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Examining the factors influencing the digital transformation of new agricultural operating entities: insights from Zhejiang, China

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The digital transformation of new agricultural operating entities (NAOEs) plays a pivotal role in advancing rural revitalization and strengthening agricultural development. Despite the significant efforts made by the Chinese government, the digitalization rate of agriculture is still relatively low. Based on a multi-case study encompassing 40 NAOEs and employing the Technology-Organization-Environment (TOE) framework alongside fuzzy-set Qualitative Comparative Analysis (fsQCA), this study explores the necessary conditions and pathways for the digital transformation of NAOEs. Additionally, we investigate the configuration factors that drive digital transformation at different levels. The study concludes that the digital transformation of NAOEs results from the interplay of multiple interacting factors rather than a single determinant. Notably, government support and manager's digital capability emerge as two necessary conditions of successful digital transformation. High-level digital transformation can be categorized into three pathways: technology-driven, technology-organization-driven, and environment-driven. In contrast, low technological factors, low technology-organization factors, and high environmental factors lead to a low degree of digital transformation. Based on these findings and the current state of agricultural digitalization in China, this study offers policy recommendations across three key areas: enhancing technical support, refining the policy framework, and developing digital capabilities. This study unveils the complex and multifaceted relationships underlying digital transformation in NAOEs, providing both a theoretical foundation and practical insights for advancing agricultural modernization and refining the supporting policy framework.

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Introduction

With the advancement of digital technologies, digital transformation has emerged as a significant global trend across various industries, with the agricultural sector also encountering unparalleled opportunities. As a core element of the "Digital China" strategy, agricultural digital transformation is not only a vital avenue for advancing agricultural modernization but also an essential strategy for achieving rural revitalization. It improves production efficiency, optimizes resource allocation, ensures national food security, and fosters sustainable and green development (Hrustek 2020; Khanna et al. 2022). To facilitate agricultural digital transformation, the Chinese government has introduced a series of policy initiatives[1]. It is anticipated that by 2025, substantial progress will be achieved in rural digital development, with the share of the agricultural digital economy in total agricultural value projected to reach 25%, accompanied by an average annual growth rate of 10.8%[2].

Digital transformation is defined as an ongoing structural change within society, leveraging digital technologies to generate new value and achieve sustainable competitive advantages(Saeedikiya et al. 2025). With the onset of a new technological revolution, digital transformation has increasingly become a pivotal trend in global agricultural development. The integration of digital technologies into traditional agricultural production not only enhances the transaction scale, market potential, and output of agricultural products but also effectively mitigates issues such as carbon emissions, resource waste, and environmental pollution (Chen and Li 2024; Lin 2024). Although the modernization of agricultural production system and the rapid development of digital technologies have accelerated agricultural digitalization, China continues to face challenges, including insufficient resource investment, low digital capability among key stakeholders, inadequate digital infrastructure, and significant gaps in technological support. To this end, the Ministry of Agriculture and Rural Affairs has implemented supportive policies and emphasized the critical role of new agricultural operating entities, encouraging eligible family farms, cooperatives, and other organizations to adopt digital transformation strategies.

New agricultural operating entities (NAOEs) are key participants and primary beneficiaries of agricultural digital transformation, serving as essential carriers for its realization(Zhou et al. 2024). On the one hand, compared to smallholders, NAOEs possess greater motivation and capacity for adopting new technologies, leveraging their inherent scale advantages to overcome typical barriers such as limited access to technology and information. On the other hand, digital technologies facilitate the transition of NAOEs from extensive production to more intensive management. As of September 2021, there were over 3.8 million family farms and 2.23 million farmer cooperatives nationwide, offering considerable advantages in intensive management, service-oriented models, and market competition.[3]. Investigating the digital transformation of NAOEs not only deepens the understanding of digital agriculture but also offers valuable insights for advancing agricultural modernization.

Current research on NAOEs has established them as key drivers of agricultural modernization, with scholars continuing to broaden the scope of their investigations. On the one hand, NAOEs not only directly incentivize farmers to lease out their land but also indirectly encourage investment, further stimulating land leasing, which plays an important role in addressing the "who will cultivate the land" dilemma, enabling large-scale agricultural operations, and improving production efficiency (Gong et al. 2019). Meanwhile, NAOEs can advance the dissemination of eco-friendly agricultural technologies by increasing the level of agricultural specialization and scale, thereby supporting green agricultural development (Yang 2021; Gou et al. 2015). Simultaneously, NAOEs can foster non-agricultural employment opportunities for farmers by encouraging land leasing and stimulating agricultural laborers to engage in local wage labor (Cheng et al. 2022). With the rise of e-commerce platforms, scholars have increasingly focused on the digital transformation of agricultural sales. By adopting agricultural e-commerce platforms for agricultural products, NAOEs can enhance their dynamic capabilities, thereby boosting the income of agricultural producers (Chen et al. 2023; Song et al. 2022; Xu et al. 2022).

In summary, scholars have acknowledged that discussions of NAOEs should occur within a digital context. However, several gaps remain in the literature. Firstly, existing studies give limited attention to leading enterprises, farmer cooperatives, and other NAOEs. Compared to smallholders, NAOEs possess advantages in intensive management, specialization, organization, and socialization, enabling them to efficiently allocate production factors and foster the development of digital agriculture. In the context of large-scale and intensive agricultural operations, examining digital transformation from the perspective of NAOEs holds greater practical significance. Secondly, digital agriculture represents the digital transformation of the entire agricultural value chain, spanning various stages from production to sales. However, existing research has predominantly concentrated on the sales stage, often overlooking the transformation of the production stage. Lastly, although some studies have examined digital transformation from a single dimension, a comprehensive framework integrating various factors and delineating the conditions and pathways for the digital transformation of NAOEs remains absent.

The digital transformation of NAOEs is a gradual process influenced by multiple factors. Firstly, technology development serves as the foundation of digital transformation. Adopting digital technologies can significantly enhance agricultural production efficiency. However, the adaptability and maturity of these technologies directly influence the outcomes of the transformation. Secondly, digital transformation extends beyond technology adoption, and it also entails an organizational-level change. Leadership capacity, decision-making support, and resource allocation are critical to the success of digital transformation. Besides these, digital literacy and training mechanisms also play a pivotal role. Finally, external factors, including government support and market demand, are important conditions influencing the digital transformation of NAOEs. Government policies can alleviate financial pressures, while market demand compels enterprises to innovate, thereby driving the transformation process. Furthermore, digital transformation typically results from the collaborative interplay of multiple factors rather than being driven by a single element, thus necessitating a comprehensive analysis based on systems thinking.

Based on these practical considerations, this paper aims to address the following essential questions:

- What are the necessary conditions for the digital transformation of NAOEs?
- How do different technological, organizational, and environmental factors interact and affect the digital transformation of NAOEs?
- How to identify the pathways of digital transformation at different levels?

To address these questions, this paper applies the Technology-Organization-Environment (TOE) framework to categorize the key factors influencing the digital transformation of NAOEs. Considering that traditional quantitative or qualitative analysis methods explore the direct or indirect effects of individual factors while neglecting the configurational effects among factors (Eller et al. 2020), this paper further employs the fuzzy-set Qualitative Comparative Analysis (fsQCA) method within the TOE framework, aiming to comprehensively identify the key drivers of digital transformation and offer a more robust and precise foundation for agricultural policy development.

Compared with relevant literature, this paper makes the following contributions: On the one hand, existing research primarily analyzes agricultural digital transformation from a macro perspective. This paper shifts focus to the micro level, examining key agents of agricultural digital transformation—NAOEs. By identifying key influencing factors from the dimensions of technology, organization, and environment, this paper provides a theoretical foundation and practical insights for achieving agricultural digital transformation. On the other hand, in contrast to traditional linear thinking, this study adopts a configurational perspective, emphasizing the complex interactions of multiple factors. Building on this, the paper further explores the causal mechanisms behind high and low levels of digital transformation in NAOEs, aiming to more precisely identify the key elements of digital transformation and provide more comprehensive theoretical support for the design and practice of digital transformation pathways for NAOEs.

