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Technical maturity and network effects of XF artificial intelligence open platform

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TECHNICAL MATURITY AND NETWORK EFFECTS OF XF ARTIFICIAL INTELLIGENCE OPEN PLATFORM

JIANG, TAO

SINGAPORE MANAGEMENT UNIVERSITY
2023

Technical Maturity and Network Effects of XF Artificial Intelligence Open Platform

JIANG, TAO

Submitted to Lee Kong Chian School of Business in partial fulfillment of the requirements for the Degree of Doctor of Business Administration

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SINGAPORE MANAGEMENT UNIVERSITY
2023

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I hereby declare that this DBA dissertation is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in this DBA dissertation.

This DBA dissertation has also not been submitted for any degree in any university previously.

JIANG, TAO

26 December 2023

Technical Maturity and Network Effects of XF Artificial Intelligence Open Platform

JIANG, TAO

Abstract

Studying the impact mechanism of the commercial value of artificial intelligence open technology platforms has theoretical and practical significance. This article aims to enrich and expand the theoretical research on technology maturity, value co creation, and network effects on open technology platforms at home and abroad through empirical research on artificial intelligence open technology platforms and ecology. This study takes XF's open technology platform case as the research object, and based on technology maturity theory, value co creation, and network effects theory, examines the network effect value creation mechanism of open technology platforms driven by technology maturity in three development stages: "capacity building period", "business model exploration period", and "ecosystem cultivation phase", and conducts empirical testing on some of the hypotheses.

The theoretical contributions of this study are mainly reflected in: firstly, this article compares open technology platforms with other platforms, especially clarifies the differences with software platforms, and supplements and improves the existing research on platform classification in platform economy. The artificial intelligence open technology platform is accompanied by an increase in technological maturity, changes in developer heterogeneity, and continuous deepening of platform network effects, driving the continuous evolution of platform form. Secondly, this article verifies the relationship between the technological maturity of artificial intelligence open technology platforms and network effects (user activity, user stickiness). After research, it was found that technology platforms exhibit differentiated technological maturity at different stages, and developer heterogeneity also varies due to this. This has a positive effect on stimulating, deepening, and expanding network effects. This means that there are two paths for the impact of technology platforms on network effects: firstly, the maturity of technology reflects the quality of platform development, and its improvement brings about an increase in user base and activity; Secondly, as complements, the heterogeneity of developers at different stages of platform development determines significant differences in risk preferences and behavioral patterns of technology adoption, which can also have a profound impact on network effects. The research conclusions of this article enrich the research on platform economy, especially network effects.

Keywords: technology maturity, developer heterogeneity, network effects, platform economic, value co-creation

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As a member of XF's entrepreneurial team, I have witnessed and participated in the company's growth over the past 20 years. During these 20 years, I have been busy with specific work and sometimes felt that I did not invest enough in broadening my horizons and cultivating humanistic literacy. Fortunately, after joining the DBA course at Cheung Kong Graduate School of Business, I learned a lot from many high-level professors at Cheung Kong. They deeply combined the research results of Western management with Chinese local management practices, constantly giving me new inspirations. I also learned a lot from interacting and communicating with DBA students from Cheung Kong. As leading figures in various industries, their thoughts, experiences, and insights in dealing with various business challenges have benefited me greatly. The completion of my doctoral thesis not only allowed me to grow academically in a systematic way but also brought me deeper thinking and strengthened my confidence in artificial intelligence as an emerging technology with huge future commercial value. The precious time spent studying and researching at Cheung Kong Graduate School of Business has been a process of further improvement for me and an opportunity to contemplate the future.

First of all, I would like to express my deep gratitude to Professor Xuesong Geng from the Singapore Management University and Professor Jing Liu from the Cheung Kong Graduate School of Business. The superb academic attainments and selfless guidance of Professor Geng have benefited me greatly in the process of my PhD thesis research. His profound insights and unique thinking have stimulated me to think more deeply about the issues. Professor Liu’s rigorous academic attitude and great encouragement for academic innovation have enabled me to explore new research fields and unearth more possibilities of the issues. The two mentors' instructive teaching and dedicated guidance are the guiding lights on my academic path.

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Chapter I

Introduction

1.1 Background

1.1.1 Research background

At present, a new round of global technological revolution and industrial transformation is flourishing, with new-generation information technologies such as artificial intelligence (cognitive large language models), 5G, big data, cloud computing, and blockchain becoming the pioneering technologies that first penetrate various fields of economic and social life. In recent years, major countries and regions have successively issued strategies and planning documents related to artificial intelligence, focusing their policies on strengthening investment and talent training, promoting cooperation and openness, and improving supervision and standard construction. The global artificial intelligence has entered a stage of accelerating strategic deployment and developing industrial applications.

The United States has been at the forefront of global artificial intelligence, establishing a comprehensive system to guide industry development in multiple dimensions such as technology, economy, ethics, and policy. This system is based on four major policy documents: "Preparing for the Future of Artificial Intelligence," "National Artificial Intelligence Research and Development Strategic Plan," "Artificial Intelligence, Automation, and the Economy," and "American Artificial Intelligence Initiative." The U.S. has implemented these policies in areas such as investment, employment, open data, job issues, and standardization research. In February 2020, the White House Office of Science and Technology Policy (OSTP) released "The American Artificial Intelligence Action: First Annual Report," which focused on investing in AI research and development, releasing AI resources, removing barriers to AI innovation, training AI talent, and creating an international environment that supports American AI innovation. The report also emphasized the commitment to building trustworthy AI in government services and tasks. Artificial intelligence has become a priority in government budgets and planning. The "2021 Federal Government Budget Report" explicitly proposed a significant increase in research and development investments in future industries such as artificial intelligence and quantum information science, as well as investments in education and vocational training. The "Endless Frontier Act," proposed in May 2020, plans to invest $100 billion in research and development of ten key technologies, including chips and artificial intelligence, over the next five years. In August 2020, the White House Office of Science and Technology Policy (OSTP), the National Science Foundation (NSF), and the Department of Energy (DOE) announced that they would provide more than $1 billion in funding for new research institutions in the fields of artificial intelligence and quantum computing.

The Chinese government also attaches equal importance to the implementation and development of artificial intelligence as an infrastructure across various industry sectors. In July 2017, the State Council issued the "New

Generation Artificial Intelligence Development Plan," in which artificial intelligence was officially defined as a new engine for national economic development. In November of the same year, four companies including XF were rated as the first batch of National Artificial Intelligence Open Innovation Platforms by the Ministry of Science and Technology. This was to fully leverage the leading role of leading enterprises and research institutions in the artificial intelligence industry, promote the construction of the national new generation of artificial intelligence open innovation platforms, and drive the technological innovation and industrial development of China's artificial intelligence. In August 2019, the Ministry of Science and Technology issued the "National New Generation Artificial Intelligence Open Innovation Platform Construction Guidelines," proposing four major tasks centered on the open and open construction of artificial intelligence. These tasks include "effectively integrating technology and industry chain resources, lowering the threshold for technology and resource use, converging the innovative strength of small and micro developers, building a complete technology and industrial ecosystem, creating a good atmosphere for all-industry collaborative innovation and entrepreneurship, and promoting high-quality economic development and improvements in people's livelihoods." Moreover, to effectively promote large-scale commercial applications of new generation information technology throughout society and accelerate the construction of new types of information infrastructure. In 2021, the "14th Five-Year Plan" specifically pointed out: "Focusing on strengthening digital transformation, intelligent upgrading, and integrated innovation support, layout and construct new types of infrastructure such as information infrastructure, integrated infrastructure, and innovative infrastructure." With the implementation of policies like "New Generation Artificial Intelligence Open Innovation Platform" and "New Type Infrastructure Construction," coupled with the continuous improvement of penetration rates in downstream application fields, the market size of China's artificial intelligence open technology platform will maintain rapid growth.

Currently, artificial intelligence is accelerating the deep integration of technology with traditional industries and scenarios, such as education, healthcare, automotive, urban development, finance, and other fields, continuously creating scalable commercial value and benefiting the public in social value. The so-called "Artificial Intelligence Open Technology Platform" refers to the infrastructure and technical capabilities related to artificial intelligence being opened up to enterprises or individual developers, lowering the threshold for technology and resource use, and promoting collaborative innovation in AI technology and industry. Specifically, the AI open technology platform has created commercial value represented by the API economy. The so-called "API economy" refers to leading technology companies opening up their capabilities and resources to developers and other partners through APIs (Application Programming Interface) to create innovative products and services, enrich intelligent applications and data, form an upstream and downstream closed-loop industrial ecosystem, and achieve substantial scale economic benefits. Developers, based on their professional knowledge and experience of specific industry scenarios, only need to directly call API capabilities to integrate and deploy capabilities and resources, quickly respond to customer and user needs, significantly lowering the entry threshold for developers and small and medium-sized enterprises into the field of artificial intelligence. In addition, open technology platforms have also played a positive role in enhancing corporate brand influence, maintaining sensitivity to the industry, obtaining innovative sources, and realizing the deepening of technology into the industry.

According to the iResearch "2020 China Artificial Intelligence API Economic White Paper", it is estimated that the market size will reach 36.66 billion yuan in 2022 and 57.99 billion yuan in 2024, with a compound annual growth rate of 26%. Taking the data disclosed by the XF open platform as an example, as of June 2023, there are as many as 4.974 million developers, and they have opened up 587 artificial intelligence capabilities, all ranking first in the industry.

1.1.2 Research significance

The platform-based business model (PBM) refers to a type of business model that realizes the co-creation of stakeholder value and risk sharing on the value network constructed within and outside the company. The concept of "platform" in the business ecosystem includes three main functions: namely, interaction interface, value creation, and network formation (Rong, 2013). Among them, the interaction interface means that ecosystem members can use the interface as a toolkit to build their own products; value creation means that the platform enables ecological partners to jointly create value; network formation means that due to the platform allowing partners to work together to create value, they will develop specific network models to compete with their competitors' ecosystems. Existing research believes that the ultimate purpose of the network platform is to stimulate network effects through value co-creation (Jiang & Li, 2016): there is an interaction between participants in the platform and bilateral markets, expanding the network scale, generating synergistic value, and enhancing the utility of platform participants. Among them, value co-creation mainly refers to product and service value co-created by enterprise producers, consumers, etc. through interaction (Jian et al., 2016). The early focus of this field was on the binary relationship between customers and enterprises, ignoring the increasingly complex and diverse corporate practices of network value contributors under the background of the network economy. In fact, core enterprises gather node participants through platforms, and the more relationships are linked by the network platform, the higher the efficiency of resource, information, and knowledge flow. Once the network scale exceeds a critical point, it will achieve positive feedback (Zhou et al., 2015), which will help realize the commercial value and social value of platform scale. The significance of this paper at the academic research level is mainly in the following aspects:

1. Despite the extensive research on software platforms, e-commerce transaction platforms, and sharing economy platforms in the field of platform economics, research on platform economics has focused on categories such as network effects and externalities, evolution of platform ecosystems, and platform governance. However, there is a clear lack of research on open technology platforms, particularly artificial intelligence open technology platforms, and value co-creation. First, there are fewer studies on open technology platforms and their ecosystem construction abroad. Research has focused on describing the basic attributes of cloud computing technology, such as its technical definitions, characteristics, and deployment methods, as well as its enterprise applications (Ross and Blumenstein, 2015; Alkawsi et al., 2015) and business impacts (Hoberg et al., 2012), and data security (Ahmed & Hoss, 2014; Esposito et al., 2017). This research neither involves the study of open technology platforms built on cloud computing nor discusses the foundational theories, network effects, and empirical studies of the formation and evolution of open technology platform ecosystems.

2. Platform-based bilateral markets may generate network effects with infinite value-added, however, existing research mainly focuses on the economic impacts and measurement methods generated under network effects, with less examination of the antecedents stimulated by network effects. In fact, technological progress is the underlying variable for changes in socio-economic development. Linking the advancement of AI-related technologies and the development of platform-based business models for research is a positive step beyond previous studies on the platform economy. For example, network effects can be divided into cross-edge network effects and same-edge network effects, where the former refers to the user size on one side of the platform being proportional to the utility of users on the other side, while the latter means that the user characteristics on one side of the platform will directly affect the behavior of users on the same side; the value spillover effect produced by consumer behavior is called network externality (Network Externality). Cheng et al. (2005) found through research that companies are more likely to implement vertical integration strategies in industries with network externalities, and network effects can raise industry entry barriers (Li, 2000). The study found that the network externality generated by value modules intensified industrial competition, thereby promoting the integration of value modules and industrial integration. Zhou et al. (2013) believe that under global network effects and local network effects, interactions between consumers will affect market competition and product diffusion, which helps accelerate information dissemination and product diffusion. Bilateral market networks built on platform business models may also impact market pricing, market structure, platform competitive strategies, etc. Bilateral market networks built on platform business models may also have an impact on market pricing, market structure, platform competitive strategy (Liu & Liao, 2013), etc.

3. Regarding the study of the relationship between technological progress and industrialization, existing theories of technological maturity, due to their suitability for specific technological scenarios and industrial structures, cannot perfectly explain the development mechanisms of new technological platforms such as artificial intelligence technology and semiconductor technology, and need to develop new explanatory logic in line with the times. The mature theories of technological maturity in the current academic community include TRL theory, TRIZ theory, bibliometric method, and technological maturity curve. The "Technology Readiness Level (TRL)" proposed by the National Aeronautics and Space Administration in the United States is actually the "technological maturity" or perfection degree, which has been widely used in the United States' military, defense, and other weapon equipment fields. Professor G.S. Altshuller of the former Soviet Union established the TRIZ (theory of inventive problem solving) technology prediction theory through research and analysis of 2.5 million patent inventions worldwide. The product technology evolution process based on TRIZ theory is similar to the growth process of species, going through four stages: infancy, growth period, maturity period, and exit period, which together form a "technology lifecycle" of a product. The bibliometric method mainly analyzes technological maturity from the perspectives of changes in the number of SCI papers and EI papers in a certain technical field, as well as trends in the ratio of journal papers to conference papers. Starting from 1995, Gartner Consulting Firm divided emerging frontier technologies into five stages: budding period, overheating

period, trough period, climbing period, and maturity period based on time and market visibility (media exposure), drawing a technological maturity curve that has become an important technical tool for evaluating emerging technologies. However, looking at the history of artificial intelligence development alone, the technological maturity curve cannot describe the multiple peaks and valleys of the wave of artificial intelligence development history, so its adaptability is not high, and new technological platforms need new explanatory logic.

4. Value Co-creation is crucial for stimulating and detonating network effects in platforms, and a deep understanding of the mechanisms of platform value co-creation is of positive significance for all parties in the platform economy to cultivate competitive advantages and increase market share. The existing theoretical perspectives on value co-creation, including customer experience, service dominance, service logic, service science, and service ecosystem, focus on the roles and relationships of enterprises and customers in value co-creation under traditional economic backgrounds (Malin & Tomas, 2015; Palumbo, 2016; Zhang et al., 2016), which cannot well explain the value creation of platforms, product service providers, and customers in the context of the artificial intelligence open platform economy. Previous research on network effects and value co-creation mainly takes bilateral market platforms such as e-commerce platforms, travel platforms, and shared rental platforms under the sharing economy background as research objects, neglecting the development of artificial intelligence open technology platforms and their ecosystems. The former mainly explores value co-creation models based on value chains. However, value chains only dissect the various activities within enterprises and their role in the final value creation, essentially a linear analysis framework for measuring input-output (Stabell & Fjeldstad, 1998). Nowadays, with the vigorous development of artificial intelligence open technology platforms and their ecosystems, the interests of various participants are increasingly reflected in the overall value network, and enterprises and platform participants, partners, users, etc. have fully connected and created more value. On the one hand, in the

network effect of the platform economy, each participant often plays a dynamic role in value co-creation, for example, enterprises are no longer providers of production value but become platforms, and real product and service providers also play the role of platform users. Therefore, the network platform economy has reshaped the main relationship of value co-creation, gradually forming a "platform-user-user" connection between various participants, and the dynamic value co-creation mechanism of multiple subjects in the platform network needs further exploration; on the other hand, the service ecosystem perspective only provides theoretical research frameworks at micro, meso, and macro levels but fails to provide research on the mechanism of action. With the continuous evolution of artificial intelligence open platforms, increasingly complex dynamic transactions are taking place between platforms and service providers, platforms and users, and service providers and users. The value network has created a new value exchange system, which requires the addition of new theoretical connotations.

Given the theoretical and practical significance of studying the impact mechanisms of business models in AI open platforms, this paper aims to enrich and expand the theoretical research on the technical maturity, value co-creation, and network effects of open technology platforms both domestically and abroad through case studies of AI open technology platforms and their ecosystems. The study takes XF's open technology platform as the research object, based on the theories of technical maturity, value co-creation, and network effects, it examines the dynamic value co-creation mechanism driven by technical maturity during three development stages: "capacity building phase", "business model exploration phase", and "ecosystem cultivation phase". It also conducts empirical investigations on some of the assumptions made.

1.2 Research structure

This paper is divided into five chapters, and the specific content of each chapter is reflected in the figure below. The content arrangement is as follows:

Chapter 1 is the full-text introduction. This chapter mainly introduces the real-world context and theoretical background on which the research is based, and proposes the issues to be studied based on this. It then presents the significant theoretical contributions and practical implications of this paper, as well as the chapter arrangement and research approach. Finally, explanations are also provided for the methods and innovative points of the article's research. This serves as an introduction.

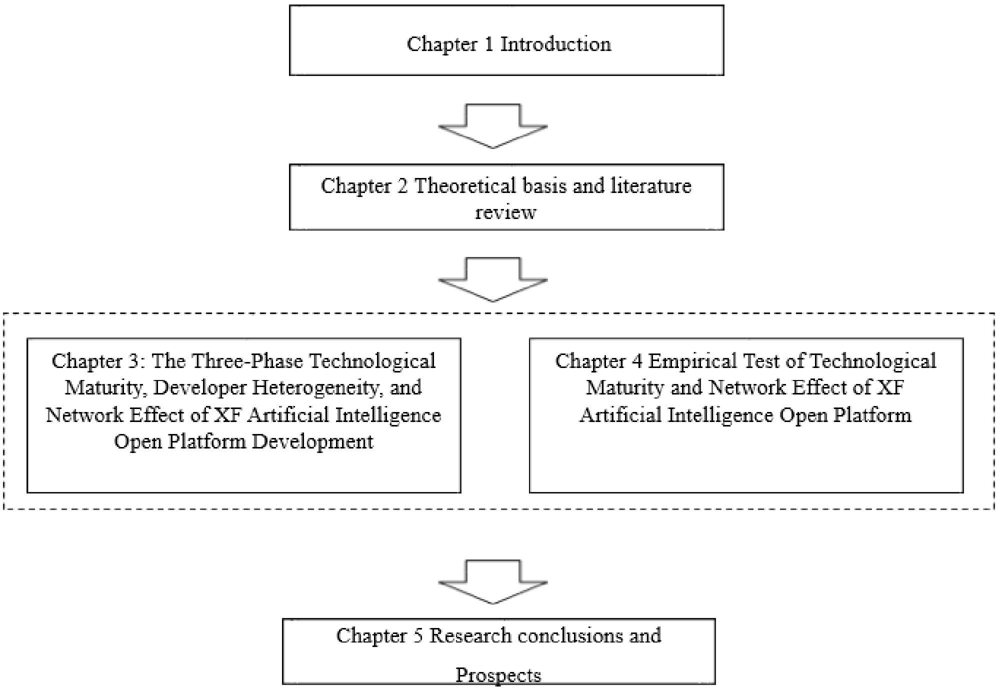
Chapter 2 is the theoretical foundation and literature review of the full text. This chapter first systematically reviews the core theories of the full text, such as "Technological Maturity Theory" and "Network Effect Theory", and then reviews existing research on the platform economy both domestically and abroad. It also points out the shortcomings of current research, which echoes with the theoretical contributions of this paper. The comprehensive review of this part is a re-understanding of existing theories and research, which is crucial for understanding the full picture of current research, and also provides a solid theoretical foundation for subsequent hypotheses and argument sections.

Chapter 3, titled "Chapter 3: Three-Phase Technological Maturity, Developer Heterogeneity, and Network Effects of XF Artificial Intelligence Open Platform Development", is based on technological maturity and value co-creation theory. It examines the stimulation, optimization, and expansion mechanisms of network effects under the value co-creation in three phases: "Capability Building Phase", "Business Model Exploration Phase", and "Ecosystem Cultivation Phase" of the AI open technology platform. This research complements and expands the study of the commercial value of open technology platform value co-creation.

Chapter 4 is titled "Empirical Examination of Technological Maturity and Network Effect in the XF Artificial Intelligence Open Platform". This study conducts an empirical examination of the relationship between technological maturity and network effect mentioned in Chapter 3, once again verifying some of the propositions and conclusions extracted from the case study.

Chapter 5 is the conclusion, development suggestions, research limitations and prospects of this paper. This paper first summarizes and generalizes the aforementioned case studies, presenting the core views and conclusions of this paper. Secondly, based on the conclusions of the case analysis, this paper puts forward development suggestions for entrepreneurs, managers and practitioners in this field. Finally, the shortcomings and defects of this study are also detailed, and a prospect is presented for the new round of artificial intelligence technology revolution triggered by chatGPT on the future decade's open technology platform business model research in artificial intelligence.

Figure 1 *Research Structure and Logical Framework*



1.3 Research method

This paper rigorously adopts a combination of theory and practice, using a research method that integrates normative hypothesis theory analysis, case study analysis, and empirical testing. The content of the research method involves the following:

First, this paper adopts the research method of systematic theoretical analysis. Firstly, this paper integrates all theories that are in line with the research of open technology platforms and applies them to each empirical theoretical analysis and mechanistic demonstration, avoiding directly proposing propositions or hypotheses. Secondly, this paper uses a strict literature analysis method to classify the themes and analyze the existing research on value co-creation, thereby providing a basis for the theoretical innovation of this study.

Secondly, this paper adopts a single-case study approach to conduct in-depth research on the dynamic value co-creation mechanism in AI open technology platforms. The purpose of case studies is not to verify theories, but to construct theories (Eisenhardt, 1989), which is mainly applicable to the following situations: firstly, the boundaries of the research problem are difficult to define; secondly, the research problem relying on existing theories is difficult to explain; thirdly, it belongs to the questions of "why" and "how", and the research process is a profile problem. Single-case studies can not only effectively deal with the above practical problems, but also have unique advantages in solving new things and phenomena (Nudurupati et al., 2015), taking into account the typicality of cases and the availability of data. Yin (1994) believes that vertical single cases can explain the overall dynamic process of case occurrence and the relationship between research objects. Given the current lack of research on open technology platforms and their ecological value in academia, and the difficulty in obtaining data from other open technology platforms due to high confidentiality, it is necessary to use the method of vertical single-case study.

Third, based on the case analysis, this paper also adopts the econometric statistical research method based on the panel data of open technology platform. This paper mainly uses correlation regression analysis, including: variable descriptive statistics, correlation coefficient analysis, collinearity before regression, heteroscedasticity and serial correlation test, and finally robustness test. Although no updated econometric statistical methods are adopted, the entire analysis process is relatively rigorous, which enhances the accuracy and reliability of empirical research.

Chapter II

Literature Review

2.1 Theory of technological maturity

2.1.1 TRL grading and evaluation theory

The "Technology Readiness Level (TRL)" proposed by the National Aeronautics and Space Administration refers to the degree of perfection or maturity of a technology, which is essentially "technology maturity." It has been widely used in the United States in the fields of military, defense, and other weapon systems. The 2009 edition of the "Technology Readiness Assessment Manual" defines technology readiness assessment as: a formal, systematic process based on a metric system that evaluates the maturity of technologies (CTEs) to be applied in R&D systems and generates an assessment report. Here, CTEs include both hardware and software. In China's "General Principles for the Evaluation of Science and Technology Research Projects" (2009), the definition of Technology Readiness Level (TRL) is: the technological maturity level of Work Breakdown Elements (WBE). The definition of Technology Readiness Level Scale (TRLS) is: a uniformly regulated measurement tool for evaluating specific technological maturity levels.

TRL, as an effective technical management tool, provides technical maturity identification for projects by identifying risks related to technology and system integration. It categorizes the technical maturity into levels to evaluate the maturity of new technologies. The National Aeronautics and Space

Administration (NASA) originally proposed a technical readiness level, dividing the standard level into nine levels.

