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Impact of Big Data Products on the Entrepreneurial Performance of E-Commerce Farmers: Evidence from China

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Abstract

Rural e-commerce, dominated by entrepreneurial farmers, is growing rapidly in developing countries, especially in China. However, with the expanding scale of e-commerce farmers, the competition is becoming fierce, and their entrepreneurial performance is facing difficulties in growth. Pioneering practices in China show that big data can promote the sustainable development of e-commerce farmers. This paper attempts to explore how big data products affect e-commerce farmers' entrepreneurial performance by using the survey data from China, and structural equation modeling. Findings show that big data products significantly improve e-commerce farmers' entrepreneurial performance. The usefulness and ease of use of and experience with big data products can enhance e-commerce farmers' entrepreneurial alertness and dynamic capabilities. The findings have important implications for how to promote entrepreneurial growth of e-commerce farmers and big data applications in rural areas.

Plain language summary

Using big data products to improve the entrepreneurial performance of e-commerce farmers

Empirical evidence from China suggests that big data products developed by e-commerce enterprises can improve the entrepreneurial performance of e-commerce farmers by enhancing their entrepreneurial alertness and dynamic capabilities. In the development process of rural e-commerce in developing countries, the empowerment of data should be paid attention to.

Keywords

big data, product attributes, e-commerce farmers, entrepreneurial performance, China

Introduction

Over the past decade or so, China has made rapid progress in rural e-commerce. According to the Ministry of Commerce of China, in 2023, the growth of platform transactions reached 30%, and the online annual rural and agricultural retail sales reached 2.49 and 590 billion yuan, respectively. Farmers—the main driver of rural and agricultural e-commerce development in China—are now called "e-commerce farmers." Such farmers are clustered in one village or cross-villages, forming e-commerce industry clusters. However, over time, the e-commerce

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Data Availability Statement included at the end of the article

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market has become increasingly competitive; thus, many e-commerce farmers are experiencing slow business growth. Specifically, e-commerce farmers are experiencing low-level homogeneous competition and a decline in prices and profit margins, leading to business difficulties (L. Li et al., 2024; Shao, 2017; Zeng, Guo, et al., 2019). Meanwhile, the rising costs of production factors threaten the survival of cost-sensitive e-commerce farmers (Guo et al., 2024; W. Tang & Zhu, 2020). Consequently, how to enhance e-commerce farmers' business performance and improve rural e-commerce sustainability have become important issues that China and other developing countries must solve.

In learning how to improve e-commerce farmers' entrepreneurial performance, scholars have focused on strengthening the roles of government and industry associations. The government should actively prioritize the changes in rural e-commerce and provide timely policy support in terms of talent, land, capital, technology, and supervision (Avgerou & Li, 2013; Jin et al., 2020; Zeng, Guo, et al., 2019). In addition, the establishment of farmers' e-commerce associations will implement self-discipline, integrate resources, and strengthen coordination (Gao & Liu, 2020; Qi et al., 2019; Zeng et al., 2017). Although the government and e-commerce association have a supporting role, and e-commerce farmers cannot grow without them, they are external causes. Their support is discontinuous, indirect, and lagging behind market changes. According to entrepreneurship theories, e-commerce farmers' entrepreneurial performance relies on improving their own internal capabilities, namely entrepreneurial alertness and dynamic capabilities. The former reflects the entrepreneur's reaction capacity to identify new opportunities (Roundy et al., 2017; J. Tang et al., 2012; Valliere, 2013), while the latter reflects the entrepreneur's process capability to transform new opportunities into actual performance (Corner & Wu, 2012; Helfat & Peteraf, 2015; Teece, 2018). Both constitute a "discovery-implement" framework and can only co-exist (Si et al., 2015; Wright & Zammuto, 2013). Therefore, learning how to improve the entrepreneurial alertness and dynamic capabilities of e-commerce farmers is the key to enhancing their entrepreneurial performance.

As e-commerce rises in China, platform enterprises represented by Alibaba and JD are now developing big data products for online merchants. In rural China, some e-commerce farmers are using e-commerce big data products to help improve their business capabilities—a noteworthy research topic. Big data products seem to effectively solve the problem of improving e-commerce farmers' entrepreneurial performance. A considerable amount of data is deposited on e-commerce platforms and is mined and analyzed, providing important guidance for online merchants' production and operation. According to Alibaba's research report on China's Taobao Village, the number of online merchants using data products in Taobao Village is growing rapidly (AliResearch, 2020). According to a rural household survey, approximately 30% of e-commerce farmers in counties with more developed rural e-commerce have used such products (L. Li et al., 2024). More online merchants are using data to gain opportunities. Relying on experience is becoming obsolete, and an efficient use of data can help upgrade online merchants. These pioneering practices in China may bring important lessons to developing countries. However, academic research is needed to determine the facts and logic behind this new phenomenon.

Therefore, this paper aims to reveal how big data products affect e-commerce farmers' entrepreneurial performance and explore the implications that can be extended to developing world. Specifically, we attempt to answer three questions: (1) Can big data products help improve e-commerce farmers' entrepreneurial performance? (2) How do big data products affect e-commerce farmers' entrepreneurial alertness and dynamic capabilities? (3) How can developing countries optimally design big data products to better empower farmers?

To answer these questions, this paper first establishes the analytical framework of big data products based on product attributes. Then, it deduces theoretically how such products can improve e-commerce farmers' entrepreneurial performance by affecting entrepreneurial alertness and dynamic ability and proposes research hypotheses. Moreover, this paper conducts an empirical study by using the survey data of e-commerce farmers from China, and the structural equation modeling (SEM) method. Results show that the usefulness and ease of use of and experience with big data products developed by e-commerce platform enterprises significantly improve e-commerce farmers' entrepreneurial performance by enhancing their entrepreneurial alertness and dynamic capabilities. The findings also confirm the positive role of the products in improving such performance and provide important implications for developing countries to enhance the sustainability of rural e-commerce.

Background

Taobao Village Phenomenon in China

Over the last decade, under the combination of various favorable conditions, China's rural e-commerce has risen very rapidly; farmers are increasingly using platforms to access the market. In the early stages of rural e-commerce, Alibaba's Taobao was a key enabler with its low entry barriers, technical difficulty, and capital requirements for farmers; consequently, there is more enthusiasm for online sales (Zeng et al., 2017). As rural online businesses are primarily based on the Taobao, the e-commerce villages are also known as "Taobao villages." AliResearch, an affiliate of Alibaba, has formulated special statistical rules and published annual research reports on China's Taobao villages since 2013. Research has been conducted on Taobao villages, which have aroused wide social concern. Some scholars use quantitative analysis methods to discuss the spatial aggregation of Taobao villages, influential factors of farmers' adoption of e-commerce, and how farmers' adoption of e-commerce affect their income, consumption, employment, and immigration decisions (M. Liu et al., 2020; Luo & Niu, 2019; Ma et al., 2020; Qi et al., 2019). Others use the case study method to conduct in-depth research on typical Taobao villages (Avgerou & Li, 2013; Gao & Liu, 2020; G. Lin et al., 2016; Zeng, Guo, et al., 2019).