The remaining structure of this paper is as follows: Section "Theoretical analytical framework" presents the theoretical analysis and constructs a theoretical framework. Section "Research design" details the research design. Section "Empirical results analysis" conducts a configuration analysis. Section "Further discussion" further discusses two necessary conditions. Section "Conclusion and Policy recommendations" proposes policy recommendations and future research directions.

Theoretical analytical framework

The Technology-Organization-Environment (TOE) framework is widely used to examine organizational behavior regarding technology adoption, with a focus on how multi-level contexts affect the effectiveness of technology usage (Tornatzky et al. 1990; Qiu 2017). The TOE framework categorizes the factors influencing technology adoption into three key dimensions: technology, organization, and environment. Technological factors primarily encompass the inherent characteristics and advantages of the relevant technology, along with its alignment with the organization. The focus is on the compatibility between technology and the organization, as well as the potential benefits derived from its adoption(Chau and Tam 1997). Organizational factors pertain to the organizational capabilities that facilitate technology adoption, including factors such as business scale, developmental stage, institutional structures, and coordination abilities (Tan et al. 2015; Walker 2014). Environmental factors primarily involve the market structure within which the organization operates, as well as external government regulations (Oliveira and Martins 2011).

Scholars have conducted extensive studies based on the TOE framework, continually expanding its relevance across various technology application contexts. For instance, Lin, utilizing the TOE framework, examined the impact of technological factors (perceived benefits and costs), organizational factors (company size, top management support, and absorptive capacity), and environmental factors (trade partners and competitive advantage) on the adoption of electronic supply chain management systems (Lin 2014). Wang and Li, also using the TOE framework, hypothesized nine factors influencing the adoption of mobile hotel reservation systems (MHRS), finding that compatibility, company size, technological capabilities, and critical quality were positively correlated with MHRS adoption, while complexity showed a significant negative correlation (Wang et al. 2016). With the increasing application of digital technology in the agricultural sector, scholars have explored agricultural digital transformation through the TOE framework. For instance, Mukherjee, applying the TOE framework, examined the challenges encountered by food and agricultural supply chains during the implementation of blockchain technology (Mukherjee et al. 2022). Li, integrating TOE theory with UTAUT theory, investigated the factors affecting vegetable farmers' adoption of Internet of Things (IoT) technology, identifying government support and technological complexity as the most significant factors influencing adoption intentions (Li et al. 2024). Huang, utilizing the TOE framework, employed fsQCA to identify key factors and pathways driving the development of rural e-commerce entrepreneurial ecosystems (Huang et al. 2024). NAOEs, as economic organizations embedded in rural communities, need to account for the combined effects of technological, organizational, and environmental factors in their digital transformation(Luo et al. 2017). Building on this, we utilize the TOE framework to analyze the digital transformation of NAOEs.

Technological dimension. Digital technology is the core of agricultural digital transformation, and there may be varying levels of applicability and implementation difficulty for different NAOEs. These entities need to assess the applicability and weakness of different digital technologies to leverage their value fully. Rogers believes that the diffusion of technology is closely related to its relative advantage, which is defined as "the degree to which an innovation is perceived as better than the idea it supersedes" (Rogers et al. 2014). In an organization, the perception of benefits associated with innovation provides economic and political legitimacy for the adoption of new technology (Premkumar et al. 1997). The relative advantage of a technology encompasses tangible and intangible benefits, such as increased sales and reduced costs. As rational economic agents, NAOEs primarily consider whether digital technology can bring potential benefits to themselves. Rogers further considers the complexity of technology, defining it as "the degree to which an innovation is perceived as relatively difficult to understand and use"(Rogers et al. 2014). The complexity of innovation is usually negatively correlated with its adoption (Mallat and Tuunainen 2008). During the digital transformation of NAOEs, they may be more inclined to choose digital technology with greater potential benefits, easier operation, and greater stability. Therefore, this paper measures the technological dimension from digital technology benefits and technological security.

Organizational dimension. NAOEs need to possess corresponding organizational and managerial capability during digital transformation. Generally, as potential decision-makers in an organization, senior management can create a conducive environment for the adoption of new technologies. They can achieve this by creating an attractive vision of how the organization can benefit, to ensure sufficient resources, and overcome resistance among members (Premkumar and Roberts 1999). Many studies have also confirmed that the support of senior leadership is positively correlated with the adoption of new technologies (Lin 2014; Teo et al. 2009). Furthermore, higher organizational learning capability enables organizations to fully utilize internal and external resources, learn from experience, adapt to environmental changes, and increase organizational adoption of technologies (Nisar et al. 2013). In practice, managers with strong digital capabilities can seize opportunities, mitigate risks, and unleash the potential value of digital technologies. Organizational learning capability, through continuous learning and reflection on experiences, can enhance the awareness and acceptance of innovations among NAOEs. Therefore, this paper measures the organizational dimension from the perspectives of manager's digital capability and organizational learning capability.

Environmental dimension. Policy and market environments are crucial supports for digital transformation. Governments can formulate relevant policies and increase support for digital transformation. Meanwhile, changes in the external market environment also pressure NAOEs to seek opportunities to adopt digital technologies (Saeedikiya et al. 2024a, 2024b). As a low-profit industry, agriculture faces dual risks from nature and the market. Additionally, investments in agricultural digital equipment are substantial, requiring strong government support. Without such support, NAOEs may lack the motivation or capacity to achieve digital transformation. Furthermore, from the perspective of competitive pressure, an organization adopts an innovation primarily to avoid the risk of competitive disadvantage. Successful innovation can lead to significant competitive advantages, avoiding potential market competitors and achieving differentiation and sustainable growth (Abrahamson and Rosenkopf 1993). Studies have shown that higher levels of competitive pressure significantly promote organizations to adopt new technologies (Lin 2014; Oliveira and Martins 2010). Meanwhile, there is a significant outflow of labor from rural areas to cities, leading to severe labor shortages in rural areas, which severely limit agriculture development. In surveys, many NAOEs expressed concerns about the future agricultural workforce. The agricultural sector urgently needs to replace labor with digital transformation. Therefore, this paper measures the environmental dimension from three aspects: government support, market competitive pressure, and labor crisis perception.

From the perspective of the outcome variable (the degree of digital transformation), the government has currently introduced a series of policy measures to encourage agricultural digital transformation, and NAOEs have also correspondingly invested in digital equipment. However, in actual research, it was found that due to the limited practical value of some digital equipment (such as sensors), NAOEs would select digital equipment based on their actual production situations. Therefore, this paper measures the degree of digital transformation from two aspects: the level of investment in digital equipment and the level of application in digital equipment.

Based on the TOE framework, this paper considers digital technology benefits, technology security, manager's digital capability, organizational learning capability, government support, market competitive pressure, and labor crisis perception as seven key antecedent variables. A model of key factors influencing the digital transformation of NAOEs is constructed accordingly (See Fig. 1).

Research design

Research methodology. To address the key question of "what combination of factors can drive the digital transformation of NAOEs," this paper employs the Qualitative Comparative Analysis (QCA) research method. The main reasons are as follows. Firstly, in contrast to traditional quantitative linear thinking, QCA can handle complex relationships between variables, focusing on the outcomes under different combinations of conditions, thus revealing the complexity and diversity. Secondly, case-oriented methods emphasize the complementary use of knowledge within cases. In contrast, condition-oriented methods mainly rely on cross-inference, focusing on relationships between sets and assisting researchers in finding differences and patterns from cross-case comparisons based on conceptual relationship knowledge, thereby analyzing causal relationships of phenomena and constructing general theories (Thomann and Maggetti 2020). Thirdly, QCA can handle medium-sized samples, not only eliminating the need for large sample requirements in traditional quantitative research but also addressing the issue of non-representative samples in case studies. It can capture more causal relationships in a smaller sample size, offering richer explanations. As pointed out by Berg-Schlosser and De Meur (2009), QCA can exploratively "help researchers generate new insights and can serve as a basis for further theoretical development or reexamination of existing theories." Based on these, this paper employs 40 cases of NAOEs to explore the causal relationships among them by using a truth table and a minimization algorithm, aiming to investigate the configuration of factors influencing the digital transformation of NAOEs.

