

Equifinal pathways of firm innovation: Evidence from Chinese wine enterprises

Heyu Zhao

Northwest A&F University

Baoyi Wang

Northwest A&F University

Hua Wang

Northwest A&F University

Hua Li

lihuawine@nwsuaf.edu.cn

Northwest A&F University

Article

Keywords: O32, O33, Q13

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10542187/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

This study investigates the multiple pathways through which digital transformation drives innovation in Chinese wine enterprises. Drawing on the resource-based view and dynamic capabilities theory, it examines how different dimensions of digitalization, production, process, and organizational, combine with firm size and regional market openness to generate high innovation outcomes. The study decomposes digital transformation into three dimensions: production, process, and organizational. Using fuzzy-set qualitative comparative analysis (fsQCA) on survey data from 202 Chinese wine firms, this study develops a configurational model comprising these three dimensions, as well as firm size and regional market openness. Four distinct configurational paths were identified, which can be synthesized into three strategic patterns: production process synergy driven, comprehensive digital synergy, and size-market supported. The results reveal that no single condition is necessary for achieving high innovation. Organizational digital transformation emerges as a core condition in most pathways. Organizational digitalization and an open market environment act as essential catalysts for converting digital investments into innovation outputs.

1. Introduction

Digital transformation is reshaping the competitive landscape of traditional industries. From manufacturing to services, digital technology is transforming firms' business operations (Bresciani et al., 2021, Vial, 2019). Existing research has confirmed the positive role of digital transformation in promoting corporate innovation, but the focus has been predominantly on manufacturing and high-tech industries (Li et al., 2023, Khin and Ho, 2018), leaving the agri-food sector, particularly the wine industry, relatively underexplored.

The wine industry, as a vital part of the agri-food sector, provides an ideal setting for exploring the complex relationship between digital transformation and innovation. Unlike many agricultural sectors, the wine industry is characterized by its comprehensive nature. Wine enterprises engage in multiple activities, including viticulture, vinification, warehousing, and marketing (Bastard and Chaillet, 2023). This long-cycle, multi-stage structure generates diverse and complex scenarios for digital transformation. For a comprehensive industry like wine, digital transformation in its production, organizational processes, and operations may each play distinct roles, and their combined effects on innovation may vary significantly.

This study employs fuzzy-set qualitative comparative analysis (fsQCA) to investigate the multiple pathways through which digital transformation drives innovation, using data collected from 202 Chinese wine enterprises. This study is based on the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) to identify the conditions influencing innovation. This study aims to answer the following research questions: How do combinations of digital transformation and other firm-level conditions collectively drive innovation in wine enterprises? Are there equivalent substitution relationships among different condition combinations? What are the critical differences between high and low levels of innovation groups?

There are three theoretical contributions of this paper. First, it decomposes digital transformation into production, process, and organizational dimensions, explicitly mapping them onto the sensing, seizing, and transforming processes of DCT. As a result, the study provides a novel theoretical lens for understanding how different digital resources drive innovation. Second, using fsQCA, it identifies four equivalent pathways to high innovation, revealing the equifinal nature of digital innovation in wine enterprises and demonstrating functional substitution across dimensions. Third, a symmetric relationship between a high-innovation path and a low-innovation path

further reveals the context-dependency of digital innovation. Organizational digital transformation capabilities and an open market environment act as essential catalysts that convert digital investments into innovation outputs.

This paper is structured as follows. Section 2 reviews the literature on digital transformation and innovation, and establishes the theoretical framework. Section 3 describes the research methods. Section 4 presents the results of the necessary condition analysis and the fuzzy-set qualitative comparative analysis. Section 5 discusses the theoretical and practical implications of the findings. Section 6 concludes the paper.

2 Literature review

2.1 The multidimensional decomposition of digital transformation

A large body of literature confirms the positive role of digital transformation in promoting innovation (Kleis and Ramirez, 2012, Lyytinen et al., 2016, Tsakalerou et al., 2025). However, the measurement of digital transformation is not uniform in the academic community. Most methods use the frequency of digital-related keywords in firm annual reports or regional digital transformation levels to measure digital transformation (Chen et al., 2024, Tang and Li, 2026, Zhai et al., 2022). However, such measurement approaches are not precise. Digital transformation is a multi-dimensional process (Appio et al., 2021, Saeedikiya et al., 2025). A multi-dimensional decomposition and measurement of digital transformation is essential.

The decomposition and measurement of digital transformation have gained support in the literature. Matt et al. (2015) point out that, when defining digital transformation strategies, digital transformation focuses on the transformation of production, processes, and organizational aspects driven by new technologies. Xing et al. (2023), using a sample of Chinese manufacturing firms, explicitly decomposed digital transformation into three dimensions, process, production, and organizational capability. Dabić et al. (2023) adopted the digital transformation scale developed by PwC (2016) to measure digital transformation from multiple dimensions.

In recent years, scholars have begun to apply DCT to the study of digital transformation (Warner and Wäger, 2019). Our study adopts this three-dimensional decomposition framework to divide digital transformation into production digital transformation, process digital transformation, and organizational digital transformation.

