4.1.4.3. Implications of Correlation Patterns

These results support the conceptual approach by suggesting that perceived regulatory, infrastructural and educational conditions are associated with self-reported startup success in urban China. They are also consistent with the qualitative findings, where respondents often referred to adaptation to state policy, the use of digital solutions and the skills learnt in tertiary education. The relatively weak correlation between cultural attitudes and self-reported startup success reflects the broader limitations of perception-based measures.

The correlations between some of the independent variables, such as RE and AF, and EB and TI, are relatively high, which means that these characteristics are closely related in the entrepreneurial ecosystem. Within the regression model, this needs to be discussed in terms of whether multicollinearity exists and to gain more understanding about the unique association of the variables. This correlation analysis provides evidence of positive relationships between major perceived enablers and self-reported venture outcomes, while the regression analysis explores their associations in the same model.

Table 6 Pearson Correlation Matrix

Constructs	RE	AF	CAE	EB	TI	EES	SS
Regulatory Environment (RE)	1.000						

Constructs	RE	AF	CAE	EB	TI	EES	SS
Access to Funding (AF)	0.683	1.000					
Cultural Attitudes (CAE)	0.482	0.644	1.000				
Educational Background (EB)	0.257	0.276	0.123	1.000			
Technology Infrastructure (TI)	0.084	0.138	0.060	0.706	1.000		
Entrepreneurial Ecosystem Support (EES)	0.013	-0.109	-0.019	0.307	0.374	1.000	
Startup Success (SS)	0.653	0.456	0.282	0.605	0.750	0.253	1.000

4.1.5. Regression Analysis

This section describes the results of the multiple linear regression modelling that has tested the predictive effect of six independent regressors on Startup Success (SS); these regressors are: the Regulatory Environment (RE), Access to Funding (AF), Cultural Attitudes toward Entrepreneurship (CAE), Educational Background (EB) and Technology Infrastructure (TI), Entrepreneurial Ecosystem Support (EES). This serves to identify variables that significantly and uniquely explain the variance in self-reported entrepreneurial success of the recent founders of AI startups in China's urban areas.

4.1.5.1. Model Fit and General Statistics

The regression equation results indicate high model fit, with about 92.2% of the variance in self-reported startup success explained by a linear combination of the six predictors ($R^2 = 0.922$). This high model fit should be interpreted cautiously, and future research should examine the model with other samples and diagnostic tests. The F value is 281.0 ($p < 0.001$), indicating that the model is statistically significant and has a good fit to the data. This F value is consistent with the relatively high correlations reported in Table 6.

4.1.5.2. Coefficient Estimates and Interpretation

The coefficients are a guide to the direction and degree of influence of the independent variables on startup success. The regression equation (simplified) is:

$$SS = -0.2768 + 0.4309(RE) - 0.0621(AF) - 0.0286(CAE) - 0.0604(EB) + 0.8819(TI) - 0.0455(EES)$$

Table 7 Multiple Linear Regression Coefficients (Dependent Variable: SS)

Predictor	B (Unstandardised)	Std. Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)	Interpretation
Constant	-0.2768	0.1734	-1.5965	0.1126	-0.6196	0.0659	Constant term
Regulatory Environment (RE)	0.4309	0.0207	20.8029	0.0000	0.3900	0.4719	Significant positive predictor
Access to Funding (AF)	-0.0621	0.0341	-1.8196	0.0709	-0.1295	0.0054	Not statistically significant
Cultural	-0.0286	0.0253	-1.1270	0.2616	-0.0786	0.0215	Not

Predictor	B (Unstandardised)	Std. Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)	Interpretation
Attitudes toward Entrepreneurship (CAE)							statistically significant
Educational Background (EB)	-0.0604	0.0249	-2.4227	0.0167	-0.1096	-0.0111	Significant negative predictor
Technology Infrastructure (TI)	0.8819	0.0387	22.8154	0.0000	0.8055	0.9583	Significant positive predictor
Entrepreneurial Ecosystem Support (EES)	-0.0455	0.0423	-1.0743	0.2845	-0.1291	0.0382	Not statistically significant

The regression analysis indicates that Technology Infrastructure (TI) and Regulatory Environment (RE) are the strongest statistical predictors of self-reported Startup Success (SS) within this sample of graduate AI entrepreneurs in China. Technology Infrastructure (TI) ($B = 0.8819$, $p < 0.001$) has the largest coefficient, suggesting that perceived access to digital infrastructure, cloud computing and hardware is strongly associated with perceived operational efficiency and venture progress. Regulatory Environment (RE) ($B = 0.4309$, $p < 0.001$) is also positively associated with self-reported success, indicating that respondents who perceived the regulatory environment as clearer or more supportive also tended to report stronger venture outcomes.

The coefficient of Educational Background ($B = -0.0604$, $p = 0.0167$) is unexpected. This may mean that formal education, as perceived by respondents, is not straightforwardly associated with self-reported startup success, possibly because of the lack of experiential learning or the disconnect between academic curriculum and entrepreneurship skills demanded by startups.

In contrast, both Access to Funding ($p = 0.0709$) and Cultural Attitudes ($p = 0.2616$), while important conceptually, have non-significant coefficients for early-stage startups. Early Stage Support ($p = 0.2845$) is similarly insignificant, possibly due to the resource-poor nature of the entrepreneurial ecosystem or institutional support.

Overall, the findings suggest that perceived technological preparedness and perceived regulatory clarity are important associations within this sample, while training gaps and uneven ecosystem support remain barriers reported by participants. This supports cautious

policy and education recommendations rather than a causal claim about what ensures AI startup success.

4.1.5.3. 4.1.5.3 Model Diagnostics and Validity

The standard errors of significant predictors are low and the confidence intervals for TI and RE do not include zero, which supports the internal stability of this model. To diagnose multicollinearity, the Variance Inflation Factor (VIF) was calculated for each of the six predictors. As shown in Table 8, all VIF values are below the conventional concern threshold of 5.0 (Hair et al., 2020). These diagnostics support the exploratory regression model, but they do not remove the limitations of self-report measures, purposive sampling or cross-sectional design.

Table 8 Variance Inflation Factor (VIF) Diagnostics — Multiple Linear Regression Model

Variable	VIF	Tolerance (1/VIF)	Multicollinearity Concern?
Regulatory Environment (RE)	2.14	0.467	No
Access to Funding (AF)	1.87	0.535	No
Cultural Attitudes (CAE)	1.43	0.699	No
Educational Background (EB)	2.31	0.433	No
Technology Infrastructure (TI)	2.19	0.457	No
Entrepreneurial Ecosystem Support (EES)	1.76	0.568	No

4.1.6. Summary of Quantitative Results

This chapter offers a statistical examination of questionnaire data from 150 graduates working on AI startup projects in urban innovation centres in China. The quantitative phase builds on the qualitative findings and examines how perceived regulatory, cultural, financial, educational and infrastructural conditions are associated with self-reported startup outcomes. It provides indicative empirical patterns that are interpreted alongside the qualitative data.

The descriptive statistical analysis shows that most respondents are young women, who report moderate to high perceptions of success in their entrepreneurial activities. The variables in Cultural Attitudes to Entrepreneurship and Access to Funding have relatively high means, whereas Educational Background and Entrepreneurial Ecosystem support are relatively lower. The results of the survey sections dealing with Regulatory Environment and Technology Infrastructure, on the other hand, are a little more varied, reflecting

differences in perceptions of institutional and infrastructure support across regions and respondent categories.

The correlation analysis indicates that the highest positive correlations with perceived startup success are in the areas of Technology Infrastructure, Regulatory Environment and Educational Background. These results are consistent with the themes found in the qualitative analysis, particularly data availability, IT infrastructure and perceived regulatory clarity. In contrast, the lowest correlations with perceived startup success are in Cultural Attitudes and Entrepreneurial Ecosystem Support, which suggests that these issues may be more complex than can be captured through simple perception-based measures.

The findings based on multiple linear regression are consistent with the importance of structural conditions. Technology Infrastructure and Regulatory Environment show the strongest statistically significant associations in the regression model. This finding supports the argument that AI entrepreneurship depends not only on individual ability, but also on enabling technological and regulatory structures. Educational Background, however, has a negative but significant coefficient, implying that while education is important, it may not be directly impacting success in a startup context (when considering other factors). On the other hand, Cultural Attitudes do not have a significant coefficient in the regression model, which seems to suggest that the impact of these factors might be secondary or contextual.

The results of the subgroup analysis for males (16.350) and females (17.100) show no statistically significant difference between the two groups ($p = 0.571$). Given the gender imbalance in the sample, this should be treated as a descriptive result only. It does not demonstrate gender equality in the AI startup ecosystem and should be complemented in future research by enquiring into experiences, opportunities and limitations that may not be revealed in subgroup means.

4.2. Qualitative Analysis

4.2.1. Introduction

The qualitative dimension of the study is required to delve into the complexities of recent graduates' experiences in the arena of AI start-ups in China. This stage is part of a mixed-methods framework to reveal the cultural, institutional and structural factors behind enterprise outcomes, particularly those that cannot be easily reduced to quantitative metrics. Even though the quantitative nature of the survey can be applied to detect patterns and relationships between descriptive and explanatory factors (including regulatory environment, access to funds and perceptions of start-up success), an in-depth interpretation of situational phenomena is only possible through the qualitative component of the research.

A total of 15 recent graduates working in major innovation centres in China (Beijing, Shanghai, Shenzhen and selected Tier-2 innovation cities) were interviewed through semi-structured interviews and their conversations were recorded or documented for qualitative analysis, subject to participant consent.

The qualitative sample intentionally included founders from Tier-1 cities because these locations concentrate AI infrastructure, venture finance, university incubators and policy support. Some Tier-2 city experience was retained to capture contrasts in regulatory clarity and infrastructure access. The gender distribution of the interview sample was not balanced, and this limits the extent to which the qualitative findings can speak to gendered differences in founder experience. Gender is therefore treated as contextual information rather than as a basis for comparative claims.

Table 9 Background of Interview Sample

Participant ID	Gender	Age Range	City (Innovation Centre)	AI Startup Sector	Role in Startup	Interview Language
P1	Female	24–29	Beijing	EdTech (AI learning analytics)	Co-founder, Recently Quit Masters	Mandarin
P2	Female	30–34	Shanghai	HealthTech (AI diagnostics)	Founder	English
P3	Male	26–31	Chengdu	LogisticsTech (AI logistics optimisation)	Co-founder	Mandarin
P4	Male	26–32	Shanghai	Robotics (process automation)	Co-founder	English
P5	Female	23–27	Beijing	AI Ethics Consultancy	Founder	Mandarin

Participant ID	Gender	Age Range	City (Innovation Centre)	AI Startup Sector	Role in Startup	Interview Language
P6	Male	28–33	Shenzhen	Smart Manufacturing	Co-founder	English
P7	Female	25–31	Shanghai	AI Data Solutions	Founder	Mandarin
P8	Female	26–30	Beijing	E-commerce AI	Co-founder	English
P9	Male	27–35	Shenzhen	Cybersecurity AI	Founder	Mandarin
P10	Female	23–28	Shanghai	AI Marketing Analytics	Co-founder	Mandarin
P11	Male	29–34	Beijing	AI Cloud Infrastructure	Co-founder	English
P12	Female	25–29	Shenzhen	Sustainable AI Applications	Co-founder	Mandarin
P13	Male	26–31	Beijing	Machine Learning Consultancy	Founder	Mandarin
P14	Female	27–32	Shanghai	AI HRTech Solutions	Co-founder	English
P15	Male	24–30	Shenzhen	AI Logistics Optimisation	Co-founder	Mandarin

Participants for the study were recruited using purposive sampling; the key criteria were: recent graduates (within five years), currently involved with an AI enterprise and willing to share these experiences in detail. The participants were well-distributed in terms of gender, industry type (such as health tech, edtech and robotics) and financing background, so as to allow for conceptual saturation and diversity of viewpoints. A sample of 15 participants was interviewed, with interview duration ranging from 40 to 75 minutes, over the course of six weeks, yielding rich qualitative data. The interviews were conducted in either Mandarin or English, as per the interviewee's preference and then transcribed and translated for analysis.

Thematic analysis was used to analyse the data using the six-step approach outlined by Braun and Clarke (2022). The process included reading the transcripts, generating initial codes, creating themes, reviewing themes, defining themes, and writing the report. Coding was not only grounded in the data but also theoretically driven, such as the themes regulatory hurdles and funding models. However, concepts emerging from data were also able to adjust to theoretical assumptions.

Table 10 Thematic Coding and Theme Development

Initial Codes	Focused Codes	Themes Developed
Confusion about AI licensing	Regulatory ambiguity	Navigating Regulatory

Initial Codes	Focused Codes	Themes Developed
Contradictory policy memos	Policy misalignment	Complexity
Delayed approvals	Bureaucratic barriers	
Policy “on thesis only”	Policy theatre	
Regional variation in process	Regulatory fragmentation	
City-to-city inconsistency	Local-national disconnect	Infrastructure as Strategic Constraint and Enabler
Cost of compute	Infrastructure barriers	
Lack of data access	Data monopoly	
Tier-2 city disadvantages	Digital inequality	
Private cloud costs	Centralised resources	Cultural Identity and Entrepreneurial Legitimacy
Pressure to appear patriotic	Symbolic compliance	
References to Xi’s slogans	Techno-nationalist framing	
Family pressure	Intergenerational tension	
Desire to innovate “the Chinese way”	Hybrid identity	Education and the Experiential Gap
Degree irrelevant	Experiential education gap	
Learned nothing about business	Peer learning	
Relying on WeChat/peers	Informal ecosystems	
No founder mentorship	Learning through doing	Ecosystem Navigation and Strategic Adaptation
Grant access via connections	Institutional gatekeeping	
Accelerator rejection	Legitimacy signals	
Pitch tailoring	Strategic ambiguity	
Misaligned funding use	Pivoting under pressure	Responses to Techno-nationalism and State Expectations
Surveillance project pressure	Compliance trade-offs	
Ideological conditions	Founder discomfort	

Table 11 Final Themes with Sub-Themes

Theme	Sub-Themes	Definition	Illustrative Quote (Pseudonym)
Navigating Regulatory Complexity	Ambiguity in licensing Policy theatre Regional inconsistency	Founders face unclear, performative, and uneven AI policy implementation.	“We submitted four applications, all rejected for different reasons in different cities.” – P2
Infrastructure as Strategic Constraint and Enabler	Cloud/data access inequality Centralisation of compute	Success depends on privileged access to core infrastructure, often monopolised or politicised.	“If you're not Tencent or backed by them, good luck getting reliable cloud at scale.” – P5
Cultural Identity and Entrepreneurial Legitimacy	Confucian duty vs. individualism Nationalist framing	Founders must navigate conflicting cultural expectations and symbolic alignment with national agendas.	“My parents want me to succeed, but they don’t understand what a startup even is.” – P4
Education and the Experiential Gap	Disconnection from practice Peer-led learning	Formal education provides theory but lacks entrepreneurial preparation; founders rely on informal learning.	“We had AI lectures, but no clue how to register a company or do taxes. I learned on Zhihu.” – P7
Ecosystem Navigation and Strategic Adaptation	Gatekeeping Strategic ambiguity Signalling	Founders adapt their identity and product to secure access to resources from opaque institutional actors.	“We call ourselves ‘AI for Social Good’—it helps when applying for grants, even if it’s a stretch.” – P9
Responses to Techno-nationalism and State Expectations	Moral discomfort Strategic compliance	Founders feel pressure to align with state narratives and surveillance agendas to survive or grow.	“We didn’t want to do facial recognition, but it’s what got us into the accelerator.” – P6

4.2.2. Navigating Regulatory Complexity

The overarching theme identified across all 15 interviews is that strategic planning in the regulatory and legal space in China is complex in the realm of AI entrepreneurship.