2.1.2 TRIZ technology prediction theory

Through the analysis of various historical data by predecessors, it has been shown that the process of technological evolution has its own laws and patterns and is predictable. In this regard, Professor G.S. Altshuller from the former Soviet Union established the world-renowned TRIZ (Theory of Inventive Problem Solving) technology prediction theory through the research and analysis of 2.5 million patent inventions worldwide. The product technology evolution process based on TRIZ theory is similar to the growth process of species, going through four stages: infancy, growth period, maturity, and exit period. These four stages constitute a "technology lifecycle" for a product. TRIZ theory treats a product as a technical system and, through the evaluation of current product technology, predicts which stage of the technology lifecycle the current product is in. Each stage corresponds to an evolutionary phase of a generation of products, which manifests over time as characteristic parameters changing along an S-curve. The product technology maturity prediction method based on TRIZ theory is to determine the position of the product on the S-curve over time by comprehensively evaluating the characteristic parameters of four curves: time-patent quantity curve, time-patent level curve, time-product performance curve, and time-profit curve, to determine the maturity of product technology.

For products in their infancy stage, there are many original things, high levels of patent protection, but they require a large amount of manpower and financial resources, and bear great technical risks. For products in the growth stage, they focus on appearance and practicality, have good profits, the number of companies gradually increases, and preliminary market competition begins to emerge. For products in the mature stage, the number of companies significantly increases, profits reach their peak, and market competition is fierce. For products in the later stage of maturity or decline stage, price wars may occur, production is concentrated towards large-scale enterprises, and the number of companies gradually decreases.

2.1.3 Product life cycle theory and A-U theory

The theory of Product Life Cycle (PLC) first proposed by Professor Vernon of Harvard University in 1966 has been gradually refined, becoming the central concept of product management and an important international investment and trade theory. Vernon divided product development into three stages: new products, mature products, and standardized products. He explained the reasons for the emergence and development of international enterprises based on the impact of product characteristics at different development stages on corporate business strategies. This theory suggests that different trade and investment strategies should be adopted at different stages of the product life cycle. In the new product stage, countries like the United States, as innovative nations, have technological and product advantages. At this time, domestic production is most beneficial, so exports should be made to meet the needs of foreign markets. In the product maturity stage, the product and technology are basically stable, and imitationists and competitors have emerged in the market. The degree of price influence on demand is significant. At this time, overseas investments are beneficial for companies to maintain and develop markets and maintain competitive advantages. In the product standardization stage, due to the widespread production technology of the product, competition mainly occurs in price. At this time, some regions with lower wages and labor-intensive production due to low costs should produce products and export them to innovative countries in reverse. The theory of product life cycle answers the dynamic transfer problem of comparative advantage and is considered an important contribution to international trade and investment theories.

Since the 1970s, Harvard's N.Abernathy and MIT's J.M. Utterback have conducted a detailed study of product lifecycles. They believe that the key to the innovation capability and innovation methods of production units lies in its evolution from a small technology-based company to a major mass producer, or determined by various stages. Based on the theory of product lifecycle curves, they analyzed the interrelationships between product innovation, process innovation, and industrial organization. They found that these three have different development characteristics and laws that link and promote industrial innovation. They introduced the concept of "dominant design", centered on product innovation, proposed an industrial innovation dynamic process model that describes the form of technological innovation distribution in industries, namely the Abemathy-Utterback innovation process model (abbreviated as A-U model), pointing out the dynamic development of product innovation, process innovation, and organizational structure over time and their impact on industrial evolution.

The A-U model posits that the product innovation activities and process innovation activities of enterprises are interrelated. At different stages of the product lifecycle, the emphasis on the two types of innovations varies, and there is a time lag between the two types of innovative activities. The two further categorize the evolution of product innovation, process innovation, and industrial organization into flow stages, transformation stages, and characteristic stages. Based on the quantity of product innovation and process innovation at different stages of the product lifecycle, one can determine the technological maturity of the product to a certain extent.

2.1.4 Bibliometric method

Bibliometric analysis primarily examines the technical maturity from the perspectives of trends in SCI paper quantities, EI paper quantities, and the ratio between journal papers and conference papers. When the growth trend of SCI papers slows down while the number of EI papers increases, it indicates that basic research in the technology is decreasing, shifting more towards engineering application research, reflecting that the technology is gradually maturing. For instance, when the ratio between journal papers and conference papers decreases, it suggests fewer conference papers, a reduced heat of debate over emerging technologies, and that the technology is beginning to approach maturity.

2.1.5 Media exposure and technological maturity curves

Gartner is a U.S.-based company engaged in information technology research and consulting, and is the most authoritative IT research and consulting firm worldwide. Gartner has the most comprehensive and professional global research team, conducting in-depth research and analysis on technologies that drive business and institutional success to assist clients in making the right choices when conducting market analysis, selecting emerging technologies, project justification, and investment decisions. Starting from 1995, Gartner Consulting has used its powerful research team and professional analysis capabilities to predict and infer the maturity evolution speed and time of various emerging and cutting-edge technologies, and divided this process into five stages: budding stage, overheating stage, trough stage, climbing stage, and maturity stage based on time and market visibility (media exposure) dimensions, drawing a technology maturity curve which has become an important technical tool for evaluating emerging technologies. Subsequently, Gartner releases an annual "Emerging Technology Maturity Curve" report each year to study and analyze the maturity and development trends of current emerging technologies.

2.1.6 Technical orbital theory

In 1962, American scholar Kuhn first proposed the concept of "Scientific paradigm" in his classic work "The Structure of Scientific Revolutions." In 1977, American scholars Nelson and Winter and others first proposed the concept of "natural trajectories" for technological development, which was later used to characterize the cumulative and evolutionary characteristics of technological development, that is, technological development is subject to the regulation of previous specific factors and environmental impacts such as economy and society, allowing it to move in a specific direction. Inspired by Kuhn's "scientific paradigm," Italian technical economist Dosi first proposed the concept of "technological paradigm" in 1982 based on summarizing the research results of predecessors, believing that if a certain technical field has significant development or breakthroughs, the corresponding technical system will form a technological paradigm, and the technological paradigm determines the field, problems, procedures, and tasks of technological research, and is a model or model for solving selected specific problems. The technological paradigm is formed by the interaction of various factors such as economy, society, institutions, and technology, and will produce positive and negative induction effects. It represents the direction of technological change and determines the trajectory of technological development. If this technological paradigm long-term dominates the direction of technological innovation in a certain field, then it forms a technological track.

The evolution of technological trajectories is a dynamic process, and it has a bidirectional interactive relationship with the technological innovation activities of enterprises. On one hand, the evolution of technological trajectories is driven by the technological innovation activities of enterprises; on the other hand, the technological innovation activities of enterprises are constrained by the technological trajectory in which they are situated. Based on the A-U theory of technological innovation and the theory of technology change cycle, Wang & Zhang (2005) constructed a general process model of technological trajectory evolution starting from the first appearance of new technologies in a certain industry. Using four time points: t0 (first appearance of new technology), t1 (formation of technology path), t2 (intermittent occurrence of technology) and t3 (formation of new technology path), the general process of technological trajectory evolution can be divided into three stages: path generation stage (technology chaos period), path locking stage (technology formation period), and path updating stage (technology update period).

The maturity of industrial technology determines the different stages of its technological trajectory evolution, and thus the corresponding choices of technological innovation strategies adopted by enterprises should also be different. In view of the different stages of technological evolution trajectory, the possible technological innovation strategies adopted by enterprises can be divided into three categories: technological lead strategy for creating paths, technological improvement strategy for extending paths, and technological transcendence strategy for breaking through paths. Corresponding to the laws of technological evolution, the three strategies also have a relationship of succession in time and coexistence in space.

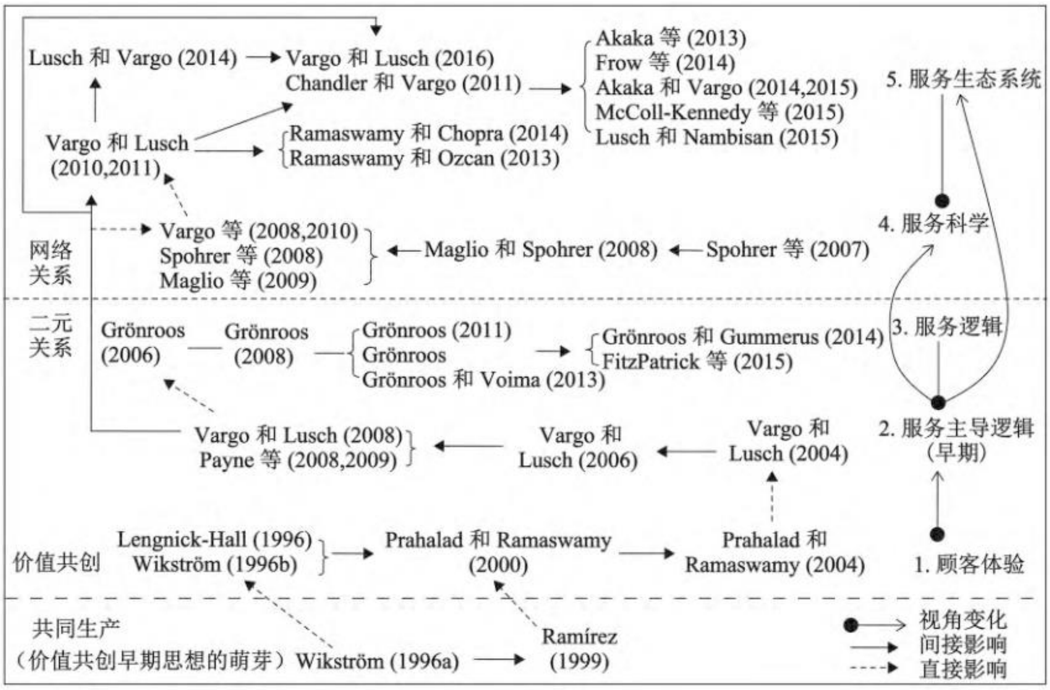
2.2 Value Co-creation Theory

2.2.1 Theoretical perspective and evolution

The so-called value co-creation refers to the continuous interaction between enterprises and customers, providing customers with valuable personalized products and services (Kohli & Grover, 2008). In this process, producers invest resources to obtain performance output, and customers invest knowledge and skills to obtain experiential value (Wu & Chen, 2012). The idea of value co-creation can be traced back to the research of service economics in the 19th century. Storch (1823) proposed that the interaction between producers and customers is conducive to the economic contribution of the service industry.

The theoretical perspective of value co-creation is constantly evolving and can be divided into six research perspectives at present, namely: co-production (Wikström, 1996), customer experience (Prahalad & Ramaswamy, 2000, 2004), service dominant logic (Vargo & Lusch, 2004; Lusch & Vargo, 2006; Vargo & Lusch, 2008), service logic (Grönroos, 2008; Grönroos, 2011; Grönroos & Voima, 2013), service science (Spohrer et al., 2007; Maglio & Spohrer, 2008), service ecosystem (Vargo & Lusch, 2010; Vargo & Lusch, 2011; Edvardsson et al., 2011). Among them, the perspectives of co-production, customer experience, service dominant logic, and service logic focus on the binary interactive relationship between enterprises and customers. However, the perspectives of service science and service ecosystem focus on the network relationship among multiple participants. As shown in the following figure 2.

Figure 2 *Evolution of the Research Perspective on Value Co-creation*



Note. The Figure is hand-drawn.

Co-creation based on co-production. Customers actively participate in the production process of enterprises, thus providing a new source of productivity. Wikström (1996) proposed that customers gradually play the role of resource providers and co-producers, and have a deep interaction with enterprises to generate value for enterprises. The key to co-production is that enterprises and customers create value together, and the interaction between enterprises and customers is the core of co-creation. However, co-production here is actually between the traditional view of enterprise-led value creation and value co-creation (Ramírez, 1999), and it is still dominated by enterprises.

Value co-creation based on customer experience. The transition from a business-led logic of value creation to value co-creation is based on a deeper understanding of the nature of value creation (Prahalad & Ramaswamy, 2004). Customer experience and feelings are important for value creation, and value is actually determined by customers (Prahalad & Ramaswamy, 2000). At this time, value co-creation tends to take a customer-centered theoretical perspective. Lengnick-Hall (1996) and Wikström (1996) emphasized in their research that the consumption experience of customers is the key activity of value creation, highlighting the subjectivity of customers in value creation. Prahalad & Ramaswamy (2000, 2004) stressed that the interaction between customers and enterprises through continuous and uninterrupted interaction to create personalized experiences, the competitive strength of enterprises comes from customer-centered value co-creation; the focus of enterprises has shifted from the intensity of interaction between customers and enterprises to creating an environment for personalized experience creation.

Value Co-creation Based on Service Dominant Logic. The service dominant logic emphasizes understanding customer value co-creation from a new economic perspective, rather than the traditional commodity economy perspective. Subsequent service logic, service science, and service ecosystems are further expansions based on the service dominant logic; however, the service dominant logic and service logic are still only examining value co-creation under the binary dynamic relationship between customers and enterprises. Vargo & Lusch (2004) merged products and services under the commodity economy perspective, proposing that the essence of the economy is services, and customers participate in the entire process of economic exchange and value creation. Vargo & Lusch (2004) proposed 8 propositions of service dominant logic, which were later revised into 11 basic propositions (Vargo & Lusch, 2016). They included customers in the process of value creation, suggesting that customers will participate in multiple links such as design, production, consumption, and value transmission, emphasizing the importance of customer orientation. Payne et al. (2008) pointed out that services are the basic content of value exchange, and customers participate in the three processes of customer value creation, enterprise value creation, and conflict.

Value Co-creation Based on Service Logic. The difference between service logic and service-led logic lies in that the former only focuses on the customer's use value creation process, with the customer's use value being the true presentation of value, while the enterprise only creates potential value. Therefore, customers are value creators, while enterprises are value promoters (Grönroos, 2011). Grönroos (2008) further divided service logic into customer service logic and enterprise service logic, with the latter mainly focusing on customer service logic; in value promotion, customers play the role of value creators, while enterprises act as value facilitators. In value realization, customers are value creators, and enterprises play both roles of value promoters and collaborators. Grönroos (2011) believes that enterprises only create potential use value, while real use value is created by customers, who can become value creators through direct interaction. Grönroos & Gummerus (2014) compared the similarities and differences between service logic and service-led logic, analyzing the essence of value creation.

Value co-creation based on service science. From the research perspective, the logic of service dominance is the basis of service science, but the focus of service systems is value creation within service systems (Maglio & Spohrer, 2008; Spohrer et al., 2008). Specifically, value co-creation in service science extends the binary relationship between enterprises and customers to networked interactions within the entire service system, emphasizing the combination of people, technology and value propositions, especially the importance of technology for resource allocation and interaction within the network. Spohrer et al. (2007) proposed that a service system is a value co-creation system structure composed of people, organizations and technologies. Maglio & Spohrer (2008) further explained the concept as follows: people, technology, value propositions in service science connect internal and external different service systems to achieve value co-creation; therefore, the unit of study in service science is the service system, and value propositions are the core content of research. Spohrer et al. (2008) believe that a service system is an open system, and realizes the interaction of service systems through three activities: proposal, negotiation and realization, and also proposed the ISPAR standard model (including interaction, service, proposal, negotiation, awareness five parts) to identify different service systems. Vargo et al. (2008) proposed that a service system enhances its adaptive ability by utilizing resources from internal and external service systems to create value for internal members. Maglio et al.

(2009) believe that exchanges between service systems are voluntary, and service systems are constantly decomposing and reconstructing over time. Vargo et al. (2010) explained in detail the relationship between service science and service dominant logic, clarifying key concepts such as service experience, value propositions, system in service science.

Based on the value co-creation of service ecosystems. The perspective of service ecosystems extends the binary interaction view between customers and enterprises that is always emphasized by service-dominated logic to a complex, extensive, loose, and coupled dynamic network system from an ecological perspective. Service science tends to study the value co-creation perspective between service systems, emphasizing the role of technology more, but does not fully consider social factors. However, in the general sense of service ecosystems, it is believed that economic participants are theoretically all important roles in value creation. In a more complex and loosely coupled dynamic network, participants achieve value creation through resource and service exchange, with institutions playing a more important role than technology (Chandler & Vargo, 2011; Vargo & Lusch, 2011, 2016).

The service ecosystem perspective has become an important viewpoint for studying value co-creation in the more complex context of the current platform economy. Vargo et al. (2008) extended the value co-creation of binary interactive relationships to a network relationship perspective through the service system perspective, but only emphasized the interaction between service systems. Vargo and Lusch (2010) based on the above proposed service ecosystem perspective emphasized that different social subjects construct various institutions to achieve value co-creation in a loosely coupled structure under the network complex environment based on their own value propositions. Vargo & Lusch (2011) further proposed an A2A oriented loose coupling spatiotemporal structure, emphasizing that resource integration, service interaction, institutions and social norms are important driving forces for value co-creation. Chandler & Vargo (2011) proposed that value co-creation is achieved through interactions at the micro, meso and macro levels, with the micro level including enterprises and customers; the meso level includes organizations and industries; the macro level focuses on all social participants, and the interactions at different levels change over time.

In the specific research, Ramaswamy & Ozcan (2013) based on the case of LEGO and RockAuto, proposed that enterprises can act as key node enterprises of the ecosystem to provide a platform for design and development, realize the integration of global resources, and create value for stakeholders. Lusch & Vargo (2014) proposed that A2A oriented service ecosystem is an automatic adjustment system created by platform integrators through sharing institutional arrangements, service exchange value creation. Akaka et al. (2013) studied international marketing phenomena from four perspectives: service exchange, value co-creation, situational value and resource integration. Lusch & Nambisan (2015) put forward the service innovation theory composed of three key elements: service ecosystem, service platform and value co-creation, where service ecosystem provides the organizational structure for participants' service exchange, service platform enhances resource density and mobility to improve the effect of service exchange, while service providers and beneficiaries participate in the process of value co-creation through resource integration.

In the digital economy era, technologies such as artificial intelligence, the Internet, and big data continue to innovate, blurring corporate boundaries, promoting the integration of technology and industry, and gradually moving towards cooperative and win-win development strategies for enterprise growth. Against this backdrop, stakeholders will actively seek cooperation to promote resource linkage, exchange, and integration, while achieving their own development and promoting the formation of service ecosystems to gain continuous competitive advantages. Therefore, focusing on the formation, development, evolution of enterprise service ecosystems, as well as the participants, roles, and mechanisms of value co-creation, is of great significance for enriching and developing new connotations of service ecosystem theory in value co-creation, and summarizing the experiences of established advanced enterprises in building ecological systems.

2.2.2 Related research on platform value co-creation

Existing research on platform value co-creation has focused on the value co-creation of the consumer internet, including the nature of co-creation between supply and demand side users, influencing factors, and execution mechanisms, but less on the value co-creation process of artificial intelligence open technology platforms. Some scholars believe that the transformation of value co-creation is conducive to business model innovation (Jiang et al., 2020); others propose that the essence of value co-creation lies in the interaction between the platform side and the user side, as well as the improvement of user experience (Yangg & Tu, 2017). Zhou (2015) proposed that value co-creation is divided into three stages: conceptual consensus, value symbiosis, and value win-win. Yang & Tu (2017) divided value co-creation into three stages based on the case of Uber: user connection, user contact, and user separation. The study of process mechanisms is mostly based on resource-based theory, institutional theory, etc. to analyze the change process and trend of value co-creation: Zhoui (2015) believes that the core of value co-creation on e-commerce platforms is technological infrastructure and institutional support. Wang et al. (2020) proposed that the value co-creation of sharing economy platforms can be divided into three stages: resource integration, supply and demand matching, and co-creation driving. Wang Jiexiang and Chen (2019) based on the cases of MOGUIXIAN and yunji, advocated that ecological participants need to formulate corresponding strategies according to the stage of the platform because the development process of the platform includes co-creation, symbiosis, and co-performance.

Only a few studies have analyzed the value co-creation model of the industrial internet. Xin (2019) proposed full-media marketing, full-channel sales, and full-link services, all of which adopted digital technology. Ma (2020) explored the "three-link" value co-creation form of the industrial internet. Cao et al. (2019) believes that empowering the industry and integrating the industrial chain are the core to realizing value co-creation in the industrial internet ecosystem.

2.3 Network effect theory

Network effects can be divided into same-side network effects and cross-side network effects. Specifically, the same-side network effect refers to that in a two-sided market, the behavior of one side of users affects the behavior and effects of the other side of users, while the cross-side network effect refers to that there is a positive relationship between the scale of one side of users and the product usage utility of the other side of users (Cao & Chen, 2010). In addition, network effects can also be classified into direct network effects and indirect network effects. The direct network effect refers to that by increasing the number of users of a certain type of product, the user efficiency of another type of product can be enhanced; while the indirect network effect refers to that there is mutual dependence on demand and technical support between basic products and auxiliary products (Li, 2000).

Direct network effects connect people or homogeneous nodes with network links, and their value increases as the number of users, nodes, and usage increase. For example, physical entity networks, communication and computer protocol networks, personal and social communication networks, social networks, and individual transfer payment networks. Indirect network effects refer to the fact that an increase in the initial product usage will drive the use and consumption of complementary products, thereby increasing the value of the initial product. For example, the increase in cars drives the construction of gas station networks; the increase in electric vehicles drives the formation of charging networks; more companies adopting cloud services drive the increase in corresponding developer numbers and applications.

In addition to this, there are also bilateral network effects, mainly referring to network structures that connect heterogeneous complementary users or connect people with goods/information/services/content, which are currently the most common and have the most unicorns. For example, achieving global matching: such as integrated e-commerce platforms, search platforms, content aggregation platforms; achieving local matching: such as Meituan, Xianyu's same city service business; achieving asymptotic matching: such as Didi, Uber and other local service platforms. Multilateral network effects refer to network structures that connect more than two types of heterogeneous complementary users. For example, from the bilateral network, another type of subject is expanded, such as news clients containing user-content creators-advertisers/merchants, and matching a variety of different roles of market subjects (individuals or institutions) to trade directly. There is also a type, although academia has not clearly defined and systematically studied, we call it "atypical network effects", which conforms to the nature of network effects, but the nodes are not human or institutional subjects; or the nodes are humans, but the connections are non-physical connections; or network effects that may only be formed after a long cycle. It may include: technical performance network effects, data network effects (Gregory et al., 2021), text standard/professional tool network effects, open source network effects, consensus network effects, informal mutual aid network effects. However, for network effect phenomena based on open technology platforms, there is currently no relevant research.

The reason for the network effect is due to factors such as network systems, infrastructure and internal information flow. Network scale, intra-network fluidity, market diversity, transfer costs are all factors that affect the network effect (Yang & Xue, 2003). The development of network scale generally goes through three key points: zero point, start-up point, saturation point. Once the critical value is broken through, a positive feedback loop of network effect will appear (He & Liang, 2010). Generally speaking, in the early stage of platform development, the number of participants is relatively important, while in the mature period, the quality of the platform is more important (Li and Penard, 2014).

2.4 Platform economy-related research

2.4.1 Platforms and classification

Altman & Tushman (2017) divide platforms into three categories: platform structure, open/user innovation structure, and ecosystem structure. Under platform structure, the platform allows direct interaction (transactions) between two or more parties, and each party is a member of the platform. Within open/user innovation structure, there is a central organization that coordinates all activities and benefits from the innovative inputs of community members. The organization interacts directly with users (who may be enthusiastic fans or primary users), innovators (who may use or not use the product but benefit by contributing in some way) and designers (who may or may not be users but provide inputs to the central organization). In specific examples, innovators provide additional inputs to the organization, such as software code, and the organization can play a strong coordinating and managing role, but most innovations and choices come from outside parties. In ecosystem strategy structure, where interactions among participants are possible (Iansiti & Levien, 2004; Moore, 1993), without a central coordinator or platform manager, ecosystem strategies can exist independently of the innovation environment of the platform and users, and the participating parties interact through various mechanisms, some of which are direct and bidirectional and some are one-way and indirect.

It can be seen that the platform structure and the open/user innovation structure still conform to the structural characteristics of centralized organizations. However, the latter is more prominent in emphasizing the contributions of innovators to the platform in a certain sense, and is closer to the strategic structure of the ecosystem. This is especially reflected in the mutual promotion and mutually beneficial relationship between the platform and its participants. This paper believes that both open technology platforms and open-source communities can be classified under this category.

