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How to promote the intention of grain enterprises to adopt smart granary technology—an fsQCA analysis based on the TOE framework

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Introduction: The adoption of smart granary systems is critical for safeguarding national grain security, yet the determinants of adoption intention in grain enterprises remain insufficiently understood.
Methods: Based on the Technology-Organization-Environment (TOE) framework, this study develops a configurational model to investigate how six antecedents, which are organizational compatibility, technological fit, resource readiness, competitive pressure, operational risk, and privacy risk, interactively relate to adoption intentions. Using fuzzy-set Qualitative Comparative Analysis (fsQCA) on cross sectional survey data from 46 middle and senior managers of grain enterprises in Fuzhou, China.
Results: (1) Adoption intention stems from combinatorial causality rather than isolated factors, with no single necessary condition identified; (2) Two dominant pathways drive high adoption intention: "technology fit support driven path" (four pathways) and "resource readiness support driven path" (five pathways); (3) Privacy risk emerges as a significant association factor in both pathways.
Discussion: The results uncover the key factors and driving pathways associated with the adoption of smart grain storage technology in grain enterprises, providing theoretical insights and practical references for promoting the widespread application of smart grain storage systems.

KEYWORDS
grain enterprises, smart granary, technology adoption, TOE framework, fsQCA

1 Introduction

Grain security constitutes a critical component of national security strategy, where effective grain storage systems play a pivotal role in mitigating post-harvest losses, stabilizing market supplies, and ensuring nutritional accessibility (Xue et al., 2024). In recent years, however, with the continuous expansion of grain reserve scales, the limitations of traditional grain storage management models have become increasingly apparent, manifesting in issues such as inefficient management and challenges in supervision (Su et al., 2012). Globally, approximately 13% of cereal production is lost during storage stages, with developing country facing disproportionately higher rates due to inadequate infrastructure (Wang et al., 2024). In China, grain storage losses account for 4.2% of annual production, translating to 35 million metric tons, which equivalent to the annual consumption of a province (Jianyao et al., 2023), which may affect the stability of national food supply chains. Consequently, optimizing the safety management of grain storage in grain enterprises has emerged as an imperative measure to ensure national grain security, as well as a significant step toward advancing the modernization of grain storage systems.

Smart granary systems is an emerging technology developed in the context of increasing demands for grain reserve security, which integrate IoT-enabled condition monitoring, cloud computing, and blockchain-based traceability, enable intelligent monitoring, precise management, and efficient scheduling of grain reserves, these systems represent a key driver in the modernization of grain warehouses (Quellhorst et al., 2020; Velesaca et al., 2021; Gitonga and De Groote, 2015). Despite these advantages, adoption rates among grain enterprises remain heterogeneous, ranging from 81% in economically advanced regions to 54% in traditional agricultural zones. Accelerating the informatization of the grain industry is not only a critical measure for modernizing grain reserve management but also an essential requirement for deepening the reform and development of the grain sector (Tireuov et al., 2018). Therefore, promoting the widespread adoption of smart granary technology in grain enterprises has become a critical issue to be addressed in the field of grain management.

Existing research has primarily focused on the technological optimization of smart grain storage (Sun and Zhu, 2013) or isolated policy analyses (Omotilewa et al., 2019), which exhibit several limitations. Firstly, most studies emphasize improvements in hardware and software, while overlooking the practical challenges of promoting smart grain storage adoption (Liu et al., 2018). Secondly, although the factors associated with the adoption intention of smart grain storage can be categorized into external and internal dimensions, existing studies predominantly rely on regression analysis methods, focusing on the net effects of individual factors while neglecting the synergistic interactions among multiple factors (Li et al., 2022). To address these research gaps, this study adopts the Technology-Organization-Environment (hereafter referred to as TOE) framework as a theoretical lens to systematically explore the synergistic effects of various factors associated with the adoption of smart grain storage systems. Additionally, fuzzy-set Qualitative Comparative Analysis (hereafter referred to as fsQCA) method is employed to identify the key drivers and conditional configurations that lead to the acceptance of smart grain storage technologies by grain enterprises.

In this context, conducting an in-depth study on the factors influencing grain enterprises' intention to adopt smart granary technology and constructing an effective application mechanism holds significant theoretical and practical value. To this end, this study covers all 12 grain storage enterprises in Fuzhou City, employing a stratified sampling method to select 46 middle and senior managers as survey respondents. Based on the characteristics of smart granary technology, the study expands the TOE theoretical framework and applies the fsQCA method to explore the associate of technological, organizational, environmental, and risk-related dimensions on the adoption of smart granary technology. By analyzing these influencing factors and proposing corresponding strategies, the study aims to facilitate the modernization and transformation of grain enterprises in Fuzhou, thereby promoting the widespread adoption of smart granary technology. On one hand, this research enriches the study of granary technology adoption and the TOE theoretical framework, while on the other, it innovatively integrates both TOE and fsQCA into the study of smart granaries, providing a key case for in-depth research on agricultural technology diffusion.

2 Theoretical foundations and model construction

2.1 The TOE framework theory

Tornatzky and Fleischer developed the TOE framework, which posits that three dimensions (technological, organizational, and environmental) influence the process of adopting and implementing technological innovations within organizations (Tornatzky and Fleischer, 1990). As a systematic analytical framework for technology application, the TOE framework has been widely employed to explore the mechanisms underlying the effects of technology across multilevel application scenarios. It has been extensively applied in various research fields, including enterprise adoption of new technologies, government e-service implementation, and enterprise resource planning (Abed, 2020; Junior et al., 2019; Qalati et al., 2021). Notably, the TOE framework does not specify the exact explanatory variables for the three dimensions, allowing scholars to adapt it flexibly based on the specific context, research questions, and scenarios under investigation (Malik et al., 2021).