Process digital transformation corresponds to the sensing component of dynamic capabilities, enables firms to rapidly capture market signals and consumer behavior insights through digital tools such as big data analytics, social media monitoring. Organizational digital transformation corresponds to the seizing component of dynamic capabilities. A study by Karadağ et al. (2024) shows that, in the formation process of dynamic digital capabilities in SMEs, organizational antecedents constitute key configurations affecting firm performance. Production digital transformation corresponds to the transforming component of dynamic capabilities. Transforming is the strategic capability of continuously integrating and reconfiguring a firm's resource portfolio to ensure long-term development and marks the final realization of innovation outcomes (Teece, 2007).

2.2 Firm size and market orientation

The impact of digital transformation on innovation does not occur in isolation but depends on firm-specific contextual conditions. Firm size especially impacts the digital transformation process. Wu et al. (2024) found that large firms are more likely to achieve a high level of digital transformation, whereas SMEs progress slowly due to

resource constraints. Jäger and Federau (2025) found that the impact of digital transformation on sustainable development is fully mediated by company size. Li et al. (2025) found that digital transformation promotes innovation investment more significantly in SMEs than in large firms. Calvo et al. (2022) used the number of employees as a core control variable and confirmed that it has a significantly positive impact on product and process innovation. The Annual Report on China's Manufacturing Industry Digital Innovation (2024) also shows that in recent years, the digital innovation level of Chinese SMEs has outperformed that of large enterprises, with their innovation processes being more dynamic. Notably, the direction of the size effect may vary depending on the research context and the outcome variable. Tian et al. (2025) found that as firm size increases, the promoting effect of external policies on digital transformation weakens.

Market openness is another important contextual condition. Market openness influences the relationship between digital transformation and innovation through multiple channels. Zhan (2023) found that a leading competitive position strengthens the promoting effect of capital market openness on digital transformation, while high-intensity competition plays a relatively negative role. Meanwhile, competitive pressure introduced by open markets forces firms to accelerate their digital transformation processes (Wang et al., 2025). Regional openness interacts with internal conditions such as firm size and R&D investment to jointly form configurational paths that drive high-level digital transformation (Zhao and Jia, 2024). Abbas et al. (2024) found that product market competition significantly and positively affects firm performance, with digital financial innovation playing a partial mediating role. The impact of market openness on innovation is highly context-dependent (Deng et al., 2025). How the interaction between market orientation and digital transformation affects innovation remains to be further explored.

2.3 Theoretical foundation and conceptual framework

This study is grounded in the RBV and DCT. According to RBV, a firm's competitive advantage stems from possessing valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In the digital era, the degree of digital transformation and the use of digital technologies have become core resources for SMEs to achieve innovation and growth (Eller et al., 2020, Bresciani et al., 2021). For wine enterprises and traditional manufacturing firms, digital transformation constitutes a novel resource bundle (Matarazzo et al., 2021). The realization of digital technology value depends on its complementarity with a firm's core competencies, namely market access, process integration, and product innovation. (Ravichandran and Lertwongsatien, 2005).

The three dynamic capabilities enable firms to integrate, reconfigure, and redeploy resources to adapt to environmental changes and drive innovation (Teece, 2014). Accordingly, the study decomposes digital transformation into the three dimensions of production, organization, and process. However, it should be emphasized that the above correspondences do not imply that all three digital transformation dimensions must simultaneously reach high levels in every successful scenario.

3. Research Model and Condition Setting

3.1 Research design

The fsQCA method is adopted for this study. QCA is designed to identify multiple equivalent pathways and to reveal complementarities and substitutions among conditions, thereby overcoming the limitations of linear models (Fiss, 2011). The effect of digital transformation on innovation may depend on the combination of multiple

conditions rather than the isolated effect of any single factor. Firms with different resource endowments may achieve innovation through different pathways.

This study collected data through a questionnaire survey of wine enterprises across multiple wine-producing regions in China. The questionnaire is collected by telephone interviews and online. Table 1 shows the detailed construct, item, and source of the questionnaire. A total of 226 questionnaires were collected, of which 202 were valid. To reduce the influence of common method bias and social desirability bias, all variables in this study were measured objectively. Digital transformation-related variables were collected through factual questions in the questionnaire, where respondents reported actual digital practices of their firms rather than subjective attitudes. Firm size was also measured by the number of employees. Regional market openness was measured using the dataset from the China Market Index Database. The multi-source, multi-method objective measurement design enhances the reliability and validity of the research data (Podsakoff et al., 2003). Before formal data collection, the research team conducted a pilot survey with five firms and invited three wine research experts to review the questionnaire. The questionnaire was refined based on pilot responses and expert suggestions. The final questionnaire contains 51 items covering various aspects of firm digital transformation and innovation. In the questionnaire, the core variables used in this study include four items for production digital transformation, seven items for organizational digital transformation, six items for process digital transformation, one item for firm size, and three items for innovation level. The remaining items are used for descriptive analysis. Harman's single-factor test was performed, and the variance explained by a single factor was 36.22%, below the 40% threshold, indicating that common method bias is not a serious concern.