Taobao Village is, in essence, an e-commerce industry cluster phenomenon with farmers as the primary body and the village as the spatial scale (Zou & Liang, 2015). With the rapidly developing rural e-commerce in China, platform companies are increasingly entering the field. E-commerce farmers in Taobao Village are now using not only the Taobao platform but also JD, Pinduoduo, Douyin, Kuaishou, WeChat, and other diversified platforms (Guo et al., 2024; Zeng, Guo, et al., 2019). China's rural e-commerce format has also expanded from traditional graphic and shelf e-commerce to more formats such as community marketing, short video marketing, and live e-commerce (L. Li et al., 2024). Therefore, at this stage, Taobao Village has surpassed Taobao itself. The research results of Taobao villages apply to all platforms. The pressure and difficulties faced by e-commerce farmers are common problems of all platforms, which are becoming competitive and have hidden barriers. Scholars usually consider Taobao Village as the research object, because it focuses on spatially highly-concentrated e-commerce farmers. Compared with the investigation of ordinary villages, that of Taobao villages can greatly reduce the search cost (Li, Guo, et al., 2021). That is, conducting research on e-commerce farmers in Taobao Village has a scale effect and convenience. Consequently, the academic community has focused on Taobao Village.

The practical evolution of many Taobao village clusters follows that of traditional industry clusters, and the whole evolution process has three phases: quantity expansion, quality improvement, and innovation. In the first stage, the rural social network helps diffuse information and stimulate the imitation learning effects of farmers. However, with the rapid expansion of cluster scale, competitive price wars inevitably break out due to high product homogeneity, causing a decline in the profit margin (L. Wan, 2015). At this time, an quality crisis can easily occur. Some farmers may choose to sacrifice product quality and carry out a low-price competition strategy, known as the "race to the bottom" (Otsuka & Sonobe, 2011), which, left unchecked, can lead to counterfeiting, a decline in the cluster's reputation, and, ultimately, its demise. To this end, local governments should take measures to strengthen product quality supervision and testing, encourage e-commerce farmers to establish industry associations to strengthen industry self-discipline, and set up industrial parks, to enter the cluster into a quality improvement period. In this phase, the number of online merchants tends to stabilize, and the improved product quality increases the cluster output value. As the cluster develops further, due to changes in the overall macroeconomic environment, land rents, labor, and other factor prices will gradually rise (W. Tang & Zhu, 2020; Zeng et al., 2024); thus, coupled with intensifying external competition from other regions, the cluster must be upgraded. Therefore, by the end of the quality improvement period, as the comparative advantage changes, the cluster should shift its profit margin from traditional manufacturing to technology research and innovation (L. Li et al., 2024). Unlike traditional clusters, a new phenomenon of digitalized operation in the research and innovation phases is occurring in the rural e-commerce clusters represented by Taobao villages. E-commerce farmers are using big data products to guide their innovations and the role of data elements in empowering industrial cluster development continues to grow (Zeng et al., 2024).

E-commerce Big Data Products in China

Data are a key to socio-economic development and the fundamental feature of a digital economy, distinguishing it from industrial and agricultural economies. With the development of big data, the role of data elements in socio-economic development will continue to increase. Big data refers to a large-scale data set exceeding the capability range of traditional database software tools in terms of collection, storage, management, and analysis (Chi et al., 2016; C. Huang et al., 2020; Rodriguez et al., 2017). It has a large data capacity, fast data transmission, diverse data types, timely data updates, and high data quality (Sheng et al., 2021). High value is created at low cost (Hanelt et al., 2021). With a rapidly developing modern society, a variety of massive digitized information is being constantly produced, collected, stored, processed, and utilized and bringing all-round social changes and profoundly affecting production and people's lives (Talaoui et al., 2023). The application of big data analysis technologies is accelerating in different industries, such as finance, insurance, network marketing, and scientific research (Bailey et al., 2019). Governments are also using big data analytics to serve citizens and to better respond to various changes (G. H. Kim et al., 2014).

Figure 1. The homepage of BA's official website.

The big data mentioned in the current literature primarily refers to the data accumulated by the government's public databases, telecom operators, and large enterprises in various industries (Farboodi et al., 2019; Goldfarb & Tucker, 2019). This paper focuses on big data products in e-commerce field, which has a research gap. At present, China's big data products based on e-commerce platforms are primarily the "Business Advisor" (BA) developed by Alibaba Group and the "Jingdong Business Intelligence" (JBI) developed by JD Group (Zeng et al., 2024).

BA, launched in August 2011, is a data-driven business analysis platform mainly providing data support, market insights and operation tools for e-commerce merchants, especially those on platforms like Taobao and Tmall (Figure 1). Through BA, merchants can view the traffic data of their stores in real time, including the number of visitors, traffic source channels and the page views of different pages, thereby accurately locating the traffic entry points and optimizing the traffic acquisition strategies. BA can also provide detailed analysis of sales data, helping merchants understand key indicators such as the sales trends, sales volume, and conversion rate of their products, thereby better planning product inventory and promotional activities. BA also covers market analysis functions. Merchants can view the development trends of their industries and market share of competitors, thereby formulating more targeted marketing strategies. In addition, it can conduct in-depth analysis of consumer behavior, including their geographical distribution, purchasing preferences, and purchase frequency, helping merchants better understand their target customer groups and achieve precise marketing. In conclusion, BA is an indispensable operational assistant for e-commerce merchants. By providing comprehensive and accurate data analysis, it helps merchants make wiser decisions, enhance the operational efficiency and competitiveness of their stores, and thus stand out in the highly competitive e-commerce market.

JBI, launched in March 2017, is a one-stop operation data open platform for JD merchants (Figure 2). JBI aims to help merchants enhance operational efficiency, reduce operational costs, and achieve precise marketing and data-driven decision-making through comprehensive and precise data analysis services. It encompasses abundant data resources, including store traffic, sales volume, order volume, product page views, sales volume, user profiles, etc. Merchants can quickly understand the real-time sales and traffic situation of their stores and keep track of the progress of major promotion tasks through the real-time data function. The traffic detail function helps merchants analyze the sources and destinations of traffic and evaluate the effect of traffic diversion. The product performance analysis module provides data such as product traffic, sales volume, and add-on purchases, helping merchants optimize product operations. JBI also has a powerful customer analysis capability, which can deeply depict user profiles and help merchants achieve precise marketing. It also offers industry trend analysis to help merchants understand market dynamics and formulate more competitive strategies. Whether it is small and medium-sized merchants or large brand owners, JBI can provide targeted data support and solutions.

Figure 2. The homepage of JBI's official website.