Amidst the accelerated digital transformation of grain storage systems, the technology adoption decisions of grain enterprises are influenced by multifaceted factors (Mwinuka and Hyera, 2022). While traditional causal analyses attempt to explain the nonlinear mechanisms driving the adoption of smart grain storage systems, they often fail to account for the synergistic interactions among technological perceptions, resource endowments, and market dynamics (Omotilewa et al., 2019). Therefore, this study applies the TOE framework to investigate the adoption intentions of grain enterprises toward intelligent storage systems, driven by two pivotal rationales.

The TOE framework's tripartite structure aligns with three critical dimensions of applications in grain reserve systems. Technologically, it evaluates the maturity and compatibility of innovations such as IoT-enabled sensing devices and big data analytics platforms; organizationally, it incorporates endogenous conditions like capital reserves, and technological compatibility capacity; environmentally, it accounts for external drivers including industry competition. This systematic taxonomy facilitates the deconstruction of complex decision-making processes. Besides, the special nature of grain enterprises, as policy-driven quasi-market entities, amplifies the framework's explanatory utility. Their adoption decisions intertwine techno-economic rationality with dual institutional constraints: compliance with state-owned asset management protocols and fulfillment of food security mandates. For instance, during technology evaluation, decision-makers must reconcile technical adaptability (technological dimension) with fiscal fund utilization norms (organizational dimension) and external operational risks in smart depot implementation (environmental dimension), a multidimensional interplay effectively deciphered through the TOE framework's configurational perspective.

2.2 Construction of the framework

In this study, we investigate the factors associated with the adoption of smart grain storage technology by grain enterprises, which is shaped by the complex interplay of internal technological factors, organizational dynamics, and external environmental conditions. These determinants do not operate in isolation; rather, they interact and converge to impact the decision-making processes of grain enterprises. Given that the construction and operation of smart grain storage involve the deep integration of advanced technologies such as the IoT and cloud computing, its complexity extends beyond the technical level to include potential risks induced by these technologies. Smart grain storage relies on the Internet of Things (IoT) architecture to achieve real-time monitoring and data interaction. The underlying technological logic of the system introduces inherent vulnerabilities, making it susceptible to risks such as network attacks and system stability flaws (Kundu and Pal, 2022). In addition, smart grain storage systems need to upload operational data, such as inventory levels and quality inspection reports, to vendor cloud platforms, which may lead to data governance conflicts, including the risk of commercial confidentiality breaches and compliance issues (Zhao and Min, 2023). Given the critical role of security in the grain industry, we also found that these risks were frequently mentioned during the survey. Due to the importance and specificity of the risk dimension in smart grain storage, it impacts the technology, organizational, and environmental dimensions within the TOE framework. Nagy et al. (2025) point out that agricultural SMEs face unique challenges due to factors such as weather, climate change, and commodity price fluctuations. The implementation of the TOE (technology, organization, and environment) framework in smart agriculture faces multiple challenges. Stjepić et al. (2021) argue that internal risks related to the organizational dimension and external risks related to the environmental dimension should be given priority consideration. Therefore, this study innovatively incorporates a risk dimension into the traditional TOE framework to provide a more comprehensive analysis. The technology dimension comprises two influencing factors: organizational compatibility and technology fit. The organizational and environmental dimensions are represented by resource readiness and competitive pressure, respectively. Additionally, the risk dimension includes two influencing factors: operational risk and privacy risk. These factors constitute the conditional variables of the analytical framework, while the intention to adopt serves as the outcome variable. For the specific relationship, see Supplementary Figure 1.

2.2.1 Technical conditions

Organizational compatibility is one of the critical factors influencing technology adoption, as evidenced by the extent to which a new technology matches the existing values, historical practices, and current needs of potential adopters (Rogers, 2003). As such, organizational compatibility serves as a significant determinant of innovation adoption. If smart granary technology is highly compatible with the existing culture, values, and work practices of grain enterprises (Dedrick and West, 2004; Ifinedo, 2011), it can mitigate organizational culture conflicts and avoid the need for extensive work process restructuring. This, in turn, reduces the additional effort and costs associated with technology implementation, thereby strengthening the willingness of grain enterprises to adopt this technology (Vichinrojjarul, 2022).

Technology fit originates from the Task-Technology Fit (TTF) theory, which refers to the degree of alignment between new technologies and an organization's existing work tasks. This concept emphasizes whether the functional characteristics of a technology can effectively support the organization's task requirements (Goodhue et al., 2000; Ramamurthy et al., 1999). When the functionality of a new technology fails to meet the organization's task needs or significantly exceeds its actual requirements, the degree of task-technology fit is low. Conversely, if the functionality of the new technology aligns precisely with the organization's work tasks, the degree of task-technology fit is high (Kim et al., 2010). This perspective examines technology adoption from the angle of technical specifications and performance, with the complexity of technology being a major constraint on the adoption of IoT and other smart warehouse technologies (Li et al., 2024). Meanwhile, the adoption of smart technologies also needs to align with a company's business model. When digital technologies are incompatible with existing device protocols, it creates data fragmentation and reduces the perceived utility of the technology (Chen and Zhang, 2022). Technology compatibility is crucial for the adoption and diffusion of technologies among users (Rezaei et al., 2020; Geng et al., 2024). If the technology is not compatible with users' existing values, needs, and experiences, the adoption of smart technologies may be limited (Oyibo and Morita, 2022).