Table 1
Questionnaire

Dimension	Item Code	Item	source
Organizational digital transformation level	Q1-7	Frequency of employee training on digital technology usage in the past three years	Stich et al. (2020)
		Number of work assistance media tools used by the enterprise	Stich et al. (2020)
		Frequency of AI usage in the past three years	Mikalef et al. (2023)
		Work assistance software that employees can proficiently use	Stich et al. (2020)
		Frequency of employees using digital work (e.g., remote data sharing, teleworking) in the past three years	Xing et al.(2023)
		Frequency of using electronic signatures in the past three years	Stich et al. (2020)
		Frequency of using cloud storage or file sharing in the past three years	Stich et al. (2020)
Process digital transformation level	Q8-13	Whether the enterprise has social media	Dabić et al. (2023)
		Whether the enterprise has a website	Dabić et al. (2023)
		Update frequency of enterprise social media	Dabić et al. (2023)
		Whether the enterprise has an online store	PwC (2016)
		Frequency of using social media to collect customer feedback in the past three years	Dabić et al. (2023)
		Whether the enterprise has used software to analyze production and sales data in the past three years	Dabić et al. (2023)
Production digital transformation level	Q14-17	Digital technologies used in the planting process in the past three years	Stich et al. (2020), Xing et al.(2023)
		Digital technologies used in the winemaking process in the past three years	Stich et al. (2020), Xing et al.(2024)
		Digital technologies used in the aging process in the past three years	Stich et al. (2020), Xing et al.(2025)
		Digital technologies used in the warehousing process in the past three years	Stich et al. (2020), Xing et al.(2026)
Firm size	Q18	Total number of employees	Xing et al.(2023)

Dimension	Item Code	Item	source
Innovation level	Q19-22	Number of patents granted in the past three years	Liu et al. (2024); Wang et al. (2024)
		Number of new products launched in the past three years	Hagedoorn & Cloudt (2003); Singh & Garg (2026)
		Number of awards received in the past three years	Zhang et al. (2014); Lopes et al. (2025)

3.2 Condition variable specification and measurement

3.2.1 Dependent variable: Firm innovation level

Drawing on the study of Haner (2002) and following the approaches of Hagedoorn and Cloudt (2003) and Zeb et al. (2021), this study adopts a multi-indicator composite measurement strategy to assess firm innovation performance. The number of patents granted, the number of new products developed, and the number of awards won in wine competitions over the past three years were used as indicators. To reduce the influence of skewed distributions while retaining zero values, one is added to each indicator, a logarithmic transformation is then applied, and the average of the transformed values is taken as a composite measure of firm innovation level.

The number of patents granted is also widely used to capture firm innovation (Wang et al., 2024, Liu et al., 2024). The number of new products is considered another core measure of innovation output (Singh and Garg, 2026, Hagedoorn and Cloudt, 2003) and directly reflects the tangible outcomes of a firm’s innovation activities. Lopes et al. (2025), in their study on the innovation capacity of Brazilian wineries, demonstrate that “product and service innovation” is a core dimension of winery innovation, and wine industry awards directly reflect achievements in this dimension. The number of awards can serve as a valid proxy for innovation (Zhang et al., 2014, Hagedoorn and Cloudt, 2003). Luo et al. (2024) find that firms winning innovation awards significantly outperform non-winners in both patent quantity and quality. The combined use of multiple indicators thus provides a more comprehensive and robust measure of a firm’s innovation level.

3.2.2 Independent variables

This study uses factor analysis to construct the condition variables of organizational digital transformation level, production digital transformation level, and process digital transformation level. To ensure the suitability of the data for factor analysis, Bartlett’s test of sphericity and the Kaiser-Meyer-Olkin (KMO) test were performed. The KMO value is 0.8837, and the p-value is 0.000, confirming the appropriateness of factor analysis. Confirmatory factor analysis (CFA) was used to assess validity, with factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach’s alpha coefficients examined. All factor loadings exceed 0.5, and all Cronbach’s alpha values exceed 0.7, indicating good reliability for each condition variable. Detailed results are presented in Table 2.

Table 2
The reliability and validity of the scale

Dimension	Item Code	Item	Factor Loading	AVE	CR	Cronbach's Alpha
Organizational digital transformation level	Q1-7	Frequency of employee training on digital technology usage in the past three years	0.5445	0.4737	0.8766	0.8364
		Number of work assistance media tools used by the enterprise	0.7081			
		Frequency of AI usage in the past three years	0.6885			
		Work assistance software that employees can proficiently use	0.7479			
		Frequency of employees using digital work (e.g., remote data sharing, teleworking) in the past three years	0.7573			
		Frequency of using electronic signatures in the past three years	0.6004			
		Frequency of using cloud storage or file sharing in the past three years	0.7893			
Process digital transformation level	Q8-13	Whether the enterprise has social media	0.7318	0.5008	0.8549	0.7922
		Whether the enterprise has a website	0.5492			
		Update frequency of enterprise social media	0.8485			
		Whether the enterprise has an online store	0.7067			
		Frequency of using social media to collect customer feedback in the past three years	0.7726			
		Whether the enterprise has used software to analyze production and sales data in the past three years	0.5926			
Production digital transformation level	Q14-17	Digital technologies used in the planting process in the past three years	0.8572	0.6165	0.8636	0.7838

Dimension	Item Code	Item	Factor Loading	AVE	CR	Cronbach's Alpha
		Digital technologies used in the winemaking process in the past three years	0.8677			
		Digital technologies used in the aging process in the past three years	0.7678			
		Digital technologies used in the warehousing process in the past three years	0.6236			

Organizational digital transformation level: Drawing on Stich et al. (2020), items related to IT integration and paperless office were selected. Additionally, following Mikalef et al. (2023), questions regarding the use of artificial intelligence (AI) were incorporated. Moreover, remote work-related items were added with reference to Xing et al.(2023).