Framework and Hypotheses

Analytical Framework of Big Data Products

The fundamental perspective of studying data products lies in product attributes, which are the basic properties in a product (T. Y. Lee & Bradlow, 2011). A product is an aggregate of a set of attributes (K. Kim & Chhajed, 2002). That is, product attributes are usually multidimensional (Scekic & Krishna, 2021), and the product presented to the consumer is the joint action of said attributes (Kumar et al., 2021). Regarding the specific dimensions of product attributes, a variety of studies exist. Some scholars divide product attributes into tangible and intangible attributes, the former being the product's physical attributes that can be directly observed, such as color, shape, volume, and other aspects, and the latter being the service and use experiences behind the product, such as feel, comfort, and customer service attitude (Anderson et al., 1994). A few scholars have further classified product attributes into two types, functional and hedonistic, depending on the product's benefits and utility to the consumer, with the former primarily focusing on its actual functional value and the latter on generating a pleasurable experience (Voss et al., 2003). Moreover, product attributes are further divided as follows: cognitive and emotional, which are, respectively, based on consumers' rational and emotional evaluations and judgments (J. Huang et al., 2022; Leclerc et al., 1994). Some scholars divide product attributes into vertical and horizontal attributes if users have consistent preference standards for them. Vertical attributes refer to the attributes that consumers have clear and unified preference standards for in product attributes, while consumers have no unified preference for horizontal attributes and often have different evaluation standards due to personal preferences (M. Huang et al., 2017; Kwark et al., 2014; Sun, 2011). Although scholars adopt different conceptualization methods for the dimensional division of product attributes, they are generally similar. In general, product attributes ultimately focus on two levels: the purely physical and humanistic levels reflecting instrumental rationality and emotional value, respectively.

Our research object involves e-commerce big data products, and their use is essentially a new technology adoption behavior (Zeng, Zhang, et al., 2019). Therefore, in our view, in addition to referring to the existing literature on product attributes, ideas from the theory of technology adoption behavior should also be incorporated. In this theory, the technology acceptance model (TAM) is regarded as a concise, rigorous, and practical tool to predict whether users will adopt new information technologies, which is suitable for situations where individuals make completely autonomous adoption decisions without other constraints (Joo et al., 2017). An e-commerce farmer's decision regarding whether to use a big data product is pure market behavior and, therefore, suitable for analysis using the TAM. The core view of the TAM is that perceived usefulness and perceived ease of use reflect the subjective evaluation of technology adopters on technical superiority and operational difficulty, respectively, and jointly determine the individual's behavioral attitude toward new technologies (Davis, 1989; Venkatesh, 2000; Venkatesh & Davis, 2000). The predictive validity of perceived usefulness and perceived ease of use in technology adoption contexts has been thoroughly demonstrated through three decades of empirical research since TAM's introduction (Xu & Du, 2018). However, simultaneously, some scholars are attempting to expand the TAM. They argue that usefulness and ease of use only reflect the product attributes at the purely physical and instrumental levels and not the emotional value level. Therefore, they added new dimensions such as perceived risk, perceived interest, and compatibility (Elkins et al., 2013; He & Huang, 2020; M. Huang et al., 2017; Lutfi et al., 2022; Pan, 2017; Petersen & Kumar, 2015; Wu & Wang, 2005). We agree with expanding the TAM from a more complete product attribute framework. Further, we advocate the use of experiential dimensions to summarize the new ideas. The experience dimension can systematically include the emotional level of the product, especially in the fields of rural e-commerce and big data products (Li, Zeng, et al., 2021). The young generation is the primary force of rural e-commerce entrepreneurship. They prioritize individual experience and are the demanders and promoters of the experience economy (Zeng & Guo, 2016). That is, the big data product analysis framework established in this paper is a three-dimensional structure of "usefulness–ease of use–experience" based on product attributes. Specifically, usefulness refers to e-commerce farmers' perception and evaluation of the role of big data products in enabling business decision-making; ease of use refers to e-commerce farmers' perceived evaluation of the difficulty of using big data products in the decision-making process of enabling operation; experience refers to e-commerce farmers' perception and evaluation of the matching degree of big data products in terms of perceived risk, perceived interest, and compatibility (Zeng et al., 2024).

Big Data Products, Entrepreneurial Alertness, and Entrepreneurial Performance

In the theory of farmer entrepreneurship, entrepreneurial alertness is regarded as a critical competency that farmer entrepreneurs must cultivate (Guo & Zhou, 2013; Hu & Wang, 2013). Entrepreneurial alertness was first defined as the capability to focus on previously overlooked entrepreneurial opportunities and respond quickly (Kirzner, 1978). Entrepreneurial alertness is a precursor to entrepreneurial opportunity identification, which in turn affects farmers' entrepreneurial behavior and entrepreneurial performance (Ardichvili et al., 2003). The higher the entrepreneurial alertness, the higher the likelihood of an individual successfully identifying an entrepreneurial opportunity and earning profits (Gaglio & Katz, 2001). Numerous research consistently demonstrates that maintaining high entrepreneurial alertness is essential for entrepreneurs to effectively identify and capitalize on business opportunities, thereby achieving strong performance (Ko & Butler, 2003; Roundy et al., 2017; J. Tang et al., 2012; Valliere, 2013).

Big data products helps to improve e-commerce farmers' entrepreneurial alertness. Before the internet age, farmers made business decisions relying on subjective judgment and accumulated experience, which had limitations like being localized, delayed, and imprecise (L. Li et al., 2024). Throughout the producer-to-consumer docking process, multiple problems arose, such as inefficient information collection and serious information distortion. The demand information in the market cannot be timely and effectively fed back to the main body of production, leading to poor decisions (Zeng et al., 2017). The Internet's greatest impact has been on information—how it flows and how we analyze it. The explosive growth of data and the development of data analysis technologies have rapidly advanced the ability to analyze information (Talaoui et al., 2023). Big data makes the information acquisition of e-commerce farmers more timely, comprehensive, and accurate, greatly reducing subjective biases and overcoming space-time limitations. The Internet has reduced intermediate links, placing operators and consumers in proximity, making it more effective for operators to make demand-oriented decisions (H. Li et al., 2014). Big data products can help e-commerce farmers grasp the dynamic information of the online market on the first attempt (Zeng et al., 2024). The presentation of rapidly changing data will constantly stimulate e-commerce farmers visually and cognitively, allowing them to keep highly alert to market changes (Elkins et al., 2013). With constant attention to market changes, the probability of e-commerce farmers discovering new opportunities will continue to increase.

Product attributes are important factors that influence product use (T. Y. Lee & Bradlow, 2011). When the levels of usefulness and ease of use of and experience with big data products are higher, their efficacy is more obvious. The usefulness of big data products is demonstrated through improved information accessibility, operational improvement, and income increase after e-commerce farmers use such products. As e-commerce farmers perceive a higher level of usefulness, their willingness to adopt big data products and behavioral efforts is more active, thus, improving their entrepreneurial alertness and ultimately contributing to enhancing their entrepreneurial performance (Pan, 2017). Regarding the ease of use of big data products, e-commerce farmers will evaluate how easily they can access data metrics, understand data indicators, and whether the data analysis process is simple or cumbersome (Zeng et al., 2024). As e-commerce farmers perceive the ease of use of big data products to be higher, they have a more open attitude toward their use, which in turn will increase their entrepreneurial alertness and ultimately contribute to enhancing their entrepreneurial performance (Wang & Cui, 2023). Similarly, the actual supply of big data products in terms of experiential factors such as perceived risk, perceived interest, and compatibility is comparable to the demand and preference of e-commerce farmers to generate perceived cooperation (J. Huang et al., 2022; Oh & Yoon, 2014), which will promote their use of big data products. Thus, it can improve entrepreneurial alertness and ultimately enhance entrepreneurial performance.