Interviewees highlighted that while AI is promoted as a national priority by the Chinese government, the implementation of such priorities at local levels is marked by a lack of consistency, bureaucratic and interpretative ambiguity. This theme highlights the impacts of regulatory uncertainty on strategic planning and the creation of further costs for start-up entrepreneurs, particularly without elite or insider networks.

4.2.2.1. Ambiguity in Licensing and AI Classification

Many members voiced the problem of product classification for their AI, but, with respect to the regulatory-administrative classification. Most countries have a license system not updated by the technical work aspect of artificial intelligence and therefore poses a compliance issue. The founder of a Beijing-based edtech startup, P1, said:

“When we applied for our operating license, we were told to specify whether our product was a ‘standard’ app or an AI system. But there was no clear guideline. Our software uses NLP to analyse student performance—so does that count as AI? No one in the department could answer. They just said, ‘Be safe and register both ways.’”

The above quote raises a common problem of not clearly delineating AI in existing categories. The result is a form of regulatory hedging, where startups take precautionary measures, such as double licensing or even commissioning an audit test, which are often unnecessary or overly cautious in order to mitigate potential future risks. This leads to unnecessary compliance costs, and uncertainty about future risks.

P2, co-founder of health AI start-up, also voiced the same concerns when the local govt began to treat their diagnostic model as an actual medical device:

"We were a diagnostic model that would be used to detect cancer of early stages; but when they consulted with us for the classification, the regulators said it is a medical device. We are a software, not a machine. But they were to be medically certified. Definitions keep on changing depending on who you talk to".

These instances point to a larger trend: AI product classification does not yet have a national framework that can be used across industries and provinces. The Ministry of Industry and Information Technology (MIIT) has released technical white papers but they are only guidance documents, and local regulators are left to interpret the definitions by themselves. This decentralisation leads to differences in regulatory requirements, even within similar technologies across different sectors.

The majority of participants (12 of the 15 total) reported licensing uncertainty, and that is why it was identified as the major subtheme in the thematic coding. At times, participants reported working for weeks or months with regulators, often resulting in delayed product service release dates or terminated plans to enter the market. This regulatory ambiguity could threaten the viability of startups with limited funding and a short lifespan.

4.2.2.2. Policy Incentives vs. Bureaucratic Barriers

Despite China's frontrunner status, all respondents reported a discrepancy between state-sponsored incentives, including innovation grants, startup districts and incubator subsidies, and the bureaucratic processes. While national plans, such as the Next Generation AI Development Plan, communicate the role of the state as a facilitator of innovation, in practice, urban-level bureaucratic processes lead to obfuscation, opacity and politicised signalling. One individual founder, P3, and in Chengdu, on the issue:

“In theory our district is a part of a national innovation zone. But when we applied for the AI [funding], the government officials told us that we must provide three years of financial reports. We have only been in business for less than three years! So it's like the incentives are a show.”

This example highlights the widespread sense of policy theatre, in which local governments appear to encourage innovation while failing to adapt policies to reflect the needs of new businesses. Three years of audited accounts, which the majority of new businesses don't have, plays out as a selection process, keeping out the very people the policy is supposed to support. P1 also referred to policy theatre to explain the dismal bureaucratic experience of multiple submissions:

“The government says AI is a national priority, but they make us resubmit documents five times. It feels like a performance—‘policy theatre,’ I call it. They want media coverage of innovation, not the messy work of actually helping startups.”

Such opinions signal a broader level of frustration with innovation policies that aren't grounded in daily situations. Researchers heard how many grant schemes are often

risk-averse, and demand proof of success or scalability to be able to receive funding, a set of criteria that again favours strong firms over the new enterprises they are meant to support. To add to the barriers, there is a role of *guanxi* (as personal networks and social capital) in accessing state support. P4, an entrepreneur in robotics from Shenzhen, explained:

“Eventually the city got funds, a municipal grant but only after we hired the services of a consultant with connections in the science bureau. Without guanxi you will never get your application heard”.

The example above illustrates the institutionalisation of informal channels of power in supposedly meritocracies. According to some respondents, channels for securing funding only became available once specialist consultants with knowledge of the administrative system were hired. While not necessarily corrupt, such practices institutionalise inequality based on elite educational or political networks. This subtheme, found in 10 of 15 interviews, suggests that while policy incentives may be publicised, they may not always be accessible to first-time entrepreneurs or entrepreneurs in peripheral locations, especially in highly decentralised innovation ecosystems.

4.2.2.3. Regional Disparities in Regulatory Clarity

Interviewees also highlighted uneven interpretations and implementation of AI policies across cities and provinces, pointing to the geographies of entrepreneurship. While it's generally considered that major cities such as Beijing, Shanghai and Shenzhen have relatively favourable and stable regulatory landscapes, second-tier cities may not have the capacity or expertise to manage national regulation efficiently. P5, a founder in Shanghai, noted the differences between the experience in Shanghai and out west:

"In Shanghai, you get clear information. The tech department even holds info sessions on AI classification. However, when I attended a conference in Xi'an, several founders informed me that they're still awaiting clarification of local policy. Same laws, different realities."

This speaks to how local capacity and policy competence shape national policy implementation. Cities such as Shanghai and Shenzhen have more fully-subsidized science parks and well-trained officials. By contrast, smaller cities may lack policy competence to support cutting-edge technologies such as AI. P2, who tried to expand to Nanjing, described:

“For the branch in Nanjing, we had to apply for the license again, even though it's the same entity and product. It's like, 'local policy applies.' It's tedious and duplicate processes.”

The decentralisation also results in redundancy and a splintering of laws, particularly on the part of startups who would want to expand across geographies. This also creates some legal risks given the possibility that the same product can be found as being compliant in one locality, and non-compliant in another, risking fines or even the license. Such a lack of equality was captured by P3, with its operations in Sichuan:

"The operation in other towns brings the experience that the startups are not equal citizens. The slogans are national but the rules are different for every few kilometres".

This inequality points to issues concerning equal access to China's AI economy. Inland participants (no matter their cities, large or small) were often less favoured than coastal participants even when their ideas and capabilities were equal or better. Rather, institutional blockages were based on geographic division. This subtheme, as was found in the interviews, is an issue for policymakers to scale up AI innovation to inland regions. Despite country plans that seek to promote inclusive growth, the differential implementation of policy defeats these priorities and entrenches centre-periphery inequalities.

4.2.2.4. Conclusion to Theme 1

The theme of regulatory complexity shows the challenges entrepreneurs face in dealing with regulatory change. This was captured by three subthemes: participants discussed the regulatory environment as unclear, inconsistent and inefficient, and therefore as a barrier to innovation. This highlights tensions between the national narrative of China's leadership in AI and entrepreneurs' on-the-ground experience, as the system is often not fully attuned to the needs of fast-moving, data-dependent startups.

This theme also appears in the quantitative phase through the association between perceived regulatory environment and self-reported startup outcomes. The qualitative results provide greater detail, revealing that not only the laws themselves, but also their interpretation and implementation are experienced as important by founders.

As China is still working on AI governance structures, it would be crucial to not only focus on how the national AI development strategy is crafted, but also on how it is executed at the city level, how its regulations are standardised and how capacity building activities are carried out, especially in the second-tier innovation system. Emerging firms on the frontiers of innovation, particularly in regulatory grey zones, cannot wait for indefinite regulatory uncertainty and for having to navigate regulatory give-and-take.

4.2.3. Funding Access and Strategic Dependencies

The second key theme that emerged during interviews related to respondents' experiences of early-stage asset mobilisation through government schemes, venture capital and angel funding, or university-based incubators. The majority of participants accepted entrepreneurship and innovation as a conspicuous part of China's government drive in AI. Yet they also constantly reiterated that capital is very unequal, uneven, socially structured and strategic.

4.2.3.1. Guanxi and Informal Networks

The practical significance of guanxi (connections), networks and informal social capital to access both "public" and "private" sources of funding was also a recurrent theme. Some entrepreneurs described their access to funding as attributable not only to product quality and technological innovation, but also to elite academic, regional, and/or political networks. P4, a Shenzhen-based robotics entrepreneur, explained:

"We eventually got our first round of funding, but from a VC that one team member's professor introduced us to - one that had funded university spinouts. [The VC] had not given us a chance without this introduction and if it wasn't for this introduction we would not have been selected."

This is how the elite university networks' social capital works to provide a type of credential to find otherwise closed funding. The more popular pathways for startups without these included the second or third tier, such as open calls and pitch competitions, which the interviewees found to be more competitive, opaque, and bureaucratic.

P2, cofounder of a health AI startup, detailed the challenges of raising seed funding in the absence of networks:

"We put in our proposal to two angel networks. One of them said they only fund companies that have one PhD. One of them said we needed to get into the media. And finally, we raised seed funding from family to build an MVP [minimum viable product]."

This suggests an uneven funding landscape, in which early-stage startups rely on informal relationships as much as on being "pitch ready". Some interviewees also indicated that

even general grants (purportedly open to all) often required insider knowledge to navigate bureaucratic complexities. P3 from Chengdu said:

“You can submit the form online, but unless someone vouches for you or you know someone at the bureau, your application just vanishes. We hired a consultant who used to work there, and suddenly our file moved forward.”

This affirmation of institutional path dependency in acquiring resources adds to the notion of "borrowing legitimacy" from processes of trust, recognition and patronage.

4.2.3.2. Risk Aversion Among Investors

The second challenge was the risk-averse attitude of state and non-government investors in AI. Despite China's global image of innovation, interviewees commonly indicated that most capital providers were risk-averse and preferred to invest in "safe" low-risk commercial segments. P1, founder of an AI-enabled edtech company, said:

“We pitched a personalised learning engine based on behavioural analytics. One investor told us it was ‘too abstract’ and asked if we could build a chatbot instead. They wanted something with quick market validation—even if it wasn’t our vision.”

This illustrates how, even in a bleeding-edge technology sector like AI, investors often expect entrepreneurs to move towards commercially tested, less risky business models like chatbots, predictive analytics or CRM automation rather than deep tech or basic research in AI. These shifts could reorient start-up journeys and lead to pivots or shifts to meet investor expectations.

This was the case also with the experience related by P5, whose company was developing AI services for ageing populations:

"They kept pushing 'when can you start making profits?' But our technology takes time to develop, it has to be worked on in real health care environments. They asked us to develop an app, maybe sell health advice. We didn't want to do that."

This narrow focus is symptomatic of criticisms of "administrative imitation" in the early stages of Chinese venture capital, which emphasize profit over technological innovation. Despite the fact national policies describe AI as a focus for future economic development, it seems financing decisions are made with predictability, rather than innovation, in mind, especially for young or non-elite entrepreneurs. Moreover, survey participants indicated

that individual investors would follow government directives. The promotion of certain verticals, such as smart cities or B2G applications, in a local science park attracted a flock of investors, amplifying herd mentalities over a diverse ecosystem. P2 remarked:

“After a Beijing AI company was listed for B2G surveillance, all VC's in our region asked if we could make our product for B2G. They no longer cared about the private sector use case.”

This practice results in strategic drift, as entrepreneurs feel compelled to adjust business plans not based on market opportunities, but due to investor shifts, which can be related to policy mimetic forms.

4.2.3.3. Strategic Trade-offs with Government Funding

While government subsidies and grants are crucial for many new AI startups, they also have darker sides, both practical and moral. Several interviewees reported that public funding was often accompanied by implicit or explicit requests for data sharing, cultural sharing in surveillance or activism. P1 listed the strings attached to a grant for AI projects by the municipality:

“The money helped us scale, but in return we had to sign a data exchange agreement with the city. This meant providing anonymized user data for public monitoring projects. It was framed as a ‘pilot collaboration,’ but we had no real choice.”

These agreements underline the compromises in the situation of subvention and independence of startups. These partnerships combine up innovation and state into a regulatory or legal type of thinking - examples such as data sovereignty or user consent - but they are not coerced. P3 recounted:

“They asked us to showcase our product at a local innovation fair, but we had to include a quote in our presentation of a Party speech. We couldn't say no but it was fated. Yes, we just went along to preserve the funding relationship with them in tact”.

The above examples point to the idea the Chinese AI ecosystem is not ideologically neutral of the matter of how to acquire resources. Even firms in industries that are adjacent to surveillance, urban management or social scoring will have an opportunity of participating in the agendas of the state which clash with their original moral compass. P4, who founded their company, first came to the attention of a provincial public security bureau, which recalled their cynicism towards business:

"They asked us to build our system for crowd surveillance during festivals. It would have been quick funding and scale. But we have rejected. It's not our preferred future that we are creating, even if it's lucrative."

According to these definitions, government grants provide a physical guarantee of survival, but they can also force them to become morally and strategically reliant. The recipients of the funding may well be forced to incline to political uniforms or even drift away from their core missions. If not accepted, its followers could miss out on the most profitable and prestigious government-sponsored accelerators and consortia. The struggle is not a Chinese challenge, but certainly it is crucial for a form of government that links technological infrastructure to national security issues and even to social governmental policy. This negotiation was described by participants as a juggle of survival, integrity and strategy.

4.2.3.4. Conclusion to Theme 2

This theme's findings demonstrate that funding ecosystems are very limited, and that the opportunities for access to funds are determined not only by market forces, but also institutional adherence, strategic fit and social networks. In all three subthemes, respondents conveyed the opinion that funding opportunities are unequal. Rather, they are shaped by founders' social networks, their ability to align with government agendas and investor risk preferences.

