RESEARCH ON DIGITAL TRANSFORMATION OF SMALL AND MEDIUM-SIZED ENTERPRISE

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Research on Digital Transformation of Small and Medium-sized Enterprises

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1 Introduction

1.1 Research background and problem formulation

1.1.1 Research Background

As we enter the 21st century, a new generation of information technology, energy technology and materials technology are leading the way to technological breakthroughs in multiple industries, ultimately driving new changes in industrial and business models. Tracing the history of enterprise development since the industrial revolution, it is evident that each technological change has fundamentally led to a significant increase in productivity. Especially in recent years, with the development of the digital economy, data has become an extremely strategic element for enterprises. In 2020, the Opinions of the State Council of the Central Committee of the Communist Party of China on Building a More Perfect Institutional Mechanism for Market-based Allocation of Factors wrote data as a new type of production factor into the document, which has important implications for the entire economy and society, including every enterprise, reflecting the new features of the Internet big data era. With the accelerated application of a new generation of information technologies such as big data, artificial intelligence, mobile internet and cloud computing, 5G, industrial internet and internet of things, unlike the previous agricultural and industrial economies, the arrival of the digital economy has changed the previous model of using only land, labour and capital as key factors of production, and data is also included in the category of factors of production. Ma Tao (2019) proposes that data has the endowment of being replicable, shareable, wirelessly growing and wirelessly supplied, and that massive, dynamic, high-growth, diversified and diverse data can become big data with stronger decision-making power, insight discovery and process optimisation capabilities through the collection, screening, processing and handling of information technology. Data is applied to industries in a multi-dimensional and multi-layered manner, magnifying productivity multipliers and creating more value than ever before, while greatly reducing costs of all kinds and making value creation more efficient.

Advanced enterprises have achieved effective embedding of data elements from product design, production, distribution and the financial activities involved, and effective integration through information integration platforms to promote precision and data between equipment operation, raw
material and component procurement, product production and sales. With the new round of industrial revolution, the development of the Internet of Things, data platforms and intelligent production is increasingly characterised by data having become a core resource. By integrating and analysing manufacturing data, product parameter data, order data and machine operation data, production control can be made efficient and accurate, costs can be effectively controlled, and production can be made more flexible and resilient. On the other hand, by promoting a data-driven supply chain and establishing a cross-organisational e-commerce platform, multi-organisational collaborative design and operation can be driven to enhance the agility of business operations. The scale of data is getting bigger and bigger, and the connotations and extensions of data are expanding. While stimulating the competitiveness of enterprises, data is also bringing new production and business models and even disruptive changes to various industries.

For enterprises, data has penetrated into the entire enterprise process, from product design, raw material procurement, production and processing, operation and management, product sales, after-sales service and other aspects, data links the entire value chain of suppliers, partner companies and customers. In the context of data elements, how to effectively capture, perceive, mine and integrate customer needs and potential demand information, and on this basis respond to market changes, determines whether an enterprise is adapted to the digital economy. The core task of enterprises lies in creating the ability to face customer needs, sense changes in customer demand and respond to changes in a timely manner, to improve organisational agility by integrating sales data and supplier data, to adjust production plans, inventory cycles and scales, to provide personalised and customised products for the market and to pinpoint customers. Based on the Internet platform, we can profile consumer behaviour and transform this profile into accurate product demand, which is then transformed into an efficient R&D system for new products, and further into a flexible production system, an agile supply chain system and a territory-wide accurate marketing system. In the enterprise production process, the data generated by the enterprise machinery and equipment can be collected through the cloud to achieve real-time perception of equipment failure, remote diagnosis and prediction of failure, coordination of repair or maintenance time, and optimisation of process control.

At present, the external market factors faced by enterprises have changed dramatically, the most obvious is the vague and variable demand, that is, enterprises are facing the VUCA era (volatility, uncertainty, complexity, vagueness), it is difficult for enterprises to produce a few
products through the traditional rhythm to keep occupying the market, which has put forward higher requirements for enterprises, if the precise grasp of the changing needs of consumers, how to provide better products than competitors. In 2013, Germany launched its "Industry 4.0" national strategy at the Hannover Messe, which is considered to be the beginning of the fourth industrial revolution, and since then the world's major economies have developed a new round of industrial revolution from their own resources. Digital transformation is a major trend in the development of the world economy, and the digital economy will become an important engine to drive high-quality economic development, and the speed of digital transformation in various industries will be greatly accelerated.

The State-owned Assets Supervision and Administration Commission of the State Council issued the Notice on Accelerating the Digital Transformation of State-owned Enterprises, systematically clarifying the basis, direction, focus and initiatives of the digital transformation of state-owned enterprises, opening a new chapter of digital transformation of state-owned enterprises, actively guiding state-owned enterprises to accurately understand changes, scientifically adapt and actively seek changes in the era of digital economy, accelerating the transformation and upgrading of traditional kinetic energy and cultivating new kinetic energy for development. It is proposed that the new round of technological revolution and industrial change is developing rapidly, and the global economy is in an unprecedented period of change of track, enterprises should take the initiative to grasp and lead the new generation of information technology change trend. It was further pointed out that digital transformation is an important engine for high-quality enterprise development, and that the digital economy represents the future direction of economic development and has become a core element of economic growth and a key area of enterprise competition. Accelerating digital transformation will accelerate new technological innovation, new product cultivation, new model proliferation and new industry development, and promote the industry to the middle and high end of the global value chain. It can be seen that digital transformation is in response to the changing trends of the new round of technological and industrial revolution, constantly using new generation information technology such as big data, smart devices, mobile internet, cloud computing and blockchain to bring into play data elements to drive enterprise innovation and value creation, enhance the ability of enterprises to survive and develop in the digital economy, accelerate the upgrading and optimisation of their business and cultivate new momentum for development.

Today, 70% of enterprises worldwide have started their digital transformation and 37% of enterprises have utilised IT technology, highlighting the role of new generation information
technology in improving enterprise productivity multipliers. Based on industrial cloud platforms and cloud services have become the main support model for promoting the integration of the Internet and manufacturing industries. Putting manufacturing on the cloud enables enterprises to focus on generating differentiated products and generating core competitiveness, using cloud computing technology to move traditional supply chains to cloud platforms, redesigning and integrating supply chain information resources, and achieving optimisation goals through effective cloud collaboration. A large amount of equipment data from manufacturing will be collected and integrated to build industrial manufacturing process mapping, promote the digitisation of the production operation process and form modern advanced production systems such as smart workshops and smart factories. Data mining will be carried out on management data to improve enterprise management decisions and reduce operating costs through data-driven synergy of people, machines and materials. Through big data to improve the added value of products, the manufacturing production model will be transformed to a personalised customisation model, promoting the generation of new business models. The 19th Party Congress report proposes to "accelerate the building of a strong manufacturing nation, accelerate the development of advanced manufacturing industries, and promote the deep integration of the Internet, big data, artificial intelligence and the real economy", which points the way for the development of digital transformation of China's manufacturing industry. Digital transformation is the starting point for many enterprises to reduce operating costs, improve operational efficiency and enhance market competitiveness, and the achievement of these goals is particularly dependent on the data element as a major driving factor. The data element has been introduced as a national strategy, representing a shift in the way the economy thinks and driving companies towards a high-quality and sustainable development model through digital transformation. There are various types of data in business operations from design, research and development, production and marketing, all the way to the user use process, and the effective embedding of data responds to different application scenarios, and companies must develop the ability to apply data elements to match them. Therefore, it is necessary to sort out the technical logic and economic logic of the digital transformation of enterprises driven by new generation information technology from the theoretical, case and empirical perspectives, to comprehensively explain the mechanism of digital transformation to promote the realisation of enterprise value creation, and to deeply analyse the methods, modes and trends of digital transformation of enterprises today.
1.1.2 Questions

Digital transformation is an important way for enterprises in China to improve the quality and operational efficiency of their products or services. In order to promote the digital transformation of enterprises, the national level has also continued to improve the institutional environment and issued a series of documents and policies to promote the continuous improvement of the digital level of enterprises. Although more and more enterprises realize the importance of digital transformation, they still face many obstacles when implementing digital transformation, mainly including organizational inertia, employee resistance, insufficient leadership and conflicting needs. Specifically, organizational inertia portrays the degree of stickiness of the organization being reformed, mostly from path dependency. When the environment changes, managers tend to leverage prior experience rather than make unfamiliar choices that might enable change, so inertia can cause a mismatch between the organization and the environment and reduce operational efficiency. Employee resistance refers to the lack of visibility into the benefits when digital technologies are introduced in an organization, and certain employees can show behavioral resistance and refuse to accept the new. Leadership deficit refers to the lack of digital experience, as well as vision and direction, in the executive team. Conflicting demands refer to a series of conflicts between traditional ways of working and new ways of working. Currently, it has become the mission of enterprises to seize the opportunities of digitalization, further embed data elements and make full use of the advantages brought by the digital economy, in which digital transformation has become the focus of attention of various industries, and also brings the following problems.

Enterprise digital transformation is system-oriented and application-light. The key to digital transformation is not how much digital technology has been purchased and how many system platforms have been built, but whether digitalization can be embedded into the core business of the enterprise and drive organizational change through technology plus capability, so that the enterprise has market-oriented agility and adaptability. With the acceleration of digital transformation, many enterprises ignore digital capability or fail to form digital capability construction goals in the early stage of digital transformation, have no unified cognition of strategic planning and implementation steps of digital transformation, lack systematic construction ideas, poor communication channels of enterprise information, and employees have no confidence in effective implementation of digital transformation. Therefore, when the digital transformation of the enterprise really reaches the
implementation stage and enters the attack stage, the short board effect will immediately appear, and finally affect the effect of digital transformation.

Enterprise is a system of creating, delivering, supporting and acquiring value, every digital transformation activity should be carried out around value creation, digital transformation is fundamentally to promote the optimization, innovation and reconstruction of enterprise value system, continuously create new value and develop new dynamic energy. Digital transformation of enterprises is not only the use of technology, but also the transformation of the overall enterprise model, which requires the reconstruction of enterprise value concept, production process, organizational structure and management mode. Under the digital business model and production operation model, data has become the most core element of the enterprise, which brings huge conversion drive to the enterprise strategy, operation and decision making, etc. For enterprises that are expecting digital production and operation and digital business model, they must plan and design the digital capability that matches the enterprise to ensure the development of digital transformation.

Digital transformation is a re-cognition and re-adaptation of a company's strategy and structure based on digital technology. From a cognitive perspective, its success depends not only on the ability to build new structures, but also on the ability to transfer them vertically across levels. Meaning construction theory explains the formation and interaction process of strategic cognition, and there are two core concepts: sensemaking and sensegiving. Meaning construction is the process of recognizing the situation, forming understanding and reconstructing meaning by actors, including organizations and individuals. Meaning construction is the basis of individual decision making and the main form of organizational cognition. In change, meaning construction refers to the process of establishing a cognitive framework and generating and reconstructing meaning according to the context in order to better understand the change. Meaning-making differs in content, role, and approach depending on roles, experiences, and competencies. In general, the top level (especially the CEO) is the initiator and designer of strategic change and takes the initiative to analyze and develop understanding of the situation. The construction of meaning at lower levels (e.g., middle and executive levels) is influenced and guided by the higher levels, which leads to the need for meaning-giving. Meaning-giving refers to the influence exerted on the cognition of others in some form so that the resulting understanding of meaning is consistent with the expectations of the meaning transmitter. It is a process of interpretation and the primary means of transferring strategic intent across layers. Meaning giving is a critical leadership behavior in change, through which
change ideas are passed on to other layers and stakeholders to generate consistent understanding and action. The middle level plays an important moderating and transferring role between the upper and lower levels, influencing both the construction of meaning at the top and the effect of practice at the bottom. The main problem faced by domestic enterprises in digital transformation is not top-level support or shortage of funds, but the enterprises' understanding of digital transformation. Many enterprises' internal cognition of digital transformation is not uniform, and there are great misunderstandings and differences, and they cannot find the entry point of digital technology into the application of specific scenarios of enterprises.

Many enterprises have vague cognition of the purpose of digital transformation, incomplete strategic plan, and great investment, but little effect in the end. Although there are favorable national policies, for most traditional industries, the realization of digital transformation lacks sufficient industry-specific solutions and relevant path guides at the strategic level and practical operation level. Digital transformation is done in enterprises with great enthusiasm, but ultimately digital transformation can not be implemented to improve the efficiency of business operations and profitability can often not be traced. Many enterprises digital transformation does not bring effective connection between production and customer demand, digital transformation must ultimately be achieved is the digitalization of business activities, data business activities, to achieve the organic combination of the two, and truly to create value.

### 1.2 Current status of domestic and international research

#### 1.2.1 Research related to data elements

Factor of production is a historical category, which constantly incorporates new elements with the development of economy and society, and has different components and different mechanisms of action in different stages of economic development. The real embedding of any production factor into the economic development process does not happen overnight, but is formed gradually in the production practice. The formation of new factors of production constantly drives the economy to higher quality development. In the digital economy, the main factors of production are data, technology and capital, while the contribution of labor and natural resources tends to decline and the role of data in the production process increases as a key factor of production (Wang Songji et al., 2020). In the long run, data factors will eventually be embedded in all aspects of production,
distribution, exchange, and consumption on a large scale to enhance total factor productivity. At present, research on the digital economy and data elements focuses on the characteristics of data elements and the value they can create.

Research on the definition of the concept and attributes of data elements. Dai Shuangxing (2020) proposes that data factors, like traditional factors of production such as labor, land and capital, are transformed from general information goods to factors of production only when they are invested in the process of product production and service provision, while data, as a new type of factor of production, also has new characteristics that are different from traditional factors of production, namely non-exclusivity, economies of scale, reproducibility and strong permeability. Tian Jie-tang et al. (2020) proposed that data elements have non-scarcity, which still exist after participating in the production process and are not consumed, but can be recycled many times, and may promote further increase of data volume in use, and there is no pollution and emission problem. It is not possible to measure the value of an enterprise or make a horizontal comparison with the amount of data of that enterprise. Zhang Xinwei et al. (2021) suggest that data elements, as a new type of production factor, need to rely on hardware and software facilities for collection, storage, and transmission when they are put into the production process, i.e., they need to be integrated with certain material carriers; on the other hand, from the viewpoint of its mechanism of action on the production process, the application of data elements needs to be deeply integrated with other production factors, i.e., similar to a catalytic effect, data. On the other hand, from its mechanism of action on the production process, the application of data elements needs to be deeply integrated with other factors of production, i.e., it is similar to a catalytic effect, in which data elements can act on other factors of production and integrate themselves into the production process while promoting the integration of other factors of production. Cai et al. (2021) suggest that low cost and large scale availability are the prerequisites for data to be widely used and become a key factor, and they are also the basic characteristics of the new key factors in all technological revolutions, while techno-economic characteristics such as non-competitiveness, low replication cost, non-exclusivity/partial exclusivity, externality, and immediacy are the characteristics of data factors and other traditional tangible factors of production such as capital, labor, and land. It is also the basis for the emergence and operation of various new economies, new business models and new modes in recent years.

The study on the definition of property rights of data elements and the distribution of benefits. The Fourth Plenary Session of the Nineteenth Central Committee of the Party of China has involved
data as a factor of production in the distribution of benefits, and Xu Kaizhou (2019) proposed that data content, data collection, and data analysis are the three aspects of data management, and data content is the essence of data, while data collection and data analysis are the ways for data to generate benefits, and the three are closely related and complementary, but for specific data, the mastery of data content, data collection methods, and data analysis methods are often different, so it is necessary to take all parties into account when allocating revenue. Wang Songji et al. (2020) propose that "the participation of data elements in income distribution" is a new theoretical and practical proposition. In order to discuss the mechanism of data elements in income distribution in the digital economy, it is necessary to clarify how data elements contribute to economic growth and define the property rights of data elements. It is further proposed that the definition of property rights of data elements should be examined from the production dimension of data elements, and the production of data elements involves two types of subjects: data element producers (data processing enterprises) and original data information providers, and the definition of property rights of data elements should also be based on these two types of subjects to make institutional arrangements. Wu Xuliang (2020) proposes that the production process of data elements involves multiple links such as perception, acquisition, transmission, storage and computation, and the diversity of participating subjects makes it particularly difficult to determine the rights and pricing of data elements. Tang (2021) argues that the core of data rights determination is theoretically to determine who controls the data, who has the right to access the data, who has the right to trade the data and who has the right to allocate the data value. As a new factor of production that is significantly different from physical factors such as land and capital, data rights must be based on the unique economic attributes of data factors and oriented to maximizing data growth for potential release and reasonably balancing multiple objectives.

For the study of value creation of data elements, Dai Shuangxing (2020) proposed that the functions of perception, memory, analysis, and decision making used by data elements are applied to the production process of enterprises, promoting the improvement of labor productivity, matching the supply and demand of enterprise products, and reducing the cost of enterprise products. Wang Lei et al. (2020) proposed that as a key production factor, data elements can enhance the efficiency of economic development from multiple channels of supply and demand, and play the role of a "multiplier" to promote high-quality economic development. Data elements directly participate in
the production and service process, which can significantly improve the level of supply-demand interface. Relying on new infrastructure and technologies such as industrial Internet, big data and artificial intelligence, data elements can promote the improvement of production efficiency from multiple dimensions. Data elements can optimize the production process of enterprises, promote the efficient and optimal allocation of resources between enterprises, promote the synergy of the industrial chain and enhance the overall competitiveness of the industry, can help enterprises to accurately grasp the small ball of users, promote the effective docking of supply and demand, and improve the level of service. Lu Feng (2020) proposed that data has become an important innovation element to promote industrial development, and the development of new business models based on data has promoted industrial transformation and upgrading and cultivation of new economic dynamics. Big data-based accurate marketing, proximity services, network credit, service quality evaluation and other services, greatly promote the supply and demand information docking, market excellence, service quality improvement; based on customer demand feedback big data R & D design model, so that enterprise R & D design more targeted and oriented, greatly enhance the ability of enterprises to respond to market demand; manufacturing big data to solve the production data workshop flow Big data in manufacturing solves the problem of workshop flow of production data, makes enterprise production more flexible, and effectively supports new manufacturing modes such as personalized customization, experience-based manufacturing, and network manufacturing. Lin et al. (2021) proposed that in the combination with the technology factor, the addition of data elements can help innovative enterprises use complementary assets more effectively, thus generating technological innovation; in the combination with the capital factor, the addition of data elements reduces the cost of enterprises to acquire complementary assets as production and marketing resources, thus generating cost innovation; in the combination with the labor factor, data elements can improve the efficiency of complementary assets generation in terms of product design and production, thus generating process innovation. Ultimately, data elements, when combined with core factors of production, greatly contribute to the innovation and development of the digital economy.

1.2.2 Information Technology Investment Related Research

Information technology is often seen as a combination of information, computer, interaction and connectivity technologies and facilitates a fundamental transformation of a firm's strategies,
operational processes, corporate capabilities, products and services in a business network. The underlying logic behind the formation of a layered modular architecture of digital technologies is that digital products can simultaneously become platforms, leading to different strategic options for firms in different strata, as two firms can compete on one stratum while collaborating on another.

The study of e-business capabilities was first proposed by Professors Zhong Weijun and Mei Shu'e of Southeast University in 2011, who defined e-business application capabilities as a set of technical, managerial, and organizational capabilities that enable and help a traditional enterprise to creatively build and use e-business systems in order to continuously acquire e-business system capabilities and thus significantly improve the competitiveness of the supply chain as a whole and nodal enterprises. Therefore, enterprise managers not only need to invest in e-business resources, but also need to pay sufficient and long-term attention to continuous IT investment, and it is necessary to redesign and optimize intra- and inter-enterprise organizational structures and business processes before building and using inter-enterprise e-business systems. Based on this, Jinnan Wu et al. (2011) further investigated the positive impact of three dimensions of e-business application capabilities: inter-firm relationship management, inter-firm technology use, and inter-firm knowledge learning on firm performance, but the relationship between inter-firm work coordination and firm performance was not supported by empirical data. Mao-Mao Chi et al. (2012) found that e-business capabilities are key to generating the performance of three types of processes (e-procurement, e-ordering and customer relationship management processes), and that enterprise managers should build their respective e-business capabilities in the three types of typical e-business processes to support internal and external information sharing and collaborative activities, so as to increase the efficiency of supply chain operations and improve process performance, which will lead to ultimate Business Performance.

A study of IT investment and IT capabilities, Ravichandran et al. (2005) found that resource endowment affects capability development, suggesting that information systems managers must develop effective resource acquisition strategies to maintain a valuable resource base and build people, technology, and relationship resources to support IS applications, and that changes in firm performance can be explained by the extent to which IT is used to support and enhance the firm's The extent to which IT is used to support its core competencies is explained by the extent to which an organization's ability to use IT to support its core competencies depends on the functional capabilities of IS, which in turn depends on the nature and type of human, technical, and relational
resources available to the IS department. Yin, Guopeng et al. (2009) show that corporate IT investments need to be effectively translated into tangible and intangible assets and organizational capital such as IT infrastructure, IT management skills, and relationship capabilities, and that attention must be paid to the organic composition of overall IT capabilities and the interaction between the three, otherwise it is difficult for companies to achieve IT adoption and uptake in business strategy, operational processes, and management decisions, and it is McLaren et al. (2011) argue that in order to compete in a highly dynamic market, companies must frequently adapt their competitive strategies and information systems, and need to focus on the strategic fit of the company's overall IS portfolio and the impact of that fit on business performance. Weihong Xie (2012) found that IT is a commodity, but IT capability is a resource capability linked to the company's own resources, which must be closely linked to other resources inside and outside the company in order to play its proper role, and IT capability has its corporate uniqueness, which cannot be imitated by other companies and is a core competitiveness of the company. Wu et al. (2015) showed that the higher the fit between IT assets and organizational business, the stronger the agility of the organization, the IT department in the organization is for the business department, and the close interaction and mutual coupling between the two departments is conducive to the smooth development of the organization's business, business innovation, and the grasp of business opportunities, as well as the timely update of the information system by the IT department or the technological innovation based on the original information system. IT coordination capability not only directly contributes to the realization of organizational agility, but also positively regulates the relationship between IT asset fit and organizational agility. Based on IT orchestration capability, enterprises can achieve global information sharing and resource coordination and integration, and monitor and track changes in market demand in real time; IT innovation capability not only contributes directly to the realization of organizational agility, but also positively moderates the positive impact of IT asset fit on organizational agility. Zhou (2016) proposed that if enterprises hope to successfully implement IT, they must pay attention to the construction of all dimensions of IT capabilities and transform technology investments into technology capabilities through various ways. Both IT initiators and recipients should proactively cooperate with upstream and downstream enterprises to achieve a win-win situation through information integration and sharing. Zhou Yu (2017) proposed that the direct source of information system application to enhance enterprise competitiveness is the support capability of information system, and this support capability is
formed by the transformation of information system capability through the intermediary role of information system operation capability, and the empirical results verify the mechanism of the role of information system capability, that is, high-quality information system capability does not directly create value, and the direct source of information system value creation is Information system support capability. Information system capability can only enhance enterprise competitiveness and improve enterprise performance by forming information system support capability through information system operation capability.

1.2.3 Digital Transformation Related Research

Digital transformation is the process of enterprises using digital technologies such as the Internet, big data and artificial intelligence to comprehensively reshape the company's strategic thinking, business processes, organizational structure and business model, build a value creation system with data as the core driver, achieve close association with stakeholders and value co-creation, and enhance the market competitiveness and innovation growth of enterprises. Under the new pneumonia epidemic, traditional enterprises are implementing Digital Transformation to enhance their digital capabilities in terms of business domains, business models, and organizational forms. Digital transformation is driven by three major drivers, namely the changing macro environment, increased market competition and personalized user needs. Digital technology updates and iterations are accelerated, and enterprises that succeed in digital transformation can better adapt to the digital changes in the external environment and maintain their original competitive advantages in the market, and digitalization has become the core driver of transformation and development of traditional enterprises. The current development status of traditional enterprises still relies on the traditional business model in terms of organization and production mode, and the degree of informationization and digitalization is low. Therefore, it is necessary to elevate digital transformation to the strategic decision-making level, and cooperate with digital transformation strategy in many aspects such as organization structure, production mode and management mode. Industry perspective digital transformation research, Xiao Xu et al. (2019) study that the development of digital technology has laid the foundation for industry to achieve high-quality development and driven industrial digital transformation, and the value dimension of industrial digital transformation is reflected in four aspects: driving industrial efficiency improvement, promoting industrial cross-border integration, reconstructing the competitive model of industrial
organizations and empowering industrial upgrading. Zhu Hailiang et al. (2021) elaborated the theoretical system of industrial digital transformation from four aspects: connotation and extension of industrial digital transformation, main features, power system, and industry chain reshaping effect, combined with the current situation of China's industrial digital development, analyzed the new opportunities and challenges faced by China's industrial digital transformation in the context of "double-cycle" new development pattern strategy, and proposed the establishment of a new industrial digital transformation system. The new opportunities and challenges of China's industrial digital transformation in the context of the new development pattern strategy of "double-loop" are analyzed, and four major policy mechanisms of "promotion mechanism, coordination mechanism, sharing mechanism and guarantee mechanism" and four major measures of "constructing digital technology system combining independent innovation and open sharing, promoting innovation and change of industrial digital mode, improving the level of industrial digital governance mode and accelerating the construction of industrial digital infrastructure" are proposed. To promote the digital transformation of China's industry, four major measures have been taken. Yao Zhanqi (2021) studied the impact of industrial digital transformation on the performance of the retail industry based on micro data of enterprises, using enterprise innovation capacity and consumption upgrade as mediating variables. The study found that: industrial digital transformation significantly and positively affects enterprise innovation capability and consumption upgrade; enterprise innovation capability significantly and positively affects consumption upgrade; enterprise innovation capability and consumption upgrade have a chain mediating effect. Therefore, policies should be formulated to accelerate the digital transformation of industry, enhance innovation capability, promote consumption upgrade, and boost the efficiency of the retail industry.

Traditional enterprises are also developing from the intelligence of production and manufacturing to virtualization and networking, accelerating digital transformation from production, sales, design, R&D and other aspects. Only by implementing digital transformation strategies and strengthening independent R&D and innovation of digital technologies can traditional enterprises adapt to the impact and changes of information technology on traditional business models and establish dynamic corporate capabilities that can adapt to the rapid development of the digital economy and technological changes in the industry. For traditional enterprises, digital transformation is not an easy task, and establishing systematic digital technologies in the process can bring great impact on traditional strategic decisions and business models. In the study of digital
transformation from the enterprise perspective, Qian Jingjing (2021) shows that the dynamic capability building of digital transformation follows the evolutionary process of "digital perception capability - digital acquisition capability - digital transformation capability"; the external driving factors of digital transformation. The external drivers of digital transformation are reflected in intelligent technology, personalized demand, online model and ecological development; the digital transformation capabilities formed by traditional enterprises through digital transformation, through changes in decision-making and operation models to make their operations more in line with market changes, changes in organization and cooperation models to promote more digital management, rapid response to external digital changes and development of response strategies.

Digital transformation has been widely discussed in academic circles and is defined by Fitzgerald et al. (2014) as "the application of innovative digital technologies to improve customer experience, channel operations, or create new business models". Singh et al. (2017) emphasize that digital transformation is about "transformation" rather than "change", enabling companies to transform themselves from their own business processes. Singh et al. (2017) emphasize that digital transformation is about "transformation" rather than "change", enabling companies to respond to the opportunities and risk control presented by digital technologies by taking holistic organizational action. At the same time, Roger (2016) argues that the root of digital transformation lies in corporate strategy rather than technology itself, and that digital technology is changing the nature of the dynamic capabilities of companies compared to their previous strategic changes. Despite the internal drive of the executive team to be able to support digital transformation in terms of business models, organizational structures and business processes, incumbent companies will still face significant challenges. One of the biggest challenges comes from external competition, and it is important to balance the relationship between existing capabilities and building digital capabilities to move away from path dependence on the past. The dynamic capabilities research framework has become a research hotspot in the field of strategic management because it explains how companies respond to rapidly changing markets and technologies, and digital change and strategic transformation based on dynamic capabilities play an important role in maintaining the competitive advantage of incumbent companies. Based on the strategic evolutionary perspective of resource matching, Bing Wang et al. (2021) concluded that traditional enterprises implementing digital transformation would encounter challenges such as organizational inertia and demand conflicts, and some enterprises in practice have successfully achieved digital transformation by resolving these challenges through
internal entrepreneurship. strategic evolution path, i.e., from intrapreneurship, to digital innovation within the organization, to external collaboration across the organization, and found that intrapreneurship can overcome organizational inertia through structural differentiation and power distribution, thus facilitating rapid renewal of organizational resources and exploration of digital innovation. Lu, Bao-chou et al. (2021) found that digital transformation of traditional enterprises is a top-down process that consists of three stages: transformation initiation, consensus formation, and transformation realization. In each stage, the binary structure formed by actors and digital technologies is the social foundation for digital transformation giving formation (i.e., stage transformation cognition), revealing four types of digital transformation giving that support enterprise transformation, including: digital strategic giving, shared digital strategic giving, digital business strategic giving, and digital business strategic realization. Meaning construction is the main mechanism that facilitates transformation giving formation; meaning deconstruction and meaning giving are the main ways in which higher-level subjects influence lower-level subjects' meaning construction and are the main mechanisms for achieving process transformation.

1.2.4 Review of existing studies

The exploration of how data elements and digital transformation participate in enterprise value creation is a hot and difficult research point in the current theoretical and practical circles. However, most of the current research on data elements and digital transformation is focused on the connotation and extension, data element characteristics, progress significance, and generalized countermeasures, and there is little systematic and in-depth research on the mechanism of the role of data elements and digital transformation in maximizing value. Digital transformation is an unstoppable trend faced by enterprises, and data is the most important core element of enterprise operation in the digital economy. It is especially important for the high-quality development of enterprises to explore how to make full use of data elements, make them effectively embedded in the enterprise operation system, accelerate the in-depth integration of digital elements with the organizational body, and drive the value-creating ability of enterprise digital transformation. Therefore, it is necessary to further explore the steps of digital transformation, the conditions of embedding data elements, the mechanism of digital transformation on enterprise resource allocation efficiency, the core process and mechanism model of digital transformation valorization on the basis of clarifying the concepts related to data elements and digital transformation, which is to improve
the resource allocation efficiency of digital transformation, promote internal and external organizational data synergy, information integration, and efficient utilization. An important theoretical and practical topic to complete digital transformation to enterprise value realization.

1.3 Digital Transformation Connotation

1.3.1 Digitalization and Digital Transformation

Digitalization and digital transformation are the most fashionable and popular topics in agriculture, industry and business in recent years, from IT circles to manufacturing industries and government departments are all discussing digitalization and digital transformation, while IT circles understand digitalization and digital transformation more from the technical point of view, exploring the technology used in digitalization and the platform to achieve it. The government and many think tanks are discussing from a macro perspective, more from the perspective of digital economy and embedding data elements, emphasizing industrial upgrading and industrial transformation. However, from the enterprise perspective, most of them start from specific business, discussing smart factory, digital supply chain, business digitization, decision informatization, market agility, information integration driving technical efficiency, etc.

Essentially, digitization is a technology concept that transforms any continuously changing input, such as text, images, or sound, into a series of separate units, represented by zeros and ones in a computer. Digitization is a combination of various technological innovations and approaches through "connectivity", using artificial intelligence, big data, mobile Internet, cloud computing, etc., to reconfigure the real world in the virtual world. Digitization is to link the real world of life and virtual digital expression, so as to seek new business models and service models.

The core essence of digital transformation is to transform the productivity and production relations that adapt to material economy and scale economy into those that adapt to digital economy and scope economy, and enterprises should accelerate the construction of a new production system that adapts to the development requirements of the digital economy era. Digital transformation is through new capacity building can give full play to the role of information technology empowerment, break the barriers of industrial technology expertise, support business on-demand call capacity to quickly respond to changes in market demand, the formation of a new model of lightweight, collaborative, social business services, dynamic response to user personalized needs,
access to diversified development efficiency, and open up new value growth space.

1.3.2 Four development stages of digital transformation

Digital transformation is not a sudden model for enterprises, but a continuous process of integration and embedding with the development of enterprises and related businesses. This integration and embedding process must follow the economic and technological laws reflecting the evolutionary path from nothing to something, from low to high, from weak to strong, from passive to active. Digital transformation is divided into five development stages: initial level development stage, unit level development stage, process level development stage, network level development stage, and ecological level development stage. Data is the key driving element of digital transformation, and organizations at different development stages generally show trends and characteristics from local to global, from internal to external, from shallow to deep, and from closed to open in acquiring, developing and utilizing data. Based on the different driving roles played by data elements at different development stages, the development strategies, new capabilities, systemic solutions, governance systems, and business innovation transformation of digital transformation have different development states and characteristics at different development stages.

Initial level development stage: Organizations at this development stage have initially carried out information (digital) technology applications within a single function, but have not yet effectively played the role of information (digital) technology to support their main business.

Unit-level development stage: Organizations at this stage have carried out (next-generation) IT applications within a single function of the main or several main businesses to improve the operational standardization and efficiency of the relevant single business. In terms of development strategy, digitalization is clearly proposed in the development strategy or special planning, and the target positioning is mainly to improve business standardization and operational efficiency, and the digitalization content is incorporated into the department-level annual plan and performance assessment. In terms of new capabilities, the construction, operation and optimization of new capabilities within a single function are supported by the use of (new generation) information technology, and the new capabilities formed are mainly used in the relevant single business. In terms of systemic solutions, the necessary equipment and facility renovations are carried out for the construction, operation and optimization of new capabilities within the scope of a single function, and (new-generation) information technology tools and instruments are applied to carry out...
optimization and functional responsibility adjustment of relevant individual businesses, and unit-level data modeling is carried out based on data collection within the scope of a single function and relevant individual businesses. In terms of governance system, the management model is function-driven and can carry out auxiliary management decisions based on data within a single function or related single business. The leadership attaches importance to and actively promotes (new generation) IT applications, sets up special teams to carry out (new generation) IT applications and O&M, and establishes a single application and O&M system, etc. In terms of business innovation and transformation, the main or key single business is digitized and a business operation model supported by (new generation) information technology means and tools is formed.

Process-level development stage: Organizations in this stage achieve process-driven optimization of key business processes and integration between key business and equipment and facilities, software and hardware, behavioral activities and other elements of the main business within the scope of business lines through process-level digitization and sensor network-level networking. In terms of development strategy, we have formulated a special strategic plan for digital transformation with the core of achieving business integration, have recognized the important value of data at the strategic level, and have incorporated the annual plan and performance assessment of digital transformation into the overall development planning and assessment system of the organization. In terms of new capabilities, we have completed the construction of new process-level capabilities that support the integration and collaboration of the main business, and each capability module of the new capabilities can be effectively applied by the relevant business links in the process. In terms of systemic solutions, we build sensor network for process-level capability construction, operation and optimization, integrate and apply IT hardware and software resources, carry out business process optimization design and functional responsibility adjustment across departments, business links and levels, and build and apply system-level digital model based on data collection and integration sharing of major equipment and business systems. In terms of governance system, the management model is process-driven, capable of carrying out cross-departmental and cross-business process digital integration management, with the organization's decision-making level and full-time first-level departments coordinating and promoting digital transformation work, forming a process-driven digital system construction, integration, operation and continuous improvement of the standard specifications and governance mechanism. In terms of business innovation and transformation, on the basis of digitalization of all key businesses of the organization,
the integration of business integration is realized along the dimensions of vertical control, value chain and product life cycle for major or key business lines.

Network-level development stage: Organizations at this stage achieve data-driven business model innovation through organization (enterprise-wide) digitalization and industrial Internet-level networking to promote the interconnection and dynamic optimization of all elements and processes within the organization (enterprise). In terms of development strategy, we have formulated a development strategy with digital organization (enterprise) as the core content, and clearly identified data as a key strategic resource and driving factor in the development strategy to accelerate business innovation and transformation and digital business cultivation. Building a digital organization (enterprise) became the core content of the organization's annual plan, and a performance assessment system covering the entire staff was established. In terms of new capabilities, we will complete the construction of network-level capabilities that support the global optimization of the organization, and realize the modularization, digitization and networking of new capabilities that can be shared and applied on demand throughout the organization (enterprise). In terms of systemic solutions, the system integration architecture of the digital organization (enterprise) is built, business infrastructure resources and capabilities are deployed on a platform to support on-demand invocation, OT networks and IT networks achieve protocol interoperability and network interconnection, online automatic collection, exchange and integrated sharing of data based on the whole elements and processes in the organization, and the organization (enterprise) level digital twin model is built and applied. In terms of governance system, the management model is data-driven and realizes self-organizational management covering the whole process of the organization (enterprise). The organization (enterprise) level digital governance leadership and coordination mechanism is established, and a data-driven digital organization (enterprise) governance system is formed to realize intelligent collaboration, dynamic optimization and interactive innovation of four elements, including data, technology, process and organization. In terms of business innovation and transformation, based on the online operation of major or key businesses and modular encapsulation and shared application of core competencies, etc., business model innovation such as networked collaboration, service extension and personalized customization is realized.

Eco-level development stage: Organizations in this stage promote open sharing and collaborative cooperation of resources, business, capabilities and other elements with eco-partners within the scope of eco-organizations, and jointly cultivate smart-driven digital new businesses
through eco-level digitization and ubiquitous IoT-level networking. In terms of development strategy, we have formulated an organizational development strategy and an ecosphere development strategy with the goal of building a symbiotic and win-win ecosystem and developing and growing digital business. We have clearly identified data as the core element driving innovation in the development strategy, carried out the construction of an intelligent-driven ecological operation system, and formulated a flexible control mechanism covering the entire strategic process of key partners in the ecosphere. In terms of new capabilities, we have completed the construction of eco-level capabilities that support open value co-creation, and are able to build an open capability cooperation platform and open value ecology with eco-partners to achieve cognitive synergy, on-demand sharing and self-optimization of eco-level capabilities. In terms of systemic solutions, a componentized, configurable, open and flexible intelligent cloud platform has been established, the OT network, IT network and Internet outside the organization are interconnected, and the organization has become the core or important contributor to the socialized capability sharing platform, realizing platform deployment, open collaboration and on-demand utilization of ecological basic resources and capabilities together with partners. In terms of governance system, the management model is intelligence-driven, employees have become partners of the organization, and a values and organizational culture with the core of ecological partners' community of destiny has been formed. In terms of business innovation and transformation, a new business model with digital business as the core has been formed, and digital business has become an important part of the organization's main business, bringing into play the innovation potential of the ecosystem and opening up a wide space for achieving green and sustainable development.