Shi & Li (2021) proposed a classification of platforms along another dimension, arguing that platforms can be divided into innovation platforms and trading platforms, where the former can be further subdivided into technical platforms (Kyprianou, 2018), industry platforms (Gawer & Cusumano, 2002), and software-based platforms (Tiwana et al., 2010), while the latter are commonly referred to as intermediary platforms (Evans & Schmalensee, 2016), multilateral platforms (Boudreau & Hagiu, 2009), sharing economy platforms (Constantiou, Marton, & Tuunainen, 2017), and peer-to-peer markets (Kyprianou, 2018). Similarly, both categories of platforms rely on the number of supply and demand side actors to increase trading efficiency through direct and indirect network effects (Armstrong, 2006; Lee, Lee, & Lee, 2006; Rochet & Tirole, 2006). Differently, innovation platforms focus on purposefully built technological infrastructures that can help complementary innovators develop complementary innovative products (Thomas, 2017; Ulrich, 1995). Trading platforms instead emphasize the network effects formed between two interdependent groups of customers (e.g. buyers and sellers) in a multifaceted market created by the platform itself (Boudreau & Hagiu, 2009; Kyprianou, 2018), with Airbnb and Uber being common examples.

Specifically, software platforms are extensible code bases of software systems that provide core functionality shared by modules interacting with each other and the interfaces through which they interact (Tiwana et al., 2010). Unlike traditional software development, these services leverage the expertise and understanding of user needs from different developer communities while platform owners may not have the skills and understanding to creatively develop new features that the original designers of the platform could not foresee. This trend is prevalent in browsers (e.g., Firefox, Chrome, and Opera), smartphone operating systems (iPhone, Android), Web services (Google Payments, Amazon Elastic Cloud), social media (Facebook, Apple Ping), marketplaces (SABRE, eBay), and game consoles (Xbox, Apple iPod Touch, Sony PlayStation).

Further, Kyprianou (2018) compared the difference between peer-to-peer platform and technological platform, he believed that peer-to-peer platforms do not need complementary parties' technology or expertise to meet consumer demand, but match existing resources on the platform side with consumer demand. Conversely, technological platforms aggregate ecological actors centered on a technological kernel, and the participants of supply side are often professionals, and the necessary and prerequisite conditions for participation tend to develop specific products with technical or professional skills and knowledge.

According to this classification, this paper believes that open technology platforms belong to the type of technology platform in innovative platforms, and compared with software platforms, the similarity between open technology platforms and theirs is that all participants on the supply side of the platform have professional technical skills and use external parties to create value. However, there are also many differences: First, software platforms belong to platform structures in organizational forms, and innovation subjects are software companies, developers and platforms are subordinate relationships. Open technology platforms belong to open/user innovation structures, although the platform still plays a coordinating role as a central organization, innovation activities no longer depend on the platform, and the platform and developers jointly create network value for ecological construction. Second, among various technology platforms, especially in various open technology platforms, standardized, modular interfaces such as USB ports, TCP/IP protocols and application programming interfaces make products and services be decomposed into smaller parts through standardized and open interfaces, and many different professional producers can contribute to a collective product almost seamlessly, thereby promoting and encouraging the growth of the platform and ecosystem (Baldwin & Clark, 2000; Furlan et al., 2014; Pil & Cohen, 2006). In open innovation (Chesbrough, 2003; West et al., 2014), enterprises obtain innovation from outside the organizational boundary through various mechanisms. Third, software platforms are extended systems of traditional software, which extend the function development generated by demand, and developers must have a deep understanding of the industry customer needs of software; while technology platforms represented by open technology platforms are based on sharing technology cores, the cognitive ability and development ability of developers' technology development are more critical. Fourth, open technology platforms are constantly evolving with the improvement of technological maturity, and the deep reason for its evolution may be due to changes in developer heterogeneity (Rietveld & Eggers, 2018), early-stage participants and mature-stage participants promote the evolution and commercialization of technology to varying degrees.

2.4.2 Network externalities and effects

In markets where internetwork compatibility matters (e.g., telephone networks, computer operating systems) or where the availability of complementary goods drives product value (e.g., movies on streaming services, apps for smartphones), a product's network externalities may account for a large fraction of its total value (Choi, 1994; Farrell & Saloner, 1992).

First, economies of scale are considered to be constant or decreasing and are easily determined through mathematical methods; whereas the returns to scale markets with strong network externalities increase continuously and calculations are more volatile. Moreover, when a technology's value is very much derived from its network externalities (the size of the user base and/or the availability of complementary products), new technologies may not be able to displace existing ones even if they have large benefits over older technologies (Schilling, 1998; Suarez, 2004). Furthermore, because complementary product producers and consumers make adoption decisions based on which technology they believe has the largest user base, the signal that is sent out can be very influential.

Secondly, when the value of complementary products is an important part of the increased earnings, a powerful incentive is provided for product developers to adopt standardized interfaces and modular production systems that enable a broad spectrum of third-party complementary product developers to create complementary products for the common platform (Matutes & Regibeau, 1988; Schilling, 1998, 2000). Letting third party developers (e.g., application developers, content creators) develop complementary functionality means that customers will have a wider array of complementary functionality at their disposal, allowing them to 'mix and match' their platform with a variety of heterogeneous complementary functionalities, it allows both the platform initiator and individual complementary producer to focus on their most robust product systems. This means that modular platform ecosystems tend to outcompete vertically integrated producers due to the benefits of specialization (Schilling, 1998, 2000).

Prior research has led to a body of studies on the effects of network externalities on functional strategies, such as pricing (Bensaid & Lesne, 1996; Gallaugher & Wang, 2002; Hagiu, 2006), investments in improving technical quality (Choi, 1994; Economides, 1996), product compatibility decisions (Besen & Farrell, 1994; Choi, 1994; J.Y.Kim, 2002), and market share and social welfare (Baake & Boom, 2001; Takeyama, 1994). In particular, there is an increasing recognition that markets exhibiting network externalities tend to require different market strategies than traditional economic theory would suggest. For example, in markets with strong network externalities, capturing large user bases early on may lead to dominant positions, so firms are motivated to use penetration pricing—sometimes below cost or free—to quickly build user bases in hopes of later recovering profits through other sources of revenue

(Csorba & Hahn, 2006; Parker & Van Alstyne, 2005). Similarly, network externalities can significantly affect IP strategies: Firms can adopt relatively "open" strategies of either freely licensing their technologies or forgoing enforcement of their patents if doing so accelerates the accumulation of user bases or complements product availability (Boudreau, 2010; Garud & Kumaraswamy, 1993; Karhu, Gustafsson, & Lyytinen, 2018; Parker & Van Alstyne, 2018; Schilling, 2011; West, 2003).

2.4.3 Platform ecosystems and company scope

The scope decisions are also crucial to the overall success of an ecosystem, where each firm must decide which products, components or activities are internally produced and which are obtained from other firms. The choice of firm scope has a significant impact on the power and influence of the firm in the ecosystem and on the success of the ecosystem as a whole (Jacobide, MacDuffie, & Tae, 2016). Standardised interfaces such as USB ports, TCP/IP protocols and application programming interfaces enable many different specialised producers to contribute to a collective product with almost seamless ease. These collective production systems are networks of symbiotic relationships between firms that are very much like biological ecosystems, and it soon became apparent to researchers that they were being referred to as "platform ecosystems" (Ceccagnoli et al., 2012; Ghazawneh & Henfridsson, 2013; Tiwana, 2015).

A growing body of research has examined when platforms subsidize complementors (Riggins et al., 1994), collaborate with complementors (Mantovani & Ruiz Aliseda, 2016), or produce complementary products in-house (Adner & Kapoor, 2010) and why these strategies change over time (Cennamo, 2018; Rietveld et al., 2020). Researchers have also begun to study horizontal mergers between platforms (Jeziorski, 2014; Zou & Jiang, 2020), which are often expected to lead to market power that may be detrimental to social welfare.

2.4.4 Heterogeneity of platforms, complementers and users

Earlier research on network externalities and platform ecosystems has tended to focus on how firms increase user base and complementary products in order to take advantage of network effects, with the size of the user base or availability of complementary goods as a generic resource (the larger the user base and/or availability of complementary goods, the greater the likelihood of success). Although quality of the platform has been considered an important variable (Suarez, 2004; Tellis et al., 2009), other sources of more subtle heterogeneity have largely been ignored. However, recent studies have begun to focus on more complex interactions between differentiated platforms and complementary goods and heterogeneous user needs (Armstrong & Wright, 2007; Tucker, 2008). Differences in aspects of the platform may be a result of high expectations for a market-specific niche that leads to a preference for that platform despite its smaller user base.

Studies have also begun to focus more on the different attributes and strategies of complementors, and the impact of exclusive complementarity on the scope of network effects has received considerable attention. Other studies have focused on the effect of the quality of complementary products on technology adoption (Kim, Prince, & Qiu, 2014) and how that effect varies over a platform's life cycle. Another study examined differences between complementary products, investigating whether and when complementary products invest in specialisation, when those decisions lead to differential levels of complementarity among platforms and the performance of complementors (Cennamo, Ozalp, & Kretschmer, 2018; Kapoor & Agarwal, 2017). Other studies have focused on the impact of choice of business model for complementors on performance (Rietveld, 2018).

In addition, some research focuses on the impact of different user heterogeneity. For example, Steiner et al. (2016) found that "core" users had very different preferences from "leisure" users and should be strategically targeted differently. Rietveld & Eggers (2018) similarly found that early adopters of a platform were more inclined to purchase more complementary and novel products than late adopters of the platform, leading to complementary products that enter the platform at different stages of the platform's life cycle having different strategic significance.The social structure of platform users may also be influential (Afuah, 2013). For example, Suarez (2005) proposed such a view that platforms should consider the strength of connections between users instead of treating the user base as several identical users; the part of the network with “tight connections” will have a greater impact on technology adoption than loosely connected users. Lee et al. (2006) similarly argued that even in the presence of network externalities, the social network structure among users would remain fragmented in technology markets because interactions and exchanges among subgroups of users may be more intense than outside the network, and it is the user base of that subgroup rather than the whole user base that affects technology adoption. More generally, studies have shown that companies can target only groups of users with different preferences to achieve or maintain success in a certain segmented market, even if there is an installed user base disadvantage (Chao & Derdenger, 2013; Suarez & Kirtley, 2012).

2.4.5 Platform governance and coordination

A growing body of research in this direction examines how the rules and norms of a platform ecosystem are developed and enforced, and how key actors in an ecosystem affect the behavior of other actors and the outcomes for the ecosystem as a whole. Recent research has begun to focus more explicitly on how (and by whom) an entire ecosystem is managed, and how one or more powerful actors in an ecosystem coordinate the behavior of their actors (Altman & Tushman, 2017; Helfat & Raubitzschek, 2018; Sampler, 2018).

If a platform ecosystem is organized by a strong “pivot” company that owns or supports the platform, then the company has both the incentive and the ability to exert influence in order to increase the overall value of ecosystem creation and its own value capture (Hukal et al., 2020; Rietveld et al., 2020). A pivot’s coordination strategy can either attract complementary products from the ecosystem (Gawer & Cusumano, 2008; Ghazawneh & Henfridsson, 2013) or encourage them to exit the platform (Tiwana, 2015). The pivot must make strategic decisions about how many and what types of complementary products it wishes to attract onto the platform. On one hand, greater ecosystem breadth and depth are often considered attractive to consumers (Rietveld et al., 2019). On the other hand, more complementary products also increase congestion costs, weaken the incentives for complementary product investment in quality and innovation, and may lead to coordination problems that actually reduce value creation for consumers (Boudreau, 2017; Boudreao & Jeppesen, 2015; Casadesus Masanell & Hałaburda, 2014; Markovich and Moenius, 2009).

The platform governance strategy also affects complementarity pricing (Dinerstein et al., 2018), quality-oriented investment (Cennamo et al., 2018), product market positioning strategy (Rietveld et al., 2018; Tae et al., 2020), incentives and punishments for complementarity bad behavior (Sampler, 2018), and the degree to which complements collaborate with each other and share knowledge and other resources to increase innovation (Huang et al., 2018).

2.5 Research related to cloud computing

2.5.1 An overview of the development of artificial intelligence open technology platform

2.5.1.1 Definition of AI open technology platform

From a broad ecological perspective, the AI open technology platform will open up AI-related infrastructure and technical capabilities to enterprises or individual developers. It will build knowledge sharing and experience exchange communities in specific fields, guiding technology-based small and medium-sized enterprises and innovative companies to carry out product research and development and application testing based on the open innovation platform. This reduces the barriers to technology and resource usage. It not only helps promote the deep integration of artificial intelligence with the real economy but also helps integrate related technologies, industrial chains, and partner resources, aggregating upstream and downstream innovative forces to construct a complete technology and industrial ecosystem, promoting domestic AI technological innovation and industry open collaborative innovation.

From a narrow technical perspective, an AI open technology platform refers to the aggregation of data, computing power, algorithms, models, and tools at the platform level. Through IaaS/PaaS/SaaS service models, it provides technical capabilities in the perception or cognition fields such as voice interaction, image recognition, and natural language understanding for enterprises or individual developers (Hoberg et al., 2012). This addresses the issues of high costs, difficulties, low efficiency, and long cycles when deploying for enterprises or individuals, providing strong support for product and service innovation. Taking the XF open platform as an example, individuals can complete the conversion from recording to text by calling the voice recognition function on the platform. Developers or enterprises can develop voice input functions for certain APPs through API interfaces. This is also the general definition of cloud computing in domestic and foreign research.

The open technology platform can be divided into three layers at the technical level: the foundational layer, the technical layer, and the application layer. Among them, the foundational layer includes data resources and computational capabilities. Resources that support computing include storage, networking, chips, etc., providing a computational foundation for AI scenario applications. Currently, cloud computing has achieved virtualization, allowing for pay-as-you-go pricing of computational resources, enhancing the configuration efficiency of computing power. Data resources encompass speech prediction, image face data, knowledge graphs, etc., and various application scenarios can run algorithms based on shared data in real-time, continuously optimizing and iterating algorithms and data. The technical layer focuses on the needs of various business scenarios, integrating technologies such as deep learning, image recognition, speech, and natural language understanding into the platform to provide interfaces for external developers. Deep learning and machine learning platforms aggregate a large number of algorithms, and developers can directly call these mature algorithms to achieve specific functions. Speech and natural language understanding platforms can effectively meet the voice application needs of various scenarios such as machine translation, virtual human communication, intelligent cabins, etc. Image recognition includes object recognition, face recognition, biometric recognition, text recognition and other technical capabilities. The application layer involves various types of applications and can be combined with different industry business segments to comprehensively improve the operational efficiency of various industries, including but not limited to education, healthcare, automotive, industrial, security and other industries, supporting the realization of the industrial internet goal across all sectors.

2.5.1.2 An overview of AI open technology platform

From a domestic perspective, the industry chain of China's artificial intelligence open technology platform can be divided into upstream infrastructure and resource providers, midstream platform service providers, and downstream application field enterprises or developers. Among them, large-scale comprehensive platforms are the most dominant entities in the artificial intelligence industry chain. In the context of comprehensive platforms, XF Open Platform can be compared with domestic and foreign platforms such as Baidu, Alibaba, Tencent, Huawei, and other open technology platforms.

As of December 2021, XF's developer base has grown by 1.5 million, a higher increase than Baidu and all other manufacturers, with the total number ranking first in the industry (4.2 million), the market share ranking first in the industry (43.05%), and the number of open AI capabilities ranking first in the industry (449), showing an overall leading performance in the industry. In particular, the XF open platform has always been at the forefront of the voice market in the industry. In 2017, at the meeting of the New Generation Artificial Intelligence Development Plan and the Launch of Major Science and Technology Projects held by the Ministry of Science and Technology, the first batch of national AI open innovation platform names was announced, proposing to build an intelligent voice national AI open innovation platform based on XF.

In terms of ecological layout, XF and Baidu have complete ecological layouts. Among them, the artificial intelligence products of XF and Ali platforms are clear, introducing promotion models for individuals and partners. Baidu's data is widely open, with a complex platform system, and its products are independent of each other. In addition, Tencent mainly uses single-point technology capabilities, mainly for its own products, and the platform product level is single. Its artificial intelligence partners are more startup projects.

In terms of competitive positioning, artificial intelligence platforms have shifted from seeking a "peak" of single-point technology to the development of an integrated AI ecosystem. The vertical integration of computational power, platform, and technical services has become a consensus among leading AI platforms. Major AI open technology platforms are accelerating their expansion from their own advantageous capabilities to industry applications, laying out to sprint towards various industries while maintaining their existing advantages, solidifying their ecosystem. In terms of voice layout, XF's open technology platform has the most comprehensive capabilities, ranking first in the industry.

From an international perspective, artificial intelligence open technology platforms that deploy based on IaaS/PaaS/SaaS provide developers with technical capabilities in perception or cognition fields such as voice interaction, image recognition, and natural language understanding. They also offer vertically customized AI solutions and fundamental AI development tools to cater to diverse requirements of businesses and developers. Domestic companies represented by XF, Baidu, Alibaba, Tencent, and Alibaba; international AI platforms include Google's Google Brain platform, Google Assistant platform, TensorFlow platform, Waymo platform, and Cloud AI platform; Microsoft's Azure platform, and Amazon's AWS platform. Overall, there are certain differences between domestic and international AI platforms in terms of industry environment, ecosystem construction, technical capabilities, and resource services, which can be summarized as follows in the table 1.

Table 1 *Comparison between Domestic AI Platforms and Foreign AI Platforms*

Difference	Domestic AI Platform	Overseas AI platform
Industry Environment	● There is a need for AI platforms with both technical and industrial value, which are tailored to China's unique characteristics. ● Chinese SMEs face significant survival pressures and are more concerned with the visible direct commercial value. There is a need for	● The main objective is to realize the technical value of developers.

	comprehensive support and rapid response from technology to business. ● There is a scarcity of AI talents, with both quantity and density lagging behind. It is necessary to lower the threshold for technical learning and enhance the ease of using technology.	
Ecological Construction	● The ecological construction is open and extensive, attracting a large number of partners to build a broad ecosystem, with relatively weak control power. ● Assisting ecological partners in quickly acquiring crucial capabilities, effectively shortening the time for product implementation, and reducing R&D, production, and sales costs.	● Ecological partner selection is cautious, ecological management is relatively conservative, emphasizing strong control, and the relationship with partners is essentially a supply-demand relationship.
Technological Capacity	● Emphasizing the simplicity and comprehensiveness of technology, reducing the threshold for technological learning. ● Deeply understand the needs of enterprises and leading easy-to-use, open comprehensive general capabilities, algorithm support in-depth and extensive, flexible and diverse deployment methods, ultra-large-scale distributed training.	● Emphasizing the comprehensiveness and universality of technical capabilities. ● Open and universal capabilities, algorithmic support is extensive and in-depth, deployment methods are flexible and diverse, and the development process has comprehensive support.
Resource Services	● Provide standard transaction processes, software services, data services, authentication, venture capital, branding, business opportunities, and partner resources. ● Provide commercial support, talent cultivation and other industrial empowerment.	● Full-process support for the development of focusing technology

2.5.2 An overview of research on open technology platform and cloud computing

2.5.2.1 Foreign research

There is limited research on open technology platforms and their ecological construction abroad. Apart from pure technical research, most studies have focused on describing the basic attributes of cloud computing, such as its technical definition, characteristics, deployment methods, and enterprise applications (Ross & Blumenstein, 2015; Alkawsi et al., 2015), commercial impact (Hoberg et al., 2012), and data security (Ahmed & Hoss, 2014; Esposito et al., 2017).

In terms of the definition and characteristic description of cloud computing.Marston et al. (2011) analyzed the cloud computing industry through the SWOT model. Hoberg et al. (2012) thoroughly explained the characteristics, adoption influencing factors, governance mechanisms, and business impacts of cloud computing through a review; among them, the characteristics section briefly explained design principles, service models, deployment models, market structures, and pricing models. The business impact section emphasized the advantages of IT (such as scalability, reduced complexity, and increased agility) and business value (reduced costs, increased market value, enhanced business-IT linkage).Goyal (2013) detailed the definitions, advantages, and some technical challenges in implementing

IaaS/PaaS/SaaS. Stieninger & Nedbal (2014) introduced the definitions, challenges, success factors, business models, impacts on companies, etc. of cloud computing from a more comprehensive perspective.Rashid & Chaturvedi (2019) elaborated on different cloud services, features, and challenges, dividing service models into private clouds, public clouds, community clouds, and hybrid clouds, introducing the definitions and advantages of IaaS/PaaS/SaaS.Lins et al. (2021) proposed the concept of AI as a Service (AIaaS) in their research and divided it into three levels: AI software services, AI developer services, and AI infrastructure services. They also discussed the characteristics of AI as a Service and potential challenges in its development.

In terms of commercial applications in cloud computing. Chang et al. (2010) introduced eight business models suitable for different organizational needs, which is of great significance to enhance the sustainability of business development. Susanto et al. (2012) systematically reviewed the advantages and disadvantages of cloud computing, as well as the opportunities and technological prospects brought by cloud computing for business, such as reduced costs in education and medical fields due to the reduction of information centers. Moghaddam et al. (2015) believe that there are risks and opportunities coexisting in the field of cloud computing, where risks are reflected in data security and privacy, resource allocation, load balancing, compatibility, scalability, data management and interoperability, etc. Senyo et al. (2018) believe that the literature on cloud computing can be divided into four categories: implementation issues, technical issues, conceptual issues and industry application issues, with technical issues being the most common (47%); only 13% of the studies used quantitative research methods; 82.5% of the studies were not based on any theoretical basis. Reim et al. (2020) proposed four steps in their study to promote business model innovation and transformation through artificial intelligence technology: deeply understand AI and the necessary organizational capabilities for digital transformation; understand the current situation of companies; cultivate necessary capabilities; promote full recognition and improve job qualifications. Sadeeq et al. (2021) proposed that IoT based on cloud computing has a variety of advantages, and explored the latest cloud infrastructure, cloud architecture, etc. Chak & Rana (2021) believed that the COVID-19 pandemic has spawned market demand for cloud computing, they sorted out research involving various characteristics of cloud computing, and simply compared the advantages of Amazon Cloud, Microsoft Cloud and Google Cloud to meet the needs of small and medium-sized enterprises. Shetty & Panda (2021) conducted cluster analysis on related research, these research topics involve cost analysis, technical advantage analysis, policy analysis and technology reference related theories of SEMs adopting cloud computing. Aldahwan & Ramzan (2022) provided an overview of 51 articles on community cloud computing and their research prevention measures. Specifically, research on PaaS mainly focuses on technical direction, for example, Albuquerque et al. (2017) found through research that in mobile application scenarios, compared with PaaS, FaaS (Function as a service) has more obvious effects, scalability, cost savings and higher resource utilization efficiency, becoming an alternative way.

2.5.2.2 Domestic research

While domestic research is similar to foreign research, it mainly focuses on the qualitative description and technological prospects of cloud computing, with a greater emphasis on the technical level. Chen & Deng (2009) provided relevant explanations for the key technologies of cloud computing, pointing out the future development prospects of this technology. Fang et al. (2010) systematically introduced the progress of the cloud computing ecosystem and its business models. The review by Zhang et al. (2010) mainly focused on related technologies of cloud computing, representative cloud computing systems, and pressing technical issues that need to be addressed in cloud computing. Zhang et al. (2016) introduced the research progress related to cloud virtualization security, cloud data security, and cloud application security.

In addition, on the research of open technology platforms, Ma et al. (2012) conducted a qualitative analysis of the technical architecture and operation model of existing open technology platforms and provided development suggestions. Song (2012) descriptively analyzed the development history and application profit model of Tencent's open technology platform. It can be seen that domestic related research has not yet risen to the stage of theoretical and empirical analysis.

In summary, existing foreign research either focuses on the pure technical progress of cloud computing or on the definition, characteristics, and enterprise applications of cloud computing. It neither involves the study of open technology platforms built on cloud computing nor discusses the fundamental theories of the formation and evolution of the open technology platform ecosystem, nor empirical research targeting commercial value. This paper enriches the case and empirical research of the open technology platform and its ecosystem from the perspective of value co-creation service ecosystems. On the other hand, it also discusses the stimulation mechanism of network effects, which is a development in the study of the causes of network effects, and has played a positive reference role for the evolution and iteration of domestic artificial intelligence platforms.

2.6 Chapter summary

This section first reviews the value co-creation theory and network effect theory involved in this study. Among them, value co-creation includes six research perspectives, while the two types of perspectives in service science and service ecosystem focus on the network relationships between multiple participants, rather than the binary relationship between customers and enterprises. Network effects include unilateral network effects, indirect network effects, and bilateral network effects. It also points out a type of atypical network effect that is less commonly focused on by the academic community at present. Although it conforms to the essence of network effects, the nodes are not connected by people or organizations as the main body, or people connect each other through non-physical objects.