Process digital transformation level: Based on the frameworks of Dabić et al. (2023) and PwC (2016), measurement items concerning digital sales channels and digital marketing were adopted.

Production digital transformation level: Following Stich et al. (2020) and Xing et al.(2023), items related to production process automation and IoT integration were selected. The degree of production process automation and IoT integration was measured across the three stages of wine production.

Firm size: Following Xing et al.(2023), firm size was measured by the natural logarithm of the number of employees.

3.3 Calibration

This study adopts the direct calibration method. The sampled wine enterprises are predominantly small and medium-sized. According to the China Wine Industry Development Blue Book (2023), above-designated-size enterprises accounted for merely 7.08% of the total, confirming that the majority of firms are small and medium-sized with limited resource endowments. All sampled firms are located within China's 11 major wine-producing regions. Given this relatively small variation among enterprises, and drawing on established research practices (Zschoch, 2011, Liu and Chen, 2024), the 95th, 50th, and 5th percentiles of the sample distribution of the outcome and condition variables are set as the full membership anchor, crossover anchor, and full non-membership anchor. Table 3 presents the calibration anchors used in this study.

Table 3
Descriptive statistics of calibration points

Variables	Non-membership	Crossing point	Full-membership	Average	Maximum	Minimum	Standard deviation
Organizational digital transformation level	-2.491	-0.217	3.360	0	6.666	-3.041	1.947
Process digital transformation level	-3.202	0.263	2.410	0	5.739	-3.202	1.733
Production digital transformation level	-1.767	-0.267	2.958	0	5.401	-1.767	1.570
Firm size	1.609	2.996	5.298	3.161	7.090	0.693	1.153
Market openness	0	1.426	3.272	1.545	4.769	0	0.988
Innovation level	5.598	6.632	9.513	7.240	10.991	2.459	1.433

4. Result

A necessary condition for either high or low innovation performance was examined. Table 4 reports the necessity test results. The results show that all consistency values are below 0.9. This finding aligns with the expectations of configurational theory: high innovation performance is not driven by a single isolated factor but rather results from the synergistic configuration of multiple factors.

Table 4

FsQCA necessity test for individual conditions This study uses fsQCA 3.0 software. Following standard fsQCA practices, the consistency threshold is set to 0.8 and the frequency threshold to 1. The PRI threshold was set at 0.6, following prior literature (Ding, 2022, Patala et al., 2021), to balance the exclusion of inconsistent configurations with the retention of theoretically meaningful pathways. The analysis identified four distinct pathways to high innovation (H1–H4), which can be synthesized into three strategic patterns: production–process synergy driven (H1), comprehensive digital synergy (H2), and size–market supported (H3–H4). Table 5 presents the configurations for both high and low innovation levels.

Independent variable	Outcome			
	High innovation level		Low innovation level	
Conditions	Consistency	Coverage	Consistency	Coverage
High organizational digital transformation level	0.7590	0.7947	0.4982	0.5247
Low organizational digital transformation level	0.5461	0.5197	0.8050	0.7706
High process digital transformation level	0.8148	0.7919	0.5524	0.5401
Low process digital transformation level	0.5268	0.5392	0.7872	0.8105
High production digital transformation level	0.7338	0.8053	0.4713	0.5203
Low production digital transformation level	0.5629	0.5142	0.8236	0.7568
High firm size	0.7884	0.8080	0.5249	0.5411
Low firm size	0.5523	0.5361	0.8138	0.7946
High market openness	0.7236	0.6459	0.7246	0.6506
Low market openness	0.6086	0.6872	0.6056	0.6879

Table 5
Antecedent configuration of high and low innovation level

Independent variable	High innovation level				Low innovation level					
	H1	H2	H3	H4	N1	N2	N3	N4	N5	N6
Organizational digital transformation level		●	●	●		⊗	⊗	⊗		⊗
Process digital transformation level	●	●	●		⊗		⊗	⊗	⊗	●
Production digital transformation level	●	●		●	⊗	⊗		⊗		●
Firm size	●		●	●	⊗	⊗	⊗		⊗	●
Market openness			●	●	●					● ⊗
Consistency	0.93	0.92	0.94	0.94	0.91	0.91	0.92	0.91	0.93	0.85
Raw coverage	0.57	0.46	0.47	0.44	0.62	0.64	0.63	0.65	0.54	0.22
Unique coverage	0.15	0.04	0.06	0.02	0.01	0.04	0.01	0.05	0.02	0.02
Overall consistency	0.9				0.85					
Raw coverage	0.69				0.81					

Note: ●core condition exists; ●peripheral condition exists; ⊗ core condition is absent; ⊗ peripheral condition is absent.