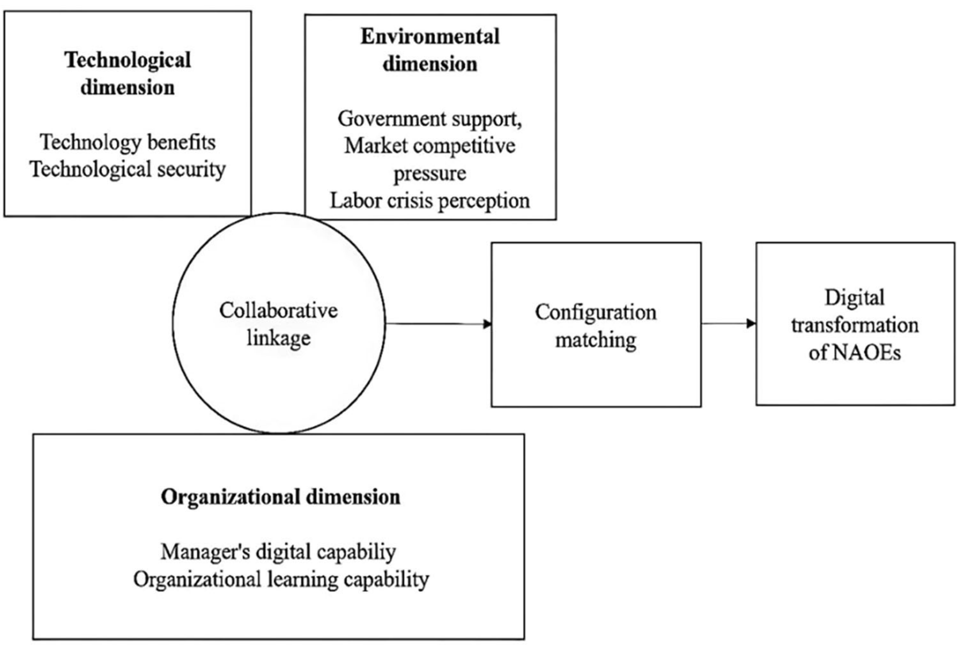

Fig. 1 Model of key factors influencing the digital transformation of NAOEs.

Data collection. This paper adopts the triangulation method, collecting data through multiple sources to validate digital transformation of NAOEs. It mainly includes primary data and secondary data, with primary data being the primary source. Primary data includes semi-structured interviews and questionnaire surveys, and the questionnaire is submitted as an attachment. Members of the research team conducted semi-structured interviews and questionnaire surveys with the leaders of NAOEs and ordinary farmers. We obtained the most authentic and comprehensive information from the interviewees in a one-on-one format without external interference. With the interviewees' permission, the interviews were recorded. The data was organized within 24 h after the interview. If there were any unclear or ambiguous issues, communication with the interviewees was conducted via phone or WeChat. Before and after the interviews, visits will be conducted to NAOEs in order to obtain intuitive data through direct observation. Secondary data includes literature, official media news reports, annual report summaries, and other relevant materials about the NAOEs. The research team was divided into three groups, each tasked with collecting relevant data from different sources. Cross-checking was conducted among the groups to ensure the authenticity and authority of the collected data, thereby ensuring validity.

Sample selection. The sample selection for this study follows the principle of theoretical sampling. Based on a deep understanding of the research questions, samples that contribute to theory development were chosen. The specific sampling approach followed the process of "establishing theoretical applicability conditions, planning the overall theoretical research—aligning with theoretical expectations—selecting cases exhibiting the same mechanism" (Ye 2019).

First, the overall case sample was selected. The theoretical framework of this study applies to NAOEs that are relatively advanced in digital transformation and hold typical significance. Zhejiang Province, as the only designated digital rural leadership zone in China, initiated its digital development early (See Fig. 2). It has encountered both challenges and gained insights that can serve as valuable references for digital development in other regions. Based on this, the researcher conducted field research on 102 NAOEs across three regions, which formed the overall case sample.

Then, Following the existing approach (Zschoch 2011), sample selection adheres to a systematic design of "maximum similarity" and "maximum diversity." Firstly, NAOEs studied in this paper primarily consist of farmer cooperatives and family farms, with crops being predominantly cash crops. This ensures maximum similarity among the cases, thereby enhancing their comparative value. Secondly, the selected NAOEs in this paper exhibit significant differences in terms of establishment time and operational scale, seeking maximum diversity within the sample system. Thirdly, the cases in this study are mainly concentrated in Wenzhou, Taizhou, and Jiaxing cities of Zhejiang Province. On the one hand, Zhejiang Province has an early start and rapid development in digital rural construction, being a leading area in national rural digitalization. It serves as a demonstration and typical region in the digitalization of agriculture nationwide. Moreover, by focusing on samples within Zhejiang Province, other regional factors are excluded, ensuring the "maximum similarity" of the samples. On the other hand, by selecting NAOEs in Wenzhou, Taizhou, and Jiaxing, this study ensures the "maximum diversity" among the cases within Zhejiang Province.

In qualitative research, particularly in case studies or in-depth interviews, the sample size depends on the richness of the sample information and the depth of the research questions. We selected 40 NAOEs as research samples, representing various agricultural entities of different scales, types, and backgrounds within Zhejiang Province, thereby ensuring the representativeness and broad applicability of the findings. The sample size of 40 enables in-depth data collection while keeping the research cost-effective and manageable, adhering to the principle of resource optimization. The information on the samples is shown in Figs. 3–6.

Variable measurement. To obtain effective micro-level data about digital transformation of NAOEs, we designed a questionnaire based on the TOE framework and the actual development of digital agriculture in Zhejiang Province. To ensure the reliability and validity of the questionnaire, several steps were taken during the design process for rigorous verification and refinement. Initially, the questionnaire was designed based on the research objectives and literature review. After that, experts and scholars in the field were invited to review the draft, ensuring coverage of all relevant variables. Subsequently, the first pilot survey was conducted. During this phase, several NAOEs were randomly selected as samples, and a combination of interviews and questionnaires was used to field-test the preliminary design. After completing the first pilot survey, discussions and analysis of the questionnaire were held, further optimizing its content to ensure effective measurement of the research's various dimensions. Following modifications and improvements, a second pilot survey was conducted to ensure that the adjusted questionnaire met the data collection needs.

Fig. 2 Research sample distribution map.

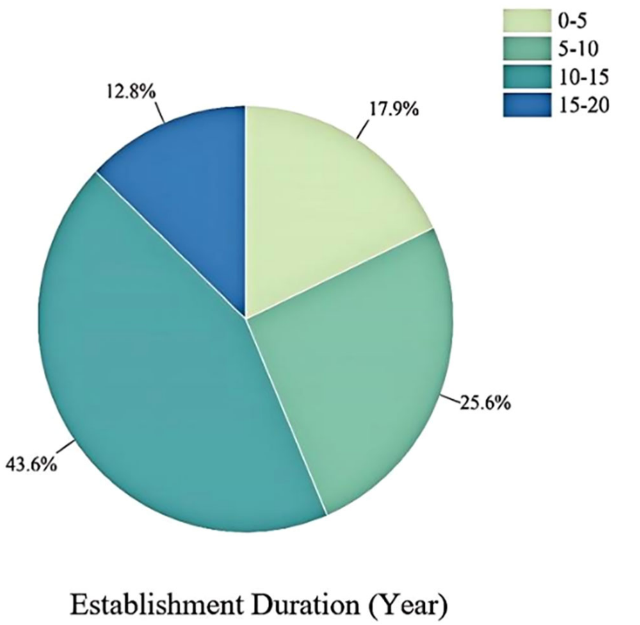

Fig. 3 Establishment duration of NAOEs.