1.4 Enterprise Digital Transformation Model

Enterprise is one of the most important forms of economic organization today, and its essence is a resource allocation mechanism, an organization that organizes and allocates resources corresponding to the market. Enterprise competition is the competition of resource allocation, and how to optimize the allocation of resources lies in whether enterprises can achieve scientific, efficient and accurate decision-making. The enterprise decision is more and more dependent on data, through data collection, cleaning, screening, integration, and will be delivered to the decision-making system at a reasonable time and in a reasonable way. These data are constantly generated and gradually penetrate into the enterprise product design, R&D, production process, product sales
There is never a shortage of new concepts in the field of information technology applications, but so far, only a few can be widely recognized. Among them are digital manufacturing, industrial Internet, Industry 4.0, etc. The concept of Industry 4.0 was proposed by German companies at the Hannover Messe in 2001, after which experts from relevant institutions published the Industry 4.0 Standardization Roadmap, and Industry 4.0 has gradually become the national industrial strategy of Germany. Its purpose is to support industrial enterprises to strengthen the research, development and application of new generation revolutionary technologies, to promote the application of information technology in manufacturing and to seize the high ground of digital manufacturing. The core of Industry 4.0 is to closely link manufacturing equipment, industrial process control, production processes, suppliers, customers, and products through information technology, enabling real-time information exchange between machines and equipment, control systems, and people. Data is the most essential feature that distinguishes Industry 4.0 from the previous industrial model. Data penetrates the whole stage of enterprise operation, including product data, operation data, value chain data and data from the external environment of the enterprise. Industry 4.0 embeds user participation through design, procurement, production, logistics, service and other aspects, and is capable of differentiated design and customized production for different customers and different products. Germany's Industry 4.0 generally represents the continuous progress of industrial production automation through self-configuration and self-optimization systems, as manifested by the following: a production line can produce different products, and through the support of information technology, it can flexibly adjust the product structure of constantly changing batches and optimize the use of production capacity; intelligent maintenance management system, through predictive maintenance management for the operator to reduce the unplanned downtime. Additional costs. In a sense, Industry 4.0 is Germany's transcendent plan for its own characteristics, the core of which is smart manufacturing, through embedded processors, memory, sensors and communication modules, linking equipment, products, raw materials, software, etc., so that products and different production equipment can be interconnected and exchange data, with the aim of improving the competitiveness of German industry, and in the new round of industrial revolution to take the lead.

A similar concept is the Industrial Internet, first published by GE in 2012 in the white paper
"Industrial Internet: Breaking the Boundaries of Intelligence and Machines". Since the release of the "Guidance of the State Council on Deepening the "Internet + Advanced Manufacturing Industry" and Developing the Industrial Internet" in 2017, the country has attached importance to the innovative development of the Industrial Internet and started to involve the key layout of the Industrial Internet, emphasizing the use of information technology to improve the total factor productivity of Chinese manufacturing, promote the integration of informationization and industrialization in a wider scope, deeper degree and higher level, and empower the transformation and upgrading of traditional industries through the industrial Internet.

The Chinese Academy of Sciences defines industrial Internet: industrial Internet is the deep integration and innovative application of new generation information technology in industry through new network, artificial intelligence, big data, etc. to establish a global network that widely connects various production factors such as people, machines and things, and forms a development platform that implements the networking of entities, data and services throughout the industrial chain. It is an important infrastructure to reshape the industrial production and service system and realize the digitalization, networking and intelligent development of industry. From the historical lineage of industrial development, the first industrial revolution is the mechanization represented by steam engine and internal combustion engine, replacing the traditional manual workshop with machinery and mechanizing the factory through water power and steam engine; the second revolution is the electrical revolution, mainly represented by batch assembly line production and electricity-driven production mode, realizing flowing production lines and semi-automatic equipment through electromechanical automatic control and other means; the third industrial revolution is the information revolution, driven by information technology to achieve fully automated production in factories, through management automation and a large number of applications of functional software (such as ERP/CRM/CAD/WMS, etc.) to greatly improve production efficiency; now is about to enter the fourth industrial revolution, through a new generation of information technology, the development direction of industrial digitalization, networking, intelligence, the emergence of things like digital twin, the emergence of new concepts such as smart factory, industrial cloud, industrial big data, etc., we can open up independent systems, eliminate information silos, and realize the evolution from physically-driven production and process-driven management to data-driven, and the evolution of employees and equipment from external instructions to self-adaptation and self-learning. The concept of Industrial Internet has been
constantly changing and evolving. Initially, it only represented industrial network facilities and technologies, and later the Industrial Internet began to expand to digital, networked and intelligent connotations, and now the Industrial Internet is not only understood from a technical point of view, but also further involves the digital economy and industrial transformation and upgrading. The Industrial Internet is not a simple application of the Internet in industry, but has a richer connotation and extension. Essentially, industrial Internet is the integration, convergence and innovation of industrial capabilities and IT capabilities, based on the comprehensive digitalization and networking of manufacturing enterprises based on the underlying equipment and facilities, where the construction of the identity resolution system supports the interconnection of all elements of industry, and the key to development is the platforming of manufacturing capabilities. It is based on the network, platform as the pivot, data as the elements, security as the guarantee, is not only the infrastructure of industrial digitalization, networking, intelligent transformation, but also the application mode of the deep integration of the Internet, big data, artificial intelligence and the real economy, and also a new industry, new industry, will reshape the enterprise form, supply chain and industrial chain.

Digitization can realize the intelligence of the whole manufacturing value chain, and the industrial Internet is the key infrastructure to realize digital manufacturing. Industrial Internet can drive digital manufacturing. Digital manufacturing is a new manufacturing method based on the digitization of information and knowledge, modern information network as the main carrier, and the use of digital, intelligent and networked technologies to improve the efficiency of product design, manufacturing and marketing, including digital design, digital process, digital assembly, digital management, etc. With the penetration of new information technology such as 5G, cloud computing, Internet of Things, big data and artificial intelligence, data resources increasingly become a key production factor, and digital manufacturing becomes the main force to promote quality change, efficiency change and power change in manufacturing development.

1.4.2 Digital Marketing and Customized Production

Enterprises are changing from production-centered to customer-centered, and big data analysis, cloud computing, information integration, e-commerce capabilities, and rapid response for building customer needs and portraits are increasingly becoming new capabilities that enterprises must have. The foundation of digital marketing construction is the ability to accurately analyze customers, real-
time sensing ability and rapid response ability. Some enterprises represented by e-commerce platform model through the long-term formation of data can accurately identify customers, send targeted advertising to customers, changing passive marketing to active marketing, more effective in providing the products or services needed by customers.

Digital marketing was birthed in the era of digital economy. Compared with traditional marketing, digital marketing with the help of advanced mobile Internet technology, big data technology, effective and low-cost marketing methods to develop new markets, to tap new consumer demand. Marketing precision, quantifiable marketing effects, and data become the salient features of digital marketing. Digital marketing connotation, there are mainly the following types of expression: "digital marketing is a digital means of marketing purposes with the help of network technology, computer technology, multimedia technology and interactive technology to achieve marketing means", "the use of digital technology for product or service marketing ", "a general term for all activities, mechanisms and processes driven by digital technology that enable the creation, dissemination, and delivery of value to consumers and other stakeholders". From the various definitions, although not for digital marketing to form a unified expression, but there is a certain consensus that with the integrated use of various types of information and data technology to achieve marketing, digital marketing is a class of marketing in favor of technology-driven marketing. Digital marketing is similar to online marketing in that it is dedicated to achieving sales goals in a virtual environment through the use of Internet and communication technologies. However, the difference is that online marketing emphasizes the promotion of consumption in the network scenario, such as advertising, bidding ranking, etc., mainly for the sales and promotion of products and services; while digital marketing emphasizes the construction of customer data platforms, advertising monitoring, data collection and analysis on top of this. Digital marketing is precisely the use of Internet, communication technology and digital interactive media to achieve marketing objectives, the use of the network, mobile devices, social media, search engines and other channels to attract consumers, to achieve marketing precision, marketing effects can be quantified, data. Concerning the content of marketing, the concern is the exploration of consumer preferences for information, and the solution is how to target the content supply. Traditional marketing for the production and dissemination of product or service content, mostly business-led, is a single subject of one-way information delivery. With the improvement of consumer data collection and analysis in the Internet environment, the information barrier between enterprises and consumers has been broken, and the
content production and dissemination has become a two-way degree. With the rise of social media, more subjects can be involved, and content production and dissemination become increasingly rich, further satisfying the different needs of thousands of people. Product marketing strategies and methods can be adjusted according to customer demand, competitive environment and inventory, digital marketing with multimedia, cross-time, interactive, anthropomorphic, ahead of time, efficient, economical and other characteristics, online marketing can also transcend the limitations of time and space and offline environment, to play the rich creativity of marketers. Using the diverse channels of digital marketing and digital technology tools, corporate marketing can add many new qualities. Based on digital marketing, enterprises combine digital marketing platforms and tools to effectively search for customer resources, classify and organize intended customers, and based on the customer portrait formed by data informatization, publish personalized marketing messages to customers filtered and segmented by custom conditions, and track user behavior data to better grasp and determine the success rate of advertising, the participation rate of marketing activities, information. The value of the digital marketing business lies in the data-driven approach.

The value of digital marketing business lies in the data-driven low-cost and high-efficiency way to deliver the most appropriate content and product information to the most accurate audience through the most suitable media channels and forms. With the advent of the digital era, the acquisition of online traffic has become the key to winning digital marketing. Nowadays, all-media digital marketing has gradually become the mainstream marketing model, webcasting, content entrepreneurship, short video, intelligent marketing has become a popular trend, "double micro a shake" (microblog, weibo, shake voice) and other online platforms with large user scale, high daily activity and user stickiness has become an important channel and the main position for business development. The core resource of mobile Internet is "traffic", and "traffic" means market. Under the traditional marketing model, various marketing tools and reach channels are isolated from each other, and it is difficult to deliver the same brand image in collaboration. Today, companies are beginning to reach customers through multiple channels, and each channel is synergistic and complementary, maintaining a consistent experience and delivering a unified message and brand image, and the online marketing platform has shifted from "public domain" to "full domain. Compared with the offline marketing model, it is not limited by time and space, which makes it more efficient and convenient to revitalize customers and expand customer base, and the cost is lower, while it can achieve accurate marketing, which is an important means of digital marketing.
From "one-way push" to "customer-centric", from "mass" to "personalized", digital marketing is moving from "one size fits all" and "one size fits all" in the traditional mass era to "one size fits all" in terms of personalized recommendations and precise reach to meet customers' individual needs.

The study of customized production emerged in the 1970s. Initially, domestic and foreign scholars' research on customized production was mainly focused on the mass customization evolved from mass production. In the 21st century, with the rapid development of science and technology and productivity level, the diversified and personalized needs of customers have become more prominent, thus, a kind of multi-variety and small-lot production method for customers' personalized needs has emerged. Customized production is a customer-oriented production method that produces products and services to meet customers' individual needs under the guidance of basic principles such as similarity and reusability and with the support of information technology, modularization technology and advanced manufacturing technology, integrating all links of the value chain and making full use of the various resources available to the enterprise. In the era of Industry 4.0, as the information-physical system connects people, machines, products and data, the production process will automatically select a most effective production method through data analysis and prediction, and use the least resources to meet customers' personalized needs. The change of this manufacturing model and the promotion of smart manufacturing will minimize the cost of customization. Customer personalized demand as the driver of the customized production value chain, is the core link of the entire value chain value-added, customer participation in custom production occurs only in the design stage, that is, after the customer determines the appearance, color and function of the product, handed over to the enterprise for production, the product in the production process without direct interaction with customers. It is not until the acceptance process and after-sales service that the customer is again involved in the value chain. The customer will participate in the whole production cycle of the product through the IT system, and the enterprise must also communicate effectively and in real time with the customer in this process, and adjust the relevant parts of the production process according to the actual demand in order to achieve a win-win situation. Customers, as the guide of customization, can put forward more diversified and in-depth personalized demands, and designers modify product modules and manufacturing process modules in response to relevant demands to achieve incremental innovation through changes in product module combinations. Through three-way integration, enterprises achieve rapid response to
customer needs and interface and cooperate with enterprises in the value network to achieve certain requirements for raw materials, product design (including process design), production management, logistics and transportation, and additional services to meet customer needs.

1.4.3 Digital just management and digital R&D

Accelerating agile and digital R&D transformation is an inevitable choice for companies facing the current environment, and companies should provide the required tools, capabilities and processes to accelerate the transformation. The primary purpose of knowledge management is to promote the continuous generation of knowledge in the process of enterprise development through advanced methods, especially to transform tacit knowledge such as personal experience into expressible explicit knowledge such as words, pictures or models, which will be stored in the company and become the company's knowledge assets. Through good knowledge management, such knowledge will not be taken away with the departure of personnel, and through continuous learning, application and iteration by the descendants, the R&D capability and efficiency of the whole enterprise will be continuously improved. The management and application of knowledge assets is the foundation of an R&D enterprise's longevity. Knowledge management is like establishing an enterprise-specific library, which not only generates and carries various kinds of knowledge, but also ensures easy access to knowledge so that employees can acquire and learn to use it in a timely manner in the course of their work. Knowledge management is a new concept proposed in recent years and is still in the process of promotion. External knowledge and common knowledge are often maintained intact due to the wide range of use and frequent pulling with the continuous generation of new projects. Through the promotion and application of digital tools in the main aspects of product development, various data and information-based knowledge of the nature of deliverables generated during the project process have been automatically deposited in various business systems during the delivery process and are clearly visible. The most difficult part of management is the experience summary in the professional field, which mostly belongs to tacit knowledge. Without a good mechanism for in-depth excavation, not only the knowledge points are easily ignored by the organization, but even the creator of knowledge himself is hardly aware that it is a valuable experience acquired through personal practice. With digital technology support, the construction of "knowledge culture" can be built by various new digital methods, and various activities can also be carried out offline to attract people to participate. No matter which culture
promotion method is used, it needs to be tailored to the company's own characteristics, management style and engineers' preferences.

Our manufacturing companies used to adopt the experience-based R&D and design model, and because of the identification, processing and assimilation of R&D-related knowledge, the technical level of identifying, processing and assimilating R&D-related knowledge is not enough, so they can only collect and process small sample data sets to improve R&D performance. The small amount of data, data quality and analysis capability cannot be guaranteed, so the analysis results can only play an auxiliary role in R&D. The R&D design mainly relies on the experience accumulation and judgment of the R&D subject. The disadvantages of this R&D model are long cycle time, high cost and high risk.

With the popularization and application of information technology, digitally driven product R&D and design can be realized, making the quality and efficiency of R&D and design qualitatively improved. The new infrastructure provides technical and tool support for enterprises, helping them to build a detailed consumer behavior portrait, helping them to improve consumer insight and even complete adaptive decision-making. The R&D design empowered by data elements can be developed according to customer needs and preferences, solving the problems of long traditional R&D cycles, high risks and high costs, and fundamentally changing the product R&D model. For example, Xiaomi seized the wind of new infrastructure and became the earliest company to lay out new infrastructure. The company regards "rice flour" as the first resource for enterprise development, and with the empowerment of new infrastructure, it allows "rice flour" to participate in the planning, design, R&D and evaluation of products through the Xiaomi ecological platform, and uses big data analysis technology to analyze hundreds of millions of opinions from rice flour, and feeds the results back to the company. We use big data analysis technology to analyze hundreds of millions of opinions from Mi fans, and feed the results into the product development and design, so as to truly achieve the R&D and design for the needs of "Mi fans". In addition, the new infrastructure provides the basis for the use of digital design technology, augmented reality (AR), virtual reality (VR), digital simulation technology under the new infrastructure and design tools to complete the simulation modeling of product parameters, and use visualization technology to clearly present. For the simulation test link with large amount of data and high requirement of computing power, data elements empower data processing power and computing power to realize digital simulation of different parameters and environments, and use digital test tools to capture the performance of
products under different parameters and environments. This design method gives full play to the strength of digital design tools, simulates the real environment of the product through digital technology, and obtains its parameter indexes under various real environments and working conditions. For experimental tests that are complex and difficult to complete in real situations, they can be completed under the digital R&D design mode, which achieves the effect of shortening the R&D cycle and improving R&D efficiency.

The digital innovation system of manufacturing enterprises is consistent, all products start from requirements, and need to collect users' requirements and ideas; followed by requirements analysis, turning requirements into something that can be structured and described, and abstracted into response points or function points for R&D. This is more about the specification of requirements, and turning user requirements from an image description into an abstract description is the embodiment of a company's R&D core competence. After analyzing the requirements, the R&D team will turn the ideas into digital models, drawings, engineering documents, and finally manufacturing, and then connect with customers through consumption and service. Through digitalized and process-oriented R&D and manufacturing process, digital and intelligent products can be realized, and efficiency can be improved; through online data collection by means of Internet of Things, data models can be established, and data thresholds can be set, which will eventually help customers to realize early warning and predictive maintenance of equipment and reduce maintenance difficulties, thus realizing digital and intelligent services.

### 1.4.4 Digital Supply Chain

Every enterprise belongs to a link in the industrial chain. To improve the competitiveness of the whole industrial chain, it is very necessary to build a cross-enterprise production system with information sharing and high coupling of resources and business. With the penetration of information technology, business activities between enterprises and enterprises in the industrial chain are gradually becoming informationized, online and networked, and enterprises begin to evolve from internal business module collaboration to industry chain collaboration between enterprises, and internal R&D and design, production and processing, and logistics and sales platforms are constantly expanded and extended to the outside, in order to achieve information integration across enterprise operations, thereby improving end-customer satisfaction with The supply chain management is a key component of the enterprise's R&D and production process.
Supply chain management is the pillar function of an enterprise other than R&D and marketing, covering planning, procurement, production, distribution and other functions. Supply chain management has a significant impact on the operating profit and capital turnover of an enterprise. The current market competition is fierce, from business to business competition has gradually evolved into the competition of each core function of the enterprise, especially at the moment when the new retail is booming and the epidemic era brings a twist, it has put forward higher requirements on the enterprise supply chain management, including the high efficiency of supply chain operation, the ability of continuous optimization of supply chain and the ability of supply chain to converge and utilize data resources. In such a fierce or even cruel competitive environment, the competitiveness of the supply chain has gradually become one of the core competitiveness of enterprises. The ability of supply chain management is not advancing or retreating, and it is crucial for enterprises to improve the efficiency of supply chain operation and optimize it continuously. Traditional supply chain management is carried out according to the enterprise's own situation, usually including planning, purchasing, manufacturing and logistics departments, of course, some enterprises may only have a part of them. Its management mode is mainly based on ERP system, most of the enterprises do not have special information system or digital tools, but still use the traditional manual way plus email, Excel, etc. for management and inter-departmental collaboration. With the development of the market, the diversification of sales channels, the development of intelligent manufacturing, and the arrival of the VUCA era, the traditional supply chain management model needs to be changed and transformed to ensure the survival and development of enterprises. Especially affected by the new crown epidemic, the digital transformation of supply chain management of manufacturing enterprises is crucial to the improvement of supply chain operation performance. At the same time, the booming development of new technologies such as cloud computing, big data, Internet of Things, artificial intelligence, blockchain, etc. also makes the digital transformation of supply chain management with technical basis and support. Digital supply chain refers to the combination of modern digital technology and supply chain model, based on the collected big data, through data, processes, intelligent algorithms and other technologies, using a variety of artificial intelligence algorithms to guide supply chain forecasting, planning, execution, decision-making and other activities, to break the barriers of information exchange in all aspects of the supply chain, to achieve a "digitally driven supply chain Supply chain management". Digital transformation is the integration of technology and business, and supply chain management in the
era of digital economy will also produce disruptive changes.

For the internal of the enterprise, on the one hand, the effective connection between various functional departments of the supply chain should be realized through digital technology or tools, such as the use of visualization tools to enhance the visualization degree and transparency of data in various parts of the supply chain; on the other hand, the collaboration process within and between various functional departments should be improved and optimized to enhance the efficiency of collaboration, effectively control risks and reduce uncertainties. For the outside of the enterprise, it should achieve mutual sharing and interoperability between upstream and downstream enterprises as far as possible, communicate with suppliers in a timely and effective manner, incorporate suppliers into the collaborative process of the enterprise, and solve customer problems effectively as soon as possible to enhance satisfaction. Wu Shugui proposed that the entry point of building digital system should be to improve the level of informationization of the whole collaborative process and the efficiency of data transmission, processing and feedback, so as to truly achieve the cycle of "that is to know that is to do" and "that is to do that is to know" and form a closed loop. The essence of digital transformation of supply chain management is an innovation and change, and its key points should include the construction of enterprise strategy, business process change, effective information system architecture design and digital tools construction, etc. Only by consolidating the foundation of these tasks, it is possible to gradually realize digital transformation according to the process of standardization, digitalization to intelligence. Supply chain management digitalization is not equal to computerization, not to install a set of digital system tools can be. It is not only the work of information department or digital department, but also the work that all employees from top to bottom of the enterprise need to participate in. The digitalization strategy of manufacturing supply chain management should focus on the combing of business processes, and the essence of digitalization is to help business operation change, so that the cart cannot be put before the horse. Enterprise management needs to strengthen the top-level design to formulate reasonable strategies; enterprise executive level needs to optimize and adjust the business, eliminate as much as possible the collaboration gap between various collaborative departments inside the enterprise and outside the enterprise and suppliers and customers, let the process through, let all the information and data flowing into the digital tool be real and effective, and discard the garbage data, so that the digital tool can really work effectively. The digital transformation of supply chain management should include choosing the appropriate digital technology and applying the
corresponding digital tools. There are many digital technologies, including Internet, big data, cloud computing, artificial intelligence, machine learning, Internet of Things, blockchain, etc.; digital tools refer to some targeted system tools, such as traditional ERP system, supplier management system (SRM), traditional statistical demand forecasting system and emerging machine learning algorithm demand forecasting system, production scheduling system, logistics management system and supply chain control towers, etc. With the development of IoT technology, it can be applied to all aspects of the supply chain, including intelligent manufacturing in factories, intelligent quality monitoring, intelligent management of inventory and even safe production management. The IoT-based information system can integrate production activities within and between enterprises to understand the production status in real time, and can realize the identification and tracking of raw materials, parts, semi-finished products and finished products. By achieving intelligent management of goods at all stages, machine spare parts can be prepared in advance and emergency plans for breakdowns can be developed to reduce production uncertainty. If IoT technology is more inclined to the intelligent management within the enterprise supply chain, blockchain technology can help improve the efficiency of inter-enterprise collaboration. The decentralized, open and transparent, safe, reliable and quasi-anonymous features of blockchain make it a promising application in supply chain management. The decentralized blockchain is used to record information throughout the supply chain, including the coordination of incoming goods, procurement, production, sales, order processing, and collaborative operations among suppliers, intermediaries, third-party service providers, and customers. It is this collaborative operation that allows each enterprise or collaborative unit in the blockchain to synchronize information and ensure the uniqueness of such information at the same point in time, eliminating information delays for all supply chain partners located on the same blockchain in a timely manner, thus reducing uncertainty in collaboration among supply chain partners. Continuous intelligent supply chain planning with technologies such as blockchain and AI simplifies and accelerates traditional processes.
2 Information Technology Innovation Resource Utilization and Economic Development

2.1. Introduction

Financial development, which is about diminishing costs incurred in the financial system (WDI, 2020), has been intensively discussed in the literature. Financial development is widely recognized and explains economic growth, and creates employment opportunities (Easterly and Levine, 2001; Zaidi et al., 2019). However, to nurture growth and finance costly projects, the improved financial system is a prerequisite. The improved financial system shifts resources from the least productive sectors to the highly productive sectors of the economy, thereby stimulating the process of invention and innovation. Hence, the financial sector plays a vital role in nurturing innovation. Due to abundant capital stock and improved financial systems, developed countries have maintained their per capita income growth. Financial deepness enhances growth by improving the efficiency of capital. Moreover, financial development affects Total factor productivity (TFP) growth, which decisively contributes to countries’ growth in per capita GDP (Easterly and Levine, 2003).

Technological innovation-led financial development has received immense importance due to the introduction of advanced technologies in the financial sector in particular and information and communication in general (Brem et al., 2016; Ho’be and Alas, 2015; Mao et al., 2020; Umar et al., 2020a). Schumpeter (1911) pioneer contribution to the role of entrepreneurs provides a base for future work in the field. Schumpeter emphasized the role of the financial sector in financing costly ventures and innovative ideas. Further research identified the role of technological innovation in financial development. In recent years, technological innovation is one of the most discussed topics.

The literature on the role of innovation-led growth is scarce till the industrial revolution took place in Europe and America. In the growth literature, Solow (1956) highlighted the importance of technological development by assuming the diminishing marginal productivity of production factors. By emphasizing technological innovation, the developed world outpace the developing world on the path towards economic development (Berg et al., 2019; Burhan et al., 2017; Harley, 2003; Umar
et al., 2020b). With the introduction of smart technology in the fourth industrial revolution, productivity growth is estimated to multiply (Cockburn et al., 2018). The Fourth industrial revolution has been significantly affected by different economic sectors, including the financial sector. The financial sector has dramatically changed the way it works and hence, providing new opportunities to investors. With the advancement of new technologies in information and communication, it has a strong association with financial sector performance, profitability, and development. However, the nexus between technological innovation and financial development has not yet received the attention of researchers. Few authors study the linkage between technological innovation and financial development (Beccalli, 2007; Brem et al., 2016; DeYoung, 2001; Ho’be and Alas, 2015; Mao et al., 2020).

Financial development has received enormous consideration from scholars and has given rise to many studies across the globe. E7 countries efficiently utilize their natural resources due to the existing improved mechanism. However, the issue of the possible impact of natural resources on financial development is debatable due to the ambiguous results in the empirical studies as there is ample evidence to validate the resource curse hypothesis by arguing that some resource-rich countries do not tend to have a high pace of financial development (Yuxiang and Chen, 2011; Solarin and Shahbaz, 2015; Badeeb et al., 2017; Beck and Poelhekke, 2017). Hence, it is important to analyze the impact of natural resource rent on financial development in E7 countries. While analyzing the resource curse hypothesis, different studies have considered human capital, trade, quality of institutions, technological innovation and R&D etc. With sufficient capital and human resources, the E7 countries significantly outpace the developing countries in terms of productivity growth. However, there is a query of whether the greater productivity and income growth in E7 countries are attributed to technological innovation in these countries. Moreover, E7 countries spend billions of dollars every year to maintain their technological innovation speed and growth in productivity. Therefore, it is essential to study the link between R&D expenditure and financial development.

Further, E7 countries have created a conducive environment for development by improving their human capacity. It is imperative to examine the contribution of human capital development in financial development. Hence, many empirical studies have been conducted to test the validity of the resource curse hypothesis (Yuxiang and Chen, 2011; Solarin and Shahbaz, 2015; Badeeb et al.,
2017; Beck and Poelhekke, 2017). However, due to the diverse nature of the model’s data and dependency on the different characteristics, the empirical literature on the impact of technological innovation, human capital, natural resources, and R&D on financial development has been scant.

This study examines the impact of technological innovation and natural resources on the financial development of seven emerging economies (such as China, India, Brazil, Mexico, Russia, Indonesia, and Turkey) from 1990 to 2017. This study contributes to the existing literature by investigating the new determinants of financial development, such as technological innovation, R&D expenditures, human capital, and income. Moreover, the study introduces an interactive term between human capital and technological innovation in the regression equation. This interactive term enables us to identify the joint effect of human capital and technological innovation in affecting financial development. Further, the study employs advanced analytical methods to analyze the determinants of financial development in E7 countries.

The paper is organized as follows: Section 2 provides the literature review, and the theoretical framework related to determinants of financial development is provided in Section 3. This section also presents the methodology used in this paper. Section 4 provides the results by employing the second-generation econometric methods. Section 5 presents the concluding remarks and policy implications.

2.2 Literature review

The literature on the role of financial development in enhancing productivity, diffusion of innovation is rich (Beck, 2011; Beck and Levine, 2004). Besides, much research was conducted to classify the possible determinants of financial development (Huang and Temple, 2005; Le et al., 2016; Shahbaz et al., 2018; Zhang et al., 2015). In the literature, human capital, trade, quality of institutions, and natural resource rent are considered important factors in explaining financial development. On the role of natural resources in affecting financial development, intensive research has been carried out to date (Badeeb et al., 2017; Beck and Poelhekke, 2017; Gu et al., 2020; Nawaz et al., 2019; Papyrakis and Gerlagh, 2004; Solarin and Shahbaz, 2015). However, the substance of empirical research has not been reached a definite conclusion regarding the relationship between natural resources and financial development. In this regard, the literature can be divided into two
major sections. On the one hand, researchers such as Solarin & Shahbaz (2015), Badeeb et al. (2017), and Beck and Poelhekke (2017) empirically test the validity of the resource curse hypothesis in a single country and panels countries analysis. These authors found ample evidence of the resource curse. On the other hand, (Erdogan et al., 2020) rejected the resource curse hypothesis and found that natural resources are a blessing. The issue is still debatable and requires further investigation. We hypothesize that natural resources significantly affect financial development. The resource curse opponents argue that developed human capital may shift the curse into a blessing by transferring the natural resources into other productive sectors of the economy. Hence, human capital positively affects financial development and, ultimately, economic growth (Ibrahim and Sare, 2018; Marchand and Weber, 2015; Rickman et al., 2017). We hypothesize that developed human capital shifts the curse into a blessing and significantly affects financial development.

On the role of technological innovation in affecting financial development, few studies are carried out to date (Beccalli, 2007; Brem et al., 2016; DeYoung, 2001; Ho’be and Alas, 2015; Pradhan et al., 2018). Technological innovation may affect financial development in multi-faceted ways: First, technological innovation improves the delivery services in banks, which improves the competitiveness position of banks and hence, results in the deepness of the financial sector (DeYoung, 2001). Second, technological innovation may affect financial development by increasing banks’ profitability, competitiveness, and performance (Ho’be and Alas, 2015). Technological innovation, which is a source of competitive advantage, is the main driver of financial sector performance (Brem et al., 2016). Moreover, continuous investment in innovation is the main driver of the financial sector’s performance (Beccalli, 2007). Hence, technological innovation in information and communication has a strong association with financial sector performance, profitability, and development. However, there is a strong complementarity between human capital and technological innovation in affecting financial development. Countries with developed human capital can shift the curse into blessing through invention and innovation. Hence, this study hypothesizes that human capital strengthens the relationship between innovation and FD.

On the role of research and development in affecting financial development, the literature is scant. The researchers have tried to establish the linkages between research and development and financial development in a one-way causal relationship. Rajan and Zingales (2003) argue that financial sector performance has a strong influence on research and development because financial
markets provide investment opportunities and transfer funds to corporate investment. This study analyzes R&D and financial development in another way around. We hypothesize that an increase in R&D expenditures significantly affects financial development.

To sum up, besides natural resources, there are other factors widely recognized as a potentially important determinant of financial development. Among others, technological innovation, R&D expenditures, human capital, income, and technological innovation are considered important factors in explaining financial development. This study contributes to the existing literature by investigating the new determinants of financial development, such as technological innovation, R&D expenditures, human capital, and income.

2.3 Model, data, and econometric methods

2.3.1 Model

To examine the determinants of financial development across E7 countries for 1990 to 2017, the empirical equation is modeled as:

$$ FD_{i,t} = \theta_1 TI_{i,t} + \theta_2 R & D_{i,t} + \theta_3 GDP_{i,t} + \theta_4 TNR_{i,t} + \mu_{i,t} $$

(1)

Where, FD represents financial development, TI represents Technological Innovation, R&D represents research and development expenditures, GDP represents Gross Domestic product, TNR is for natural resource rent.

Following DeYoung (2001), (Hoˇbe and Alas, 2015), Brem et al. (2016), and Beccalli (2007), we expect a positive impact of TI. on FD, i.e., $\theta_1 = \frac{\partial FD}{\partial TI} > 0$. Technological innovation increases banks’ profitability, competitiveness, and performance, which in turn affects financial development. Hence, we expect a strong impact of technological innovation in the fields of information and communication on financial sector performance. This study introduces R&D as a determinant of financial development. Following Beccalli (2007), we expect a positive association between R&D expenditures and financial development, i.e., $\theta_2 = \frac{\partial FD}{\partial R & D} > 0$. Continuous investment in innovation is the main driver of the financial sector’s performance (Beccalli, 2007).
Previous research related to financial development considered income (represented by GDP) as the most significant factor in explaining FD. The theoretical underpinning for the positive relationship between income and financial development is based on the wealth effect; a higher per capita income increases the demand for the improved financial sector. Moreover, higher income per capita reflects institutional development in E7 countries, i.e., $\theta_3 = \frac{\partial FD}{\partial GDP} > 0$.

This study introduces natural resources as determinants of financial development. The existing empirical studies offer mixed results on the relationship between the two variables. On the one hand, researchers such as Solarin and Shahbaz (2015), Badeeb et al., (2017), Beck and Poelhekke (2017), Nawaz et al., (2019), and Zhang and Brouwer (2020), confirmed the resource curse hypothesis's validity, while researchers such as Papyrakis and Gerlagh (2004) and Xu et al. rejected the resource curse hypothesis and considered resources a blessing. Following Solarin and Shahbaz (2015) and Nawaz et al., (2019), we expect a negative association between TNR and FD. The theoretical justification is that due to "Dutch disease," countries with abundant natural resources increase their exports instead of transforming them into domestic production (Dwumfour and Ntow-Gyamfi, 2018). Hence, we expect a negative impact of TNR on FD in E7 countries, i.e., $\theta_4 = \frac{\partial FD}{\partial TNR} < 0$.

In the subsequent model, the variables of human capital are included as additional explanatory variables. The empirical equation is modeled as:

$$ FD_{k,t} = \theta_1 T I_{k,t} + \theta_2 R & D_{k,t} + \theta_3 GDP_{k,t} + \theta_4 T NR_{k,t} + \theta_5 H C_{k,t} + \mu_{k,t} $$ (2)

Where HC represents human capital. Following Marchand and Weber (2015), Rickman et al., (2017), and Ibrahim and Sare (2018), human capital is expected to positively affect financial development, i.e., $\theta_5 = \frac{\partial FD}{\partial HC} > 0$. In model 3, an interactive term is introduced in the model in order to identify the joint effect of HC and TI.

$$ FD_{k,t} = \theta_1 T I_{k,t} + \theta_2 R & D_{k,t} + \theta_3 GDP_{k,t} + \theta_4 T NR_{k,t} + \theta_5 H C_{k,t} + \theta_6 H C * T I_{k,t} + \mu_{k,t} $$ (3)
2.3.2 Data

This study uses financial development as a dependent variable. Moreover, the study uses Technological Innovation, R&D, GDP, natural resource rent, human capital as explanatory variables. The data on Technological Innovation, Financial Development Index are sourced from IMF. The data on the Human Capital Index is obtained from Penn World Table 9.1. The data of Total natural Resources Rent % of GDP, R&D Expenditures % of GDP, and GDP measured in constant, 2010 US dollars are sourced from World Bank, 2020.

2.3.3 Econometric methods

Contrary to traditional econometric methods, this research applied advanced econometric techniques for empirical analysis. To check the potential problems in panel data, this study checks cross-sectional de- pendency (CSD) and slope heterogeneity (SH) by employing the Pesaran CSD test and (Pesaran and Yamagata, 2008) SH test. Ignoring these two issues may lead to inefficient and inaccurate estimates (Su et al., 2021, 2020) and (Ali et al., 2020). As economic integration grows, the cross-sectional dependency is of considerable importance (Hao et al., 2021). Hence, different shocks have spillover effects due to countries’ strong interconnectedness in the globalized world (Su et al., 2020a). For this purpose, this study applied the CSD test by (Pesaran, 2004) and the SH method by (Pesaran and Yamagata, 2008). This study employs (Im et al., 2003) test and (Pesaran, 2007) test to check the stationarity of variables. Since (Im et al., 2003) deals only with heterogeneous slopes and fails to consider the cross-section dependence, the (Pesaran, 2007) test can deal with the cross-sectional dependence and heterogeneous slopes. The general (Pesaran, 2007) test equation is shown below:

$$\Delta Y_{i,t} = \phi_1 + \phi_2 X_{i,t-1} + \phi_3 Y_{i,t-1} + \sum_{l=0}^{p} \phi_{l,1} \Delta Y_{i,t-l} + \sum_{l=0}^{p} \phi_{l,2} \Delta Y_{i,t-l} + \tau_{it}$$

(4)

Where and shows cross-section averages. Similarly, CSAIPS equation is provided as:

$$\text{CSAIPS} = \frac{1}{N} \sum_{i=1}^{N} \text{CADF}_i$$

(5)
Where, CADF is cross-sectional ADF. After the stationary test, this study uses the Westerlund (2007) cointegration method. This test can address both heterogeneous slope issues and cross-sections. The test uses the following test statistics:

\[ G_i = \frac{1}{N} \sum_{i=1}^{N} \frac{\tilde{a}_i}{SE(\tilde{a}_i)} \]

\[ G_\alpha = \frac{1}{N} \sum_{i=1}^{N} T\tilde{a}_i \]

\[ P_T = \frac{\tilde{a}_i}{SE(\tilde{a}_i)} \]

\[ P_\alpha = T\bar{a} \]

This study uses an advanced method augmented mean group (AMG) introduced by (Eberhardt, 2012), which is stable compared to the mean and pooled mean groups. The AMG equation is provided as:

\[ \Delta Y_{i,t} = \theta_{1,t} + \theta_{2,t}\Delta EV_{i,t} + \theta_{3,t} UCF_{i,t} + \theta_{4,t} \sum_{r=2}^{T} TNR_{r,t} + \theta_{5,t} HC_{i,t} + \theta_{6,t} HC^* TI_{i,t} + \mu_{i,t} \quad (6) \]

In an equation, the dependent variable is denoted by \(Y_{i,t}\), \(EV_{i,t}\) is for all explanatory variables such as technological innovation, human capital, GDP, total natural resources rent, research, and development expenditures. Unobservable common factors represent by \(UCF_{i,t}\) and TD is a time dummy (Mrabet et al., 2019).

Besides the AMG method, this study also uses (Dumitrescu and Hurlin, 2012) causality test. Since the presence of CSD and heterogeneity provide inefficient results if simple causality tests are used. Therefore, a more robust approach to check the causality among variables are tested using Dumitrescu and Hurlin (2012) method. This test can be used to have \(T\), which is the total number of periods greater than \(N\) (number of cross-sections). The null hypothesis supports no causal relationship, while the alternative suggests the existence of a causal relationship among variables.

### 2.3.4 Results and discussion

The results of Table 1 indicate that the variables suffer from cross-sectional dependency. The lower part of Table 1 shows the results of the slope homogeneity of the model. The significant values
of delta tide and adjusted delta tide implies that the model has gradient slope heterogeneity. Due to CS dependency and slope heterogeneity problems, this study is confined to employ second-generation unit root and cointegration techniques.

The results of unit root tests (IPS and CADF) are presented in Table 2. We used two specifications of the tests: constant, with constant, and trend. The results of the IPS test (with constant and trend) indicate that the variables such as TNR, GDP, HC, and FD are stationary at the first difference, while the remaining two variables, such as TI and R&D, are stationary at level. However, the CADF test results (with constant and trend) indicate that all variables except FD are stationary at first difference. These results direct us to employ (Westerlund 2007) Panel Cointegration test, which in addition to its applicability to mix the order of integration, also handles CSD and slope heterogeneity.