While guanxi and elite credentials might be guardrails for founders, they restrict opportunities for founders without privileged connections, especially those who come from non-elite universities or inland provinces. At the same time, investors' risk aversion reduces the willingness to experiment and reproduce their own investment priorities shaped by policy, steering startups away from risky uses. Even critical sources of community or public financing may be governed by expectations about ethical data use or product priorities, or even sustainability.

These findings can be connected to resource dependence theory, which maintains that organisations are bound by their dependence on resources, especially when these are in the hands of various powerful institutions with vested interests. A politicised and performative model of innovation exaggerates this reliance. In the case of Chinese AI startups, therefore, entrepreneurship must be understood in terms of a hybrid service-market model. Finally, in Theme 2 we present a second key question facing the Chinese AI ecosystem: the need to create a financing environment that is not only strategically targeted, but also entrepreneurially conducive for founders to experiment and innovate without fear of failing the expectations of dominant policy or investors.

4.2.4. Cultural Narratives and Entrepreneurial Identity

Alongside their challenges in business and development, the interviewees often discussed the cultural and psychological factors shaping their entrepreneurial experiences. This team explores the impact of generational, social and family values on interviewees' perceptions of risk, success and the ethical aspects of their AI entrepreneurial pursuits. Despite the official rhetoric that strikingly emphasises entrepreneurship as modern and patriotic, in the research interviewees provided varied and even contradictory answers: they were both motivated by culturally driven narrative and limited by traditional roles and expectations. The majority of participants pointed to entrepreneurship as a step away from the Chinese notion of job security, where their families and the older generation often prized working for the government (gongwuyuan) and in large organisations. Interviewees recognised that starting a business is always on the verge of failure. But they also observed a new cultural trend in younger generations of Chinese college and university graduates to see failure as no longer ugly, but merely as something to be learned from. P1 expressed:

“My father inquired me as to why I had quitted a Huawei job offer. He added I was playing with fire. However, as far as I am concerned, making a startup (despite failing in the future) is about the creation of something of mine. This state of mind was not there in theirs.”

This story shows an intergenerationally reconfigured definition of success, in which the focus of "right living" is not just on providing financial security, but also on perceived personal well-being, demonstrated through personal achievement, creative independence, and social change. This knowledge took many forms via Silicon Valley expressions, such as pivot, failing fast or product-market fit which the interviewed entrepreneurs used to position themselves as part of an international entrepreneurship community. However, these English words were often coupled with Chinese aspirations, such as maintaining family pride or contributing to the nation. P4, whose startup business is related to smart manufacturing, said:

“It is not just about making money, but to prove to myself and my family that, 'I can be the leader of something big'. I want to say to others, 'I did a great start up, even though I lost, I tried'”.

Hence, this mix of individual pursuits and moral obligations provides an example of hybridity. In this case, global entrepreneurial principles are mediated through the Confucian values of persistence, industriousness, and social connectedness. Thematic

analysis shows that 11 of the 15 interviewees cited the need for self-actualisation, rather than just financial gain, as a primary motivator for start-up activities.

4.2.4.1. Redefining Failure and Success

While there is a shift in the cultural attitude toward success among young graduates, parental pressure remains a strong force. A significant number of participants indicated that their parents questioned, doubted or imposed several conditions on their entrepreneurship. Parents were also classically risk-avoidant, gender binary, and filial piety (such as in one-child families). Female founder of an AI healthcare start up (P2):

"My parents did allow me to study but when I told them that I would not work in a hospital and I would not work in any non-China company, my parents were scared. They thought AI was a trend. They asked me: When will I have a job? When will I have a stable income?"

This quote exemplifies the intergenerational differences between perceived social expectations and risk-taking in entrepreneurship, particularly female founders who have to juggle both career and gendered norms. Several female participants also mentioned that while men were often encouraged to follow their dreams, it was indirectly suggested that women chose more stable options, such as teaching, administration, or getting married to have children. A co-founder from a rural province, P5, responded:

"The behaviour of my parents is not supportive at first. They don't know what a startup is. They think I am jobless. My mother is scared because of the talks of neighbours. I just tell them that I work on AI in the city. It sounds more impressive to them."

Many participants symbolically transact cultural norms in entrepreneurial space. However, while parents are often initially unsupportive, many participants stated that they were later more supportive as they received external legitimacy (such as media attention, support from investors, or from university or government laboratories). Thus, legitimacy provides a type of legitimating support so one may take risks while not abandoning tradition entirely. The importance of face (or mianzi) also emerged as a significant factor in participants' ambition. Success was not just beneficial to them, it may also boost the reputation of their families or help to convince sceptical family and friends of their abilities.

4.2.4.2. Social Expectations and Family Pressure

The last cultural narrative that influenced entrepreneurial identity was perceptions of a larger national or social utility of AI entrepreneurship. Some respondents spoke of a sense of patriotic responsibility and of seeing their projects not simply as potential business

opportunities, but also as contributing to China self-reliance in technology as well as its competitiveness on the world stage. P3 stated:

"It is not about developing products but national development. China cannot always depend on technology imports, we must lead the way and work towards the future".

This attitude is part of the general ideology whereby the state positions AI as a key force of productivity and a national critical resource. Some interviewees offered governmental propaganda on themes like technological independence, innovation-education and development-entrepreneurship as rationale for pursuing a career. The idea of AI for good was also mentioned by the interviewees, linking their work to a notion of common good rather than to business. P5, one of the founders in the rural province, added:

"My hometown is very traditional. People don't get the concept of startups. My mother is concerned about what people will say if I'm not working. I just tell them that I'm working with AI in the city. It sounds better or more mainstream."

This insight reveals the symbolic negotiations many participants engage in as they meet cultural expectations and entrepreneurial goals. While there was some pushback, many participants reported that their parents' resistance faltered when they had legitimating experiences, such as media attention or interest from potential investors, or when they were able to form partnerships with universities or state laboratories. In this way, legitimacy provides a face-savings mechanism to take risks without straying too far from family culture. Family reputation (or *mianzi*) was also important in how participants understood their goals. It was not just to make personal profit, but to also enhance their families' position in society or prove to their friends that it was a good choice to pursue entrepreneurship.

4.2.4.3. Nationalism, Responsibility, and AI for Good

A second cultural identity of the entrepreneurial spirit was that there is something "good" about AI entrepreneurship. Some of its members felt a strong sense of patriotic duty and participation in their venture was seen as helping China become technologically self-reliant and as an enterprise to be proud of globally. P3 stated:

"We're not just making products, we're making the future of our country. China can't rely on technology from the West forever. It's our duty to continue innovating."

This perspective is consonant with a broader state-based rhetoric about AI as a productivity enhancer and national treasure made by the government. A number of other participants mentioned official proactively popularising the idea of technological sovereignty and building the country on innovation as a driving factor, particularly those who were educated in Party-affiliated universities or had experiences as interns in government. P1 elaborated:

“When I read about the US chip bans, I realised our tech independence is fragile. That made me more determined to work in core AI. It’s not just business—it’s duty.”

These narratives confirm entrepreneurship as a moral and political activity and other forms of industry as perceived to be high tech and vital, such as semiconductors, robotics, or medical AI. They also spoke about AI for good, positioning themselves as delivering social good with their entrepreneurship. P4 shared:

“We want our tool to assist factory workers, not eliminate jobs. Technology should be empowering. And that’s what I want to do.”

Notably, the geopolitical significance of AI on the side of a nation state is enhanced. However, the interviewees are more focused on social, ethical impact and sustainability. This tension highlights a complex cultural identity, nationalism, pragmatism and humanism.

4.2.4.4. Conclusion to Theme 3

The cultural and identity related aspects of entrepreneurship show a complex interplay of impulsions, conflicts and change among young Chinese entrepreneurs in the AI sector. Participants are confronted with a tension between the traditional Chinese culture of respect for elders (filial piety) and a new culture of novelty, independence, and globalisation. While young entrepreneurs are constrained by these cultural factors, particularly in connection with gender roles, fear of failure and honour of one's family, they are also stepping outside their familiar environments in an effort to redefine their own concepts of success in the context of Chinese culture.

These results could be related to Hofstede's notions of long-term orientation and collectivism, in that they demonstrate a family-oriented society that is process-oriented (order) and obedient. Yet, they also reflect global entrepreneurial principles, such as autonomy, creativity and social status. This dual character implies that AI startups are not just economic, but also cultural, experiments, through which young generations experiment with what is culturally and socially perceived to be possible, desirable and acceptable.

4.2.5. Gaps in Entrepreneurial Education

One key focus for participants was the value of their university education in preparing for AI entrepreneurship. While all respondents were university graduates, many of them - most of whom had attended prestigious universities - lamented the absence of entrepreneurial or practical aspects in their tertiary education. This theme is a reflection of the disconnect between educational content and entrepreneurship readiness, participants' evaluation of the benefit of international study or informal training, and the growing tendency for people to rely on informal peer networks to start businesses.

4.2.5.1. Lack of Practical Skills in University Curriculum

Majority of participants indicated their university degrees (especially in engineering, computer science or AI) were "mostly theoretical and did not prepare me for the necessary skills for building a startup". While they appreciated the theoretical challenges of their technical studies, they also lamented lack of legal, managerial and business skills that were of crucial importance after they had started their business. P1 explained:

"We studied machine learning models in detail, but no one taught us how to explain them to investors or clients. There was no training in business planning, IP law, or even writing a grant proposal."

This is symptomatic of a systemic problem in Chinese universities: STEM education remains siloed from entrepreneurship training, with the latter often offered as optional courses rather than as dedicated entrepreneurship programs. This limits the potential of academic research for AI entrepreneurs, whose work often operates at the boundaries of policy, ethics, and product-market fit. P3, an entrepreneur in logistics optimisation, said:

"When I graduated first in my computer science class I had no idea how to set up a company; I had to look things up on Google, and ask older friends, and it was a very hard process of rediscovery."

The discomfiture in this comment is part of a general feeling about the lack of correlation between academic and professional success. For some participants, the "shock of the new" in moving from campus to startup culture was pronounced and accrued poignantly in light of the lack of organisations to support students after graduation.

4.2.5.2. Role of International Exposure

Students who had studied overseas or undertaken short exchanges frequently noted that they built confidence as entrepreneurs and adaptability through exposure to models of innovation, mentorship, and startups outside of China. A UK postgraduate graduate and founder of an AI diagnostic program (P2) reported:

"In Bristol, we had weekly seminars with entrepreneurs. They taught us how to develop lean prototypes, test assumptions with users and talk about value creation. There was so much chaos but it was real. I felt I had a head start when I returned to China."

This suggests that off campus study not only delivers technical skills but also cultural skills for managing the messiness and risk necessary for experimentation, skills which may not be fully developed in Chinese education systems with an emphasis on learning through exams. Students appreciate Western professors' openness, the value of team work, reviews and critiques, and the preference for market and not academic excellence. However, interviewees also said cultural translation isn't easy. Several reported challenges translating foreign ideas and models into the Chinese regulatory and language environment. A returned student from Canada (P4) said:

"I've learnt pitching in English, but investors here are different. I needed to train myself on certain things about product-market fit and storytelling in China."

This suggests that entrepreneurship education needs to be tailored to the Chinese environment with reference to international best practices. Interviewees recommended building "mixed-incubators" and mentorship programs combining local and global know-how.

4.2.5.3. Learning-by-Doing and Informal Peer Mentoring

Most participants who felt they received inadequate education alluded to using informal, peer-based channels of "know-how", such as startup WeChat communities, internet forums, demonstration days, or founder networks. These groups served as lifebelts because they peppered immediate feedback, support and sharing. P5, who developed an AI fintech platform, said:

"I got most of my education from speaking to people who had raised money, hired people and failed. I joined three different groups of start-up founders in WeChat - that was life-saving - not the degree itself."

We detected peer networks as knowledge centres that filled in the institutional gaps. Participants deemed them more real, rich and relevant forms of contact than institutional entrepreneurship offices or university-organised competitions - which they often suggested were showmanship or stuffed with the sons and daughters of elites. P3 was among those who commented:

"The university entrepreneurship centre assisted us with branding and the structure of the slide deck, but there were no business owner mentors. We got the sense it was more PR than helping."

Many participants recommended that universities teach more founder-led and less theoretical education, where coursework would be developed and delivered by founders. Suggestions included the creation of AI-focused entrepreneurship bootcamps that would embody data, model, finance, business model and value model considerations. Significantly, some participants had been proactive in avoiding or delaying graduate degrees by moving towards entrepreneurship, due to the rigidity and non-relevance of their academic curriculum. P1 explained:

“I started a master’s in data science, but I quit after one semester. The curriculum was outdated, and I was already building something more cutting-edge with my team. Education should support reality, not delay it.”

This decision reflects a shift in learning legitimacy from the university to other types of learning environments, such as startups, where experimentation, failure and re-creation become the key.

4.2.5.4. Conclusion to Theme 4

This theme highlights that the Chinese university education system is not fully aligned to support the dynamic needs of AI entrepreneurship, particularly for new graduates who have to negotiate regulatory and technological complexities in the real world. It was repeatedly argued by participants that, although mainstream management and engineering curricula were rigorous, they were ineffective in equipping students to tackle business, legal and interpersonal challenges in building scalable ventures. The lack of experiential, cross-disciplinary and contextually diverse education was perceived as keenly, particularly among new founders in unfamiliar environments of regulatory and fundraising.

4.2.6. Infrastructure and Digital Inequality

Beyond cultural, educational and legal challenges, interviewees continually reported uneven access to the broader AI infrastructure, such as cloud-based services, data platforms, computing resources, and connectivity as a major barrier to business growth. While infrastructure investment is expected to be a core part of China's national AI strategy, interviewees pointed out that resource allocation across different cities, funding processes and technical areas is not equitable. This theme breaks down into three key sub-themes: cloud service access, data, and threats from government surveillance in digitised business.

4.2.6.1. Cloud Service Costs and Limitations

Nearly all interviewees highlight the importance of cloud computing services for the foundation and scaling of AI businesses. However, high-end services, particularly powerful clusters with Graphics Processing Units (GPUs) for model training, are costly. Many interviewees had adopted the free tiers of Tencent Cloud, Alibaba Cloud, or Baidu, but had to abandon them when their usage limits were quickly reached. P1, founder of an AI-powered edtech platform, explained:

“We started on Alibaba Cloud’s free tier, but once we hit a few hundred users, the service throttled. To maintain stable performance, we had to pay ¥3,000 per month. That’s almost half of our monthly budget.”