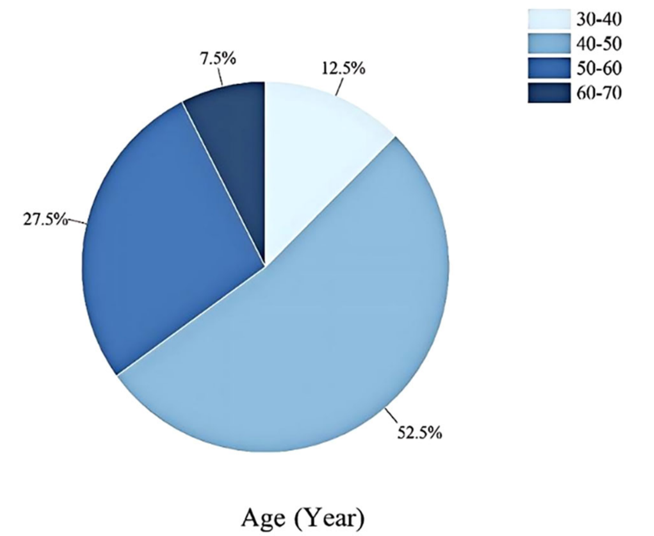

Fig. 5 Age of managers.

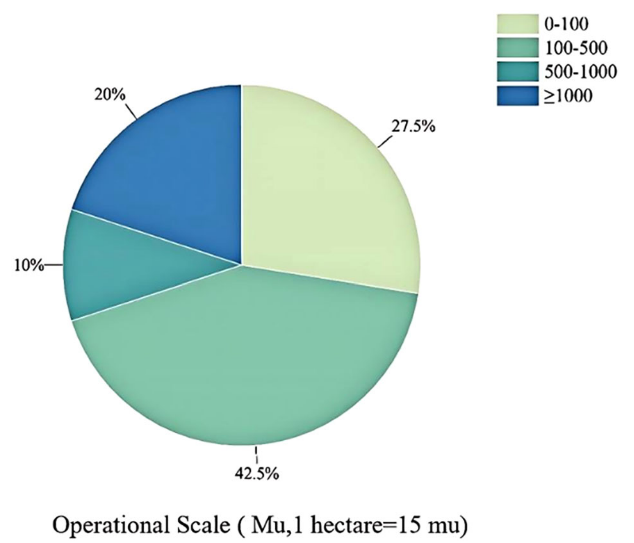

Fig. 4 Operational scale of NAOEs.

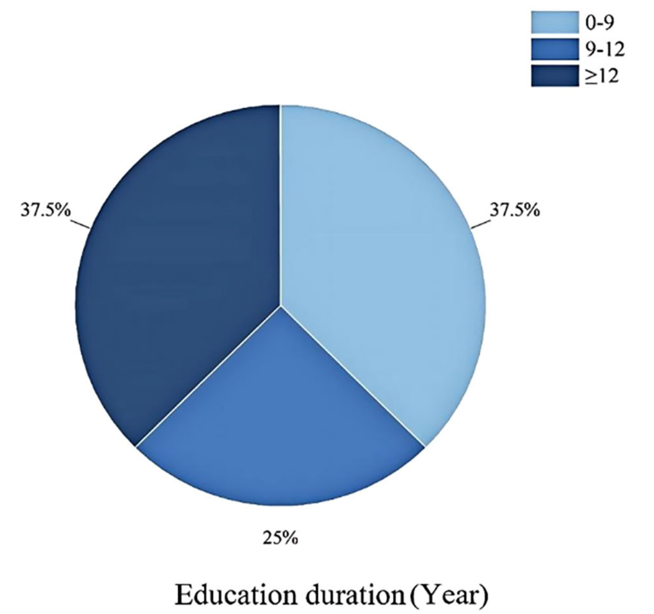

Fig. 6 Education duration of managers.

Concurrently, multiple methods were employed to assess the questionnaire. First, Cronbach's α coefficient was calculated, revealing that the α values for all variables exceeded 0.8, indicating strong internal consistency. Additionally, a repeat test was conducted with respondents after a two-week interval, and the results demonstrated a correlation coefficient of 0.85, indicating high stability. For inter-rater consistency, the Kappa coefficient was calculated, yielding a value of 0.90, demonstrating strong consistency between raters. Through this series of design and verification steps, a questionnaire with high reliability and validity was developed.

This paper conducts exploratory factor analysis on the initial variables in the questionnaire. Specifically, factor analysis rotation is performed using the method of maximum variance, and principal component analysis is applied to extract the factors. After multiple attempts and judgments of the variables, variables with loadings on common factors less than 0.5 are eliminated, and finally, 21 variables are retained. Based on the above theoretical analysis and the maximum loadings of factor variables, the common factors are named, including the degree of digital transformation of NAOEs (X1-X2), benefits (X3-X5), security (X6-X8), manager's digital capability (X9-X11), organizational learning capability (X12-X14), government support (X15-X16), market competitive pressure (X17-X18), and labor crisis perception (X19-X22). The variables in the formal questionnaire adopted a Likert five-point scale, which is shown in Table 1 and Fig. 7.

Variable calibration. In social science research, individual measurements may be influenced by external interference or errors. By averaging multiple variables, these random factors can be "eliminated," resulting in a measurement value that is closer to the actual variable value (Blalock 1971). The mean score method is particularly suitable for cases involving multiple indicators that measure different dimensions or aspects, where each indicator contributes relatively equally to the variable. Each variable in this

Table 1 Main model variables.

	Variables	Variable measurement
Technological dimension	Degree of digital transformation of NAOEs (Digital)	Level of investment in digital equipment (X1) Degree of application of digital equipment (X2)
	Technology benefits (Profit)	Do you think digital technology can significantly improve the quality of agricultural products? (X3) Do you think digital technology can significantly increase the price of agricultural products? (X4) Do you think digital technology can significantly reduce agricultural production costs? (X5)
	Technology security (Safe)	What do you think about the reliability (stability) of digital technology? (X6) How do you rate the adaptability of agricultural digital technology? (X7) How do you rate the operability (complexity) of agricultural digital technology? (X8)
Organizational dimension	Manager's digital capability (Manager)	Digital resource management capability (X9) Digital opportunity seizing capability (X10) Digital risk decision-making capability (X11)
	Organizational learning capability (Learning)	Knowledge absorption capability (X12) knowledge sharing capability (X13) Knowledge application capability (X14)
Environmental dimension	Government support (Government)	Digital funding subsidy level (X15) Digital training intensity (X16)
	Market competitive pressure (Market)	Market uncertainty (X17) Degree of competition in the market (X18)
	Labor crisis perception (Labor)	What do you think about the current level of labor shortage? (X19) What do you think about the future level of labor shortage? (X20) What do you think about the current labor prices? (X21) What do you think about the future labor prices? (X22)

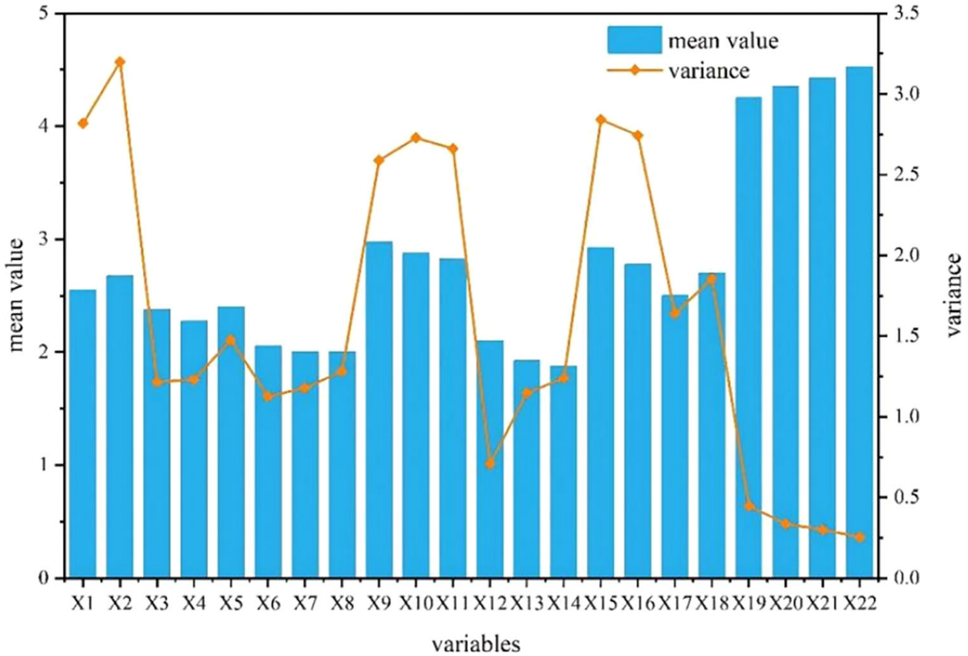

Fig. 7 Descriptive statistics of variables X1–X22. Note: The meanings of X1–X22 are shown in Table 1.

study is measured by 2–4 sub-items. The design of multiple items generally captures the variables more comprehensively and accurately, thereby enhancing the validity and reliability(Roberts and Priest 2006). Therefore, this study follows Zhang's approach (Zhang 2022) by calculating the mean score of variables as the final score to avoid the bias that may arise from over-reliance on a single score.