Therefore, if smart granary technology demonstrates a high degree of task-technology fit with the work tasks of grain enterprises, such as enabling intelligent monitoring, precise management, and efficient scheduling of grain storage (Lutz and Coradi, 2022), the intention of grain enterprises to adopt this technology will be strengthened.

2.2.2 Organizational conditions

Resource readiness refers to the financial resources, human resources, and other assets that an organization has prepared for a new technology before introducing it (Zhao et al., 2008). For smart grain silos, financial resources need to cover the procurement costs of the system, installation costs, and subsequent maintenance and upgrade expenditures. Additionally, these financial resources also include government subsidies (Omotilewa et al., 2019; Geng et al., 2024), household income (Maguza-Tembo et al., 2017), agricultural insurance (Li et al., 2022), and any other factors related to capital accumulation. Human resources refer to the availability of technicians at the grain enterprises who are skilled in operating and maintaining the smart grain silo system (Grandon and Pearson, 2004; Mehrtens et al., 2001; Yu and Tao, 2009; Chen et al., 2025). Furthermore, the completeness of infrastructure such as IoT sensors and communication networks is a physical prerequisite for the implementation of technology (DeBoer and Erickson, 2019).

Financial allocation plays a fundamental material support role, and the cost of technology has a significant negative impact on the adoption of IoT technologies. Government subsidies can enhance adoption willingness by easing financial constraints (Yan et al., 2013; Vasavi et al., 2025). Especially in the grain industry, where profit margins are limited, the high initial costs for both software and hardware have become major barriers to technology adoption (Yan et al., 2013; Zhao et al., 2024). Moreover, the perceptions and attitudes of technology users play an extremely important intermediary role in the actual usage of the technology (Chuang et al., 2020). Thus, resource readiness includes the completeness of elements such as funding, talent, and infrastructure prepared for the technology's application. Its level directly determines the feasibility and sustainability of technology adoption.

2.2.3 Environmental conditions

It is often assumed that competition in an industry will have a positive impact on the adoption of new technology, with competitive pressure being the pressure felt by firms competing in the market (Redmond, 2013). This would be even more evident if the new technology directly affects competition. Factors such as uncertainty in the market environment, competitors, and industry trends can put pressure on the development of grain enterprises (Premkumar and Roberts, 1999). Adoption of smart grain warehouse technology can enhance customer supervision and improve the efficiency of grain import and export; grain is a bulk commodity with high trading volume, and once it loses the favor of customers, it will lose larger profits (Wright, 2011; Kumar and Kalita, 2017). Therefore, to gain an advantage in the competitive grain industry, grain enterprises need to change the traditional way of stockpiling and introduce smart granary technology, which will become an important way to enhance the competitiveness of grain enterprises and gain growth space.

2.2.4 Risk conditions

Risk constitutes a critical determinant in agricultural technology adoption due to three primary dimensions: First, climate risk is the primary risk faced by agricultural enterprises, with climate change represents a serious threat to agricultural technology adoption (Senyolo et al., 2021), while risk management strategy selection directly impacts farm production costs and resource allocation (Vigani and Kathage, 2019). Second, corporate governance and operational risks substantially influence agricultural operations (Ahmad et al., 2024; Barmuta and Tuguz, 2021), particularly in relation to innovative approaches to production risk management and infrastructure development, as highlighted by Hryvkivska et al. (2024). Finally, financial risk remains the most extensively examined category, with da Costa (2024) emphasizing that "effective financial risk management in agriculture requires a multifaceted approach that integrates mitigation strategies for various types of risks."

This study categorizes risk into operational risks and privacy risks. Operational risks refer to technical failures, cybersecurity threats, and system stability issues that smart granary technologies may face during actual use (Mu et al., 2024; Botschner et al., 2024). Since smart granary technology is highly dependent on the Internet, IoT, and electronic information processing technologies, it may face a variety of risks during its operation, such as malware attacks, data leakage, network outages, or system crashes (Lydia et al., 2022; Smith et al., 2011). These risks may not only affect the normal operation of smart grain depots, but also lead to the loss or tampering of grain storage data, which in turn poses a serious threat to the operational security and management efficiency of grain enterprises. Therefore, this uncertainty will affect the intention of grain enterprises to adopt smart granary technology. Privacy risk is the concern about the possibility of leakage of personal or organizational sensitive data when businesses adopt new technologies (Amiri-Zarandi et al., 2022). As an Internet and IoT-based service, the operation of smart grain warehouse technology requires uploading grain storage data and management information from grain enterprises to the provider's cloud-based platform for processing and storage (Agarwal et al., 2024; Lydia et al., 2022). Therefore, for grain enterprises, this data uploading and sharing mechanism may lead to privacy leakage risks, such as data being accessed, misused, or leaked by unauthorized third parties, which also affects their intention to adopt the technology.