Summarizing the above analysis, we propose the following hypotheses:

H1: The usefulness of big data products positively affect e-commerce farmers' entrepreneurial alertness.
H2: The ease of use of big data products positively affect e-commerce farmers' entrepreneurial alertness.
H3: The experience of big data products positively affect e-commerce farmers' entrepreneurial alertness.
H4: The entrepreneurial alertness of e-commerce farmers positively affect their entrepreneurial performance.

Big Data Products, Dynamic Capabilities, and Entrepreneurial Performance

Derived from the resource-based view, dynamic capability stresses that enterprises should cultivate an acute ability to adapt to external changes, enabling timely and strategic resource integration and restructuring, which greatly benefits their business performance (Chien & Tsai, 2012; P. Y. Lee et al., 2018; Pan, 2017; Teece, 2018; Wilden et al., 2013; Yi et al., 2006). For a long time, farmers could not effectively identify, accurately perceive, and timely respond to external market demand, leading to difficulties in the increase of farmers' operating income (L. Li et al., 2024; Markelova et al., 2009; Wiggins et al., 2010; Zhang & Hu, 2014). Moreover, farmer's management decisions rely on experience, imitation, and luck; thus, they are prone to make mistakes and have higher risks (Zeng et al., 2024). The external market changes cannot be spread to farmers in a timely way, leading to extremely poor dynamic capacities due to which they appear very passive when participating in the market and often increase production without increasing income (Zeng et al., 2017). Hence, finding ways to effectively boost farmers' dynamic capabilities is essential to tackling the issue of raising their income (Cai et al., 2023).

However, the use of big data products contributes to improving the dynamic capabilities of e-commerce farmers. By utilizing these products, e-commerce farmers can access a range of optimal parameter combinations for their goods, such as color, weight, flavor, price, logistics, and other aspects, to identify the existing deficiencies in their operation (L. Li et al., 2024; Zeng, Zhang, et al., 2019). This is crucial because the e-commerce market is highly competitive, and weak decision bias will be amplified under the multiplier effect mechanism of the Internet (Zapata et al., 2013). The online market is changing all the time, and operators must always keep themselves up-to-date and even lead the trend. Through big data products, e-commerce farmers can track live market movements, particularly competitor updates and trending product information (Zeng et al., 2024). Moreover, big data can not only provide accurate information timely but also develop intelligent predictive functions (Lokers et al., 2016). Prior to this, people could only collect and process information about past events; however, big data includes data not only about past and present events but also about future events through machine learning (Waga & Rabah, 2014), which allows operators to gain greater predictability.

The extent to which big data products promotes e-commerce farmers' dynamic capabilities and entrepreneurial success depends significantly on the attribute level of such products. Existing studies have shown that product attributes directly influence consumers' perception toward products, which significantly impacts their use of products (Dubé et al., 2003; Scekic & Krishna, 2021). Product attributes allow consumers to create associations before purchasing products, thereby initiating a psychological simulation of the product's usage state (Kumar et al., 2021). In this process, consumers will produce judgments, which will further impact the formation of consumers' attitudes toward the product as well as its use efficacy (Pham & Taylor, 1999). Another study has proved that after understanding and judging the various product attributes, the consumer will use comprehensive thinking to evaluate the product's overall image, and the higher the consumer's satisfaction with such image, the more helpful they will consider product efficacy to be (Mittal & Kamakura, 2001). In practice, e-commerce farmers gain insights into the attributes of big data products via free trials, obtaining introductory information about them, searching for relevant information on web pages, and learning the experiences of other farmers. If e-commerce farmers understand the high level of usefulness and ease of use of and experience with e-commerce big data products, they will develop a more open attitude of acceptance and willingness to use such products, thereby, improving their dynamic capabilities and ultimately contributing to enhancing entrepreneurial performance (Cai et al., 2023).

Summarizing the above analysis, we propose the following hypotheses:

H5: The usefulness of big data products positively affect e-commerce farmers' dynamic capabilities.

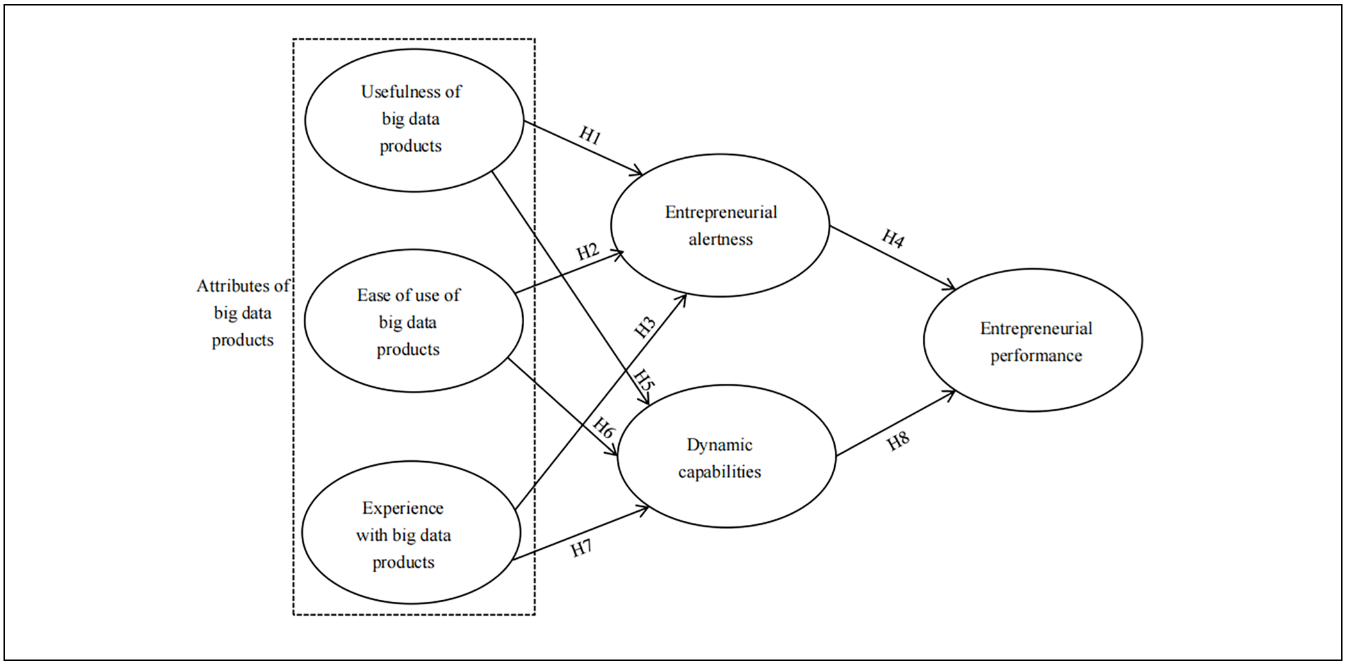

Figure 3. Theoretical model.