The qualitative comparative research method is based on Boolean logic, where variables need to be labeled as fuzzy sets. Fuzzy sets allow the values of variables to continuously vary between 0 and 1, reflecting their degree of membership in the set. Therefore, it is necessary to calibrate the variable range between 0 and 1. Following the approach of Du (2017), this study sets the values of the three anchors—fully non-subordinate point, cross-subordinate point, and fully subordinate point—at 5%, 50%, and 95%, respectively. The specific anchor values for each variable are shown in Fig. 8. After calibration, there are instances where the data equals 0.5. Following Fiss (2011), these instances are

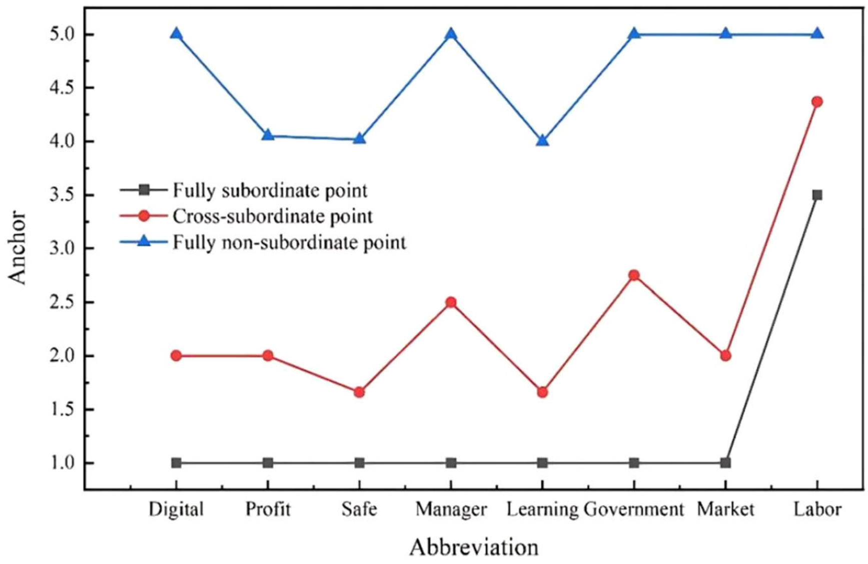

Fig. 8 Specific anchor values for each variable. Note: The meanings of each variable are shown in Table 1.

uniformly replaced with 0.501. This study employs fuzzy set Qualitative Comparative Analysis (fsQCA). Unlike crisp set Qualitative Comparative Analysis (csQCA), which uses binary data, fsQCA allows variables to be continuous data ranging from 0 to 1.

Empirical results analysis

This paper uses fsQCA3.5 software to analyze standardized data. Firstly, necessary condition analysis is conducted on individual factors to explore whether there are necessary conditions for the digital transformation of NAOEs. Secondly, by calculating the truth table, the path of the digital transformation of NAOEs is constructed. Finally, based on research cases and literature, existing paths are further interpreted.

Necessity analysis. Before conducting the configuration analysis, we perform a necessity analysis to test whether there is a single condition that is necessary for digital transformation of NAOEs. Consistency represents the degree to which the outcome variable is observed under the given condition variable, with values ranging from 0 to 1. A higher consistency value indicates a stronger causal relationship. Coverage represents how much of the observed outcome variable can be attributed to the condition variable among all observed cases, with values ranging from 0 to 1. A higher coverage value indicates that the condition variable has a greater impact on the outcome variable (Alamá-Sabater et al. 2019). When the consistency of a condition exceeds 0.9, it is considered a necessary condition for obtaining the outcome (Cruz-Ros et al. 2017; Greckhamer et al. 2018). Table 2 presents the results of the necessary condition analysis. Only the consistency levels of "Manager" and "Government" are higher than 0.9, while the consistency levels of other variables are all below 0.9, indicating that "Manager" and "Government" are necessary conditions for digital transformation of NAOEs. Further analyzing the coverage, the coverage of the antecedent conditions ranges from 0.208 to 0.980, indicating that the antecedent conditions have a strong explanatory power for the outcome variable. Only the consistency level between ~Manager and ~Government exceeds 0.9, while the consistency levels of other variables are all below 0.9, indicating that ~Manager and ~Government are necessary conditions for the low-degree digital transformation of NAOEs. Furthermore, in terms of coverage, the coverage of the antecedent conditions ranges from 0.161 to 0.934, indicating that the antecedent conditions have strong explanatory power for the outcome variable.

Table 2 Necessity analysis of digital transformation for NAOEs.

	Digital		~ Digital	
Antecedent conditions	**Consistency**	**Coverage**	**Consistency**	**Coverage**
Profit	0.809	0.900	0.255	0.251
~ Profit	0.327	0.331	0.899	0.806
Safe	0.847	0.836	0.338	0.295
~ Safe	0.286	0.328	0.812	0.824
Manager	0.910	0.975	0.169	0.161
~ Manager	0.217	0.228	0.973	0.905
Learning	0.594	0.579	0.640	0.552
~ Learning	0.540	0.629	0.512	0.528
Government	0.939	0.980	0.170	0.157
~ Government	0.192	0.208	0.978	0.934
Market	0.453	0.519	0.636	0.643
~ Market	0.688	0.681	0.525	0.459
Labor	0.721	0.816	0.314	0.315
~ Labor	0.395	0.394	0.816	0.721

"~" indicates the negation of preceding conditions.

Configurational analysis. Unlike necessity analysis, configuration analysis is used to identify patterns among causal relationships and conditional variables. Comparing different cases identifies the combination of conditional variables that lead to specific outcomes. From a set-theoretic perspective, configuration analysis explores whether sets composed of different antecedent conditions are subsets of the outcome variable set. Specifically, we applied the Proportional Reduction in Inconsistency (PRI) filtering to the truth table associated with reliable results. PRI below 0.5 may lead to contradictory configurations of the same causes and different outcomes. Schneider and Wagemann(Schneider and Wagemann, 2012) argued that the consistency level for sufficient conditions should not be less than 0.75. Following Cheng's approach (Cheng 2016), we set the consistency threshold to 0.8.

Table 3 High degree of digital transformation influence factor configuration of NAOEs.

		High degree of digital transformation				
		P1a	**P1b**	**P2**	**P3a**	**P3b**
Condition variable	Profit	1	1	1	1	1
	Safe	1	1	1		
	Manager	●	●	●	●	●
	Learning			1		1
	Government	●	●	●	●	●
	Market	◎			◎	
	Labor		1		1	1
	Raw coverage	0.524	0.573	0.453	0.472	0.420
	Unique coverage	0.032	0.021	0.013	0.018	0.018
	consistency	0.989	1	0.988	1	1
Overall solution consistency				0.702		
Overall solution coverage				0.992		

Note 1: "●" and "◎" respectively represent the presence and absence of a condition, while blank spaces indicate that the condition may or may not exist. Core conditions are marked with large "●" and "◎"; edge conditions are marked with small "● " and "◎."
Note 2: Raw coverage indicates the share of results explained by a particular solution. Unique coverage indicates the share of results explained by each condition in the causal configuration.