The study also analyzed and compared the open technology platform with other platforms of existing research, in addition, the open technology platform is also a type of technology platform in the innovation platform, and the main difference between it and software platform is: First, software platform belongs to platform structure in organizational form, innovation subject is software enterprise, developer and platform are subordinate relationship. While open technology platform belongs to Open/User Innovation structure, although the platform still plays a coordinating function as a central organization, innovation activities no longer depend on the platform, and the platform and developers together create network value for ecosystem construction. Second, among various technology platforms, especially among various open technology platforms, standardized, modular interfaces such as USB ports, TCP/IP protocols and application programming interfaces make products and services be decomposed into smaller parts through standardized and open interfaces, many different professional producers can contribute to a collective product almost seamlessly, thereby promoting and encouraging the growth of the platform and ecosystem (Baldwin & Clark, 2000; Furlan et al., 2014; Pil & Cohen, 2006). In open innovation (Chesbrough, 2003; West et al., 2014), enterprises obtain innovation from outside the organizational boundary through various mechanisms. Third, open technology platforms are constantly evolving with the improvement of technological maturity, and the deep reason for its evolution may be due to changes in developer heterogeneity (Rietveld & Eggers, 2018), early-stage participants and mature-stage participants have different degrees of promoting the evolution and commercialization of technology.

Chapter 3

Three-Phase Technological Maturity and Network Effect

3.1 Research design and case presentation

3.1.1 Research design

First, this paper adopts the research method of systematic theoretical analysis. Firstly, this paper integrates all theories that are in line with the research of open technology platforms and applies them to each empirical theoretical analysis and mechanistic demonstration, avoiding directly proposing propositions or hypotheses. Secondly, this paper uses a strict literature analysis method to classify the themes and analyze the existing research on value co-creation, thereby providing a basis for the theoretical innovation of this study.

Secondly, this paper adopts a single-case study approach to conduct in-depth research on the dynamic value co-creation mechanism in AI open technology platforms. The purpose of case studies is not to verify theories, but to construct theories (Eisenhardt, 1989), which is mainly applicable to the following situations: firstly, the boundaries of the research problem are difficult to define; secondly, the research problem relying on existing theories is difficult to explain; thirdly, it belongs to the questions of "why" and "how", and the research process is a profile problem. Single-case studies can not only effectively deal with the above practical problems, but also have unique advantages in solving new things and phenomena (Nudurupati et al., 2015), taking into account both the typicality of the case and the availability of data. Yin (1994) believes that vertical single cases can explain the overall dynamic process of case occurrence and the relationship between research objects. Given the current lack of research on open technology platforms and their ecological value in academia, and the difficulty in obtaining data from other open technology platforms due to high confidentiality, it is not possible to use multi-case comparison methods. Therefore, the method of vertical single-case study is adopted.

In terms of obtaining case data, based on the research scope and issues of this paper, in order to improve the reliability and validity of the case study, this paper adopts multiple data sources, corresponding to different data collection methods. The focus of data collection for the XF artificial intelligence open platform is: the collaboration methods of various participating entities in the open technology platform, platform rules, platform support measures, commercialization paths and economic value of the open technology platform, etc. Data materials are mainly from internal historical documents, meeting materials, reporting materials, etc., as well as various public information, such as audited financial reports, market research reports of the open technology platform, company information disclosures and news reports, etc. The diversified information sources help to form verification in different dimensions, construct a complete evidence chain, and improve the reliability and validity of the case study.

3.1.2 Case introduction: XF artificial intelligence open platform

The XF Open Platform and XF Input Method are key Internet services within XF. This paper focuses on the XF Artificial Intelligence Open Platform as a research subject, examining the dynamic value co-creation and commercial value of AI open technology platforms, thereby revealing the intrinsic mechanism affecting corporate value of open technology platforms. The reason this paper chose the XF Artificial Intelligence Open Platform as a single case study is mainly based on the following considerations: First, the case is typical. The XF Artificial Intelligence Open Platform was established in 2010 and is an A.I. technology and ecosystem service platform built upon XF's leading international AI research achievements. In recent years, it has attracted numerous developers and capabilities, rich platform applications, fast growth rates, and large commercialization spaces, representing a typical platform business model under the trend of artificial intelligence. Second, the case is novel. Existing research on value co-creation mainly focuses on e-commerce platforms, travel platforms, etc., with few studies on AI open technology platforms and their ecosystems, indicating a gap in related research. Moreover, using the XF Artificial Intelligence Open Platform as a research carrier can further develop theories on value co-creation and network effects, and provide more beneficial explorations into the operational mechanisms and impacts of such platforms on the business economy.

3.2 Case analysis and findings

The maturity of technology may both impact the platform's value and its developmental stage. This paper introduces the "Lifecycle of Open Technology Platform Ecosystem (abbreviated as OTPE)" which consists of three phases: the capability building phase, the business model exploration phase, and the ecosystem cultivation phase. During the capability building phase, the types of technologies on the platform are relatively limited, with some technologies still requiring ongoing refinement in terms of usability, stability, and accuracy, thus falling into an early stage of technological maturity. In the business model exploration phase, as various AI technologies continue to advance in their maturity, the number of mutually supportive technologies continues to increase, offering developers a richer selection in application innovation and a better user experience. Developers and platforms collaboratively create commercial value. During the ecosystem cultivation phase, as the number of users of innovative applications developed by developers increases, and the flywheel effect of data and algorithms strengthens, technologies related to perceptual intelligence on the platform (such as speech recognition, speech transcription, speech synthesis, machine translation, etc.) have reached a fully usable state, better supporting developers' innovations. Moreover, the development threshold for capability users continues to decrease, the developer community continues to expand based on redefined boundaries, new application scenarios keep emerging, and more demands are put forward for new technologies. The levels of technological maturity and richness have attracted three different types of developers: early-stage. Their risk avoidance, willingness to pay, and innovation preferences all show significant differences. They co-create value with the platform during the aforementioned three stages.

3.2.1 Capacity phase: technology maturity, early-mover developers, and the network effect of open technology platforms

3.2.1.1 Technology maturity and developer profile

1、The Characteristics of the Technological Era

From 2010 to 2014, the mobile internet was just emerging, and the ecosystem from network to end users was still in its very early stages. The market share of Nokia and Motorola's mobile phones was constantly declining. In 2014, Motorola's mobile phone business was acquired by Lenovo, and Nokia's mobile phone business was acquired by Microsoft. Meanwhile, Xiaomi and Huawei, with their high cost-performance and Internet marketing strategies, quickly gained market recognition and increased their efforts to expand internationally.

In the field of artificial intelligence, early adopters of technology initially experimented with voice technology and capabilities on their self-developed APPs or hardware and software products, but encountered various problems, such as poor performance or slow response. At that time, there were very few open technology platforms, and Baidu, Alibaba, and Tencent did not provide related services. There were some small companies in the industry, such as

Yunzhisheng, who also provided similar services, but the service stability was poor, specifically manifested as poor performance under 3G networks. Therefore, at that time, only XF's products were available. Large domestic BAT companies did not invest heavily in the open technology platform in the field of artificial intelligence. XF cultivated an environment for artificial intelligence through the form of an open technology platform, making AI technologies represented by voice technology usable and stable, and creating an AI infrastructure that lowered the development threshold.

As one of the significant applications of artificial intelligence, Apple's intelligent voice assistant, Siri, was launched in 2011. Its capabilities allow the phone to read messages, inquire about weather, set alarms via voice, etc., supporting natural language input and offering conversational responses, attracting widespread attention and debate in the market. Many people are amazed by Siri's intelligent voice recognition and response capabilities, considering it a significant advancement in AI technology. At the same time, Siri has become a major selling point for Apple products, attracting the attention and purchases of many consumers and serving as an important representative for numerous mobile phone manufacturers exploring research in the AI field.

2、Strategic Development of XF Open Platform

Strategic Decision of the Open Platform in 2010: In 2010, there were over 1.5 billion mobile users worldwide and more than 700 million internet users. It was internally agreed that mobile communication and the internet had become the two fastest-growing, highest-potential, and most promising businesses in the world at that time, and mobile terminals had a natural demand for voice. Additionally, management judged that, given the high idle rate of IT hardware facilities invested by enterprises and the widespread waste of resources, companies such as Amazon, Microsoft, Google, and IBM all launched cloud computing products and services. The future IT market will be dominated by cloud computing. The XF open platform was initially called the "XF Voice Cloud Platform". Management believed that the mission of the XF voice cloud should be: using voice services like electricity and water, "on-demand access".

From the perspective of technical supply, the platform aims to provide developers with the latest and best voice synthesis and most accurate voice services from the very beginning, improving the usability and ease of use of technology, providing reliable services under unstable network environments, and offering personalized services based on consistent services. Ultimately, seven major indicators have been formed for the design of cloud service platforms: accessible anytime and anywhere, easy to expand, scalable in size, rapid response, quick optimization, security, and easy to use.

Strategic Decision for Open Platform in 2011: Starting from 2011, targeted monitoring of several indicators was initiated, including availability, response time, efficiency for fault discovery and resolution, etc. For example, the overall availability reached 97% in 2011, and the response time for 2G networks was less than 2 seconds, and for 3G networks was also less than 2 seconds. In terms of problem-solving approaches, there is a continuous enhancement of service security and reliability. Through the automated deployment of business and full automatic operation and maintenance, the security of protocols and data on the server side are strengthened. At the same time, with the continued expansion of service capacity, more voice capabilities are actively promoted and opened.

Strategic Decision of Open Platform in 2012: In 2012, mobile internet giants launched their own assistant products one after another. Meanwhile, the number of applications based on the voice cloud platform reached 9,000. Six major indicators were further defined in terms of technical service quality, including: user interaction experience (comprehensive usability and response time under different networks such as 2G, 3G, and wifi), client processing efficiency (real user interaction time and frequency), service access (service connection rate, network latency), cloud platform scheduling (service stability, involving data access, service distribution, process scheduling), voice engine processing (processing time of voice and dictation engines), and business services (business success rate such as translation).

Strategic decision for the open platform in 2013: Management believes that the best cloud platforms are characterized by being reliable, easy-to-use, and valuable. Here, "reliable" means: accurate, functional reliability, high recognition rate, good synthesis effect; stable, trustworthy; smooth, quick response; robust, consistent performance in various environments. "Easy-to-use" means: low threshold, easy to use; fast progress, continuous improvement, new features; rich tools, easy to debug and analyze; personalized, can satisfy users' good interaction; good service, establish good interaction with users. "Valuable" means: new features, bringing a brand new interactive experience for applications; new users, bringing more users and stronger user stickiness for applications; new value, bringing more value to applications through interaction data.

In 2013, mobile internet giants and domestic competitors alike introduced their own voice open platforms. For the XF voice cloud platform, the core task for that year was still to optimize platform performance and provide the most reliable voice services in the industry: enhancing service quality, continuously improving call-in rate, success rate, and response time; delving into personalized capabilities, offering stable personalized services, integrating evaluation services and voiceprint services. At the same time, to extend the value of voice and enhance application and user stickiness, a semantic platform was also opened up, allowing partners and users to participate in the advancement of the semantic engine. The year 2013 also marked the beginning of big data in the mobile internet era. The open platform constructed a voice cloud big data analysis platform, applied personalized technology, screened user intentions and preferences from massive information, laying the foundation for achieving precise advertising and personalized recommendation capabilities.

Management judgment, the future of human-computer interaction faces huge market opportunities, XF voice cloud needs to achieve early occupancy and layout, and is based on developers to build the open platform that users need: easy to use and suitable for development, provide backend capabilities such as operations and data analysis, provide distribution and dissemination capabilities for applications, provide monetization capabilities for applications, etc., so as to face the competition of various voice cloud platforms.

In 2014, the strategic decision for the open platform was made: the core technical indicators such as the integrated average usability and service stability of the XF voice cloud platform have been continuously improved. In terms of technological richness, the XF open platform has become the most advanced natural interaction open platform in the industry, offering leading comprehensive interaction capabilities such as voice, semantics, and facial recognition. Mobile APPs have become the core application scenarios for voice technology, with the XF voice open platform occupying a market share of 60% in the mobile app market, far ahead of other competitors. It has also begun to provide technical services for intelligent hardware and smart homes in the field of the Internet of Things. Against this backdrop, management is considering how to provide commercialization for the platform and developers. The main approach is to establish a mobile advertising aggregation platform based on big data analysis, and an advertising development plan was formulated at the end of the year.

3、 Technical Maturity of XF Open Platform

During the capacity building period (2010-2014), the XF open platform was still in the stage of capability accumulation. As a capability provider, it empowers innovative and entrepreneurial developers with technical capabilities related to voice technology. At this time, the innovation of artificial intelligence applications mainly revolves around the development of intelligent voice-related human-computer interaction applications. In order to better serve developers, the XF open platform has effectively improved the maturity of platform technology through the following efforts:

First, continuously improve the technical indicators of key core technologies. In the field of speech recognition, gradually increase the speech recognition rate and speed; in the field of speech synthesis, gradually improve the clarity and naturalness of speech synthesis. When AI attracts enough market attention, and at the same time, the usability and stability of the product are improved, meeting user needs, the growth rate of developers will rapidly increase. Particularly crucial is that even if only market promotion is used and there is a lack of stable improvements in effects and usability, users' network effect still cannot be generated.

Secondly, continuously improve the stability and availability of cloud services in complex network environments. Before 2014, due to the low bandwidth of traffic in 2G and 3G networks at that time, the application stability was also relatively low. At that time, providing AI capabilities in the form of cloud services faced many technical problems related to resource allocation, which required constant upgrading and transformation after initial deployment. For example, after the data traffic reaches a certain level, it is necessary to consider load balancing, as well as setting up multiple data centers, which not only involves data backup but also complies with the principle of proximity to improve access efficiency. China Mobile, which has the most mobile users, adopted the TD-LTE standard, which has significant problems in network stability, response speed, and reliability. The XF development platform optimized the SDK (Software Development Kit) specifically for 3G networks. In 2014, when 3G switched to 4G networks, the platform optimized both network scenarios to ensure smooth operation under 4G networks.

Third, the marginal service cost under scaled services is continuously reduced through algorithm optimization. This includes using more efficient algorithms, reducing the amount of computation, and lowering memory consumption. In the field of deep learning, the computational and storage requirements of models can be reduced through techniques such as pruning, quantization, and compression.

The participants in the first stage are relatively simple, only platforms and developers, and the capabilities provided to the outside world are mainly in voice. The early adopters of the first stage of developers have the following characteristics:

First, the preference for innovation is strong, but the lifespan of the product is shorter. From 2010 to 2014, there were many APPs developed based on Android and Apple's IOS, but they generally couldn't survive due to immature technology and difficulties in commercialization. After 2015, more and more products centered around artificial intelligence have emerged, and the survival rate of these products has greatly increased. At the same time, with the increase in industry scenarios suitable for voice applications, non-AAP applications represented by front-end information systems have added functions related to artificial intelligence to meet the demand for digital transformation. For example, call center systems that can significantly reduce labor costs and improve collaboration efficiency are beginning to grow.

Secondly, although the willingness to pay is strong, due to greater survival pressure, the ability to pay is weaker. Relevant studies on the life cycle of platforms generally believe that participants, users, or complements in the early stages of platform development usually have a stronger willingness to pay and pay a higher relative price for it. The reason is that they can tolerate various problems encountered in technology use to gain early experience, and even create new product experiences for other users to seize market advantages through re-creation. However, due to the survival ability of innovative developers, the willingness to pay is somewhat suppressed, supporting free over paid, and moreover, the mentality of requesting for free exceeds actively sharing without expecting anything in return.

3.2.1.2 Platform value co-creation

The first stage of participants, although limited to only the platform and developer groups, has initially established the co-creation rules and incentive mechanisms of the platform, which have a driving effect on attracting a large number of developers to use the platform capabilities. In order to attract more developers to use the platform, offline activities were held by the platform in 2013-2014. The main marketing promotion method is through word-of-mouth dissemination brought about by good product effects. Second, in the first stage, the platform only provides empowerment for developers without charge, is not eager to commercialize, plays a very strong incentive role, and significantly reduces the usage barriers for developers who are willing to integrate AI into product functions. The reason for free is not only due to the weak payment ability of developers, but also because the scale of developers and paid income on the platform is small. Third, the technical support provided in this stage is called "XF partner care", a professional online technical support team is set up on the platform to answer questions encountered by users in the process of integrating AI capabilities through forums, QQ groups, work orders, etc. It is worth noting that a large number of disabled developer users are also using the platform's capabilities for product research and development, and disabled users have thus become beneficiaries of related barrier-free products. Fourth, in terms of platform management, considering the high cost of artificial intelligence in the first stage of research and operation, the platform is also continuously improving usability and effectiveness while reducing marginal costs, reducing the cost of scaled replication, and breaking potential obstacles to future commercialization. From the perspective of developers' contributions to the platform, the continuous use of developers serving users will promote the evolution of platform products, which is conducive to the analysis of different scenarios and specific problems solved by the platform, and better meets the demands of developers.

3.2.1.3 Network effect motivation

The following table shows the development of XF Artificial Intelligence Open Platform in product services, platform network effect and competitive situation from 2011 to 2014.

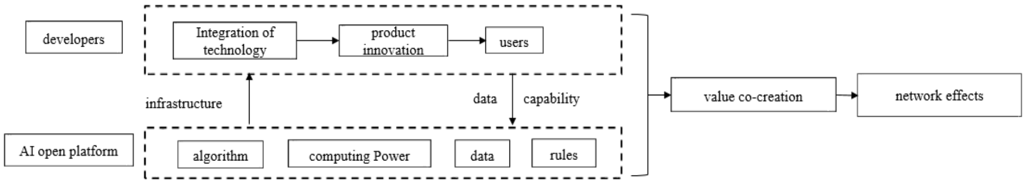
Table 2 *Network Effect Motivation*

Year	Evolvement of Technological Maturity	Platform Network Effect
2011	• Speech synthesis, recognition and other key technologies are still unsatisfactory in terms of accuracy, effect, and response time. The main focus of the technical team is on optimizing interaction experience and service quality (usability, response time).	• The number of voice users is rapidly growing to 10 million; the number of daily voice services has increased from nearly ten thousand to more than three million • Developer Enrollment: 2,000 application submissions, 60 active applications, integrated into the mobile internet.
2012	• Continuously improve the interaction experience, service quality (usability, response time, security) • Automated operation and maintenance, reducing operational costs • Open up more speech capabilities • • Personalized data storage-based, personalized services are provided, and data analysis services begin to be provided	• There are 18,000 developers, supporting over 100 clients, with 0.9 thousand applications. • The XF speech point has been launched, and various applications based on the XF voice cloud have reached 9,000. • The monthly retention rate of new users increased to 28.02%. • The formation of the developer community is in its infancy • Integrating third-party advertising platforms, utilizing the user advantage of the voice cloud as the end for advertising, bringing revenue to the voice cloud developers.
2013	• Significant advantage in response speed and availability over competitors • Optimize the voice interface, reduce the difficulty of development, and provide flexible customization capabilities • The quality of service has been improved, and the connection rate, success rate, and response time have been continuously optimized. • Based on voice cloud big data, applying personalized technology to filter the required information from massive information.	• The number of developers is 38,000, with 350 million terminals, 6000W active users, and 3600W daily usage. With 3600W daily usage, 57 million monthly active users, 4.74 million daily active users, 23,000 applications, 3,259 active applications, the monthly retention rate for new users is 30.04%, and there are 24,000 partners. • The number of various applications based on the XF voice cloud has reached 23,000. • Initiate the concept of creating an "XF Cloud Interaction Ecosystem" (platform,

	• Delve deep into personalized capabilities, provide stable personalized services, integrate evaluation services and voiceprint services. • Open Semantic Platform, allowing partners and users to participate in the advancement of semantic engines • Preliminarily constructing a big data platform to provide internal and external big data and operational support. • Constructing a cloud platform service system, including the cloud platform service systems for users, developers, product operation personnel, operation and maintenance personnel, and development and testing personnel. • Providing cloud + terminal capabilities such as speech synthesis, speech recognition, semantic understanding, handwriting, voiceprint recognition, and voice wake-up, covering various aspects of human-computer interaction.	content services, advertising platform, users, terminal manufacturers)
2014	• Continuously enrich the types of technical services on the platform, and in December 2014, the platform opened facial recognition and voiceprint recognition, which accelerated the growth of developers.	• There are 78,000 developers, with a monthly active user scale of the voice cloud reaching 110 million, an increase of 94.1% compared to the same period in 2013, and a daily active user count of 9.61 million. • There are 53,000 applications, with 6,957 active applications, and 800 million terminals. • The monthly retention rate for new users is 39.67%. • The voice open technology platform occupies 60% of the mobile app market.

According to the above discussion, Proposition 1 is proposed: In the platform capability building period, by providing single-point technical capabilities, algorithm and other technical resources, using rules and so on, the value of convergence of platform rules and resources was created, which met the developers' willingness to try AI technology development; for the platform, more developers using feedback helps the platform continuously optimize technical availability and stability, build a big data platform to converge personalized data, and lay a data foundation for precise advertising monetization. At this stage, most technologies are still in a state close to availability or basically available, and the technical capabilities and effects are still accumulating and improving. The platform continues to polish product usability, and the scale of developers and users continues to increase, stimulating network effects.

Figure 3 *Value Co-creation and Network Effect during the Capacity Building Period*



3.2.2 Business model exploration phase: technology maturity, business developers and the network effect of open technology platforms

3.2.2.1 Technology maturity and developer profile

1、The Characteristics of the Technological Era

The period from 2015 to 2018 was a crucial stage in the development of mobile communication technology in China. During this phase, the 4G network was widely promoted and popularized, laying a solid foundation for the rapid growth of mobile internet. In 2015, the number of 4G users in China experienced explosive growth, reaching 383 million, and continued to rise to 700 million in 2016, accounting for over 50% of mobile phone users. With the widespread adoption of the 4G network, user satisfaction and trust in mobile networks have gradually increased.

In addition, the popularity of 4G networks has driven the boom in the smartphone market. In 2018, China's smartphone shipment reached 631 million units, accounting for approximately 97.5% of the mobile phone shipments during the same period. Smartphones have become the primary communication tool in people's daily lives, gradually replacing feature phones in the market. At the same time, with the popularization of 4G networks, various innovative applications based on 4G technologies have emerged, such as mobile payment, mobile e-commerce, mobile food delivery, mobile travel, and mobile social media. These applications have greatly enriched people's daily lives and promoted the rapid development of the mobile internet industry. Smart hardware and robots have also begun to appear, and by 2016-2017, smart hardware began to show an explosive trend. Among them, the widespread adoption of mobile payment has opened up the payment infrastructure for various industries. As the business models of mobile internet and smart hardware become clearer, both platforms and developer teams need to focus on commercialization as a key task. The platform needs to consider how to support top developers and help them generate revenue first.

2、Strategic Development of XF Open Platform

Strategic Decisions for Open Platform in 2015-2016: In the voice user network type of 2016, the usage rate of WIFI and 4G significantly increased, from 18.8% and 59.5% in 2015 to 21.7% and 65.9% in 2016. The number of new developers and applications on the voice cloud platform in 2016 exceeded the total of the past five years, and the demand for voice interaction of intelligent hardware, especially robots, was significantly higher than mobile APPs, greatly accelerating the development of the open platform. Specifically, in some industry applications such as office business, financial management, shopping discounts, educational learning, communication social, convenient life, and parent-child interactions, the call volume growth rate surpassed any year, which is related to the transformation of traditional enterprise services to the Internet.

In 2016, compared to other competitors, XF's voice cloud platform already held the leading market share, especially dominating in areas such as reading and robotics. Management widely believes that 2016 marked the first year of voice cloud monetization, taking the initiative to establish a developer certification system to distinguish different developer groups, mining commercial value through differentiated services, especially providing more comprehensive capabilities and service guarantees for enterprise-level developers.

Strategic Decision of the Open Platform in 2017: In addition to monitoring technical stability and usability indicators, management also focuses on key indicators such as open platform access, visit time, account registration number, developer certification number, and call volume. Since 2017, the XF voice cloud platform has changed its name to "XF Artificial Intelligence Open Platform", proposing the goal of "promoting the ecosystem with business". This is specifically manifested as: providing different levels of services for developers, in the form of an open platform, using artificial intelligence technology, products and solutions to empower all industries outside the company's core industry; finding those customers with continuous commercial value and promising entrepreneurial teams, providing sufficient services, obtaining commercial benefits, and building a benign and healthy ecological platform based on commercialization capabilities.

The strategic vision of the platform is also updated:

Section 3, Technical Platform: The platform integrates various AI capabilities and technical services, becoming a cloud service platform that offers convenient and rapid AI integration for developers and end-users.

Secondly, Ecological Platform: becoming a leading AI ecological platform in China, providing technical products, solutions and cloud services for corporate clients, start-up teams, students and AI enthusiasts, forming a healthy and robust AI ecosystem.