H6: The ease of use of big data products positively affect e-commerce farmers' dynamic capabilities.
H7: The experience with big data products positively affect e-commerce farmers' dynamic capabilities.
H8: The dynamic capabilities of e-commerce farmers positively affect their entrepreneurial performance.

Integrating the above eight hypotheses, this paper constructs a theoretical model as shown in Figure 3.

Empirical Strategy

Data

This paper uses the data collected from a field household survey conducted by our research team from July to August 2022. We selected 15 typical Taobao villages in Zhejiang Province as survey subjects, such as Bainiu Village, Maxiao Village, Yuping Village, Xindu Village, and Qingyanliu Village. We have chosen Zhejiang Province as the research subject because the local development of rural e-commerce is in a leading position in China (Li, Zeng, et al., 2021). Zhejiang province has the largest number of Taobao villages in China, and the scale is significantly ahead of other provinces. Thus, the investigation of Taobao villages in Zhejiang can easily capture a group of e-commerce farmers with the first use of big data products, to provide support for empirical research. We chose 15 typical Taobao villages for investigation, after considering both representativeness and feasibility. "These villages have been awarded the title of *China Taobao Village*. Their e-commerce started earlier, developed rapidly, and received wide attention. They are distributed in Hangzhou, Jinhua, Lishui, Taizhou, and other different cities and primarily deal in nuts and fried goods, clothing and apparel, outdoor products, tea, water heaters, shoes, and other different types of products" (Zeng et al., 2024). Our investigation not only had to be within the scopes of time, energy, and funds but also consciously ensured that the main areas could be covered in terms of geographical distribution and industry type. We randomly investigated 30 e-commerce farmers in each village. Taobao Village has a strong commercial atmosphere, and e-commerce farmers have different degrees of busyness. Thus, samples are difficult to obtain through planned sampling methods, which would cause uncertainty. The chance sampling method was adopted to adapt to this situation, which was convenient both for us and the e-commerce farmer participants. During the survey, all participants volunteered and were free to participate or not. All questionnaires are anonymous. The questionnaire does not involve deep privacy issues for the participants, and they may choose to answer or not to answer any of the questions. Participants were informed of our commitment that the survey data would be used only for academic research. After eliminating the questionnaires with many missing values, the final number of valid questionnaire samples is 418.

The descriptive statistics of the surveyed e-commerce farmers are reported in Table 1. According to the

Table 1. Basic Characteristics of the Surveyed E-Commerce Farmers.

Variables	Definition	Mean	*SD*
Gender	Male = 1, female = 0	0.505	0.501
Age	Under 30 = 1, 30–50 = 2, over 50 = 3	1.660	0.536
Years of education	Senior high school/technical secondary school or below = 1, junior college/bachelor degree = 2, bachelor degree or above = 3	1.914	0.684
Whether enterprise operation or not	Yes = 1, No = 0	0.259	0.439
Whether registered trademark or not	Yes = 1, No = 0	0.364	0.482
Duration of e-commerce business	Less than 2 years = 1, 2–5 years = 2, more than 5 years = 3	1.742	0.774
Main e-commerce business format	New e-commerce business formats = 1, traditional e-commerce business formats = 0	0.586	0.844
Main product type	Agricultural products = 1, non-agricultural products = 0	0.273	0.446

Note. Quoted from Zeng et al. (2024).

Table 2. Content of Scale Measure Items for Big Data Product Attributes.

Product attributes	Content of measurement items	Sources
Usefulness of big data products	V1: Data products are very useful in the process of online store operation	Davis (1989),
	V2: Data products effectively help me understand market information	Venkatesh (2000),
	V3: With data products, online store business decisions become more accurate	Venkatesh and Davis (2000),
Ease of use of big data products	V4: Learning how to use data products is easy for me	Yang (2016)
	V5: Mastering the functions of the data product is easy for me	
	V6: With the existing knowledge, I can use the data products	
Experience with big data products	V7: When I use data products, I do not worry about the risks	Wu and Wang (2005),
	V8: The data product is quite interesting, I like to use it	Elkins et al. (2013),
	V9: The interface design of the data product is quite user-friendly	Yang (2016)
	V10: The data metrics provided by the data product are quite comprehensive	
	V11: The purchase price of data products is acceptable	
	V12: There are too few free experience features for data products	

Note. Quoted from Zeng et al. (2024).

statistical description results, the basic characteristics of the sample objects are consistent with the overall objective situation, which is very close to the information mentioned in other fields of literature related to Taobao villages. This implies that the samples have good reliability.

Variables

The independent variables are the attributes of big data products, which are examined from three perspectives: usefulness and ease of use of and experience with big data products. The attributes are measured on a scale ranging from 1 to 5, as detailed in Table 2.

The dependent variable is e-commerce farmers' entrepreneurial performance, and the mediating variables are entrepreneurial alertness and dynamic capability. They are also measured on a scale, as shown in Table 3, ranging from 1 to 5.

Method

The key variables involved in this paper are all connotative concepts. They involve the perception of psychological and consciousness levels, which are difficult to measure directly and accurately and need to be measured in the form of scales. Therefore, SEM is suitable for testing the relationship between them. SEM is a statistical method to analyze the relationship between latent variables based on their covariance matrix, which is an important tool for multivariate data analysis (Piao et al., 2012). Traditional statistical methods cannot effectively deal with these latent variables, which are difficult to measure directly and accurately, while SEM can deal with both latent variables and their indices (Hair et al., 2019). Traditional regression analysis is subject to limitations such as not being allowed to have more than one dependent or output variable, intermediate variables not being included in the same single model as the predictors, predictors being assumed to be free of measurement

Table 3. Content of Scale Measure Items for the Dependent Variable and Mediating Variables.

Variables	Content of measurement items	Sources
Entrepreneurial performance	V13: At present, e-commerce profits are very good V14: E-commerce orders are growing fast V15: E-commerce operations have not encountered financial difficulties V16: The goals set at the beginning have been achieved V17: Social status has been greatly improved compared to before engaging in e-commerce V18: I am satisfied with the current income level	McDougall et al. (1994), Cooper and Artz (1995), Wall et al. (2004)
Entrepreneurial alertness	V19: Even on a vacation, I always think about e-commerce V20: I would spend an evening talking about e-commerce V21: When I am not at work, I am always thinking about e-commerce	Ardichvili et al. (2003), Guo and Zhou (2013), Hu and Wang (2013)
Dynamic capabilities	V22: If I know about a new technology or product, I will look for an opportunity to experience it V23: Among my friends and family, I was one of the first to try out new technology V24: I am willing to participate in the use of new technology, even if it costs a little money and time V25: I will acquire external cutting-edge knowledge on time V26: I will quickly and accurately understand and master new knowledge acquired from outside V27: I will digest and absorb the new knowledge acquired from outside V28: I am good at responding quickly to market changes and external opportunities V29: I will update the management mode as needed	Yi et al. (2006), Pan (2017), Chien and Tsai (2012), Wilden et al. (2013), P. Y. Lee et al. (2018)

Note. Quoted from Zeng et al. (2024).

error, and multiple covariances between predictors hindering the interpretation of results. SEM is not limited by these aspects (Alqudah et al., 2019). In this paper, SEM will be used to verify the effects of the three attributes of big data products on the entrepreneurial alertness and dynamic capabilities of e-commerce farmers, respectively, as well as the effects of the latter two factors on their entrepreneurial performance.