For the frequency threshold, it should include 75% of the cases after setting the frequency threshold. Following Zhang's approach (Zhang 2019), we set the frequency threshold to 1. By setting the PRI and frequency threshold criteria, we obtained the truth table and configuration paths that meet the requirements.

High degree of digital transformation of NAOEs. Table 3 shows the configuration of digital transformation for NAOEs. The consistency level of each configuration ranges from 0.988 to 1, indicating that each configuration can highly explain the outcome variable. The raw coverage rates are all above 0.4, indicating that each configuration explains more than 40% of cases. Furthermore, the overall consistency level is 0.702, indicating that the overall configurations can highly explain the outcome variable. The overall coverage rate is 0.992, suggesting that the configurations can explain 99.2% of cases. The fsQCA3.5 software reports complex solutions, parsimonious solutions, and intermediate solutions. This paper primarily reports intermediate solutions supplemented by parsimonious solutions (Fiss 2011). "Solid circles" and "hollow circles" are used to represent the presence and absence of a specific condition, respectively. Blank spaces indicate that the condition can either be present or absent. "Large circles" denote core conditions, while "small circles" represent peripheral conditions.

The five configurations presented in Table 3 represent sufficient condition combinations for digital transformation of NAOEs. From the perspective of individual conditions (horizontal), government support and manager's digital capability are critical conditions for the digital transformation of NAOEs, playing a central role in all configurations. From the perspective of each configuration (vertical), in Configuration P1a (Profit × Safe × Manager × Government × Market), excluding the market, technological benefits and technological security serve in an auxiliary capacity. In Configuration P1b (Profit × Safe × Manager × Government × Labor), technological benefits, technological security, and the sense of labor crisis serve an auxiliary function. In Configuration P2 (Profit × Safe × Manager × Learning × Government), technological benefits, technological security, and organizational learning capabilities serve in an auxiliary capacity. In Configuration P3a (Profit × Manager × Government × Market × Labor), excluding the market, technological benefits and the sense of labor crisis serve an auxiliary function. In Configuration P3b (Profit × Manager × Learning × Government × Labor), technological benefits, organizational learning capabilities, and the sense of labor crisis serve an auxiliary function. In response to the complex relationships outlined above, this study will further analyze these five configurations in depth, incorporating case studies.

fsQCA effectively identifies five distinct pathways for digital transformation of NAOEs. Building on the approach of Chen and Sendra (Chen and Tian 2022; Sendra-Pons et al. 2022), the logical characteristics of the five configurations presented in Table 3 are further summarized. Configurations with similar conditions are consolidated, ultimately yielding three models of high degree of digital transformation for NAOEs: technology-driven, technology-organization-driven, and environment-driven.

Technology-driven: NAOEs can leverage digital technologies to precisely monitor and analyze agricultural production conditions, optimize the use of inputs, and enhance the efficiency of resource utilization, which reduces production costs and enhances the quality of agricultural products. For instance, the manager of QQ Farm believes that digital technology can substantially increase income, particularly under adverse environmental conditions, by ensuring both product yield and quality. PP Farm utilizes digital technology to accelerate the ripening of bayberries by 20 days, enhancing their sweetness by 2% compared to traditional bayberries and achieving a price of 240 yuan per kilogram. Furthermore, with the aid of comprehensive and precise data analysis, NAOEs are better equipped to mitigate various risks, such as environmental changes and market fluctuations (Eller et al. 2023). For example, JGZ Cooperative installed digital devices such as automatic film rolling, temperature control sensors, and integrated water and fertilizer systems, enabling remote operation and timely responses to extreme weather conditions. YP Farm analyzes market data through the "Yi Nong Xiao" service platform to guide production decisions and product pricing, thereby reducing the risk of unsold goods. Regarding the security of digital technologies, although they may occasionally experience instability, such disruptions are generally within a controllable range. For instance, the manager of QQ Farm stated that the equipment used in the digital application process rarely malfunctions and is generally manageable. Agricultural operations are also conducted based on temperature and humidity data provided by the digital platform.

Technology-organization-driven: Technological and organizational factors play a crucial role in driving the digital transformation of NAOEs. For certain entities, relying solely on technological factors is insufficient to drive their digital transformation, and organizational factors are equally vital. Digital transformation is a prolonged and intricate process that demands leaders to possess extensive leadership and management skills, identify opportunities and risks in the process, and allocate the necessary resources to achieve these objectives (Salamzadeh et al. 2024). For instance, the manager of XY Cooperative recognized the potential benefits of digital technologies early on and was among the first to apply for and secure approval for digital transformation projects. This resulted in bayberries ripening 15–20 days earlier, with prices increasing by 4–5 times compared to conventional bayberries. XY Cooperative also established a Party branch and regularly organizes training sessions to educate members on bayberry cultivation techniques and the use of digital technologies. Considering the low water pressure on the mountain, the manager of CX Farm has made continuous improvements to address the agricultural needs better. He also promoted

Table 4 Low degree of digital transformation influence factor configuration of NAOEs.

		Low degree of digital transformation				
		P1a	**P1b**	**P2a**	**P2b**	**P3**
Condition variable	Profit	◎	◎	◎		
	Safe	◎	◎			◎
	Manager	◎	◎	◎	◎	◎
	Learning	1			◎	1
	Government	◎	◎	◎	◎	◎
	Market		1		◎	1
	Labor			◎	◎	1
	Raw coverage	0.540	0.570	0.752	0.313	0.175
	Unique coverage	0.0703	0.0224	0.133	0.00644	0.000107
	consistency	0.9845	0.996	0.981	0.980	0.988
Overall solution consistency		0.878				
Overall solution coverage		0.986				

Note 1: "●" and "◎" respectively represent the presence and absence of a condition, while blank spaces indicate that the condition may or may not exist. Core conditions are marked with large "●" and "◎"; edge conditions are marked with small "● " and "◎."
Note 2: Raw coverage indicates the share of results explained by a particular solution. Unique coverage indicates the share of results explained by each condition in the causal configuration.

improved digital technologies to neighboring farmers and partnered with Jiujang College to establish a production, education, and research collaboration base.

Environment-driven: Environmental factors, particularly the sense of labor crisis, play a critical role in driving the digital transformation of NAOEs. With urbanization and industrialization, a large number of rural laborers have migrated to cities. The decline in rural labor often results in increased labor costs, especially during peak agricultural seasons when substantial manual labor is needed. Digital technologies offer a comparative advantage in performing repetitive, labor-intensive tasks, thereby alleviating rural labor shortages to some extent. Additionally, digital equipment typically incurs lower long-term operating costs, which can help alleviate the pressure of rising agricultural labor costs. For instance, the manager of JY Cooperative stated that the workers they currently employ are aged between 60 and 70, and given the expected future decline in available labor, they recognize the need to introduce digital technologies. The manager of YP Farm mentioned that traditional manual spraying requires two workers to spend an entire day completing the task. In contrast, smart spraying equipment can accomplish the same task in just a few minutes with more even results.

Low degree of digital transformation of NAOEs. Table 4 shows the configuration of low-degree digital transformation of NAOEs. The consistency level of each configuration ranges from 0.980 to 1, indicating that each configuration can highly explain the outcome variable. The raw coverage rate is all above 0.175, indicating that each configuration explains over 17.5% of cases. Furthermore, the overall consistency level is 0.878, indicating that the overall configurations can highly explain the outcome variable. The overall coverage rate is 0.986, indicating that the configurations can explain 98.6% of cases. The fsQCA3.5 software also reports complex solutions, parsimonious solutions, and intermediate solutions. This paper primarily reports intermediate solutions supplemented by parsimonious solutions (Fiss 2011).