The Westerlund (2007) cointegration test results indicate a long-run relationship between FD and its determinants in these three models. The long-run relationship is evident from the significant values of all four test statistics (Table 3).

Given the CSD, slope heterogeneity, and mix order of integration and stable long-run relationship, this study employs the AMG technique. The results of the estimation of model 1 show that TI, TNR, GDP, and R&D are important variables affecting FD in the long run. By introducing human capital in model 2, the statistical accuracy is improved. First, the positive and significant coefficients of TI, income (GDP), R&D, and human capital indicate that the increase in these factors has improved the financial development of E7 countries. To be specific, technological innovation positively affects financial development, which supports the earlier findings of DeYoung (2001), Brem et al., (2016), and Beccalli (2007). Brem et al., (2016) argue that technological innovation may affect financial development by increasing banks’ profitability, competitiveness, and performance (Hobe and Alas, 2016). Technological innovation, which is a source of competitive advantage, is the main driver of financial sector performance. Moreover, DeYoung (2001) argues that technological innovation improves the delivery services in banks, which improves banks’ competitiveness position and, hence, results in the deepness of the financial sector.

The variable natural resource rent is negatively related to financial development in all three models. These results support the findings of (Solarin and Shahbaz, 2015) and (Gu et al., 2020). Due to Dutch disease, countries with abundant natural resources increase their exports instead of
transforming them into domestic production. Due to these reasons, an abundance of natural resources in E7 countries negatively affects financial development (Dwumfour and Ntow-Gyamfi, 2018). GDP is positively related to financial development in all three models. This might be because a higher per capita income increases the demand for the improved financial sector (wealth effect). Moreover, higher income per capita reflects institutional development, which results in financial development. The results further show that the variables R&D is positively related to financial development in all three models, which support the earlier findings of Beccalli (2007). Beccalli (2007) argues that continuous investment in innovation is the main driver of the financial sector’s performance.

In model 3, we introduce an interaction term between human capital and technological innovation to observe both these variables’ joint effect. Based on the coefficient of the interaction term (HC*TI), we confirm that human capital strengthens the relationship between TI. and FD. Hence, there is a strong complementarity between HC and TI in affecting FD Countries with developed human capital are able to shift the curse into blessing through invention and innovation (Table 4).

For robustness check, this study employs the mean group method. The panel causality test results indicate that there is a bi-directional causality of FD with the variables GDP, HC, R&D, TI, and TNR. Any policy to target an increase in income, technological innovation, R&D expenditures, human capital, and natural resources significantly changes the financial development. Moreover, any policy to target improves financial development significantly change income, technological innovation, R&D expenditures, human capital, and natural resources (Table 5).

<table>
<thead>
<tr>
<th>Variables</th>
<th>TI.</th>
<th>FD</th>
<th>HC</th>
<th>TNR</th>
<th>RD</th>
<th>GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistic</td>
<td>17.11***</td>
<td>14.33***</td>
<td>23.48***</td>
<td>14.35***</td>
<td>14.59***</td>
<td>22.11***</td>
</tr>
<tr>
<td>P-Values</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Delta_tilde</td>
<td>6.532****</td>
<td>6.412***</td>
<td>6.412***</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Note:***is for significance at 1% level.
### Table 2

Unit root tests results.

<table>
<thead>
<tr>
<th>Variables</th>
<th>IPS Level C</th>
<th>CADF Level C</th>
<th>IPS 1st difference</th>
<th>CADF 1st difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C&amp;T</td>
<td>C&amp;T</td>
<td>C&amp;T</td>
<td>C&amp;T</td>
</tr>
<tr>
<td>TNR</td>
<td>-1.14</td>
<td>-1.80</td>
<td>-1.69</td>
<td>-2.07</td>
</tr>
<tr>
<td>GDP</td>
<td>3.68</td>
<td>-0.91</td>
<td>-1.58</td>
<td>-2.22</td>
</tr>
<tr>
<td>HC</td>
<td>-0.47</td>
<td>2.11</td>
<td>-1.91</td>
<td>-2.20</td>
</tr>
<tr>
<td>FD</td>
<td>1.30</td>
<td>-0.28</td>
<td>-2.20</td>
<td>-2.58</td>
</tr>
<tr>
<td>TI</td>
<td>0.79</td>
<td>-1.17</td>
<td>-2.017</td>
<td>-2.55***</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>1.29</td>
<td>-1.80</td>
<td>-1.74</td>
<td>-2.07</td>
</tr>
</tbody>
</table>

Note: *, **, *** is significance level for 10%, 5%, 1%. C and T means constant and trend.

### Table 3

Panel cointegration.

<table>
<thead>
<tr>
<th>Models</th>
<th>Gt</th>
<th>Ga</th>
<th>Pt</th>
<th>Pa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-1</td>
<td>-6.06***</td>
<td>-20.68***</td>
<td>-69.66***</td>
<td>-85.34***</td>
</tr>
<tr>
<td>Model-2</td>
<td>-5.90***</td>
<td>-14.12</td>
<td>-71.07***</td>
<td>-58.96***</td>
</tr>
<tr>
<td>Model-3</td>
<td>-5.94***</td>
<td>-22.46***</td>
<td>-63.84***</td>
<td>-121.57***</td>
</tr>
<tr>
<td>HC*TI)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>
Note: *, **, *** is significance level for 10%, 5%, 1%. [] & () contain Z-values and P-values, respectively.

Table 4
Empirical results of augmented mean group technique.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model-1</th>
<th>Model-2</th>
<th>Model-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>TI</td>
<td>0.0573*** (0.000)</td>
<td>0.042*** (0.039)</td>
<td>0.055** (0.037)</td>
</tr>
<tr>
<td>TNR</td>
<td>-0.096*** (0.004)</td>
<td>-0.079* (0.078)</td>
<td>-0.062* (0.064)</td>
</tr>
<tr>
<td>GDP</td>
<td>0.120** (0.039)</td>
<td>0.135*** (0.000)</td>
<td>0.142*** (0.000)</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>0.087** (0.047)</td>
<td>0.058** (0.041)</td>
<td>0.038* (0.087)</td>
</tr>
<tr>
<td>HC</td>
<td>-</td>
<td>0.087** (0.032)</td>
<td>0.092* (0.062)</td>
</tr>
<tr>
<td>HC*TI</td>
<td>-</td>
<td>-</td>
<td>0.065** (0.028)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.671*** (0.000)</td>
<td>1.532*** (0.000)</td>
<td>2.314*** (0.000)</td>
</tr>
</tbody>
</table>

Note: *, **, *** is significance level for 10%, 5%, 1%. Model-1, 2 & 3 are estimated using AMG.

Table 5
Results of dumitrescu Hurlin panel causality test:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP does not cause FD</td>
<td>13.46***</td>
<td>0.000</td>
</tr>
<tr>
<td>FD does not cause GDP</td>
<td>7.17*</td>
<td>0.095</td>
</tr>
<tr>
<td>HC does not cause FD</td>
<td>13.72***</td>
<td>0.000</td>
</tr>
<tr>
<td>FD does not cause HC</td>
<td>12.12***</td>
<td>0.000</td>
</tr>
<tr>
<td>R&amp;D does not cause FD</td>
<td>10.17***</td>
<td>0.000</td>
</tr>
<tr>
<td>FD does not cause R&amp;D</td>
<td>6.95*</td>
<td>0.078</td>
</tr>
<tr>
<td>TI does not cause FD</td>
<td>8.55**</td>
<td>0.010</td>
</tr>
</tbody>
</table>
FD does not cause TI 15.93*** 0.000
TNR does not cause FD 9.54*** 0.009
FD does not cause TNR 10.61* 0.098

Note: *, **, *** is significance level for 10%, 5%, 1%.

2.4 Conclusion and policy specification

The issue of financial development has received enormous attention from researchers and has given rise to many studies across the globe. However, due to the diverse nature of the data and dependency of the model on the different characteristics, the empirical literature on the determinants of financial development has been scant. This study examines the impact of natural resources on financial development across E7 countries from 1990 to 2017. This study contributes to the existing literature by investigating the new determinants of financial development, such as technological innovation, R&D expenditures, human capital, and income. Moreover, the study introduces an interactive term between human capital and technological innovation in the regression equation. This interactive term enables us to identify the joint effect of human capital and technological innovation in affecting financial development. Further, this study employs advanced analytical methods to analyze the determinants of financial development in E7 countries. To estimate the determinants of financial development across E7 countries over the period of 1990 to 2017, this study uses the AMG technique. The econometric methods provide reliable results: i) variables are cross-sectionally related, and the model has slope heterogeneity; ii) variables are a mixed order of integration; iii) in all three models, FD and its determinants have a long-run relationship; iv) natural resources, technological innovation, income, human capital, and R&D expenditures are important variables affecting FD; v) human capital strengthens the relationship between technological innovation and financial development. Hence, there is a strong complementarity between human capital and technological innovation in affecting financial development. Countries with developed human capital are able to shift the curse into blessing through invention and innovation.

In terms of practical implication, we suggest that in order to shift the resources curse into a blessing, there is a dire need to transform natural resources into the most productive sectors, which
can increase value added exports and improve financial sector performance. Hence, the policy of natural resource utilization may be revisited. Moreover, human capital, technological innovation, and continuous investment in R&D can shift the curse into a blessing by transferring the natural resources into other productive sectors of the economy.
3 Digital service platform adoption application behavior study

3.1 Introduction

Since Tencent launched WeChat in 2011, WeChat has gradually become a comprehensive platform for social, business and information integration from the initial communication tool, and has thus become the focus of new media. Over the past period of time, with the formulation of the national rural revitalization strategy and the rapid promotion of the integrated development of one, two, three industries in rural areas, various business entities in the agricultural field have realized that agricultural development cannot be supported by science and technology (Lin et al., 2018). The demand for agricultural science and technology is widespread, and the demand subjects are very scattered, so it is very suitable to adopt the new media such as WeChat public number to expand the communication channels. In the context of the increasing maturity of WeChat public number technology and the improvement of users' information literacy, many regional government agencies and agriculture-related enterprises have invested a lot of human and material resources in opening and maintaining WeChat public numbers to enhance their own influence and brand awareness, or to better provide quality and convenient services to agricultural production and business subjects. However, many agricultural science and technology WeChat public numbers lack attention to user behavior and fail to provide targeted services and content pushing from the user's perspective, resulting in poor communication effect of WeChat public numbers. In view of this, it is important to analyze the factors influencing user adoption of agricultural science and technology WeChat public numbers and their mechanism of action, in order to enhance user recognition and acceptance of agricultural science and technology WeChat public numbers.

At present, there is no research on the adoption behavior of agricultural WeChat public numbers in China, but there have been multiple studies on the adoption behavior and usage intention of WeChat public numbers. However, agricultural WeChat public websites have different user groups and user demand characteristics from those of news and information, art and culture, and life and health WeChat public websites, and have higher expectations on the authority, authenticity, and usefulness of information. Therefore, this paper will study the adoption behavior of agricultural WeChat public numbers of family farm operators based on the information system success model
and trust theory, and finally make suggestions for the operation of agricultural WeChat public numbers based on the analysis results in order to promote better development of agricultural WeChat public numbers.

3.2 Theoretical basis and assumptions

3.2.1 Information System Success Model

The D&M ISS model, first proposed by DeLone and McLean, has been widely used to evaluate the success of information systems in the field of information management through continuous improvement. Initially, the model consisted of six dimensions: system quality, information quality, user satisfaction, system usage, individual impact, and organizational impact. Later, in order to better fit the progress of academic research on system success, DeLone and McLean further revised and extended the information system success model to include a new dimension of service quality, which combines system quality and information quality to better assess information system quality from a global perspective (DeLone and McLean, 2004; Akter et al., 2013). In addition, the mandatory system use is replaced with intention to use, which enables better evaluation of non-mandatory ones such as e-commerce systems. The system quality characteristics, information quality characteristics, and service quality characteristics of WeChat Public have an important impact on user value perceptions and satisfaction. Deficiencies or defects in the quality of agricultural WeChat public websites can easily lead to a decrease in customers' intention to use them. The "quality-value-use" chain in classical marketing theory is fully applicable to WeChat, and the multi-dimensional quality conceived by users has an irreplaceable driving role in user satisfaction and usage intention.

1) Information quality

The information quality of agricultural science and technology WeChat public website refers to the system characteristics such as matching the information pushed by WeChat public website with the information needs of agricultural science and technology, and the information content is adequate, the information is accurate, and the information has timeliness. Information quality is one of the important factors affecting users' attitude and their intention to use (Akter et al., 2013). High information quality can bring high satisfaction to the public number of agricultural science and technology, which eventually has an effect on users' attitude and makes them inclined to use this
WeChat public number. And lack of high level of information quality, user satisfaction will decrease due to the increase of information quality expectation gap (Gao and Bai, 2014). Therefore, the following hypothesis is proposed.

H1a: Information quality has a positive effect on user satisfaction.
H1b: Information quality has a positive effect on users' intention to use.

2) System quality

Agricultural science and technology WeChat public website is an information system based on the WeChat platform, and the system quality of the WeChat platform itself is constantly optimized in the process of development, and is of a high level in terms of system quality. Therefore, the system quality in this paper refers to the assessment of the performance of the agricultural science and technology WeChat public website, including the measurement of indicators such as ease of use, accessibility, reliability and response time of information. The lack of a high level of system quality may create usage possibilities and inconveniences for users, who in turn may question the high quality service capabilities of the WeChat public website, ultimately reducing user satisfaction and intention to use (Wu and Wang, 2016). Therefore, the following hypothesis is proposed.

H2a: System quality has a positive effect on user satisfaction.
H2b: System quality has a positive effect on user intention to use.

3) Service quality

The service quality of agricultural science and technology WeChat public number refers to the strength of support that users receive from the main body of agricultural science and technology WeChat public number operation, emphasizing the assessment of users' perceived service level (Chatterjee et al., 2018). Since the services provided by agricultural science and technology WeChat public numbers are mainly network-based, the improvement of service quality is especially critical. If the subjects operating agricultural science and technology WeChat public websites can provide timely answers to users' doubts and questions, timely information push, provide information interaction, and reasonably integrate and optimize online and offline services, they may significantly improve user satisfaction and intention to use (Sun et al., 2017). Therefore, the following hypothesis is proposed.

H3a: Service quality has a positive effect on user satisfaction.
H3b: Service quality has a positive effect on users' intention to use.

4) User satisfaction and willingness to use
User satisfaction is a state reflected by the user's psychological perception, which is a sense of pleasure and satisfaction generated by the customer after the provision of agricultural science and technology WeChat services, indicating a relative relationship between the user's prior expectations of agricultural science and technology WeChat and the actual feelings obtained after actual use (Li et al., 2016). If this measure of psychological state is expressed numerically, it is satisfaction. In general, an increase in user satisfaction is bound to increase usage intention and actual usage, and an increase in user usage intention is bound to increase actual usage (Chang et al., 2017). Therefore, the following hypothesis is proposed.

H4a: user satisfaction has a positive effect on user intention to use.

H4b: user satisfaction has a positive effect on actual user use.

H5: User intention to use has a positive impact on actual user use.

3.2.2 Trust theory

The focus of trust theory is to explain the development and maintenance of long-term relationships between the subjects and users of WeChat (Slade et al., 2015). The application of agricultural science and technology may be risky, and as the party promoting agricultural science and technology is not the main bearer of risk. Users' trust in agricultural WeChat public numbers is a positive prediction of their service behavior and a judgment of their competence, honesty and goodwill. If users have higher trust in agricultural WeChat public numbers, they will believe that this public number can provide better information or services, and thus increase their satisfaction with this public number and have stronger intention to use it (Slade et al., 2015). Therefore, it is hypothesized that.

H6a: user trust has a positive effect on user satisfaction.

H6b: User trust has a positive effect on user intention to use.

As a result, the research model of adoption behavior of agricultural WeChat public users constructed in this paper is shown in Figure 1.
3.3 Research Methodology

3.3.1 Scale design and data collection

This study draws on the existing mature scale design, and modifies and adjusts it according to the characteristics of agricultural weibo, forming a scale suitable for this study, as shown in Table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Code</th>
<th>Question item</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Quality</td>
<td>INFQ1</td>
<td>The information provided by the Agricultural Science and Technology WeChat is professional</td>
<td>Li (2018)</td>
</tr>
<tr>
<td></td>
<td>INFQ2</td>
<td>Agricultural science and technology WeChat public website provides information content in vivid language</td>
<td>Lee (2014)</td>
</tr>
<tr>
<td></td>
<td>INFQ3</td>
<td>The information provided by the Agricultural Science and Technology WeChat is accurate and reliable</td>
<td>Huang et al. (2018)</td>
</tr>
<tr>
<td>System Quality</td>
<td>SYSQ1</td>
<td>Agricultural science and technology WeChat public interface design is clear and simple to operate</td>
<td>Zhao et al. (2019)</td>
</tr>
<tr>
<td>Category</td>
<td>Item</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>------------------------------------------------------------------------------------------------</td>
<td>-------------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Service Quality</strong></td>
<td>SYSQ2 Agricultural science and technology WeChat public does not exist spam advertising, the use of reassurance and reliability</td>
<td>Sun (2017)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SYSQ3 Agricultural science and technology WeChat public number can be normal login access at any time</td>
<td>Huang (2018)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ1 Agricultural science and technology WeChat public information push timely</td>
<td>Huang (2018)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ2 Agricultural science and technology WeChat public number timely response to user inquiries</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ3 Agricultural Science and Technology WeChat provides regular orientation services</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Trust</strong></td>
<td>TRUS1 Trustworthy institutions, organizations or individuals belonging to agricultural science and technology WeChat public numbers</td>
<td>Slade E (2015)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TRUS2 Agricultural science and technology WeChat public can protect the security of personal information</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Satisfaction</strong></td>
<td>SATI1 The information from the agricultural science and technology WeChat public website was very inspiring to me</td>
<td>Shen (2017)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI2 I am very satisfied with the help given by Agri-Tech WeChat</td>
<td>Li (2018)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI3 In general, I am positive about the evaluation of agricultural science and technology weibo</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI4 For me, using Agri-Tech WeChat is a wise choice</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Intention to use</strong></td>
<td>CUSE1 I plan to follow the agricultural science and technology WeChat public number</td>
<td>Chang (2017)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE2 I plan to recommend agricultural technology micro-signals to my friends</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE3 In due course I will use the Agri-Tech WeChat public</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Actual use</strong></td>
<td>ACTU1 I have used the Agri-Tech WeChat public website several times during this period</td>
<td>Moon (2001)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ACTU2 I often use the agricultural science and technology WeChat public</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this paper, all items were tested by field and online questionnaires on a 5-point Likert scale, where "1" indicates strongly disagree or strongly disagree, "5" indicates strongly agree or strongly agree, and "3" indicates neutral or unsure. "3" means neutral or unsure. In order to ensure the...
reasonableness of the questionnaire, five experts in this field were invited to review the questionnaire before it was finalized, and 20 family farm operators were pre-surveyed, and the questionnaire was modified according to the experts' opinions and the problems that emerged from the pre-survey, and the expression of the questionnaire items and the order of the questions were adjusted to form the official questionnaire. The basic information of the subjects is shown in Table 2.

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Quantity</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>146</td>
<td>86.9%</td>
</tr>
<tr>
<td>Female</td>
<td>22</td>
<td>13.1%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20-30</td>
<td>47</td>
<td>28.0%</td>
</tr>
<tr>
<td>31-40</td>
<td>72</td>
<td>42.9%</td>
</tr>
<tr>
<td>41-50</td>
<td>48</td>
<td>28.6%</td>
</tr>
<tr>
<td>Over 50</td>
<td>1</td>
<td>0.6%</td>
</tr>
<tr>
<td>Education level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Junior high school and below</td>
<td>28</td>
<td>16.7%</td>
</tr>
<tr>
<td>High school/junior high school</td>
<td>95</td>
<td>56.5%</td>
</tr>
<tr>
<td>College</td>
<td>37</td>
<td>22.0%</td>
</tr>
<tr>
<td>Bachelor's degree and above</td>
<td>8</td>
<td>4.8%</td>
</tr>
</tbody>
</table>

In terms of frequency of use and length of use, most family farm operators continue to visit for less than one year, the frequency of visit is relatively high, most visit 2-4 times a week, reaching 73.8%, and the daily length of visit for agricultural science and technology WeChat public number is basically under an hour, less than half an hour accounted for 85.1%.

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Quantity</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration of continuous visits</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than six months</td>
<td>57</td>
<td>33.9%</td>
</tr>
<tr>
<td>6 months - 1 year</td>
<td>92</td>
<td>54.8%</td>
</tr>
<tr>
<td>1-3 years</td>
<td>17</td>
<td>10.1%</td>
</tr>
<tr>
<td>3-5 years</td>
<td>2</td>
<td>1.2%</td>
</tr>
<tr>
<td>More than 5 years</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>
### 3.3.2 Measurement model

The measurement model was tested by exploratory factor analysis. Using SPSS analysis yielded a final KMO statistic value of 0.778 and passed the significance test at the 0.001 level, and after selecting the variance maximization rotation, a total of seven factors were presented, cumulatively explaining 68.958% of the variance variance. In this study, Cronbach’s $\alpha$ values and composite reliability CR values were used to measure the reliability of the scale, and mean extracted variance AVE and standard factor loadings were used to respond to the convergent validity of the variables. The Cronbach’s $\alpha$ values for all variables of the questionnaire were greater than 0.7, indicating that the scale in this study had high reliability. Validity measures were mainly measured by factor loadings, CR and AVE. As shown in Table 4, the factor loadings of all the measures were greater than 0.7, indicating that the measures had good reliability; the composite reliability CR of all the constructs was greater than 0.8, indicating that each factor had high reliability; and the AVE was greater than 0.5, indicating that the measurement model had good convergent validity.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Measurement items</th>
<th>Standard factor loadings</th>
<th>Cronbach’s $\alpha$</th>
<th>Compound reliability CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Quality</td>
<td>INFQ1</td>
<td>0.902</td>
<td>0.874</td>
<td>0.923</td>
<td>0.799</td>
</tr>
<tr>
<td></td>
<td>INFQ2</td>
<td>0.889</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INFQ3</td>
<td>0.890</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System Quality</td>
<td>SYSQ1</td>
<td>0.875</td>
<td>0.758</td>
<td>0.855</td>
<td>0.665</td>
</tr>
<tr>
<td></td>
<td>SYSQ2</td>
<td>0.844</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SYSQ3</td>
<td>0.719</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service Quality</td>
<td>SERQ1 0.816</td>
<td>0.833</td>
<td>0.897</td>
<td>0.744</td>
<td></td>
</tr>
<tr>
<td>-----------------</td>
<td>-------------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ2 0.916</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ3 0.853</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust</td>
<td>TRUS1 0.721</td>
<td>0.871</td>
<td>0.902</td>
<td>0.607</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TRUS2 0.836</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>SATI1 0.865</td>
<td>0.903</td>
<td>0.932</td>
<td>0.775</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI2 0.906</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI3 0.896</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI4 0.853</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intention to use</td>
<td>CUSE1 0.752</td>
<td>0.864</td>
<td>0.898</td>
<td>0.595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE2 0.824</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE3 0.725</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual use</td>
<td>ACTU1 0.863</td>
<td>0.701</td>
<td>0.870</td>
<td>0.770</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ACTU2 0.892</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

When the square of the AVE value of each variable is greater than the correlation coefficient between that variable and the other variables, and the correlation coefficient between the variables is less than 0.85, it indicates that the constructs have good discriminant validity between them. Table 5 shows that the square root of the AVE of each variable is significantly smaller than the correlation coefficient between the variables, and the correlation coefficient between any of the variables is less than 0.85, indicating that the constructed measurement model has good discriminant validity.

**Table 5 Discriminant validity analysis**

<table>
<thead>
<tr>
<th>Information Quality</th>
<th>System Quality</th>
<th>Service Quality</th>
<th>Trust</th>
<th>Satisfaction</th>
<th>Intention to use</th>
<th>Actual use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Quality</td>
<td>0.894</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System Quality</td>
<td>0.459</td>
<td>0.815</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service Quality</td>
<td>0.148</td>
<td>0.189</td>
<td>0.863</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### 3.3.3 Structural model

The SmartPLS 3.0 software was used to fit the model to the 168 sample data obtained and the Bootstrap algorithm (N=1000) was used to test the significance of the path of the structural model. The model fit coefficients and significance are given in Figure 2.

<table>
<thead>
<tr>
<th></th>
<th>Trust</th>
<th>Satisfaction</th>
<th>Intention to use</th>
<th>Actual use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust</td>
<td>0.021</td>
<td>0.552</td>
<td>0.537</td>
<td>0.241</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.085</td>
<td>0.398</td>
<td>0.140</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.158</td>
<td>0.271</td>
<td>0.128</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.779</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.358</td>
<td>0.358</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.880</td>
<td>0.506</td>
</tr>
</tbody>
</table>

Note: ** and *** indicate p<0.01 and p<0.001, respectively.

![Figure 2 Model results](image_url)

The explanatory power of the model is measured by the R2 value, which shows the explanatory power of the variance variance of the observed variables. The R2 = 0.391 for information quality, system quality, service quality and trust on satisfaction, and R2 = 0.482 for quality, satisfaction and trust on users' intention to use the WeChat public website, indicate that the explanatory power of the variance of the independent variables reached 39.1% and 48.2%, respectively, which is greater than the acceptable critical value of 0.3, and the constructed model has good explanatory power.
As seen in Figure 2, information quality has a significant positive effect on satisfaction ($\beta = 0.460, p<0.001$) and on user intention to use ($\beta = 0.227, p<0.01$), hypotheses H1a, H1b hold; system quality has a significant positive effect on satisfaction ($\beta = 0.145, p<0.01$), system quality has no significant positive effect on user intention to use ($\beta = 0.099, p>0.05$) has no significant effect, hypothesis H2a holds, hypothesis H2b does not; service quality has a significant positive effect on satisfaction ($\beta = 0.149, p<0.001$), service quality has no significant effect on user intention to use ($\beta = -0.046, p>0.05$), hypothesis H3a holds, hypothesis H3b does not. There is a significant effect of satisfaction on user intention to use ($\beta = 0.285, p<0.001$) and actual use ($\beta = 0.150, p<0.01$), hypothesis H4a,H4b holds; there is a significant positive effect of user intention to use on actual use ($\beta = 0.436, p<0.001$), hypothesis H5 holds; there is a significant positive effect of trust on satisfaction ($\beta = 0.174, p<0.001$) had a significant positive effect on satisfaction ($\beta = 0.174, p<0.001$) and no significant effect on user intention to use ($\beta = 0.047, p>0.05$), hypothesis H6a holds and H6b does not.

3.3.4 Intermediation effect test

The path coefficients of information quality, system quality, service quality, trust to intention to use, and satisfaction to intention to use path coefficients were calculated in the path analysis, and the test results revealed that the path coefficients of system quality, service quality, and trust to intention to use were not significant, while satisfaction had a significant positive effect on intention to use. Therefore, according to the suggestion of literature (Zhou, 2015), the mediating role of satisfaction in the influence of information quality, system quality, service quality, and trust on intention to use needs to be further analyzed.

Most previous tests for mediating effects in structural equation models have been tested using the Sobel method, and Hayes' study suggests that the data parameter distributions may not satisfy normality in the PLS method, so the traditional Sobel method for testing effects will be biased (Hayes, 2009; Hayes and Scharkow, 2013). As suggested by Nitzl and Roldan's study (Nitzl et al., 2016), estimating the relevant parameters using the bootstrapping algorithm in PLS can effectively test for mediation effects. As shown in Table 5, the t-value test showed that all path coefficients passed the significance test at the 0.05 level with positive 95% intervals and did not contain zeros, verifying that satisfaction plays a mediating role between information quality, system quality, service quality, trust and intention to use.
Table 5 Satisfaction mediation effect test

<table>
<thead>
<tr>
<th>Indirect effect pathway</th>
<th>Indirect effects Point estimate</th>
<th>Bootstrap 1000 times</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SE</td>
<td>T</td>
</tr>
<tr>
<td>Information quality → satisfaction → intention to use</td>
<td>0.131</td>
<td>0.046</td>
<td>2.877</td>
</tr>
<tr>
<td>System quality → satisfaction → intention to use</td>
<td>0.041</td>
<td>0.020</td>
<td>2.037</td>
</tr>
<tr>
<td>Service quality → satisfaction → intention to use</td>
<td>0.043</td>
<td>0.018</td>
<td>2.319</td>
</tr>
<tr>
<td>Trust → Satisfaction → Intention to use</td>
<td>0.050</td>
<td>0.020</td>
<td>2.527</td>
</tr>
</tbody>
</table>

3.4 Discussion

3.4.1 Discussion of the results

Based on the information system success model and trust theory, this paper uses structural equation modeling to conduct an empirical study on the adoption behavior of users of agricultural science and technology WeChat public websites, and the results show that.

(1) Information quality is the core factor that affects users' satisfaction and intention to use agricultural weibo. It is said that the higher the information quality of agricultural WeChat public website, the higher the satisfaction of users and the higher their intention to use it. Therefore, if an agricultural WeChat number provides professional scientific and technical information that can help users reliably in agricultural production and operation, the more users will adopt the WeChat number.

(2) Although system quality and service quality do not have a direct impact on the intention to use agricultural WeChat public numbers, they can indirectly influence the intention to use through user satisfaction. It shows that if the agricultural WeChat public number expands its influence effect, it must design a simple and clear interface that is easy for users to operate, in addition to timely and thoughtful communication and interaction with users is also essential. These will certainly increase the satisfaction level of users, which in turn will enhance their intention to use and actual adoption behavior.

(3) The data fit indicated a significant positive relationship between trust and satisfaction. Trust theory is a test of users' perceptions of long-term relationships with agricultural WeChat public
numbers. This indicates that the credibility of agricultural WeChat public numbers is one of the important factors in the formation of user satisfaction and is a key element in the construction of the relationship between WeChat public numbers and users, and trust is expressed as a reduction in the user's expectation of the risk of use. Therefore, the higher the credibility of the WeChat public number, the more willing users are to adopt it.

3.4.2 Research significance and limitations

The existing research literature mainly studies the user adoption behavior of library WeChat public numbers, but no research related to agricultural science and technology WeChat public numbers has been found. This paper is based on the perspective of a typical user of agricultural science and technology WeChat public numbers-family farm operators-to study the adoption behavior of agricultural WeChat public numbers, which has some practical significance. This study also combines the information system success model and trust theory to expand the research perspective of adoption behavior based on WeChat users, and the findings of this study will be useful for future research based on this theory.

The study in this paper inevitably contains certain limitations. First, the sample adopted a non-probability sampling method and the sample size is relatively small, which may limit the generalizability of the findings. Secondly, the agricultural products operated by family farmers are different, and it is not possible to conduct group studies for planting and farming. Future studies can remedy these shortcomings and conduct further research and studies.
4 Digital service platform continuous use behavior study

4.1 Introduction

As a product of information and network technology, the WeChat public platform has been favored by many social subjects since its launch by Tencent in 2011 with its social media features such as interaction and entertainment. In 2017, Tencent released the 2017 WeChat Data Report, which showed that the number of monthly active public accounts was 3.5 million, an increase of 14% relative to 2016. According to the report, many enterprises and organizations use WeChat public numbers as an important source of business and operational value, viewing them as an effective social media promotion channel (Guo and Du, 2018). With the rapid development of WeChat public numbers, agricultural science and technology WeChat public numbers have also started to appear in large numbers. On agricultural science and technology WeChat public numbers, new technologies and knowledge are disseminated faster and become a useful platform for agricultural science and technology services and science and technology promotion by using modern information technology means. However, in the context of the booming development of agricultural science and technology WeChat public numbers, the attention of users also began to be dispersed, weakening the promotion effect of agricultural science and technology WeChat public numbers. In particular, many agricultural WeChat public numbers have problems such as slow content update, insufficient information authenticity and reliability, and weak interactivity, which seriously affect users' experience and perceived value, thus gradually weakening their willingness to continue using them and even eventually canceling their attention. Therefore, the quality of agricultural science and technology WeChat public numbers has become a key point for their continuous use by users, and how to improve quality to attract and retain users has become a problem that most agricultural science and technology WeChat public numbers need to solve urgently.

There is still a lack of research on agricultural science and technology WeChat public number, and similar research mainly focuses on the following aspects: First, comprehensive research on WeChat public number, for example, Guo Aifang et al. analyzed the influence of information
characteristics on WeChat public number users' sustained attention, and concluded that information theme fit, accuracy, innovation and usefulness have a significant positive influence on users' sustained attention (Guo et al., 2017); second, research on library WeChat public number, for example, Chang Guilin et al. For example, Chang Guilin et al. used the expectation confirmation model and media system dependence theory to systematically study the factors influencing the willingness of library WeChat public number users to continue to use (Chang et al., 2017). Based on the success model of information system, Sun Shaowei et al. constructed a model of users' willingness to continuously use WeChat public numbers of university libraries from the perspective of users' perceptions and tested it by using structural equation modeling (Sun et al., 2017). Thirdly, studies on agricultural journals' WeChat public numbers, such as Jin Huiping and Lu Manxin analyzed the factors influencing the user stickiness of agricultural science journals' WeChat public numbers and the actual effects of the main factors from the users' perspective, and their studies showed that experience demand, service demand and push content were the main factors influencing user stickiness (Jin and Lu., 2017). In general, few existing studies have addressed the aspect of agricultural science and technology WeChat public numbers, and the exploration of user behavior of agricultural science and technology WeChat public numbers is also missing. To this end, based on the information system success model, we explore the factors and mechanisms influencing users' satisfaction and willingness to continue using agricultural science and technology WeChat public numbers, with a view to providing references for the development of agricultural science and technology WeChat public numbers.

4.2 Theoretical basis

4.2.1 Agricultural Science and Technology WeChat Public Website

WeChat Public is a functional module based on the WeChat platform. Individuals and businesses can apply for accounts on the WeChat Public platform, through which they can interact and communicate with readers by publishing specific text, pictures, voice and video. At present, there are various types of WeChat public numbers: news and information, art and culture,
entertainment and music, life and health, and so on. In this paper, we take agricultural science and technology WeChat public number as the research object, based on agricultural science and technology information and service provision. Agricultural science and technology information and services, from the viewpoint of content, are highly integrated scientific and technological resources in agricultural production and social and economic development, which include: practical agricultural technologies such as planting, breeding and plant protection; agricultural production materials such as agricultural machinery and good seeds; information resources of agricultural varieties of crops and economic crops, basically covering information resources of science and technology, popular science, information and services. Therefore, an overview of the above content defines agricultural science and technology weibo as a network platform established by agricultural research institutes, agriculture-related universities, agricultural enterprises, government agricultural departments and institutions and agriculture-related scholars to meet their agricultural science and technology information needs by providing agricultural science and technology information to agricultural business subjects.

Based on the definition, this paper selects more than 40 commonly used WeChat public numbers as research objects, such as Chinese vegetables and southern vegetables in the crop category, farmers' farming technology and agricultural assistant in the agronomy category, world agrochemical network, modern pesticide and China new fertilizer network in the product category, agricultural guide, agricultural and market magazine and agricultural alliance network in the magazine category, and more than 40 commonly used WeChat public numbers as research objects, such as eco-agriculture and Sino-Green organic sink in the ecological agriculture category, to carry out questionnaire survey.

### 4.2.2 Information System Success Model

The information system success model constructed by Delone and Mclean is currently the most widely used model in the field of information management (Zhang et al., 2018; Cheng and Jin, 2018; Zhang, 2017). The D&M model initially considered that the success of an information system is judged by the user's experience and perception of the system, and then the quality of the information system can be measured and judged. Since then, two scholars have further modified and expanded
the D&M model, identifying three factors - system quality, information quality and service quality - as determinants of user satisfaction and system adoption (Dlone and Mclean, 1992). The model summarizes the success of information systems as the result of the success of system quality, information quality, and service quality, where system quality success is expressed as the success of the measured technology, information quality success is expressed as the success of the measured semantics, and service quality success is expressed as the success of the interaction with users. Based on the information system success model, many scholars have carried out research in different fields in practical application and use in conjunction with the research context. Li Zongfu, Guo Shunli combined with the characteristics of archival WeChat public websites to incorporate information quality, service quality, and interaction quality into the model to explore the key factors and mechanisms of action that affect users' willingness to use it consistently (Li and Guo, 2017). Li Jinhua and Chen Xinxin used full evaluation as a theory to construct a model of user satisfaction influencing factors of academic WeChat public websites from two dimensions of information content quality and information utility quality to study the influence of information content quality and information utility quality on user satisfaction (Li and Chen, 2018). Huang Yuanhao et al. introduced information quality, platform quality, service quality and user information security to construct a model of continuous use of tourism WeChat public number users, and studied the inner mechanism of users' willingness and behavior of continuous use on tourism WeChat public number (Huang et al., 2017). Since the essential attribute of agricultural science and technology WeChat public number is information dissemination, intrinsic quality and social influence are the two bases of the dissemination effect. Therefore, this paper adopts an improved quality construct in the D&M model and incorporates social influence as a common research variable.

4.3 Research hypothesis and model

4.3.1 Satisfaction

Satisfaction is a psychological experience of users' use of agricultural science and technology WeChat public number, that is, the degree of matching between users' perceived expectations and experience, which is a key factor affecting users' willingness to continue using (Bhattacherjee, 2001;
On the contrary, if users have high satisfaction with agricultural science and technology WeChat public number, they are more likely to stop using the WeChat public number until they unfollow it. Based on this, the research hypothesis is proposed.

H1: User satisfaction of agricultural science and technology WeChat users positively influences the willingness to continue using it.

4.3.2 Information Quality

Information quality refers to the assessment of the effect of information quality of users when they use Agri-Tech WeChat. Delone and Mclean in their study concluded that information quality can be measured by indicators such as timeliness, accuracy, relevance and persistence of information (Dlone et al., 2014). Information quality is one of the most important factors influencing the success of information systems and can have a significant impact on both user satisfaction and willingness to use. According to Jing Li et al., when users perceive higher quality of information content, they are more likely to have positive evaluations, and also generate higher satisfaction and willingness to continue using (Li, 2017). Based on this, the research hypothesis is proposed.

H2a: The information quality of agricultural science and technology Weibo positively affects user satisfaction.

H2b: The information quality of agricultural science and technology WeChat public websites positively affects users' willingness to continue using them.

4.3.3 System quality

System quality refers to users' assessment of the performance of their WeChat system itself when using Agri-Tech WeChat Public Website. Delone and Mclean in their study concluded that system quality can be measured by indicators such as ease of use, accessibility, reliability and flexibility of information (Dlone et al., 2014). Dong et al. found that both system quality and information quality have a significant impact on Facebook user satisfaction (Dong et al., 2014). If the agricultural science and technology WeChat public website is safe and reliable, accessible anytime and anywhere, the interface function design is simple and clear, and users can easily grasp
the operation method, then users' satisfaction will definitely increase and there will be stronger willingness to continue using it. Based on this, the research hypothesis is proposed.