Third, service platform: becoming a one-stop "A.I. + industry, platform + track" solution provider, providing deep customization solutions for enterprise-level large customers, universal solutions for small and micro developers, and channels for service providers to monetize. A value service supply chain has been established for both enterprise-level and non-enterprise-level users.

Strategic Decision for Open Platform in 2018: In this year, a general strategy for the development of open platforms was proposed: based on AI capability authorization, building an artificial intelligence ecosystem around open platforms, and providing AI capabilities and empowering commercialization for enterprises and developers. In 2018, the advertising business of open platforms entered a stage of scale profitability, while AI technology authorization achieved break-even.

3、Technical Maturity of XF Open Platform

During the capacity building phase, developers oriented towards AAP were predominant. Although they had a high willingness to pay, their survival status was poor due to immature technology and difficulties in implementing applications, limiting their ability to pay. Starting from 2015, some developers have gradually generated some payments. Most capabilities on open technology platforms have entered the usable stage or even fully usable status. Moreover, technologies such as speech, semantics, and natural language understanding continue to enrich, establishing themselves as leading industries in the field of artificial intelligence, laying the foundation for application innovation and product innovation.

The characteristics of the technological maturity presented during this period are specifically reflected in:

Section 3, in the context of a constantly expanding range of technologies, continuously improves relevant technical indicators, such as speech recognition accuracy, speech synthesis fluency, semantic recall rate, etc. The blended application of online and offline has a better experience under different network environments.

Secondly, based on the characteristics of 4G networks, optimize artificial intelligence algorithms and models to maintain high accuracy and real-time performance under conditions of network latency and limited bandwidth, while also considering the user needs of 3G networks.

In the second stage (2015-2018), also known as the "Business Model

Exploration Period", the heterogeneity of developers further evolved. Developers in this stage showed significant improvements in abilities such as payment and risk resistance, which is referred to as "commercial developers" in this paper. The heterogeneity is reflected in three aspects:

Section 3, on the distribution of domains. The first stage is dominated by APP developers, including robots and a small number of intelligent hardware developers. In the second stage, APPs have become the content and service centers for users in various fields, including O2O, social category, video category, finance, travel, live streaming, takeout, knowledge payment, payment, etc. At the same time, many types of intelligent hardware have developed, and robots have experienced rapid growth. Especially in 2016-2017, intelligent hardware began to break out.

Secondly, in the role played by artificial intelligence. In the first stage, developers only innovate products based on AI. After 2015, the use and popularity of AI technology in products gradually increased, becoming a unique differentiator in products. From the first stage to the second stage, the significance of AI for developers becomes increasingly important.

Third, on developer appeal. What business developers want to buy is products and technologies that can achieve "change-driven". With the first mover advantage in implementing this change in the industry, business developers often hope to get some benefits ahead of competitors, whether it's lower product costs, faster product marketing, more complete customer services, or other similar business advantages. Business developers want to be the first group to receive these benefits to gain a differentiated competitive advantage. They hope that this change will fundamentally separate new products from existing ones. At the same time, business developers are also prepared to tolerate some failures in new products.

3.2.2.2 Platform value co-creation

The mechanism of value co-creation in the second stage mainly revolves around two major aspects: collaboration for commercialization and empowering developers. First, to promote traffic monetization for joint downstream developers, the construction of the XF advertising platform lays the foundation for a platform ecosystem model centered on developers and APPs. Making money through traffic is a direction widely recognized by the market, and internet giants such as BAT entered this field around 2015.

According to market research, nearly 70% of the popular apps in the Top50 list at that time were using XF's technical capabilities, and the Top50 internet applications covered 90% of the entire internet traffic. The growth of device terminals was also very rapid. In 2016, the mobile phone shipment volume increased by 18.7% year-on-year, which was the highest in history, and XF covered a considerable number of terminals for C-end users. Moreover, the types of terminals or APPs covered by XF are comprehensive. Therefore, both XF's own internet APPs and developers' various applications and smart hardware enable the platform and developers to have a higher potential monetization ability of the traffic pool. XF builds an internet marketing advertising platform, and developers not only access the platform's technical capabilities but also connect to the traffic platform to obtain monetization methods based on capability building. Furthermore, developers monetize through internet marketing, and the platform can cultivate a group of paid developers. At the same time, within a certain range of usage, free technical services continue without interruption to cultivate a broad developer ecosystem. It can be seen that ecological quality is a natural prerequisite for successful commercialization monetization.

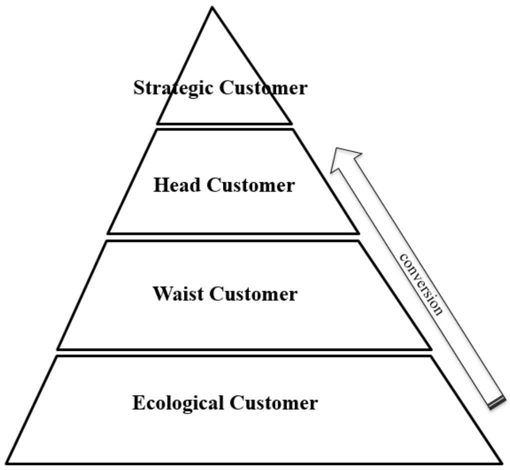
Secondly, in 2018, the service platform was launched, gradually forming a "D (developer)-D" trading model. The service platform is a free trading platform between developers and between the platform and developers, which allows the open technology platform to gradually separate from the single role of the first-stage capability platform. The platform has built a credit system for service providers in the service market, improving the credibility of both merchants and demanders.

However, before the service platform goes online, if developers create solutions based on specific scenarios, they hope to sell them on the platform to other developers. The open technology platform allows developers with core technologies to showcase and sell their capabilities or technical solutions on the platform, completing preliminary commercial activities.

Third, given the high threshold for AI development, the platform established AI University in 2017 to provide technical products, solutions, and cloud services for corporate clients, startup teams, students, and AI enthusiasts, forming a healthy AI ecosystem. Fourth, incubation. Starting from 2017, the platform invests in small and micro enterprises through micro-equity, with more than 100 enterprises incubated as of 2021, some of which have already achieved their initial public offerings with the support of the platform. Fifth, brand empowerment. First, companies that meet the requirements can obtain XF ecological partner brands and receive endorsement from the XF ecological system; Second, XF provides micro-equity and technical support to enhance the communication effect between developers and brand merchants; Third, an annual "1024 Developer Festival" is held to release products and technological ecology, deeply connecting developers and partners. Developers attend exhibitions to make contact with potential partners and customers, enhancing their industry brand recognition. The open technology platform also sets up a series of user agreements for users and gradually improves them, including service guarantee agreements, order agreements, user instructions, user certification, enterprise certification, service agreements, creation rules, privacy agreements, personal information protection, etc.

In 2018, the platform categorized customer types into strategic customers, head customers, waist customers, and a large number of ecological customers based on their contribution to revenue volume. In terms of technical support, there was a start to set up technical support teams for serving large customers and ecological customers separately, especially for head and strategic customers, and a small number of waist customers, providing one-on-one follow-up technical services. For the remaining ecological customers and most of the waist customers' requests, common needs were resolved, and unsolvable needs were improved through product optimization and upgrades. In addition, the platform conducts regular surveys of developers' satisfaction and needs every year. In the second stage of customer structure, it is preliminarily judged that there is a power-law distribution relationship between customer structure and revenue. First, the top 20% of customers account for nearly 80% of revenue, while a large number of long-tail customers contribute less than 20% of revenue. Second, the proportion of repeat customers is only 20%, but they even contribute more than 80% of revenue.

Figure 4 *Customer Structure*



The contribution of developers to the platform is reflected in helping the platform find its industry direction and provide decision-making basis. In 2020, under the pandemic situation, the usage of online education and online office has surged dramatically, with a very fast growth rate for developers, far exceeding previous years. This provides sufficient data support for platform decision-making.

3.2.2.3 Network effect optimization

The following table shows the development of the XF Artificial Intelligence Open Platform in product services, platform network effects, and competitive situation from 2015 to 2018. In the second stage, the platform can help developers monetize their income through advertising platforms and continuously enhance the market competitiveness of their products through AI technology platforms, thereby attracting more developers to join the platform. Comparatively, the growth rate of developers in the first stage was faster than that in the second stage, but there were more experimental innovations and the growth rate of calls did not exceed that of the second stage. Overall, in the second stage, both developers and call volume increased rapidly.

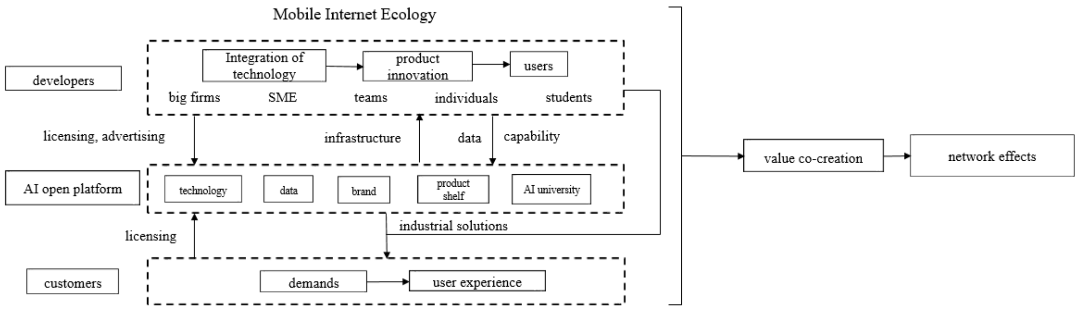
Table 3 *Network Effect Optimization*

Year	Evolvement of Technological Maturity	Platform Network Effect
2015	• The hierarchical service and platformed authorization strategy is shaped, continuously reducing the cost of user services • Achieve multi-dimensional service scheduling at the application level, user level, business level, and county/city level, ensuring a high-quality experience for head customers. • In 2015, the cost of one million voice cloud services was 5.58 yuan, compared to 11.2 yuan in 2014 and 12 yuan in 2013. The cost of voice cloud services significantly decreased in 2015.	• There are 121,000 developers, with 1.23 billion terminals and a monthly active user count of 179 million, and a daily active user count of 20 million. There are 11,133 active applications; the voice cloud has a daily active user count of 20 million and an application count of 96,000. • XF developer activity is significantly higher than other speech open technology platforms. • 7 exhibitions, 9 forums, 7 salons. • Participation of companies in innovative incubator cooperation across multiple cities. • Preliminarily realized the layout of platform eco-model.
2016	• Build industry solutions for games, live streaming and other industries	• Lay the foundation for a developer/app-centric platform ecosystem model. • The developer growth exceeds the sum of the past 5 years, with 254,000

	• Graded service branding P-D-C mode: Service grading oriented to enterprise developers	developers, 198,000 apps, and 19,000 active apps. In the voice cloud, the daily service volume reached 3.133 billion times in 16 years, a year-on-year increase of 141.4%. The daily active users of the voice cloud were 37.5 million, with each active user having 12.6 sessions per user. • Among the voice cloud developers, 22.4% are individual developers, indicating that enterprises are primarily small start-ups. • The total number of robot applications in intelligent hardware has broken through 10,000, with a market share of 85% in the field of intelligent hardware and robots. • The potential of live streaming, games, translation and other fields is emerging. • Establish an open technology platform developer certification system, distinguishing between developer groups. • Establish the Open Technology Platform Fund to form the XF startup ecosystem. • holding the first 1024 developer day.
2017	• 27 industry solutions, planning AI+ track construction • 30% self-developed, and the rest provided by the developer to users.	• There are 510,000 developers, 390,000 applications, and 100,000 community interactions; In 2017, the number of developer accounts and application numbers on the open technology platform increased by 49% and 48% respectively. The number of community interactions increased by 67%, and the number of paid orders increased by 78%, showing significant growth. • 15,000 certified developers, with a certification rate of approximately 2%; 25,000 certified apps, and 3,600 certified entrepreneurial teams. • Total volume of service 4 billion.
2018	• Continuously layout AIoT strategy and industry solutions • Relying on iFLYOS, realize the system-level ecological layout; establish the voice interaction standards for internal and external products; build a operable C-end user system.	• There are 920,000 developers with 171 open capabilities. • Accelerate the transition of customer groups from small B to large B. • 1024 developer festivals were held; the online platform capabilities reached 200, with a monthly active user increase of 6,000-10,000.

Based on the above argument, this paper proposes Proposition 2: In the exploration period of platform business model, the platform creates platform connection and commercial monetization value by providing comprehensive technical capabilities, brand management, incubation, AI university, etc., and developers can meet the needs of complex scenarios by invoking diversified and relatively mature technical capabilities. At this stage, the depth and breadth of connections between participating subjects are enhanced through identity authentication, micro-equity, etc. between the platform and developers to form a mobile and consumer Internet platform ecosystem; a partnership relationship is formed between the platform and developers; the platform brings commercial value monetization for developers, partners and platforms through precision marketing based on big data, realizes cost reduction and efficiency improvement through technology optimization, and some developers become subscribers of the platform; in addition, the optimization of compliance mechanism by the platform further improves the transparency of connections and enhances the trust basis for all parties to participate in value creation. The above factors stimulate the network effect in the second stage.

Figure 5 *Value Co-creation and Network Effect in the Exploration Phase of Business Models*

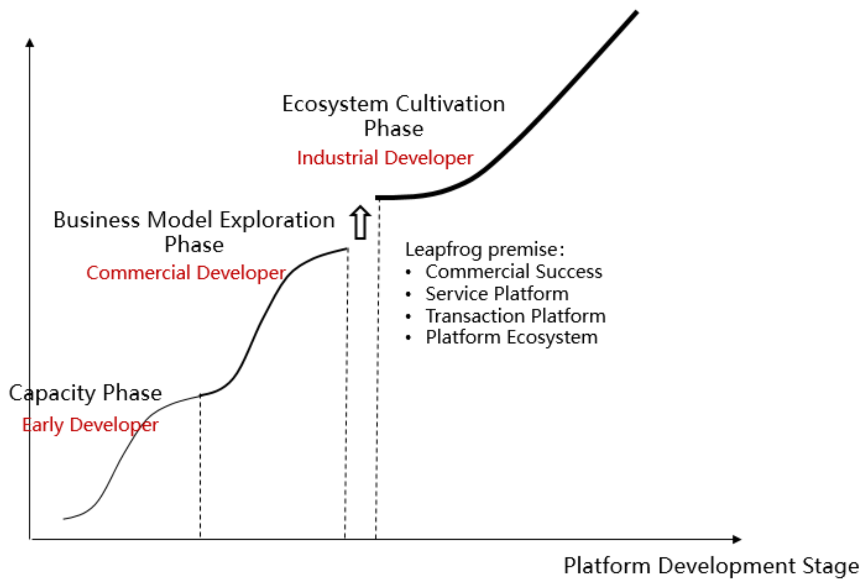


3.2.3 Ecosystem cultivation phase: technology maturity, industry developers and open technology platform network effects

Moore (1996) proposed the concept of business ecosystem and business ecosystem life cycle, he believed that the life cycle of business ecosystem can be divided into four stages (BLEC), namely Birth, Expansion, Authority and Renewal. Moore (1996) believes that in the birth stage, companies will carefully observe new opportunities to establish value chains and create value for customers; in the expansion stage, business ideas will obtain value for a large number of customers and have the potential to extend the concept to a vast market; in the authority stage, the value-added process tends to be stable, and the business platform pulls partners together to provide platform development value; in the renewal stage, a new business ecosystem will be born from a mature business community through the birth of new ideas and innovations. Rong et al. (2013) believe that open strategy appears in the birth and cultivation stages of the ecosystem.

The second stage, characterized by the monetization of business models and value co-creation mechanisms of brand effects, provides an important development foundation for the rapid growth period of open technology platforms entering a new stage. The first stage of open technology platforms focuses on technological refinement and capability building, while the second stage reflects the overall comprehensive strength of the platform. In particular, XF helps developers successfully implement AI applications in different industries, and also enhances the commercial monetization capabilities of developers, thereby enabling the platform to withstand market shocks and enter the "non-continuous" third stage ("ecosystem cultivation phase") of development.

Figure 6 *Three Stages of Development for the Open Technology Platform Ecosystem*



3.2.3.1 Technology maturity and developer profile

1、The Characteristics of the Technological Era

During 2019-2022, the advancement of 5G construction has become a new growth point. According to the report of the International Telecommunication Union (ITU), more than 140 operators around the world began commercial use of 5G networks in 2019, and it is estimated that by 2025, more than 1300 operators will provide 5G services worldwide.

However, the growth rate of mobile internet and C-terminal applications has gradually slowed down. According to the China Internet Network Information Center (CNNIC), the scale of mobile internet users in China reached 1.36 billion in 2019, with a year-on-year growth rate of only 3.3%, far lower than the high-speed growth seen in previous years. This phenomenon is also reflected globally, where the growth of mobile internet users has approached saturation. At the same time, the mobile internet markets of travel, e-commerce, short videos, etc. have also shown an oligopoly trend, with a few large enterprises occupying a dominant position in the market. For example, in the field of live short videos, top companies such as TikTok and Kuaishou have already occupied a large market share, making it difficult for other small and medium-sized enterprises to enter this market.

In this context, an increasing number of enterprises have begun to turn their attention to the B-end industry application market. According to relevant report data, the scale of the B-end application market has been expanding during this period, especially in the fields of smart education, smart city, medical health, etc., with continuous expansion of application scenarios and a very broad market prospect.

2、Strategic Development of XF Open Platform

Strategic Decision for Open Platform in 2019: In 2019, on the platform technology authorization business, we continuously explored the opening of mature new technologies. Based on the vigorous development of transcription, synthesis, and evaluation, we explored the commercial applications of translation, OCR and other technologies. At the same time, we continuously improved the usability and stability of solutions in industries such as learning and office work. The open platform gradually entered the "dual-track operation stage of ecology and business", where the active users and call volume are the ecological indicators, and capability authorization is the business indicator. The open platform's commercialization is based on the scale of fees for customer stratification, with different customers implementing corresponding product content and customer business service mechanisms: for ecological customers, the focus is on nurturing and harvesting, with an emphasis on promoting hierarchical advancement to the next level by enhancing product dimensions and encouraging user activity; mid-tier customers mainly focus on increasing average revenue per customer; top-tier customers implement VIP service to ensure renewal rates; strategic customers actively respond to company strategic cooperation.

Strategic Decisions for Open Platforms from 2020-2022: Since 2020, efforts have been made to promote the openness of new technologies such as multilingual technology, AI interaction, and virtual humans on open platforms, as well as offering various solutions for industry clients in the form of industry SAAS (Software as a Service). At the 2021 Developer Day, XF Open Platform released its 2.0 strategy, collaborating with leading industry players who possess both resources and platform capabilities to jointly build the foundational infrastructure for the industry and promote the implementation of industry applications.

3、Technical Maturity of XF Open Platform

This paper posits that during the ecological cultivation phase, the technical maturity exhibits the following characteristics:

First, the relevant technologies of perceptual intelligence (machines can listen and speak, see and recognize) have basically entered the mature stage, gradually reaching a fully usable state, better supporting product application innovation. However, cognitive intelligence represented by natural language understanding (machines can understand and think) is still in the exploration period. For example, current large-language models are focusing on ChatGPT in 2022 and GPT-4 in 2023.

Secondly, the stability and availability of cloud services need to be continuously improved in complex network environments. A major feature of 5G networks is low latency. For AI applications that require real-time interaction, such as voice recognition and real-time translation, cloud services need to optimize algorithms and resource scheduling to reduce response time and provide a better user experience. To better adapt to the 5G network environment, AI cloud services need to be integrated with edge computing. By deploying AI models at the network edge, data transmission delay can be reduced, and real-time performance can be improved. To accommodate the high concurrency and volatility characteristics of 5G networks, AI cloud services need to have automated scaling and fault tolerance capabilities. Through automated resource scheduling, load balancing, and fault recovery mechanisms, the availability and stability of cloud services in a 5G network environment are ensured. Additionally, under the 5G network environment, AI cloud services need to strengthen data security and privacy protection measures. Through encryption technology, access control, data isolation, etc., the security and privacy of user data are effectively protected.

Third, the marginal service costs under scaled services are continuously reduced. Currently, the platform improves the algorithms and structures of large language models, enhancing the performance and efficiency of the models while reducing resource consumption. At the same time, as the scale of users and data continues to expand, a flywheel effect is formed, continuously thinning the marginal cost of research and development. For customer reasoning needs, cloud services can be purchased to improve the flexibility and usage efficiency of resource utilization.

During the business model exploration stage, commercial developers hope to gain a differentiated first-mover advantage through transformative technologies or products, thereby realizing the monetization of commercial value on a survival basis. In contrast, during the third stage (i.e., the "ecosystem cultivation phase"), industry participants want to buy an "efficiency improvement" of the existing product operations. They seek minimal separation between new and existing products, hoping to see technological advancements but not fundamental changes. They wish to improve technological innovation but not completely disrupt the existing business operations of companies. Most importantly, industry participants do not want to accept other new products and are unwilling to personally test and eliminate various faults that arise in innovative products. Once they decide to use a certain product, industry participants hope that the product technology can not only operate normally but also closely integrate with their existing technical foundation.

3.2.3.2 Platform value co-creation

Taking 2022 as a boundary, the platform value co-creation before the breakthrough of large model technology: Given that the capabilities of some developers cannot meet the scenario demands of industry clients, the platform began to directly serve industry clients from 2019, not limited to only providing AI capabilities for developers. At this time, both "P (platform)-D (developer)-C (customer)" and "P-C" service models coexist. The application standards of artificial intelligence in different industry fields are weak, and the platform needs to face different types of AI demands. In response to this trend, the strategy adopted by the platform is to first build an industry baseline with leading industry players, define the norms of AI applications in the industry, and thus avoid large-scale inefficient customization in the industry to precipitate industry general product applications. During the domestic epidemic period, the call volume of work and life scene applications in open technology platforms has significantly increased, and AI is rapidly integrating into social, travel, office, reading, education, and other aspects. At the same time, new types of developers such as digitalization, metaverse, and industrial internet are also emerging continuously, and overseas developers have also become an important user group that cannot be ignored. Robots need open technology platforms to lead and realize new growth for developers. XF can build an XF robot artificial intelligence platform around the virtual human interaction platform and robot hardware platform, build a robot ecosystem, empower the robot industry, and generate industry leadership and scale effects. In terms of developer ecosystem operation strategy, it is necessary to carry out regional operations, approach developers, establish local operation mechanisms, carry out regional operations with major regions, and deeply operate urban bases with cities as units.

After the breakthrough in large model technology, the platform values co-creation: After the release of the XF Spark large model, the development platform opens up the ability interface of the Spark cognitive large model, assistant scenarios, and plugin market, which allows developers to create AI applications with powerful natural language understanding capabilities at a low cost and high efficiency. In addition, an AI Spark Camp ecosystem plan has been launched, providing resources such as technical empowerment, talent discovery, production and sales services, and entrepreneurial support for developers, building a new artificial intelligence industry ecosystem with developers. Taking the discovery and cultivation of large model talents as an example, XF has joined forces with the first batch of 22 key national universities to set up an AI Spark Camp on campus, guiding college students in large model technology research and innovative applications, and cultivating leading talents in the era of general artificial intelligence; it will also launch a large model competition in 2022, selecting excellent developer teams, discovering high-quality innovative projects, and promoting industry-academia-research linkage.

3.2.3.3 Netwok effect extension

The following table shows the technological maturity evolution and network effects development of the XF Artificial Intelligence Open Platform from 2019 to 2022. During this stage, developers first broke through one million, and reached nearly 4 million by 2022, with a user base ranking first in the industry; moreover, the capabilities provided for users have become increasingly abundant, reaching over 500 in 2022, establishing the platform's leading position in the field of perceptual intelligence.