4.1 Production process synergy driven: H1

H1 comprises production, process digital transformation, and firm size as core conditions, while organizational digitalization is absent from this pathway. Digital transformation of production and supply chains directly improves operational efficiency and product innovation capability. Larger enterprises, by leveraging scale advantages, can reduce production costs and improve efficiency through the digitalization of production and process operations. At the same time, process digital transformation enables firms to capture market demands, through social media monitoring, and synchronize production with market signals.

A further analysis of the cases covered by this pathway reveals that it covers 60 firms, of which 21 are uniquely covered. These uniquely covered cases exhibit the highest average number of innovation awards (approximately 68 awards) compared to cases uniquely covered by other pathways. A Kruskal–Wallis test comparing uniquely covered cases across pathways yielded a p-value of 0.0483, indicating significant differences in innovation outcomes across pathways. This suggests that production digitalization leads to production optimization, enabling firms to improve wine quality, which in turn attracts industry recognition and awards. Such recognition enhances brand reputation, creating a virtuous cycle between production quality and market performance, ultimately reinforcing innovation outcomes.

4.2 Comprehensive digital synergy: H2

H2 comprises organizational, process, and production digital transformation as core conditions, with regional market openness as a peripheral condition. Firm size is not a required condition in this pathway, suggesting that it represents a viable innovation route for micro and small enterprises. H2 emphasizes the full synergy of all three digitalization dimensions, supported by an open market environment. Firms achieve process digitalization through online promotion and social media engagement, adopt software and AI tools to support operations and enable flexible work arrangements, and implement production digitalization through equipment upgrades. Comprehensive digital transformation reduces operating costs, optimizes resource allocation, and improves factor allocation efficiency, thereby promoting technological progress and ultimately innovation. In terms of innovation outcomes, firms following this pathway tend to concentrate their innovation efforts on quality improvement, reflected in a higher proportion of awards rather than patents or new product introductions.

4.3 Size-market supported: H3 and H4

H3 and H4 are grouped together as size–market supported pathways due to their structural similarity. These pathways take market openness, firm size, and certain digital transformation dimensions as core conditions. H3 highlights the synergy between organizational and process digitalization, while H4 highlights the synergy between organizational and production digitalization. Compared to other pathways, firms covered by these pathways are larger in size (average 133 employees), and their innovation outputs are more focused on products and patents. Organizational digitalization does not function in isolation; rather, by combining with process or production digitalization, it creates a structural empowerment effect that enables firms to integrate internal and external resources more effectively and amplify innovation performance.

4.4 Low innovation configurations

N1-4 show that firms simultaneously lack multiple dimensions of digital transformation, process, production, and organizational, and also have small firm size. Among these, the path with all three digital transformation dimensions absent exhibits the highest unique coverage, making it the most representative low-innovation pattern. This finding inversely confirms that high innovation requires multi-dimensional digital synergy. N5 shows when a firm operates in a region with high market openness, the absence of process digital transformation and scale advantages still hinders innovation.

Notably, H1 and N6 exhibit a symmetric relationship. The former shows that the three conditions alone can drive high innovation, while the latter reveals that when organizational digital transformation and market openness are both absent, the same digital inputs lead to low innovation. This symmetry reflects that innovation depends on organizational digital transformation capabilities and an open market environment. Both are essential catalysts for converting digital investments into innovation outputs. Without these catalysts, even advanced digital production and operation systems may trap firms in a high investment but low returns due to internal integration failures and limited external demand. In summary, the low-innovation configuration analysis and the high-innovation analysis complement each other symmetrically.

4.5 Robustness checks

To ensure the reliability of the findings, this study conducted two robustness checks: a permutation test and a sensitivity analysis. Although QCA is inherently deterministic and does not rely on statistical inference, we performed a permutation test proposed by Braumoeller (2017) using the QCAfalsePositive package in R to assess whether the identified configurations might be driven purely by random factors. This test randomly shuffles the membership scores of the outcome variable (INV) while keeping the calibration of all condition variables

unchanged, and then re-runs the full fsQCA analysis for 1,000 random permutations. The consistency of the resulting solution is recorded for each permutation, thereby constructing an empirical distribution under the null hypothesis. The consistency of the four configurations obtained from the original QCA analysis is then compared with this distribution, and p-values for each path are calculated. The results show that the p-values for all four configurations are below 0.05 (see Table 6). This indicates that the identified configurations are statistically significant and unlikely to be caused by random noise in the data, supporting the robustness of the original fsQCA results.

Table 6

Permutation tests of configurations In QCA, the choice of the PRI consistency threshold can affect the final solution. To test the sensitivity of the results to this parameter, following common practices in the literature (Greckhamer et al., 2018, Schneider and Wagemann, 2012), we increased the PRI threshold from 0.60 to 0.65 while keeping all other parameters unchanged, and re-ran the sufficiency analysis. After the adjustment, the number of truth table rows decreased slightly, and the Boolean minimization produced a new set of configurations. Specifically, among the four originally identified configurations, H2 no longer appeared because its PRI consistency fell below 0.65; however, H1, H3, and H4 remained as combinations of core or peripheral conditions, with only minor changes in their consistency and coverage (see Table 7). Moreover, no completely different configurations emerged, indicating that the main conclusions of this study are reasonably robust.