H3a: System quality of agricultural science and technology weibo positively affects user satisfaction.

H3b: The system quality of Agri-Tech WeChat positively affects users' willingness to continue using it.

4.3.4 Quality of Service

Service quality refers to the assessment of users' normative expectations and perceived service level of their WeChat public number services when using agricultural science and technology WeChat public numbers. Delone and Mclean in their study concluded that system quality could be measured by indicators such as responsiveness and interactivity (Dlone et al., 2014). When constructing the WeChat public number evaluation index system, Huang Wei et al. included WeChat public number system quality, WeChat public number pushed information quality, but also WeChat public number service quality as the first level index, and the study found that information push timeliness, message response mode, online and offline realization linkage, etc. have high weight in WeChat public number evaluation index (Huang et al., 2018). Whether the service of agricultural science and technology WeChat public number is timely, whether it can give timely reply to users' inquiries and whether it has some interaction with users, all these problems solved well will increase users' satisfaction and enhance their determination to continue using it. Based on this, the research hypothesis is proposed.

H4a: The service quality of agricultural science and technology WeChat public websites positively affects user satisfaction.

H4b: The service quality of agricultural science and technology WeChat public websites positively affects users' willingness to continue using them.
4.3.5 Social Impact

Social influence refers to the attitude of people who have important influence on users when they use or experience the services provided by agricultural science and technology WeChat public number that they should or should not use this WeChat public number. The current development of China's agricultural science and technology service system is formed by the public welfare agricultural technology extension system belonging to government departments, which establishes a government-led agricultural science and technology extension network with sound institutions and complete personnel. The government influences family farms' willingness to use agricultural science and technology WeChat public numbers consistently by opening agricultural science and technology WeChat public numbers or by recommending WeChat public numbers model through scientific and technical personnel (Huang et al., 2017). Based on the improved D&M model, this paper explores users' satisfaction with the use of agricultural science and technology WeChat public numbers and their willingness to use them consistently from the perspective of family farm operators by adding the factor of social influence, which is fully consistent with the social network characteristics of family farm operators. Based on this, the research hypotheses are proposed.

H5: Social influence positively affects users' willingness to continue to use agricultural science and technology WeChat public numbers.

Based on several hypotheses mentioned above, the research model of this paper is constructed as shown in Figure 1.
4.4 Study Design

4.4.1 Scale design

The purpose of this study is to reveal the factors influencing users' willingness to continuously use agricultural science and technology WeChat public numbers and to explore the relationship between WeChat public number quality and users' willingness to continuously use agricultural science and technology WeChat public numbers. Based on the study of other literature, this paper determines that the quality of agricultural science and technology WeChat public numbers consists of three constructs: information quality, system quality and service quality, and combines three constructs: social influence, satisfaction and willingness to continue using, and finally determines the measurement indexes corresponding to each construct, which are shown in Table 1 from the specific sources. All the measurement items are tested using a 5-point Likert scale, where "1" means strongly disagree or strongly disapprove, "5" means strongly agree or strongly approve, and "3"
means neutral or unsure. In order to ensure the rationality of the questionnaire, five experts in the field were invited to review the questionnaire before it was finalized, and a pre-survey was conducted through 20 family farm operators. The questionnaire was revised according to the experts' opinions and the problems that emerged from the pre-survey, and adjustments were made to the expression of question items and the order of question items before the official questionnaire was finally formed.

### Table 1 Study variable design

<table>
<thead>
<tr>
<th>Variables</th>
<th>Code</th>
<th>Question item</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>INFQ1</td>
<td>The information provided by the Agricultural Science and Technology WeChat is professional</td>
<td>Li (2018)</td>
</tr>
<tr>
<td>Quality</td>
<td>INFQ2</td>
<td>Agricultural science and technology WeChat public website provides information content in vivid language</td>
<td>Lee (2014)</td>
</tr>
<tr>
<td></td>
<td>INFQ3</td>
<td>The information provided by the Agricultural Science and Technology WeChat is accurate and reliable</td>
<td>Huang (2018)</td>
</tr>
<tr>
<td>System Quality</td>
<td>SYSQ1</td>
<td>Agricultural science and technology WeChat public interface design is clear and simple to operate</td>
<td>Zhao (2019)</td>
</tr>
<tr>
<td></td>
<td>SYSQ2</td>
<td>Agricultural science and technology WeChat public does not exist spam advertising, the use of reassurance and reliability</td>
<td>Sun (2017)</td>
</tr>
<tr>
<td></td>
<td>SYSQ3</td>
<td>Agricultural science and technology WeChat public number can be normal login access at any time</td>
<td>Huang (2018)</td>
</tr>
<tr>
<td>Service Quality</td>
<td>SERQ1</td>
<td>Agricultural science and technology WeChat public information push timely</td>
<td>Huang (2018)</td>
</tr>
<tr>
<td></td>
<td>SERQ2</td>
<td>Agricultural science and technology WeChat public number timely response to user inquiries</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ3</td>
<td>Agricultural Science and Technology WeChat provides regular orientation services</td>
<td></td>
</tr>
<tr>
<td>Social Impact</td>
<td>SOCI1</td>
<td>Agricultural extension workers recommend this WeChat public number</td>
<td>Yuan (2016)</td>
</tr>
<tr>
<td></td>
<td>SOCI2</td>
<td>Other family farm operators recommend agricultural science and technology WeChat public</td>
<td>Self-Set</td>
</tr>
</tbody>
</table>
4.4.2 Data collection

The target of this questionnaire survey is family farm operators who have followed the public number of Agricultural Science and Technology WeChat. It was mainly conducted through field survey. There were 213 questionnaires distributed and 194 questionnaires were collected, excluding those that did not meet the requirements and those with incomplete information, 168 questionnaires were valid, with an efficiency rate of 78.9%. Among the valid samples, the family farm operators were mainly male, the age range was concentrated in 20-50 years old, the education level was basically above high school/junior high school, and all of them had the experience of using agricultural science and technology WeChat public number, so the survey results were highly representative. The basic information of the subjects is shown in Table 2.

<table>
<thead>
<tr>
<th>CUSE1</th>
<th>In the future I will continue to pay attention to agricultural science and technology WeChat public number</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUSE2</td>
<td>In the future, I intend to maintain or even increase the frequency of using agricultural technology WeChat public</td>
</tr>
<tr>
<td>CUSE3</td>
<td>I will always check the news pushed by the WeChat public number of agricultural science and technology</td>
</tr>
<tr>
<td>CUSE4</td>
<td>When I encounter a problem, I will first think of solving it through the agricultural technology WeChat public</td>
</tr>
<tr>
<td>CUSE5</td>
<td>Among the WeChat public websites, the Agricultural Science and Technology WeChat public website is one of my top choices</td>
</tr>
<tr>
<td>CUSE6</td>
<td>I have a high opinion of agricultural science and technology weibo in general</td>
</tr>
</tbody>
</table>
Control variables | Quantity | Percentage
--- | --- | ---
Gender | | |
Male | 146 | 86.9%
Female | 22 | 13.1%
Age | | |
20-30 | 47 | 28.0%
31-40 | 72 | 42.9%
41-50 | 48 | 28.6%
Over 50 | 1 | 0.6%
Education level | | |
Junior high school and below | 28 | 16.7%
High school/junior high school | 95 | 56.5%
College | 37 | 22.0%
Bachelor's degree and above | 8 | 4.8%

In terms of frequency of use and length of use, most family farm operators continue to visit for less than one year, the frequency of visit is relatively high, most visit 2-4 times a week, reaching 73.8%, and the daily length of visit for agricultural science and technology WeChat public number is basically under an hour, less than half an hour accounted for 85.1%.

Table 3 Time and frequency of users' use of agricultural science and technology WeChat public numbers

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Quantity</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration of continuous visits</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Less than six months | 57 | 33.9%
6 months - 1 year | 92 | 54.8%
1-3 years | 17 | 10.1%
3-5 years | 2 | 1.2%
More than 5 years | 0 | 0%
| Access Frequency | | |
1 time or less per week | 12 | 7.1%
2-4 times per week | 124 | 73.8%
Almost daily visits | 32 | 19.0%
4.5 Data Analysis

Partial least squares analysis is suitable for situations where the number of samples is relatively small and the normality characteristics of the sample distribution are not necessarily required, as well as for situations where the model is more complex. In this study, SmartPLS 3.0 software, a common software for partial least squares analysis technique, was used for the analysis.

4.5.1 Measurement model

The measurement model was tested by exploratory factor analysis. The SPSS analysis yielded a final KMO statistic value of 0.828 and passed the significance test at the 0.001 level, and the selection of variance maximization rotation presented a total of six factors that cumulatively explained 71.28% of the variance variance. In this study, Cronbach’$\alpha$ values and composite reliability CR values were used to measure the reliability of the scale, and mean extracted variance AVE and standard factor loadings were used to respond to the convergent validity of the variables. The Cronbach’$\alpha$ values for all variables of the questionnaire were greater than 0.7, indicating that the scale in this study had high reliability. Validity measures were mainly measured by factor loadings, CR and AVE. As shown in Table 4, the factor loadings of all the measures were greater than 0.7, indicating that the measures had good reliability; the composite reliability CR of all the constructs was greater than 0.8, indicating that each factor had high reliability; and the AVE was greater than 0.5, indicating that the measurement model had good convergent validity.

<table>
<thead>
<tr>
<th>Length per visit</th>
<th>Less than half an hour</th>
<th>143</th>
<th>85.1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Half hour - 1 hour</td>
<td>22</td>
<td></td>
<td>13.1%</td>
</tr>
<tr>
<td>More than 1 hour</td>
<td>3</td>
<td></td>
<td>1.8%</td>
</tr>
</tbody>
</table>

Table 4 Results of reliability and convergent validity tests
<table>
<thead>
<tr>
<th>Factor</th>
<th>Measurement items</th>
<th>Standard factor loadings</th>
<th>Cronbach’ α</th>
<th>Compound reliability CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Quality</td>
<td>INFQ1</td>
<td>0.902</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INFQ2</td>
<td>0.889</td>
<td>0.874</td>
<td>0.923</td>
<td>0.799</td>
</tr>
<tr>
<td></td>
<td>INFQ3</td>
<td>0.890</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System Quality</td>
<td>SYSQ1</td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SYSQ2</td>
<td>0.844</td>
<td>0.758</td>
<td>0.855</td>
<td>0.665</td>
</tr>
<tr>
<td></td>
<td>SYSQ3</td>
<td>0.719</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service Quality</td>
<td>SERQ1</td>
<td>0.816</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SERQ2</td>
<td>0.916</td>
<td>0.833</td>
<td>0.897</td>
<td>0.744</td>
</tr>
<tr>
<td></td>
<td>SERQ3</td>
<td>0.853</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Each</td>
<td>SERQ3</td>
<td>0.853</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Impact</td>
<td>SOCI1</td>
<td>0.835</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SOCI2</td>
<td>0.918</td>
<td>0.709</td>
<td>0.870</td>
<td>0.770</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>SATI1</td>
<td>0.865</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI2</td>
<td>0.906</td>
<td>0.903</td>
<td>0.932</td>
<td>0.775</td>
</tr>
<tr>
<td></td>
<td>SATI3</td>
<td>0.896</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SATI4</td>
<td>0.853</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Willingness to continue using</td>
<td>CUSE1</td>
<td>0.752</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE2</td>
<td>0.824</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE3</td>
<td>0.725</td>
<td>0.864</td>
<td>0.898</td>
<td>0.595</td>
</tr>
<tr>
<td></td>
<td>CUSE4</td>
<td>0.821</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE5</td>
<td>0.751</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CUSE6</td>
<td>0.749</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

When the square of the AVE value of each variable is greater than the correlation coefficient between that variable and the other variables, and the correlation coefficient between the variables is less than 0.85, it indicates that the constructs have good discriminant validity between them. Table 5 shows that the square root of the AVE of each variable is significantly smaller than the
correlation coefficient between the variables, and the correlation coefficient between any of the variables is less than 0.85, indicating that the constructed measurement model has good discriminant validity.

### Table 5 Discriminant validity analysis

<table>
<thead>
<tr>
<th>Information Quality</th>
<th>System Quality</th>
<th>Service Quality</th>
<th>Social Impact</th>
<th>Satisfaction</th>
<th>Willingness to continue using</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Quality</td>
<td>0.894</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System Quality</td>
<td>0.459</td>
<td>0.815</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service Quality</td>
<td>0.148</td>
<td>0.189</td>
<td>0.863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Impact</td>
<td>0.294</td>
<td>0.236</td>
<td>0.421</td>
<td>0.877</td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>0.552</td>
<td>0.398</td>
<td>0.271</td>
<td>0.358</td>
<td>0.880</td>
</tr>
<tr>
<td>Willingness to continue using</td>
<td>0.537</td>
<td>0.360</td>
<td>0.227</td>
<td>0.482</td>
<td>0.521</td>
</tr>
</tbody>
</table>

### 4.5.2 Structural model

The SmartPLS 3.0 software was used to fit the model to the 168 sample data obtained and the Bootstrap algorithm (N=1000) was used to test the significance of the path of the structural model. The model fit coefficients and R² values are given in Figure 4.
Figure 4 Model results

The explanatory power of the model is measured by the $R^2$ value, showing the explanatory power of the variance variance of the observed variables. As can be seen in Figure 4, $R^2 = 0.361$ for information quality, system quality and service quality on satisfaction, and $R^2 = 0.444$ for WeChat quality, satisfaction and social influence on users' intention to continue using, indicate that the explanation of the variance of the independent variables reaches 36.1% and 44.4%, respectively, which is greater than the acceptable threshold of 0.3, and the constructed model has good explanatory power.

As can be seen from Figure 4, satisfaction has a significant positive effect on users' willingness to continue using ($\beta = 0.174$, $p<0.001$), hypothesis H1 holds; information quality has a significant positive effect on satisfaction ($\beta = 0.455$, $p<0.001$) and on users' willingness to continue using ($\beta = 0.293$, $p<0.001$), hypotheses H2a,H2b holds; system quality has a significant positive effect on satisfaction ($\beta = 0.156$, $p<0.01$), system quality has no significant effect on users' intention to continue using ($\beta = 0.066$, $p>0.05$), hypothesis H3a holds, hypothesis H3b does not hold; service quality has a significant positive effect on satisfaction ($\beta = 0.174$, $p<0.001$), and There is no
significant effect of service quality on users' willingness to continue using ($\beta = -0.020$, $p>0.05$), hypothesis H4a holds and hypothesis H4b does not hold; there is a significant effect of social influence on users' willingness to continue using ($\beta = 0.307$, $p<0.001$), and hypothesis H5 holds.

4.5.3 Mediating effects of satisfaction

The path coefficients of system quality to users' intention to use continuously and service quality to users' intention to use continuously were calculated in the path analysis, and the test results revealed that the path coefficients of system quality to users' intention to use continuously and service quality to users' intention to use continuously were not significant, while satisfaction had a significant positive effect on users' intention to use continuously. Therefore, further analysis of the mediating role of satisfaction in the influence of information quality, system quality, and service quality on users' intention to use consistently is needed according to the recommendations of the literature (Zhou et al., 2015). The method of Nitzl and Roldan, combined with the parameters estimated by the bootstrapping algorithm in PLS, was used to verify whether the mediating effect was significant (Hayes, 2009; Hayes, 2013; Nitzl et al., 2016). As shown in Table 6, the t-value test shows that all path coefficients pass the significance test at the 0.05 level, with positive 95% intervals that do not contain zeros, verifying that satisfaction mediates the effect of information quality, system quality, and service quality on users' intention to continue using.

<table>
<thead>
<tr>
<th>Indirect effect pathway</th>
<th>Indirect effects</th>
<th>Bootstrap 1000 times</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point estimate</td>
<td>SE</td>
<td>T</td>
</tr>
<tr>
<td>Information quality-&gt; Satisfaction-&gt; User's willingness to continue using</td>
<td>0.104</td>
<td>0.036</td>
<td>2.89</td>
</tr>
<tr>
<td>System quality-&gt; Satisfaction-&gt; User's willingness to continue using</td>
<td>0.036</td>
<td>0.018</td>
<td>2.00</td>
</tr>
<tr>
<td>Service quality-&gt; Satisfaction-&gt; User's willingness to continue using</td>
<td>0.040</td>
<td>0.016</td>
<td>2.50</td>
</tr>
</tbody>
</table>
4.6 Conclusion

4.6.1 Discussion of results

This study uses the information system success model constructed by Delone & Mclean, adds social influences and extends it to the field of agricultural science and technology WeChat, trying to reveal the influencing factors and their mechanism of action on the willingness to continuously use agricultural science and technology WeChat. The results of the study show that information quality has both direct and indirect effects on the willingness to continuously use agricultural science and technology WeChat public numbers through satisfaction; system quality and service quality have indirect effects on the willingness to continuously use agricultural science and technology WeChat public numbers through satisfaction; and social influence has a direct and significant positive effect on the willingness to continuously use agricultural science and technology WeChat public numbers. The results also indicate that there are some differences in the effects and paths of action of information quality, system quality and service quality on the willingness to continuously use agricultural science and technology WeChat public numbers.

First of all, information quality has the most direct role and the greatest influence on the willingness to continue using agricultural science and technology WeChat public numbers. Agricultural science and technology WeChat public number is different from the general entertainment and news public number, which has a strong professional and user-specific Therefore, agricultural science and technology WeChat public number users have stronger demand and expectation for high-quality information, and the high-quality demand requires that the information released by agricultural science and technology WeChat public number must be true and objective. As agricultural science and technology has a greater impact on agricultural production activities, high-quality information is relatively important to users, because of this, the users of agricultural science and technology WeChat public number with high information quality are relatively at a high level of satisfaction and continued use of the will. Therefore, agricultural science and technology WeChat public numbers should pay particular attention to the quality of information, optimize the content of public number science and technology information by clarifying the scientific and technological needs of users, strictly control the quality level of information,
guarantee the authenticity and reliability of content, and improve the effectiveness of agricultural science and technology information with high professionalism and authority.

Secondly, system quality and service quality have no direct influence on the willingness to continue using agricultural science and technology WeChat public number, but have an indirect influence through satisfaction. User satisfaction of agricultural science and technology WeChat public number largely comes from system quality and service quality. When the agricultural science and technology WeChat public number platform has clear hierarchy, easy to operate function navigation, strong interactivity and problem solving ability, users will have higher expectation of satisfaction, and then form stronger satisfaction and finally enhance their willingness to continue to use. Therefore, we should not only pay attention to the design and release of information content, but also strive to build the quality of the system, optimize the page, and do a good job of interaction with users and timely answers to questions.

Finally, social influence has a direct role in the willingness to use agricultural science and technology WeChat public number continuously. The willingness of family farm operators to continuously use agricultural science and technology WeChat public numbers not only depends on the quality and satisfaction of WeChat public numbers, but also is influenced by the role of social influence factors. When agricultural technology promoters actively recommend agricultural technology WeChat public numbers or see other family farm operators actively adopt agricultural technology WeChat public numbers, family farm operators' willingness to use them consistently will be influenced by external subjects such as media or agricultural technology promoters. When promoting agricultural science and technology WeChat public numbers, pay attention to word-of-mouth communication in the dissemination process, form a network effect, and proactively establish close ties with agricultural technology promoters so that they can become the pushers of users' continuous use.

4.6.2 Research significance and limitations

This paper analyzes the specific influence paths and mechanisms of system quality, information quality and service quality of agricultural science and technology WeChat public numbers on family farm operators' willingness to use them consistently, using user satisfaction as a mediator, and
analyzes the role of the mediating effect among them. The significance of the study is mainly reflected in the following aspects: first, it combines the current hot topics such as technology-driven rural revitalization and rural industrial integration, and takes agricultural science and technology WeChat public numbers and family farm operators as the research objects, further expanding the research scope of WeChat public number users' usage behavior and willingness; second, with the help of the information system success model, it analyzes the three dimensions of system quality, information quality and service quality to users' willingness to continuously use, further refining and extending the research related to the characteristics of WeChat public numbers; third, using structural equation modeling to analyze WeChat public number users' usage behavior, providing a new research idea and analytical framework.

There are still some shortcomings in this study, mainly in the following two points: first, the selection of the sample is mainly concentrated in Jiangsu province, and the sample size collection is also on the low side, which basically meets the requirements of structural equation model analysis, but considering the sampling bias, it may cause some errors, and further improvement is needed in the follow-up study; second, the model incorporates fewer variables, which leads to an overly simple model structure, and it is necessary to further expand the model on this basis in the future. In the future, it is necessary to further expand the model on this basis.
5 Research on e-commerce value creation based on information integration perspective

5.1 Introduction

With the development of globalized and networked economy, the operational environment and market environment faced by enterprises will become increasingly complex. In this context of fierce market competition, only companies that use internal and external information, deal with various uncertainties quickly, and respond effectively to market changes can have a competitive advantage, and this capability is organizational agility (Narayanan et al., 2015). Companies are now increasingly relying on information technology, including process management, knowledge and communication technologies, to enhance their organizational agility. Companies with high organizational agility continually explore opportunities for competitive behavior in their product market space and integrate the knowledge and assets necessary to capture those opportunities. Organizational agility is the foundation for capturing organizational performance as companies continuously improve and redefine value creation through innovation in products, services, channels and market segments (Junni et al., 2015; Zhou et al., 2015).

Throughout the current business environment, e-commerce has been widely used and gradually integrated into various businesses of enterprises, and the internal and external process operations of organizations are increasingly dependent on the support of e-commerce systems. In addition to the perspectives of business environment and technology environment, more scholars have found that e-commerce perspective can enhance organizational agility (Mei et al., 2013; Chi et al., 2017). However, although the role of e-business on organizational agility is so important in a competitive environment, little is known about how e-business can support organizational agility and thus enhance performance. For example, many leading agricultural enterprises have built ERP, SCM, OA, and other information support platforms under the call of "Internet+Agriculture". CRM For example, many leading agricultural enterprises have built e-commerce support systems that integrate ERP, SCM, OA, and other information support platforms under the call of
"Internet+Agriculture", but ultimately their performance in terms of organizational agility is very different. Therefore, it is necessary to further investigate how to use e-business to drive organizational agility and thus provide e-business support to enhance organizational agility. To this end, this paper analyzes the mechanism of e-business capability to organizational agility from the perspective of information integration, raises the issue of e-business value creation, emphasizes the support of e-business capability to information integration, analyzes the role of information integration in the process of e-business capability penetration to organizational agility, and constructs a concept from e-business resources to e-business application capability to organizational agility from the perspective of information integration based on dynamic capability view and process foundation view. The conceptual model from e-business resources to e-business application capability to organizational agility is constructed from the perspective of information integration based on dynamic capability view and process base view, and theoretical hypothesis is proposed to analyze the composition of e-business capability and the role of information integration. Finally, the theoretical hypothesis of this paper is tested by using questionnaires to reveal the inner mechanism of the influence of e-business capability on organizational agility.

5.2 E-Commerce Based Organizational Agility

Organizational agility is an inherent ability of a business to deal with often unexpected changes in the business environment by responding quickly and innovatively to exploit them as opportunities for growth and prosperity (Zhang and Sharifi, 2000). There are two types of organizational agility: market agility and operational agility. Market agility refers to a company's ability to respond quickly by continuously acquiring information and improving products or services to meet customer needs, with an emphasis on dynamic, customer characteristic-based adjustments and the ability to make judgments under conditions of uncertainty (Sambamurthy and Bharadwaj, 2003). Operational agility refers to the ability to respond quickly to changes in market or demand within a company's internal business processes (Sambamurthy and Bharadwaj, 2003), which highlights flexible and responsive operations as a key foundation for quickly and fluidly transforming innovation initiatives in the face of change. Both types of agility require constant innovation and change, with the former focusing on entrepreneurial thinking and the latter emphasizing rapid execution/realization.
E-Business systems are the foundation for enterprises to acquire, deploy, combine and reorganize information resources to support and enhance business strategies and workflows, and have a great deal to do with realizing business value and maintaining competitive advantage. However, e-business systems do not naturally enable organizational agility and in many cases even exhibit hindering effects. The mechanism and effects of e-commerce and information technology on organizational agility vary considerably among many scholars' studies and can be summarized into three types: the first type of study concludes that e-commerce technology use can promote the generation of organizational strategic agility, that the technical level and behavioral capabilities of information technology personnel have direct or indirect effects on the realization of organizational agility, and that information technology has a positive impact on organizational agility by enhancing Organizational agility is achieved by improving the organization's ability to perceive and respond to changes in the environment (Fink and Neumann, 2007); the second study concludes, in contrast, that the staleness and rigidity of information systems impede organizational agility, that over-reliance on technology and formal data and report-based analysis may paralyze managers' ability to see and act quickly to capture opportunities and inhibit enthusiasm for learning and innovation, and that an overemphasis on data integration and process automation of Information systems that overemphasize data integration and process automation may also create rigidity in the face of change and unexpected barriers (Newell and Galliers, 2006); a third study concludes that e-business technology can both facilitate and impede organizational agility (Overby, 2006), and that e-business technology can facilitate agility by extending and enriching corporate knowledge and processes, but may also impede organizational agility because of the fixed nature of the system. Several opposing research findings motivate this paper to continue this area of research in an attempt to uncover where the differences between theoretical studies lie.

5.3 Theoretical Models and Assumptions

This paper reveals the process of creating agility by analyzing the essential connotation of information integration and its antecedents and consequences, firstly, defining information integration, analyzing the connotation and characteristics of information integration from customer and supplier dimensions; secondly, identifying the technical and organizational factors affecting
information integration in the current environment in terms of e-commerce; finally, analyzing the impact of information integration on organizational agility. The existing research classifies the determinants of information integration into e-business basic capability at the technical level and e-business application capability at the management level (Zhong et al., 2010), where e-business basic capability is the basic technical resource capability that supports the platform of enterprise informatization and networking, which is the basis and premise of information integration; while e-business application capability is a dynamic capability more embodied in inter-enterprise relationship management capability, technology application capability, and is the basis for enterprises to use e-business to effectively build up information integration. It is the ability to use e-commerce to effectively establish, maintain and develop relationships with other participating partners, especially upstream and downstream enterprises, and is a necessary capability for successful information integration (Zhong et al., 2011). In summary, we establish a mechanism model of e-business capability affecting organizational agility based on dynamic capability view and process-based view, and analyze the formation of e-business capability and the role of information integration, which affects organizational agility by supporting information integration. The research model is shown in Figure 1.
5.3.1 Information Integration and Organizational Agility Creation

Although there is no academic consensus on the definition of organizational agility, it is easy to see that there is a common understanding of the definition of organizational agility. It is believed that organizational agility is the ability of a company to quickly grasp and react to environmental threats and market opportunities (Sambamurthy and Bharadwaj, 2003). Achieving organizational agility requires the organic integration of large amounts of distributed data and information from customers and suppliers, which relies on information integration. This includes not only customer-related information integration, but also supplier-related information integration (Jose and Pedro, 2016). Information integration breaks through inter-organizational functional barriers, makes enterprise processes more efficient, facilitates synchronized demand management, and increases production flexibility (Wong et al., 2011). Previous studies have found that the ability to integrate information linked to various synergistic mechanisms (producer-market, producer-other actors in the supply chain) enhances organizational agility, and that rapid information feedback and information sharing across organizational boundaries enables firms to innovate and act competitively on consumer-based market opportunities to help ensure that the supply of a product or service is synchronized with the true demand in the market (Roberts and Grover, 2012), hence the hypothesis that

H1: Information integration has a direct positive effect on organizational agility.

5.3.2 E-commerce capability hierarchy and impact on information integration

According to the relevant literature (Zhong et al., 2010; Zhong et al., 2011), e-business capabilities are divided into two categories, e-business system capabilities and e-business application capabilities. E-commerce system capability focuses on the input and resource base in e-commerce, which can support enterprises to obtain the required information resources and
accomplish the basic task functions conveniently, but due to the rapid development of e-commerce technology, these basic resource capabilities can be easily obtained through purchase and development, which cannot bring core competitive advantage to enterprises, for example, almost any enterprise can purchase from the market a high-quality and stable For example, almost any enterprise can buy a high-quality and stable e-commerce system from the market, so it is a low-level capability. With the in-depth research on e-commerce capability, e-commerce application capability is gradually distinguished from e-commerce system capability (Lai et al., 2008), which is the ability of enterprises to effectively allocate and utilize their own and business partners' e-commerce technical resources and complementary resources, and effectively use e-commerce system to support collaborative business operation and strategy implementation with external affiliated enterprises. It is characterized by enterprise heterogeneity and uniqueness, and can never be formed through purchase and replication. Low-level e-business system capability is the basis for the formation of high-level e-business application capability, and high-level e-business application capability is an extension of low-level e-business system capability. In terms of information integration, e-business system capability is provided by enterprises with stable technical infrastructure that can support enterprises to obtain the required information resources and accomplish basic task functions conveniently, while e-business application capability provides strong support for the sharing of internal and external information and the integration and coordination of organizational functions (Wong et al., 2012). Therefore, the following hypothesis is proposed in this paper.

H2: E-commerce system capabilities have a direct positive effect on information integration.

H3: E-commerce application capabilities have a direct positive effect on information integration.

H4: E-commerce system capability has a direct positive effect on e-commerce application capability.

5.3.3 Impact of e-business capabilities on organizational agility

The application of e-commerce has brought significant changes to enterprises, and its impact is far-reaching. High-quality e-commerce system provides an integrated information platform for
market information and operational adjustment of enterprises. By providing real-time, stable and comprehensive data, it helps enterprises to carry out effective and rapid decision-making behavior in the face of changes in market and customer demands, and assists them to adjust and optimize their organizational structure and business processes, making them more flexible and efficient (Lu and Ramamurthy, 2011). The integration of information technology into organizational management to form dynamic capabilities enables companies to improve communication and linkages between internal and external partners with market-oriented objectives, and to reorganize organizational resources for strategic adjustment and effective allocation, so that companies can adapt to a customer- and product-centric market environment to the greatest extent possible (Van et al., 2006). Therefore, the following hypothesis is proposed in this paper.

H5: E-commerce system capabilities have a direct positive effect on organizational agility.

H6: E-commerce application capabilities have a direct positive effect on organizational agility.

Part of the literature (Zhu, 2004) suggests through empirical tests that there is some complementarity between e-business system capabilities at the technical level and e-business application capabilities at the managerial and organizational levels, i.e., the system-based capabilities at the low level of e-business interact with the e-business application capabilities at the high level of e-business. Accordingly, this paper proposes the hypothesis of the complementary roles of e-business system capabilities and e-business application capabilities.

H7: E-commerce system capability and e-commerce application capability have a positive interaction effect on organizational agility.

5.3.4 Impact of Organizational Agility on Business Performance

A high level of organizational agility allows companies to expand the range of competitive actions and feasible responses they can choose when faced with changes in the external environment, thereby controlling market risks and uncertainties and ultimately improving business performance [7]. That is, when a firm perceives changes in the external environment, it has the opportunity to choose a flexible organizational structure, a new business model, a new way of delivering products or services, and to publish a new value proposition that allows the firm's process improvements to better match the dynamic market, which is ultimately reflected in the firm's performance in the form
of increased profits, better customer satisfaction, lower operating costs for the firm, etc. (Taradar et al., 2017). Therefore, the following hypothesis is proposed in this paper.

H8: Organizational agility has a direct positive effect on firm performance.

5.4 Research Methodology

5.4.1 Measurement tools

The measurement scales in this paper were taken from the existing literature and fine-tuned to the research context, which can ensure the content validity, structural validity and reliability of the scales. The designed questionnaire is divided into two modules, the first part is about the filling in of basic information of the respondents, and the second part is the variable measurement items formed by each construct in the research design, using the LIKERT 5-point scale. Firstly, a small-scale pre-survey was conducted on 20 leading agricultural enterprises, and the questions were revised for those with ambiguous and unclear understanding, so that each question item was finally measured accurately and without ambiguity.

The e-business competencies are designed with reference to the Zhong Weijun et al. scale (Zhong et al., 2010; Zhong et al., 2011), which distinguishes e-business competencies as e-business system competencies, e-business technology application competencies, and e-business relationship management competencies. Among them, e-business technology application competency and e-business relationship management competency belong to the second-level concept of e-business application competency. E-commerce system competence consists of system quality, information quality and service quality. E-commerce technology application capability includes four topics, e-business strategy development, e-business system operation experience, e-business system function integration experience and inter-enterprise information exchange process development; relationship management capability includes five topics, providing support for business partners to participate in e-business, intra-enterprise e-business department linkage and communication, inter-enterprise e-business department linkage and communication, rational arrangement of participation Information integration uses the scale of Zhou, Yaohua et al. (2017), which contains six questions on sales end information, customer relationship management, customer purchase characteristics,
production planning, inventory information and market forecast information sharing. Organizational
gility was measured using the Lu (2011), Tallon (2008), and Zhou et al. (2015) scale, which
cludes two dimensions: operational agility and market agility. The operational agility includes
three questions, namely, meeting customer customization requirements, adjusting product structure,
and reallocating resources. Market agility consists of 4 questions, namely, responding accurately to
changes in customer needs, providing exactly what customers want, responding quickly to new
products or services from competitors, and market scope expansion. Business performance was
measured using the Zhu Shuting et al. (2017) scale which includes 6 question items, namely,
transaction accuracy, logistics cost, product service quality, customer loyalty, transaction efficiency,
and sales revenue.

5.4.2 Data collection

The data in this paper were obtained from a field survey in Shanghai, Jiangsu and Zhejiang.
According to the theoretical model set using a five-point Likert scale, respondents scored according
to their actual situation, with higher scores showing a higher degree of agreement, with a value of 1
indicating complete disagreement, a value of 3 indicating uncertainty, and a value of 5 indicating
complete agreement. A total of 350 questionnaires were distributed, 348 validly returned
questionnaires were initially screened and re-screened, and 7 unqualified questionnaires were
deleted. A total of 341 questionnaires entered the final stage of data analysis and model fitting.

In terms of respondent position, 65.7% of the respondents were managers of the company's
operations department (e.g., purchasing, ordering, or after-sales service) and 34.3% were IT
directors. An independent sample t-test revealed that there was no significant difference between
the responses of the two groups of business and IT departments to the questionnaire at the p<0.05
significance level. In general, they have a better understanding of the overall business situation and
e-commerce technology application, which ensures the validity of the questionnaire data.

5.4.3 Common method deviation control

In the questionnaire, if the same questionnaire is filled by one person from the beginning to the
end, there may be the problem of Common Method Variance (CMV), which affects the quality and
authenticity of the data. In this paper, a variety of measures such as procedural control and statistical
control are taken to control common method bias, for example, in some enterprises each part of the same questionnaire can be filled out by different positions, and other methods; Harman one-way test is applied to the returned sample data, and the unrotated is the first principal component factor variance is significantly less than 40% and does not account for the majority, so it may be due to the survey method single data. The common method bias of the source has no significant effect in the study of this paper.

5.5 Empirical Analysis

Structural equation modeling includes two stages: measurement model and structural model. Among them, the test of the measurement model is mainly to study the reliability and validity of the scale data, and this paper uses SPSS and SmartPLS to test the data. The structural model mainly evaluates the explanatory power of the model and the significance of the path. SmartPLS is used because it does not have excessive requirements on the data distribution patterns, is suitable for exploratory studies and complex structural models, and supports higher-order measurement models.

5.5.1 Measurement model evaluation

Since the organizational agility scale was modified from the relevant literature in this paper, in order to ensure the validity of the scale structure, this paper first conducted exploratory factor analysis for information integration, the extraction method used principal component analysis, and the maximum variance method was used for selection, the analysis results showed that the KMO test value was 0.76, which was greater than the critical value of 0.7, and the Bartlett's spherical test value was 1057, and p < 0.001, indicating that it is suitable for factor analysis, and the cumulative explanatory power of the variance of the two factors reached 71.90%, and the 2 factors were named operational agility and market agility, respectively.

From Table 1, it can be seen that in each construct all factor loadings are greater than 0.6, Cronbach's $\alpha$ values and combined reliability of all dimensions are greater than 0.8, and from the average variance extracted (AVE) values, all constructs are greater than 0.586, which are greater than the threshold value of 0.5 for the measure of convergent validity, which indicates that the intrinsic quality of the constructed model is more desirable. The strength of the discriminant validity
of the scale can be seen in Table 2, because the correlation coefficients of all the constructs with other constructs are smaller than the square root of the AVE of the constructs themselves, and all can be considered that the discriminant validity of the model is relatively good.

Table 1 Factor loadings, Cronbach’s $\alpha$ and composite reliabilities

<table>
<thead>
<tr>
<th>Idea</th>
<th>Measurement indicators</th>
<th>Factor load</th>
<th>Cronbach’s $\alpha$</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IORM1</td>
<td>0.841</td>
<td>0.897</td>
<td>0.924</td>
<td>0.710</td>
</tr>
<tr>
<td></td>
<td>IORM2</td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM3</td>
<td>0.803</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM4</td>
<td>0.885</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM5</td>
<td>0.805</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EBSY1</td>
<td>0.849</td>
<td>0.843</td>
<td>0.904</td>
<td>0.759</td>
</tr>
<tr>
<td></td>
<td>EBSY2</td>
<td>0.916</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EBSY3</td>
<td>0.846</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INTE1</td>
<td>0.847</td>
<td>0.929</td>
<td>0.944</td>
<td>0.738</td>
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<tr>
<td></td>
<td>INTE2</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INTE3</td>
<td>0.828</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INTE4</td>
<td>0.867</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INTE5</td>
<td>0.885</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>INTE6</td>
<td>0.870</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>OPAD1</td>
<td>0.878</td>
<td>0.844</td>
<td>0.906</td>
<td>0.763</td>
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<tr>
<td></td>
<td>OPAD2</td>
<td>0.865</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>OPAD3</td>
<td>0.877</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>MAGI1</td>
<td>0.655</td>
<td>0.857</td>
<td>0.903</td>
<td>0.701</td>
</tr>
<tr>
<td>Conceptual dimension</td>
<td>Title</td>
<td>EBAC</td>
<td>EBSY</td>
<td>INTE</td>
<td>ORA</td>
</tr>
<tr>
<td>------------------------------</td>
<td>----------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>-----</td>
</tr>
<tr>
<td>E-commerce</td>
<td>Application capability</td>
<td>9</td>
<td>0.885</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-Commerce System Capabilities</td>
<td>3</td>
<td>0.567</td>
<td>0.871</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information Integration</td>
<td>6</td>
<td>0.704</td>
<td>0.473</td>
<td>0.859</td>
<td></td>
</tr>
<tr>
<td>Organizational Agility</td>
<td>7</td>
<td>0.581</td>
<td>0.356</td>
<td>0.739</td>
<td>0.766</td>
</tr>
<tr>
<td>Corporate Performance</td>
<td>6</td>
<td>0.414</td>
<td>0.454</td>
<td>0.415</td>
<td>0.480</td>
</tr>
</tbody>
</table>

### 5.5.2 Structural model analysis

In this paper, using SmartPLS 3.0, which is commonly used as a data analysis tool in the field of e-commerce and information technology, the sample data from the survey was applied to fit the
research model and the path coefficients of the structural model were tested for significance using the Bootstrap algorithm (N=1000). The fitted path coefficients and $R^2$ values are given in Figure 2.