From the perspective of individual conditions (horizontal), a lack of manager's digital capability and government support can lead to a low level of digital transformation of NAOEs. From the perspective of each configuration (vertical), in Configuration P1a (Profit × Safe × Learning × Manager × Government), the absence of technological benefits and security, regardless of market conditions or labor crises, will lead to a low level of digital transformation. In Configuration P1b (Profit × Safe × Manager × Government × Market), the absence of technological benefits and security, regardless of organizational learning ability or labor crises, will lead to a low level of digital transformation. In Configuration P2a (Profit × Manager × Government × Labor), the absence of technological benefits and labor crises, regardless of organizational learning, market competition, or technological security, will lead to a low level of digital transformation. In Configuration P2b (Manager × Learning × Government × Market × Labor), the absence of organizational learning, market competition, and labor crises, regardless of technological benefits and security, will lead to a low level of digital transformation. In Configuration P3 (Safe × Manager × Learning × Government × Market × Labor), the presence of organizational learning, market competition, and labor crises, regardless of technological benefits, will influence the low level of digital transformation. Based on this, this study further identifies three factors influencing the low level of digital transformation for NAOEs: low technological factors, low organizational-environmental factors, and high environmental factors.

Low technology factors: Low technological factors are the dominant factors leading to low-level digital transformation of NAOEs. In practical terms, agricultural production faces many uncertainties. As risk-averse agricultural operators, they are generally unwilling to adopt uncertain technologies unless these technologies can bring relatively certain production benefits. Some agricultural operators are concerned about the security and accuracy of digital technologies and are hesitant to adopt them. For example, the head of XX Cooperative said, "Although soil sensors can monitor temperature and humidity, different grape varieties have different requirements, which require experience rather than digital technology. Advanced technologies are not always better. If digital devices break down and are not repaired in time, it could cause significant losses to the grapes."

Low organizational-environmental factors: Low organizational-environmental factors can also lead to low-level digital transformation of NAOEs. For example, TT Farm has a relatively small planting scale and does not need to hire too many workers. With stable sales channels, the farm does not intend to adopt digital technologies. Similarly, JS Farm also has a small operating scale and only hires temporary workers during the busiest season. With good sales performance, the farm is currently planning to enhance prices and build a brand by cultivating and promoting "taste tomatoes" without planning to choose digital transformation.

High environmental factor: Studies have proven that the expected sales price and income of agricultural products are the primary factors influencing farmers' adoption of digital technologies (He 2014; Wang 2013). In reality, the agricultural product market is unpredictable. Agricultural operators need to fully consider market changes to ensure that investing in digital technologies can bring high returns. Moreover, there often exists a "lemon market" where high-quality products cannot achieve high premiums, leading to NAOEs being afraid to take risks and adopt digital technology. "The prerequisite for digital transformation is that the products need to be sold," said the person responsible for agriculture from CS Town in Wenzhou. "Without sales assurance, many agricultural operators are afraid to adopt digital technologies." According to the case studies, many NAOEs do not easily choose digital transformation due to the lack of stable sales channels.

Robustness test. This paper examines the robustness of the configuration analysis results by increasing the consistency level. Referring to Du's practice (Du 2017), the consistency level is raised from 0.8 to 0.9 to observe whether there are any changes in the number of configuration paths and configuration path parameters. The test found that after increasing the consistency level, the number of configuration paths remains the same, and there are no significant changes in the configuration path parameters. This indicates that the above-mentioned configuration path analysis is robust.

Further discussion

Both government support and manager's digital capability are necessary conditions for digital transformation of NAOEs. Furthermore, when considering the sufficient conditions, regardless of whether it is high-level or low-level digital transformation, the combination of influencing factors always includes government support and manager's digital capability as the core conditions. This illustrates that regardless of the specific configuration, the digital transformation of NAOEs always requires the two conditions.

The government plays a significant role in digital transformation of NAOEs. On the one hand, agricultural digital transformation requires substantial investment, which is unlikely to be solely financed by NAOEs. As the leader of NT Cooperative mentioned, "The cost of digital equipment is high, and we will not purchase without government subsidies." On the other hand, agricultural digital technology faces risks and uncertainties. According to prospect theory, farmers, as loss avoiders, would opt for current certain gains through traditional production methods. Hence, most NAOEs are not inclined to take the risk of choosing digital transformation easily. As the head of the Agricultural and Rural Bureau of Wenling City stated, "The government needs to do a good job in the application and demonstration of digital technologies, allowing NAOEs to gain a deeper understanding of the potential risks and benefits. Even failed practices can help farmers avoid pitfalls." From a policy perspective, a series of policy measures have been introduced from the central to the local level to encourage the digital transformation of agriculture. For example, in 2019, the "Outline of Rural Digital Development Strategy" proposed accelerating the construction of rural information infrastructure, developing the digital economy in rural areas, and promoting the digital transformation of agriculture. The "Digital Agriculture and Rural Development Plan (2019–2025)" and the "Digital Rural Development Action Plan (2022–2025)" further clarified the focus and direction of agricultural digitization. Local governments actively implement the central strategy for rural digitalization. For instance, in 2020, Guangdong Province introduced the "Guangdong Digital Agriculture and Rural Development Action Plan (2020–2025)", which outlined 11 key tasks, including establishing the Guangdong Digital Agriculture Development Alliance and organizing the Greater Bay Area Digital Agriculture Cooperation Summit. In 2021, Zhejiang Province issued the "Zhejiang Province Rural Digital Construction 14th Five-Year Plan", focusing on rural industrial digitization from five aspects, including strengthening digital technology applications and promoting agricultural production digitization. From specific practices, the majority of NAOEs have received a certain proportion of subsidies from the government. For example, WM Farm invested 1 million yuan to construct a 3-acre digital greenhouse, with 70% of the funding subsidized by the government. XY Cooperative invested 85,000 yuan to build a 1-acre digital greenhouse, with a 60% government subsidy. CD Cooperative invested 1.2 million yuan to construct a 45-acre digital greenhouse and received a 30%–40% subsidy from the Zhejiang Agricultural Technology Promotion Fund. Government support effectively reduced the financial pressure on NAOEs and accelerated their pace of digital transformation.

From the perspective of manager's digital capability, managers with strong digital skills enable NAOEs to quickly adapt to the evolving external environment, promptly seize and assess opportunities and risks, and secure sustainable competitive advantages (Petani et al. 2023). Dynamic capabilities theory emphasizes how organizations build and sustain a competitive advantage by identifying opportunities, perceiving risks, and allocating resources in uncertain environments. Digital transformation of NAOEs can be viewed as a process of building and refining a series of dynamic capabilities. Specifically, when facing technological changes, NAOEs must be keenly aware of the opportunities digital technology offers and promptly seize policy dividends. Case studies show that farmer cooperatives successfully achieving digital transformation often received government subsidies. Simultaneously, cooperatives must clearly understand potential risks in current agricultural operations and take timely action to mitigate them. For instance, in response to rural labor shortages, managers may opt for digital production technologies that effectively replace labor. After identifying opportunities and risks, NAOEs integrate internal and external resources to maximize benefits for all parties through a gradual strategy. The gradual strategy facilitates risk diversification and eases the learning curve challenges. According to case studies, NAOEs first select the most suitable digital equipment based on their needs, conduct trials on small-scale plots, and, once familiar with the technology, gradually scale up and ultimately select the most effective digital tools. Additionally, due to differences in resource endowments among agricultural operators, some of them possess significant capital, marketing capabilities, or social networks, often termed "rural elites" (Liang and Hendrikse 2013). During digital transformation, farmers with an innovative spirit are more likely to seek new market opportunities, which can lead to "elite capture"(Clegg 2006). Local governments tend to look for "rural elites" to carry out agricultural digital transformation, thereby forming a "capture of elites." According to the case studies, all the operators who successfully achieved digital transformation are local rural elites with a certain degree of innovation or political identity. They are able to seize digital development opportunities in a timely manner and allocate resources based on their circumstances to mitigate risks.