3 Research method and data

3.1 Research method

This paper adopts fsQCA for the following reasons: first, qualitative comparative analysis requires that the case itself includes a cause structure in which multiple factors interact, i.e., it is caused by more than one cause, and there must be a grounded theory to support the case collusion (Ragin, 2014). The multiple cause variables selected in this paper are categorized according to the TOE model, and a certain number of research theories on the interrelationships between the antecedents and the correlation between the antecedents and the outcome variables have been formed in the academic community, so there exists a sufficient theoretical basis (Zhang and Du, 2019); Secondly, it is written in the article of Teng (2023) that the method can analyze small and medium-sized samples (10 or 15–50), and at the same time, the ideal number of conditions is between 4 and 7. Therefore, in this paper, 6 cause variables and 46 case samples are selected, which meets the applicable requirements; thirdly, at present, QCA is divided into three analysis methods according to the type of variables: csQCA (clear set qualitative comparative analysis), mvQCA (multi-valued set qualitative comparative analysis), and fsQCA (fuzzy set qualitative comparative analysis), and mvQCA and csQCA are suitable for dealing with category problems only, whereas fsQCA not only can deal with category problems, but also problems with degree changes and problems with partial affiliation, i.e., cases have an affiliation score between 0 and 1.

3.2 Data collection

This study adopts the questionnaire research method for data collection, the questionnaire adopts the proven and mature scale as the basis, all the variables are based on the references of the existing literature, and at the same time, according to the characteristics of the grain enterprises and the smart granary. Smart grain warehouse technology requires the integration of automation equipment, data collection technologies, and management systems, becoming a more flexible automated warehouse (Ellithy et al., 2024). The corresponding improvement is made, and the expressions of the original items are improved to better suit the purpose of this study. For example, "The use of cloud computing is compatible with your company's corporate culture and value system" was changed to "Whether the use of smart granary technology is in line with the company's positioning and development strategy," and "The company has the necessary in-house resources for the implementation of cloud computing" was changed to "The company has the necessary resources for the implementation of cloud computing." Resources" was changed to 'The company has sufficient funds to purchase, use and maintain the smart granary technology'. A Likert scale was used to measure the variables in this paper for later analysis of fsQCA. Due to the fact that the distinction between the three levels of the Likert scale is slightly smaller; the seven levels are slightly more complex. In the end, this paper adopted a five-level Likert scale, in which the answers to each question are categorized into 1–5 levels, with "1" meaning "strongly disagree," "5" meaning "strongly agree," and "5" meaning "strongly agree." "For items that are precedent variables, the higher the score, the greater the adequacy of the results." For items that are outcome variables, the higher the score, the more likely it is that the technology will be adopted.

In this study, the samples selected for this study are from Fuzhou, a coastal city in southeastern China, based on the following two considerations: First, its climate composition; second, its promotional value. Fuzhou is located on the southeastern coast and has a subtropical monsoon climate, with an average annual temperature ranging from 18 °C to 26 °C and an average annual humidity of 77%. Under normal conditions, grain stored in such an environment is susceptible to damage from pests, mites, and microorganisms (Lin and Chen, 2020). Moreover, Fuzhou holds a unique and significant position in China's overall grain reserves and is one of the national-level comprehensive emergency security bases. Therefore, the application of smart grain warehouse technology in Fuzhou is particularly crucial and holds great potential for broader promotion. Additionally, Fuzhou has already laid a solid foundation for the technology, having achieved the first-ever "visualization of grain storage ecology" in a provincial-level grain depot. Fuzhou has a total of 12 grain enterprises, and our sample covers all of them. Within these 12 enterprises, we conducted stratified sampling, selecting middle and senior managers as survey subjects. This is because the adoption of smart grain warehouse technology is primarily a decision made by middle and senior management, while frontline staff mainly operate the machines and do not play a role in selecting the technology. Among these 12 enterprises, we used stratified sampling to select 46 final survey samples from department managers and senior managers. We then used a questionnaire to gather their views on the adoption of smart grain warehouse technology. All participants participated in this survey voluntarily and anonymously, and informed consent was obtained before participation. The scores of each condition variable were averaged by summing the scores of the corresponding questions; the three measurement questions of the outcome variable were interchangeable. The scales are shown in Supplementary Table 1.

A total of 54 questionnaires were distributed to middle and senior managers of grain enterprises in Fuzhou City, with 49 returned (response rate: 90.7%). To ensure data validity, we implemented a two-tier screening protocol consistent with survey methodology standards. First, questionnaires exhibiting substantial incompleteness (>20% missing responses) were excluded ($n = 3$). Second, to address potential response bias, additional questionnaires showing patterned responses—defined as identical answers across all Likert-scale items—were removed ($n = 3$). Consequently, 46 valid questionnaires were retained for analysis, representing an effective response rate of 93.9%. This rigorous screening aligns with established data quality control practices in organizational research (Podsakoff et al., 2003; Saunders et al., 2018). The 46 questionnaires of the respondents can be briefly sorted out the following situation. Among the valid samples, there are 35 males and 11 females, accounting for 76.08 and 23.91% of the total sample, respectively. The age of the respondents is mostly concentrated in 46–55 years old, accounting for 67.39% of the total number of researchers, indicating that the middle and senior staff are basically middle-aged people, and there are more male managers. Educational background: 54.38% are undergraduates and 45.62% are junior colleges or below. Nine of the respondents' companies have used the smart granary technology, and 37 have not.

3.3 Tests of reliability and validity

The study used SPSS 25.0 and fsQCA 3.0 for data analysis. SPSS 25.0 was used to calculate the normal distribution of the instrument, descriptive statistics, and reliability and validity tests. The software fsQCA 3.0 was used to calibrate the questionnaire data, analyze the necessary conditions, construct truth tables and configure the analysis, and model the presence of results (high satisfaction) and the absence of results (non-high satisfaction). Tests of reliability and validity of data, normality of distribution and calibration of questionnaire data were preprocessing forms of fsQCA standardized analysis.