![Figure 2 Path coefficients and $R^2$ values](image)

After confirming that the construct measures have reliability and validity, the next step is to assess the results of the structural model, which consists of two main tasks, assessing the predictive power of the model and the significance of the coefficients between the constructs. The most commonly used criterion to evaluate the structural model is the Coefficient of Determination ($R^2$), which is used to measure the explanatory power or predictive accuracy of the model. As can be seen in Figure 2, the explanatory power of $R^2$ for e-business system capability to e-business application capability is 0.322, $R^2$ for e-business system capability and e-business application capability to information integration is 0.504, $R^2$ for e-business capability and information integration to organizational agility is 0.557, and $R^2$ for organizational agility to business performance is 0.231, all of which are greater than the minimum threshold value of 0.2.

As can be seen from Figure 2: The path coefficient between information integration and organizational agility is 0.661 and is significant at the $p<0.001$ level showing a strong positive relationship between the two, which shows that hypothesis H1 is confirmed. The path coefficient between e-business system capability and information integration is 0.109, significant at the $p<0.05$ level, and the path coefficient between e-business application capability and information integration...
is 0.642, significant at the p<0.001 level, showing that e-business capability has a significant effect on information integration, and hypotheses H2 and H3 are confirmed. Within e-business capability, the path coefficient between e-business system capability and e-business application capability is 0.567, significant at the p<0.001 level, and hypothesis H4 of e-business capability hierarchy is confirmed. The path coefficient between organizational agility and firm performance is 0.480, which is significant at the p<0.001 level, proving that organizational agility has a direct positive effect on firm performance. However, the path coefficient between e-business competency and organizational agility is reached 0.05 level of significance, which means that e-business competency has no significant direct positive effect on organizational agility, and hypotheses H5 and H6 are not valid.

5.6 Tests for interaction and mediating effects

The method suggested by the literature (Zhu et al., 2017) and others is used here to test the interaction effects between factors, using the standardized interaction terms provided by SmartPLS to analyze the complementary effects of e-business system capabilities and e-business application capabilities. When performing the interaction effects test in SmartPLS, it is required that the constructs involved in the interaction term analysis are in the form of reflective measures, and all the constructs involved in this paper meet this condition. It can be seen from Figure 2 that not only the effect of e-business system capability and e-business application capability on organizational agility is not significant, but also the effect of their interaction terms is not significant. Therefore, hypothesis H7 is not supported.

The results of structural equation analysis in which the paths of e-business system capability and e-business application capability on organizational agility are not significant indicate that e-business capability has no direct effect on organizational agility, and the following information integration intermediary effect test is conducted. The traditional way to conduct the mediating effect is through Sobel test, but the latest research literature shows that Sobel test is not suitable for indirect effect test under PLS analysis, the reason is that the parameter distribution of the survey data does not necessarily meet the normal distribution, but the premise of using Sobel test is that the parameter hypothesis condition must meet the requirement of normality, the consequence of forcing the use of the test is to produce a large bias (Hayes, 2009; Hayes, 2013). As a feasible alternative, the
parameters can be estimated in conjunction with the bootstrapping algorithm in SmartPLS, thus testing whether the mediation effect is significant (Nitzl et al., 2016).

As shown in Table 4, the t-value test showed that all path coefficients passed the significance test at the 0.05 level with positive 95% interval and did not contain zero, verifying that information integration plays a mediating role between e-business system capabilities and organizational agility, and between e-business application capabilities and organizational agility.

### Table 4 Test for mediating effects of information integration

<table>
<thead>
<tr>
<th>Indirect effect pathway</th>
<th>Indirect effects</th>
<th>Bootstrap 1000 times</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point estimate</td>
<td>SE</td>
<td>T</td>
</tr>
<tr>
<td>E-Business System Capability - Information Integration -&gt; Organizational Agility</td>
<td>0.072</td>
<td>0.035</td>
<td>2.057</td>
</tr>
<tr>
<td>E-Business Application Capability - Information Integration -&gt; Organizational Agility</td>
<td>0.424</td>
<td>0.049</td>
<td>8.653</td>
</tr>
</tbody>
</table>

### 5.7 Results and Discussion

In this paper, we developed a new scale of organizational agility, validated the hierarchical structure of e-business competencies, constructed a model of the role of e-business competencies to organizational agility, and tested the mediating effect of information integration, and the main findings include: ① Validation of the hierarchical structure of e-business competencies and the higher-order model of organizational agility. Previous scholars proposed the hierarchical theory of e-business competencies through theoretical and empirical studies, which argued that the basic resource competencies in e-business competencies belong to low-level competencies, while the e-business application competencies belong to high-level competencies, and the low-level competencies function through high-level competencies. In this study, the path coefficient between e-business system competency and e-business application competency is significant at the p<0.001 level, thus verifying the existence of hierarchical structure of e-business competency. (ii) The
hierarchical validating factor analysis found a higher-order model of organizational agility. This paper assumes that operational agility and market agility are first-order potential factors and have common higher-order influencing factors. The validating factor analysis shows that the higher-order measurement model has better validity and reliability and overall fit, supporting the use of second-order reflective hierarchical models of operational agility and market agility. (iii) PLS path analysis identified the transmission role of information integration in the creation of organizational agility.

E-commerce system capabilities and e-commerce application capabilities do not have a direct impact on organizational agility, but rather have an indirect impact on organizational agility through information integration. This finding is consistent with the related literature that e-business resources affect firm performance through a mediating process and that there are mediating variables in the impact of e-business capabilities and organizational resources on firm performance.

The research in this paper can provide the following applications: ① The construction of e-business capability is a multi-dimensional capability construction, which includes both the investment of e-business infrastructure equipment and facilities and the cultivation of e-business application capability. E-commerce system capability is the foundation, which has an important influence on the formation of e-commerce application capability. The integration of two dimensions of e-commerce capability provides a stable and effective foundation force for information integration, so that enterprises can go through information integration to build and enhance organizational agility in facing market opportunities and responding to customer needs, thus realizing organizational value. ② Information integration is a particularly important intermediary force in the formation of organizational agility capabilities, and enterprise e-commerce capabilities should consider the information integration process simultaneously. Enterprises should pay attention not only to internal information integration but also to external information integration, actively develop relationships with other actors in the supply chain, and create an environment of close cooperation. Through information integration, enterprises can have a better time to respond and react positively when facing market opportunities and challenges. Any company should consider the trade-off between building information integration and response functions, as companies lacking this capability will not be able to execute effective measures in a complex market environment.
5.8 Conclusion and outlook

The idea that e-commerce enhances organizational agility has been a hot topic of academic research in recent years. However, related studies have been holding conflicting views, with some studies arguing that e-business capabilities are effective in enhancing organizational agility, and a large number of scholars arguing through case and empirical studies that e-business plays an inverse role in organizational agility. This paper partially resolves the paradox of this research by arguing that e-business system capabilities and application capabilities do not have a direct effect on organizational agility, which explains that firms with the same e-business investment, and even purchase the same hardware and software, but have very different organizational agility, so these resources do not play a direct role, and there is also a mediating force of information integration, and only those firms that have successfully transformed into information integration through e-business Only those companies that have successfully transformed their e-commerce capabilities into information integration can improve organizational agility. It is hoped that the research in this paper will serve as a catalyst for further research on the mechanism of the role between e-commerce and organizational agility, cross-industry and cross-regional comparisons, and the relationship between organizational agility and innovation capability (Shuradze, 2018), further expands the research ideas and research scope.
6 A study of e-commerce value creation based on organizational agility perspective

6.1 Introduction

In 2017, the "Central Committee of the Communist Party of China and State Council After the strategic plan of "cultivating new agricultural business subjects " was clearly put forward in "Several Opinions on Accelerating the Cultivation of New Dynamic Energy for Agricultural and Rural Development by Deepening the Structural Reform on the Supply Side of Agriculture", the new agricultural business subjects represented by multi-level agricultural leading enterprises are growing in number, expanding in scale and the fields they operate in are constantly They have played a central role in promoting the development of modern agriculture and the supply-side structural reform in agriculture, and have become a force that cannot be ignored in the direction of modern agriculture leading to the implementation of rural revitalization strategy (Zhang, 2018).

However, related research shows that leading agricultural enterprises generally have outstanding problems such as poor information on sales channels, information asymmetry, and the inability to establish a stable connection mechanism between production and marketing of agricultural products (Ruan et al., 2017), which ultimately reflects that leading agricultural enterprises cannot quickly predict and perceive changes in the market environment, and thus cannot make timely operational adjustments and effective responses, i.e., lack of organizational agility (Lu et al., 2011). The widespread use of e-commerce can provide leading agricultural enterprises with real-time and accurate data information, which becomes a core element in the formation process of organizational agility of leading agricultural enterprises. E-commerce capability is both a sustainable capability formed on the basis of e-commerce resources and a demonstration of the network relationship capability between the enterprise and other subjects in the supply chain (Wu et al., 2009). Therefore, based on the resource-based view theory and the relationship perspective theory, the mechanism of the role of e-commerce capability on organizational agility of leading agricultural enterprises and how to effectively apply e-commerce capability to enhance their organizational agility are studied.

6.2 Literature Review

6.2.1 E-commerce capabilities

The open and interconnected nature of the Internet has generated an e-commerce model that
has enabled many enterprises, including agricultural enterprises, to apply e-commerce systems at the strategic or tactical level in order to achieve profit growth and cost reduction (Lin and Hu, 2017). Moreover, the use of e-commerce technology among organizations can provide effective technical support and integration for information sharing and process integration among supply chain subjects, and the boundary between the business operation mode of enterprises and traditional enterprises has also undergone significant changes, and the supply chain has gradually transitioned from relatively loose outsourcing of products and services to seamless integration of information (Frohlich et al, 2017). Zhu et al. argue that defining e-commerce from the perspective of transactions and online display capabilities as the ability of supply chain enterprises and customers to handle business through the Internet, which accelerates the speed of response to customer demand and improves the quality of products and services (Zhu, 2004). And Zhou et al. consider e-commerce capability as the ability of enterprises to share information, coordinate processes, trade goods and promote inter-organizational synergy among supply chain subjects with the help of network and information technology (Zhou, 2017). Therefore, according to related literature (Wu and Zhong, 2009; Zhou and Wan, 2017; Zhong et al., 2010; Zhong et al., 2011; Wu and Jin, 2011), this paper classifies e-commerce capability of leading agricultural enterprises into three dimensions: relationship management capability, technology utilization capability, and system foundation capability.

### 6.2.2 Information Integration

One possible way to improve the organizational agility of leading agricultural firms is information integration, in which firms share a variety of information frequently with each other, develop production plans, and deliver the right products to the market in a timely manner. Therefore, most scholars regard information integration as the basic model of supply chain cooperation. Zhou et al. found that enterprises using e-commerce systems can continuously update the upper and lower limits of inventory in the system and transmit integrated information to suppliers through a web interface, which improves the efficiency of the entire product supply chain through information integration (Zhou and Wan, 2017). Wu, Jinan et al. argue that e-commerce operations in enterprises should strengthen close ties with suppliers in existing relationships and exchange key business data and information with each other, and that the construction and use of activities within and between
organizations must be accomplished in an efficient and effective manner, which can only rely on the integrated information provided by strong e-commerce capabilities (Wu and Yang, 2011). Therefore, this paper conceptualizes information integration as customer information integration and supplier information integration.

### 6.2.3 Organizational Agility

Both industrial and agricultural products are facing fierce market competition, thus organizational agility as a special strategic core competency has attracted wide attention from theoretical and industrial circles, but the relevant definitions have not been fully unified. Sambamuthy (2003) defines organizational agility as the ability of a firm to quickly acquire information and seize market opportunities by controlling the necessary facilities, core technical knowledge and some relational resources. Van et al. (2006) consider organizational agility as the ability to respond quickly in a complex environment that is constantly changing and unpredictable, both internally and externally. Lu et al. (2011) define organizational agility as a capability of an organization to quickly deal with various uncertain events and make organizational self-adjustment by monitoring changes in the organizational environment. Integrating the views of previous authors, this paper considers organizational agility as the ability to provide customers with satisfactory products or services in the rapidly changing market environment by effectively adjusting and utilizing internal and external resources to form the core competitiveness of the organization in terms of speed and flexibility. In this paper, we adopt the research results of literature (Lu et al., 2011) to classify organizational agility into market agility and operational agility. Market agility is an enterprise's ability to respond quickly to customer products or services to meet customer needs by adjusting resources in the face of dynamic changes in the market, emphasizing the enterprise's sensing and behavioral strategies to changes in the external environment. Operational agility is an enterprise's ability to adjust its internal workflow and organizational structure in the face of changes in the market environment, emphasizing the adjustment of internal resources and structure.

In summary, although there are abundant research results related to the basic concept and mechanism of e-business capability at home and abroad, so far only the mechanism of the use of information system on enterprise agility or enterprise performance has been studied, but there is no
empirical research on the influence of e-business capability on organizational agility, and there is no empirical research specifically in leading agricultural enterprises. The research on e-commerce capability and organizational agility is not deep enough, and lacks consideration of intermediate variables, such as the role of information integration in the transmission; the relationship between e-commerce capability and information integration in the process of continuous optimization of agribusiness supply chain, and the lack of sufficient understanding of these issues. Therefore, the research on the mechanism of the role of e-commerce capability, information integration and organizational agility is particularly important and urgent, and the results of the empirical research have certain guiding significance for the management practice of leading agricultural enterprises.

6.3 Theoretical basis and research hypothesis

6.3.1 Theoretical basis

In the early days of research, the resource-based view suggested that the resources possessed by a firm that have special value, are difficult for competitors to obtain or imitate, and are difficult to substitute are seen as sources of strategic advantage for the firm (Hart and Dowell, 2011). The formation of sustainable competitive advantage can only come from the rational use of these heterogeneous and inimitable resources. According to the resource-based view, e-commerce, as the introduction and utilization of new technologies in enterprises, can bring long-term competitive advantage to enterprises through process re-engineering of their business processes and value chains (Zhong et al., 2010). As the research progresses, the relational perspective theory suggests that the key resources possessed by the enterprise can help the enterprise form network relationships with other enterprises, and such external network relationships are the main source of competitive advantage for the enterprise (Dyer and Singh, 1998). According to the relational perspective theory, in the application of e-commerce, enterprises gradually form strategic-level partnerships with upstream and downstream enterprises in the supply chain to achieve timely information transmission and sharing, thus forming a competitive advantage.
6.3.2 Basic and application capabilities of e-commerce systems

The e-business hierarchy view considers that e-business competency contains two levels, the lower level is the e-business system base competency, while the e-business application competency is at the higher level, and the e-business application competency contains two dimensions (relationship management competency and technology usage competency). The level of system foundation capability has a greater impact on e-commerce applications (Zhong et al., 2011). The e-business system infrastructure capabilities such as system interconnection, standardization and modularization can form an integrated application platform to support the effective use of e-business system and ensure the realization of inter-enterprise data sharing, information transfer and enterprise cooperation based on this foundation (Zhong et al., 2010). Therefore, the following hypothesis is proposed in this paper.

H1a: Positive effect of e-business system base capabilities on relationship management capabilities.

H1b: Basic e-business system competencies have a positive effect on the ability to use technology.

6.3.3 E-commerce capabilities and information integration

Information integration includes two aspects of integration, customer information integration as well as supplier information integration. Customer information integration includes real-time information at the point of sale, sales forecast, customer analysis and customer relationship management; supplier information integration includes sharing demand forecast information, sharing inventory information, and sharing market demand information. Organizational information integration is the result of the combined influence of internal and external factors such as external market, production plan of supply chain enterprises, technical conditions, and internal business processes, and requires the support of high-quality e-business capabilities (Soto-Acosta and Merono-Cerdan, 2008). Therefore, this paper proposes the following hypothesis.

H2a: The ability to use e-commerce technology has a positive effect on information integration.

H2b: Positive effect of e-business relationship management capabilities on information
H2c: e-business system infrastructure capabilities have a positive effect on information integration.

6.3.4 E-Commerce Capabilities and Organizational Agility

The ultimate goal of adopting e-business is not the introduction of technology per se, but the hope that the e-business system can smooth the internal and external workflow, reduce the cost of information acquisition and respond to the changes in the external market in a timely manner, and ultimately form a unique competitive advantage that is difficult to imitate by enterprises. Therefore, the integration of e-commerce system with enterprise market response and organizational management is an inevitable process, through the operation of e-commerce system to effectively allocate and adjust enterprise resources, and form a market-centered operation system. Zaheer et al. found that the innovative use of e-commerce can help enterprises accurately grasp market dynamics and predict market changes, and timely adjust the product structure (Zaheer A and Zaheer S, 1997). Therefore, this paper proposes the following hypothesis.

H3a: The ability to use e-business technology has a positive effect on organizational agility.
H3b: e-business relationship management capabilities have a positive effect on organizational agility.
H3c: e-business system base capabilities have a positive effect on organizational agility.

6.3.5 Information Integration and Organizational Agility

The application of information through proactive innovation can help companies to accurately grasp and anticipate information on market price fluctuations and adjust their product mix in a timely manner. Most of the scholars believe that information application acts as an enabler in enhancing organizational agility, such as Mathiassen and Vainio's study that the correct use of information enables organizations to quickly perceive and respond to changes in the external environment, and once information management is organically integrated with operational strategies, it is possible to reorganize and reallocate strategic resources in the face of changes in the market and to The maximum adaptation to customer needs (Mathiassen and Vainio, 2007). In order to more
clearly identify the impact of information integration on different dimensions of organizational agility, this paper investigates the impact of information integration on two dimensions of organizational agility. Therefore, this paper proposes the following hypothesis.

H4: Information integration has a positive effect on organizational agility.

Based on the resource-based view theory and relational perspective theory, this paper makes basic assumptions about the relationship between e-business capability, information integration, and organizational agility, and constructs a research model as shown in Figure 1.

![Figure 1 Theoretical model of e-business capabilities, information integration and organizational agility](image)

This paper introduces the control variable as firm size, which is represented by the number of employees. The number of employees is a commonly used control variable and is generally one of the effective variables representing firm size, so it is included in the set of control variables in this paper.

### 6.4 Research Methodology

#### 6.4.1 Scale development and questionnaire design

The use of well-established scales used in the existing literature was able to ensure the validity and reliability of the measurement instrument. The initial questionnaire was developed by using the
measurement items from the existing domestic and international empirical literature adjusted to the industry characteristics of leading agricultural enterprises. The Likert 5-point scale was used for most of the questions, except for some basic information about the respondents, i.e., leading agricultural enterprises. Based on the principle of convenience sampling, a small-scale pre-study of the initial questionnaire was conducted among 20 leading agricultural enterprises, and the questions that were not clearly expressed were removed and redesigned to form the final questionnaire based on two indicators: indicator significance and Cronbach's $\alpha$ value.

The e-business competency uses the Zhong Weijun et al. scale, which includes three dimensions: e-business system basic competency, technology application competency, and relationship management competency. The system foundation competency consists of three questions, which are composed of e-business system quality, e-business system information quality, and e-business system service quality. The technology application capability includes 4 items, including the development of cross-enterprise e-commerce strategy, rich experience in system development, rich experience in system integration, and the establishment of a smooth information exchange process between enterprises. Relationship management capabilities include five topics, namely, providing resources to support business partners' participation in inter-enterprise e-commerce, conducting frequent direct contact and communication within cross-enterprise working groups, conducting frequent direct contact and communication between cross-enterprise working groups, rationalizing the authority and responsibility of all participating enterprises, and developing enterprise information exchange and privacy protection policies.

The information integration was done using the scale of Zhou et al. (2017), which includes two dimensions of customer information integration and supplier information integration. Customer information integration includes 3 questions, sales end information acquisition, customer behavior characteristics and customer relationship management. Supplier information integration includes 3 questions, sharing production plan, sharing inventory information, and sharing market forecast information.

Organizational agility was measured using the Ravichandran, Tallon, and Yu Zhou et al. scale (Tallon, 2008; Bharadwaj et al., 2013; Zhou et al., 2015), which includes two dimensions: operational agility and market agility. Operational agility consists of 3 questions, i.e., anticipating environmental changes, responding quickly to changes in the external environment, and reallocating
resources. Market agility consists of 5 questions, i.e., identifying products in demand by customers, providing product information, identifying customer groups, market scope expansion, and market response rate.

6.4.2 Sample and data collection

The data in this paper were obtained from field surveys in Jiangsu and Zhejiang. According to the theoretical model set using a five-point Likert scale, respondents scored according to their actual situation, with higher scores showing a higher degree of agreement, with a value of 1 indicating complete disagreement, a value of 3 indicating uncertainty, and a value of 5 indicating complete agreement. A total of 350 questionnaires were distributed, 348 validly returned questionnaires were initially screened and re-screened, and 7 unqualified questionnaires were deleted. A total of 341 questionnaires entered the final stage of data analysis and model fitting.

In terms of respondent position, 65.7% of the respondents were managers of the company's operations department (e.g., purchasing, ordering, or after-sales service) and 34.3% were IT directors. An independent sample t-test revealed that there was no significant difference between the responses of the two groups of business and IT departments to the questionnaire at the p<0.05 significance level. In general, they have a better understanding of the overall business situation and e-commerce technology application, which ensures the validity of the questionnaire data.

6.4.3 Data analysis method selection

Structural equation modeling is currently a very popular statistical analysis technique in the social sciences, capable of combining factor analysis and regression analysis, enabling researchers to simultaneously detect relationships between measured and latent variables and between latent variables. Therefore, this paper uses SmartPLS, one of the mainstream software in structural equations, to test the data, because SmartPLS has no strict requirements and restrictions on sample data distribution and sample size, and supports exploratory studies with more complex structures. The structural model mainly evaluates the explanatory power of the model and the significance of the hypothesized paths.
6.5 Results

6.5.1 Measurement model

To ensure the rationality and validity of the scale, exploratory factor analysis was first conducted on the survey data using the maximum variance rotation method in the principal component analysis method. After using factor analysis, it was found that the KMO test value was 0.936, Bartlett's sphericity test value was 11023.261, and the p-value was much lower than the critical value, and the cumulative variance explained by the seven factors reached 73.166%. The seven factors were named as system foundation capability, relationship management capability, technology utilization capability, customer information integration, supplier information integration, operational agility, and market agility. Information integration consists of two factors: customer information integration and supplier information integration. Organizational agility consists of two factors: operational agility and market agility. As can be seen from Table 1, the factor loadings of the dimensions contained in each concept are greater than 0.5, and there is no cross-load factor after rotation in SPSS factor analysis, which meets the requirement of measuring the one-dimensionality of the concept. The Cronbach's $\alpha$ of each construct containing dimensions are higher than the critical value of 0.7 respectively, which indicates that the model has good measurement reliability.

The composite reliability (CR) of all dimensions is greater than 0.6 as seen in Table 2, indicating the ideal intrinsic quality of the model. From the average variance extracted values (AVE), all constructs are greater than 0.7, and all constructs AVE are greater than the threshold value of convergent validity measure 0.7. The strength of the discriminant validity of the scale can be seen in Table 2, because the correlation coefficients of all constructs with other constructs are less than the square root of the constructs' own AVE, and all can be considered that the discriminant validity of the model is relatively good.

Table 1 Factor loadings, Cronbach's $\alpha$ and composite reliabilities

<table>
<thead>
<tr>
<th>concept</th>
<th>Measurement indicators</th>
<th>Factor load</th>
<th>Cronbach's $\alpha$</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relationship Management Capabilities</td>
<td>IORM1</td>
<td>0.841</td>
<td>0.897</td>
<td>0.924</td>
<td>0.710</td>
</tr>
<tr>
<td>Conceptual dimension</td>
<td>Measurement</td>
<td>IORM</td>
<td>IOTA</td>
<td>IOSY</td>
<td>INTE</td>
</tr>
<tr>
<td>---------------------</td>
<td>-------------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>IORM</td>
<td>IORM2</td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM3</td>
<td>0.803</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM4</td>
<td>0.885</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IORM5</td>
<td>0.805</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ability to use technology</td>
<td>IOTA1</td>
<td>0.830</td>
<td>0.848</td>
<td>0.898</td>
<td>0.687</td>
</tr>
<tr>
<td>IOTA</td>
<td>IOTA2</td>
<td>0.863</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IOTA3</td>
<td>0.816</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IOTA4</td>
<td>0.807</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System Base Capabilities</td>
<td>IOSY1</td>
<td>0.849</td>
<td>0.843</td>
<td>0.904</td>
<td>0.758</td>
</tr>
<tr>
<td>ISOY</td>
<td>IOSY2</td>
<td>0.916</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IOSY3</td>
<td>0.846</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information Integration</td>
<td>CUST1</td>
<td>0.920</td>
<td>0.905</td>
<td>0.941</td>
<td>0.841</td>
</tr>
<tr>
<td>INTE</td>
<td>CUST2</td>
<td>0.921</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Second order)</td>
<td>CUST3</td>
<td>0.910</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supplier Information Integration</td>
<td>SUPL1</td>
<td>0.933</td>
<td>0.943</td>
<td>0.964</td>
<td>0.898</td>
</tr>
<tr>
<td>SUPL</td>
<td>SUPL2</td>
<td>0.961</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Second order)</td>
<td>SUPL3</td>
<td>0.950</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operational Agility</td>
<td>OPAD1</td>
<td>0.878</td>
<td>0.844</td>
<td>0.906</td>
<td>0.763</td>
</tr>
<tr>
<td>OPAD</td>
<td>OPAD2</td>
<td>0.865</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>OPAD3</td>
<td>0.877</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market Agility</td>
<td>MAGI1</td>
<td>0.655</td>
<td>0.857</td>
<td>0.903</td>
<td>0.701</td>
</tr>
<tr>
<td>AGIL</td>
<td>MAGI2</td>
<td>0.697</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Second order)</td>
<td>MAGI3</td>
<td>0.687</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAGI4</td>
<td>0.691</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAGI5</td>
<td>0.731</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2 Results of the differential validity test of the scale
6.5.2 Structural model

Using SmartPLS 3.0, which is commonly used as a data analysis tool in the field of e-commerce and information technology, this paper applies the 341 sample data obtained from the survey to fit the research model and performs significance tests on the path coefficients of the structural model using the Bootstrap algorithm (N=1000). In this paper, firm size was introduced into the model as a control variable affecting organizational agility, and the model was fitted. The path coefficients and $R^2$ values for the model fit are given in Figure 2.
The explanatory power of the model is tested by the squared value of the complex correlation ($R^2$), which indicates the extent to which the variance of the observed variables is explained. As can be seen in Figure 2, the $R^2 = 0.505$ for e-business system foundation capability, technology utilization capability and relationship management capability for information integration, $R^2 = 0.573$ for e-business capability and information integration for organizational agility, and $R^2$ for system foundation capability for technology utilization capability and relationship management capability are 0.332 and 0.250, respectively, indicating that the explanation of the variance of the independent variables reaches 50.5%, 57.3%, 33.2%, and 25.0%, respectively, and all of which are greater than or close to the acceptance level of 0.3, indicating that the model has good explanatory power. The path coefficients as well as their significance were tested using the Bootstrap algorithm (N=1000) method, and Table 3 reports the results of the hypothesis tests and the corresponding theoretical hypotheses.

Table 3 shows that: H1a ($B=0.500^{***}$, $p<0.001$), H1b ($B=0.576^{***}$, $p<0.001$), H2a ($B=0.260^{***}$, $p<0.001$), H2b ($B=0.423^{***}$, $p<0.001$), H2c ($B=0.113^*$, $p<0.05$), H3b ($B=0.135^{**}$, $p<0.01$), H4 ($B=0.667^{***}$, $p<0.001$) the hypotheses hold, and H3a (0.008, $p>0.05$) and H3c (-0.029, $p>0.05$) the two hypotheses do not hold and the influence of size on organizational agility is not significant.
### Table 3 Hypothesis testing

<table>
<thead>
<tr>
<th>Assumptions and paths</th>
<th>Path coefficient (B)</th>
<th>T-value</th>
<th>p-value</th>
<th>Hypothetical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a: System Foundation Capabilities → Relationship Management Capabilities</td>
<td>0.500***</td>
<td>9.854</td>
<td>&lt;0.001</td>
<td>Support</td>
</tr>
<tr>
<td>H1b: System Foundation Competencies → Technology Utilization Competencies</td>
<td>0.576***</td>
<td>12.809</td>
<td>&lt;0.001</td>
<td>Support</td>
</tr>
<tr>
<td>H2a: Ability to use technology → Information Integration</td>
<td>0.260***</td>
<td>4.178</td>
<td>&lt;0.001</td>
<td>Support</td>
</tr>
<tr>
<td>H2b: Relationship Management Capabilities → Information Integration</td>
<td>0.423***</td>
<td>7.511</td>
<td>&lt;0.001</td>
<td>Support</td>
</tr>
<tr>
<td>H2c: Systems Foundation Capabilities → Information Integration</td>
<td>0.113*</td>
<td>2.421</td>
<td>&lt;0.05</td>
<td>Support</td>
</tr>
<tr>
<td>H3a: Technology Utilization Capabilities → Organizational Agility</td>
<td>0.008</td>
<td>0.156</td>
<td>&gt;0.05</td>
<td>Not supported</td>
</tr>
<tr>
<td>H3b: Relationship Management Capabilities → Organizational Agility</td>
<td>0.135**</td>
<td>2.669</td>
<td>&lt;0.01</td>
<td>Support</td>
</tr>
<tr>
<td>H3c: System Foundation Capabilities → Organizational Agility</td>
<td>-0.029</td>
<td>0.669</td>
<td>&gt;0.05</td>
<td>Not supported</td>
</tr>
<tr>
<td>H4: Information Integration → Organizational Agility</td>
<td>0.667***</td>
<td>16.207</td>
<td>&lt;0.001</td>
<td>Support</td>
</tr>
</tbody>
</table>

### 6.5.3 Mediating effects test

Path coefficients were calculated in the path analysis for technology use capability to organizational agility, system base capability to organizational agility, and information integration to organizational agility, and the test results revealed that the path coefficients for technology use capability to organizational agility (0.135, p>0.05) and system base capability to organizational agility (-0.029, p>0.05) were not significant, while information integration had a positive effect on
organizational agility (0.667, p<0.001). Therefore, further analysis of the mediating role of e-commerce application capabilities and information integration in the impact of agility is needed, as suggested in the literature (Zhou et al., 2015).

In the past, most scholars have used the Sobel test to study indirect effects. Hayes' study shows that the Sobel test is not suitable for mediating effects testing because the normality requirement must be satisfied in its parameter assumptions, but the distribution of survey data often does not fully satisfy this condition, thus generating some test bias (Hayes, 2009; Hayes, 2013). As an alternative, the method of Nitzl and Roldan, combined with the parameters estimated by the bootstrapping algorithm in PLS, was used to verify whether the mediation effect was significant (Nitzl et al., 2016). As shown in Table 4, the t-value test shows that all path coefficients pass the significance test at the 0.05 level with positive 95% intervals that do not contain zeros, verifying that e-business application capabilities play a mediating role between system base capabilities and information integration, and that information integration plays a mediating role between e-business capabilities and organizational agility.

Table 4 E-commerce application capability and information integration mediation effect test

<table>
<thead>
<tr>
<th>Indirect effect pathway</th>
<th>Indirect effects</th>
<th>Bootstrap 1000 times</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Point estimate</td>
<td>SE</td>
<td>T</td>
</tr>
<tr>
<td>Ability to use technology -&gt; Information integration -&gt; Organizational agility</td>
<td>0.174</td>
<td>0.042</td>
<td>4.09</td>
</tr>
<tr>
<td>System Foundation Capabilities -&gt; Information Integration -&gt; Organizational Agility</td>
<td>0.075</td>
<td>0.031</td>
<td>2.38</td>
</tr>
<tr>
<td>Relationship Management Capability -&gt; Information Integration -&gt; Organizational Agility</td>
<td>0.283</td>
<td>0.042</td>
<td>6.68</td>
</tr>
<tr>
<td>System Foundation Capability -&gt; Technology Application Capability -&gt; Information Integration</td>
<td>0.150</td>
<td>0.036</td>
<td>4.12</td>
</tr>
<tr>
<td>System Foundation Capability -&gt; Relationship</td>
<td>0.212</td>
<td>0.035</td>
<td>6.02</td>
</tr>
</tbody>
</table>
6.6 Analysis and Discussion

6.6.1 Discussion of study results

The results of the data fit verified the e-business capability hierarchy. From the analysis results of the basic model, it can be seen that hypotheses H1a (0.500, p<0.001) and H1b (0.576, p<0.001) hold, indicating that the system base capability in e-business capability is shown to be a relatively low-level capability, and its role is largely dependent on the e-business application capability (technology application capability and relationship management capability) intermediary role. Hypothesis H3a (0.008, p>0.05) and hypothesis H3c (-0.029, p>0.05) do not hold, indicating that the system foundation and technology application competencies in e-business competencies do not directly support organizational agility. Analysis of the fit results in Figure 2 reveals that hypothesis H3a (0.135, p<0.01) holds, and relationship management capabilities in e-business competencies have some direct impact on organizational agility, as well as an indirect impact on organizational agility through information integration.

From Figure 2, we can see that information integration has a significant effect on organizational agility, while neither e-business technology application capability nor e-business system foundation capability has a significant direct effect on organizational agility, and the path coefficient between information integration and organizational agility is much larger than the path coefficient between e-business relationship management capability and organizational agility, that is, the effect of information integration on organizational agility is larger than the effect of other factors. The results indicate that the role of information integration on organizational agility is greater than the role of other factors. The results suggest that, in a certain context, although relevant studies indicate that e-business capabilities are an important tool for improving organizational agility, information integration is fundamental for companies to continuously improve organizational agility.
6.6.2 Research significance

In view of the realistic background of information asymmetry and information distortion, based on the specificity of the industry in which leading agricultural enterprises operate, the mechanism of the effect of e-commerce on organizational agility of leading agricultural enterprises is studied based on resource-based view theory, relationship perspective theory and e-commerce capability hierarchy theory.

This study has the following theoretical contributions. First, the study of e-commerce capability has been covered in the literature, but most domestic studies have directly applied the conceptual models of foreign scholars and rarely studied by industry. In view of the heterogeneity of industries, e-commerce capability and transmission mechanism must have its own special mechanism. This paper combines the localized factor of leading agricultural enterprises, which is more relevant to reality, and the findings of this study enrich the theoretical research on Chinese enterprises. Third, as a further supplement to the previous studies, it verifies the hierarchical characteristics of e-commerce capabilities from an empirical perspective and enriches the theoretical composition of e-commerce capabilities.

From the viewpoint of practical value, first of all, e-commerce capability a multi-dimensional layer concept, enterprises to give full play to the role of e-commerce systems, not only need to build a strong system infrastructure capabilities, but also in e-commerce application capabilities, including the reasonable development of e-commerce strategic planning to support business, the establishment of a smooth information exchange system between enterprises and so on should have sufficient investment, otherwise expensive E-commerce technology equipment can not play the proper efficacy. Secondly, e-commerce capability is the most important factor in the formation of organizational agility, but information integration plays an important intermediary role in it, indicating that the sharing of sales, inventory, and production planning information, etc. provides a guarantee for organizational agility, and enterprises should pay attention to the collaboration within and outside the organization to obtain effective information resources. To strengthen the information integration capability of leading agricultural enterprises and realize the strategic service tendency of information, it is necessary to effectively integrate information from multiple channels in the enterprise and focus on the innovation capability in information system integration.
6.7 Conclusion

Based on the systematic analysis of the concepts and structural levels related to e-commerce capabilities, this paper constructs a conceptual model from e-commerce capabilities to information integration to organizational agility, and considers the interrelationship of different sub-capabilities in e-commerce capabilities and the influence mechanism on organizational agility of leading agricultural enterprises. The empirical research method proves that the system foundation and technology application competencies in e-commerce competencies have no significant direct influence on organizational agility of leading agricultural enterprises, but achieve indirect influence through the mediating role of information integration; the relationship management competencies in e-commerce competencies have both direct and indirect influences on organizational agility.

There are still shortcomings and room for expansion in this study. First, there is not yet a unified understanding of the concepts related to e-business capability in the academic community, so a measurement scale with a broad consensus cannot be provided and needs to be further explored. Second, the influencing factors of organizational agility are complex, and e-business capability may be only one of the important aspects. Future research can consider adding other factors to make the structure of the model more consistent with the actual context. Finally, the data collected in this paper come from the eastern region, and future data can be further collected from leading agricultural enterprises in the central and western regions for validation, and can compare whether there are regional differences in transmission mechanisms.
7. Research on the mechanism of digital quality management driving enterprise environment innovation

7.1 Introduction

During the nineteenth century, businesses worldwide rapidly consumed huge natural resources to maximize their revenue (Ji et al., 2021; Shahzad et al., 2020; Umar et al., 2022). This trend has caused a sharp decline in natural resources reserves Goodwin et al. (2022), such as oil and gas but has also considerably damaged the natural environment in the form of air, water, and soil pollution (Wang, Mirza, et al., 2020). The ongoing campaign led by environmentalists to enrich public awareness regarding the diminishing resources and environmental deviations has received significant attention in the last decade (Bibi et al., 2021; Naseer et al., 2020; Su et al., 2021). This campaign has increased the public’s awareness about the consumption of natural resources by businesses, particularly the manufacturing industries (Kumari et al., 2022). It has encouraged them to put significant pressure on businesses to follow environment-friendly practices and take measures to restructure their processes Wang, Xue, et al. (2020) so that the emissions of dangerous gases and liquids that cause air, soil and water pollution can be reduced (Xiao et al., 2022).

Considering the environmental deterioration and public pressure, the European Union (EU) signed an agreement, i.e., the Paris Agreement, to reduce the emission of greenhouse gases by 40% by 2030 and bring it to zero by 2050 (Kulanovic & Nordensvard, 2021).