Table 4 *Netwok Effect Extension*

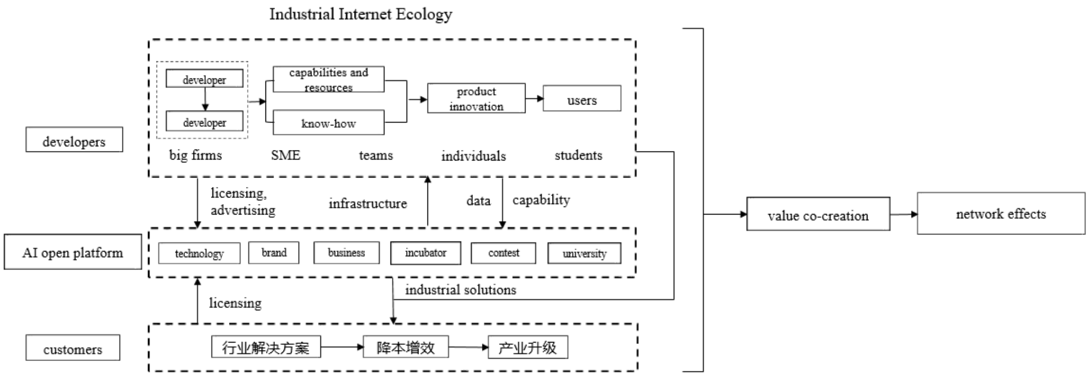
Year	Evolvement of Technological Maturity	Platform Network Effect
2019-2022	• Emphasizing the enhancement of capabilities in minor languages, transcription, evaluation, and synthesis surpass competitors. Promoting openness in transcription and evaluation, and laying out text recognition, translation, etc. • Focus on breaking through industry customer schemes and opening up more privatized services • The diversified industry clients cover entertainment social/video live streaming/reading scenarios in the Internet, enterprise informatization, online learning, intelligent manufacturing, etc. • The product and service portfolio is diversified, covering areas such as API technology authorization, AI product solutions, multilingual support, voice interaction, industry solutions, and virtual human interaction solutions.	• In 2019, the number of developers on the XF open platform reached 1.12 million, providing AI technology capabilities and solutions for various industries totaling 287 items. • In 2020, the XF open platform has publicly exposed 396 AI capabilities and solutions, aggregating over 1.756 million developer teams. In the field of intelligent voice, XF's comprehensive strength holds a leading position among the first-tier teams. • In 2021, the XF open platform gathered a total of 2.93 million developers, offering 449 AI capabilities and solutions to the public. • In 2022, the XF Open Platform gathered a team of 3.981 million developers, with a total of 1.646 million applications. It has opened up 559 AI capabilities and scenario solutions.

Open technology platforms, as technical platforms, often face a large number of technical demands, necessitating the creation of rich standardized products and solutions that meet these demands. However, while there is demand aggregation, the number of developers capable of meeting these demands is still relatively small, leading to insufficient supply capacity. Currently, the proportion of demands that can be met by open technology platforms in the industry is less than 10%. This paper believes that the emergence of explosive network effects relies on the large-scale aggregation of demanders and the rapid increase in the number of suppliers to form effective supply.

During the capacity building phase, the network effect begins to emerge. In the business model exploration phase, relying on commercialization platforms, service platforms, and brand potential construction, the network effect is significantly enhanced. During the ecosystem cultivation phase, in order to further expand the network effect, the platform needs to strengthen its role as a platform ecosystem builder. First, by attracting more developers from various fields to join and connect widely, it can continuously improve the prosperity of the developer ecosystem. The XF Star Fire large model's provision of API interfaces is expected to attract more developers focusing on the middle layer of the industry and industry applications. Second, by leveraging the service platform to stimulate and promote transactions, it can increase the interaction frequency between buyers and sellers. Third, by attracting more industry participants to deeply explore standard applications in the industry, it can attract more industrial developers.

Based on the above argument, this paper proposes Proposition 3: During the platform eco-cultivation period, the platform gathers a large number of partners through decentralization to build and expand a distributed ecosystem with higher connection strength, connection complexity, and action depth between participants. Specifically, the platform creates platform ecosystem value by providing more transformative technologies, as well as resources such as brands, business opportunities, incubator investment, competitions, knowledge learning, etc., to provide developers with scenario-based, differentiated, customized solutions and services beyond technical capabilities; developers can also realize "D–D" market transactions through the service platform of open technology platforms to meet more detailed personalized needs and form a prosperous technology transaction market. For the platform, the influence of the open platform increases with the diversification of platform participants, at the same time, industry demand and data sources from developer user side are more abundant, and the source of commercialization of the platform is more diverse. In addition, developers from all walks of life will continue to propose more new technology requirements based on business scenarios, which will help drive the platform to develop more transformative technologies and apply them deeply to various scenarios. The above helps stimulate network ecological effects and achieve open collaborative innovation.

Figure 7 *Value Co-creation and Network Effect during Ecosystem cultivation phase*



3.3 Conclusion and discussion

3.3.1 Theoretical construction and conclusion

This paper divides the lifecycle of XF, a technology platform, into three phases: the capability building phase, the business model exploration phase, and the ecosystem cultivation phase. During the capability building phase, most technical capabilities on the platform still need to be continuously polished in terms of usability, stability, and accuracy. In the business model exploration phase, almost all technologies on the platform are close to or have reached full usability, and developers and the platform have jointly created commercial value. In the ecosystem cultivation phase, new technologies continue to emerge, re-entering a new cycle of technological development. Additionally, the threshold for developers to create has continued to decrease, and the developer community has been expanding based on redefined criteria. Beta testers, commercial developers, and industry participants each co-create value with the platform during these three phases, and their risk avoidance, willingness to pay, and innovation preferences all show significant differences.

During the platform's capability building phase, the innovative preferences of early-stage developers are strong, but due to their low technical maturity, they have a shorter survival lifecycle. Although their willingness to pay is strong, their ability to pay is weak due to greater survival pressures. In this stage, the platform creates value by providing single-point technical capabilities, algorithmic resources, usage rules, etc., satisfying the needs of developers based on AI technology development. During this stage, the platform continuously refines the usability and practicality of its technology, promotes the sharing and integration of technical resources and capabilities, and diverse and heterogeneous resources quickly flow and transfer between the platform and developers. The scale of developers and users continues to increase, stimulating network quantity effects.

During the exploration phase of the platform business model, commercial developers began to offer various APPs and intelligent hardware products in different fields of content and services. They paid more attention to the unique differentiated advantages that AI plays in the products. They hope to purchase products and technologies that can achieve "transformative promotion" to gain a differentiated competitive advantage. In the second stage, the platform creates platform connection and commercial monetization value through providing relatively mature comprehensive technical capabilities, brand management, innovation incubation, AI university, etc. Developers can satisfy the complex needs of customers by calling on diversified technical capabilities. In this stage, the connection depth and breadth between the platform and developers, the platform and customers, and developers and customers are enhanced through identity authentication, micro-equity, etc. The platform brings commercial value realization for developers, partners, and the platform through precise marketing based on big data, and achieves cost reduction and efficiency increase through technical optimization.

The second stage, characterized by the monetization of business models and value co-creation mechanisms of brand effects, provides an important development foundation for the rapid growth period of open technology platforms entering a new stage. The first stage of open technology platforms focuses on product polishing and capability building, while the second stage reflects the overall comprehensive strength of the platform. In particular, XF helps developers successfully implement AI applications in different industries, and also enhances the commercial monetization capabilities of developers, thereby enabling the platform to withstand market shocks and enter the "non-continuous" third stage ("ecosystem cultivation phase") of development.

During the platform ecosystem cultivation phase, technological breakthroughs in large language models have led to the emergence of new technologies and a richer array of application scenarios. Industry participants, as new players, hope that artificial intelligence will bring efficiency improvements and technological innovations to the existing industry, but not fundamental changes. In the third stage, in order to further exploit network effects, the platform gathers a large number of partners through decentralization, building and expanding a more widely connected distributed ecosystem. The connection strength, connection complexity, and depth of action between participants are higher, especially in accurately matching more high-quality developers with diverse needs. Specifically, the platform creates platform ecological value by providing resources such as technology, brand, business opportunities, venture capital, competitions, knowledge learning, etc., offering scenario-specific, differentiated, and customized solutions and services for industry clients beyond technical capabilities. Developers can also realize "D-D" market transactions through the service platforms of open technology platforms. All of these contribute to achieving open collaborative innovation.

3.3.2 Theoretical contributions

The theoretical contributions of this chapter are mainly reflected in three aspects:

First, this paper proposes for the first time the three stages of the Open Technology Platform Ecosystem (abbreviated as OTPE) lifecycle: the capability building stage, the business model exploration stage, and the ecosystem cultivation stage. During the capability building stage, most technical capabilities on the platform still need to be continuously polished in terms of usability, stability, and accuracy. In the business model exploration stage, almost all technologies on the platform are close to or have reached a fully usable state, and developers and the platform have jointly created commercial value. During the ecosystem cultivation stage, new technologies continue to emerge, re-entering a new cycle of technological development.

Additionally, the threshold for developers to create has continued to decrease, and the developer community has expanded in scale based on redefined foundations. Early adopters, commercial developers, and industry participants respectively co-create value with the platform during these three stages. Their risk avoidance, willingness to pay, and innovation preferences all show significant differences. Changes in technology maturity and developer characteristics drive the continuous evolution of AI technology platforms.

Secondly, this paper posits that open technology platforms, classified as technological platforms within innovative platforms, are organized in an Open/User Innovation structure. The evolution of their technological maturity drives the emergence, optimization, and expansion of network effects in open technology platforms, which is a dynamic core characteristic distinct from other platforms. Although open technology platforms partially conform to the characteristics of bilateral network effects, developers and between developers and platforms achieve technical capability uploading, calling, or resource sharing through plugins and interfaces, rather than through goods or information. Therefore, technological platforms represented by AI open technology platforms bring about network effects based on standardization and modularization, distinguishing them from other platform types and their classical network effects.

Thirdly, from the theoretical perspective of value co-creation, co-production, customer experience, and service-dominated logic focus on the binary interactive relationship between enterprises and customers. However, the perspectives of service science and service ecosystem are concerned with the dynamic network relationships among multiple ecological participants. Previous research on value co-creation has mostly focused on e-commerce platforms, travel platforms, and other aggregated traffic platforms as research subjects. This paper breaks through the "customer-enterprise" binary interaction in the platform economy's "production-dominated logic" and "customer-dominated logic", and for the first time verifies the dynamic and diverse "platform-product service provider-customer" relationship by studying the commercial and social value dynamic co-creation mechanism of artificial intelligence open technology platforms, and develops the research on the diverse network relationship of value co-creation "service ecosystem". In terms of multilateral relationship interactions, the binary relationship between enterprises and customers is gradually transforming into a dynamic network where different stakeholders participate together, and the value co-created by all participants on the platform is evolving from exchange value to platform ecological value and social value. The study found that on the one hand, the network platform economy reshapes the main relationship of value co-creation, forming a "platform-developer-user" connection among participants, that is, the open technology platform no longer acts as a provider of production and services but becomes a true empowering platform, and the developer community simultaneously plays the dual roles of product provider and platform user. On the other hand, at different stages of platform development (i.e., "capacity building period", "business model exploration period", "ecosystem cultivation phase"), there are different value co-creation structures and mechanisms, the relationships and connections among participants are changing, and customer types show a "pyramid" hierarchical classification trend, indicating that the value co-creation of the platform economy is a dynamic process (Agrawal et al., 2015). Therefore, the theoretical perspective of value co-creation has evolved from co-production and customer experience to service ecology perspective.

3.4 Chapter summary

This chapter first establishes the theoretical foundation for the study of Open Technology Platform Ecosystem (OTPE) around the network effects brought about by the openness of technology platforms, the heterogeneity of developers and platform evolution, and the boundaries between platforms and ecosystems. Secondly, in the case analysis, taking XF Artificial Intelligence Open Platform as an example, its evolution process is divided into three stages based on changes in technical maturity and developer heterogeneity: the capability building phase, the business model exploration phase, and the ecosystem cultivation phase.

Chapter 4

Empirical Examination of Technological Maturity and Network Effect

4.1 Hypothesis to be tested

4.1.1 Technical maturity is correlated with platform user activity and user stickiness

There are relatively more research and evaluation systems for technology maturity, and the existing theories of technology maturity cannot explain the development mechanism of new technology platforms such as artificial intelligence technology and semiconductor technology because they are adapted to specific technical scenarios and industrial structures. It is necessary to develop new explanation logics with the times.

The technical readiness level TRL system proposed by the National Aeronautics and Space Administration divides the standard levels into nine levels: discovery of basic principles, formation of technical schemes, verification of schemes, formation of units and verification, formation of subsystems and verification, formation of prototypes and verification, application verification in real environments, user verification approval, and promotion (Stanley, 1974; Chase, 1978). Roper (1991) believes that the ratio of journal paper numbers to working meeting paper numbers can be used to determine technological maturity. Benot Godin (1996) believes that the shift from keywords describing general characteristics of technology to technology implementation keywords indicates that technology has begun to enter the mature stage. Wang & Zhang (2005) use four time points t0 (new technology first appears), t1 (technology path is formed), t2 (technology intermittently appears), and t3 (technology path is formed) to divide the general process of technology orbit evolution into three stages, namely path generation stage (technology chaos period), path locking stage (technology formation period), and path updating stage (technology update period). In contrast, Gartner, a well-known information technology research and consulting company in the United States, has issued an emerging technology maturity curve report every year since 1995. The technology maturity curve (HypeCycle) is a curve used to describe how the exposure or visibility of new technologies changes over time. It reflects the dynamic process of a new technology from birth to gradual maturity, as well as its predictive function for evaluating the development cycle of the technology.

This paper argues that the technology maturity curve can generally reveal the development status of emerging technologies in two ways: one is to describe the process and trend of a single technology gradually maturing, so as to evaluate the technology maturity and make decisions on whether to adopt innovation based on this; the other is to take multiple technologies within a technology cluster as objects, and evaluate the different maturity of technologies within the cluster at a certain time cross section by comparing their relative positions on the curve. As a criterion for predicting and evaluating innovation, technology maturity measures the current development maturity of various technologies within an AI technology cluster.

Existing platform economy research on network effects mainly focuses on the network effects of software platforms, e-commerce trading platforms, sharing economy platforms and their economic impacts. For example, Katz & Shapiro (1985) proposed that "network effect strength refers to the value brought to consumers or the willingness of consumers to pay for each additional user (installation base), different network markets may show different network effect strengths". Birke (2009) believes that network effects contain three types: direct network effects, indirect network effects and bilateral market network effects. Direct network effects refer to the fact that individual utility increases with the presence of others in the same network; indirect network effects are generated by the complementary relationship between goods, which means that the expected utility (or sales volume) of basic goods increases as complementary products increase, and in turn, the availability of complementary products also depends on the installation base of basic goods (Birke, 2009); bilateral market network effects refer to the fact that user groups at different terminals affect each other through a platform (Rochet & Tirole, 2006). Gregory et al. (2021) believe that the widespread adoption and spread of artificial intelligence on today's platforms require a reexamination of its network effects. This paper believes that although the network effects on XF open platform conform to the essence of network effects, nodes are nonhuman or institutional subjects, and usually nonphysical connections, such as technical performance network effects, data network effects (Gregory et al., 2021), open source network effects and so on. The phenomenon of network effects based on open technology platform is exactly what this paper studies.

From the perspective of XF open platform, this paper believes that technological maturity mainly affects the network effect of artificial intelligence technology platform through the following ways.

First, the technical indicators of key core technologies are continuously improved, and stable effects are continuously output. Second, continuously reduce the marginal service cost under scaled services. Third, continuously improve the richness of technologies such as speech, semantics, natural language understanding. Fourth, gather developers through value co-creation such as brand empowerment, technical support, capital incubation. Fifth, developers have significantly improved their ability to pay, resist risk and so on.

The specific mechanism of action has evolved step by step with the development of three stages of the XF artificial intelligence open platform:

In the platform capability building period, the convergence value of platform rules and resources was created by providing single-point technical capabilities, algorithm and other technical resources, using rules, etc., which met the developers' need to try out AI technology development; for the platform, more developers using feedback helps the platform continuously optimize technical availability and stability, build a big data platform to converge personalized data, and lay a data foundation for precise advertising monetization. At this stage, most technologies are still in a state close to usability or basically usable, and the technical capabilities and effects are still accumulating and improving. The platform continues to polish product usability, and the scale of developers and users continues to increase, stimulating network effects.

In the monetization period of business model, the platform creates platform connection and commercial monetization value through providing comprehensive technical capabilities, brand management, incubation, AI university, etc., and developers can meet the needs of complex scenarios by calling for diversified and relatively mature technical capabilities. At this stage, the platform and developers enhance the depth and breadth of connections between participating subjects through identity authentication, micro-equity, etc., forming a mobile and consumer Internet platform ecology, and form a partnership between the platform and developers; The platform brings commercial value monetization to developers, partners and platforms through precision marketing based on big data, realizes cost reduction and efficiency improvement through technology optimization, and some developers become subscribers of the platform; In addition, the optimization of compliance mechanism by the platform further improves the transparency of connections and enhances the trust basis for all parties to participate in value creation. The above factors stimulate the network effect in the second stage.

During the platform ecological cultivation period, the platform gathers a large number of partners through decentralization to build and expand a widely connected distributed ecology, with higher connection strength, connection complexity, and action depth between participants. Specifically, the platform creates platform ecological value by providing more transformative technologies, as well as resources such as brands, business opportunities, incubation investment, competitions, knowledge learning, etc., to provide developers with scenario-based, differentiated, customized solutions and services beyond technical capabilities; developers can also realize “D–D” market transactions through the service platform of open technology platforms to meet more detailed personalized needs and form a prosperous technology transaction market. For the platform, the influence of the open platform increases with the diversification of platform participants, at the same time, industry demand and data sources from developer user side are more abundant, and the sources for commercialization of the platform are more diverse. In addition, developers from all walks of life will continue to propose more new technology requirements based on business scenarios, which will help drive the platform to develop more transformative technologies and apply them deeply to various scenarios. The above helps stimulate network ecological effects and achieve open collaborative innovation.

For the XF artificial intelligence technology platform, the open technology platform has experienced three stages of development: capacity building period, business model exploration period, and ecological cultivation period. The AI technology capability cluster that is open to users in this platform is accompanied by increasingly clear technical routes, continuously improving the availability and ease of use of technology, and also presents different degrees of maturity. The maturity of the AI technology cluster in the open technology platform may have a significant impact on enhancing the network effect of the platform. This paper will verify two hypotheses related to technological maturity and platform network effect.

Hypothesis 1: As the technology maturity increases, the number of active users significantly increases, and the network effect is enhanced.

Hypothesis 2: As the maturity of technology increases, the intensity of single-user calls rises. More frequent high-quality interactions between users and the platform reflect an increased dependency on the platform and enhanced user stickiness. The network effect is further strengthened.

4.2 Research design

4.2.1 Research samples and data sources

This paper focuses on the technical capabilities of the XF Artificial Intelligence Open Platform, including 126 abilities such as voice wake-up, real-time voice transcription, online speech synthesis, voiceprint recognition, machine translation, and lexical analysis. The data was collected over six years from 2017 to 2022, covering both the exploration phase of the development platform's business model and the cultivation phase of its ecosystem. The choice of 2017 as the starting year is due to the fact that around 2017, the capability classification of the open technology platform was more comprehensive, and there was a richer accumulation of data, which facilitates the verification of related hypotheses. In addition, using years as a granularity unit is too coarse to reflect the precise changes in actual business scenarios, so the granularity of time is refined to monthly levels.

In terms of obtaining variable data, technical maturity is obtained through manual annotation by technical experts based on technical acceptance criteria. The number of application calls and the intensity of single-user calls are obtained through manual collation and acquisition.

4.2.2 Regression model and variables explanation

In order to verify the two hypotheses of this paper, this paper will be examined by constructing two regression equations. First, in analyzing the mechanism of the impact of different technological maturity on the network effect of open platform, this paper verifies hypothesis 1 through the construction of regression equation (1), and verifies hypothesis 2 through the construction of regression equation (2).

$$users_{i,t} = \alpha_0 + \alpha_1 maturity_{i,t} + \alpha_2 ARPU_{i,t} + \alpha_3 apps_{i,t} + \alpha_4 requests_{i,t} + \alpha_5 income_{i,t} + Month.t + \varepsilon_{i,t} \quad (1)$$

$$intensity_{i,t} = \beta_0 + \beta_1 maturity_{i,t} + \beta_2 ARPU_{i,t} + \beta_3 apps_{i,t} + \beta_4 requests_{i,t} + \beta_5 income_{i,t} + Month.t + \varepsilon_{i,t} \quad (2)$$

Among them, users in Eq. (1) represents the number of active users (i.e. developers) who produce corresponding calls for the ith technology capability, and this variable is used in this paper to measure the user activity brought by the technical capability of the open technology platform. The intensity in Eq. (2) represents the average actual call volume per user corresponding to the ith technology capability on the platform, and this variable measures the user's use stickiness and dependence on the platform, further verifying the network effect strength of the development platform as a technical platform, thus verifying that the network effect does not only depend on the installation base and user scale (Rietveld and Schilling, 2020).

Maturity refers to the technical maturity of an open technology platform's ability to open up to the outside world, with levels ranging from M1 to M4. The technical maturity is assigned values from 1 to 4 in descending order. According to the expert annotation system and standards, the existing technical capabilities of the open technology platform that are open to the outside world can be divided into five maturity states: M1 (laboratory state), M2 (close to usable state), M3 (basically usable state), M4 (verified usable state), and M5 (fully usable state). Considering that the types of technologies that have been put on the open technology platform for commercialization with the outside world have actually stepped out of the laboratory state and initially reached the usable state, that is, the M1 stage. Therefore, the technical maturity variable of the research model does not consider the laboratory state. This paper explains the technical maturity as follows:

M1 Approaching the state of readiness: In the M1 stage, the technology is in the process of being developed and there are some initial functional realizations, but further development and optimization is still required.

Although not yet at a fully usable level, the technology has shown promise and may already have attracted attention. At this stage, there are usually some prototypes or samples available to demonstrate the basic concepts and functionality of the technology. Users may be able to experience some core features, but there may still be some issues and limitations.

M2 Basic Available State: In the M2 stage, the technology has reached a basic available state, and the main functions have been realized and stabilized. Users can use the technology to complete core tasks, and serious problems will not be encountered during use. Although there may still be some minor issues and room for improvement, the technology has sufficient practicality. This stage is usually accompanied by formal testing and user feedback to ensure the stability and usability of the technology.

M3 verified available status: In the M3 stage, the technology has been fully tested and validated in different situations. All core functions are stable and reliable, and users can use the technology widely to solve problems in real environments. At this stage, user feedback and performance data are usually used to further optimize the technology and may introduce some additional functions and improvements. Documentation and support resources for the technology may also be strengthened to help users better use and understand the technology.

M4 Fully Available State: In the M4 stage, the technology has reached a fully available state where all functions are implemented and thoroughly tested. The technology performs well in multiple use cases and environments, and users can rely on it to meet their needs. In addition to basic functions, some advanced functions and enhanced features may be introduced to meet the needs of different users. At this stage, the stability, performance, and security of the technology have been fully verified, and there may be a wide user base.

The control variables and related measurement methods of this paper are: The number of apps invoked by each technology capability. The average revenue per user (ARPU). The number of requests for each technology capability. The monthly income of the platform. Month.i represents a time virtual variable, which can effectively eliminate the possible interference of time trends on the results and better analyze the impact of other variables on the target variable.

The related variables and specific measurement methods of the above equation are shown in Table 5.

Table 5 *Variable Definition*

Dependent Variable	User Activeness (users)	The number of active users or developers who invoked the item i technical capability produces
	User Stickiness (intensity)	The average actual number of calls per user for item i technical capability is used to measure the user usage stickiness, platform dependence, and further verify the network effect strength of the development platform as a technical platform.
Independent Variable	Technical Maturity (maturity)	The item i technical capability maturity, grade M1-M4, is assigned a value of 1-4 respectively
Control Variable	The Number of Calls To the Application (apps)	The number of application invocations corresponding to the ith technical capability
	Single User Contribution Revenue (ARPU)	Average revenue value contributed by each user
	Invocations (requests)	The Invocations Corresponding to the item i Technical Ability
	Platform Incom (income)	Platform metrics, referring to the total

		amount of revenue generated by each technical capability of the platform on average per month.
	Time Dummy Variable (Month.t)	Effective elimination of temporal trends may have a confounding effect on the results.

Stata 14 was used for the empirical part of the paper. The choice of Stata is as follows:

Powerful data processing capability: Stata can handle various types of data, including panel data, longitudinal data, cross-sectional data, etc. It has a rich set of data processing commands that allow for data cleaning, transformation, organization, and analysis.

Statistical analysis functions: Stata provides a wide range of statistical analysis functions, including descriptive statistics, hypothesis testing, variance analysis, regression analysis, covariance analysis, cluster analysis, time series analysis and so on. Users can input corresponding commands through the command interface to perform the analysis.

Plotting functions: Stata has built-in plotting tools that can create various types of charts and visualization effects, such as scatter plots, histograms, pie charts, box plots, fitted curves, etc. Users can conveniently use these tools for data visualization and presentation.

Programming power: Stata has powerful programming capabilities, and users can implement complex data processing and analysis tasks by writing scripts or programs. The programming language of Stata is concise and clear, making it easy to learn and use.