This is an illustration of a structural problem: while cloud computing is in principle non-scarce, the growth of cloud computing is limited by the capacity to pay. The cost of computing infrastructure can slow down the development and roll-out of products in nascent AI companies that lack institutional backing or stronger funding. P4, who built an image processing model using deep learning, added:

“The GPU-based servers we need are designed for enterprise, not startups. We can't afford to leave the server running all day, so we train models in batches during evenings and hope nothing goes wrong.”

These anecdotes show that infrastructure is not just a technical resource, but also a pace-maker and a quality gauge of AI. A few interviewees stated we need government-facilitated cloud credits, especially for firms registered with incubators or in accordance with China's AI goals. Interestingly however, others have tried to access cloud resources from outside, such as cloud resources from other countries through VPNs (Amazon Web Services (AWS) or Google Colab), but have cited legal uncertainty and data localisation issues as reasons for caution. Hence, there is a growing resistance between Chinese cyber-sovereignty and startups' need for low-cost and reliable providers.

4.2.6.2. Uneven Data Access and Fragmented Platforms

The second infrastructural challenge was high-quality datasets, which participants found technically restrictive and politically contentious. Despite the massive amount of digital data generated in China, much of it was limited to a specific industry or siloed in government databases, or even guarded by big tech corporations. An entrepreneur (P3) for a logistics AI start-up said:

“We wanted to develop a model to predict the last-mile delivery with traffic data. But the datasets are either out of date, or incomplete, or the city transportation bureau owns them. Without collaboration, there's no access.”

This statement speaks to the privately-owned nature of data infrastructure, where cities and the internet elite viewed their datasets as valuable assets. Where open datasets exist, interviewees' grievances related to data formats, documentation and quality control (notably clean data) which introduces more work and risks into the development process. P5, who builds sentiment analysis models, said:

"We scraped open posts from Xiaohongshu, but there's lots of noise and slang. We had to develop a manual labeling pipeline. It took weeks before we could start experimenting."

In addition, data scarcity is not just a technical issue that can be identified but also an ethical/legal one. Some interviewees were frustrated with aren't clear restrictions on data scraping, personal health data and model development, due to China's evolving data privacy legislation. One of the pioneers of health AI, P2, said:

"We tried to use some publicly available data from hospitals for training, but after reading the Personal Information Protection Law (PIPL), we were unsure if it was legal - even with anonymised data. We couldn't find a definitive answer from anyone."

Data issues put founders in a dilemma where they either have to work very conservatively and miss out on innovation, or develop fast and risk litigation. Thematic analysis indicated 12 out of the 15 participants identified data access and regulatory errors as significant sources of stress and wasted time. In addition, participants from second-tier cities noted data-related resources are frequently located in state labs, top hospitals, and pilot zones in Beijing and Shanghai.

4.2.6.3. Cybersecurity, Privacy, and State Scrutiny

The third form of infrastructural constraint relates to the emotional and operational implications of government surveillance and cybersecurity audits. Respondents involved in facial recognition, geolocation or biometric data in particular seemed concerned with the legal, reputation and compliance risks. P1 explained:

"When we added facial ID verification to our learning app, we suddenly got a warning from the local cybersecurity unit. We had to explain our storage policy, encryption method, and user consent process—even though it was opt-in."

This example demonstrates that regulatory compliance notices from the government are reactive and non-transparent, and startups may not know they are not compliant until they are identified. As with large organisations that have internal legal advice, small startups may feel paralysed in interpreting and responding to cybersecurity laws, many of which are

very dynamic and not well presented. A more worrying aspect was noted by P4, an AI surveillance businessperson:

"We were requested to modify our motion detection software to use in a public space. The application wasn't illegal, but it raised questions for us. Where do we draw the line? The authorities wouldn't clarify."

Scenarios like this are emblematic of a new grey zone of governance, in which technical compliance and regulatory safety don't always align. Participants noted a phenomenon of "compliance fatigue", which describes the emotional and time costs associated with working in an ever-evolving and uncertain governance space while attempting to remain legally safe. The stakes are higher for those supporting cross-border or international AI customers or frameworks.

4.2.6.4. Conclusion to Theme 5

This theme highlights that supposedly neutral or technical infrastructure is a key component of the politics of AI entrepreneurship. In terms of access to computing, data provisioning, and cybersecurity threat prevention, startups are subject to considerable inequality and uncertainty that shapes their innovation potential, and ethical stance as entrepreneurs. These insights would help characterise the empirical finding that Technology Infrastructure is the most important vector for startup success. Likewise, they provide a qualitative account of the invisibilities and gatekeeping that underlie China's infrastructural system, including differences across jurisdictions.

4.2.7. Ecosystem Navigation and Strategic Adaptation

This last theme explores the way recent graduates navigate broader institutional and entrepreneurial ecosystems, including incubators, science parks, accelerators, and administrative bureaus. Rather than these ecosystems being a background condition, participants observed that they are active spaces which can help shape strategic action, resource allocation and organisational legitimacy. This theme is grounded in three interrelated subthemes: gatekeeping and bureaucratic burdens, pivoting in response to institutional obstacles, and geographic inequalities in structures and access to institutional ecosystems.

4.2.7.1. Institutional Gatekeeping and Administrative Burden

Institutional gatekeepers, particularly state-provided science parks and incubators, were frequently cited by participants as critical gatekeepers. While these ecosystems offer resources, including funding, space and advice, as well as policy announcements and news, they tend to be gated by an informal system of gatekeepers, elites and red tape. P3, a founder in Chengdu, nostalgically recounted:

"I applied for a national incubator for AI, and they said we needed two patents, proof of revenue and a letter from a lab in a university. We are two people with a prototype. Who are these for anyway?"

P1, from Beijing, described the heavy administrative and largely paper-based bureaucracy required to even be able to apply to government-based accelerators:

"The paperwork is endless—tax certificates, IP filings, bank audits, HR contracts. Every form has to be stamped by multiple departments. If one thing is wrong, you start over. It's exhausting."

Interview participants also suggested this kind of frictions frequently come with an expectation for "showcase governance", in which exposure (like press releases and opportunities for photos) is favoured over active support. P5 reflected:

"The tech park director wanted to promote us at a conference, but when we asked him to help us hire some programmers, he said that was not his remit."

This quote recognises the transactional nature that a good deal of founders see in interactions between ecosystems in which symbolically fitting (i.e. that the relevant appear to encourage innovation) is more important than effectiveness.

4.2.7.2. Pivoting and Strategic Ambiguity

To overcome institutional lock-in, some participants spoke about strategic pivoting to accommodate funding, regulatory or investor needs by changing their business models, brand descriptions, or technical descriptions. This did not necessarily reflect innovation processes, but at times strategic responses. AI Health founder P2 revealed:

"The first idea to develop an early detection diagnostic engine. Our success in getting these technologies through was? You know, that worked really well when we decided to repackage it as a smart-city technology, then as a public-healthcare screening device. It's the first product in a different package."

While strategic ambiguity can aid in aligning with access-to-resources criteria, it can put long-term goal-setting at risk, particularly when pivots are driven by "mission creep" or policy-definition expectations rather than market demands or user feedback. P4, founder of a vision-based systems start-up, described this type of shift:

"We let go of small business, and we started to sell to the state. We don't like to but this is where the market is and you don't sustain or you perish."

This kind of behaviour is in line with the idea of institutional bricolage, in which entrepreneurs use second-hand and recycled tools, identities and narratives to navigate multiple (and inconsistent) sets of institutional logics. While flexible, this approach also signals a lack of coherent strategy and market directions. Without corporate stability, startups must continually "adapt" their product as well as product definition and meaning-making in the process.

4.2.7.3. Ecosystem Asymmetry

There were also marked differences between the types and quality of innovation systems between Tier-1 cities (e.g. Beijing, Shanghai, and Shenzhen) and second-tier cities (e.g. Nanjing, Xi'an, Chengdu). Access to funding, mentorship, international recognition, and transparency were just some of the differences. P3 lamented not being at the centre of innovation:

"We don't have the big accelerators in Beijing or Shenzhen. Way out here, you hear you get announcements, not results. We don't get demo days or global VCs, and even the training programs."

This suggests that China's national innovation program is still anchored in cities with established technology clusters, political and infrastructure density. The survey responses from less-developed cities indicated that these respondents thought of themselves as marginalised, both figuratively and literally. P5 compared:

"If I want to meet an investor in Qunchun in Shanghai, [I can] go to a coffee shop, go to a hackathon, and get a business license in one day. [In my city], I need to take a train to register my [thesis form with a red tape], and [it] takes a month for approval."

This lack of mobility is not only about infrastructure, but also ecosystem competency: tacit knowledge of how to secure grants, source talent or manage IP. Some respondents noted that, beyond Tier-1 cities, *guanxi* (connections) often substituted formal processes, where knowing the right people was key. This can lead to systemic reproductions of entrepreneurial inequality, in which "where you live matters". While existing local initiatives have aimed to mitigate this (as described by participants as soft-landing programs and online platforms), participants noted that access to national ecosystems remains tightly concentrated and controlled.

4.2.7.4. Conclusion to Theme 6

The discussion of strategic response and ecosystem management in this section points to structural inequalities, bureaucratic transactions and acts of adaptation in the entrepreneurial response in China's AI start-up ecosystem. Institutions such as incubators and science parks play an important role in service provision, but can also be seen as gatekeepers because they favour elite affiliations, formal certification, and political endorsement - often at the expense of innovation from the "bottom up". Cultural participants were especially adept in their capacity to re-invent, pivot, or "roll with the punches". As this adaptability makes clear, this incurs various costs such as lack of strategic focus, emotional burnout and loss of purpose. Furthermore, spatial inequality significantly factors in, as extra-Tier-1 founders face systematic access, legibility and responsiveness issues.

5. Discussion

5.1. Introduction

The objective of this study was to explore the effects of regulatory, cultural and infrastructural processes on self-reported entrepreneurial success for recent graduates turned AI entrepreneurs in Chinese cities. To contribute to China's national strategy to become an AI leader, this research set out to understand how macro-intentions of policies are received and negotiated in practice at the micro level: of entrepreneurs in the form of a new generation working with constrained resources and bureaucratic and cultural complexities. The study was particularly interested in how they navigate the institutional environment, shape their entrepreneurial approach, and construct their entrepreneurial identities in the innovation system.

A mixed-method approach was adopted to fulfil this goal. The quantitative phase encompassed a survey of 150 founders of AI start-ups which statistically examined the associations between Regulatory Environment, Finance and Financial Resources, Educational Background and Cultural Attitudes, Technology Infrastructure and Perceived self-reported entrepreneurial succession. This showed the impact of Technology Infrastructure and Regulatory Environment on self-reported entrepreneurial success was significant, although educational background and cultural attitudes had a weaker or even negative impact in the multivariate regression model.

A note on interpretation is necessary before discussing the findings. The quantitative results measure founders' perceptions of regulatory, cultural, educational, infrastructural and ecosystem conditions, together with self-reported startup success. They should therefore be read as evidence of perceived relationships within the sample rather than as objective measures of the external environment. The qualitative findings help explain how these perceptions were formed and how founders acted on them.

This chapter examines the research findings in Chapter 4. It reflects on them in the context of the study objective, which was to explore the effects of regulatory and cultural aspects on entrepreneurial experiences of recent graduates with AI startups in urban China. To achieve Research Objectives 1-3, the discussion offers a critical analysis of the identified themes in light of the theories outlined in Chapter 2 - Institutional Theory, the Resource-Based View, and the Entrepreneurial Ecosystem Theory. This chapter breaks

down a comprehensive narrative of graduate AI entrepreneurship as it is impacted by a variety of institutional, infrastructural and cultural factors, and also draws connections to the literature.

5.2. Institutional Ambiguity and Regulatory Complexity

Drawing on the findings in Section 4.2.2, which provided details of the participant's perception of regulatory uncertainty and policy guilt, introduce the role of institutional ambiguity on business decisions among recent AI graduates. This builds on the theories and findings of Institutional Theory and state-led innovation policy. The perceived regulatory clarity emerged as one of the strongest associations with self-reported startup success in this sample in the quantitative and qualitative phases of this study. Multivariate linear regression analysis showed a strong positive association of the regulatory environment on the perceived performance of startups (standardized $\beta = 0.451$, unstandardized $B = 0.4309$, $p < 0.001$), which aligns with the notion that clear, consistent and accessible regulatory regimes are essential for entrepreneurial performance. But the quantitative pattern does not fully capture a much more complex reality, as the qualitative analysis shows, with *de facto* legal uncertainty, a decentralised regulatory administrative practice and symbolic compliance. The interviews demonstrated that many surveyed entrepreneurs found it hard to determine whether their AI offerings fell under any of the existing laws, particularly if their products touched upon multiple areas such as health, education or public security (Yu, 2023). For instance, one health-tech interviewee reported her software could be considered a possible medical device for registration, even though her software is simply a computer diagnostic tool. This highlights a lack of standardisation of regulation as local bureaucracies might not have the necessary expertise or focus on implementing national policies.

The Chinese regulatory system seems to involve a number of institutional features. While national AI strategies provide general frameworks, local expectations and enforcement practices differ. Participants described some of these interactions as a form of policy theatre, where the symbolic enactment of support masks a lack of institutional action and coordination. This interpretation comes from the interview data and is used here as an empirical theme rather than as a claim already established by the cited literature.

In the context of the current study, this is in line with the notion of institutional entrepreneurship, which describes how actors try to change or navigate institutions. Yet, when we adopt this concept when it comes to Chinese AI startups, the power differential between nascent entrepreneurs and bureaucratic elites means that institutional change is rare. Rather, institutional drift is quite common, with actors making choices to follow the rules, disregard them, or creatively reinterpret rules within their survival strategies. This results in a space between formally correct rules and instrumental action. There are two policy implications. First, standardisation and sector-specific advice is urgently required for AI systems (Smuha, 2021). The development of a common regulatory code, developed through industry, academia and government partnerships, will better reduce the informational and administrative frictions for early startups. Second, decentralised policy implementation should not be uncoordinated. This means active efforts by the state to build national capacity (e.g. capacity-building programs with government officials to understand regulation) and provide advice to founders on navigating regulatory hurdles.

In summary, the quantitative data and evidence show that regulatory clarity can be productive, while the qualitative evidence shows that regulatory clarity is skewed, contingent and negotiated. Unlike a passive attitude, entrepreneurs are actively involved in negotiating regulation. Without explicitly recognising these interactions, it is hard to build an innovation-enabled environment in this rapidly growing and complex AI sector in China.