Generally, the whole analysis process of SEM includes at least reliability analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), model fit evaluation, and path coefficient analysis (Hair et al., 2019; J. Lin et al., 2015; Wu & Wang, 2005). As the variables are measured in the form of scales, the data quality of the measurements must be tested to ensure the validity of the empirical results. Reliability analysis involves assessing the consistency and dependability of measurement outcomes. EFA is a statistical technique employed to uncover the underlying structure among multiple observed variables. Each variable involved in this paper has multiple measurement indicators. Indicators of the same variable have a certain correlation, and indicators of different variables have certain discrimination. EFA should be used to analyze the discriminant and convergent validities among multiple indicators of the variable. CFA is used to analyze whether the relationship between variables and corresponding measurement terms conforms to the logical relationship designed by the researchers. Model fit evaluation primarily involves evaluating the degree of fit between the model and data to ensure the validity of the model. This process includes checking the model parameters for irregularities and using various indicators to evaluate the model fit. Path coefficients are used to analyze the strength of the direct relationship between variables. In the SEM framework, the path coefficient represents the strength of the direct relationship between different variables in the model. These coefficients are usually standardized, indicating that they express the number of standard deviations by which one variable is expected to change when the other variable changes by one standard deviation. Path coefficients are similar to regression coefficients in regression analysis, but they are used for more complex model structures.

Results

Reliability Analysis

Cronbach α value is usually used to measure the magnitude of the reliability value of variables in the scale, ranging from 0 to 1. The closer a variable's Cronbach α value is to 1, the higher its reliability. In Table 4, the Cronbach α values of each variable, calculated by SPSS 22.0, range from .712 to .936, indicating that the scale has high reliability. Additionally, the Cronbach α value of each variable decreased after deleting a measure item, indicating that each measure item played an important role in measuring its own variable.

Table 4. Results of the Reliability Analysis.

Variables	Cronbach's α	Measurement items	Cronbach's α after deletion of measurement items
Usefulness of big data products	.923	V1	.903
		V2	.861
		V3	.903
Ease of use of big data products	.875	V4	.835
		V5	.833
		V6	.801
Experience with big data products	.712	V7	.595
		V8	.578
		V9	.556
		V10	.582
		V11	.576
		V12	.910
Entrepreneurial performance	.936	V13	.923
		V14	.927
		V15	.935
		V16	.916
		V17	.921
		V18	.921
Entrepreneurial alertness	.895	V19	.853
		V20	.842
		V21	.857
Dynamic capabilities	.907	V22	.952
		V23	.886
		V24	.886
		V25	.884
		V26	.883
		V27	.887
		V28	.887
		V29	.886

EFA

In this paper, SPSS 22.0 was used for EFA. The calculation results of the principal component analysis method based on maximum variance rotation showed that the KMO value of the sample was .946, which was significant at the .001 level and higher than the critical value of .80, indicating that the data of this study were suitable for factor analysis (Cang & Wang, 2021). The rotated 6 factors extracted 77.592% of the information of the variable. The load value of each measure item in its own variable was higher than 0.50, while the load value in other variables was lower than 0.50, indicating that the scale in this study had good convergent and discriminant validities (Cang & Wang, 2021).

CFA

Table 5 reports the results of CFA. Average variance index (AVE) refers to the average extracted variance of each factor, and the AVE value reflects the convergent validity of the measure term. Its critical value is 0.50, and the AVE value of each variable in this study ranges from 0.651 to 0.807, indicating that the measure terms have good convergent validity. Composite reliability (CR) refers to the measure of the internal consistency in scale items, and a CR value greater than 0.7 indicates a good reliability of the factor (Cang & Wang, 2021). In this study, the CR value of each variable is between 0.847 and 0.938, indicating that each measure item has good reliability (Cang & Wang, 2021).

Discriminant validity refers to the degree of difference between the measure items of different variables, which reflects the closeness between the measure item and the corresponding variable (Cang & Wang, 2021). To test discriminant validity, the correlation coefficient matrix between the variables and the square root of the AVE value of each variable should be calculated first. If the square root of the AVE value of a variable is greater than the correlation coefficient between it and other variables, the variable has good discriminant validity (Lu & Teng, 2013). The test results of discriminant validity are shown in Table 6. The square root of the AVE value of each variable (boldface numbers on the diagonal in Table 6) is larger than the correlation coefficient between it and other variables (except 0.887), indicating that the measure items of the variable have good discriminant validity on the whole (J. Wan et al., 2019).

Table 5. AVE and CR Analysis for Each Variable.

Variables	Measurement items	AVE	CR
Usefulness of big data products	V1 V2 V3	0.807	0.926
Ease of use of big data products	V4 V5 V6	0.700	0.873
Experience with big data products	V7 V8 V9 V10 V11 V12	0.628	0.847
Entrepreneurial performance	V13 V14 V15 V16 V17 V18	0.715	0.938
Entrepreneurial alertness	V19 V20 V21	0.742	0.896
Dynamic capabilities	V22 V23 V24 V25 V26 V27 V28 V29	0.651	0.932

Table 6. Square Root of AVE Values and Correlation Coefficients for Variables.

Variables	Usefulness of big data products	Ease of use of big data products	Experience with big data products	Entrepreneurial alertness	Dynamic capabilities	Entrepreneurial performance
Usefulness of big data products	**.900**					
Ease of use of big data products	.786	**.840**				
Experience with big data products	.735	.887	**.790**			
Entrepreneurial alertness	.558	.521	.491	**.860**		
Dynamic capabilities	.625	.633	.654	.848	**.810**	
Entrepreneurial performance	.483	.664	.700	.622	.763	**.850**

Model Fit Evaluation

Before analyzing whether the relationship between variables conforms to the hypothesized relationship designed in this paper, AMOS was used to measure the fit index of the scale used. As shown in Table 7, all measured results are in line with good reference standards. In general, the hypothetical model proposed in this study fit the actual observed data well, and the SEM had good fit validity and external quality.

Testing of Theoretical Hypotheses

In this paper, AMOS is used to verify the hypothesis test in the previous section. The path coefficients and their

Table 7. Model Fitness Test.