In the reliability test, the total Cronbach's Alpha value of the questionnaire is 0.806, usually the Cronbach's Alpha coefficient value of the total scale is greater than 0.8 is excellent, which also indicates that the data base of this study has good internal consistency. The KMO value is 0.611, and the significance < 0.001, which indicates that the results of the questionnaire have authenticity and accuracy. In conclusion, the questionnaire passed the reliability test and can be used for the next data analysis.

3.4 Data calibration

Calibrating and converting data into sets is a prerequisite for analysis and research using the fsQCA method. The questionnaire of this study utilized a five-point Likert scale, which was used as the basis for data calibration. Following established research conventions (Rihoux and Ragin, 2009; Fiss, 2011; Greckhamer and Mossholder, 2011; Misangyi and Acharya, 2014), this study employs direct calibration methods using logistic functions to distribute raw data across three qualitative anchors: 1 (full membership), 0.5 (crossover point), and 0 (full non-membership) (Ragin, 2008), an approach widely adopted in QCA studies globally (Greckhamer, 2011; Garcia-Castro and Francoeur, 2016; Greckhamer, 2016; Delmas and Pekovic, 2018; Tan et al., 2019), i.e., calibrated the "Complete non-membership point" to 0.05, the "Intersection point" to 0.5, and the "Complete membership point" to 0.5, and the "very uncertainty" to 0.95, respectively. Was calibrated at 0.05, "uncertain" at 0.5, and "very consistent" at 0.95. The calibration anchors for each variable are shown in Supplementary Table 2.

4 Results

4.1 Necessity analysis

The necessity analysis aims to identify the conditions that are indispensable for the outcome. Following the approach of the founders of fsQCA, a consistency threshold of 0.9 is used as the criterion for determining necessity. When the consistency of a specific condition is greater than or equal to 0.9, that condition can be considered a necessary condition for the outcome. Conversely, when the consistency of a specific condition is less than 0.9, it is not considered a necessary condition for the outcome (Ragin, 2008; Schneider and Wagemann, 2012). This method has been widely used in QCA research papers, such as those by Rihoux and Ragin (2009), Fiss (2011), García-Castro et al. (2020) and Zhang et al. (2020), and so on. Furthermore, Schneider and Wagemann (2012) also suggested that the coverage should exceed 0.5, and we have adopted a dual indicator framework of consistency and coverage for the necessity analysis. The results of the necessity analysis are shown in Supplementary Table 3.

From the table, we can observe that none of the individual antecedent conditions in this study reach or exceed the 0.9 consistency threshold, while the coverage for all conditions is above 0.5. This indicates that there is no single antecedent condition that is absolutely necessary or indispensable for the formation of high adoption intentions for smart grain warehouse technology in grain enterprises. In this case, it is appropriate to conduct fsQCA-based configurational analysis.

4.2 Configuration analysis

The program using fsQCA3.0 produces 3 solutions based on different simplifying assumptions: complex solution (without logical residue), intermediate solution (only logical residuals that are consistent with theoretical and practical knowledge are used), and parsimonious solution (all logical residuals are used regardless of their consistency with theoretical and practical knowledge). In general, intermediate solutions are superior to complex and parsimonious solutions. This is because intermediate solutions achieve a balance between complex and parsimonious solutions in terms of complexity. More importantly, it is the product of theory and experience complementing each other. However, due to the lack of clear theoretical expectations from existing studies about the relationship between the six conditional variables in this paper and the willingness to adopt smart granaries, no explicit counterfactual analysis is made in the software analysis. Following the practice of mainstream research, this paper presents mainly intermediate solutions in the results, supplemented by parsimonious solutions (Schneider and Wagemann, 2006).

Ragin (2014) argues that antecedent conditions for a particular outcome can be categorized into core and non-core elements based on whether or not their presence is necessary. If an antecedent condition appears in both the intermediate and parsimonious solutions, the antecedent condition is considered to be a core element. If it appears only in the intermediate solution but not in the parsimonious solution, it is a non-core element. It can be said that the main difference between core and non-core elements is the closeness of the relationship with a particular outcome. Following Ragin and Fiss' form of symbolic expression, a solid circle (●) indicates the presence of a condition, a forked circle (⊗) indicates the absence of a condition, and a space indicates that the condition may or may not occur. Large circles denote core conditions, i.e., conditions that are present in both intermediate and simple solutions. In contrast, small circles indicate auxiliary conditions, i.e., conditions that exist only in intermediate solutions (Fiss et al., 2014). Based on these usage criteria, the results of the histogram analysis are shown in Supplementary Table 4.

The results show that there are nine different paths to generate intention to adopt smart granary at the middle and senior levels of grain enterprises. An analysis of intermediate and parsimonious solutions identified four paths to Technology Fit-Core Driven and another five paths associated with Resource Readiness-Core Driven (see Supplementary Table 4), highlighting the multifaceted and complex nature of the factors associated with the intention. As shown in Supplementary Table 4, the overall coverage of antecedent conditions of smart granary adoption intention is 0.63, which means that the results obtained in this study explain nearly 63% of the reasons for the adoption intention of smart granary at the middle and senior levels of the grain enterprises, which shows strong explanatory power; the overall consistency level is 91.2%, which indicates that the combination of these antecedent conditions can be considered as a consistent and sufficient configurations associated with the adoption of smart granary at the middle and senior levels of the grain enterprises.

4.2.1 Technology fit support driven

Configuration H1 of Supplementary Table 4 shows that a configuration with a high degree of technology fitness as the core condition can increase the intention of the middle and senior levels of grain enterprises to adopt the smart granary.