5.3. Infrastructure as a Strategic Limit and Facilitator

The quantitative analysis provided indicative evidence that perceived Technology Infrastructure is strongly associated with self-reported success among recent graduate AI entrepreneurs in this sample. This construct had a strong standardised regression coefficient ($\beta = 0.910$, unstandardised coefficient $B = 0.8819$, $p < 0.001$), but the result should be interpreted as a perception-based statistical association rather than proof that infrastructure objectively determines venture success.

Our qualitative findings offer an understanding of why infrastructure is important. The digital infrastructure element of the Chinese AI strategy includes government-supported cloud computing, 5G, and datasets. But while trying to support early entrepreneurs, interviewees pointed out that these resources were difficult to access, costly, or were

unevenly distributed (Sayler, 2020). Both P1 and P4 noted that public cloud resources were only helpful in the early stages of model training, after which their benefit decreased. P4 also noted that the cost of GPU was increasing rapidly and was more than their operating expenses. Others tried to access infrastructures from overseas, such as AWS or Google Colab, but were frustrated by the lack of clarity around the legality of VPN and cloud policy on data localisation.

This lack of access creates a two-tiered innovation economy where large-scale and financially well-resourced organisations are able to continuously train models, store datasets and deploy their products with relative ease. Smaller startups might have to use alternative means, such as training on weekends or at night. These scenarios reflect broader debates about the digital divide, which is as much about the ability to use the digital capabilities of equipment and connectivity as it is about possessing these in the first place. This divide is further compounded by data access issues (Rane et al., 2024). Interviewees explained that labelled, high-quality, high quantities of data are monopolised by digital platforms, such as Baidu, Tencent, and Alibaba, or managed by the state.

Further, concerns about the enforcement and compliance of cybersecurity and data management suggest the infrastructure implications of China's government regulatory style of digital governance. Some interviewees reported that local authorities conducted surprise audits, were aware of their strict data storage policies and feared a model trained on non-domestic standards be seen as insecure (Pratomo et al., 2023). As these accounts reveal, infrastructure is not only a technical but also a political issue; it is a space where entrepreneurial endeavour is at odds with national cyber-sovereignty. We can draw parallels with techno-nationalism. While China's national AI-driven agenda, as part of a broader strategy to strengthen the state, may be a powerful motivator for development of AI, the nationalisation of the digital economy may limit the actions of startups that lack capital and control resources: they lack state proximity or state protection. Startups are thus positioned in a unique position: to support national innovation on the one hand and to respond to a compliance and state-controlled infrastructure system on the other.

Nonetheless, respondents also identified infrastructure as a double-edged sword. Where state grants, incubator participation, subsidised compute credits or access to collaborative data were available, founders reported shorter time to market. Founders in Tier-1 cities also described better access to pilot zones, R&D labs and cloud-skills training. This supports

the interpretation of infrastructural centralisation: cities such as Beijing and Shenzhen may concentrate digital assets in ways that deepen interregional disparities. The practical implication is that AI policy should consider infrastructure access for small entrepreneurs, including compute resources, open data and technical training.

5.4. Entrepreneurial Legitimacy and Cultural Identity

Following the evidence presented in Section 4.2.4, this section deals with the cultural influence of cultural norms, particularly guanxi and vertical legitimacy, on graduate entrepreneurs' entrepreneurial identity. It draws on the research on cultural entrepreneurship presented in Chapter 2. Although there is no significant statistical relationship between Cultural Attitudes toward Entrepreneurship and firm performance in the quantitative part, qualitative information is more informative and suggests a more elaborate cultural interaction. In this sense, the cultural element is related to social capital, particularly guanxi networks, which affect the access to resources, mentoring and legitimacy in the Chinese AI-related industry. Despite the limited variance in the quantitative data, the qualitative data show that Confucianism and trust through interpersonal relations play a significant role in shaping the opportunity to collaborate and access funding. In this way, culture facilitates startup success, by increasing social capital, which helps overcome resource and institutional deficiencies (Que et al., 2019; Peters, 2022).

The respondents' inner-conflicts about legitimacy and risk-taking, as well as the meaning of their acts, were heavily influenced by both traditional Chinese family values and trends in the global startup industry. Most entrepreneurs expressed a duality of entrepreneurship: notions of individual achievement and benefits to the community intersected with Confucian ideals of family leadership, harmony and social responsibility. As P1 described, families and extended family members usually expressed doubt about starting a startup, particularly when this decision meant abandoning a secure job. Such generational tensions reflect the persistence of cultural expectations surrounding security, stability and prestige, especially in single child families (Mishra et al., 2020).

A number of founders also described barriers related to gendered cultural pressures, citing that many women in the workforce faced implicit cultural tensions between contributing to society as individuals and the potential of childbirth. Despite not being overtly

discriminatory, implicitly gendered roles added additional identity work to the already tough task of early entrepreneurship. Cultural identity also served as an incentive and a guide in such circumstances (Lambert and Stevens, 2024). Some of the most common ways participants expressed their patriotic pride were by contributing to China's AI development or helping local communities via socially useful services. This was in line with state discourse that equates AI with a public good, but participants' attitudes were more personal and less political as they were linked to morals rather than party ideology.

These results suggest that in China, entrepreneurship is justified in terms of different symbolic economies, including economic, social, familial and political expectations. Startups are economic activities, but they are also narrative projects, where entrepreneurial performance needs to be relatable to diverse stakeholders. Entrepreneurs need to balance authenticity and acceptability, ambition and humility, independence and compliance. These dynamics of cultural fit are reflected not only in intrinsic motive, but also in pitch design; founders often adjust their pitch to different audiences, including government providers or foreign venture capital. Cultural attitudes therefore do not operate as a simple independent variable; they operate through other institutional and relational factors. Motivated founders may underperform without resources, information and policy clarity. Culture does not directly determine success, but it may affect the conditions that shape perceived success, desirability and rewards.

This study is important in recognising the regulatory, cultural and infrastructural factors on the entrepreneurial journeys of young recent graduates starting an AI startup in China. The mixed-methods results corroborate the research that highlights the critical role of state impact in the Chinese innovation ecosystem, in particular, regulation, data and infrastructure (Zenglein and Holzmann, 2019). However, this research adds to this literature by suggesting that regulatory uncertainty and not regulation itself is the critical barrier faced by entrepreneurial startups. In this sense, it challenges the deterministic theories that see a positive bias in Chinese governance toward innovation. The quantitative finding of the predictive power of digital infrastructure and regulatory certainty confirms earlier discussions on ecosystem factors. But the qualitative insights shed new light by demonstrating that the impact of macro-level digital factors on founders vary between individuals with different network and institutional knowledge resources.

Furthermore, the study contends that the Resource-Based View is strengthened by showing that, while human capital is significant, its potential is limited by experiential gaps in entrepreneurship education, signalling a mismatch between formal and experiential skills. Through cultural analysis of guanxi and Confucian principles, and with the continuing debate about them, the research also shows how young entrepreneurs struggle with cultural tensions between traditional and innovative cultures. All these findings point to the refined empirical critique of oversimplified perspectives of China's AI system and provide further insight into the previously underexplored challenges of graduate startups.

5.5. The Experiential Gap and Education

While much is spoken about Educational Background (as part of developmental advantage), the quantitative data of the research surprisingly showed that Educational Background is not positively correlated with AI start-up success. This is evocative of the original predictions of human capital theory and suggests inherent flaws of higher education system in China. The entrepreneurs concerned were well educated but they often presented a stark disconnect between academic life and startups. The interviews suggested that most participants were well-educated high-tech graduates from large higher education institutions, such as computer science and AI. Yet they consistently described their education as "too theoretical" and "too niche". For example, P1 said:

“We were taught everything about machine learning models, but no one taught us how to communicate them to investors or clients. There was no business-planning training, no IP law training, and no training in writing a grant proposal.”

This is an indication of the pedagogical gap between the development of knowledge and the skills to employ knowledge of innovation (such as AI) given the uncertain and ever-changing innovation environment, as defined by Giuggioli and Pellegrini (2023).

In the Chinese AI entrepreneurial ecosystem, universities seemed to be focused on thinking rather than acting. This impacted participants' capacity to convert knowledge into business opportunities. P3 explained that he was the top student in his computer science class each semester, but he did not know how to form a company: "I learned to Google about it and ask my senior Chinese friends." These examples highlight that skills need to be learned and practised in order to be transformational.

The value of international experience also underscores the need for it. International students expressed greater confidence in entrepreneurial activities and flexibility in part due to participatory teaching and market-focused project development and mentorship. P2 said:

"We did seminars in Bristol every week with entrepreneurs, and they told us about how to build thin slices and test user assumptions and how to create value. It was random, but it was real".

Such statements are consistent with the value of experiential education as stated in the global entrepreneurship literature (Furman and Seamans, 2019; Flores-Viva and García-Peñalvo, 2023), which provides an educational strategy that focuses on managing uncertainty, the innovation process and learning from failure.

Of note, the constraints of formal education approached several founders to peer-based learning ecologies. Peer-to-peer networks through WeChat, online platforms, and a formal networks of alumni provided forums for sharing practical knowledge, moral support, and lessons of survival. As P5 observed:

"I went to school talking to other people who had done funding, who had done hiring, who had done that. [Those conversations] were worth more for me than school."

The findings are consistent with the function of informal entrepreneurship ecosystems as a compensating response to institutional absence or weakness, as noted by Gueguen et al. (2021) and Tula et al. (2024) in relation to ecosystem relational capacity. Given these gaps, there are clear policy and practice implications.

In summary, while education is the starting point for developing entrepreneurship, it has failed to equip students with the skills necessary for the hybrid, complicated and institution-specific field of AI startups. Such a gap in experience needs to be addressed if China is to further deepen its mass entrepreneurship movement.

5.6. Ecosystem Navigation and Strategic Adaptation

As the qualitative study reveals, Chinese entrepreneurs in AI, particularly new graduates, not only need to navigate the regulatory landscape, but also the power asymmetries throughout the ecosystem, which the entrepreneurs have to navigate. They claimed that

they have to adapt, learn, and act in accordance with strategic scripts written by funding bodies, agencies and big-tech companies. This predicament can be best understood with the Resource Dependence Theory (RDT), which highlights that organisations were constrained by their dependence on external resources in the hands of dominant actors (Ahmed, 2024). The interviews and statements of different founders illustrate that ecosystem gatekeeping was based on quality (or innovation) and institutional authority and elites. As the quote above shows, institutional barriers contribute to path dependency and exclude non-elite or first-generation founders. So, strategic ambiguity becomes a critical tool for founders to overcome these constraints.

Responding to shifting government priorities, founders adapted their business models, rhetoric and even morals. P2, founder of an AI health startup, said:

“We initially planned to work on a diagnostic engine. When smart city technology was in the media, we pitched it as a mass health screening system. The same product but different pitch.”

This is consistent with Roundy's (2022) description of signalling, where entrepreneurial teams tailor their pitch to the expectations of investors and policymakers, at the expense of the original vision. It is also a symbolic gesture of what Letherby et al. (2012) might describe as symbolic compliance, or "going along with the program".

This semantic flexibility can be viewed as part of the institutional gaps and policy uncertainties in today's rapidly evolving China's AI ecosystem. This leaves startups with little choice but to do sense-making to suit various clients, a dynamic but stressful approach. Moreover, strategic ambiguity often led to immoral outcomes. Some entrepreneurs did not want to "join the dots" to drive messaging, espionage, or politically dictated funding priorities. As P3 commented:

"We were asked to put a Party quote in our deck".

There are important consequences for ecosystem planning. Participants' accounts suggest that symbolic codes and elite power in gatekeeping processes can restrain the development of new modes of innovation and exclude less orthodox founders. This may limit diversity and inclusion in ecosystems, particularly among non-STEM founders, rural founders and other underrepresented entrepreneurs. Policy should therefore consider not only the total

amount of support available, but also the institutional arrangements through which support is distributed.

To conclude, the interactions of Chinese AI entrepreneurs with the ecosystem should be seen not as a process of resource mobilisation, but one of code-switching and adapting to changing institutional demands. Adapting strategically is essential, but doing this in a performative manner is detrimental to innovation, authenticity and sustainability. A more diverse, ethically grounded (and allowable) environment with space for entrepreneurial agency is required for a healthier ecosystem.

5.7. Integrative Insights: Intersections, Tensions, and Trade-offs

An interpretative synthesis of the findings suggests a dynamic web of regulatory permission, infrastructural support, cultural norms and educational training, which serves as both limiting and potentially enabling factors for founders of AI start-ups in urban China. These factors are not in isolation; they reside in differentiated pressure ecosystems that shaping entrepreneurship in dynamic ways. While regulatory regimes espouse mass innovation, they are unevenly applied through cities. Uncertainty for entrepreneurs in licensing, categorisation and regulation exists, particularly in areas of AI cross-cutting legal and/or industry boundaries.

Tech scaling involves infrastructure, which is unevenly and politically allocated (Borenstein and Howard, 2021). Geographic and economic inequality is exacerbated through spatial variation in access to cloud computing and high quality data, which is dependent on proximity to public sector agencies and/or corporate monopolies. Higher education continues to be a source of entrepreneurial capacity, yet it does not necessarily teach skills required to navigate these barriers to starting a business, and becomes a source of knowledge through informal networks. At the same time, cultural values, filial piety, collectivism, and the moral dimensions of success are lurking, particularly for the first-time or female entrepreneurs.

These combined forces result in a disjuncture between policy and practice. Despite the central government explicitly advocating for innovation among younger generations, and a more distributed model of innovation for startups, the means for this support is weak, conservative and exclusive. This places entrepreneurs in a dilemma of agency and structure. They want to innovate and make their own way, but are structurally dependent on

gatekeeping institutions for funding, legitimacy and infrastructure (Arenal et al., 2020). Such a paradox is also amplified by the disjoint between global startup cultures and local institutional regulatory forces. Participants were open to adopting international startup models, such as lean, agile and open source product development. Yet they had to continually adapt these norms to meet the demands of Chinese politics, markets, and cybersecurity. This results in strategic ambivalence and a gap between internal and external messages.

To conceptualise these factors, a layered ecosystem pressure model can be used. It comprises three coevolving levels: the micro level (self, team, and peer learning); the meso level (institutional actors, incubators, and local politics); and the macro level (national strategy, techno-nationalism and global debates about AI ethics). These three levels interact to shape the founder's strategy. These levels aren't hierarchical; they create a spectrum of opportunities and constraints that need to be managed, adjusted to, and continually told a story about. Such a framework presents a valuable lens to understand the evolution of entrepreneurial ecosystems in other emerging technologies industries within a highly regulated environment.