Configurations	Consistency (Observed)	95% CI of Consistency	p-adj
H1	0.9334735	[0.630, 0.777]	0
H2	0.9242604	[0.661, 0.815]	0
H3	0.9346255	[0.646, 0.806]	0
H4	0.9407116	[0.659, 0.821]	0

Table 7

The robustness test (Adjust PRI cutoff)

Independent variable	High innovation level		
	H1	H3	H4
Organizational digital transformation level		●	●
Process digital transformation level	●	●	
Production digital transformation level	●		●
Firm size	●	●	●
Market openness		●	●
Consistency	0.933	0.935	0.941
Raw coverage	0.569	0.473	0.437
Unique coverage	0.153	0.057	0.021
Overall consistency	0.913		
Raw coverage	0.647		

5. Discussion

5.1 Contributions

Based on an integrated framework of RBV and DCT, this study employs fsQCA to explore the configurational effects of five factors, production digital transformation, process digital transformation, organizational digital transformation, firm size, and regional market openness, on the innovation level of wine enterprises.

This study advances the decomposition of digital transformation into production, process, and organizational dimensions and maps these dimensions onto the sensing, seizing, and transforming processes of DCT. The study identifies four equivalent pathways to high innovation, demonstrating the equifinal nature of digital innovation in wine enterprises. Functional substitution is observed both across digital transformation dimensions and across configurational paths. This finding demonstrates that innovation does not depend on any single fixed model. By incorporating firm size and regional market openness as contextual conditions, this study extends configurational analysis to traditional agri-food industries and complements linear models that are unable to capture such substitution and interaction effects, providing a novel theoretical lens for understanding how different digital resources contribute to innovation.

Firm size and regional market openness appear in three of the four high-innovation pathways, indicating that scale advantages and an open market environment are important contextual conditions for digital innovation. Firm size reflects resource endowment and risk-bearing capacity (Eveland et al., 1990); market openness, from an environmental perspective, provides signals regarding external knowledge acquisition, competitive pressure, and institutional support (Xing et al., 2023).

A noteworthy symmetric relationship emerges between the high-innovation path and the low-innovation path. When organizational digital transformation and market openness are both absent, the same digital inputs lead to low innovation. This symmetric phenomenon reflects the context-dependency of digital innovation. Organizational digital transformation capabilities and an open market environment are essential catalysts for converting digital investments into innovation outputs. This insight complements the theoretical contribution on functional substitution by highlighting that such substitution is not unconditional; it critically depends on either the presence of organizational capabilities or an enabling external environment. The symmetric analysis thus deepens the understanding of how the same digital transformation inputs can lead to divergent innovation outcomes, reinforcing the value of a configurational approach for studying complex, non-linear phenomena.

The findings offer actionable guidance for managers and policymakers. Organizational digitalization should not be viewed as a substitute for other digitalization dimensions but rather as an amplifier. Once a firm has built a foundation in production or process digitalization, introducing organizational digital management platforms and digital strategic planning can significantly boost innovation performance. Firms should pay attention to external environmental signals. When regional market openness is high, active participation in cross-border exhibitions, digital trade platforms, and industry alliances facilitates access to external knowledge and technology. For resource-constrained SMEs, the findings offer low-cost innovation alternatives. Digital transformation does not always guarantee linear innovation returns (Usai et al., 2021); rather, firms should strategically combine the digitalization dimensions that best match their resource endowments and market contexts.

5.2 Limitations and future research

This study has several limitations that suggest avenues for future research. First, with cross-sectional data, we cannot fully determine the temporal sequence between digital investments and innovation. Future research could employ longitudinal QCA or panel data to track the dynamic evolution of digital transformation processes. Second, this study did not include potentially relevant conditions such as entrepreneurship, team digital literacy, government subsidies, or industry competition intensity. Future models could extend the configurational framework to explore the interactions between these factors and the existing conditions. Third, this study focuses exclusively on Chinese wine enterprises, which limits the generalizability of the findings. While the contextual characteristics of Chinese wine firms, small scale, resource constraints, and a traditional production orientation, may resonate with other agri-food sectors in developing economies, cross-regional and cross-industry comparative studies are needed to validate the external validity of the conclusions. Finally, although configurational analysis reveals multiple equivalent pathways, it cannot quantify the marginal contribution of each pathway to innovation nor rule out unobserved heterogeneity. Future research could combine mixed methods to deepen mechanistic explanations.

6. Conclusion

By adopting a configurational perspective, this study uncovers multiple pathways for digital innovation in wine enterprises, offering differentiated strategic choices for resource-constrained small and medium-sized enterprises and providing a theoretical basis for policy design in the digital transformation of traditional industries.

Declarations

Author Contribution

All authors contributed to the study conception and design. Conceptualization by H.W. and H.Z.; Project administration by H.W.; Material preparation, data collection and analysis were performed by H.Z., B.W.; the first draft of the manuscript wrote by H.Z.; Supervision, review and editing by H.L. All authors reviewed the manuscript.