Stata is superior to statistical analysis software such as Matlab in handling large-scale data sets and performing complex statistical analyses, while Matlab has advantages in numerical calculation and matrix operations. Stata is mainly used in the fields of management science, economics, and statistics, while Matlab is more widely used in engineering, scientific computing, and other fields.

The operations involved and related instructions in Stata14 are as follows:

Prepare data: Prepare the data and ensure that it is clean, with no missing values or outliers.

Importing Data: Open Stata, click "File", then click "Open", select the data file, and click "Open". If the data is panel data, you need to use the command "tsset" to inform Stata first.

Data tidying: Use the command "describe" to view basic information about the data, such as the names, types, and missing values of variables. If you need to transform or organize the data, you can use commands like "gen", "rename", "drop", etc.

Constructing regression equation and dividing dependent variables and independent variables: Determine the dependent variable (explained variable) and independent variable (explanatory variable). The regression model between dependent variables, independent variables and control variables is established using the regression command “reg/xtreg/xtgls” and so on.

View regression results: Stata automatically displays regression results, including coefficients, standard errors, t-statistics, P values, and more. More detailed results can be viewed by using the commands estimates or margins.

Output Results: After obtaining satisfactory regression results, the results can be output to files or tables using commands such as "estout", "estimates", and "margins" for subsequent analysis or reporting.

4.3 Empirical results and analysis

4.3.1 Descriptive statistics

The descriptive statistics of the main variables in each model are shown in Table 6. The whole sample involves 126 technical capabilities, with a time span from 2017 to 2022 and a total number of samples of 3607. For each variable in the sample, the maximum value of users is 10534, the minimum value is 1, the standard deviation is 2076, the mean is 706.9, and the median is 45, which shows that there are significant differences in actual user activity among different technical capabilities. The maximum value of intensity is 1.110e+08, the minimum value is 1, the standard deviation is 9.356e+06, the mean is 1.697e+06, and the median is 5671, which further shows that based on the above differentiated user base and scale, there are also significant differences in user dependence and loyalty to the platform. In addition, the maturity level of technical maturity ranges from M1 to M4. From the descriptive statistical results, it can be known that the median of maturity is 3, which can be inferred that most of the capabilities on this technical platform tend to be mature, and the entire platform has also entered a stage where its development tends to be stable.

Table 6 *Sample Descriptive Statistics*

（From 2017 to 2022, spanning a period of 66 months, there were 126 technical capabilities assessed and a sample size of 3,607）

Variables	Mean	S.D.	Minimum	Maximum	Median
users	706.9	2076	1	10534	45
intensity	1.697e+06	9.356e+06	1	1.110e+08	5671
maturity	2.916	1.021	1	4	3
ARPU	7690	12144	28.05	146679	4518
apps	918.8	2845	1	16281	49
requests	2.350e+09	1.190e+10	1	1.310e+11	202734
income	1.382e+06	658073	253754	2.916e+06	1335372

Table 7 is the correlation matrix between the main variables, and the results of the Pearson correlation coefficient show that the correlation coefficients between the main variables are all below 0.6, which can be preliminarily judged that there is no multicollinearity among the variables.

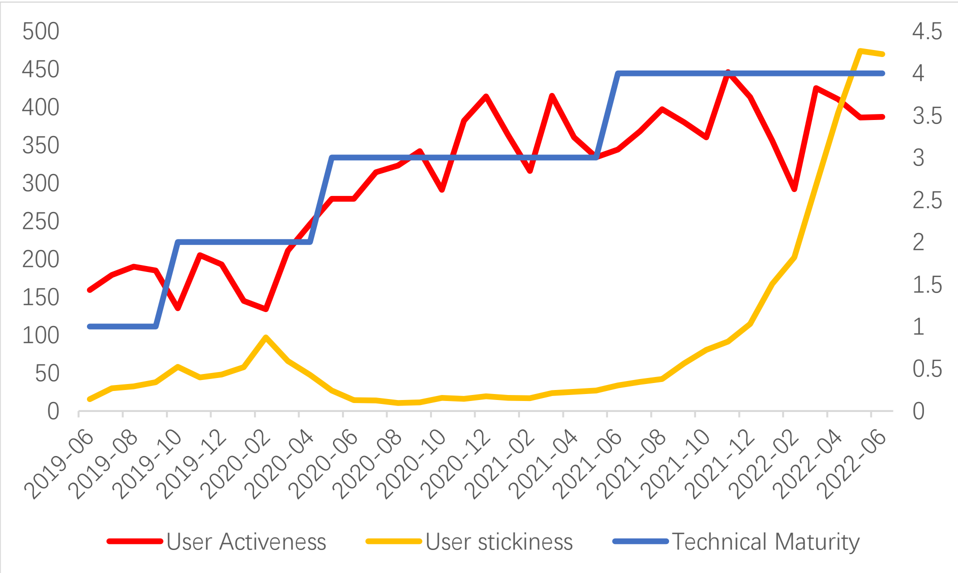
Table 7 *Matrix of Correlation Coefficients of Variables*

	users	intensity	maturity	ARPU	apps	requests	income
users	1						
intensity	0.0594*	1					
maturity	0.1257*	-0.0503*	1				
ARPU	0.1654*	0.1897*	-0.0418	1			
apps	0.2931*	0.0503*	0.1227*	0.1581*	1		
requests	0.2149*	0.4653*	-0.0360	0.1897*	0.2139*	1	
income	-0.1205*	-0.1316*	0.3790*	-0.1158*	-0.1241*	-0.1419*	1

In addition to the descriptive statistical results of Table 4.2, given that the platform has a profound foundation in technical directions such as speech, semantics, and natural language understanding, the study also conducts a preliminary analysis of relevant indicators for core technical capabilities representative of AI open technology platforms, including real-time speech transcription, online speech synthesis, machine translation, and lexical analysis (only partially demonstrated capabilities).

Real-time Speech Transcribing: As can be seen from the figure, with the advancement of technology maturity, user activity (number of active users) has steadily increased, while user stickiness (frequency of single user invocations) has accelerated after entering 2022. This may be related to the company's wide use of transcription capabilities by C-end users in intelligent hardware.

Figure 8 *Real-time Speech Transcribing: Technical Maturity and Active Users, User Stickiness*



Online Speech Synthesis: As the technology matures, user activity has risen with frequent fluctuations, not directly linearly correlated with technical maturity, while user stickiness has significantly increased. This indicates that the number of active users is gradually increasing, but the average amount used per user has significantly improved, reflecting that this technology capability is being used intensively by some developers.

Figure 9 *Online Speech Synthesis: Technical Maturity and Active Users*

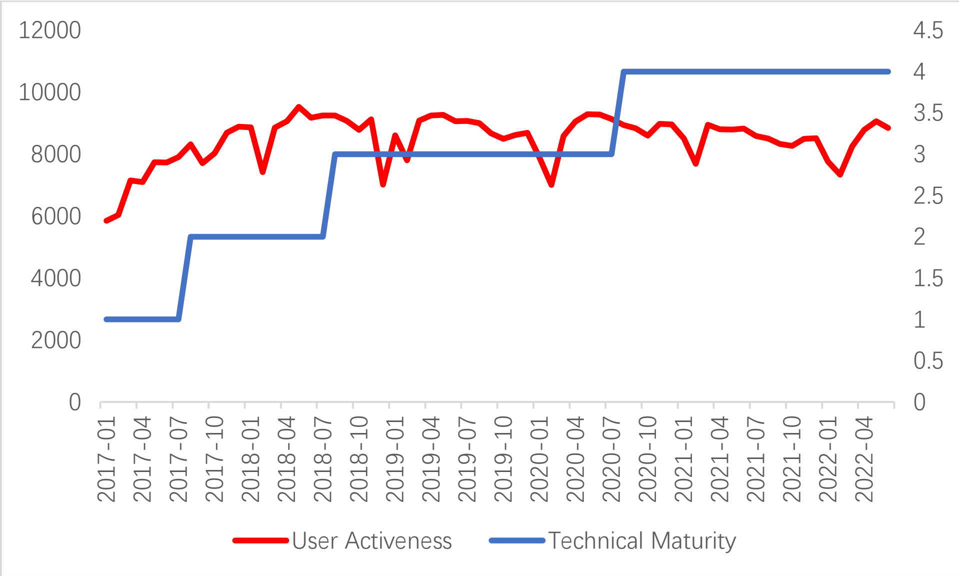
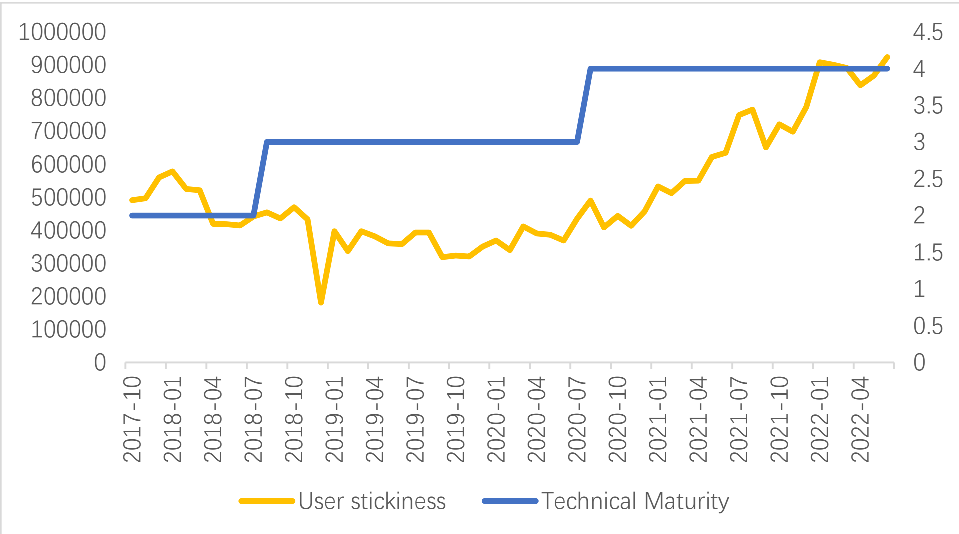


Figure 10 *Online Speech Synthesis: Technical Maturity and User Stickiness*



Machine Translation: As the maturity of the technology increases, the number of active users of this technical capability significantly rises. The frequency of user calls, or user stickiness, is in an unstable state of development. However, this technology entered the M3 stage earlier, and the fluctuations in user stickiness are not due to technical reasons but may be caused by market conditions.

Figure 11 *Machine Translation: Technical Maturity and ctive Users*

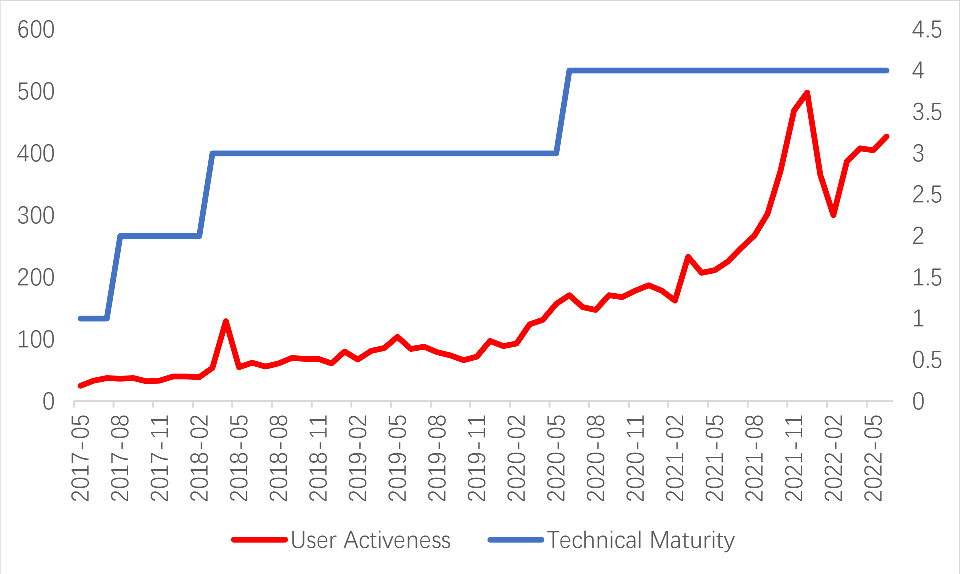
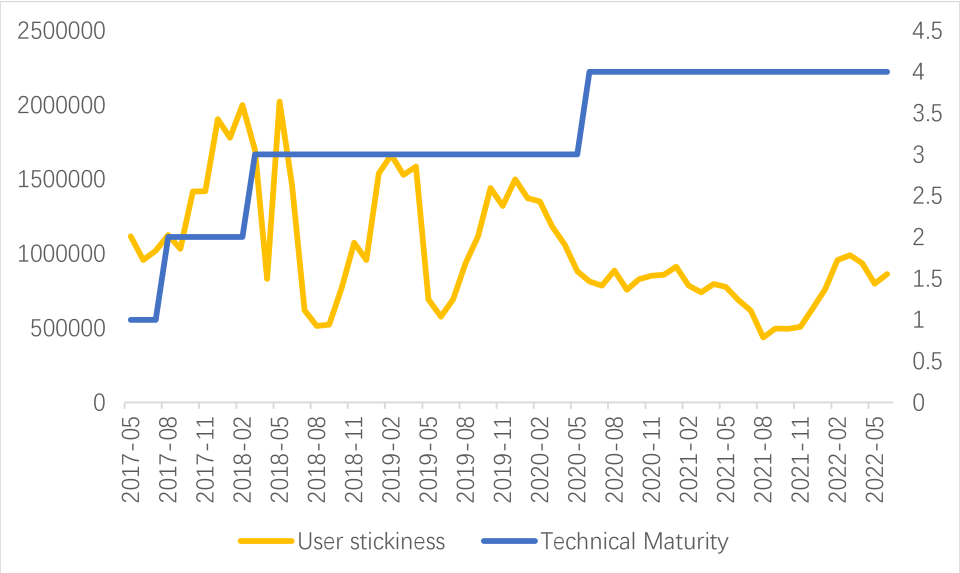


Figure 12 *Machine Translation: Technical Maturity and User Stickiness*



Lexical Analysis: Although the trend of active users has fluctuated, it is still in an overall state of improvement. User stickiness is rising within the vast majority of observation intervals. There was a certain degree of decline in the second half of 2021, followed by a subsequent upward boost.

Figure 13 *Lexical analysis: Technical Maturity and Active Users*

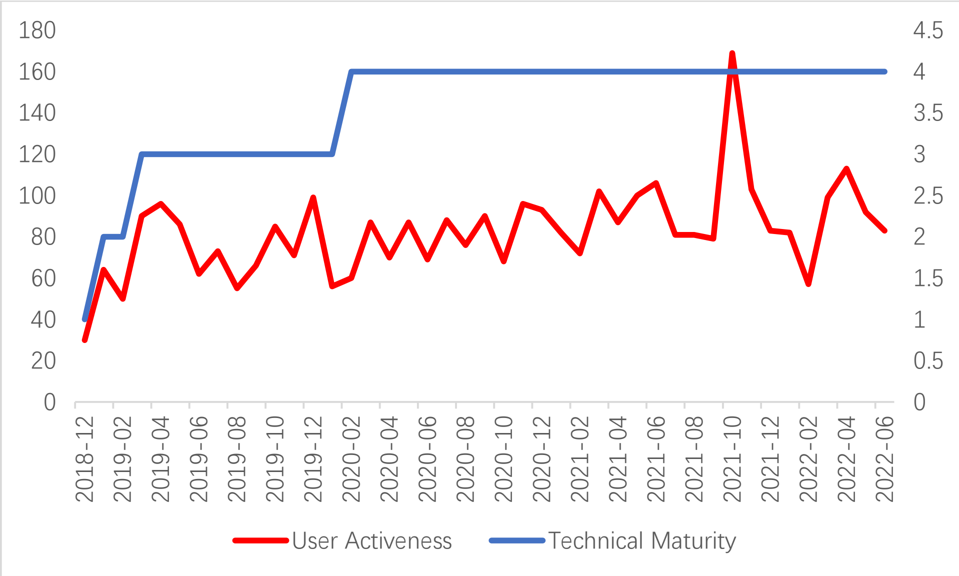
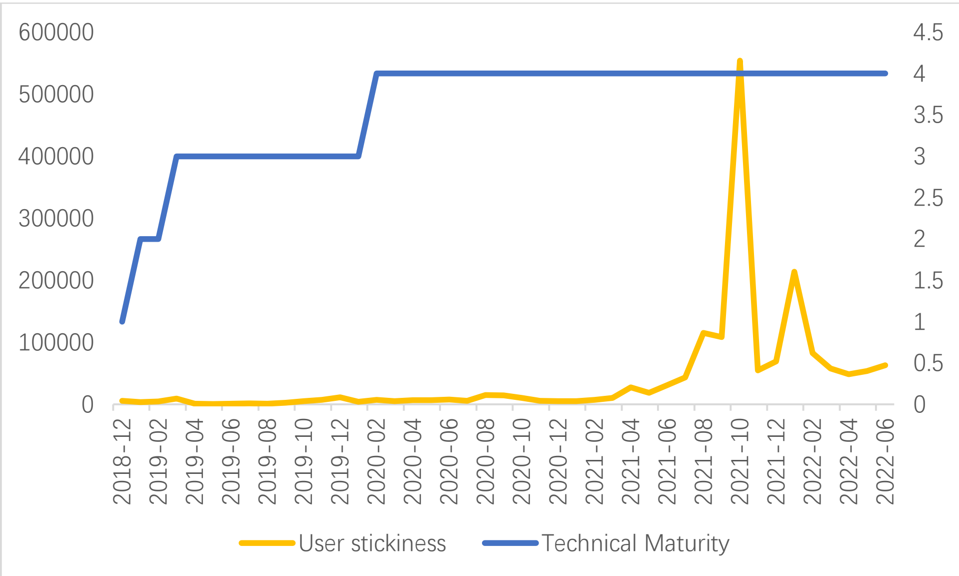


Figure 14 *Lexical analysis: Technical Maturity and User Stickiness*



4.3.2 Regression results

There are 3 regression models in this paper, and the regression results are shown in Table 8. The xtreg command in Stata is used to estimate the panel data model of this paper: The panel data model allows researchers to analyze the effects of individuals and time, as well as the interaction effect between individuals and time, thus providing a deeper understanding of the data; Using the xtreg command for regression analysis can help researchers better control the heterogeneity between individuals and provide a deeper insight into the dynamics of time, thereby more accurately evaluating the impact of explanatory variables on the dependent variable. Specifically:

The model (2) validates the result of regression equation (1), according to which the regression coefficient of maturity is positive, and the P value is 0.001 at the level of 1%, which is significant, indicating that with the improvement of technological maturity, user activity increases, network effect is enhanced, and hypothesis 1 of this paper is proved.

The model (4) validates the result of regression equation (2), which indicates that the regression coefficient of maturity is positive, and the P value is 0.001 at the level of 1%, which is significant. It can be seen that the improvement of technology maturity brings about the enhancement of user use stickiness, further validating the network effect strength of open technology platform itself, thus supporting hypothesis 2 in this paper.

Table 8 *Empirical Results*

Explanatory Variables	Model (1)	Model (2)	Model (3)	Model (4)
maturity		31.24***		0.0383***
		(5.975)		(0.0084)
ARPU	0.0046***	0.0041***	4.98e-06**	4.27e-06**
	(0.0012)	(0.0012)	(2.32e-06)	(2.11e-06)
apps	0.280***	0.713***	-7.52e-05***	-7.82e-05***
	(0.0409)	(0.0070)	(3.52e-06)	(3.64e-06)
requests	2.32e-08**	1.95e-09***	0.943***	0.948***

	(9.44e-09)	(2.79e-10)	(0.0109)	(0.0106)
income	-0.0024*	3.85e-06	5.58e-08	3.67e-08
	(0.0013)	(4.66e-05)	(1.10e-07)	(1.13e-07)
Month.i	YES	YES	YES	YES
N	477	475	477	475
R^2	0.2374	0.3168	0.3168	0.3340

Note. (1) *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively; (2) The parentheses indicate the standard error.

4.3.3 Robustness test

(1) Regression analysis for the two stages of business model exploration and ecological cultivation

From 2010 to 2014, developers oriented towards AAP were predominant. Despite a high willingness to pay, the lack of mature technology and difficulties in implementing applications led to poor survival conditions and limited ability to pay. In the second stage (2015-2018), also known as the "business model exploration period", most capabilities on open technology platforms have entered the phase of large-scale verification and subsequent availability, forming a leading industry status for related technologies such as voice, semantics, and natural language understanding on open technology platforms, bringing possibilities for application innovation. The platform also launched a traffic commercialization platform, attracting more developers with technical capabilities. The heterogeneity of developers has gradually evolved, and developers in this stage have significantly improved their abilities in terms of payment and risk resistance. Therefore, based on data from the second stage alone for empirical testing again, the robustness level can be verified. After analysis, it was found that the results of Model (2) and Model (4) still support the verified hypothesis.

As a comparison, we also conducted a regression analysis for the third stage, namely the "ecosystem cultivation phase". The regression results still support the above hypothesis and can alleviate the potential endogeneity problem in this paper to a certain extent.

After comparison, it is found that under the same dependent and explanatory variables, the regression coefficients of the two equations can be directly compared. In the regression results of the third stage of ecosystem cultivation phase (2019-2022), the regression coefficient of model (2) is 28.72, which is higher than that of model (2) in the regression results of the second stage of business model exploration period (2015-2018). This may indicate that in the third stage, the explanatory effect of technical maturity on the number of active users is stronger, and the positive impact of technical maturity in the third stage is more obvious, which is consistent with the previous argument that technical maturity consistently drives the network effect of platform users. In addition, the regression coefficients of models (4) are basically consistent, which means that the user use stickiness and user platform dependence effects brought by technical maturity in the second and third stages are consistent, further indicating that technical maturity has a positive network effect enhancement effect on both user activity and user use stickiness in the three stages of open platform development. This reflects that AI open platform as a technical platform is different from other open platforms, that is: The supply of technical platforms always pulls demand and meets demand, promoting the continuous upgrading and development of the platform.

Table 9 *Robustness Test (Business model exploration period, 2015-2018)*

Explanatory Variables	Model (1)	Model (2)	Model (3)	Model (4)
maturity		19.35**		0.0555**
		(9.226)		(0.0219)
ARPU	-0.002***	-0.0008	-3.49e-06	-2.09e-07
	(0.0005)	(0.0008)	(2.75e-06)	(2.97e-06)
apps	-5.958**	0.818***	0.0001***	0.888***
	(2.423)	(0.0229)	(5.06e-05)	(0.0076)
requests	4.73e-08**	5.32e-10**	0.842***	1.27e-06
	(2.33e-08)	(2.71e-10)	(0.0162)	(8.35e-07)
income	0.0196***	0.0002	2.32e-06***	0.0555**
	(0.0029)	(0.0002)	(8.48e-07)	(0.0219)
Month.i	YES	YES	YES	YES
N	43	43	43	43
R^2	0.2505	0.3415	0.2371	0.3714

Note. (1) *, ** and *** denote the significance level of 10%, 5% and 1%, respectively; (2) The standard error is in parentheses.

Table 10 *Robustness Test (Ecosystem cultivation phase, 2019-2022)*

Explanatory Variables	Model (1)	Model (2)	Model (3)	Model (4)
maturity		28.72***		0.0543***
		(6.262)		(0.0010)
ARPU	0.004***	0.0037***	5.51e-06**	3.45e-06
	(0.0013)	(0.0013)	(2.61e-06)	(2.77e-06)
apps	0.260***	0.709***	-0.0001***	-0.0001***
	(0.0422)	(0.0071)	(6.24e-06)	(6.32e-06)
requests	7.45e-08***	2.32e-09***	1.016***	1.019***
	(1.36e-08)	(5.31e-10)	(0.0122)	(0.0127)
income	-0.0033*	9.41e-06	-6.85e-08	-1.03e-07
	(0.0017)	(6.00e-05)	(1.01e-07)	(1.37e-07)
Month.i	YES	YES	YES	YES
N	434	432	434	432
R^2	0.2864	0.3612	0.2402	0.4123

Note. (1) *, ** and *** denote the significance level of 10%, 5% and 1%, respectively; (2) The standard error is in parentheses.

Furthermore, considering that developers are mainly concentrated in first-tier cities such as Beijing, Shanghai, Guangzhou, and Shenzhen, a regression analysis was conducted specifically for developers in these cities to eliminate the potential interference of location. The regression results still support the aforementioned hypothesis.

(2) Regression analysis for specific technical capabilities

This paper selects typical technical capabilities, including speech recognition, speech synthesis, natural language processing unfolding analysis. The regression results are as follows: The regression results show that whether it is speech recognition, speech synthesis or natural language processing, the technical maturity of these typical capabilities and user activity, user stickiness are positively correlated.