5.8. Development of the Layered Ecosystem Pressures Model

The Layered Ecosystem Pressures Model was developed from the integration of the quantitative and qualitative findings rather than imposed at the beginning of the study. The regression results indicated that perceived technology infrastructure and perceived regulatory environment were the strongest positive predictors of self-reported startup success. The interviews then showed why these two factors mattered: founders described infrastructure, regulation, funding, legitimacy and cultural expectations as overlapping pressures rather than separate barriers.

The model has three layers. The outer institutional layer comprises national AI policy, data governance, licensing expectations and local implementation practices. The middle ecosystem layer comprises funding, incubators, university support, cloud/data access and platform dependence. The inner founder layer comprises graduate experience, technical competence, business knowledge, family expectations, guanxi and entrepreneurial identity. These layers interact: for example, a founder's lack of business experience becomes more consequential when regulatory guidance is unclear, and limited guanxi becomes more consequential when access to infrastructure or funding is mediated through elite networks.

The model is best understood as an interpretive framework for this empirical setting, not as a universal theory of AI entrepreneurship. Its contribution is to show how recent graduate founders experience AI startup formation as a layered process in which institutional ambiguity, ecosystem asymmetry and founder-level resource gaps reinforce one another.

5.9. Contributions to Knowledge

The thesis makes its strongest contribution empirically and practically. It provides evidence on how recent graduate AI founders in China perceive and navigate regulatory ambiguity, infrastructure access, cultural legitimacy and ecosystem support. The theoretical contribution is more modest: the study applies and combines institutional theory, entrepreneurial ecosystem theory and a limited RBV perspective to interpret this empirical setting, rather than claiming to transform each of these theories.

This study offers four contributions to knowledge: methodological, empirical, theoretical and practical. The framework described in Chapter 2 suggested the regulatory environment, cultural milieu and ecosystem resources was combined to influence the entrepreneurial resources of recent graduates of AI. This study extends the Resource-Based View (RBV) by showing that in the context of AI entrepreneurship in China, intangible resources such as regulatory knowledge, *guanxi*, and adaptive capability, complement tangible resources. It connects RBV to the institutionalised startups and illustrates the use of scarce resources to create value within regulatory and cultural boundaries. Therefore, RBV is expanded with an institutional-cultural dimension to better explain emerging market entrepreneurship.

From a methodological perspective, the study provides an example of how a mixed-method approach can examine the both-and nature of AI entrepreneurship in China by exploring statistical associations while also examining underlying processes. On one side, participants' accounts suggest that self-reported success is associated with perceived infrastructural and regulatory conditions; on the other side, it is also shaped by interpretive and narrative dimensions of founder entrepreneurship and institutional engagement. By joining quantitative patterns with qualitative interpretation, the research shows the complementary value of both methods.

Empirically, the study offers a fresh view point on AI entrepreneurship in second-tier urban clusters, which are under-acknowledged. It draws out the idea of innovation under

constraint through the experiences of postgraduate engineers who, in many instances, lacked elite connections and political clout. It also highlights the geographies of opportunity in China's innovation economy. In doing so, it adds to the case by Letherby et al. (2012) that institutions are persistent yet contested areas. The results add to the original framework by showing that regulatory constraints are not merely imposed on entrepreneurs from the outside, but are part of a process that generates pressure, and affects strategy development. This implies that agency needs to be understood as relational.

Pragmatically, the results offer insights for incubators, universities, and policymakers. They imply that support should not be limited to financial and other resource provisioning, but also include institutional clarity, more action-oriented learning, and psychological and moral support for founders to cope with political expectations. This type of support is essential for building a sustainable and inclusive AI innovation ecosystem in China and even possibly the rest of the state-led innovation systems.

5.10. Concluding Remarks and Transition

The discussion chapter has re-interpreted the insights through the lenses of Institutional Theory, experiential learning, Resource Dependence Theory and entrepreneurial bricolage. It has detailed the regulatory, infrastructure, educational and cultural factors in China's urban AI ecosystems and their perceived influence on startup strategies. Quantitatively, infrastructure and regulation were the strongest statistical associations with self-reported success in this sample; qualitatively, participants' accounts suggest how these pressures are experienced and navigated.

A key take-away is that Chinese startup founders are not only innovators and strategists, but also cultural and institutional hackers. Thus, their achievements are not just based on money or computer programming skills, but also on their abilities to manoeuvre, practise and perform in a fragmented, risky, and political arena for entrepreneurship.

These interpretive insights are drawn on to inform the final chapter, which sets out the implications of the study. This chapter discusses the main research limitations from methodological, geographical and theoretical perspectives, and suggest future areas of research on entrepreneurship in frontier technologies and regulated innovation regimes. It will revisit the core contribution of this research and recommend a multi-dimensional, contextual, and multi-level frameworks for studying entrepreneurship in China.

6. Conclusion and Future Recommendations

6.1. Conclusion

The aim of this study was to critically examine how regulatory systems, technology infrastructure, cultural norms, and educational background interact to shape the entrepreneurial pathways of recent university graduates entering the artificial intelligence (AI) start-up industry in China's major cities. As China aims to lead the global AI race, the Chinese government has emerged as a key source of large-scale innovation and entrepreneurship, particularly in cities such as Beijing, Shanghai, and Shenzhen. They serve as hubs of urban experimentation, data governance and state-driven innovation. Government enthusiasm for AI, such as the 2017 release of the New Generation Artificial Intelligence Development Plan, has further encouraged the early-stage development of AI. Yet, despite this grand narrative, there remains a paucity of knowledge about how first-time entrepreneurs perceive these state-led initiatives, especially as they relate to enterprise found within dynamic institutional settings.

These circumstances required a design capable of exploring not only the institutional issues associated with startup outcomes, but also how founders interpreted the environment's challenges and opportunities. As a result, this study used a mixed-methods approach, offering exploratory quantitative patterns and detailed qualitative insight. The quantitative questionnaire strand allowed the study to explore connections between factors such as regulatory certainty, infrastructure and self-reported startup success, while the qualitative interviews supported interpretation of how these conditions were experienced by founders.

The results of the study are empirical, theoretical and practical, as outlined in this chapter. It begins by summarising the core quantitative and qualitative findings, and its integrated implications. It then discusses how the study advances theory, method, and stakeholder targeted recommendations. Finally, it explores the limitations of the study and suggestions regarding directions for future research on the interdependence of innovation, identity and institutional power in China's AI economy.

The statistical results presented in the research offer indicative empirical evidence that perceived technology infrastructure and perceived regulatory clarity are associated with self-reported success among AI startups led by young entrepreneurs. As reported in Section 4.1.5, the regression analysis suggested two variables (Technology Infrastructure

and Regulatory Environment) with the strongest association with self-reported startup success in this sample.

The qualitative data provided a contextual depth for these quantitative trends by grouping them into six more in-depth themes. The first theme, Regulatory Alpha, highlighted that the interviewees were confronting problems around licensing grey zones, changing compliance standards and the local enactment of national AI strategies. Founders tended to perceive a gap between "innovation policy" and administration, an exasperating gap they called policy theatre. This is in line with the quantitative link between regulatory certainty and venture performance, but it also shows how entrepreneurs developed coping strategies, such as "theatre" and hedging, to deal with regulatory uncertainty.

The second theme, Infrastructure and Digital Inequality, complemented the quantitative finding about technology access. Contestants talked about the lack of access to cloud computing, the need for expensive GPU-rental schemes, as well as the difficulty acquiring "clean" data held by tech giants or state organisations. While the quantitative results established the statistical importance of infrastructure, the qualitative results revealed its heterogeneous nature. Geographical location or lack of elite capital in cities outside the first-tier were particularly affected, showing how infrastructure's benefits often accrue to elite centres, contradicting the national narrative of inclusive innovation.

The third theme, Cultural Identity and Entrepreneurial Legitimacy, examined the discourse and emotions of creating a startup. Cultural perceptions did not have a statistically significant impact on startup performance but interviewees described the performative dynamics of starting a business in China in detail. The interviewees explained how they tried to develop a sense of entrepreneurial identity while engaging with their families, the discourse of nationalism, and of entrepreneurship in the West.

The fourth theme, The Experiential Education Gap, provides insight into the negative association of Educational Background on startup performance, by suggesting that there is a disconnect between academic degrees and entrepreneurial skills. They had domain-specific knowledge, but lacked managing regulatory uncertainty, fundraising, team building, and market testing skills. This result contradicts human capital theory, which holds that human capital skills are acquired through formal schooling, and instead shows that proficiency in AI entrepreneurship is gained through experience and training.

The fifth theme, Ecosystem Gatekeeping and Strategic Adaptation, focused on startups' bargaining with unpredictable selection processes, symbolism and inequality. Interviewees noted that they would often change their stories to suit government agencies, investors, or incubators, consistent with signalling theory and entrepreneurial bricolage. The need to appeal to incubators, grants or the media meant that founders needed to craft a specific persona: one that aligned with government priorities, depicted credibility and obfuscated their resource limitations.

The sixth theme, Founders' Responses to Techno-nationalism and Political Expectations, revealed entrepreneurs' awareness and reaction to China's techno-nationalism. Respondents struggled to decide whether to align their businesses with government initiatives, particularly when it meant sacrificing their product focus and/or moral compass. This synthesis is captured in a Layered Ecosystem Pressures Model, where founders are integrated across institutional layers. The micro layer includes individual and team dynamics, such as motivation, identity and learning. The meso layer includes incubators, local policy actors, finance and institutional brokers. The macro layer includes national AI strategy, ideological discourse, techno-nationalism and global AI ethics. All layers influence entrepreneurial strategy, but the intersection of layers has the greatest impact on strategy success.

The Layered Ecosystem Pressures Model refines the initial conceptual model by interpreting the survey variables as perceived ecosystem pressures embedded in nested institutional forces. The quantitative regressions indicate associations involving perceived regulatory knowledge and infrastructure access, while the qualitative themes explain how these challenges are experienced as barriers, affordances and identity markers. By linking statistical association with meaning, the model suggests that AI entrepreneurship among recent graduates is shaped by layered institutional, ecosystem, cultural and geopolitical influences, rather than any single factor.

LAYER 4 — MACRO-POLITICAL

Techno-nationalism

Geopolitics State Strategy AI Sovereignty Pressures Tech Decoupling

The highest-order environmental forces where nation-states pursue technological self-reliance as a strategic imperative. This layer shapes the competitive landscape through export controls, investment screening, and digital sovereignty initiatives.

- **Geopolitics:** US-China tech rivalry creates bifurcated innovation ecosystems and talent flows
- **State Strategy:** National AI strategies, indigenous innovation policies (自主创新)
- **AI Sovereignty:** Data localization, compute access restrictions, foundation model controls
- **Tech Decoupling:** Supply chain realignment, entity list restrictions, talent barriers



LAYER 3 — REGULATORY

Institutional Environment

Regulation Data Laws Licensing Funding Controls

Formal institutional structures that govern entrepreneurial activity through regulatory frameworks, compliance requirements, and resource allocation mechanisms that directly constrain or enable venture formation.

- **Regulation:** Industry-specific rules, algorithmic governance requirements, safety standards
- **Data Laws:** GDPR, PIPL, cross-border data transfer restrictions impacting AI development
- **Licensing:** Business permits, professional credentials, platform access requirements
- **Funding Controls:** Foreign investment review, government grant allocation, subsidy eligibility



LAYER 2 — MARKET STRUCTURE

Entrepreneurial Ecosystem

Infrastructure Incumbents Incubators VC Access

The immediate competitive and support environment providing resources, mentorship, and market access. This layer determines the practical feasibility of venture creation and scaling opportunities for graduate founders.

- **Infrastructure:** Cloud computing access, development tools, API ecosystems, technical resources
- **Incumbents:** Platform gatekeepers, corporate venture arms, potential acquirers/competitors
- **Incubators:** University programs, accelerators, science parks, mentorship networks
- **VC Access:** Seed/early-stage capital availability, investor networks, government-backed funds



LAYER 1 — SOCIO-CULTURAL

Cultural Foundation

Guanxi (关系) Confucian Norms Risk Perception Legitimacy

Deep-rooted cultural values and social norms that shape entrepreneurial cognition, risk attitudes, and relationship-based resource mobilization strategies fundamental to founder identity and decision-making.

- **Guanxi:** Relational networks for resource access, trust-building, reciprocal obligations in business
- **Confucian Norms:** Hierarchy respect, collective harmony, face (面子), family expectations
- **Risk Perception:** Uncertainty avoidance, failure stigma, career path security preferences
- **Legitimacy:** Social approval of entrepreneurship, status of founders, education prestige



CORE — AGENT LEVEL

Entrepreneurial Agency

Graduate Founder Strategy Opportunity Recognition Resource Mobilization Strategic Adaptation

The focal unit of analysis where graduate founders exercise strategic choice within multilayered constraints. Agency manifests through opportunity identification, resource orchestration, and adaptive navigation of contextual pressures to create viable ventures.

- ★ **Opportunity Recognition:** Identifying gaps created by techno-political shifts and institutional changes
- ★ **Resource Mobilization:** Leveraging guanxi, university ties, and ecosystem support for venture building
- ★ **Strategic Adaptation:** Pivoting in response to regulatory changes and market conditions
- ★ **Identity Navigation:** Balancing cultural expectations with entrepreneurial ambition

Figure 2 Layered Ecosystem Pressures Model (Designed by Author)

6.2. Applied Theoretical Implications

The findings suggest that institutional theory is the most useful theoretical lens for this thesis because founders repeatedly described ambiguity, legitimacy and local implementation as central to their experience. Entrepreneurial ecosystem theory helps explain how support is unevenly distributed across cities and networks. RBV is used more cautiously to understand founders' resource gaps, especially in technical infrastructure, managerial experience and relational capital.

Institutional Theory is a key way that the study of entrepreneurial behaviour has been examined, particularly in its trinity of regulatory, normative, and cultural-cognitive institutions. But, according to this study, in China's AI industry, the regulatory system is not only dominant, but also disjointed and performative. Interviewees described variations in licensing regulations, excessive government bureaucracy and regional unevenness in policy implementation to advance the national AI strategy. This is important, as these findings suggest a disjunction between formal institutional settings and practices. This constates decoupling in institutional practice, in which policies are ritual symbols, rather than resources. In turn, entrepreneurs adapt to these circumstances not only by accepting, rejecting or bypassing institutional demands, but also through "strategic compliance": forms of identity display that fulfil a function of "quasi-adherence" to institutional constraints while maintaining some level of operating autonomy. This adds to Scott's theorisation of institutions by foregrounding the activism of founders on the margins of incoherence.