Data Availability

The data are available from the authors upon reasonable request.

References

1. Abbas J, Balsalobre-Lorente D, Amjid MA, Al-Sulaiti K, Al-Sulaiti I, Aldereai O (2024) Financial innovation and digitalization promote business growth: The interplay of green technology innovation, product market competition and firm performance. *Innov Green Dev* 3(1):100111
2. Appio FP, Frattini F, Petruzzelli AM, Neirotti P (2021) Digital Transformation and Innovation Management: A Synthesis of Existing Research and an Agenda for Future Studies. *J Prod Innov Manage* 38(1):4–20
3. Association CRDVP (2023) China wine industry development blue book. Research, Beijing
4. Barney JBJJ, o. M (1991) Firm Resour Sustained Competitive Advant 17:120–199
5. Bastard A, Chaillet A (2023) Digitalization from vine to wine: Successes and remaining challenges - A review, *BIO Web of Conferences*, Vol. 68

6. Braumoeller BF (2017) Guarding Against False Positives in Qualitative Comparative Analysis. *Political Anal* 23(4):471–487
7. Bresciani S, Huarng K-H, Malhotra A, Ferraris A (2021) Digital transformation as a springboard for product, process and business model innovation. *J Bus Res* 128:204–210
8. Calvo N, Fernández-López S, Rodríguez-Gulías MJ, Rodeiro-Pazos D (2022) The effect of population size and technological collaboration on firms' innovation. *Technol Forecast Soc Chang* 183:121905
9. Chen L, Tu R, Huang B, Zhou H, Wu Y (2024) Digital transformation's impact on innovation in private enterprises: Evidence from China. *J Innov Knowl* 9(2):100491
10. Dabić M, Obradović Posinković T, Vlačić B, Gonçalves R (2023) A configurational approach to new product development performance: The role of open innovation, digital transformation and absorptive capacity. *Technol Forecast Soc Chang* 194:122720
11. Deng F, Tan Y, Ni M (2025) Capital market liberalization and corporate digital transformation: Evidence from China's Stock Connect programs. *Finance Res Lett* 84:107808
12. Ding H (2022) What kinds of countries have better innovation performance?—A country-level fsQCA and NCA study. *J Innov Knowl* 7(4):100215
13. Eller R, Alford P, Kallmünzer A, Peters M (2020) Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *J Bus Res* 112:119–127
14. Eveland J, Tornatzky LG, Fleischer M (1990) Technological Innovation as a Process, pp. 27–50
15. Fiss PC (2011) Building better causal theories: a fuzzy set approach to typologies in organization research. *Acad Manag J* 54(2):393–420
16. Greckhamer T, Furnari S, Fiss P (2018) Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organ* 16:1–14
17. Hagedoorn J, Cloudt M (2003) Measuring innovative performance: is there an advantage in using multiple indicators? *Res Policy* 32(8):1365–1379
18. Haner U-E (2002) Innovation quality—a conceptual framework. *Int J Prod Econ* 80(1):31–37
19. Jäger J, Federau M (2025) Digitalization, Sustainable Development, and the Role of Company Size: Evidence From Germany, Austria, and Switzerland. *Sustain Dev* 33(6):9352–9371
20. Karadağ H, Şahin F, Karamollaoğlu N, Saunila M (2024) Disentangling the dynamic digital capability, digital transformation, and organizational performance relationships in SMEs: a configurational analysis based on fsQCA. *Inf Technol Manage* 27(2):141–157
21. Khin S, Ho TCF (2018) Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *Int J Innov Sci* 11(2):177–195
22. Kleis L, Ramirez R (2012) Information Technology and Intangible Output: The Impact of IT Investment on Innovation Productivity. *Inform Syst Res* 23:41–59
23. Li S, Gao L, Han C, Gupta B, Alhalabi W, Almakdi S (2023) Exploring the effect of digital transformation on Firms' innovation performance. *J Innov Knowl* 8(1):100317
24. Li X, Xu J, Lu C, Lv Y (2025) Corporate Digital Transformation, Financing Constraints and Innovation Input, in *Proceedings of the 2025 4th International Conference on Big Data Economy and Digital Management (BDEDMD 2025)*, Ningbo, pp. 246–255