Configuration H1a: The core conditions include high technology fit, high operational risk, and high privacy risk, with high organizational compatibility as a peripheral condition. Managers meeting this configuration path (consistency = 0.984) exhibit a strong interest in smart granary technology. This suggests that even in the presence of high operational and privacy risks, managers are more inclined to adopt the technology when organizational compatibility and job fitness align well with smart granary operations. The association of resource readiness and competitive pressure is relatively weaker in this configuration.

Configuration H1b: Its core conditions are high technology fit, non-high resource readiness, high operational risk and high privacy risk, while high competitive pressure is a secondary condition. Most of the grain enterprises or grain enterprises that fulfill the configuration path H1b (consistency of 0.983) still show high willingness to adopt smart granary despite resource shortage and high risk. This indicates that despite insufficient resource reserves and high operational and privacy risks, middle and senior managers may still be inclined to adopt smart granary technology if it can significantly improve the grain storage efficiency and monitoring capabilities of grain enterprises, and is highly adaptable to existing workflows, and if the granaries are in a highly competitive market environment.

Configuration H1c: High technology fit, non-high operational risk, and non-high privacy risk as core conditions, and non-high organizational compatibility and high resource readiness as edge conditions. The technology can be highly adapted to existing grain storage and monitoring processes with low operational risks (e.g., system failure) and privacy risks (e.g., data leakage), and the management of the grain bank shows a high willingness to adopt it. Even though the compatibility with the future long-term development strategy of the grain bank is low, the sufficient reserve of financial and technical resources provides a strong guarantee for the introduction of the technology. In addition, due to the lower competitive pressure in the grain market in the region, the grain depot is able to focus more on internal technology optimization and efficiency enhancement to achieve efficient operation of the smart grain depot.

Configuration H1d: High technology fit, non-high operational risk, and non-high privacy risk as core conditions, and high organizational compatibility and high competitive pressure as edge conditions. This suggests that when the smart granary fits well with the company's way of working and is accompanied by low operational and privacy risks, if the smart granary technology is highly compatible with the organization's culture and development strategy, and if there is a high level of competitive pressure in the region's grain market, middle and senior managers may raise funds through loans or external financing to promote the implementation of the smart granary. In a competitive market environment, upgrading technology and operational efficiency is key to maintaining competitiveness.

4.2.2 Resource readiness support driven

Configuration H2 of Supplementary Table 4 shows that a configuration with high resource readiness as the core condition can increase the willingness of the middle and senior levels of grain enterprises to adopt the smart grain warehouse.

Configuration H2a: High resource readiness and high privacy risk as the core conditions, and high technology fit, non-high competitive pressure, and non-high operational risk as the edge conditions. It means that when a company has sufficient resource reserves (e.g., capital, technical talents) and the competitive pressure in the market is small, even though the smart granary technology may have high privacy risk (e.g., data leakage potential), managers may still tend to adopt the smart granary technology as long as the technology can be highly adapted to the company's existing way of working and the operational risk is low.

Grouping H2b: High resource readiness and high privacy risk as core conditions, and non-high organizational compatibility, non-high technology fitness and high competitive pressure as edge conditions. It means that even though the smart granary technology may have high privacy risk and low compatibility of the technology with the company's future development strategy and existing working methods, the company has the willingness to adopt the smart granary due to the sufficient reserve of financial and technical resources of the granary, as well as the high competitive pressure in the market. In a highly competitive market environment, rapid improvement of technology and operational efficiency is the key to maintaining competitiveness, and the adequacy of resource reserves can effectively mitigate potential problems arising from technology compatibility and privacy risks.

Grouping H2c: High resource readiness, high organizational compatibility, and high privacy risk as core conditions, and non-high competitive pressure and high operational risk as marginal conditions. It suggests that with sufficient resource readiness and high organizational compatibility, firms may still show high willingness to adopt smart granary technologies even if they are subject to privacy risk and operational risk and have low competitive pressure in the market. This path reveals that driven by both sufficient resources and higher organizational compatibility, firms are more inclined to achieve internal optimization through technology upgrades, while the association between privacy and operational risks is relatively weakened. Although technology suitability may be limited, resource reserve and organizational compatibility provide important guarantees for technology implementation and drive firms' technology adoption decisions.

Grouping H2d: when high resource readiness and high organizational compatibility are the core conditions and high competitive pressure and non-high operational risk are the edge conditions. It indicates that when both resource readiness and organizational compatibility are high, accompanied by high competitive pressure and low operational risk, the company's middle and senior management will support the adoption of the smart granary regardless of the match between the way of working and the smart granary, and whether there are risks to privacy.

Grouping H2e: High willingness to adopt can be generated when high resource readiness and high organizational compatibility are the core conditions, and when high job fitness, high operational risk and non-high competitive pressure are the edge conditions. This grouping implies that when resource readiness is high and the smart granary fits the company's orientation and way of working, even the absence of competitive pressures and possibly operational and privacy risks will lead the company to adopt the smart granary.

4.3 Robustness analysis

In order to reduce the randomness and sensitivity caused by the threat of parameterization and to avoid errors in the results due to the researcher's subjectivity, it is necessary to test the robustness of the results in the QCA. Schneider and Wagemann (2012) suggest that when the researcher makes slightly different, but equally reasonable parameterizations, the findings are robust if the changes in the conclusions of the study are very subtle. The robustness check will be conducted using two methods as follows:

(1) Adjusting the PRI consistency level. The PRI consistency threshold is adjusted from 0.75 to 0.8 for robustness test, and the results are shown in Supplementary Table 5. Compared with Supplementary Table 4, the consistency of the solution is changed from 0.912 to 0.925, and the coverage of the solution is changed from 0.630 to 0.617, which indicates that the change is very slight; at the same time, from the viewpoint of the grouping paths, the overall grouping paths have not changed significantly except for the change of some core conditions. Combining the above two analyses, it can be considered that the grouping path of this paper is robust.