During the late 20th century, total quality management (TQM) was popularized through the superior quality of Japanese products (Kumari, Abbas, et al., 2021). It is a well-established fact that TQM possesses the potential to enhance individual and organizational performance as its target is to ensure improvement in processes through efficient and effective use of resources (Li, Zhao, et al., 2018). It also provides footing to businesses in achieving a competitive edge (Tasleem et al., 2018). For this reason, dynamic firms take it as an integral part of their business strategy (Abbas & Kumari, 2021). Considering the intensification of stakeholders’ pressure, several companies have started to link their principal business strategies with the subsequent strategies, such as knowledge management, sustainable development, quality management, etc. (Hwang et al., 2022). Corporate
sustainable development (CSD) is a green strategy that integrates organizational development with environmental, social, and economic aspects of development (Karim et al., 2022). The ultimate objective of CSD is to develop a balance of resources not only between contemporary organizations and society but also for future generations and businesses (Abbas & Dogan, 2022). To achieve sustainable development (SD) goals, organizations must re-engineer their traditional operational processes and capitalize on the latest tools and technology to produce environment-friendly products/services (Kazmi & Abbas, 2021). In this regard, green innovation has critical importance.

Innovation refers to introducing something new (product or process/service) or making significant improvements to existing products or services (Awan, 2020). Environmental innovation, also known as green innovation, is a novel concept and has gained the spotlight in recent literature (Su, Li, et al., 2022). According to Xie et al. (2019), green or eco-innovation focuses on developing goods and services which enable firms to achieve corporate sustainability with a particular focus on environmental protection (Ielasi et al., 2018). It also enables the society and economy to develop through technological modernization (Fernando et al., 2019) as it is grounded on new technological knowledge. Technological advancement plays the most significant role in green growth (Al-Rahmi et al., 2020). However, innovation generally requires a considerable volume of time and money. For this reason, a fundamental question is can environmental innovation enable firms for SD?

(Fernando et al., 2019) analyzed the association between environmental innovation and business performance and said that ecological innovations have the potential to improve service innovation, leading to enhanced business performance (Dorflitner & Grebler, 2022). On the contrary, Li, Jin, et al. (2018) said that environmental innovation activities hinder organizational and economic development activities in China (Su, Khan et al., 2022). The literature indicates disagreement on the relationship between environmental innovation and CSD. Moreover, the question, which is still inclusive and warrants exploration, is, can quality management systems (QMS) in organizations boost environmental innovation and SD activities? Even though several academicians have examined QMS, organizational growth, and environmental management from diverse standpoints, the nexus of QMS, environmental innovation, and CSD is yet to be explored (Song et al., 2020; Zhang, Rong, et al., 2019). A few studies in the literature have adopted a multivariate statistical technique followed by structural equation modeling (SEM) to analyze whether QMS in organizations impacts their green innovation and SD activities or not? The researchers based their arguments on the United Nations Sustainable Development (UNSD) goals
and the ‘Green Theory’ concepts as the foundation to investigate the link between the studied variables. Thus, this research aims to address the following questions;

RQ1: Does a quality management system facilitates organizations in achieving their environmental innovation goals?

RQ2: Does a quality management system facilitates organizations in achieving their sustainable development goals?

RQ3: Does organizational environmental innovation activities facilitate it in achieving its sustainable development goals?

In the present research, the QMS practices are based on the American ‘Malcolm Baldrige National Quality Award’ (MBNQA), namely leadership, customer focus, strategic planning, process management, HRM, and information and analysis. Environmental innovation is measured through the process and product innovation, while CS is measured via economic, social, and environmental aspects. The researcher took contextual factors, such as industry type (manufacturing and services) and organizational size (medium and large), as control variables so that the question of whether these factors play a significant part in the relationship among the studied variables or not, can be investigated. The findings of this study will benefit the industrialists, ecologists, governments, and other participants to understand how quality management activities in organizational operations help firms achieve environmental innovation and sustainability goals. It will also suggest measures to be taken by organizations of different sizes to capitalize on quality activities to comply with the United Nations’ agenda for sustainable development.

7.2 Literature review

7.2.1 Sustainable development

The UNSD goals originate from the Brundtland Commission Report ‘Our Common Future’ presented in the United Nations General Assembly (UN, 1987). The report focuses on environmental issues caused by businesses’ sharp consumption of natural resources to maximize their revenue (Su et al., 2020). The report defined SD as ‘the development which fulfils the current generation’s needs without compromising future generations’ ability to satisfy their needs’. The United States Environmental Protection Agency (USEPA) defined SD as the ability to create and maintain an environment in which nature and humans can exist in harmony, and that satisfies the social and
economic needs of the existing and future generations (EPA, 2003). Elkington (2018) proposed the word triple bottom line (TBL) for the three aspects of SD: economic, social and environmental development.

The environmental aspect concentrates on preserving the natural resources and environment, such as clean air, water, and soil, protection of forests and glaciers, and a special focus on minimum consumption of non-renewable resources (Su et al., 2020). In social sustainability, organizations concentrate on societal development and human well-being, such as achieving customer satisfaction through product and service quality, ensuring better working environments, training and development of people, social justice, and measures for the safety and health of employees. Finally, the economic aspect relates to organizational income and expenditures, such as the cost of production, sale, and profitability (Fu et al., 2022).

7.2.2 Green theory

The green theory is a multidisciplinary philosophy popularized by Eckersley (2010) with a special focus on globalization and environmental sustainability. It also focuses on governance, social responsibility, and human rights. Green theory aims to achieve international development by ensuring domestic, national, and international sustainability. It suggests that to build a sustainable society (Yang et al., 2022). There must be a limit to the growth rate since unprecedented economic growth during the preceding decades mainly relied on fossil fuel consumption (Ji & Zhang, 2019), resulting in environmental issues (Orzes & Sarkis, 2019). Ecologists have urged corporations to incorporate eco-friendly strategies in their operations, which positively impact environmental and economic sustainability (Xie et al., 2022). Moreover, the United Nations Global Compact (UNGC) announced that corporations must capitalize on green technology in their operations (UNGC, 2018).

With the evolution of green theory, environment-friendly processes, particularly environmental innovation, have recently been popularized. Environmental innovation is the creation of a novel idea or the improvement of existing products or processes that significantly improve the natural environment compared to other alternatives (Umar et al., 2020). Corporate sustainability is a broad concept and substantially relies on innovation (Khan & Abbas, 2022). In this scenario, eco-innovation can be a pivotal tool for achieving SD. Environmental innovations can enable corporations to manufacture high-quality, environment-friendly products by utilizing minimum resources, fulfilling customers’ needs and enhancing their satisfaction and loyalty (Kumari, Ali, et
7.2.3 Quality management and environmental innovation

QMS has huge significance in organizational strategic competencies. The American Society for Quality (ASQ) defined quality as ‘knowledge and skills for human welfare and development, and the promotion of safety, security, and reliability standards of products for public use’ (ASQ, 2018). Based on this definition, two meanings of quality can be generated. Firstly, the traits of an invention, either a good or service, should be able to meet the public needs; secondly, it must not have any deficiency (Su et al., 2020). Since QMS aims to ensure continuous improvement via capitalizing on modern tools, techniques, and values (Deng et al., 2022), firms implement it to minimize operating costs and enhance productivity and quality, leading to enhanced customer satisfaction (Fatima et al., 2021) and improved organizational performance.

QMS has multiple core values in different models, known as Business Excellence Models (BEMs). The three most popular BEMs are the ‘European Foundation for Quality Management’ (EFQM), the ‘Swedish Institute for Quality’ (SIQ), and the ‘Malcolm Baldrige National Quality Award’ (MBNQA). The MBNQA is an American quality award and contains soft and hard elements of QMS (ASQ, 2018). The model has been acknowledged as a significant mechanism for several organizations (public and private) in transforming their administrative principles, operational efficiencies, and achieving competitive advantage. Considering the significance of the MBNQA model, in this study, researchers focused on its 6 aspects, specifically leadership, strategic planning, customer focus, process management, information and analysis, and human resource management (HRM). (Ooi, 2014; Prajogo & Cooper, 2010) also have studied these variables in their research. Figure 1 illustrates the relationship between QMS practices, environmental innovation, and CSD.
Considering the environmental deterioration and natural resources deterioration, environmental innovation and QMS has become critically important (Al-Rahmi et al., 2020; Zhang et al., 2022). As per y, environmental innovation mainly refers to technological advancement, specifically focusing on environmental protection and bringing essential reforms in production and operational processes. It generates a positive effect on the environment and leads to knowledge spillover, resulting in a double externality effect (Wang, Mirza, et al., 2020). This makes firms consider alternative ways of investing in such technologies, such as government subsidies. (Zhang, Yao, et al., 2019) proposed that state provision is imperative to motivate firms to invest in green technologies and promote a green business environment.

According to (Xie et al., 2019), environmental innovation has two domains, i.e. process innovation and product innovation. Process innovation focuses on minimizing the usage of resources in the production and operations processes through which unprocessed material is transformed and converted into the final product or service (Khan et al., 2022). It also pays special attention to minimizing waste causing pollution in water and air, enabling a sophisticated switch from fossil energy to bioenergy and minimum utilization of non-renewable resources. It also brings a systematic improvement in operational processes, which leads to the proficient use of resources (Ahsan et al., 2020). Another uniqueness of process innovation is that it enables firms to improve
the quality of a product or introduce a new product, which can help firms expand market share and increase their competitive advantage (Imran & Abbas, 2020).

The focus of product innovation is on improving the composition of existing products/services in a way that they consume biodegradable or materials that are not toxic or utilize a minimum of non-renewable resources (Calza et al., 2017). Thus, the product innovation aims to redesign the product in a way that involves environment-friendly inputs to counter hazardous elements and can be recycled (Yu & Huo, 2019). Eco-product innovation changes the view of the product lifecycle from product development to distribution and from consumption to recycling. (Abbas, 2020c) stated that eco-process innovation facilitates and provides a foundation for eco-product innovation. Organizations that capitalize on eco-products and processes tend to achieve a competitive advantage (Stucki, 2019). The literature provides multiple studies on the role of QMS in employees and organizational performance [such as (Psomas & Antony, 2017; Shafiq et al., 2017)]. It also sheds a brief light on the relationship between QMS and a firm’s environmental management system [for example, a study by (Tasleem et al., 2018)]. However, it is yet to be explored whether organizational QMS impacts their eco-innovation activities. For this reason, the following hypothesis is proposed.

H1: Organizational quality management system has a significant positive effect on environmental innovation

To examine the dimension-level relationship, the following sub-hypotheses are proposed.

H1a: Quality management system possesses a significant positive effect on process innovation

H1b: Quality management system possesses a significant positive effect on product innovation

7.2.4 Quality management and corporate sustainability

Firms complying with QMS can manage resources more effectively than others (Abbas, 2020c). Such organizations enable their employees to become more productive and competitive and enjoy more profitability, customer satisfaction, and trust (Mahmood et al., 2014, 2020). QMS and CSD can be associated with each other since QMS not only aims to enhance institutional performance through continuous improvement and customer satisfaction but also ensures that resources are not wasted, predominantly natural resources, which are the core objectives of SD (Safdar et al., 2020). Moreover, similar to SD, QMS also has a durable impact by considering how business activities impact society and firm productivity over a longer time (Lee, 2020). Abbas (2020c) stated that SD is a continuous process that exclusively focuses on integrating quality in ecological, social, and
economic aspects. Therefore, organizations should ensure that the quality concept is applied from acquiring resources to delivering the product or service.

With the emergence of environmental deterioration and global warming, environment-friendly practices have become the most vital and popular concept in the last few years (Zhang, Rong, et al., 2019). In particular, industrial giants, such as China, which have deeply relied on natural resources for energy purposes, have started paying increased attention to green innovation, renewable energy methods, and recycling (Ji & Zhang, 2019). However, a key concern for organizations relating to green innovation is how it will affect their profitability. During the last ten years, because of economic reforms and business-friendly policies, multiple developing countries in the Asian region have experienced substantial economic growth; however, SD is a key concern for stakeholders. Like other regions, most developing countries in Asia have mainly relied on fossil energy, which has resulted in severe environmental issues, such as air and water pollution (Shahzad et al., 2020).

Different countries have started projects to protect the natural environment and promote eco-friendly practices in their regions. For instance, the government of Pakistan initiated multiple projects to promote green development, such as the accomplishment of the ‘One Billion Tree Tsunami’ project in 2017 (WEF., 2018), the ongoing five-year project of ‘Ten Billion Tree Tsunami’ started in 2018 (Constable, 2018), and the ‘Punjab Green Development Program’ (World Bank, 2018). These projects are focused on improving the natural environment and promoting green innovation and development in the country. The government is taking significant initiatives to encourage businesses to follow green quality strategies in their processes.

The literature on the relationship between QMS and CSD presents inconsistent results. For example, Chaithanapat et al. (2022) studied the role of quality management practices in green organizational performance from Chinese manufacturing firms’ perspectives and found an insignificant relationship between them. However, (Chaudhry et al., 2022) identified a positive relationship between these variables. Siva et al. (2016) conducted a literature review study on the link between quality and sustainability. They also mentioned inconsistent and contradictory findings between these variables. Thus, this phenomenon warrants further exploration. For this reason, the following hypothesis is proposed

H2: Quality management system has a significant positive effect on corporate sustainable development

To examine the dimension-level relationship, the following sub-hypotheses are proposed.
**H2a:** Quality management system possesses a significant positive effect on corporate environmental sustainability

**H2b:** Quality management system has a significant positive effect on corporate social sustainability

**H2c:** Quality management system possess a significant positive effect on corporate economic sustainability

### 7.2.5 Environmental innovation and sustainable development

All businesses across the world face three elementary issues in their operations, i.e., 1) inputs, 2) outputs, and 3) amount of wastage. These three aspects are linked, and their volume is determined by the quality of the processes (Abbas, 2020b). Low-quality products or services damage organizational reputation (Li, Wang, et al., 2018) and cause waste of human efforts and natural resources, leading to poor economic and environmental performance (Habib et al., 2019). Crude oil and coal have largely been considered as one the major sources of energy for businesses across the world (Ji & Zhang, 2019). However, economic growth based on fossil fuels has several limitations since such energy channels are exhaustible and damage the environment through their by-products, such as carbon dioxide (Abbas, 2020a).

The increased social awareness about declined natural resources has caused significant pressure on businesses to follow environment-friendly practices (Rossiter & Smith, 2018). Moreover, after the UNGC call, organizations worldwide have begun to consider their responsibilities to human rights, labour, and social and environmental aspects (UNGC, 2018). Dynamic businesses are reshaping their operational processes by introducing eco-friendly products and processes and shifting from fossil fuel to renewable or biodegradable energy sources (Chaudhry et al., 2022). However, a key concern in such transformation is that it should ensure the protection and restoration of the natural environment and guarantee firms’ economic development (Cai & Li, 2018).

Technological development is central to transforming organizations (Shakoor et al., 2021), especially shifting from traditional production and operation processes to green ones (Alamri et al., 2020). Environmental innovation allows organizations to develop new or improve existing products or processes so that their production and operations processes have zero or minimal impact on the natural environment (Song et al., 2020). It also enables firms to either use recyclable material as
input or obtain the maximum output with minimum consumption of resources with minimal to zero waste and emissions causing air, water, soil, and other environmental pollution (Ahmad et al., 2020). (Yuan & Xiang, 2018) emphasized that organizational development should be linked with eco-innovation as it facilitates the protection of the natural environment. However, firms will invest only in those activities that will help them enhance their financial performance (Zhang, Rong, et al., 2019). Therefore, environmental innovation and development activities should be compatible with firms’ long-term goals. In this regard, the government must play its pivotal role by providing technical expertise and infrastructural support to firms, which act as the foundational slabs of eco-innovation and development.

Fernando et al. (2019) proposed that eco-innovation significantly influences corporate environmental sustainability in China. Moreover, through effective QMS and innovation strategies, firms can acquire a competitive advantage in the current competitive business environment (Li, Zhao, et al., 2018). Zeng et al. (2017) stated that QMS facilitates’ innovation capabilities in Chinese firms which further leads to corporate sustainability. However, (Li, Jin, et al., 2018) found a negative link between QM practices and green innovation activities in the same country. The literature provides inadequate and conflicting answers to this question. Moreover, this relationship has rarely been explored outside China. Hence, the subsequent hypothesis is drawn.

H3: Environmental innovation possesses a significant positive effect on corporate sustainable development

To examine the dimension-level relationship, the following sub-hypotheses are proposed.

H3a: Environmental innovation has a significant positive influence on corporate environmental sustainability

H3b: Environmental innovation possesses a significant positive effect on corporate social sustainability

H3c: Environmental innovation possesses a significant positive effect on corporate economic sustainability

7.3 Methodology

This section contains information about the adopted methodology, including target population and sampling, followed by measurement instruments, a description of the control variables, data analysis, measurement, structural models’ results, and hypotheses’ results.
7.3.1 Target population and sampling procedure

The statistical data was collected from five major cities located in Pakistan named Karachi, Islamabad, Lahore, Sialkot, and Faisalabad. The researchers focused on firms registered with the Securities and Exchange Commission of Pakistan (SECP). SECP is the federal regulatory body for businesses and is the most inclusive database for organizations operating in the country. Organizations having ISO 9001 and 14001 certification or have applied for it or even intend to apply for ISO 14001 certification were approached. The authors collected data from managerial staff, including the frontline, middle and upper level of manufacturing and services firms, because they have the latest information regarding organizational practices and policies. Besides, their role is imperative as they are disseminators responsible for implementing policies within their teams. The data was collected from July 2019 to October 2019 by personal visit and e-mail correspondence. Yu et al. (2019) followed a similar approach in their studies. The researchers distributed 672 questionnaires, and 311 completed responses were received, out of which only 291 were used for the final analyses. Of this, 52.58% of responses were received from medium-size firms and 47.42% from large-sized firms. Furthermore, 58.76%, i.e., 171 responses were received from companies in the manufacturing sector, and 48.11%, i.e., 140, were received from services sector firms. Detailed demographic information is presented in Table 1.

<table>
<thead>
<tr>
<th>Particulars</th>
<th>Description</th>
<th>Value</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total received responses</td>
<td>Medium organization</td>
<td>153</td>
<td>52.58%</td>
</tr>
<tr>
<td></td>
<td>Large organization</td>
<td>138</td>
<td>47.42%</td>
</tr>
<tr>
<td>Job Position</td>
<td>Lower management</td>
<td>143</td>
<td>49.14%</td>
</tr>
<tr>
<td></td>
<td>Middle management</td>
<td>111</td>
<td>38.14%</td>
</tr>
<tr>
<td></td>
<td>Upper management</td>
<td>37</td>
<td>12.71%</td>
</tr>
<tr>
<td>Industry type</td>
<td>Manufacturing</td>
<td>171</td>
<td>58.76%</td>
</tr>
<tr>
<td></td>
<td>Services</td>
<td>140</td>
<td>48.11%</td>
</tr>
<tr>
<td>Gender</td>
<td>Male</td>
<td>172</td>
<td>59.11%</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>114</td>
<td>39.18%</td>
</tr>
<tr>
<td></td>
<td>I prefer not to disclose</td>
<td>5</td>
<td>1.72%</td>
</tr>
<tr>
<td>Years of Experience</td>
<td>Up to 5 years</td>
<td>63</td>
<td>21.65%</td>
</tr>
</tbody>
</table>
7.3.2. The measurement instrument

The researchers divided the study instruments into three segments. The first section contained thirty-six items linked with the MBNQA model’s six dimensions for QMS. Strategic planning was estimated via six items, leadership via five items, HRM via eight, customer focus by seven items, information and analysis via five items, and process management through five items. The constructs utilized for the first segment were withdrawn from Saraph et al. (1989), Kaynak (2003), Prajogo and Sohal (2006), and Fuentes et al. (2006). The second segment contained ten items for two dimensions of environmental innovation specifically; product innovation and process innovation (five items for each dimension), and the items were utilized by Amores-Salvadó et al. (2014) and Kam-sing Wong (2012). The final segment comprised fourteen items associated with three aspects of CSD such as economic, social, and environmental sustainability. Economic sustainability was measured via four items, whereas social and environmental sustainability via five items. The items were followed by (Turker, 2009; Wijethilake, 2017).

The data was collected on a five-point Likert scale (1 signified strongly disagree and 5 as strongly agree). (Hinkin, 1998) suggested that a pilot study was employed to check the validity and reliability of adopted constructs concerning Pakistan. The data was collected from 30 organizations (one person from each firm) situated in Lahore. According to Yurdugül (2008), a sample of 30-50 is enough for an initial survey. Out of 30, 21 were approached online, and 9 were self-administered. As suggested by Yurduğul, the reliability of collected data was checked using Cronbach’s alpha test. The values for internal consistency of constructs ranged from 0.82 to 0.97, which is in harmony with Hair et al. (2010) minimum condition of 0.7 value. The researchers started the comprehensive survey based on the initial survey.

7.3.3 Description of control variables

This study comprises two control variables, specifically industry category and organizational

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<table>
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<tbody>
<tr>
<td>6-10 years</td>
<td>116</td>
<td>39.86%</td>
</tr>
<tr>
<td>11-15 years</td>
<td>79</td>
<td>27.15%</td>
</tr>
<tr>
<td>More than 15</td>
<td>33</td>
<td>11.34%</td>
</tr>
</tbody>
</table>

Source: Author’s Estimation.
size. The reason to incorporate organizational size as a control variable is that large corporations own more assets, resources, and infrastructure than small or medium-sized ones. The researchers followed Huo et al. (2014) suggestions and categorized organizations into medium and large sizes, keeping in mind the number of employees. Firms with fewer than 200 were considered medium size, and firms exceeding 200 employees were regarded as large size firms. Yu et al. (2019) also incorporated a similar approach in their research. The industry category is another control variable in this research, including services and manufacturing. The author took the industry group as a control variable as the working style of the manufacturing industry is different, and the issues faced by this industry vary from the services industry.

7.4 Analysis of data

The SEM technique was employed to observe the relationship among variables i.e., QMS, environmental innovation, and CSD. The researchers used SPSS v.25 for statistical analyses and Amos v.25 for structural analyses. Prajogo and Cooper (2010) state that SEM practice can eradicate biases effect; these biases are caused by errors in measurement and form latent constructs hierarchy. (Lee, 2010) suggest that multivariate assumptions, like adequate sample size, evaluation of multi-collinearity, and unbusiness should be fulfilled to implement SEM. The appropriateness of the sample size was examined via the Kaiser-Meyer-Olkin (KMO) test and presented a 0.923 value. This value is in harmony with Kaiser and Rice (1974) minimum condition of 0.6 and signifies the adequacy of the sample size. Variance inflation factor (VIF) was employed to examine the multi-collinearity element with a value of 2.251, according to Hair et al. (2010) requirement of a value below 4, thus representing no existence of multi-collinearity. Schwarz et al. (2017) outlined common method bias (CMB) as a serious concern in quantitative research. The current research examined CMB via Harman’s single factor test, which represents a value of 39.43%. Podsakoff et al. (2012) proposed that if the result of a single-factor is below 50% of overall variance, CMB does not impact results. Thus, we can state that there is no issue related to CMB in data. The empirical results indicate that the data fully meets the multivariate statistical assumptions for SEM.

7.4.1 Evaluation of the measurement and structural model

To analyse the association between latent variables and their factors via a measurement model,
confirmatory factor analysis (CFA) was employed. According to Hinkin, CFA assures the unidimensional and fitness of the statistical model. The reliability of the data was examined through Cronbach alpha which highlighted the value of 0.903. This result is under Peterson’s (1994) lowest condition of value of 0.8, along with Lance et al. (2006) requirement of 0.7. Thus, we can state that measurement possesses adequate reliability. The researchers further examined discriminant and convergent validity. Awang (2012) and (Hair et al., 2010) suggested that factor loading is utilized to analyze convergent validity, and the best loading value is above 0.6 for established items. Besides, according to Molina et al. (2007), the minimum value for average variance extracted (AVE), should be greater than 0.5 for all constructs. Additional details regarding quantity of items, their loading, AVE values and composite reliability is present in Table 2.

Table 2. Reliability and validity of the instrument.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Factor Loading Ranges</th>
<th>Composite Reliability</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leadership</td>
<td>5</td>
<td>0.541-0.931</td>
<td>0.902</td>
<td>0.641</td>
</tr>
<tr>
<td>Strategic Planning</td>
<td>6</td>
<td>0.722-0.878</td>
<td>0.856</td>
<td>0.609</td>
</tr>
<tr>
<td>Customer Focus</td>
<td>7</td>
<td>0.745-0.905</td>
<td>0.839</td>
<td>0.611</td>
</tr>
<tr>
<td>Process Management</td>
<td>5</td>
<td>0.742-0.868</td>
<td>0.877</td>
<td>0.631</td>
</tr>
<tr>
<td>Human Resource Management</td>
<td>8</td>
<td>0.658-0.912</td>
<td>0.913</td>
<td>0.629</td>
</tr>
<tr>
<td>Information &amp; Analysis</td>
<td>5</td>
<td>0.723-0.914</td>
<td>0.886</td>
<td>0.658</td>
</tr>
<tr>
<td>Environmental Sustainability</td>
<td>5</td>
<td>0.715-0.912</td>
<td>0.823</td>
<td>0.602</td>
</tr>
<tr>
<td>Social Sustainability</td>
<td>5</td>
<td>0.748-0.911</td>
<td>0.879</td>
<td>0.619</td>
</tr>
<tr>
<td>Economic Sustainability</td>
<td>6</td>
<td>0.687-0.916</td>
<td>0.902</td>
<td>0.621</td>
</tr>
<tr>
<td>Process Innovation</td>
<td>5</td>
<td>0.732-0.897</td>
<td>0.867</td>
<td>0.669</td>
</tr>
<tr>
<td>Product Innovation</td>
<td>5</td>
<td>0.812-0.919</td>
<td>0.894</td>
<td>0.636</td>
</tr>
</tbody>
</table>

Note: Average variance extracted (AVE) value should be \( \geq 0.5 \) (Molina et al., 2007).

Composite reliability value should be \( \geq 0.7 \) (Molina et al., 2007).

Source: Author’s Estimation

Researchers executed a discriminant validity test to assure that all constructs are different from each other empirically. For discriminant validity, Fornell and Larcker (1981) suggested that the variance of constructs must be greater than others. Moreover, if the square root values of AVE possess a high correlation among pair indicators, it is also considered another important indicator.
of discriminant validity. Hair et al. (2010) state that the independent variables’ pair correlation values should not exceed 0.9. All results presented in Table 3 follow Hair et al. (2010) and Fornell and Larcker (1981), and all constructs possess ample discriminant validity.

Table 3. Constructs’ discriminant validity.

<table>
<thead>
<tr>
<th>Construct</th>
<th>LD</th>
<th>SP</th>
<th>CF</th>
<th>PM</th>
<th>HRM</th>
<th>IA</th>
<th>ENS</th>
<th>SS</th>
<th>ECS</th>
<th>EPDI</th>
<th>EPCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>LD</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.801</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SP</td>
<td>0.469</td>
<td></td>
<td>0.780</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF</td>
<td>0.512</td>
<td>0.532</td>
<td>0.782</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM</td>
<td>0.521</td>
<td>0.523</td>
<td>0.513</td>
<td>0.794</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HRM</td>
<td>0.454</td>
<td>0.513</td>
<td>0.495</td>
<td>0.532</td>
<td>0.793</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IA</td>
<td>0.423</td>
<td>0.554</td>
<td>0.564</td>
<td>0.512</td>
<td>0.576</td>
<td>0.812</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENS</td>
<td>0.523</td>
<td>0.572</td>
<td>0.569</td>
<td>0.487</td>
<td>0.562</td>
<td>0.564</td>
<td>0.776</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SS</td>
<td>0.495</td>
<td>0.511</td>
<td>0.512</td>
<td>0.523</td>
<td>0.495</td>
<td>0.474</td>
<td>0.579</td>
<td>0.787</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECS</td>
<td>0.532</td>
<td>0.563</td>
<td>0.534</td>
<td>0.497</td>
<td>0.565</td>
<td>0.425</td>
<td>0.564</td>
<td>0.490</td>
<td>0.788</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPDI</td>
<td>0.499</td>
<td>0.578</td>
<td>0.610</td>
<td>0.575</td>
<td>0.553</td>
<td>0.585</td>
<td>0.486</td>
<td>0.523</td>
<td>0.597</td>
<td>0.818</td>
<td></td>
</tr>
<tr>
<td>EPCI</td>
<td>0.589</td>
<td>0.499</td>
<td>0.496</td>
<td>0.543</td>
<td>0.453</td>
<td>0.483</td>
<td>0.613</td>
<td>0.554</td>
<td>0.477</td>
<td>0.543</td>
<td>0.797</td>
</tr>
</tbody>
</table>

ECS=Economic Sustainability, SS=Social Sustainability, ENS=Environmental Sustainability, EPCI=Eco-process Innovation, EPDI=Eco-product Innovation, IA=Information & Analysis, HRM=Human Resource Management, PM=Process Management, CF=Customer Focus, SP=Strategic Planning, LD=Leadership; Bold and italic values are AVE square root value for each construct.

Source: Author’s Estimation.

Kaynak (2003) emphasized checking out the goodness of fit of the statistical model by focusing on seven determinants, i.e. normative fit index (NFI), chi-square to the degree of freedom ($\chi^2$/DF), root mean square error of approximation (RMSEA), the goodness of fit index (GFI), comparative fit index (CFI), adjusted goodness of fit index (AGFI), and standardized root mean squared residual (SRMR). The tucker-Lewis index (TLI) was further included in the study to assure the measurement and structural model fitness. The results display that the value of $\chi^2$/DF is 1.152 and is clearly below 2 as suggested by Byrne (1989) and also is under Bagozzi and Yi (1988) condition to be less than 3. Moving on towards analysis of NFI, CFI, TLI, GFI, and AGFI, shows the value is pretty fine, above 0.9 as advised by McDonald and Marsh (1990), Bagozzi and Yi (1988), Bollen (1986), Bentler and
Bonett (1980) and Byrne (1989). The value of RMSEA is 0.029, significantly below the maximum allowed value of 0.08, as (Browne & Cudeck, 1992) recommended. To end with, the SRMR value is 0.0366, fulfilling the 0.8 criteria proposed by Hu and Bentler (1998). After estimating the statistical model, the authors analyzed the structural model with results specifying a $\chi^2$/DF value of 1.154. Additionally, the results of these fit indices i.e. NFI, CFI, GFI, AGFI, and TLI are beyond 0.9 value and are in harmony with McDonald and Marsh (1990) and Bagozzi and Yi (1988). The value of RMSEA is 0.033, which fulfills the condition of Browne and Cudeck (1992) Finally, the structural model’s SRMR value is 0.0337, which is in accordance with Hu and Bentler (1998) (refer to Table 4 for further specifications). Keeping in view the outcomes further, we can state that the chosen structural models and their measurements perfectly fit with the data collected.

<table>
<thead>
<tr>
<th>Goodness of fit measures</th>
<th>CMIN/DF</th>
<th>NFI</th>
<th>GFI</th>
<th>AGFI</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>ARMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommended value</td>
<td>≤3</td>
<td>≥0.9</td>
<td>≥0.9</td>
<td>≥0.9</td>
<td>≥0.9</td>
<td>≤0.08</td>
<td>≤0.08</td>
<td>≤0.800</td>
</tr>
<tr>
<td>Measurement model</td>
<td>1.152</td>
<td>0.919</td>
<td>0.917</td>
<td>0.908</td>
<td>0.947</td>
<td>0.958</td>
<td>0.029</td>
<td>0.0366</td>
</tr>
<tr>
<td>Structural model</td>
<td>1.154</td>
<td>0.932</td>
<td>0.957</td>
<td>0.929</td>
<td>0.949</td>
<td>0.938</td>
<td>0.033</td>
<td>0.0337</td>
</tr>
</tbody>
</table>

### 7.4.2. Analysis of hypotheses

The hypotheses were analyzed following the SEM technique using AMOS v. 25 software. The structural analysis exhibits that QMS possesses a significant positive effect on environmental innovation with $b$ and $p$-values of 0.228 and 0.032; therefore, H1, i.e., Quality management system has a significant positive effect on environmental innovation, is accepted. QMS also showed a significant positive effect on CSD with a $b$ value of 0.217 and a $p$-value of 0.019, leading to the acceptance of H2, i.e., a quality management system has a significant positive effect on corporate sustainable development. Finally, environmental innovation also depicts a significant influence on CSD with $b$ and $p$-values of 0.299 and 0.004, respectively. Hence, all the principal hypotheses, i.e., H1, H2, and H3, are accepted. However, the dimensional analysis presented mixed results.
Environmental innovation revealed an insignificant effect on corporate social sustainability with b and p-values of 0.138 and 0.063. Therefore, the sub-hypothesis H3b, i.e., environmental innovation's significant and positive effect on corporate social sustainability, stands rejected. All the other-dimensional analyses showed a significant positive impact, resulting in the acceptance of sub-hypotheses H1a, H1b, H2a, H2b, H2c, H3a, and H3c. The detailed results of these hypotheses are given in Table 5.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Constructs</th>
<th>Coefficient</th>
<th>Critical ratio</th>
<th>p-Value</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>QMS→EI</td>
<td>0.228</td>
<td>2.209</td>
<td>0.032*</td>
<td>Supported</td>
</tr>
<tr>
<td>H1a</td>
<td>QMS→EPCI</td>
<td>0.213</td>
<td>2.261</td>
<td>0.013*</td>
<td>Supported</td>
</tr>
<tr>
<td>H1b</td>
<td>QMS→EPDI</td>
<td>0.191</td>
<td>2.219</td>
<td>0.021*</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>QMS→CSD</td>
<td>0.217</td>
<td>2.275</td>
<td>0.019*</td>
<td>Supported</td>
</tr>
<tr>
<td>H2a</td>
<td>QMS→ENS</td>
<td>0.221</td>
<td>2.325</td>
<td>0.009*</td>
<td>Supported</td>
</tr>
<tr>
<td>H2b</td>
<td>QMS→SOS</td>
<td>0.161</td>
<td>1.204</td>
<td>0.041</td>
<td>Supported</td>
</tr>
<tr>
<td>H2c</td>
<td>QMS→ECS</td>
<td>0.273</td>
<td>2.483</td>
<td>0.006*</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>EI→CSD</td>
<td>0.299</td>
<td>3.373</td>
<td>0.004*</td>
<td>Supported</td>
</tr>
<tr>
<td>H3a</td>
<td>EI→ENS</td>
<td>0.357</td>
<td>4.173</td>
<td>0.001**</td>
<td>Supported</td>
</tr>
<tr>
<td>H3b</td>
<td>EI→SOS</td>
<td>0.138</td>
<td>1.794</td>
<td>0.063</td>
<td>Not supported</td>
</tr>
<tr>
<td>H3c</td>
<td>EI→ECS</td>
<td>0.218</td>
<td>2.113</td>
<td>0.039</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Control Variables

| Firm size | FS→EI       | 0.029       | 0.910          | 0.291   | Insignificant |
|           | FS→CSD      | 0.031       | 0.887          | 0.574   | Insignificant |
|           | FS→EPCI     | 0.069       | 0.994          | 0.392   | Insignificant |
|           | FS→EPDI     | 0.049       | 0.826          | 0.403   | Insignificant |
|           | FS→ENS      | 0.084       | 0.110          | 0.121   | Insignificant |
|           | FS→SOS      | 0.081       | 1.244          | 0.048*  | Significant   |
|           | FS→ECS      | 0.041       | 0.532          | 0.601   | Insignificant |

| Industry type | Ind-Typ→EI | 0.093       | 1.539          | 0.037*  | Significant   |
|               | Ind-Typ→CSD | 0.042       | 0.278          | 0.045*  | Significant   |
|               | Ind-Typ→EPCI | 0.048      | 0.834          | 0.042*  | Significant   |
|               | Ind-Typ→EPDI | 0.042      | 0.643          | 0.038*  | Significant   |
7.5 Discussing the results

This research is conducted to study the influence of QMS on environmental innovation and CSD. The data was collected from the junior, middle, and senior managers of medium and large-sized manufacturing and services firms. As per the results, QMS significantly positively affects environmental innovation. This finding corresponds to (Abbas, 2020a) study that TQM expands the process innovation capabilities of businesses. But, it contradicts Li, Zhao, et al.’s (2018) finding that quality management program negatively affects green technology and green management innovation in Chinese manufacturing organizations.

QMS involves several processes, including continuous improvement, customer focus, efficient utilization of resources, and information and analysis. Dynamic organizations tend to ensure improvement in their operations through innovation to fulfil customers’ and stakeholders’ requirements and comply with environmentally-friendly regulations. Quality committed organizations try to capitalize on available resources to foster innovation capabilities and provide a breakthrough in green products and processes. The results indicate that the firms that participated in the study are proficiently benefiting from QMS within their setup concerning eco-innovation, and it can be said that senior managers in these firms are demonstrating a strong commitment to quality and eco-friendly practices, as Tideman et al. (2013) proposes leadership commitment has critical importance in achieving organizational objectives. Moreover, environmental protection through green technology and innovation and related regulation by the government of Pakistan has encouraged businesses to link quality management practices with eco-friendly technology.

The results also point out that QMS positively and significantly affects CSD. This finding complies with Usrof and Elmorsey (2016) work implying that TQM positively affects organizational and economic sustainability. This also further supports Tasleem et al. (2018) finding that quality committed organizations experience better financial sustainability than those with an inadequate focus on quality assurance. This result indicates that QMS in the sampled firms significantly enables
them to achieve SD goals. When a firm aims for SD, along with a comprehensive system such as QMS that facilitates workers to improve their performance through customer focus, updated information, analysis, etc., this will empower organizations to manufacture the finest products with minimal input of resources enabling firms to achieve SD objectives.

The result shows that environmental innovation has a significant positive relationship with CSD. This complies with Xie et al. (2019) study, which indicated that green innovation influences organizational financial performance positively. It also relates to (Abbas, 2020c) finding that eco-innovation and organizational performance are positively related. However, it contradicts Li, Jin, et al. (2018) finding that organizational green innovation activities hinder financial growth. According to sustainable development theory and green theory, green innovation activities allow firms to gain the trust of customers, suppliers, society, government, and other stakeholders. Pakistan is a developing country where industries have relied heavily on natural resources to produce products and services, thus causing severe damage to the natural environment. Over the last decade, the government of Pakistan has taken multiple initiatives to protect the natural environment, such as Punjab Green Development Program (World Bank, 2018), the ‘Ten Billion Tree Tsunami’ started in 2018 (Constable, 2018), the ‘One Billion Tree Tsunami’ project completed in 2017 (WEF., 2018), etc. The government of Pakistan is also encouraging businesses to invest in environmentally friendly technologies. Moreover, the rigorous environmental regulations and significant penalties for non-compliance have motivated corporations to invest in environment-friendly technology and achieve SD goals through ecological innovation.

The dimensional analysis indicated that QMS substantially positively affects environmental product and process innovation. It also strongly impacted the environmental, social, and economic dimensions of sustainability. This demonstrates the sampled firms are adequately complying with their socio-environmental responsibilities. Environmental innovation highlighted a significant positive impact on environmental and economic sustainability. However, it displays an insignificant influence on social sustainability. Hence, it can be said that the sampled firms need to pay adequate attention to their social responsibilities. Multiple scholars, such as (Guerrero-Villegas et al., 2018) and (Asrar-ul-Haq et al., 2017), have stated that organizational social activities significantly enhance performance. Therefore, it is recommended that the sampled firms link their business strategies with quality and social activities to acquire the benefits as reaped by socially responsible firms.