Fitness index	Reference standard	Results of actual measurements
CMIN/DF	1–3 is excellent, 3–5 is good	4.625
RMSEA	<0.05 is excellent, <0.08 is good, <0.1 is acceptable	0.093
NFI	>0.9 is excellent, >0.8 is good	0.862
RFI	>0.9 is excellent, >0.8 is good	0.834
IFI	>0.9 is excellent, >0.8 is good	0.888
TLI	>0.9 is excellent, >0.8 is good	0.865
CFI	>0.9 is excellent, >0.8 is good	0.888

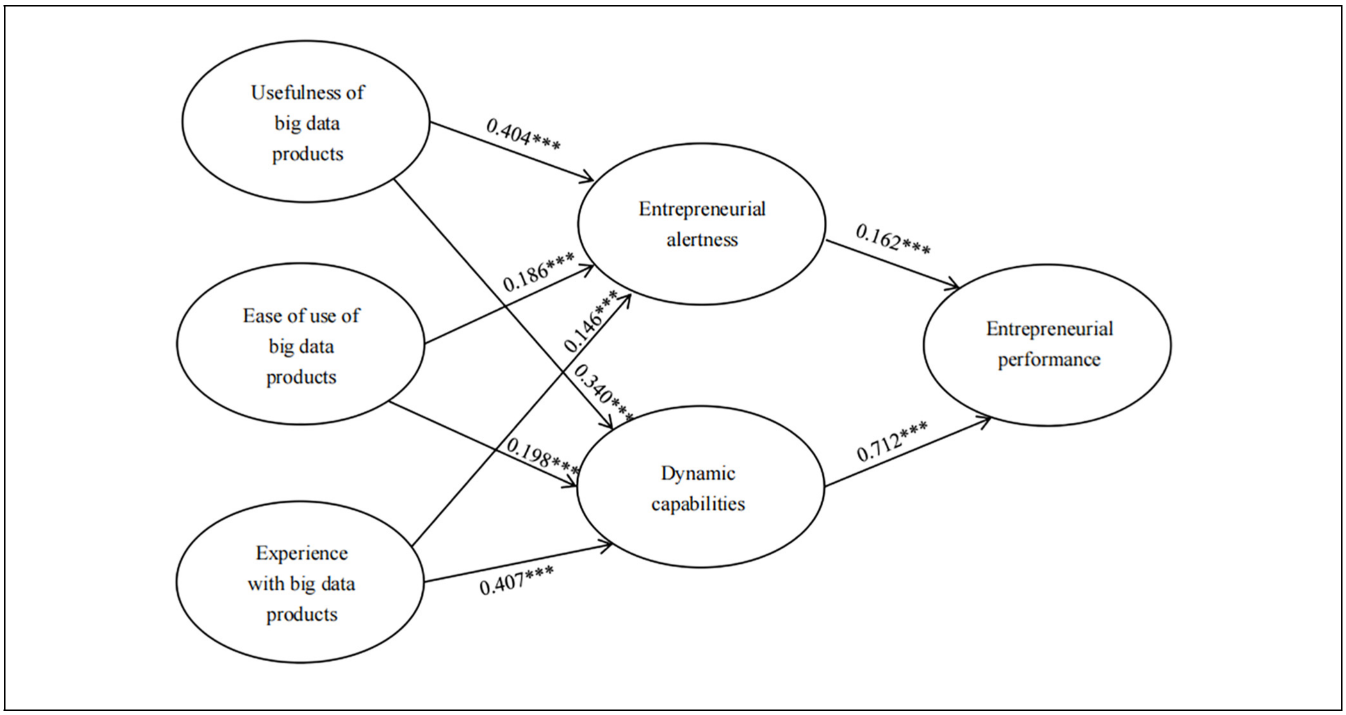

Figure 4. Model test results.
$^{**}p < .01$; $^{***}p < .001$.

significance levels are reported in Figure 4. The usefulness and ease of use of and experience with big data products are positively significant at the level of .001 on entrepreneurial alertness and dynamic capabilities (excluding experience with big data products on entrepreneurial alertness, which is positively significant at the level of 0.01). H1, H2, H3, H4, H5, and H6 are all verified. In addition, entrepreneurial alertness and dynamic capacity significantly and positively affect e-commerce farmers' entrepreneurial performance at the levels of 0.01 and 0.001, respectively, with the path coefficient of the former being 0.162 and the latter being 0.712. H7 and H8 are also verified.

Discussion

This paper makes two academic contributions to the literature as follows. First, it helps to expand the research on farmers' e-commerce entrepreneurship. The rise of Taobao Village in China has aroused scholars' unprecedented research enthusiasm for farmers' e-commerce entrepreneurship. In the initial stage, many studies focused on the drivers of farmers' e-commerce entrepreneurship and the socioeconomic effects of their participation in it (Avgerou & Li, 2013; Couture et al., 2021; Leong et al., 2016; Li, Guo, et al., 2021; M. Liu et al., 2020; Luo & Niu, 2019; Ma et al., 2020; Qi et al., 2019). Since then, with the changing competitive environment of the e-commerce market, farmers' e-commerce entrepreneurship has begun to face various challenges and constraints, especially those farmers with low human capital (Guo et al., 2024; L. Li et al., 2024; Shao, 2017; W. Tang & Zhu, 2020; Zeng, Guo, et al., 2019). Scholars are now focusing more on how governments and industry associations can help improve the sustainability of e-commerce farmers (Gao & Liu, 2020; Jin et al., 2020; Qi et al., 2019; Zeng, Guo, et al., 2019). We propose a new view on applying big data products to research farmers' e-commerce entrepreneurship and expands the research framework of this new field as only a few existing research reports and academic papers have briefly addressed it (AliResearch, 2020; Guo et al., 2023; L. Li et al., 2024). They describe only the basic status quo of this new phenomenon, but the theoretical logic behind it remains unexplored. The findings prove that the impact of big data products is positive and effective. Compared with governments and industry associations, the role of big data products is more direct and continuous. In other words, big data products are deeply embedded in the daily operations. Thus, this study establishes the connection between big data and farmer entrepreneurship. Farmer entrepreneurship research is an important branch of development economics. The theory of farmer entrepreneurship has long revealed the roles of entrepreneurial alertness and dynamic capabilities on improving entrepreneurial performance (Guo & Zhou, 2013). The empirical results of this paper support these conclusions again. Simultaneously, the empirical results show that compared with entrepreneurial alertness (path coefficient = 0.162, see Figure 4), dynamic capabilities have a greater effect on entrepreneurial performance (path coefficient = 0.712, see Figure 4). Entrepreneurial alertness is usually embodied as the identification of new entrepreneurial opportunities, which is a relatively short-term awareness process, while dynamic capability is manifested as a long-term behavior throughout the entire business process (Zhao et al., 2020). Therefore, dynamic capabilities have a relatively large impact on entrepreneurial performance. Moreover, when entrepreneurial opportunities are effectively identified, strong dynamic capabilities are needed to fully transform them into significant performance.