(2) Substitution of outcome variables. When designing the questionnaire in this paper, three similar and interchangeable questions were designed for the outcome variables. In the previous section, the answer to "Do you agree that the company should use smart grain storage technology" was used as the outcome variable for the QCA analysis. Therefore, for the robustness test, the answer of "Do you want to use smart silo technology in grain storage business" is used, and the results are shown in Supplementary Table 6. Compared with Supplementary Table 4, the consistency of the solution is changed from 0.912 to 0.893, and the coverage of the solution is changed from 0.630 to 0.589, which indicates that the change is very slight; meanwhile, from the perspective of the grouping paths, in addition to H1a, no similar grouping paths can be found in the robustness test of Supplementary Table 6, and the other 8 grouping paths have not changed significantly except for the change of some core conditions. Therefore, it can be considered that all the group paths except H1a in this paper are robust.

5 Discussion

5.1 Theoretical contributions and practical implications

This paper examines the willingness to adopt smart granaries and explores the reasons that affect their acceptance. Specifically, it uses the fsQCA methodology to analyze and obtain the associations between configurational and two core paths, i.e., high job fitness, and high resource readiness, on this issue, which provides a new research perspective and is more contextualized.

As far as the theoretical contribution is concerned: this paper adopts the fsQCA method to conduct a configuration study on the willingness of grain enterprises to adopt smart granary technology. It is found that under different combinations of six conditions, there exist nine configuration paths that can lead to the intention of grain enterprises to adopt this technology. According to the equivalence principle of the fsQCA method, although these paths contain different combinations of conditions, they may all lead to the same outcome. This finding remedies a limitation of the existing literature: traditional studies have mostly used net effects analysis, which makes it difficult to capture the complex interactions between conditions, leading to fragmented and inconsistent findings (Huang et al., 2023). In contrast, the fsQCA method can effectively integrate these fragmented results and reveal multiple concurrent causal relationships, providing a new perspective for understanding the complex mechanisms of smart granary technology adoption. In addition, this study extends the application of TOE theory by combining it with the fsQCA method and applying it to the field of smart agriculture for the first time. This attempt not only enriches the theoretical framework of smart granary technology adoption, but also provides new theoretical support for the promotion of smart agriculture technology. Meanwhile, the findings of this paper provide theoretical guidance for the modernization and transformation of grain enterprises, which helps to promote the transformation of grain warehouse management from the traditional mode to the direction of intelligence and digitalization. Finally, this paper provides new methods and references for subsequent research. By introducing the fsQCA methodology, this study demonstrates its application potential in analyzing complex socio-technical systems and provides methodological references for future exploration of similar issues, such as the adoption mechanisms of other agricultural technologies.

In terms of practical contributions, this study provides important practical guidance for the adoption of smart granary technology in grain enterprises. The findings reveal the key factors affecting adoption willingness and their combination paths, which provide a scientific decision-making basis for the management of grain enterprises. By identifying the core conditions such as job fit, resource readiness, and operational risk, grain enterprises can more comprehensively recognize the potential value of smart warehouse technology in enhancing management efficiency, optimizing resource allocation, and improving grain quality (Wang, 2022; Min, 2015). These findings help grain enterprises optimize grain storage management processes, reduce grain losses, and promote their transformation from traditional management modes to intelligent and digital (Song, 2022).

In addition, this study provides technology improvement recommendations and rollout strategy support for smart granary technology vendors. For example, suppliers can lower the technology adoption threshold by enhancing system compatibility (Saurabh and Dey, 2021; Yadav et al., 2020). Specific measures include optimizing the layout and design of the user interface, providing detailed operation manuals, and providing on-site one-on-one training services for grain enterprise employees to ensure that they are proficient in the use of the technology (Murali et al., 2016). At the same time, suppliers should establish a 24/7 after-sales service system to solve problems in the process of using the technology in a timely manner, so as to improve user satisfaction and technology adoption (Kundu and Ramdas, 2022).

The results of the study also have important reference value for policy making. As an emerging technology, although smart granary have significant advantages in improving grain storage management efficiency and reducing losses, the high cost of hardware and software equipment required in the early stage has become a major obstacle to the adoption of the technology in many grain enterprises (Singh and Jayas, 2024; Kolli et al., 2023). In order to alleviate this financial pressure, the government should further increase the policy support for the adoption of smart granary technology in grain enterprises. For example, the government can reduce the financial burden of grain enterprises by formulating preferential policies such as tax exemptions, financial subsidies, and loan interest subsidies (Ma et al., 2018; Gulati et al., 2012). In addition, the government can also set up a special fund to support the research and development and promotion of smart granary technology, so as to promote the modernization and transformation of grain enterprises and enhance the ability to guarantee national grain security (Zhao et al., 2017).

5.2 Practical implications

Empirical results show that resource readiness is the primary core driver across the nine configurational pathways. As a key prerequisite for the implementation of smart grain warehouse technology, resource readiness must be achieved through a dual-track mechanism, consisting of the construction of a multi-level technical support system and the strengthening of management assurance, working in coordination. Additionally, risk prevention and control must be systematically integrated to enhance the resilience of the technology.