25. Liu B, Wang Y, Jiang N, Zhang X (2024) The impact of digital industrialization and industrial digitalization on regional green innovation efficiency in China -From the perspective of the innovation value chain. *J Clean Prod* 478:144015
26. Liu Y, Chen L (2024) Analysis on the performance configuration of green innovation in enterprises under the background of digital transformation—research on fsQCA based on TOE framework. *Logistics Sci-tech* 2:1–6
27. Lopes LFD, Silva DJCd, Teixeira CS (2025) Innovation capacity of Brazilian wineries: an integrated approach using the fuzzy Delphi and random forest methods. *Wine Econ Policy* 14(1):97–116
28. Luo L, Cheng Z, Ye Q, Cheng Y, Smyth R, Yang Z, Zhang L (2024) Nonmonetary awards and innovation: Evidence from winning China's Top Brand Contest. *China Econ Rev* 86:102190
29. Lyytinen K, Yoo Y, Boland RJ Jr. (2016) Digital product innovation within four classes of innovation networks. *Inform Syst J* 26(1):47–75
30. Matarazzo M, Penco L, Profumo G, Quaglia R (2021) Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *J Bus Res* 123:642–656
31. Matt C, Hess T, Benlian A (2015) Digital Transformation Strategies. *Bus Inform Syst Eng* 57:339–343
32. Mikalef P, Lemmer K, Schaefer C, Ylinen M, Fjørtoft SO, Torvatn HY, Gupta M, Niehaves B (2023) Examining how AI capabilities can foster organizational performance in public organizations. *Government Inform Q* 40(2):101797
33. Patala S, Juntunen JK, Lundan S, Ritvala T (2021) Multinational energy utilities in the energy transition: A configurational study of the drivers of FDI in renewables. *J Int Bus Stud* 52(5):930–950
34. Podsakoff P, MacKenzie S, Lee J-Y, Podsakoff N (2003) Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J Appl Psychol* 88:879–903
35. PwC (2016) Industry 4.0: Building the digital enterprise
36. Ravichandran T, Lertwongsatien C (2005) Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective. *J Manage Inform Syst* 21:237–276
37. Saeedikiya M, Salunke S, Kowalkiewicz M (2025) The nexus of digital transformation and innovation: A multilevel framework and research agenda. *J Innov Knowl* 10(1):100640
38. Schneider CQ, Wagemann C (2012) Set-Theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis. Cambridge University Press, Cambridge
39. Singh AP, Garg S (2026) Measuring innovation—a composite index of innovation volume at firm level, *Scientometrics*. 131(2):1067–1118
40. Stich V, Zeller V, Hicking J, Kraut A (2020) Measures for a successful digital transformation of SMEs. *Procedia CIRP* 93:286–291
41. Tang J, Li Q (2026) Brand culture innovation, digital transformation, and the performance of agribusiness firms. *Int Rev Financial Anal* 110:104825
42. Teece DJ (2007) Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg Manag J* 28(13):1319–1350
43. Teece DJJJ, o. IBS (2014) dynamic capabilities-based entrepreneurial theory multinational *Enterp* 45:8–37
44. Tian M, Wang Y, Han L, Yang Z (2025) Impact mechanism and contribution measurement of digital transformation on scale expansion of Chinese enterprises. *Socio-Economic Plann Sci* 102:102331

45. Tsakalerou M, Abil A, Ribiere V, Lukhmanov Y, Tynybayeva N (2025) The innovation capability equation: A systematic review of global determinants of SME's success. *J Innov Knowl* 10(4):100757
46. Usai A, Fiano F, Petruzzelli A, Paoloni P, Briamonte M, Orlando B (2021) Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *J Bus Res* 133:327–336
47. Vial G (2019) Understanding digital transformation: A review and a research agenda. *J Strateg Inf Syst* 28(2):118–144
48. Wang B, Khan I, Ge C, Naz H (2024) Digital transformation of enterprises promotes green technology innovation – The regulated mediation model. *Technol Forecast Soc Chang* 209:123812
49. Wang J, Wang Y, Song J (2025) Import competition and business digital transformation in a global openness framework: incentive or inhibition. *J World Econ* 48(2):44–75
50. Warner KSR, Wäger M (2019) Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Plann* 52(3):326–349
51. Wu C-H, Chou C-W, Chien C-F, Lin Y-S (2024) Digital transformation in manufacturing industries: Effects of firm size, product innovation, and production type. *Technol Forecast Soc Chang*, Vol. 207
52. Xie W, Wang Z, liu Y, Li S (2024) *Annual report on China's manufacturing industry digital innovation (2024)*, Social Sciences Academic Press (China), Beijing
53. Xing X, Chen T, Yang X, Liu T (2023) Digital transformation and innovation performance of China's manufacturers? A configurational approach. *Technol Soc* 75:102356
54. Zeb A, Khan F, Hussain K, Rabnawaz M, Zeb F (2021) The competing value framework model of organizational culture, innovation and performance. *Bus Process Manage J* 27(2):658–683
55. Zhai H, Yang M, Chan KC (2022) Does digital transformation enhance a firm's performance? Evidence from China. *Technol Soc* 68:101841
56. Zhan W (2023) Can stock market liberalization promote digital transformation of enterprises?—A quasi-natural experiment of Mainland-Hong Kong stock connect trading system. *J Beijing Inst Technol (Social Sci Edition)* 25(4):159–172
57. Zhang GP, Yu J, Xia Y (2014) The Payback of Effective Innovation Programs: Empirical Evidence from Firms that Have Won Innovation Awards. *Prod Oper Manage* 23(8):1401–1420
58. Zhao J, Jia H (2024) Configurational paths of factors influencing enterprise digital transformation: a dynamic QCA analysis based on enterprise panel data. *J Shandong Youth Univ Political Sci* 40(4):48–79
59. Zschoch MA (2011) Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques, Benoit Rihoux and Charles Ragin, eds., Thousand Oaks CA: Sage Publications, 2009, pp. xxv, 209, *Canadian Journal of Political Science*, Vol. 44 No. 3, pp. 743–746