Second, this study expands the research of big data products in rural areas. Evolving big data technologies have brought new opportunities to develop farmers in developing countries. Theoretically, by capturing and mining massive data, farmers can improve agricultural productivity (Lokers et al., 2016; Waga & Rabah, 2014). However, in concrete practice, agricultural big data analysis has not yet achieved ideal results (Nandyala & Kim, 2016). Some scholars argue that at present, big data in developing countries is small in scale and lacks diversity, supply of effective infrastructure for collecting and analyzing big data, and professional human resources and analysts (Rodriguez et al., 2017; Sawant et al., 2016). Additionally, big data technologies will primarily benefit highly educated large-scale farmers (Oluoch-Kosura, 2010). How to make farmers in developing world generally benefit from big data technology is a very critical topic. Few studies exist on the factors influencing farmers' adoption of farm management information systems (Carrer et al., 2017; Pivoto et al., 2018), the willingness to share farm data with big data platforms (Turland & Slade, 2020), and the use of remote sensing data to guide the behavior and benefits of farm precision agriculture production (Coble et al., 2018; Toscano et al., 2019). Unlike the existing literature, we provide a new approach on product attributes for big data applications in rural developing world. Further, this paper creatively constructs a big data product attribute construct framework with three dimensions of usefulness, ease of use, and experience and expands the TAM. Perceived usefulness and perceived ease of use are the hard core parts of the TAM. However, this article argues that these two variables do not cover the entire perspective of product attributes. Consumers still may not use the product, even if a product is useful to users and easy to use, as they will also consider the risk of use, the use of fun, the degree of humanization of the product, and other factors. Thus, a dimension should be introduced to the TAM that reflects the product's emotional value to the user. This paper introduces the dimension of experience, making the investigation of product attributes more comprehensive. The perceived risk theory suggests that consumption risks arise from unpredictable outcomes. When using products, consumers might face unforeseen or undesirable circumstances that result in unsatisfactory experiences or losses (Elkins et al., 2013). E-commerce farmers, especially risk-averse ones, may not use big data products out of concerns about payment security, data accuracy, data timeliness, privacy security, and other aspects (Zeng et al., 2024). The theory of perceived fit posits that users' adoption choices are heavily shaped by how well they perceive a new technology to match their daily lives, personal experiences, preferences, needs, and core values (Oh & Yoon, 2014). Specific to big data products, e-commerce farmers' actual supply of big data products in terms of the price level, fun, comprehensiveness, and humanized design will contrast with their own needs and preferences, resulting in perceived compatibility, and ultimately affecting their behavioral decisions on using such products (Zeng et al., 2024). Big data products are relatively fresh and cutting-edge things for any e-commerce farmers, and they also need a learning process in which, the usefulness of, ease of use of, and experience with big data products are the foundation, driving force, and guarantee, respectively, and are indispensable. From the empirical results, the usefulness of big data products is the most critical product attribute and plays the largest role, reflecting their basic status (path coefficients = 0.404 and 0.340, see Figure 4). Moreover, ease of use has less impact on entrepreneurial alertness and dynamic capabilities than usefulness (path coefficients = 0.186 and 0.198, see Figure 4), which is primarily because of the younger e-commerce farmers. The younger generation of farmers has higher education and learning abilities, which allow them to withstand greater technical complexity. The experience of the product is also very important, especially, because the marginal impact on dynamic capabilities is very obvious (path coefficient = 0.407, see Figure 4). This highlights the need to incorporate the experience dimension into the TAM.

The practical value of this paper is to provide an empirical basis for further promoting the combination of big data and farmers. It suggests that we should always adopt a dynamic vision of technology convergence to view digital practices in developing countries. This paper confirms that with the advent of digital age, the dividends of big data are also spreading to farmers. The application of big data will help promote the growth of farmer entrepreneurship. With the continuous development of rural e-commerce and big data analysis technologies, the application of big data products will gradually enter the accelerated development stage, and the positive effect of big data use will further emerge. Although the products mentioned in this article are only one type of application of big data, it is not developed specifically for farmers and agriculture. However, the theoretical analysis and empirical findings are also applicable to other types of big data products. At present, China is beginning to establish big data for the entire agricultural industrial chain, prioritizing several distinctive agricultural products such as pigs, garlic, peanuts, and citrus. We firmly believe that the positive impact of big data on farmer entrepreneurship has good prospects for development.

From a policy perspective, the findings have important implications for formulating relevant government policies. Governments in the developing world should take the initiative to improve the understanding of big data, enhance support for e-commerce skills training in big data applications, and subsidize low-income farmers for using big data products. To establish rural public databases, governments should prioritize improving their data product attributes in a complete way. Governments should stimulate the extensive participation of farmers in the construction of agriculture-related databases, timely feedback on the needs of farmers, and constantly promote the iterative upgrading of public database construction. As farmers in developing countries have low digital literacy (B. Liu & Zhou, 2023; Magesa et al., 2023), big data products should be designed to meet the characteristics of digitally disadvantaged groups. At present, the supply of digital terminals and services suitable for older adults and people with disabilities cannot meet their actual demand. Developing countries need to prioritize exploring how to better serve rural older adults and vulnerable populations through straightforward digital products.

Concluding Remarks

Conclusions

Based on constructing the analytical framework of big data products from the view of product attributes and combining it with the theory of farmer entrepreneurship, this paper theoretically explains how big data products improve e-commerce farmers' entrepreneurial performance. Then, this paper uses the questionnaire samples of 418 e-commerce farmers from China, and the SEM method to empirically examine the theoretical hypotheses. The main conclusions we obtained are as follows: (1) The e-commerce big data products have a significant positive effect in improving e-commerce farmers' entrepreneurial performance. This provides micro-level explanations and empirical evidence for new e-commerce big data applications in rural China. (2) E-commerce big data products improve e-commerce farmers' entrepreneurial performance by improving their entrepreneurial alertness and dynamic ability. That is, such products are a special external cause that can enhance the inherent ability of e-commerce farmers. It acts as sustainable empowerment at the human capital level. (3) As for the product attributes, big data products should have good performance in the three dimensions of usefulness, ease of use, and experience, which all have a significant positive impact on the entrepreneurial alertness and dynamic capabilities of e-commerce farmers.

Limitations

This study has some limitations. First of all, the research object is limited to e-commerce farmers in Zhejiang, which is representative to a certain extent but also has its own characteristics. An expanded geographical range of the sample will certainly help to get more reliable conclusions. Second, the sample size is not large enough. China is a populous country, and there is still much room for the improvement of sample size. Finally, the research methods should be expanded. In this paper, the SEM is tested based on cross-section data. If a multi-year follow-up survey can be conducted, a regression analysis of causality based on panel data will further enhance the rigor of the study.

Future Research

The application of big data products has undoubtedly opened a new vision and space for the academic development of rural e-commerce. Future studies should pay attention to the new phenomenon in China regarding the following aspects: First, in addition to product attributes, we can also consider the specific behavioral characteristics of e-commerce farmers, such as the use time, use frequency, and expenditure amount of big data products. Second, besides entrepreneurial performance, future scholars can also consider the impact of big data products on income inequality, happiness, resilience, and other aspects. Third, future scholars should expand the scope of the investigation area and collect large sample data and panel data. Fourth, future scholars should use more rigorous empirical methods such as DID, PSM-DID, and instrumental variable regression; however, there are many technical constraints to overcome in this process.

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Ethical Considerations

The study was conducted in accordance with the Declaration of Helsinki. The authors ensure that the research does not cause any mental or physical harm to the respondent, and protect the safety and rights of the respondent.

Consent to Participate

Informed consent was verbally obtained from all subjects involved in the study.

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Data Availability Statement

The data will be provided upon request to the corresponding author.

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