Table 11 *Robustness Test (Selected Technical Capabilities)*

	speech recognition		speech synthesis		speech synthesis	
	users	intensity	users	intensity	users	intensity
maturity	29.40**	0.196**	112.1*	0.189***	10.38***	0.296***
	(14.95)	(0.0971)	(167.2)	(0.0440)	(2.898)	(0.0312)
ARPU	-0.0036	6.92e-05***	-0.0118	-1.79e-05***	-0.000200*	5.11e-06***
	(0.0032)	(2.16e-05)	(0.00908)	(2.39e-06)	(0.000119)	(1.04e-06)
apps	0.631***	-0.000296***	0.840***	-7.55e-06***	0.904***	-0.00214***
	(0.0118)	(6.27e-05)	(0.0108)	(2.85e-06)	(0.0315)	(0.000338)
requests	2.35e-08**	1.336***	1.63e-08***	1.101***	-1.26e-07***	0.402***
	(9.46e-09)	(0.285)	(3.01e-09)	(0.0299)	(2.94e-08)	(0.0210)
income	-2.88e-05	-2.36e-07	0.000952**	2.62e-07***	5.11e-05***	-6.21e-07***
	(7.84e-05)	(4.53e-07)	(0.000376)	(9.89e-08)	(4.13e-06)	(4.54e-08)
Month.t	YES	YES	YES	YES	YES	YES
N	183	183	91	91	53	53

Note. (1) *, ** and *** denote the significance level of 10%, 5% and 1%, respectively; (2) The standard error is in parentheses.

4.4 Chapter summary

This chapter conducts empirical tests on the propositions in Section 3 regarding the exploration period of business models and ecological cultivation, as well as two hypotheses in Section 4, based on the backend data of the open technology platform for artificial intelligence. The conclusions are as follows:

(1) With the advancement of technological maturity, the number of active users corresponding to the technical capabilities on the open technology platform for artificial intelligence has significantly increased, reflecting that the network effect brought about by the user scale on this platform has been enhanced. (2) With the improvement of technological maturity, the intensity of single-user calls has increased, indicating that users' interaction with the platform, dependence on it, and usage stickiness have been strengthened, which will further reinforce the network effect of the platform.

Chapter 5

Conclusions and Prospects

5.1 Theoretical contributions

This research project on the open platform of artificial intelligence, based on the previous achievements in the theory of platform-based business models, systematically analyzes the impact factors brought about by the new technology variable of artificial intelligence on the platform business model. It is a supplement and extension to the platform business model. The specific theoretical contributions include the following aspects:

First, this paper verifies the relationship between the technical maturity of AI open technology platforms and network effects (user activity, user stickiness). Through research, it was found that the technical platform presents differentiated technical maturity at different stages, which has a positive effect on the stimulation, deepening, and expansion of network effects. This paper proposes three phases of the "Open Technology Platform Ecosystem (abbreviated as OTPE) life cycle": the capability building phase, the business model exploration phase, and the ecosystem cultivation phase. During the capability building phase, the types of technologies on the platform are relatively few, and some technologies still need continuous polishing in terms of usability, stability, and accuracy, belonging to an early stage of technical maturity; during the business model exploration phase, with the continuous improvement of various AI technologies in terms of technical maturity, the types of mutually supportive technologies are continuously enriched, bringing developers more choices in application innovation and better product experience, and developers and platforms jointly create commercial value; during the ecosystem cultivation phase, as the number of users of innovative applications created by developers continues to increase, and the flywheel effect of data and algorithms continues to strengthen, technologies related to perceptual intelligence on the platform (such as speech recognition, speech transcription, speech synthesis, machine translation, etc.) have reached a fully usable state in terms of technical maturity, better supporting developers' innovation. Moreover, the development threshold for capability users continues to decrease, the developer community continues to expand on the basis of being redefined, application scenarios continue to emerge, and new demands are put forward for new technologies. The levels of technical maturity and technological richness have attracted three different types of developers: experimental developers, commercial developers, and industry participants. Their risk avoidance, willingness to pay, and innovation preferences all show significant differences. They co-create value with the platform in the above three stages.

This means that the impact of technological platforms on network effects has two paths: firstly, technological maturity reflects the quality of platform development, and its improvement brings about an increase in user base and activity; secondly, developers, as complementors, have heterogeneity at different stages of platform development, which determines significant differences in risk preferences and behavioral patterns of technology adoption, and also has a profound impact on network effects. The research conclusions of this paper enrich the study of the platform economy, especially the research on network effects.

Secondly, the technical maturity consistently drives the network effect of platform users. That is, both in terms of user activity and user usage stickiness, it has a positive network effect enhancement effect in all three stages of open platform development. This reflects that the AI open platform, as a technical platform, is different from other open platforms. That is: the supply of the technical platform always pulls demand and meets demand, promoting the continuous upgrading and development of the platform.

In practice, this paper compares the differences between open technology platforms and other Internet commercial platforms, supplementing and improving the existing platform economy research on platform classification. In the practical dimension, three types of open technology platforms are proposed: traffic sharing platforms, OS-type open technology platforms, and technology engine-type open technology platforms. Among them, traffic sharing platforms and OS-type open technology platforms are demand-side traction platforms, while technology engine-type open technology platforms lead the technological innovation from the supply side. The technological innovations led by such platforms often have explosive, disruptive, and pioneering characteristics, meeting the needs of the transformation and upgrading of traditional industries in digitalization.

Academic definitions from previous scholars further validate the aforementioned viewpoints. Shi & Li (2021) believe that platforms can be divided into innovation platforms and trading platforms. Innovation platforms can be further categorized into technical platforms (Kyprianou, 2018), industry platforms (Gawer & Cusumano, 2002), and software platforms (Tiwana et al., 2010). Trading platforms typically include intermediary platforms (Evans & Schmalensee, 2016), multilateral platforms (Boudreau & Hagiu, 2009), sharing economy platforms (Constantiou, Marton, & Tuunainen, 2017), and peer-to-peer markets (Kyprianou, 2018). Through this study, it is found that open technology platforms belong to the type of technical platforms within innovation platforms. The similarity with software platforms lies in the fact that participants on the supply side of the platform are all developers with professional technical skills who use external parties to create value. The difference is:

The software platform is a scalable codebase based on the software system, which provides core functions shared by modules interacting with it. It is an extension of functions generated from requirements, and developers must have a deep understanding of the industry customer needs of the software (Tiwana et al., 2010). In terms of organizational structure, it belongs to the platform structure, with software companies as the main innovation entity, and developers and platforms are subordinate. However, open technology platforms belong to the Open/User Innovation structure. Although the platform still plays a coordinating role as a central organization, innovative activities no longer rely on the platform. Both the platform and developers jointly create network value for ecosystem construction. In contrast, open technology platforms focus on sharing technical cores. The developers' cognitive and developmental abilities in their respective fields are crucial.

With the maturity of artificial intelligence technology, the heterogeneity of developers changes, the network effect of the platform continues to deepen, and the form of the platform continues to evolve. This has been verified in the cases and empirical research in this paper. At present, there is no research showing that software platforms also have a similar evolution logic.

Standardised, modular interfaces such as USB ports, TCP/IP protocols and application programming interfaces in each of the technological platforms, especially in each of the open technological platforms enable products and services to be broken down into smaller parts through standardised and open interfaces, enabling many different specialist producers to contribute to a collective product almost seamlessly thereby facilitating and encouraging growth of platforms and ecosystems (Baldwin & Clark, 2000; Furlan et al., 2014; Pil & Cohen, 2006).

Thirdly, this paper provides relevant definitions for the maturity of artificial intelligence technology, which is also of significant reference value for enriching related measurements. Unlike measuring the maturity of emerging technologies through media attention, this paper draws on the approach of the U.S. Space Agency's TRL (Technology Readiness Level/Technology Proficiency Grade) to measure technological maturity and proposes that the maturity of artificial intelligence technology can be divided into five maturity states: laboratory state, near-ready state, basic usable state, verified usable state, and fully usable state.

Fourthly, previous studies on value co-creation have mainly focused on e-commerce platforms, travel platforms, and other aggregate traffic platforms as research subjects. This paper breaks through the "production-led logic" and "customer-led logic" of the "customer-enterprise" dual interaction in the platform economy. For the first time, by studying the dynamic and diverse relationships of "platform-product service provider-customer", it verifies the dynamic co-creation mechanism of commercial and social values of artificial intelligence open technology platforms, and develops the multi-network relationship research of value co-creation "service ecosystem".

The study found that, on the one hand, the network platform economy reshapes the subject relationship of value co-creation, and gradually forms a "platform-developer-user" connection among participants. That is, open technology platforms no longer act as providers of production and services, but become true empowering platforms. The developer community also plays the dual roles of product providers and platform users. On the other hand, in different stages of platform development (i.e., "capacity building phase", "business model exploration phase", "ecological cultivation phase"), there are different value co-creation structures and mechanisms, and the relationships and connections between participants are changing. This indicates that the value co-creation of the platform economy is a dynamic process (Agrawal et al., 2015). Therefore, the theoretical perspective of value co-creation has evolved from co-production and customer experience to service ecology. In terms of multilateral relationship interactions, the binary relationship between enterprises and customers is gradually transforming into a dynamic network with the participation of different stakeholders. The value co-created by all participants on the platform is evolving from exchange value to platform ecological value and social value.

5.2 Practice insights

First, the advancement of technical maturity will significantly increase user activity and the enhancement of usage stickiness. This implies that, in the current context where cognitive intelligence large models have profoundly transformed production efficiency across various industries, accelerating the maturation of new technologies is of great significance for enhancing the network effects of each platform.

Secondly, in the era of the platform economy, the roles of various participants in value co-creation have become diversified, and frequent transitions between roles are occurring, with increasingly blurred boundaries. Companies are no longer the dominant figures in the value co-creation process within traditional value chains, but have become ecosystem builders that stimulate and promote platform value creation. Therefore, companies need to change their development approach, shifting from attracting customers to participate in the co-creation process to building ecosystems, forming and solidifying a system environment conducive for all participants to realize dynamic value.

Thirdly, given the absence of rigorous academic research on open technology platforms and ecosystems both domestically and internationally, this case study of the XF AI open platform and its ecosystem can help relevant practitioners deeply understand the evolution and development of open technology platforms from the perspectives of business logic and technical logic of system ecology, as well as their positive impact in the process of AI industrialization. The development path and growth curve of the XF AI open platform represent the "open collaborative innovation" of open technology platforms, providing a typical paradigm for the phased development of AI open technology platforms through the "capacity building period", "business model exploration period", and "ecosystem cultivation period", which is worth learning and drawing lessons from for domestic open technology platforms.

5.3 Research deficiency and future perspectives

First, this study requires a large amount of internal operational data from artificial intelligence open platforms. Currently, this research only covers the XF artificial intelligence open platform. Due to the constraints of the openness of operational data from major internet companies' artificial intelligence open platforms, this research cannot conduct a systematic horizontal comparison analysis of data from various domestic and foreign artificial intelligence open platforms. Therefore, the conclusions drawn from the research need further verification in the commercial practices of other artificial intelligence open platforms across the industry. This is the biggest regret of this research project.

Looking at existing research, many studies in the field of platform economy both domestically and abroad are limited by data acquisition, unable to conduct detailed empirical analysis. Future research can consider conducting comparative studies based on artificial intelligence open technology platforms from multiple companies under the same theme, thereby further verifying the proposition hypothesis proposed in this paper.

Second, the number of existing variables in XF open platform is small, and the dimension of unfolding analysis is dominated by main effects, so this paper combines the case of XF open platform development to unfold the argument. In the future, with the continuous enrichment of data dashboard indicators, it can be tried to carry out analyses such as situational moderation role, mediation role, etc. More valuable conclusions can be obtained.

Third, the technology maturity plays a role in each stage, and without considering new technologies of large models, many technology maturities of the third stage are more inclined to be verified available or reach the fully available state, and there may be inconsistencies in technology maturity. To explain this problem, this paper is also illustrated in the robustness test, and the regression coefficient of the third stage is slightly stronger than that of the second stage, which may mean that the impact of technology maturity on user activity and user stickiness has persistence.

Fourth, at the stage where large models become a new breakthrough in artificial intelligence technology, new technologies are emerging continuously, R&D thresholds are constantly lowering, and the number of developers is achieving rapid growth with the lowering of R&D thresholds. The continuous breakthrough of large model innovation has the potential to bring profound changes to the business model of open platforms, which is worth the continuous observation and research of scholars in related fields in the next 10 years.

Since 2022, the wave of cognitive intelligence large language models ignited by American high-tech companies has profoundly impacted the ecological development of open technology platforms. On November 30, 2022, the American artificial intelligence research company OpenAI released ChatGPT; on February 3, 2023, ChatGPT reached over 100 million monthly active users in its 60th day of operation, and New Bing integrated with ChatGPT reached over 100 million daily active users in just one month, becoming the fastest growing internet application product in history. On March 15, OpenAI announced the release of the large multimodal model GPT-4, which Microsoft sees as an early version of general artificial intelligence. On March 24, OpenAI announced that it would open up the API of the ChatGPT model, allowing developers to integrate ChatGPT into their own applications and services through the API, and can also integrate third-party plugins. In his developer conference, Jensen Huang, CEO of NVIDIA, compared ChatGPT with the iPhone, calling it the "iPhone moment" of artificial intelligence.

On May 6, 2023, XF released the XF Spark large model and upgraded it twice consecutively on June 9 and August 15. XF provides developers with development interfaces, allowing them to create AI applications with cross-domain knowledge and powerful natural language understanding capabilities at low cost and high efficiency. At the same time, they can also build Spark assistants covering various fields such as marketing, learning, and programming through simple natural language instructions. This means that ordinary users can also become developers by using appropriate questions to contribute creatively to the creation of AI applications, and the developer community is gradually moving from a professional role to mass popularity. At a stage where large models have become a new breakthrough in AI technology, new technologies are constantly emerging, research and development thresholds are constantly lowering, and the number of developers is rapidly increasing as research and development thresholds decrease. The breakthroughs of these technological innovation variables may bring profound changes to the business model of open platforms, which are worth observing and researching by scholars in related fields for the next 10 years.

References

Agrawal, A. K., Kaushik, A. K., & Rahman, Z. (2015). Co-creation of social value through integration of stakeholders. *Procedia-Social and Behavioral Sciences, 189*, 442-448.

Ahmed, M., & Hossain, M. A. (2014). Cloud computing and security issues in the cloud. *International Journal of Network Security & Its Applications, 6*(1), 25.

Albuquerque Jr, L. F., Ferraz, F. S., & Oliveira, R. F. (2017). Function-as-a-service x platform-as-a-service towards a comparative study on Faas and Paas. *ICSEA*, 206-212.

Aldahwan, N. S., & Ramzan, M. S. (2022). Descriptive literature review and classification of community cloud computing research. *Scientific Programming, 123*,190-220.

Alkawsi, G. A., Mahmood, A. K., & Baashar, Y. M. (2015). Factors influencing the adoption of cloud computing in SME: A systematic review. *International Symposium on Mathematical Sciences and Computing Research (iSMSC). IEEE*, 220-225.

Chak, Y. N., & Rana, M. E. (2021). A theoretical review of cloud computing services in big data analytics 2021 international conference on data analytics for business and industry (ICDABI). *IEEE, 2021*, 76-83.

Chang, V., Wills, G., & De Roure, D. (2010). A review of cloud business models and sustainability. *2010 IEEE 3rd International Conference on Cloud Computing. IEEE*, 43-50.

Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal, 35*(1), 1-23.

Choi, J. P. (1994). Network externality, compatibility choice, and planned obsolescence. *The Journal of Industrial Economics, 42*, 167-182

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review, 4*(4), 532-550.

Esposito, C., Castiglione, A., & Pop, F. (2017). Challenges of connecting edge and cloud computing: a security and forensic perspective. *IEEE Cloud Computing, 4*(2), 13-17.

Farrell, J., & Saloner, G. (1992). Converters, compatibility, and the control of interfaces. *Journal of Industrial Economics, 40*, 9-35.

Gawer. A, & Cusumano, M. A. (2014). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management, 31*(3), 417-434.

Goyal, S. (2013). Software as a service, platform as a service, infrastructure as a service——a review. *International Journal of Computer Science & Network Solutions, 1*(3) 53-67.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review, 46*(3), 534–551.

Hoberg, P., Wollersheim, J., & Krcmar, H. (2012). The business perspective on cloud computing. *Literature Review of Research on Cloud Computing. 2012*.

Li, P., Zhou, R., & Xiong, Y. (2020). Can ESG performance affect bond default rate? Evidence from China. *Sustainability, 12*.

Li, S., Song, X.，& Wu, H. (2015). Political connection，ownership Structure，and corporate philanthropy in China：A strategic-political perspective. *Journal of Business Ethics，129*(2), 399-411.

Liu, X. (2019). The role of enterprise risk management in sustainable decision-making: a cross-cultural comparison. *Sustainability, 11*.

Kim, M. C.， & Kim, Y. H. (2014). Corporate social responsibility and shareholder value of restaurant firms. *International Journal of Hospitality Management, 40*, 120-129.

Kohli, R. & Grover, V. (2008). Business value of it: an essay on expanding research directions to keep up with the times. *Journal of the Association for Information Systems, 9*(1), 23-39.

Kuhn, T. S. (1962). The structure of scientific revolutions. *Chicago: University of Chicago Press*.

Kyprianou, C. (2018). Creating value from the outside in or the inside out: How nascent intermediaries build peer-topeer marketplaces. *Academy of Management Discoveries, 4*, 336-370

Li, Z. W. (2014). The role of quantitative and qualitative network effects in B2B platform competition. *Managerial and Decision Economics, 35*, 1-19.

Lins, S., Pandl, K. D., & Teigeler, H. (2021). Artificial intelligence as a Service. *Business & Information Systems Engineering, 63*(4), 441-456.

Makni, R., Francoeur, C. & Bellavance, F. (2009). Causality between corporate social performance and financial performance: evidence from Canadian firms. *Journal of Business Ethics, 189*, 409-422.

Malin, H. N., & Tomas, B. (2015). Co-creation as a strategy for program management. *International Journal of Managing Projects in Business, 8(*1), 58-73.

Margolis, J., Walsh, J., & Misery. (2003). loves companies: rethinking social initiatives by business. *Administrative Science Quarterly-ADMIN SCI QUART, 48*, 268-305.

Matutes, C., & Regibeau, P. (1988). “Mix and match”: product compatibility without network externalities. *The RAND Journal of Economics, 19*: 221-234

Mcwilliams, A., & Siegel, D. (2001). Corporate social responsibility：A theory of the firm perspective. *Academy of Management Review, 26*(1), 117-127.

Menon, B., Krkkinen, L. & Wuest, O. (2020). Industrial internet platform provider and end-user perceptions of platform openness impacts. *Industry and Innovation, 7*(4), 363-389.

Metrick, A., Gompers, P. A， & Ishii, J. L. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics, 118*(1), 107-156.

Mitchell, R. K., & Agle, B. (1997). Toward a theory of stakeholder identification and salience: defining the principle of who and what really counts. *Academy of Management Review, 22*(4), 853-886.

Minutolo, M. C., Kristjanpoller, W. D., & Stakeley, J. (2019). Exploring environmental, social, and governance disclosure effects on the S&P 500 financial performance. *Business Strategy and the Environment, 6*(89).

Moore, H. J. (1990). Property Rights and the Nature of the Firm. *Journal of Political Economy, 98*(6), 1119-1158.

Nelson, R., & Winter, S. G. (1977). Research of a useful theory of innovation. *Research Policy, (5),* 36-76.

Nelson, S. & Winter, L. (1982). An evolutional theory of economic change. *Harvard University Press.*

Nudurupati, S. S.，Bhattacharya, A.， Lascelles, D.，& Caton, N. (2015). “Strategic sourcing with multi- stakeholders through value co-creation：an evidence from global health care company” . *International Journal of Production Economics, 166*, 248-257.

Palumbo, R. (2016). Contextualizing co-production of health care: a systematic literature review. *International Journal of Public Sector Management, 29*(1), 72-90.

Pamaswamy, V., & Gouillart, F. (2010). The power of co-creation: built it with them to boost growth, *Productivity and Profits. Free Press*.

Pinho, N.，Beirão G., & Patrício L. (2014). Understanding value co-creation in complex services with many actors. *Journal of Service Management*, *25*(4), 470-493.
Prahalad, C. K., & Ramaswamy, V. (2000). Co-opting customer competence. *Harvard Business Review*, *25*(1).
Prahalad, C. K., & Ramaswamy, V. (2004). Co-creating unique value with customers. *Strategy and Leadership*, 32(3), 4-9.
Rashid, A., & Chaturvedi, A. (2019). Cloud computing characteristics and services a brief review. *International Journal of Computer Sciences and Engineering*, 7(2), 421-426.
Reim, W., Åström, J., & Eriksson, O. (2020). Implementation of artificial intelligence (AI) a roadmap for business model innovation. *AI*, *1*(2), 180-191.
Revelli, C., & Viviani, J. L. (2015). Financial performance of socially responsible investing (SRI): what have we learned? A meta-analysis. *Business Ethics A European Review*, *24* (2), 158-185.
Rong, K., Lin, Y., Shi, Y., & Yu, J. (2013). Linking business ecosystem lifecycle with platform strategy: a triple view of technology, application and organisation. *International journal of technology management*, *62*(1), 75-94.
Ross. P, K, & Blumenstein, M. (2015). Cloud computing as a facilitator of SME entrepreneurship. *Technology Analysis & Strategic Management*, *27*(1), 87-101.
Sassen, R.，Hinze, A. K.，& Hardeck, I. (2016). Impact of ESG factors on firm risk in Europe. *Journal of Business Economics*, *86*(8), 867-904.
Schilling, M. A. (1998). Technological lockout: An integrative model of the economic and strategic factors driving technology success and failure. *Academy of Management Review*, *23*, 267-284.
Schilling, M. A. (2000). Toward a general modular systems theory and its application to interfirm product modularity. *Academy of Management Review*, *25*, 312-334
Senyo, P. K, Addae, E., & Boateng, R. (2018). Cloud computing research A review of research themes, frameworks, methods and future research directions. *International Journal of Information Management*, *38*(1), 128-139.
Shetty, J. P., & Panda, R. (2021). An overview of cloud computing in SMEs. *Journal of Global Entrepreneurship Research*, *21*.1-14.
Shi, X., Li, F., & Chumnumpan, P. (2021). Platform Development Emerging Insights from a Nascent Industry. *Journal of Management*, *47*(8), 2037–2073.
Song, H., Zhao, C.，& Zeng, J. (2017). Can environmental management improve financial performance: an empirical study of a-shares listed companies in China. *Journal of Cleaner Production*, *141*(10), 1051-1056.
Stabell, C. B., & Fjeldstad, O. D. (1998). Configuring value for competitive advantage: on chains, shops and networks. *Strategic Management Journal*, *19*(5).
Stieninger, M., & Nedbal, D. (2014). Characteristics of cloud computing in the business context a systematic literature review. *Global Journal of Flexible Systems Management*, *15*(1), 59-68.
Surroca, J., Trib, J. A., & Waddock, S. (2010). Corporate responsibility and financial performance: the role of in-tangible resources. *Strategic Management Journal*, *31*(5), 463-490.
Susanto, H., Almunawar, M. N., & Kang, C. (2012). A review of cloud computing evolution individual and business perspective. *Available at SSRN*, *123*.
Tee, R. & Gawer, A. (2009). Industry architecture as a determinant of successful platform strategies: a case study of the i-mode mobile Internet service. *European Management Review*.
Tiwana, A., Konsynski, B., & Bush, A. A. (2010). Platform evolution Coevolution of platform architecture, governance, and environmental dynamics. *Information*

Systems Research, *21*, 675-687.
Vance, S. C. (1975). Are socially responsible corporations good investment risks?. *Management Review, 64*(8), 19-24.
Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. *Journal of Marketing, 68*(1), 1-17.
Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: continuing the evolution. *Journal of the Academy of Marketing Science, 36*(1), 1-10.
Weber, O. (2014). Environmental, social and governance reporting in China. *Business Strategy and the Environment, 23*(5), 303-317.
William, J. & Abernathy, M. (1978). Patterns of industrial innovation. *Technology review, 19*, 40-47.
Zhang, F., Qin, X., & Liu, L. (2020). The Interaction effect between ESG and green innovation and its impact on firm value from the perspective of information disclosure. *Sustainability, 12*(5), 1866.
Zhang, M., Zhao, X., & Voss, C. (2016). Innovating through services, co-creation and supplier integration: cases from China. *International Journal of Production Economics, 171(*2), 289-300.