Considering the contextual effect, the current study also involves two control variables:
organizational size (medium and large) and industry category (manufacturing and services). The inclusion of firm size as a control variable significantly affected social activities. This means that firm size significantly regulates the organizational level of social participation, and large organizations are more likely to participate in social development activities than small ones. The insignificant impact of firm size linked with green innovation, CSD, and their other dimensions indicates that QMS is similarly imperative for firms of all sizes to accomplish green innovation and QM goals. This means that if firms, irrespective of their size, implement QMS programs in their operations, medium and large-size firms can enjoy the benefits of QMS from CSD and innovation perspectives.

The analysis of the industry category also indicated a significant impact on environmental innovation and CSD. It also exhibited significant results for eco-product and process innovation and environmental sustainability dimensions. These significant results indicate that industry type substantially controls the effect of environmental innovation and CSD. It also highlights that the significance of environmental process, product innovation, and corporate environmental sustainability varies from industry. Manufacturing industries are more likely to implement QMS to enhance their performance in earlier mentioned areas than services industries. One of the key reasons could be the differences in the operations of both industries. The insignificant result of industry type with social and economic sustainability indicates that regardless of the industry type, it is QMS that enables firms to achieve social and economic sustainability.

7.6 Research implications and limitations

The current research’s findings indicate the imperativeness of institutionalizing QMS in corporations. It also accords with the supporters of QMS’s claims that the efficient execution of QMS has the potential to strongly flourish an organization’s capabilities to be an environmentally friendly organization and achieve SD goals. Hence, to obtain the maximum benefits from QMS, top management should ensure that its practices are being implemented in their organizations in the true spirit. This research also holds up with ideas of the MBNQA model, i.e., quality operations in an organization lead to excellent outcomes. Therefore, it is recommended that organizations should go along with EFQM, MBNQA, and SQA quality models and associate them with business strategies to accomplish green innovation and SD goals. This study further enlightens the role of QMS that manufacturing firms must achieve green innovation and CSD goals than services. One of the key
reasons could be the heavy reliance of manufacturing firms on using natural resources as raw materials, which are converted into the final product. Regardless a firm is medium-sized or large, QMS is just as important. So, this research delivers a sense of belief to the managerial staff of medium-size firms in case they implement the QMS in its true spirit. It will contribute to their firms equally to large firms. The constructive results of QMS in environmental innovation and CSD in organizations located in Pakistan direct towards if organizations apply and properly execute QMS practices, regardless of a nation’s development level, that will enhance their innovation and SD capabilities.

Comparable to other studies, this research also comprises a few limitations. The researchers collected the data by contacting managers and requested them to operationalize the research instrument, keeping in view the corporation’s achievements and productivity; therefore, collected information is based on managers’ perceptions and may have caused biases in data. Other researchers should engage non-managerial staff in their studies as well. Even though the CMB test is analyzed properly, the likelihood of bias can’t be completely eradicated. Hence, along with opinion, the hard data of corporations, specifically annual financial reports, exhibits further indication regarding the role of QMS in CSD and environmental innovation.

Moreover, the sample was generated from the front line, middle, and upper-level managers and didn’t include the operational staff, though their opinion may help with further insights. Thus, in prospective studies, researchers may involve them in further unravelling aspects of the subject matter. It is further suggested that prospective researchers should include other countries, as well as the present study, which is limited to different cities of Pakistan.

7.7 Conclusion

The present study examines the nexus of QMS, CSD, and environmental innovation through SEM from Pakistani manufacturing and services firms’ perspectives. The researchers examined the influence of QMS on CSD and environmental innovation, trailed by the impact of environmental innovation on CSD. Results illustrate that QMS facilitates firms for ecological innovation and CSD. Eco-innovation further strengthens firms to attain SD goals. According to the contextual analysis, QMS is similarly imperative as environmental innovation and SD are for organizations, specifically medium and large firms. However, manufacturing firms need to pay more attention to eco-innovation and SD activities than services firms.
8 Data Element Embedding and Firm Performance: The Influence of ESG Investment

8.1 introduction

Under the background of "Internet + manufacturing", enterprises are faced with fierce market competition and changing consumer demands. Consumers hope that enterprises can respond to their individual needs through different channels, and change from the original pursuit of product quality to pursuit of consumer experience. This change makes the large-scale mass production model in the industrial economy era no longer appropriate, and enterprises need timely and accurate data to coordinate internal and external business activities of the organization, which makes data one of the basic elements in business success (Moyano-Fuentes and Martinez-Jurado, 2016). An enterprise is an organizational form linked with the effective allocation of resources. In essence, the competition among enterprises is a battle over the resource allocation efficiency. The accuracy, timeliness and effectiveness of resource allocation by enterprises is based on the correct data transmission inside and outside the organization, and the full mining and effective use of data increases the allocation and use efficiency of economic resources. Like traditional production factors, data factors can directly improve the enterprise production efficiency, but the difference between data factors and other factors is that when data factors are embedded in any factor such as labor, capital, and technology, it will produce a value multiplication effect. Seen from long-term development trends, data elements will eventually be embedded in production links on a large scale, thus increasing total factor productivity and creating an important impact on the resource allocation efficiency, which results in increased labor productivity, shortened production time, reduced production costs and circulation costs. In this way, it increases the final product value, accelerates the reproduction cycle of the industrial chain, thereby bringing about huge value creation under the condition of
equal costs.

ESG is a new sustainable development concept about the integration and coordinated development of environment, society and corporate governance. It provides enterprises and investors with a comprehensive framework that integrates environmental, social and corporate governance, and conveys a development view of pursuing integration of economic and social values (Atan et al., 2018; Huang, 2021). Data element embedding is an enterprise information sharing infrastructure that runs through business functions and information exchange and coordination among business partners. Despite its importance, data element embedding is also affected by the relationship between the organization and external subjects (Closs and Savitskie, 2003). These findings suggest that the value creation of data elements is highly dependent on other antecedent processes. Therefore, it is very necessary to conduct empirical research on the value creation process of ESG investment-driven data elements. The research results will help enterprises better understand the mechanism by which data element embedding affects enterprise performance, so that we can effectively use data element embedding to achieve enterprise performance and actively enhance the strategic competitiveness of enterprises.

Although the academic and business circles have noticed the impact of environmental characteristics and organizational agility on the value creation of data elements, there is no unified understanding and definition of how to describe and reflect environmental characteristics and organizational agility. Hence, from the perspective that ESG drives data element embedding, this paper defines and measures enterprise environmental characteristics and organizational agility, analyzes the impact of environmental characteristics and organizational agility on the action process of data elements, establishes a theoretical model by which data element embedding affects enterprise performance based on contingency theory, and puts forward research hypotheses, trying to analyze the composition of data elements, the role of organizational agility and environmental characteristics. Moreover, it tests the theoretical model through empirical research methods to reveal the mechanism by which data element embedding affects enterprise performance.
8.2 Value of data elements based on contingency theory

The contingency theory shows that an enterprise organization is a subsystem in an open social macro system that is affected by the internal and external environment. The internal elements and external environmental background and conditions of each organization are rather different. Enterprises should maintain the best adaptation to the environment by taking effective organizational management models and measures. The effect of management is highlighted in the interaction between the management model and the various elements of the organization, and enterprise performance is a result of the matching between its organizational strategic behavior and internal and external environmental conditions (Drazin and Van de Ven, 1985). This process requires enterprises to adopt effective organizational strategies and processes to handle the specific external conditions in front of them. The most important core of contingency theory is to enable organizations to adapt to the environment. When the organizational environment changes complexly, enterprises need to explore new markets, discover changes in consumer needs, and develop new products or services in a targeted manner. In this process, enterprises need to integrate new market information, perform differentiated restructuring of the organization, and even expand new subsystems or new production processes to adapt to changes in the environment.

Contingency theory regards the organization as an open system that continuously exchanges information and follows a factor-process-performance path (Schoonhoven, 1981). Factors refer to the pre-factors and environments in the context. For instance, market demand fluctuations cause uncertainty and opportunities for enterprises, and then affect the organization operation process. Process means the organization and management of these pre-factors or adaptation to these pre-factors, such as information sharing, organizational operation adjustment and so on. Performance refers to the result of this series of actions and processes.

According to contingency theory, this paper argues that data element embedding is a strategic behavior of an organization to improve its coordinated operation process and benefit enterprise performance (C. W. Y. Wong et al., 2011). The productivity of
data elements lies in the fact that they can essentially drive and stimulate the enterprise potential, achieve self-reform, self-transformation, and self-control of enterprises, and cope with various internal and external uncertainties through the agility in efficient coordination, so that the technology chain, product chain, value chain and even the space chain of enterprises can be effectively expanded and reconstructed, making the enterprise production and operation process more closely coupled with the consumer market, thus enabling agile and flexible management, forming information aggregation in the virtual space, thereby driving enterprise organization and market innovation. Therefore, enterprises cannot ignore the impact of environmental factors on the relationship between organizational agility and organizational performance driven by data elements. Contingency theory provides appropriate theoretical guidance for studying the factors influencing the process in which data element embedding leads to enterprise performance.

8.3 Theoretical models and hypotheses

Based on the contingency theory, this paper establishes a mechanism model regarding the impact of ESG investment on enterprise performance, analyzes the composition of data elements and the main characteristics of organizational agility, and investigates the mechanism by which ESG investment affects enterprise performance through data element embedding and organizational agility. Where, according to the relevant theories, the intervening effect of enterprise environmental factors on the value creation process of data elements is proposed, the characteristics of environmental factors are measured by environmental uncertainty, and the effect of data element embedding on organizational agility is analyzed. The theoretical model is shown in Figure 1.
8.3.1 Organizational agility

Economic globalization and intensified corporate competition have put pressure on enterprises in their efforts to maintain a competitive advantage in such an unstable environment. In the face of fierce competition and dynamic environment, enterprises need to take competitive behaviors (such as constantly developing new products or improving service accuracy, etc.), integrate limited resources and organizational capabilities to drive organizational agility. Organizational agility is the ability to innovate and respond quickly to capitalize on opportunities for growth and prosperity in the face of uncertainty in the business environment, which is an extension of the concept of strategic flexibility in response to unstructural change (Zhang and Sharifi, 2000). Existing literature generally explains organizational agility from two perspectives: market agility and operational adjustment agility (Lu and Ramamurthy, 2011). Market agility refers to an enterprise’s ability to respond proactively and exploit opportunities through continuous monitoring and rapid delivery of products or services to meet consumer needs. Market agility emphasizes dynamic, proactive growth-oriented corporate thinking about decision-making and judgment under conditions of
change or uncertainty (Sambamurthy et al., 2003). Operational adjustment agility is the ability to adjust business processes and resources at the internal level of an enterprise to meet changes in the market or demand. Operational agility emphasizes the flexibility and rapid response capability of an enterprise's internal operating processes in the face of changes. Enterprises with high organizational agility have the skills to take competitive actions and respond flexibly to changes in the environment, and provide consumers with new product or service needs, thereby effectively reducing operating costs, increasing product-market fit and market share, thus acquiring higher profit and value (Chen and Wang, 2014). Therefore, the following hypothesis is made:

H1: Organizational agility is positively correlated with enterprise performance.

8.3.2 ESG investment and data element embedding

In 1997, the relevant United Nations agencies proposed that environmental, social and corporate governance factors must be incorporated in the corporate decision-making process. Many financial institutions and non-governmental third-party institutions then began to pay attention to and promote ESG concepts, information disclosure and ESG evaluation (C. W. Y. Wong et al., 2011). At the same time, social rating agencies have gradually established a comprehensive multi-dimensional evaluation system, which further strengthens enterprises’ emphasis on ESG concepts. ESG investment can not only enhance the external signal of the enterprise, reduce the enterprise financing cost by alleviating information asymmetry and agency problems, but also can establish a good social image of the enterprise and strengthen the relationship between the enterprise and its stakeholders (Yoon et al., 2018). ESG investment helps to win the trust and support of various stakeholders, strengthens the long-term cooperative relationship between enterprises and all parties in the supply chain, and then helps enterprises gather the data resources required for operation, thereby achieving sustainable development of enterprises. Hence, the following hypotheses are proposed:

H2A: ESG investment positively affects the external data element embedding of
H2B: ESG investment positively affects enterprise performance.

Data element embedding means a high-level stage in utilization of enterprise information technology and other electronic resources. Sharing the integrated information between internal departments and external cooperative enterprises through electronic tools will facilitate cross-functional collaboration inside and outside the enterprise, which is represented as interaction and sharing of timely, accurate and standardized data between organizational functions within and outside the enterprise (Yoon et al., 2018). Previous research proposed multiple levels of data element embedding to support business coordination (C. W. Y. Wong et al., 2011). Data element embedding, on the one hand, can drive enterprises to accurately identify consumer needs and dynamic changes, and then provide precise marketing, targeted advertising, a price system beneficial to users, high-quality personalized services, and faster product and service iterations, thereby gaining market competitiveness and increasing profits. On the other hand, it can drive the reduction of organizational operating costs, the improvement of operating efficiency, and the improvement of production quality, so that higher operating performance is possible. As one of the key factors in enterprise success, data element embedding also provides an open communication and information sharing mechanism between enterprise functional entities and supply chain partners to support enterprises to take appropriate performance improvement actions (C. W. Y. Wong et al., 2011). For example, Dell continuously adjusts its production plan according to the market demand and makes suppliers adjust the production plan continuously, so that the production gradually approaches the real market needs in the process of continuous adjustment. Dell and its suppliers share so much information in the process that they work in close coordination as a unit. Integration of enterprise production plans and dealer procurement plans can help enterprises adapt to market demand changes and produce customized products. At the same time, order plans can be updated in time before market activities, so that enterprises and partners can jointly achieve the goal of improving performance. It can be said that data element embedding provides a collaborative mechanism to support the completion of intra and inter-
enterprise tasks and reduce operating costs, thus bringing obvious first-mover advantages to enterprises. In the future, to some extent, enterprises will rely on digital element embedding to achieve competitiveness and sustainable growth (Sambamurthy et al., 2003). Hence, the following hypothesis is proposed:

H2C: External data element embedding positively affects enterprise performance.

Enterprises with agile responses can quickly take countermeasures against sudden changes in market demand. How to develop this ability? The first suggestion given is data sharing among supply chain members. Enterprises that actively participate in ESG activities also display higher consumer satisfaction and a sense of identity with supply chain enterprises, which weakens the differences between enterprises and external stakeholders, brings all-round, multi-level effects to the enterprise’s operations and resource allocation, and then subtly increases organizational agility. Data element embedding emphasizes that in the mode of resource sharing, the long tail theory means to meet the ever-changing individual needs of consumers through multi-variety production in small batches, and let enterprises and other enterprises form economic benefits via the division of labor and cooperation. Wherein, the production operation mode, organizational management mode and service system will all be oriented towards rapid response. High data element embedding provides a timely and accurate support platform for enterprise operation adjustment and market response, thus enabling enterprises to conduct real-time dynamic analysis through real-time integration of internal and external data, quickly grasp market dynamics, adjust corresponding strategies and behaviors, adjust enterprise operations, optimize the process, and provide timely and rapid decision-making response (Fink and Neumann, 2007). Hence, the following hypotheses are made:

H3A: ESG investment positively affects organizational agility.

H3B: External data element embedding positively affects organizational agility.

8.3.3 The moderating effect of environmental uncertainty

The accelerated iteration of technology, the high penetration of the industry and
the blurring of boundaries all make many enterprises face uncertainty. Such uncertainty
is a result of superposition of various factors. For example, the innovation cycle has
gradually shortened from the original long time, the information technology-driven
integration of industries makes it difficult to distinguish one industry from another, and
the boundaries are becoming more and more blurred. Strong competition does not
necessarily come from traditional competitors, but may come from dimensionality
reduction strikes from other industries (for instance, the emergence of new energy
vehicles affects traditional vehicle industry, etc.). Therefore, enterprises strive to
expand the previously unfamiliar market, which further accelerates the environmental
instability. At the same time, with the rapid economic development and the constant
technological innovation, consumer needs are gradually becoming diverse and
personalized, and the business environment also exhibits a non-stationary trend
(Newkirk and Lederer, 2006). In the field of business management research,
environmental uncertainty is used as one important moderating variable to measure
organizational behavior. The so-called environmental uncertainty refers to the
unpredictable and non-sustainable unstable state or change of the business environment
(Wang et al., 2015). Tallon et al. also suggested using environmental uncertainty as an
important contextual variable in the information economy and information
management (Tallon, 2008). Regarding the impact of original ESG investment and data
element embedding on organizational agility, we ignore the contextual variable of the
environment. Therefore, it is difficult to reflect the situational dependence in the
realization of value embedded in data elements. Hence, the following hypothesis is
made:

H4A: Environmental uncertainty moderates the relationship between ESG
investment and enterprise organizational agility.

H4B: Environmental uncertainty moderates the relationship between external data
element embedding and enterprise organizational agility.
8.4 Research methods

The data in each value creation link of data elements of manufacturing enterprises are acquired by questionnaire survey, the impact of organizational agility on enterprise performance is analyzed by structural equation method, the impact of data element embedding on organizational agility and enterprise performance is tested, and the moderating role of environmental uncertainty level in the impact of data element embedding on organizational agility is analyzed.

8.4.1 Scale development and questionnaire design

The data collection herein adopts the questionnaire survey method, the measurement variables basically come from the existing literature, and there is a certain guarantee on the measurement reliability and validity. Before the official questionnaire came out, a small-scale pre-investigation was carried out. According to the investigation results, the expressions and sentences of the questionnaire items were revised to form the final questionnaire. Except the basic enterprise information, the 5-point Likert scale was used. ESG investment originated from socially responsible investment (SRI), which means the three most important consideration factors in socially responsible investment. From this perspective, we selected the three benchmarking institutions for ESG research: the Sustainability Accounting Standards Board (hereinafter referred to as SASB) as a non-profit organization, Morgan Stanley Capital International (hereinafter referred to as MSCI) as an index research and development enterprise, and Standard & Poor's (hereinafter referred to as S&P), then compared the similarities and differences in ESG research process. We found that SASB, MSCI and S&P have quite different starting points in designing the ESG evaluation system, but all lead to the same goal. These ESG index systems can provide us with an analysis template for sustainable development and green development, and provide investors with a starting point for analysis framework and index. SASB selected five important aspects for evaluation, including Environment, Social Capital, Human capital,
The data element embedding was measured by the scales of Wong, Moyano-Fuentes, Roberts (C. W. Y. Wong et al., 2011; Moyano-Fuentes and Martínez-Jurado, 2016; Roberts and Grover, 2012), etc., organizational agility was measured by the scales of Lu, Sambamurthy, et al. (Lu and Ramamurthy, 2011; Sambamurthy et al., 2003), environmental uncertainty was measured by the scale of Wong, Newkirk, Wang et al. (Lu and Ramamurthy, 2011; Newkirk and Lederer, 2006; Wang et al., 2015), and enterprise performance was measured by the scales of Wong and Narayanan (C. W. Y. Wong et al., 2011; Narayanan et al., 2015).

8.4.2 Data collection

The surveyed areas are mainly concentrated in Shanghai, Jiangsu, Zhejiang and other Yangtze River Delta regions in China. In these regions, the manufacturing industry is relatively developed, and the application of information technology is relatively early, which is typical and representative. The survey data mainly comes from two sources. The first way is to distribute 125 questionnaires in college MBAs, and the second way is to conduct field research or postal research through alumni resources. The questionnaire was filled out by the head of the information technology department, ESG management department or marketing department of the enterprise. A total of 400 questionnaires were distributed in this way. A total of 317 questionnaires were recovered from the three research channels, and the questionnaire recovery rate reached 79.25%. The validity of the recovered questionnaires was screened. 21 questionnaires filled in with incomplete information, contradictory information, and almost with the same options, and 9 questionnaires by respondents whose positions did not meet the requirements and who did not understand information technology and information management were eliminated. Therefore, a total of 287 questionnaires entered the final data analysis and model fitting stage.
8.4.3 Common method bias control

In the survey, the questionnaire is often completely filled out by one person, and there may be a problem of common method bias. In data analysis, two main steps are taken to address the problem of common method bias. First, adopt reasonable program control and process control, conduct anonymous survey and adjust the order of questionnaire items to control the questionnaire. Second, conduct Harman single factor test on the final survey data. In factor analysis, the variance of the first principal component factor is explained as 32.7% when there is no rotation, which has a significant statistical advantage, so it can be considered that the common method bias has no significant effect in this study.

8.5 Empirical analysis

This paper uses SPSS23 and SmartPLS3.0 as tools to conduct data research, tests the reliability and validity of the scale, calculates the influence of various variables, judges the fitness of the model and finally verifies the hypothesis of the model on this basis.

8.5.1 Evaluation of measurement tools

The minimum Cronbach's value of the construct in this paper is 0.822, and the minimum value of the combined reliability (CR) is 0.880, which far exceeds the critical value of 0.7, so the measurement model of the construct has relatively high reliability. The minimum value of the standardized factor loadings of all measurement items is 0.708, which is higher than the critical value of 0.6, indicating that the measurement model has high convergent validity. The average variance extracted value (AVE) for all constructs is above the critical value of 0.5. Through exploratory factor analysis, the maximum variance method is used for rotation, the Kaiser-Meyer-Olkin measurement test value is 0.854, which approaches 1, and the Bartlett sphericity test value is 4289.83, with a degree of freedom of 276. The significance is less than 0.001, and the factor
variance explained amount reaches 70.8%. The validity test is mainly to check the discriminant validity, which is measured by the square root of the average variance extracted value (AVE) greater than the correlation coefficient of the corresponding construct. The data in this paper meet the requirements, and it can be said that the discriminant validity of the scale is within a reasonable range.

Table 1 Reliability and validity analysis of the measurement model

<table>
<thead>
<tr>
<th>Constructs and Measurement Items</th>
<th>Factor Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ESG investment</strong></td>
<td></td>
</tr>
<tr>
<td>Cronbach’s $\alpha=0.833$, CR=0.882, AVE=0.599</td>
<td></td>
</tr>
<tr>
<td>Environment</td>
<td>0.782</td>
</tr>
<tr>
<td>Social capital</td>
<td>0.786</td>
</tr>
<tr>
<td>Human capital</td>
<td>0.738</td>
</tr>
<tr>
<td>Business model &amp; innovation</td>
<td>0.814</td>
</tr>
<tr>
<td>Leadership and governance</td>
<td>0.747</td>
</tr>
<tr>
<td><strong>External data element embedding</strong> Cronbach’s $\alpha=0.852$, CR=0.886, AVE=0.565</td>
<td></td>
</tr>
<tr>
<td>Enterprises exchange information electronically with business partners</td>
<td>0.712</td>
</tr>
<tr>
<td>Enterprises and business partners develop electronic business models</td>
<td>0.693</td>
</tr>
<tr>
<td>Electronic information shared by enterprises and business partners is accurate</td>
<td>0.739</td>
</tr>
<tr>
<td>Electronic information shared by enterprises and business partners is timely</td>
<td>0.759</td>
</tr>
<tr>
<td>Electronic information shared by enterprises and business partners is standardized</td>
<td>0.822</td>
</tr>
<tr>
<td>The information shared by enterprises and business partners can meet the needs of business activities</td>
<td></td>
</tr>
<tr>
<td><strong>Organizational agility</strong> Cronbach’s $\alpha=0.854$, CR=0.896, AVE=0.633</td>
<td></td>
</tr>
<tr>
<td>Enterprises can respond to changes in consumer needs in a timely manner</td>
<td>0.749</td>
</tr>
<tr>
<td>The enterprise can respond in time to the competitors’ launch of new products or services</td>
<td>0.797</td>
</tr>
<tr>
<td>Enterprises can reallocate resources in view of changes in demand</td>
<td>0.802</td>
</tr>
<tr>
<td>Enterprises can increase or decrease products or services in a timely manner to facilitate sales</td>
<td>0.856</td>
</tr>
</tbody>
</table>
Enterprises can timely and accurately identify consumer needs 0.768

**Environmental uncertainty** Cronbach’s $\alpha=0.781$, CR=0.848, AVE=0.585
Demand for products/services is always fluctuating in this industry 0.840
It is difficult to predict/observe competitor actions 0.850
Consumer attitude towards product/service is unpredictable 0.678
The impact of new technology on the industry is uncertain 0.673

**Enterprise performance** Cronbach’s $\alpha=0.831$, CR=0.880, AVE=0.594
The productivity of the enterprise is above the industry average 0.767
The product quality/service level of this enterprise is higher than the peer average 0.779
The operating cost of the enterprise is lower than the peer average 0.765
The enterprise’s market share is higher than the peer average 0.720
The consumer satisfaction of this enterprise is higher than the peer average 0.819

<table>
<thead>
<tr>
<th>Construct</th>
<th>ESG investment</th>
<th>External data element embedding</th>
<th>Organizational agility</th>
<th>Environmental uncertainty</th>
<th>Enterprise performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESG investment</td>
<td>0.782</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>External data element</td>
<td>0.523</td>
<td>0.754</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>embedding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational agility</td>
<td>0.640</td>
<td>0.456</td>
<td>0.772</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Environmental uncertainty</td>
<td>0.365</td>
<td>0.424</td>
<td>0.323</td>
<td>0.862</td>
<td></td>
</tr>
<tr>
<td>Enterprise performance</td>
<td>0.411</td>
<td>0.248</td>
<td>0.573</td>
<td>0.221</td>
<td>0.804</td>
</tr>
</tbody>
</table>

### 8.5.2 Model Fit

In PLS path analysis, the GoF index is generally used to measure the fitness or
goodness of fit of the model. The calculation method of GoF is 
\[ GoF = \sqrt{communality \times R^2} \], where \( communality \) and \( R^2 \) respectively measure the 
predictive ability and explanatory ability of the model, and \( communality \) is the mean 
of the common degree values of all endogenous latent variables involved in the model, 
\( R^2 \) is the mean of the variances of all latent variables involved in the model. As a 
measure of the global model fit in PLS, the large, medium and small critical values of 
the GoF parameters are 0.36, 0.25, and 0.10, respectively. The global matching 
parameter of the research model is 0.465, which is much larger than the critical value 
of 0.36, indicating that the model has a high degree of global fitness.

8.5.3 Theoretical hypothesis verification

Structural equation based on partial least squares does not require very high data 
volume and data distribution of survey samples, which is suitable for exploratory 
research and is widely used in the fields of information technology and strategic 
management. In this paper, SmartPLS, a typical software in PLS, is used for data fitting 
and analysis. Table 3 reports the hypothesis testing results without considering 
moderating effects.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path</th>
<th>Path Coefficient</th>
<th>T Value</th>
<th>Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Organizational Agility → Enterprise</td>
<td>0.535</td>
<td>9.069</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>Performance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H2A</td>
<td>ESG Investment → External Data Element Embedding</td>
<td>0.523</td>
<td>10.907</td>
<td>Supported</td>
</tr>
<tr>
<td>H2B</td>
<td>ESG Investment → Enterprise performance</td>
<td>0.090</td>
<td>1.240</td>
<td>Not supported</td>
</tr>
<tr>
<td>H2C</td>
<td>External Data Element Embedding → Enterprise Performance</td>
<td>-0.043</td>
<td>0.814</td>
<td>Not supported</td>
</tr>
</tbody>
</table>
It can be seen from Table 3 that the path coefficient between organizational agility and enterprise performance is 0.535, which is significant at p<0.001, indicating that there is a strong positive relationship between organizational agility and enterprise performance, so hypothesis H1 is verified. The path coefficient between ESG investment and external data element embedding is 0.523, which is significant at p<0.001, suggesting that ESG investment has a direct and significant impact on external data element embedding, so hypothesis H2A is verified. The path coefficients between ESG investment, external data element embedding and organizational agility are 0.554 and 0.166, respectively, which are significant at p<0.001 and p<0.05, respectively, indicating a certain positive relationship between the variables, so hypotheses H3A and H3B are verified. However, the path coefficient between ESG investment, external data element embedding and enterprise performance does not reach the critical significance level of 0.05, so hypotheses H2B and H2C are not established, that is, data element embedding has no significant direct impact on enterprise performance.

**8.5.4 Analysis of mediating effect**

In the path analysis, the path coefficients from ESG investment to enterprise performance, from external data element embedding to enterprise performance, and from organizational agility to enterprise performance are calculated. The test results show that the path coefficients from data element embedding to enterprise performance are insignificant, while organizational agility has a significant positive impact on enterprise performance. Therefore, according to the recommendations of the literature (Tarafdar and Qrunfleh, 2017), there is need to further analyze the mediating role of organizational agility in the impact of data element embedding on organizational agility.

In the past, most mediating effect tests in structural equation models were tested by the Sobel method. Hayes' research shows that the data parameter distribution in the
PLS method may not meet the normality requirement, so the traditional Sobel method is biased in effect test (Andrew F. Hayes, 2009; A. F. Hayes and Scharkow, 2013). According to the research recommendations of Nitzl and Roldan (Nitzl et al., 2016), by using the bootstrapping algorithm in PLS to estimate the relevant parameters, it is possible to effectively test the mediating effect. As shown in Table 4, the T-value test shows that all path coefficients pass the significance test at the 0.05 level, and 95% of the intervals are positive numbers, excluding 0, which verifies that organizational agility plays a mediating role between data element embedding and enterprise performance.

Table 4 Test of the mediating effect of organizational agility

<table>
<thead>
<tr>
<th>Indirect Effect Path</th>
<th>Indirect Effect Point Estimation</th>
<th>Bootstrap 1000 times</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SE</td>
<td>T</td>
</tr>
<tr>
<td>ESG investment → organizational agility</td>
<td>0.296</td>
<td>0.039</td>
<td>7.590</td>
</tr>
<tr>
<td></td>
<td>ESG investment → enterprise performance</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESG investment × environmental uncertainty</td>
<td>0.296</td>
<td>0.039</td>
<td>7.590</td>
</tr>
<tr>
<td></td>
<td>External data element embedding × environmental uncertainty</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.089</td>
<td>0.031</td>
<td>2.87</td>
</tr>
<tr>
<td></td>
<td>organizational agility → enterprise performance</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

8.5.5 The moderating effect of environmental uncertainty

SmartPLS provides a cross-product method for moderating effect verification, but the requirement for the interaction term is that it must be a reflective construct. The constructs studied herein are all reflective and meet the preconditions for application. Before calculation, the data must be normalized to generate new interaction constructs ESG investment × environmental uncertainty, external data element embedding × environmental uncertainty. Then, we calculate the impact of the new interaction construct on organizational agility and use bootstrapping algorithm to estimate the coefficient significance. The calculation results show that environmental uncertainty negatively moderates the relationship between internal data element embedding and enterprise organizational agility, so H4A is confirmed. However, environmental
uncertainty has no significant impact on the relationship between external data element embedding and enterprise organizational agility, so H4B is not supported, as shown in Table 5.

Table 5 Moderating effect test of environmental uncertainty

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path</th>
<th>Path Coefficient</th>
<th>T Value</th>
<th>Test Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>H4A</td>
<td>ESG Investment × Environmental Uncertainty → Organizational Agility</td>
<td>-0.884</td>
<td>1.923</td>
<td>Supported</td>
</tr>
<tr>
<td>H4B</td>
<td>External data element embedding × environmental uncertainty → organizational agility</td>
<td>0.389</td>
<td>0.823</td>
<td>Not supported</td>
</tr>
</tbody>
</table>

From the results in the above table, it can be seen that the path coefficient of the product terms ESG investment and environmental uncertainty with respect to organizational agility is -0.884, which is significant (P<0.05, T>1.923), indicating that environmental uncertainty negatively moderates the impact of ESG investment on organizational agility. For each standard deviation increase in environmental uncertainty, the slope of ESG investment against organizational agility decreases by 0.884 standard deviations. Neither of the other moderation paths passes the significance test, indicating that environmental uncertainty may not play a moderating role in the impact of external data element embedding on organizational agility. In order to make the results of the moderating effect more visible, this paper divides the environmental uncertainty into two groups, one with one standard deviation above the mean and one with one standard deviation below the mean. According to the organizational agility prediction equation after adding the interaction term, the interaction diagram 2 is plotted.
As can be seen from the above figure, when environmental uncertainty is at a lower level, ESG investment has greater impact on organizational agility, which further confirms the conclusion that environmental uncertainty negatively moderates the impact of ESG investment on organizational agility.

8.6 Discussion and enlightenment

8.6.1 Main findings

This paper develops a new scale on data element embedding in manufacturing enterprise, conducts confirmatory factor analysis on corresponding constructs, builds a value creation model for enterprise data elements, and conducts mediation path analysis and moderating effect test. The main findings are as follows:

8.6.1.1 Hierarchical characteristics and action mechanism of organizational agility driving factor

According to the survey data, two factors are extracted through confirmatory factor analysis, which proves that the driving factors of organizational agility are divided into two constructs: ESG investment and external data element embedding.
Different from existing research, this paper verifies the conclusion that ESG investment has a significant direct impact on the external data element embedding of enterprises. This conclusion directly shows that data element embedding by ESG investment is a reasonable path, and a good ESG investment background provides a good guarantee for the external data element embedding of enterprises. Previous studies either blended ESG investment and external data element embedding into one, or regarded them as two separate parts, ignoring the structural and hierarchical effects within ESG investment. In addition, at a practical level, ESG investment is the trigger for enterprise performance improvement, so enterprises should strengthen data sharing channels and data quality construction between internal agencies and with external cooperative enterprises (Lai et al., 2008), thereby strategically preparing for good performance.

8.6.1.2 Organizational agility is the bridge between enterprise data element embedding and performance

The study found that neither ESG investment nor external data element embedding had a direct impact on enterprise performance, while organizational agility had a direct impact on enterprise performance. Through the mediating effect, it is tested that ESG investment and data element embedding play a positive role through organizational agility. This finding provides some guidance for how to improve enterprise performance. Therefore, when enterprise managers make strategic decision-making on data element embedding, they should timely direct data elements to drive the improvement of organizational agility, thereby ensuring high enterprise performance. At present, the main domestic and foreign literatures still focus on the direct effect of data element embedding on enterprise performance (Junni et al., 2015; Zhang and Sharifi, 2000), and hardly study the mediating effect of organizational agility.

8.6.1.3 The moderating effect of environmental uncertainty

Through the moderating effect, it is verified that environmental uncertainty plays a negative moderating role in the impact of corporate ESG investment on organizational agility, but environmental uncertainty does not make external data element embedding significantly affect organizational agility. That is to say, lower environmental uncertainty better helps us form corporate organizational adjustment and market
responsiveness through corporate ESG investment. In the context of Chinese management, ESG investment is relatively easy for many enterprises, and the effect of ESG investment on organizational agility is effective when the degree of environmental uncertainty is low. However, once the market environment faced by enterprises changes drastically and consumer demands constantly change, corporate ESG investment is far less stable than the external data element embedding, so it is necessary to pay attention to the impact of the environment in ESG investment (C. Y. Wong et al., 2011).

8.6.2 Management enlightenment

From the perspective of practical application value, the main management enlightenments are as follows:

First of all, under the circumstance of low environmental uncertainty, enterprises should pay attention to ESG investment. The final purpose is how to combine new consumers, new production models, new products, etc. with data analysis to drive the business process speed and enhance enterprise competitiveness. Enterprises should pay more attention to data elements from a strategic perspective, and realize that enterprises are not making ESG investments to just reach relevant standards, but there is need to transit to data application capabilities. Through the training of IT capabilities among technical and managerial staff (Sun et al., 2020), the introduction of advanced information system software and hardware, and the cultivation of internal information sharing systems, it may be easier to achieve the prerequisite driving conditions for organizational agility. Enterprises should establish a collaborative mechanism in the aspects of human, finance, material, production, supply, and sales to realize the organic integration of internal resources, build an advanced environmental-society-governance framework within the enterprise, effectively utilize the internal data resources of the enterprise, optimize the internal management process, improve the management level and governance efficiency, thus laying a solid foundation for the enterprise to expand the use of external data elements.

Secondly, in the context of high environmental uncertainty, enterprises should not
only pay attention to ESG investment, but also strengthen the construction of external data element embedding. Market information is crucial to suppliers, manufacturers and downstream retailers in the entire industry chain, but enterprises in different positions in the entire industry chain have certain differences in the way and ability to access information. Distributors and retailers in the downstream of the industry chain directly face consumers, who possess an incomparable advantage in accessing market information, and can directly predict products and adjust relevant market decisions based on the first-hand data of consumers. However, production enterprises in the upstream cannot directly access market information. Therefore, if they have a good information exchange system with distributors or retailers, through horizontal and vertical information sharing, enterprises can improve their grasp of market information and adjust production and operation processes in a timely manner. In this regard, in order to ensure that all subjects in the industrial chain can effectively share information, core enterprises can build an information sharing system as an information platform for the entire industrial chain to provide effective information services to participating subjects and enable the optimal embedding level of external data. For example, in recent years, the auto retail industry faces fierce competition. Many enterprises integrate supply chain information sharing, connect downstream sales information with information such as the factory's internal ERP system, and establish an e-commerce platform or implement ERP/MES system extension, so that internal enterprise information is shared with upstream supply chain, which can effectively improve organizational agility in the context of environmental uncertainty. Therefore, in the face of different environments, enterprises should grasp a reasonable "degree" between ESG investment and external data element embedding with a limited budget.