The study also adds to research on entrepreneurial bricolage surrounded by ideological saturation. Participants were not just assembling limited material and financial resources; they were also forging rhetorical and political bricolage, such as adapting their technologies to new policy-speak or labelling their products as state-recognised social products. This is a manifestation of a new type of bricolage, which is not just material but symbolic. It is also a matter of rhetoric as well as resourcefulness in a regime of state-led innovation.

Citing Resource Dependence Theory, these results indicate entrepreneurs are very sensitive to the power imbalance in the ecosystem. They are dependent upon politically allocated

resources, such as use of the cloud, grants and incubator approval and agile, often to the detriment of mission. While RDT has concentrated on the responses of organisations to market power relations, this research shows that in a semi-authoritarian country, dependencies are not only market-based, but also bureaucratic and ideological. Entrepreneurs are subject to two forms of dependence in the form of capital and infrastructure dependence and institutional dependence. As a result, their signalling, shifting strategies and "re-branding" is representative of institution-based risk weighing rather than customer-based thinking.

These findings can also be interpreted through signalling theory. In conventional startups, observable signals such as founder characteristics, patent portfolios or accelerator connections are often used to communicate quality. In this study, participants' accounts suggest that signals may also include ideological alignment and state-related affiliations. This should be treated as an application of signalling theory to the empirical context rather than a claim to broaden the theory itself.

A further implication concerns experiential learning. Participants' accounts of learning by doing, trial and error, peer networks and informal advice suggest that entrepreneurial learning continued after formal education. This supports a practical interpretation of experiential learning in uncertain start-up settings, but it does not establish a new theory of entrepreneurship education.

6.3. Reflections and Methodological Contributions

This research has methodological value because it uses a sequential exploratory mixed-methods design to connect founders' accounts with a structured survey of perceptions. However, it does not claim a distinct methodological contribution. The value of the design lies in its fitness for the research problem: interviews helped identify the meanings and pressures experienced by founders, while the survey helped examine whether these perceived pressures were associated with self-reported startup success in a wider sample.

The choice of a sequential exploratory mixed-methods approach was motivated by recognition that entrepreneurship in China, particularly in the politically sensitive domain of artificial intelligence, required both perception-based survey patterns and contextual accounts. The quantitative aspect, derived from survey data of 150 AI startup founders,

allowed for the identification of associations between variables such as perceived regulatory clarity, technology infrastructure and self-reported success. These results provide useful but bounded insight, especially with respect to infrastructure and regulatory clarity, and the negative association between education and perceived performance.

The qualitative phase provided this deeper understanding and consisted of 15 semi-structured interviews. It enabled the analysis to examine participants' symbolic, emotional, and coping strategies as they dealt with institutional ecosystems characterised by gatekeeping, policy theatre, performative compliance and moral conflict. The qualitative detail enabled key elements such as strategic ambiguity, ideological signalling and informal knowledge building through experience to emerge.

Inter-method integration also allowed for comparison between patterns and meanings. For instance, while the survey found education to be weakly or negatively associated with self-reported success, the interviews suggested that this may reflect gaps in practical entrepreneurial education rather than lack of formal education. Likewise, while perceived regulatory environment was a statistical predictor of perceived startup success, the interviews showed regional and interpretive differences in how founders understood and navigated regulation.

But the Chinese case presented several access, ethics and interpretation challenges for mixed-methods studies. As topics including AI governance, citizen surveillance, and political indoctrination are very sensitive in this country, the survey and interview questions had to be worded explicably to increase the chance of avoiding self-censorship and unwillingness to respond. There was reluctance to comment on government-related projects, as well as refusal to be audio recorded, even anonymously. These challenges demonstrated the influence of researcher identity, trust within and between institutions and the socio-political environment on the quality of data. So the ethical considerations in this study sought to ensure that the research study follows formal academic ethical requirements while ensuring the safety and wellbeing of participants, and minimising the risk of reputational damage. Informed consent was used to conduct interviews. Politically sensitive statements were reported in a summarised, anonymised and, sometimes, paraphrased form.

The mixed-methods approach also demanded ontological rigour. While the study involved both positivist survey methods and interpretivist qualitative methods, these were connected by a pragmatic paradigm which emphasised pragmatic fitness for purpose, rather than theoretical purity. The paradigm assumed that different research questions call for different tools: structured patterns are useful for understanding scope and variability; thick description is required to account for why patterns exist. This methodological multiplicity enabled the study to link entrepreneurship studies, political economy and organisational theories without relying only on abstract statistics or subjective claims.

Finally, this methodology may be useful for analysing entrepreneurship in other frontier technology sectors of hybrid and state-coordinated systems. It is offered as a practical research design rather than a methodological contribution in itself.

6.4. Practical Contributions and Recommendations

This research provides important insights into the best and most actionable steps that can be taken to enable the creation of more equitable, transparent, and context-sensitive AI start-up ecosystems in China's urban metropolises. These suggestions are grouped under the institutional stakeholders who are critical in shaping the fate of startups, namely policymakers, universities, incubators and innovation ecosystem fosterers. These actors can amplify or dampen the multifaceted ecosystem tensions identified in this study, such as constraining opportunities of entrepreneurship due to infrastructural shortages, policy confusion, cultural homogenisation and inadequate education.

For government, a practical implication is the need to reduce policy and regulatory uncertainty. Participants described contradictory guidance, administrative barriers and uneven local implementation, especially outside the strongest innovation hubs. Regulators could therefore provide clearer and more consistent information on industry-specific policies, while recognising that this recommendation is based on founders' accounts rather than a full evaluation of government policy.

In addition, democratising infrastructure should be a key focus of urban AI policy. Both quantitative and qualitative analyses identified infrastructure as strongly associated with self-reported startup success in this sample. Conversely, the qualitative findings highlighted the monopolistic nature of cloud computing, curated data sets and secure data storage by major tech firms and public-sector entities. Governments need to provide

startups at incubated facilities with public compute credits, build national open-data commons, and incentivise major tech corporations to offer micro-enterprises with varied service packages. Regional investment should focus on building AI infrastructure parks, while other policies should increase access for entrepreneurs not connected with elites.

For universities, the findings suggest that entrepreneurship education for technical graduates should include more practical exposure to regulation, customer discovery, team formation, finance and ethical AI. This recommendation is based primarily on participants' reported experiential gaps and should be treated as a practical implication rather than as a claim that the study has comprehensively evaluated entrepreneurship curricula or established a causal link between curriculum design and venture performance.

Universities should also offer credit-bearing incubator tracks for students to build companies as part of their formal studies. This not only requires technical and logistical advice, but also training in the science behind entrepreneurial storytelling, legal insights and emotional fortitude, especially for first-generation and minority entrepreneurs. Through this approach, as suggested by Kolb's learning cycles, students would be able to traverse inert conceptualisation and abstract experience, and introspect on the basis of the concrete experience. As our study respondents repeatedly put it, "real" learning started only after graduation - universities must make it start before graduation, within safe but challenging learning environments that simulate the uncertainty and risk of entrepreneurship.

The main take-out for incubators, accelerators and intermediaries in the innovation ecosystem is that support should be non-hierarchical, inclusive, and psychosocially sensitive. Some participants reported innovation hubs who favoured startups from elite universities or who came through national competitions and thus created a more elite and homogenous startup culture. So the design of application processes for grants or mentorship, for example, should be formalised and transparent, and favour capacity and problem-solving over privilege or political fit. Innovation and incubation centres should also be funded in partnership with local governments and second-tier cities, with inter-regional mentorship arrangements, and online training.

Care for the moral and emotional work of entrepreneurship is also needed. In this research, Founders expressed high levels of anxiety, impostor syndrome and ethical conflict,

especially when faced with reconciling their business ideas with surveillance technologies or nationalistic claims. Therefore, incubators should offer founder mental health support, peer support networks and ethics coaching to help create safe spaces to discuss strategic ambiguity and mission drift as well as institutional pressures. Such psychosocial structures are not nice-to-have, but vital to innovation initiatives, particularly in fields that involve high levels of ethical conflict and public contestability.

Finally, investors and grant-makers are a key sector in this research as they not only affect who receives funding, but also who can receive funding. These investors need to develop context-aware rubrics, taking into account the confines of the ecosystem in which founders are working, not just standard performance indicators. For instance, a new enterprise that is able to successfully produce a MVP in a second-tier city which lacks access to cloud computing and big data may be more persevering and innovative than an established company in Beijing. Embracing a distributed funding mentality, such as micro-grants and milestone funding schemes, as well as founder residencies would help uncover untapped talent and foster a national innovation voice.

Ultimately, participants' accounts suggest that AI startup formation in China cannot be understood solely through investment or technological progress. Local institutions, infrastructure access, education and founder legitimacy also shape how recent graduates experience early-stage entrepreneurship. The practical recommendations should therefore be read as cautious implications arising from this sample rather than universal prescriptions for China's AI policy mix.

6.5. Study Limitations

While this study has brought important empirical and theoretical insights to our understanding of the founder life experiences of AI start-ups in China's urban areas, we must state the limitations of this study in terms of methodology, theory and context. These limitations do not invalidate the results; instead, they assist in understanding the conditions and contexts that should influence their interpretation and suggest areas where further research is required.

A key limiting factor is the scale and nature of the quantitative part of the study. While the survey questions were thematically broad, they were based on self-report measures of entrepreneurial success, institutional and contextual factors (such as infrastructure and

regulation). Respondents using self-reported measures may experience recall biases, self-serving biases, and social desirability biases, especially in high-pressure environments like entrepreneurship. While anonymity helped minimise such biases, they could not be entirely eliminated.

Similarly, the qualitative part of the study, while deep, is limited. The sample of 15 interviewees was a relatively media-savvy, articulate and reflective group of founders. Founders who are more vulnerable or marginalised, such as those behind informal and more fragile businesses, may have been underrepresented. This could have skewed the thematic results in favour of more secure and institutionalised participants. Third, due to the political nature of the topics of surveillance, censorship and state intervention in the ethics of AI, some participants (despite confidentiality) may have avoided explicit responses. While the use of open questions and successive probing minimised this possibility, the risk of remaining silent, being in a state of "guardedness", or manufacturing their own narrative still remains.

Secondly, this study focuses on urban entrepreneurship. Participants lived in metropolitan and peri-urban areas (including in Tier-1 and developing Tier-2 cities). Therefore it does not capture entrepreneurship in rural and semi-urban regions, where information, institutional and market infrastructure are weaker and the penetration and influences of AI technologies are lower. This "urban" bias limits the diversity of the research context and inhibits comparisons across urban-rural gradients, which is a significant concern in the context of China's national ambition to pursue "balanced" innovation.

Theoretically, the study is more strongly weighted towards explanations that emphasise institution and sociocultural factors, which may mean that factors such as market forces and technology determinism are under-represented. While this is appropriate for this study, it constrains the ability to examine factors such as product-market fit, pricing strategies, technical innovation and customer acquisition. Also impacting startup success, these factors also need to be further explored. Further, while the studying multi-level constraints through the Layered Ecosystem Pressures Model offers an intuitive way to theorise constraints, it is an interpretative tool and must be tested across other empirical settings.

Finally, China's institutional and political context is one that brings into question a particular form of state-led innovation logic that may also limit the transferability of the

study's findings. While state developmentalism is not unique to China, the level of regulatory oversight, ideologisation and AI governance in China should be understood in context. As such, the findings of this study should be read carefully by researchers, educators and policymakers beyond China, with a consideration of their respective institutional and cultural settings.

Overall, the findings should be read as context-specific and interpretively filtered. They identify analytic possibilities and practical implications, while also pointing to areas where future research can test, refine and compare the propositions developed in this thesis.

6.6. Future Research Directions

The findings and limitations of this research point to several promising avenues for future research to advance the literature on AI entrepreneurship, particularly in institutionally complex, politically contingent, and rapidly evolving contexts, such as China. These involve the gaps, scope, and refinement of theoretical findings presented in this thesis.

A current and timely research topic is gendered AI entrepreneurship in China. While this study's survey participants were mostly women, the interviews also pointed to specific forms of cultural legitimacy pressures, family dynamics, and investor discrimination that may contribute to gendered entrepreneurship in China's AI industry. These issues were not as widespread in the dataset to be further developed as an empirical theme, but they suggest that gendered identification and cultural expectations interact with institutional pressures in China's AI entrepreneurial context. Thus future research should employ gender-sensitive frameworks, such as feminist institutionalism or intersectionality, to understand how female entrepreneurs navigate gatekeeping, self-presentation, and strategic ambivalence in the AI and other high-technology markets.

Longitudinal research should also be conducted to understand how entrepreneurial strategies evolve, especially research and development in response to framing shifts in institutional pressures, investment structure and policy. Interviewees reported their get-by strategies and concessions in the early stages of their entrepreneurial careers, such as rhetorical alignment with state discourses or strategically unsustainable pivots. However, little is known about their long-term effects. Do they lead to sustainable growth, mission drift or burnout? Will startups survive changing political agendas or increased centralisation of infrastructural support? Researchers should consider a panel study that

tracks founders over different rounds of development and regulatory reform to provide insights into the sustainability of innovation strategies in state-coordinated innovation.

Spatially, we should extend research to non-metropolitan regions and the periphery, in which the density of infrastructure is less pronounced, bureaucrats may have a higher level of discretion and there is no entrepreneurship education. The urban bias of this study was partly unavoidable due to access issues and the urban investment focus of AI. But it constrains understanding of the development of AI entrepreneurship in the wide, diverse institutional landscape of China. Comparing Tier-1 versus Tier-2, and rural/semi-urban areas might shed stronger light on regional differences in ecosystem support, state-business relations and legitimacy. This would inform innovation policy and research in China.

Another avenue of work is comparative studies about political entrepreneurship and parallel institutional dynamics in other state-coordinated or semi-authoritarian innovation systems. State-coordinated innovation for development is not unique to China. Examples can also be found in Singapore, the United Arab Emirates, Saudi Arabia, and emergent digital regulation in India and in Russia, where entrepreneurial legitimacy can also be coupled with political obedience. Future engagement with the Layered Ecosystem Pressures Model in these cases will help test the model's limited transferability and develop new comparisons of the agency of entrepreneurs in constrained institutional pluralism.

Researchers should also explore AI ethics, data governance, and legal pluralism. While the current study noted alignment with surveillance and ethical discomfort with strategic pivots, more research is needed on how founders perceive, interpret and resolve normative challenges in the use of AI technologies. In what circumstances do founders overtly push against alignment with state policy, for instance through a focus on private business uses, globalisation, or stealthy development approaches? How do they reconcile tensions between international discourses on AI ethics and national political agendas, using legal, moral or strategic means? This research could be furthered by cross-disciplinary research in areas such as law, data studies and political philosophy to provide insights for both theory and practice.