From an international perspective, digital transformation of agriculture is heavily reliant on policy support and manager's digital capability (Dana et al. 2022). On the one hand, governments worldwide offer substantial support through policies, financial subsidies, and the development of digital infrastructure. For instance, the Dutch government has launched the "Smart

Agriculture Program" and provided financial subsidies to assist agricultural operators in adopting advanced sensor technologies and big data analytics, thereby enhancing crop yields and resource use efficiency. Through the "National Digital Agriculture Strategy," the Israeli government supports agricultural enterprises in developing automated irrigation systems and precision fertilization technologies, facilitating the adoption of cutting-edge agricultural technologies. On the other hand, manager's digital capability is critical to driving the successful transformation. Managers must possess not only digital literacy but also the capacity to integrate these technologies deeply into all facets of agricultural production. For instance, John Deere in the United States has advanced the use of IoT, AI, and big data in agricultural production by enhancing digital training. Similarly, Sundrop Farms in Australia successfully executed the digital transformation of greenhouse agriculture through the application of digital technologies. Consequently, the success of digital transformation frequently results from the collaborative efforts of governments and agricultural operators. In the context of China's agricultural digital transformation, government support and manager's digital capability are indispensable. As digital technology levels improve and devices become more widespread, digital transformation will permeate "ordinary households," gradually transitioning from "elite capture" to "mass capture." Meanwhile, agricultural operators will decide whether to digitally transform based on their actual development needs, with the market becoming a pivotal force driving agricultural digital transformation.

The conclusions of this study align with existing research in several respects, particularly regarding the role of government support and manager's digital capability in driving digital transformation of NAOEs. Existing studies generally agree that governments can provide the external conditions necessary for digital transformation through financial support, technical incentives, and other mechanisms, and manager's digital capability directly influences the adoption and implementation of digital technologies. Building on this, this study further examines the configurational factors of digital transformation at various levels. Regardless of whether the digital transformation is at a high or low level, government support and manager's digital capability remain central factors driving the transformation. Particularly in the case of low-level digital transformation, the absence of adequate government support and manager's digital capability often impedes progress. This study unveils the complex and multifaceted relationships underlying different levels of digital transformation of NAOEs, providing both a theoretical foundation and practical insights for advancing agricultural modernization and refining the supporting policy framework.

Conclusion and policy recommendations

This study employs the fsQCA method to analyze the factors influencing high-level and low-level digital transformation of NAOEs from a configurational perspective, using data from 40 surveyed entities. The main conclusions are as follows: The digital transformation of NAOEs is not driven by a single factor but is the result of the interaction of multiple factors. Government support and manager's digital capability are necessary conditions for achieving digital transformation. Government support provides external drivers, enabling them to overcome barriers related to funding, technology, and information. Manager's digital capability determines whether the organization can fully leverage technological innovations and management tools, thereby adapting quickly to changes in the external environment and achieving efficient transformation. High-level digital transformation can be categorized into three pathways: technology-driven, technology-organization-driven, and environment-driven. In contrast, low technological factors, low technology-organization alignment, and high environmental factors result to low-level digital transformation. Promoting digital transformation of NAOEs necessitates a comprehensive consideration of various factors, with emphasis on government support and t manager's digital capability.

Based on this, the study proposes the following three policy recommendations:

First, strengthen technological support and improve digital infrastructure construction. On the one hand, the government, industry associations, and universities can take the lead in establishing industry-university-research cooperation platforms, setting up collaborative projects based on the specific needs of agricultural cooperatives' digital transformation, and ensuring that research outcomes truly meet the practical needs of agricultural production. On the other hand, accelerating the construction of information infrastructure to narrow the digital divide between urban and rural areas (Saeedikiya et al. 2024a, 2024b; Wu et al. 2023). At the same time, the government should strengthen its supervision and guidance of agricultural digital transformation, actively offering digital skills training courses for NAOEs at different levels to ensure the sustainability of agricultural digital development.

Second, improve the policy support system and promote the integration of digital technology into NAOEs. NAOEs should focus on the integration of technology adoption and organizational structure optimization during their digital transformation. To this end, the government should introduce supporting policies such as talent introduction and management model innovation to help agricultural entities achieve dual improvements in management mechanisms and technological applications. Meanwhile, the government can encourage agricultural enterprises to undergo organizational reforms through tax incentives, financing support, and other means, driving the organic integration of digital technology with modern agricultural management systems.

Third, cultivate the digital capabilities of agricultural operators and improve the rural digital talent system. Enhancing digital capabilities is crucial for driving agricultural digital transformation. Therefore, it is necessary to encourage farmers to participate actively in digital agriculture-related training and practices. This can be done through both online and offline methods, such as TikTok live streaming and on-site explanations, to conduct digital technology training. At the same time, talent introduction policies should be improved, attracting talent to rural areas through housing subsidies, tax incentives, and other means, leveraging the role of talent as role models and guides.

Theoretically, this paper provides a meaningful exploration of the multi-path mechanisms underlying digital transformation of NAOEs. Practically, based on the analytical results, this paper offers policy recommendations to promote the digital transformation of NAOEs, emphasizing the importance of collaboration between government support and agricultural operating entities. However, this study also has certain limitations. Firstly, in terms of variable selection, although this study constructs antecedent conditions based on the TOE framework, digital transformation is a multidimensional and dynamic process. As such, some influential factors may have been overlooked. Future research could consider incorporating other theoretical frameworks, such as behavioral economics and institutional economics, to broaden the variable perspective and more comprehensively identify the influencing factors. Secondly, the data used in this study were drawn from Zhejiang Province, a region with a relatively high level of agricultural digitalization, which limited the representativeness of the samples. Significant differences in economic development, social structures, and natural conditions exist across eastern, central, and western China, leading to varying characteristics in the paths and outcomes of digital transformation. Future studies could consider expanding the sample coverage to include data from different regions and various types of new agricultural operating entities. Comparative studies can be conducted to further explore how factors such as policy incentives, technological innovation, and managerial capabilities function under diverse regional contexts, and how tailored support policies can be formulated to promote digital transformation accordingly.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Notes

1 For example, in 2020, the Ministry of Agriculture and Rural Affairs issued the "Digital Agriculture and Rural Development Plan (2019–2025)"; in 2021, the State Council issued the "14th Five-Year Plan for Advancing Agricultural and Rural Modernization"; and in 2022, the Office of the Central Cyberspace Affairs Commission and others released the "Key Points of Rural Digital Development Work in 2022".

2 Data Source: "Digital Agriculture and Rural Development Plan (2019–2025)" issued by the Ministry of Agriculture and Rural Affairs and the Office of the Central Cyberspace Affairs Commission in 2021.

3 Data Source: Report on the Promotion of Organic Integration between Small-scale Farmers and Modern Agriculture by Accelerating the Construction of a New Agricultural Operating System issued by the State Council in December 2021.

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Author contributions
YZ performed data analysis, drawing all the legends and tables. YZ and FL wrote the main manuscript text. MT and FL conceptualized, reviewed, and edited the article, and provided financial support. FL supervised and verified the article. YZ and MT revised the paper according to the reviewers' comments and responded.

Competing interests
The authors declare no competing interests.

Ethical approval
This study was approved by the Ethics Committee of Business School of Wenzhou University on 21 June 2023(approval number: WZU20230621006). This study is part of a more extensive study on the digital transformation of new agricultural operating entities. Ethical approval covers all aspects of the research, including questionnaire surveys and in-depth interviews, data analysis, and the publication of research findings. This committee reported on the appropriateness of the procedure followed for the study and all research procedures were conducted following the Declaration of Helsinki and its later amendments.

Informed consent
All participants were farmers of legal age and accepted voluntary participation. Before the survey, all respondents received comprehensive information detailing the study's aims and objectives. Anonymity was rigorously guaranteed to ensure that all collected data would be used solely for academic research purposes and that participation involved no foreseeable risks or ethical compromises. In addition, participants were clearly advised before their engagement that their participation was entirely voluntary and that they possessed the unequivocal right to withdraw from the survey at any point without consequence or prejudice. The researchers would inform the participants that submitting the questionnaire would be considered as their consent. The questionnaires submitted by the farmers are regarded as a record and evidence of their informed consent. The questionnaire was administered between August to November 2023.

Additional information
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