Finally, although different enterprises invest heavily in ESG investment, they must ultimately drive organizational agility through data elements. Seen from the outside of the enterprise, consumer needs are constantly changing, and competitors constantly appear, which puts forward new requirements for enterprises. That is, there is need to abandon the traditional experience management model, adopt digital element embedding to grasp market demand information and competitive information through
data analysis. Through fast and accurate strategic and tactical decision-making, they need adjust organizational structure, production mode, product type, etc. to gain a competitive advantage. Organizational agility is a special ability of an organization, which is not a form of an organization, but means the ability of an organization to respond quickly, change flexibly, and empower actions. The difference between agile enterprises and other enterprises is that they are always consumer-oriented and continuously innovate products or services. For example, when developing a new product for consumers, they actively learn the consumer's attitude towards new product design solutions and continuously seek feedback and comments from consumers. Because the process from production to sales is too complicated for many manufacturing enterprises, although a lot of data has been accumulated for a long time, the data scores separately belong to each department or system and cannot be fully utilized. In addition, in order to better improve agility, the relevant decision-making departments of enterprises impose higher and higher requirements for ESG investment specifications, and the requirements for external data granularity become more and more refined. However, enterprise organizations find it difficult to effectively match the current operation, resulting in certain bottlenecks in the process in which ESG investment and data elements drive organizational agility, so effective value creation is impossible. Therefore, it is necessary to establish a scenario-based data application, use effective digitalization of operations, carry out forward-looking design and strategic planning for the overall goal, time and space of specific operations digitalization to empower organizational agility, and make full use of internal and external resources to create agility-oriented processes, so that the products or services provided by an enterprise are differentiated from those of its competitors, thus creating unique value recognized by consumers, which is the basis for maintaining the sustainable development of the enterprise. This not only reflects the adoption of digital technology, but also involves all-round reform in business strategies, management models, organizational processes, etc., which improves the internal and external information communication capability of the enterprise, breaks down internal and external information barriers by relying on real-time information sharing and increases
8.7 Conclusion

In the context of Chinese manufacturing enterprises, this paper studies the mechanism by which ESG investment and data element embedding affect enterprise performance, collects data by questionnaire survey, and fits the data using structural equation model. The research results show that corporate ESG investment and data element embedding have no direct and significant impact on enterprise performance, but have indirect effects on enterprise performance through organizational agility. At the same time, the research results also show that under different levels of environmental uncertainty, the impact of data element embedding on organizational agility will change. Specifically, the higher the level of environmental uncertainty, the lower the effect of ESG investment on organizational agility. Of course, this study also has some shortcomings. First, the data collected by the survey are cross-sectional data of enterprises, lacking time series data under dynamic conditions, which may affect the interpretation of the problem. In the future, some enterprises will be followed up for a long time. Secondly, the research model only considers the mediating effect of organizational agility. However, there may be other factors related to enterprise performance in practice (Shuradze et al., 2018). Future research will add other factors to improve the explanatory power and application effect of the model.
9 The impact of digital technology pressure on the job performance of manufacturing employees: The moderating effect of green innovation

9.1 Introduction

With the continuous application of emerging technologies such as artificial intelligence, big data, blockchain, and cloud computing, emerging production methods with data as the core production factor and digital technology as the driving force have attracted widespread attention (Edelmann and Francoli, 2020; Jackson and Dunn-Jensen, 2021; Mutsvairo et al., 2021). Digitalization is becoming a driving force for industrial innovation (Ding et al., 2020; Phillips et al., 2011), and various countries are strategically deploying digital economic development (Adler-Milstein, 2021; Bertola and Teunissen, 2018; Mansur et al., 2021; Wang G. et al., 2019). As an integrated economy, the digital economy takes digital knowledge and information as key production factors, and plays its role in activation, innovation and empowerment by integrating with the real economy (Baporikar and Baragde, 2021; Cheng and Gao, 2021). Its core lies in the application of a new generation of information technology in the real economy. As the main body of the real economy, the manufacturing industry is becoming more and more mature in the new generation of digital technologies such as intelligent manufacturing, Internet of Things, big data, and artificial intelligence, and its application focus has shifted to the supply side. Under the trend of digital economy (Ben Youssef et al., 2021; Truby and Brown, 2021), it has become the main application area in which the digital economy will play an innovation-driven role (Borangiu et al., 2019; Holmström, 2022; Jafari-Sadeghi et al., 2021).

The transformation of manufacturing is driven by a range of enabling digital tools and internet technologies, and has revolutionized strategic capabilities and business processes (Zapata et al., 2020). This enables a higher level of flexibility,
reconfigurability and intelligence in manufacturing (Savastano et al., 2019). At the same time, it cannot be ignored that green technology with the characteristics of high efficiency, low carbon and recycling is an inevitable choice for the development of human society (Debenedetti et al., 2021; Ngo and O'Cass, 2009). Some scholars have pointed out that the knowledge spillover effect of the digital economy forces the optimization and reduction of manufacturing costs within the industrial system, and enhances the linkage and responsiveness with the external environment, so as to achieve the goals of ecological environment governance and resource protection in the process of technological innovation (Aaron and Jason, 2008). The technological progress and the application of digital communication technology contained in digital transformation can effectively improve the efficiency of enterprise production factor utilization and energy efficiency (Moyer and Hughes, 2012). Therefore, it is an inevitable trend for the manufacturing industry to rely on digital technology to break the boundaries of corporate innovation, reduce transaction costs, and improve the level of cooperative innovation to promote the development of corporate green innovation (Bo and Kexin, 2021; Quintana-García et al., 2021; Yu Y . et al., 2021). Green innovation is the innovation of developing or improving technology to realize processes, products, services or management (Hojnik and Ruzzier, 2016), and has the dual value attributes of helping enterprises to form differentiated competitive advantages and promoting environmental protection (Asadi et al., 2021); Saunila, 2017). Green innovation is the key to adhere to the synergy of economy, society and environment to achieve sustainable development, and it is also an important driving force for promoting industrial upgrading and building a green economic system (Berrone et al., 2013).

Under the dual main line of digitization and greening, manufacturing enterprises continue to increase investment, expansion and application of digital technology to gain competitive advantage. The use of digital technology requires employees to continuously learn and adapt to new digital technologies, and constantly to adjust work processes and methods (Naidoo, 2018; Sami and Pangannaiah, 2006; Yuan et al., 2021), which inevitably leads to the negative impact of emerging technologies on employees such as job insecurity, task overload and fatigue (Ayyagari et al., 2011; Kashif et al.,
2017; Mehmood and Hussain, 2017). In the mechanism of negative impact on employees when digital technology moves from experiment to application, what role does green innovation play in enterprises? This paper selects job satisfaction as an intermediary variable, focuses on digital technology pressure and role pressure, discusses its impact on the job performance of manufacturing employees, and analyzes the mechanism of green innovation. The theoretical hypothesis of this paper is tested by the questionnaire survey method, and the impact of the digital technology pressure perceived by the employees of the manufacturing industry on their job performance under the background of the digital economy and green economy is revealed.

9.2 Research background

9.2.1 Pressure of digital technology

The development of digital technology has driven the rise of the digital economy, which has profoundly affected the industrial structure and economic growth pattern. On the one hand, the accelerated expansion of digital industrialization has become a new economic growth point. On the other hand, the acceleration of the digitalization process has a negative effect on the application of digital technology, especially in the attitudes and perceptions of employees towards digital technology (Ben Youssef et al., 2021; Díaz Andrade et al., 2021).

The psychologist Brod (1984) proposed the concept of "technical stress", defined it as "a malady caused by the inability to cope with new computer technology", and pointed out that technical stress manifests itself in two distinct and related ways, that is, resisting technology or indulging in technology in some form. Weil and Rosen (1997) extended the concept of technological stress, they believed that technological stress cannot be regarded as a disease, it is the negative impact of technology on people's attitudes, thoughts, behaviors and psychology. Arnetz and Wiholm (1997) defined technical stress as "a state of poor physical and mental arousal exhibited by individuals who rely on computers for work when they find themselves unable to cope with work
tasks", focusing on describing the reactions or symptoms of technical stress. Wang (2008) proposed that technical stress is a reflection of uneasiness, fear, tension or worry when an individual contacts, learns and uses computer technology due to the complexity of the technology or the rapid upgrading of the technology; then it will lead to psychological and psychological stress. Emotional aversion (e.g., feeling that technology interferes with normal living conditions), thus hindering further learning and use of technology. Tarafdar et al (2007) discussed the specific environmental requirements caused by technological pressure, and extracted five dimensions of the source of technological pressure: work overload caused by technology, intrusion of technology into life, complex and difficult technology, and insecurity caused by technology, the uncertainty brought about by technology, and the concept of technological stress was standardized in subsequent research: the stress experienced by individuals in the use of information technology (Tarafdar et al., 2019). From the above research on technical pressure, it can be seen that digital technology pressure is a new manifestation of information technology pressure in the digital age. Table 1 sorts out the definitions of connotations in the relevant literature.

**Table 1 Definition of digital technology pressure**

<table>
<thead>
<tr>
<th>Source</th>
<th>Digital Technology Pressure Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brod (1984)</td>
<td>A malady caused by an inability to cope with new computer technology</td>
</tr>
<tr>
<td>Weil and Rosen (1997)</td>
<td>The negative impact of digital technology on people's attitudes, thoughts, behavior and psychology</td>
</tr>
<tr>
<td>Arnet and Wiholm (1997)</td>
<td>Individuals who rely on computers for work, when they find themselves incapable of coping with work tasks, show a state of poor physical and mental arousal</td>
</tr>
<tr>
<td>Wang (2008)</td>
<td>A reflection of unease, fear, tension or worry when an individual contacts, learns and uses computer technology due to the complexity of the technology or the rapid upgrading of the technology</td>
</tr>
<tr>
<td>Tarafdar (2019)</td>
<td>The pressure individuals feel when using information</td>
</tr>
</tbody>
</table>
9.2.2 Role pressure

Role pressure theory states that anyone in an organization is directly or indirectly connected to other people. This connection may be in the workflow, authority hierarchy, or from outside the organization (e.g., family, friends, etc.). Role pressure is often defined as a composite structural concept (Demerouti et al., 2001; Meijman and Mulder, 2013). Kahn et al. (1964) proposed a Role Episode Model that pointed out that cross-border workers need to interact with multiple role-expectant senders (such as customers, colleagues) in order to obtain information, task requirements or help. But when they feel vague role expectations, overloaded role requirements, or conflicting expectations of different roles, these expectations or requirements manifest as a stress.

At the same time, some scholars have different divisions of role stress. Hardy and Conway (1988) divided role stress into six levels: in addition to role ambiguity, role conflict, and role overload, it also includes role inconsistency and insufficient role ability. Gilboa et al. (2008) pointed out that the role pressure of employees mainly includes seven types of pressure, including role ambiguity, role conflict, role overload, lack of job security, conflict between work and family life, environmental uncertainty, and work environment constraints. Among the sources, role ambiguity may be the least challenging type of stressor, and role ambiguity has a greater negative impact on employee job satisfaction than role burden and role conflict. This paper accepts that role stress generally considered in academic circles includes three components: role ambiguity, role conflict, and role overload. Among them, role ambiguity refers to the obvious difference in the expected information (behavior or performance level) received by individuals for the role they play. The result caused by insufficiency; role conflict is defined as an individual facing two or more role expectations at the same time, when one of them is expected to be met, but it will conflict with another expectation, so a role conflict occurs; A conflict between role senders, where different senders have appropriate expectations, causing the role client to experience a conflict
that prioritizes those role pressures, he or she must decide which pressures to obey and which to defer (Kahn et al., 1964).

### 9.2.3 Green innovation

Since the Industrial Revolution, global problems such as resource scarcity and environmental degradation caused by economic development have continued to intensify, and the international community has begun to recognize the importance of sustainable development (Bernauer et al., 2007). Innovation is the soul of economic development (Ben Youssef et al., 2021; Laursen and Salter, 2006), and green thinking contains the requirements of saving resources in today's society. Therefore, green innovation has become an inevitable choice for enterprises to obtain competitive advantages under environmental regulation. James (1960) first defined green innovation. In his book Driving Green Innovation, he defined green innovation as innovation in green products and green processes that can reduce environmental pollution. Rennings (2000) introduced the concept of ecological innovation. He believed that green innovation is different from other general types of traditional innovation, and has the characteristics of double externalities. Kemp (2011) made an in-depth explanation of ecological innovation based on a dynamic perspective. He believes that as long as the damage to the environment can be reduced, it is conducive to environmental friendliness and resource conservation, and the production of environmentally friendly products, transformation of production processes, innovation of technology, Innovations that optimize the system are called environmental innovations, which further enriches the connotation of green innovation. Oltra and Jean (2005) believe that green innovation is a systemic innovation in production and practice, which protects the environment in the long term by improving products and processes. Chen C.-L. et al. (2012) defined green innovation as innovation in product and process management. Organizations achieve energy conservation, emission reduction and environmental protection by developing green products and designing new processes and processes.

This paper argues that green innovation is essentially a synthesis of technical, organizational and market issues (Foxon and Andersen, 2009), which refers to dual-
purpose innovation under the constraints of economic benefits and environmental protection. Green innovation has both risk and benefit characteristics, making it difficult to determine its impact on economic benefits (Zeng et al., 2021). Compared with general environmental protection measures and traditional technological innovation, green innovation, as a forward-looking strategy to solve environmental problems, can exert the dual value effects of environment and finance on the establishment of enterprise technical barriers and the cultivation of long-term competitive advantages. This is a key element for enterprises to seize the future market and achieve sustainable operation (Huang Z. et al., 2019; Li D. et al., 2017). However, corporate green innovation faces a natural development bottleneck. On the one hand, it relies on heterogeneous information resources and multi-level capital investment, and on the other hand, its typical dual externalities will deepen the uncertainty of green innovation (Brunnermeier and Cohen, 2003; El-Kassar and Singh, 2019; Karimi Takalo et al., 2021). At present, the theoretical research on green innovation is in a new stage, and some scholars conduct research from the perspective of moral driving. They believe that as the main body of green innovation, enterprises should not only consider the benefits of investors and stakeholders, but also consider the impact on the social environment, and should undertake due corporate social responsibility (Guo et al., 2021; Shen et al. al., 2021; Zhang and Berhe, 2022). Most foreign scholars refer to green innovation as socially responsible investment, and believe that green innovation is a behavior that takes into account environmental standards, social responsibility, and benefits. Eyraud et al. (2013) believe that green innovation is an investment behavior based on environmental criteria, social criteria and value criteria. Green investment is also known as triple surplus investment due to the consideration of the three bottom lines of environment, society and economy. Giovanni et al. (2012) pointed out that the implementation of green production practices by enterprises will improve environmental performance and thus be recognized by stakeholders. This paper believes that green innovation, as a new hybrid practice combined with environmental goals, not only requires reducing energy consumption and pollution in the manufacturing process, but also plays an important role in carbon emission reduction (Lee and Min, 2015; Yan et al., 2021), at the same time, it also builds a green and low-
carbon technology system through the reform and adjustment of the internal organizational structure, work process and even the training of employees, etc., to provide conditions for enterprises to achieve green and long-term sustainable development (Mehmood and Hussain, 2017).

9.3 Theoretical models and assumptions

Based on the above analysis, this paper takes employees who use ICT in manufacturing enterprises as the research object, and discusses the mechanism of digital technology pressure on employees' work performance from the perspective of green innovation. Considering that studies have shown that job satisfaction is closely related to job performance, job satisfaction is introduced as an intermediary variable to investigate the impact of digital technology pressure and role pressure on job performance, and the moderating role of green innovation in it. The research model is shown in Figure 1:

![Figure 1 Research Model](image-url)
9.3.1 The effect of job satisfaction on job performance

Job satisfaction is a description of employees' evaluation of their overall work conditions, their personal emotional awareness gradually formed in their long-term work experience, and their psychological satisfaction with the work environment and the work itself. Job performance is more likely to be affected by positive emotions such as job satisfaction, mainly because positive emotions can change individual behaviors and expand positive agency, thereby motivating individual job performance (Garmendia et al., 2021). For example, when an individual feels positive emotions, he will be willing to take the initiative to overcome work difficulties and integrate additional resources to improve work efficiency. Positive emotions also make individuals willing to spend more time focusing on complex work environments, prompting individuals to enhance the potential link between tools and efficiency, and increase flexibility in the use of resources and tools at work. According to positive emotion expansion-construction theory, job satisfaction as a positive emotion can make employees break through the inherent work mode and promote employees to pursue novel and efficient ideas and actions (Bartoll and Ramos, 2021). Robins (1996) pointed out that the higher the employee's job satisfaction, the higher the overall performance level of the enterprise, and the two are significantly positively correlated. Judge et al. (2001) found through empirical research that there is a significant positive effect between the two variables. Therefore, this paper proposes the following assumptions:

H1: Employee job satisfaction has a direct positive effect on job performance.

9.3.2 The effect of stress levels on job satisfaction

According to relevant literature (Tarafdar et al., 2007), work stress in the digital context is divided into two categories, digital technology stress and role stress. The impact of information technology-induced changes on organizations is mainly reflected in two aspects (Joshi, 1989): on the one hand, information technology directly triggers changes in technical systems, that is, changes in tasks and processes; on the other hand, it has indirect effects on social systems, that is, the impact on roles, compensation systems, and authority structures. Therefore, the application of information technology
has changed the roles of individuals in organizations (Barley, 1990), and brought certain role pressures to employees. Digital technology stress and role stress are essentially two important work stressors. Tarafdar et al. (2007) studied the relationship between these two work stressors, that is, the higher the perceived computer technology stress, the higher the role stress. Therefore, the following assumptions are made:

H2: Digital technology pressure has a direct positive impact on role pressure.

Khan et al. (2013) used multiple regression to empirically analyze the impact of information technology pressure on employee job satisfaction in Pakistani university librarians. The negative impact of information technology insecurity on employee job satisfaction is particularly significant. Kumar et al. (2013) research on information technology pressure of IT professional employees found that IT professional employees have higher requirements for information technology competency, and must use and face information technology in their daily work, which is more likely to generate information technology pressure, and increase the negative evaluation of employees to work, reduce job satisfaction. Through a survey of Indian scholars, Jena (2015) used structural equation model analysis to show that information technology pressure will lead to a decline in scholars' job satisfaction, which in turn reduces the quality of their academic research.

Ho-Jin and Cho (2016) showed through empirical analysis that job uncertainty and work overload brought about by too fast information technology update significantly increase employees' information technology pressure and significantly reduce employees' job satisfaction. Suh and Lee (2017) found that the use of information technology at work can cause employees to feel pressure, and continuous excessive pressure will significantly negatively affect employee job satisfaction. Based on the existing research, information technology stress is common among employees of different countries or industry backgrounds, and it has a significant and direct negative impact on employees' job satisfaction. A study found that about 20% of IT workers experienced role stress, which made them feel fatigued, reduced job satisfaction and organizational commitment, and even increased turnover intentions (Moore, 1998). Therefore, this paper proposes the following assumptions:

H3: Digital technology pressure has a negative impact on job satisfaction;
H4: Role stress has a negative impact on job satisfaction.

9.3.3 The impact of digital technology pressure and role pressure on job performance

The stress interaction model believes that the generation of stress is the result of the interaction between the individual and the environment, which is affected by the individual's perception and evaluation of things. Individuals perceive and evaluate things differently, and the consequences of stress are bound to be different (Contreras and Gonzales, 2021). Traditionally, work stress is divided into two types: challenging stress and hindering stress. Challenging stress is considered by managers as obstacles that need to be overcome in order to learn and achieve goals, which can promote personal growth, make individuals have positive emotions and work hard to solve problems; hindering stress is an unnecessary factor that hinders personal growth and goal achievement. It is potentially harmful to individual growth or interests, and it is easy for individuals to have negative emotions and find excuses to avoid work (McTernan et al., 2013; Rafiee et al., 2013).

However, most scholars (Jamal, 1985; James G. Miller, 1960; Kim and Lee, 2006; Ng and Feldman, 2012; Seipp, 1991) agree with the negative theory of work stress and believe that work stress has a negative impact on job performance. With the digitization of manufacturing, employees often perceive changes in the nature of workflow and tasks at work. Employees often struggle to adapt to these changes and even resist these realizations, resulting in lower job performance. At the same time, when a person is exposed to contradictory, incompatible, or inconsistent role requirements, he or she experiences role conflict. This can happen when he or she is asked to meet the requirements of more than one role, and those expectations may be inconsistent with another role, such as compliance with one role making compliance with the other difficult.

Role overload occurs when an individual's role requirements exceed his or her capabilities in terms of difficulty level or workload. Quantitative role overload describes situations where there is simply too much to do, and qualitative role overload
involves instances where the work that needs to be done is too difficult for the individual to do. Role overload can also occur when a person has to fulfill many different roles than he or she can manage effectively. In this case, the individual is exposed to too many demands from different roles and only becomes overwhelmed. Various studies have found that role stress can negatively impact job performance. It reduces work quality and productivity because it creates conditions that impair an individual's ability to perform tasks effectively (Naidoo, 2018). Therefore, this paper proposes the following hypotheses:

H5: Digital technology pressure has a negative impact on job performance;
H6: Role pressure has a negative impact on job performance.

9.3.4 Moderating effect of green innovation

Companies can initiate green innovation or ecological innovation on the basis of green product innovation and green process innovation. For more environmental issues, companies can consider green innovation or ecological innovation as a business opportunity (Bocken et al., 2014; Zhu et al., 2012). Green innovation means green products and processes that modify existing product designs to reduce any negative impact on the environment at any stage of the product life cycle (Chen Y.-S. et al., 2006). Green innovation plays a key role in driving the industry towards sustainable production, and green innovation facilitates the development of sustainable manufacturing programs (Huang H. et al., 2021). On the one hand, the green innovation strategy focuses on the long-term development of the enterprise, so the initial investment can be effectively transferred through cost reduction and green product differentiation; Stakeholder relationships form growth advantages (Li W. and Ouyang, 2020; Yu X. et al., 2021). Wei et al. (2013) used survey data from 3960 individual employees in China and found that perceived innovation had a significant positive impact on employees' job satisfaction. They believe that nurturing employees' interest and commitment to innovation may make them feel that the company is dynamic and keeping up with changes in the environment, which can effectively reduce any anxiety caused by environmental uncertainty, thereby increasing job satisfaction. Therefore, first, according to the reasoning at the firm level by De Roeck and Delobbe (2012), it
is believed that green innovation may generate higher profits, while employees through
direct or indirect means (such as increased wages, improved workplace environment,
higher employment levels) may offset the effects of work stress. Second, a green
innovation-oriented environment can also (more or less) align with certain personal
characteristics of employees. These environments allow one to find and give meaning
to his/her work efforts and reduce the effects of stress. Therefore, this paper proposes
the following assumptions:

H7: Green innovation weakens the negative impact of digital technology pressure on
job satisfaction;

H8: Green innovation attenuates the negative impact of digital role pressure on job
satisfaction.

9.4 Research Methods

9.4.1 Measuring tools

The measurement scales in this paper are all from the existing literature and fine-
tuned according to the research background, which can ensure the validity of the scale
content, the validity of the structure and the reliability. The designed questionnaire is
divided into two modules. The first part is about filling in the basic information of the
respondents, and the second part is the variable measurement items formed by each
construct in the research design, using the LIKERT 5-point scale. First, a small-scale
pre-investigation was carried out on 20 manufacturing enterprises, and the questions
were ambiguous in understanding and revised, and finally each item was measured
accurately and without ambiguity. The digital technology pressure scale reference
(Ragu-Nathan et al., 2008) scale was designed and adjusted and modified to make the
scale more in line with the background of digital transformation in manufacturing and
the characteristics of digital technology applications. Role stress is also based on the
role stress scale in the technical stress questionnaire of Ragu-Nathan et al. (2008),
which divides role stress into three dimensions: role ambiguity, role conflict, and role
overload. Regarding job satisfaction, this paper draws on the Minnesota Satisfaction
Scale compiled by Weiss (1997), which is widely used because of its good reliability
and validity. It measures employee job satisfaction from multiple dimensions. In addition, according to the research of Huang et al. (2015), the green innovation in the scale includes items such as green product innovation and green process innovation.

9.4.2 Data collection

The data in this paper are obtained from field surveys in provinces in the Yangtze River Delta region of China. The 5-point LIKERT scale was used according to the theoretical model, and the respondents scored according to their actual situation. The higher the score, the higher the degree of approval. A value of 1 indicates complete disagreement, a value of 3 indicates uncertainty, and a value of 5 indicates complete agreement. A total of 210 questionnaires were distributed, and 181 were recovered effectively. The 181 questionnaires that were recovered were initially screened and re-screened, and 4 unqualified questionnaires were deleted. A total of 177 questionnaires entered the final data analysis and model fitting stage. From the perspective of the industries of the respondents, 35.0% of the respondents are engaged in the machinery manufacturing industry, 25.4% are in the electronic communication industry, 15.3% are in the chemical and pharmaceutical industry, and 22.6% are in the video industry. In the clothing industry, 1.7% of the respondents chose other industries.

9.5 Empirical Analysis

Structural equation modeling includes two stages: measurement model and structural model. Among them, the test of the measurement model mainly studies the reliability and validity of the scale data, and the structural model mainly evaluates the explanatory power of the model and the significance of the path. In this paper, Smart PLS3.0 is used to test the data, because it does not have high requirements on the shape of data distribution, and is suitable for exploratory research and complex structural models.

9.5.1 Evaluation of measurement models

Since the pressure scale is modified according to the relevant literature, in order to
ensure the validity of the scale structure, this paper firstly conducts exploratory factor analysis on the pressure construct, and the extraction method is selected by principal component analysis and maximum variance method. The analysis results show that the KMO test value is 0.843, which is greater than the critical value of 0.7, the Bartlett sphericity test value is 1207.756, and p is less than 0.001, indicating that it is suitable for factor analysis. The cumulative explanatory power of the variance of the two factors reached 71.989%, and the two factors were named digital technology pressure and role pressure respectively.

It can be seen from Table 2 that all factor loadings in each construct are greater than 0.7, the Cronbach's α values of all dimensions are greater than 0.7, and the combined reliability is greater than 0.8. From the average variance extraction value (AVE), all constructs are greater than 0.6, which are all greater than the critical value of convergent validity measure of 0.5. This indicates that the built intrinsic model is of good quality. The discriminant validity of the scale can be seen from Table 3. Because the correlation coefficients between all constructs and other constructs are smaller than the square root of the AVE of the construct itself, it can be considered that the discriminant validity of the model is relatively good.

### Table 2 Factor loadings, Cronbach's α and composite reliability

<table>
<thead>
<tr>
<th>Construct</th>
<th>Measurement standard</th>
<th>Factor Loading</th>
<th>T-test</th>
<th>Cronbach’s α</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital technology</td>
<td>TS1</td>
<td>0.790</td>
<td>17.245</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pressure</td>
<td>TS2</td>
<td>0.908</td>
<td>47.579</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>0.903</td>
<td>42.401</td>
<td>0.911</td>
<td>0.934</td>
<td>0.740</td>
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<tr>
<td></td>
<td>TS4</td>
<td>0.901</td>
<td>42.647</td>
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<tr>
<td></td>
<td>TS5</td>
<td>0.791</td>
<td>19.059</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RS1</td>
<td>0.747</td>
<td>10.991</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Role pressure</td>
<td>RS2</td>
<td>0.838</td>
<td>55.086</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RS3</td>
<td>0.861</td>
<td>37.867</td>
<td>0.888</td>
<td>0.918</td>
<td>0.693</td>
</tr>
<tr>
<td></td>
<td>RS4</td>
<td>0.877</td>
<td>34.514</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RS5</td>
<td>0.784</td>
<td>21.366</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construct</td>
<td>Item</td>
<td>Digital technology pressure</td>
<td>Role pressure</td>
<td>Green innovation</td>
<td>Job satisfaction</td>
<td>Work performance</td>
</tr>
<tr>
<td>----------------------</td>
<td>------</td>
<td>-----------------------------</td>
<td>---------------</td>
<td>------------------</td>
<td>------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>Digital technology</td>
<td>5</td>
<td>0.860</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pressure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Role pressure</td>
<td>5</td>
<td>0.404</td>
<td>0.832</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green innovation</td>
<td>3</td>
<td>-0.283</td>
<td>-0.519</td>
<td>0.839</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job satisfaction</td>
<td>4</td>
<td>-0.384</td>
<td>-0.683</td>
<td>0.412</td>
<td>0.804</td>
<td></td>
</tr>
<tr>
<td>Work performance</td>
<td>4</td>
<td>-0.405</td>
<td>-0.617</td>
<td>0.822</td>
<td>0.548</td>
<td>0.833</td>
</tr>
</tbody>
</table>

Table 3 The discriminant validity test results of the scale
9.5.2 Structural model analysis

This paper uses the commonly used Smart PLS 3.0 in the field of psychology as a data analysis tool, applies the survey sample data to fit the research model, and uses the Bootstrap algorithm (N=1000) to test the significance of the path coefficient of the structural model. Figure 2 presents the fitted path coefficients and $R^2$ values.

![Figure 2: Path coefficient and $R^2$ value](image)

Note: *$p<0.1$, **$p<0.05$, ***$p<0.001$*

Figure 2 Path coefficient and $R^2$ value

After confirming the reliability and validity of the construct measurement, the next step is to evaluate the results of the structural model, which mainly includes two aspects of work, evaluating the significance of the coefficients in the prediction of the model and between the constructs. The most commonly used criterion for evaluating structural models is the coefficient of determination ($R^2$), which is used to measure the explanatory power or predictive accuracy of the model. As can be seen from Figure 2, the explanatory power $R^2$ value of technical pressure to role pressure is 0.163, the explanatory power $R^2$ value of technical pressure and role pressure to job satisfaction is 0.514, and the explanatory power R2 value of technical pressure and role pressure to
job performance is 0.431.

It can be seen from Figure 2 that the path coefficient between job satisfaction and job performance is 0.204, and at the level of p less than 0.05, it significantly shows that there is a strong positive relationship between the two, and the hypothesis H1 is confirmed. The path coefficient between digital technology pressure and role pressure is 0.404, and the level of p less than 0.001 significantly shows that digital technology pressure has a strong positive impact on role pressure, assuming that H2 is proved. The path coefficient between digital technology stress and job satisfaction is -0.129, p is greater than 0.05, not significant, and hypothesis H3 is not supported. The path coefficient between role stress and job satisfaction is -0.571, and it is significant at the level of p less than 0.001. Role stress has a significant negative impact on job satisfaction, assuming that H4 is proven. The path coefficient value between digital technology pressure and job performance is -0.159, p is greater than 0.05, not significant, and does not support hypothesis H5. The path coefficient between role stress and job performance is -0.413, which is significant at the level of p less than 0.001, indicating that role stress has a negative impact on job performance. Hypothesis H6 is confirmed.

9.5.3 Moderating effect and mediating effect test

Here we examine the interaction effects between factors, and use the standardized interaction terms provided by Smart PLS to analyze the complementary effects of green innovation and two types of work stress. When the interaction effect test is performed in Smart PLS, the construct involved in the interaction term analysis is required to be a reflective measurement form. All the constructs involved in this paper meet this condition. From Figure 2, it can be seen that the interaction term between green innovation and digital technology pressure has a path coefficient of -0.168 on job satisfaction, and it is significant at the level of p less than 0.001. It shows that green innovation can reduce the impact of technical pressure on job satisfaction, assuming that H7 is proved. The path coefficient of the interaction term between green innovation
and role pressure on job satisfaction is -0.089, which is not significant. It shows that green innovation does not have a significant moderating effect on the transmission of role pressure on job satisfaction, and Hypothesis 8 does not hold.

The following is a mediation test. The traditional way to carry out the mediation effect is through the Sobel test, but the latest research literature (Hayes, 2009; Hayes and Scharkow, 2013) shows that the Sobel test is not suitable for the indirect effect test under the PLS analysis. The reason is that the parameter distribution of the survey data does not necessarily meet the normal distribution, but the premise of using the Sobel test is that the parameter assumptions must meet the normality requirements, and the consequence of using it is a large test deviation. As a viable alternative (Hayes, 2009; Hayes and Scharkow, 2013), parameters can be estimated by combining the bootstrapping algorithm in Smart PLS to test whether the mediation effect is significant (Nitzl et al., 2016). The results of the mediation effect test are shown in Table 5.

<table>
<thead>
<tr>
<th>Indirect effect path</th>
<th>Indirect Effect Point Estimation</th>
<th>Bootstraps1000 Times</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital technology pressure→Role Stress→Job</td>
<td>-0.230</td>
<td>0.053</td>
<td>4.358</td>
</tr>
<tr>
<td>Digital technology pressure→Job Satisfaction→Job performance</td>
<td>-0.026</td>
<td>0.019</td>
<td>1.390</td>
</tr>
<tr>
<td>Digital technology pressure→Role pressure→Job</td>
<td>-0.047</td>
<td>0.023</td>
<td>2.030</td>
</tr>
<tr>
<td>Digital technology pressure→Role performance</td>
<td>-0.167</td>
<td>0.049</td>
<td>3.380</td>
</tr>
</tbody>
</table>
As shown in Table 5, the T-value test shows that the path coefficient from technical pressure to job satisfaction, and then to job performance cannot pass the significance test at the 0.05 level. The other three paths have passed the significance test, and the 95% interval is negative, excluding 0. It is verified that role pressure plays a mediating role between technical pressure and job satisfaction; role pressure and job satisfaction play a mediating role between technical pressure and job performance; role pressure plays a mediating role between technical pressure and job performance.

9.6 Results and Discussion

The new generation of information technology covers the design, production, management, sales and service of manufacturing enterprises, and can control, monitor, detect, forecast and other production and operation activities based on data analysis and mining generated by each link. It can play a role in shortening the research and development cycle, increasing the real-time procurement, improving production efficiency and product quality, reducing energy consumption, and responding to customer needs in a timely manner. Under the digital transformation of the manufacturing industry, the application of information technology is the fundamental driving force for the sustainable development of manufacturing enterprises, and the value creation process of digital technology is inseparable from the application ability and enthusiasm of enterprise employees. However, the traditional industry mainly focuses on the innovation and profits brought about by the application of digital technology, and seldom pays attention to the impact of the application of digital technology on employee job satisfaction, especially in the current large-scale promotion of digital transformation in the manufacturing industry. Although the academic community generally believes that the use of digital technology can improve the economic performance of enterprises (Quinton et al., 2018), the relationship between digital technology and employee job performance, such as job satisfaction, has been rarely explored by researchers, especially in which negative impact mechanisms and issues related to employee job satisfaction in digital adoption failures. For the
sustainable development of manufacturing enterprises, it is necessary to seek to provide employees with psychological motivation and barriers to use information technology. This understanding of the relationship between the application of information technology to employee job performance goes beyond correlational studies and partially addresses causality and driving mechanisms. Based on the theory of resource conservation, this research studies the impact mechanism of digital technology pressure and enterprise green innovation on job satisfaction and job performance, so it can provide certain decision-making reference for manufacturing enterprise managers.

First, digital technology pressure and role pressure have a negative impact on job satisfaction and job performance. Therefore, in the context of digital transformation, manufacturing enterprises need to take measures to reduce the pressure brought by the large-scale use of information technology. Through this, employees are motivated to generate higher job satisfaction and higher levels of creativity and performance. Specifically, enterprises cannot blindly speed up the introduction of digital technology. When making digital development plans and work arrangements for employees, they need to consider the pressure of employees’ learning and use, and should assign work tasks that match their capabilities. The degree of digital technology pressure should be carefully considered, so that the digital technology pressure perceived by employees should not be too high. At the same time, when formulating digital transformation plans, enterprises should put employee learning and development on the agenda, formulate clear ability training plans for employees, reduce the pressure of digital technology perceived by employees, and enable employees to match their abilities with work tasks. Doing so enables them to generate higher levels of satisfaction, which in turn improves job performance. Second, job satisfaction mediates the relationship between digital technology pressure and job performance. From the perspective of management, job satisfaction plays an important role in the sustainable development of enterprises and the improvement of individual work performance of employees. Therefore, in a sense, both individual employees and manufacturing enterprises will gain certain benefits from performance improvement. Similar to related theories, job satisfaction is a non-external driving force for employees to improve job performance, but a spontaneous
internal driving force. Especially in the high-tech manufacturing industry, employees are more likely to show strong job satisfaction, which can explain the strong competitiveness of many high-tech companies in the market. Improving employee job satisfaction isn’t enough by caring. Regularly communicating this information to employees through newsletters, rewards, informal recognition, and other forms of communication can effectively drive satisfaction. Generally speaking, job satisfaction comes from the matching of employee work ability and job position. With the embedding of digital technology in manufacturing operations, employee work ability may lag behind. It is necessary for enterprises to deploy learning and development plans to strengthen employee skills training. It enables employees to keep pace with the times and adapt to the digital environment, which further drives the improvement of work performance by improving job satisfaction. Third, green innovation can significantly reduce the negative effect of digital technology pressure on job satisfaction. Employees' perception of digital technology pressure in the process of work can gradually drive employees to change their psychological states with positive feelings about the work itself and other related aspects, such as work environment, work status, and work methods. These form an intrinsic primary measure and emotional experience of the quality of professional life of employees. Our research shows that digital technology pressure will reduce job satisfaction, but green innovation can effectively moderate the negative impact of digital technology pressure on job satisfaction, and can weaken its adverse effect. This shows that green innovation can enhance the prestige of the enterprise, enhance the employee's sense of identity and pride in the enterprise, and thus stimulate the employee's loyalty to the manufacturing enterprise. Beyond the immediate, well-known economic benefits of green innovation, developing an inclusive culture can bring additional benefits and contribute to reducing the pressure on digital technology. If manufacturing companies want to turn employees' pressure into creativity in the digital transformation environment, they must actively advocate the concept of green investment. By encouraging employees to participate in green innovation practices and decision-making, employees can increase their sense of control and confidence in job requirements. It can weaken the negative effects of digital technology pressure, thereby
promoting the improvement of employee job satisfaction and showing a higher level of creativity. Specifically, enterprises can encourage employees' willingness and skills to participate in green innovation practices through targeted cultural shaping and professional training. Another important feature of our study is the effect of green innovation moderators on role stress. Interestingly, the negative impact of role stress on job satisfaction was not moderated by green innovation.

9.7 Conclusions and future research

The application of digital technology and increasing investment in green innovation to achieve sustainable development are the two major themes facing the manufacturing industry at present. They are both opportunities and challenges, and risks and benefits coexist. Some studies believe that work stress has a significant negative inhibitory effect on employee job satisfaction and job performance, and some studies believe that stress is motivation, and empirically analyzes the positive impact of work stress on employee job performance. This paper gives its own point of view and basis on this dispute. The impact of digital technology pressure and role pressure on job performance is negative, and green innovation is innovatively introduced in this action path, with job satisfaction as an intermediary variable, gives the mechanism of the effect of digital technology pressure on the job performance of manufacturing employees. It is hoped that this paper can broaden the perspective of digital technology research, provide evidence of the impact of digital technology applications on micro-individuals, and provide enlightenment and warning for manufacturing enterprises to deal with the two development trends of digitalization and green innovation in the future.

Based on the perspective of resource conservation theory, this study studies the impact mode of manufacturing employees' job performance under the pressure of digital technology. Although some research results have been achieved, there are still many shortcomings, which can be further explored in future research. First, employees engaged in digital technologies in manufacturing generally perceive more stress from their work environment, but some employees exhibit less stressful outcomes (if low job
satisfaction, low job motivation, etc.). This suggests that perceived stress does not necessarily lead to negative work outcomes. In the future, it is necessary to conduct a group study on the pressure of digital technology. Second, from the perspective of sample selection, the survey samples of this study are from workers in ICT-related positions in manufacturing enterprises in the Yangtze River Delta region of China. The research samples are relatively narrow in terms of regional release, industry nature and job positions. Employees in different industries, positions, and experiences have different perceptions of digital technology pressure. This requires expanding the scope of investigation on this issue in the future, selecting employees from different industries as much as possible, and enriching the survey positions to improve the feasibility of the research results, so as to make a powerful decision-making reference for corporate decision-making. Third, digital technology pressure of employees, as a psychological perception measure of individual field-related skills application ability and intrinsic work motivation in a certain environment, is not only affected by the situation, but also related to other factors, such as individual characteristics. Based on this research, future research can control the influence of diverse external factors to improve and clarify how employees choose their behavioral strategies when faced with different types of digital technology pressure in different situations, and then affect their job performance.
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