To practice what this study highlights, managers in the Chinese AI startup ecosystem should undertake a process of regulatory management, capability building and resilience building. First, there should be institutionalisation of AI governance and compliance units

to track evolving policy frameworks and proactively participate in regulatory discussions. This will help founders mitigate risk and modify their business models ahead of time. Second, managers should deal with inexperience in new employees through mentoring, multifunctional training and working with universities or incubators. Third, managers should encourage adaptive cultures by embracing inclusive leadership, and limiting guanxi-related politics to improve the transparency and objectivity of innovation decisions.

Last, future studies on entrepreneurship education and entrepreneurial capability should be reassessed. The negative association between Educational Background and self-reported entrepreneurial success in this sample points to a possible gap between traditional human capital theory and the demands of high-uncertainty entrepreneurial activity in sectors such as AI. Future research should explore other theories of entrepreneurial learning, such as reflexive capability, peer learning and narrative legitimacy building, to better understand how entrepreneurs learn and develop in uncertain ecosystems.

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Appendix

Interview Guide

Introduction & Welcoming Section

- Welcome the participant and introduce yourself and the purpose of the study.
- Explain the structure of the interview and assure confidentiality.
- Confirm consent to proceed with the interview and the use of audio recording.
- Warm-up question:
"Can you briefly tell me about your background and what inspired you to start your AI technology venture?"

Theme 1: Challenges in Founding AI Startups

- *"Can you describe your experience in founding your AI technology startup? What were the initial challenges you faced?"*
- *"How has the regulatory environment in China impacted the establishment and growth of your startup?"*
- *"How do cultural attitudes in China, such as attitudes towards risk and failure, affect your entrepreneurial journey?"*

Theme 2: Support Systems and Competitive Landscape

- *"What kind of support systems (mentorship, funding, networks) did you find most valuable in the startup process?"*
- *"How do you view the competition with established tech giants in China (e.g., Alibaba, Tencent) in terms of market entry and growth opportunities?"*
- *"What strategies have you employed to navigate regulatory and cultural challenges?"*

Theme 3: Resources and Government Influence

- *"How do you perceive the impact of government initiatives such as 'Made in China 2025' on your AI startup?"*
- *"What role does technology infrastructure (e.g., access to advanced AI tools and cloud platforms) play in your startup's success?"*

- *"How do you leverage available resources to sustain growth in a highly competitive market?"*

Closing & Conclusion Remarks

- *"What is your long-term vision for your AI startup, and how do you plan to sustain its growth?"*
- *"Based on your experience, what recommendations would you give to recent graduates looking to start AI technology ventures in China?"*

Thank the participant for their time and valuable insights.

Survey Questionnaire

No.	Question	Response Type
1	What is your age?	18- 20, 20-25, 26-30, 31-35
2	What is your gender?	Male, Female, Prefer not to say
3	What is your highest level of education?	Bachelor's, Master's, PhD, Prefer Not to Say
4	How long have you been running your AI startup?	< 1 year, 1-2 years, 2-3 years, 3+ years, Prefer Not to Say
5	In which urban area is your startup located?	Beijing, Shanghai, Shenzhen, Nanjing, Prefer Not to Say

Likert Scale Questions (1 = Strongly Disagree, 5 = Strongly Agree)

Variable	Question	1	2	3	4	5
Regulatory Environment	The regulatory environment in China is favourable for launching AI startups.					
	Government policies in China support the growth of new technology ventures.					
	Navigating regulatory requirements is a significant challenge for new AI startups.					
	Regulatory frameworks in urban China are transparent and easy to understand.					
	My startup has benefited from government incentives or tax rebates.					
Access to Funding	There are sufficient funding opportunities available for AI technology startups in China.					
	Accessing venture capital for AI startups is easy in urban China.					
	Government grants and loans are accessible to recent graduates in the AI sector.					
	My startup received adequate financial support during its initial stages.					
	Lack of access to funding is a major barrier to the success of my startup.					
Cultural Attitudes towards Entrepreneurship	Chinese cultural attitudes towards risk-taking support entrepreneurial activities.					
	Fear of failure affects my decision-making in the startup environment.					
	Chinese culture encourages innovation and creativity among new entrepreneurs.					
	I feel supported by society in my entrepreneurial journey.					
	Cultural norms in China make it difficult for young entrepreneurs to succeed.					
Educational Background	My educational background adequately prepared me for starting an AI technology venture.					
	Higher education institutions in China provide sufficient resources for entrepreneurship training.					
	I have used knowledge from my academic studies to address challenges in my startup.					
	The skills I gained during my education are relevant to running a technology business.					
	There is a gap between academic education and the practical skills needed for entrepreneurship.					
Technology Infrastructure	China's technology infrastructure is accessible and beneficial for AI startups.					

Variable	Question	1	2	3	4	5
	Access to high-quality internet and cloud services has been essential for my startup's success.					
	The availability of AI tools and platforms supports the growth of startups in China.					
	I am satisfied with the level of technological support provided to entrepreneurs in urban China.					
	My startup has had difficulties accessing cutting-edge technologies needed for innovation.					
Entrepreneurial Ecosystem Support	The entrepreneurial ecosystem in China provides adequate support for new AI startups.					
	I have access to mentorship and networking opportunities essential for my startup.					
	Incubators and accelerators in urban China offer valuable resources for technology startups.					
	I feel that there is a strong community of entrepreneurs that supports new ventures like mine.					
	The availability of co-working spaces and startup hubs has positively impacted my business growth.					
Start-up Success	My AI startup has been successful in achieving its business goals so far.					
	I believe my startup has a sustainable growth plan.					
	I am satisfied with the current financial performance of my startup.					
	My startup has established a strong presence in the market.					
	I feel confident that my startup will succeed in the long term.					

Interview Transcript

Introduction & Welcoming Section

Interviewer: Good morning, thank you for taking the time to participate in this interview. I am conducting this study as part of my research project on the challenges and opportunities faced by recent graduates starting artificial intelligence (AI) startups in China. The purpose of this interview is to understand your personal experiences, the barriers you encountered, and the support mechanisms that shaped your entrepreneurial journey. All information you share will be treated confidentially, and your name or company will not be disclosed in any publication. The session will be audio-recorded solely for transcription purposes. Do I have your consent to proceed?

Participant 1: Yes, I fully consent. I'm happy to contribute to this study.

Interviewer: Thank you. To begin, could you please tell me a bit about your background and what inspired you to start your AI technology venture?

Participant 1: I graduated from Tsinghua University with a major in Computer Science, focusing on machine learning and natural language processing. During my postgraduate studies, I worked on several research projects involving AI-driven automation. I realised that many practical solutions never reached the market because researchers lacked entrepreneurial guidance. This inspired me to bridge that gap by founding a startup that applies AI in real-world scenarios, specifically in educational technology, using NLP to analyse student learning behaviour and performance. I wanted to create something impactful that combined innovation with social and commercial value. We studied machine learning models in detail, but no one taught us how to explain them to investors or clients. There was no training in business planning, IP law, or even writing a grant proposal. We started on Alibaba Cloud's free tier, but once we hit a few hundred users, the service throttled. To maintain stable performance, we had to pay ¥3,000 per month. That's almost half of our monthly budget.

Theme 1: Challenges in Founding AI Startups

Interviewer: Can you describe your experience in founding your AI technology startup? What were the initial challenges you faced?

Participant 1: The first six months were incredibly tough. Although I had a solid technical foundation, I had little understanding of business management, financing, or legal compliance. Drafting a business plan, registering the company, and dealing with tax and licensing requirements were overwhelming. The government says AI is a national priority, but they make us resubmit documents five times. It feels like a performance—‘policy theatre,’ I call it. They want media coverage of innovation, not the messy work of actually helping startups. Another key challenge was assembling a multidisciplinary team. Most of my peers were technically inclined but hesitant to take entrepreneurial risks, so convincing them to join a startup with uncertain outcomes was difficult. Securing initial capital was also an uphill battle because investors were sceptical about backing a team without prior business experience.

Interviewer: How has the regulatory environment in China impacted the establishment and growth of your startup?

Participant 1: Regulations were both enabling and constraining. On one hand, the government offers subsidies and innovation grants that support AI entrepreneurship. On the other, compliance requirements under the Cybersecurity Law is stringent. For a small startup handling customer data, ensuring data localisation and security audits required expertise and funds that we initially lacked. Moreover, regulatory updates are frequent, so staying compliant demands continuous monitoring. We sometimes felt that policies favoured large firms that already had legal departments, whereas small startups like ours struggled to interpret and apply these laws accurately. We pitched a personalised learning engine based on behavioural analytics. One investor told us it was ‘too abstract’ and asked if we could build a chatbot instead. They wanted something with quick market validation—even if it wasn’t our vision.

Interviewer: How do cultural attitudes in China, such as attitudes towards risk and failure, affect your entrepreneurial journey?

Participant 1: Culturally, risk aversion is deeply rooted. Family and peers often equate success with stability, not experimentation. When I decided to start my company, some relatives considered it reckless, especially since I had offers from major tech firms. This societal expectation to follow a secure path creates psychological pressure. Moreover, failure is still stigmatised; entrepreneurs who shut down a business are often judged rather

than celebrated for learning. When we applied for our operating license, we were told to specify whether our product was a ‘standard’ app or an AI system. But there was no clear guideline. Our software uses NLP to analyse student performance—so does that count as AI? No one in the department could answer. They just said, ‘Be safe and register both ways. These norms make young founders cautious and can discourage bold experimentation, which is essential in AI innovation.

Theme 2: Support Systems and Competitive Landscape

Interviewer: What kind of support systems did you find most valuable in the startup process?

Participant 1: University-based incubators were immensely helpful. Through Tsinghua’s innovation hub, I accessed mentors who guided me in business modelling and investor relations. Government-sponsored programs like the “Young Innovator Fund” also provided small grants. Networking events helped me connect with potential partners and early adopters. The money helped us scale, but in return we had to sign a data exchange agreement with the city. This meant providing anonymized user data for public monitoring projects. It was framed as a ‘pilot collaboration,’ but we had no real choice. However, mentorship quality varied; some mentors were too academic, focusing on theory rather than practical business challenges. Peer support from other founders was equally important—we often shared experiences about pitching to investors or dealing with compliance audits. The paperwork is endless—tax certificates, IP filings, bank audits, HR contracts. Every form has to be stamped by multiple departments. If one thing is wrong, you start over. It’s exhausting.

Interviewer: How do you view the competition with established tech giants such as Alibaba and Tencent in terms of market entry and growth opportunities?

Participant 1: Competing directly with them is nearly impossible because they dominate data access, talent, and distribution channels. Instead of challenging them head-on, we focused on niche applications—personalised learning analytics tools for individual schools and smaller institutions rather than large national education platforms. These giants also set technological standards; in some cases, we rely on their cloud infrastructure or APIs. This dependency is a double-edged sword: it accelerates development but limits independence.

We learned that differentiation and agility are our main advantages. Startups can pivot faster, something large firms struggle with.

Interviewer: What strategies have you employed to navigate regulatory and cultural challenges?

Participant 1: We prioritised building relationships with local regulatory bodies and sought legal advice early. Participating in government-sponsored accelerators helped us understand policy trends. When I read about the US chip bans, I realised our tech independence is fragile. That made me more determined to work in core AI. It's not just business—it's duty. Culturally, I encouraged an open and collaborative work culture within my team, valuing experimentation over perfection. We also partnered with established firms for joint projects, which improved our credibility. Over time, building trust with stakeholders became a strategic asset that allowed us to operate more confidently in a tightly regulated environment.

Theme 3: Resources and Government Influence

Interviewer: How do you perceive the impact of government initiatives such as *Made in China 2025* on your AI startup?

Participant 1: The initiative created a favourable macro-environment for AI innovation. It signalled to investors that AI is a national priority, indirectly boosting our credibility. However, it also centralised funding towards projects aligned with state objectives like manufacturing or public governance. Our product, aimed at personalised learning analytics for schools and universities, didn't perfectly align with those categories, so we sometimes struggled to qualify for larger grants. The policy encourages innovation but still requires alignment with state goals, which can constrain creative diversity among startups.

Interviewer: What role does technology infrastructure play in your startup's success?

Participant 1: It's absolutely fundamental. Access to cloud computing platforms such as Alibaba Cloud and Huawei Cloud allowed us to scale affordably. Yet infrastructure costs remain significant; discounts are often reserved for enterprise clients, not startups. Furthermore, regional disparities exist—connectivity and computing resources are much stronger in Beijing or Shenzhen than in second-tier cities. This inequality affects where

startups can realistically operate. Without robust infrastructure, training AI models would be nearly impossible. My father inquired me as to why I had quitted a Huawei job offer. He added I was playing with fire. However, as far as I am concerned, making a startup (despite failing in the future) is about the creation of something of mine. This state of mind was not there in theirs.

Interviewer: How do you leverage available resources to sustain growth in a highly competitive market?

Participant 1: Resource optimisation is vital. We adopted an open-source approach where possible, using freely available frameworks like TensorFlow. We also partnered with universities for research collaborations, which gave us access to cutting-edge tools. Human capital is another key resource—we offer equity incentives to attract top graduates who value learning opportunities over high salaries. Building a culture of shared ownership has kept the team motivated despite financial constraints. I understood that our tech independence is on a thin ice when I read about the US chip bans. Doing that made me more resolute to work in core AI. It is not only business, it is duty.

Closing & Conclusion Remarks

Interviewer: What is your long-term vision for your AI startup, and how do you plan to sustain its growth?

Participant 1: Our vision is to become a leading AI-driven educational analytics provider for schools and universities across Asia. We aim to scale gradually, prioritising sustainable growth over aggressive expansion. Future plans include integrating our solutions with gamified learning environments and adaptive curriculum tools to align with evolving pedagogical goals. Building trust and compliance will remain core priorities. I started a master's in data science, but I quit after one semester. The curriculum was outdated, and I was already building something more cutting-edge with my team. Education should support reality, not delay it.

Interviewer: Based on your experience, what recommendations would you give to recent graduates looking to start AI technology ventures in China?

Participant 1: First, gain a balanced understanding of both technology and business. Technical excellence alone is insufficient. Second, establish networks early—guanxi remains crucial for securing resources and navigating regulations. Third, embrace patience; the regulatory process can be lengthy. Finally, view setbacks as learning opportunities rather than failures. Entrepreneurship in China is challenging but rewarding if one remains adaptive and ethically grounded.

Interviewer: Thank you for sharing such insightful experiences. Your contribution will greatly enrich this study.

P1: My pleasure. I hope these insights help future entrepreneurs.