In terms of technical support, the cultivation of endogenous capabilities requires the targeted development of internal technical core teams, focusing on enhancing their ability to identify and handle technical risks such as equipment protocol heterogeneity and algorithmic false alarms. This will reduce external technical dependency and prevent potential risks related to technology malfunctions. At the same time, an institutionalized simulation exercise mechanism should be established. This mechanism would involve deep cooperation with technology suppliers to conduct stress testing and failure injection drills, exposing system vulnerabilities and optimizing emergency plans, while allowing employees to gain experience in handling unexpected technical risks. The construction of an open innovation network should also involve industry associations sharing risk case databases, introducing professional consulting firms to customize risk hedging solutions, and integrating external resources to mitigate risks associated with technical complexity.

In terms of management assurance, strategic top-level design requires the management to integrate technology risks into the core decision-making agenda. When setting quantitative objectives, risk tolerance thresholds should be established simultaneously, and a dynamic monitoring and evaluation mechanism should be implemented to provide real-time alerts for organizational risks. Policy resource collaboration should focus on securing government disaster insurance subsidies, technical transformation risk compensation funds, and other risk-sharing mechanisms to alleviate damage to equipment or grain storage losses caused by extreme weather conditions.

Empirical results also show that technology fit is the second largest core driver across the nine configurational pathways. Technology fit, as the core pathway for releasing technological effectiveness, should focus on optimizing talent structure, empowering grassroots staff, and driving the coupling of technological functions with actual needs, while transforming risk control into performance gains through human-machine collaboration.

In the dimension of talent empowerment, differentiated skill enhancement should add a risk identification module in training content. AR-based simulation training should be developed for older employees, with behavioral correction to reduce human-related risks. Innovation in industry-education integration mechanisms requires collaboration with universities to develop risk prevention and control courses, simulating scenarios such as pest outbreaks and equipment failures in training bases, to cultivate technical risk response capabilities in compound talent. The construction of a talent development ecosystem should promote government inclusion of safety certifications in vocational systems and strengthen risk responsibility awareness through the sharing of accident cases on industry platforms.

In terms of technology fit, optimizing the human-machine interaction interface should involve embedding risk prompt functions when simplifying operation processes, labeling high-risk operation points in user manuals, and ensuring that after-sales services cover urgent fault handling. Demand-driven custom development should involve precise communication of business risk needs to suppliers, encouraging the development of redundant verification algorithms to ensure that the technological solutions match actual risk scenarios. Strengthening technological value recognition should empirically demonstrate the benefits of risk control, using data comparisons to eliminate cognitive biases. This strategy, following the principle of minimizing risks, aims to reduce operational risks through interface optimization, solidify preventive behaviors through training and certification, and transition technology adoption from 'usable and easy to use' to 'safe and reliable' (Venkatesh et al., 2003; Lin and Huang, 2023).

6 Conclusion

This study conducted a questionnaire survey of 46 middle and senior managers of grain enterprises in Fuzhou, and used the fsQCA method to explore the configurational pathways associated with the intention of grain enterprises to adopt smart granary technology. The results of the study indicate that the intention of grain enterprises to adopt this technology co-occurs with by multidimensional factors, and that a single factor does not constitute a necessary condition for it; rather, it is the combined configuration of these conditions that is associated with the formation of adoption intention.

Specifically, the study identifies two typical path patterns: one is the path with high technology fitness as the core condition (containing four grouped paths), and the other is the path with high resource readiness as the core condition (containing five grouped paths). These findings provide new perspectives for understanding the complex mechanisms of adopting smart granary technologies in grain enterprises. In addition, privacy risk is an obvious association in both paths.

Of course, this study also has some limitations: (1) The data in this paper were obtained from middle and senior managers of grain enterprises in Fuzhou City, and despite the rigorous questionnaire design and data collection process, there may still be measurement bias. (2) The findings of this paper are limited to explaining the willingness of grain enterprises in Fuzhou City to adopt smart grain silos. Although Fuzhou City is representative as a pioneer region in the application of smart grain silo technology, the applicability of its conclusions to other regions in China (e.g., the central and western regions with different resource conditions) still needs to be further verified. (3) This paper adopts cross-sectional data, which can reveal the key factors affecting adoption willingness and their combination paths, but cannot clarify the causal relationship between variables. Since willingness to adopt technology is a dynamically changing variable, future research can track its trend over time through longitudinal data to better understand the formation mechanism and development law of willingness to adopt.

Through this research, it is hoped that the intention of grain enterprises in Fuzhou City to adopt smart granary technology can be further promoted, thus accelerating the improvement of granary technology in Fuzhou and enhancing food security stability, while providing a reference for the wider dissemination of this technology. Moving forward, we will continue to collect data on a broader scale and conduct dynamic and continuous research on the adoption of smart granary technology.

Data availability statement

The datasets presented in this article are not readily available because if further data is needed, kindly reach out to us by email. Requests to access the datasets should be directed to 64745483@qq.com.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. All participants participated in this survey voluntarily and anonymously, and informed consent was obtained before participation.

Author contributions

XD: Funding acquisition, Conceptualization, Writing – review & editing, Writing – original draft, Methodology. XH: Methodology, Writing – review & editing, Formal analysis, Writing – original draft. XWa: Resources, Writing – review & editing, Investigation. MZ: Writing – review & editing, Conceptualization, Formal analysis. XWu: Methodology, Writing – review & editing, Software.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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