https://doi.org/10.17221/271/2023-AGRICECON

Research on the promotion effect and mechanisms of digital empowerment of food enterprises

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Citation: Li P.L., Xuan Y. (2024): Research on the promotion effect and mechanisms of digital empowerment of food enterprises. Agric. Econ. – Czech, 70: 60–72.

Abstract: Based on panel data from 2010 to 2020 of 151 A-share listed food-related enterprises in China, this research uses a fixed-effect model to analyse the impact of digital transformation on total factor productivity (TFP) in food-related enterprises. Our findings indicated that digital transformation has a positive and significant catalytic effect on TFP improvement in food-related enterprises. The mechanism test revealed that both cost-saving and innovation capacity enhancement effects of digital transformation contributed to the promotion of TFP improvement in these enterprises. Moreover, our heterogeneity analysis suggested that digital transformation is more effective in enhancing TFP in state-owned enterprises (SOEs) in the food-related industry, indicating that SOEs play a representative role in promoting advanced productivity in agricultural development. We also found that capital-intensive and technology-intensitve food-related enterprises were experiencing productivity paradox traps. Our results confirmed that digital transformation brings catch-up effects to labor-intensive food-related enterprises and those located in major grain production regions. Overall, this research can provide valuable insights for policymakers to upgrade the digital-enabled food industry.

Keywords: digital transformation; food-related enterprises; mechanism testing; total factor productivity

China's government emphasised that achieving high-quality development is the foremost objective in the pursuit of modernisation. To advance this objective, it is crucial to foster a profound integration between the digital and the real economy while also concentrating efforts on enhancing total factor productivity (TFP). Despite China's successful entry into the digital economy era, the level of enterprise digitisation remains relatively low. According to the CAICT (2022) released by the China Academy of Information and Communications Technology (CAICT), a divergence can be observed between the escalating digital demands of Chinese consumers and the sluggish pace of enterprise digitisation. Notably, the primary industry encounters substantial obstacles in its digital transformation, with a meagre digital penetration rate of merely 8.6%, significantly lagging behind that of developed nations like the United Kingdom, Germany, and South Korea.

The development of digital technology has ushered in new prospects and momentum for China's food

Supported by Postgraduate Research & Practice Innovation Program of Jiangsu Province, China, Project No. KYCX21_1445; Doctoral Project of Institute of Food and Strategic Reserves Nanjing University of Finance and Economics, China, Project No. BSZX2021-10.

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https://doi.org/10.17221/271/2023-AGRICECON

industry. The new generation of technological revolution and digitalisation presents opportunities for the structural upgrading of the food industry, as well as for enhancing the quality of food consumption through improved consumer purchasing power and diversified demand. These opportunities have also put forward new requirements for the transformation of the food industry. Within the framework of comprehensively promoting rural revitalisation, industrial revitalisation remains the foremost priority. Digital transformation is not only imperative for bolstering the penetration of digital technology in agriculture, but also necessary for addressing the digital economy's shortcomings in the agricultural and rural sectors. Especially in the current complex and changing external environment, the development of digital technology should play a pivotal role in ensuring national food security, increasing farmers' income, enhancing agricultural competitiveness, and fostering sustainable agricultural development.

Relying on digital transformation to promote the modernisation of the food industry is the general trend. Since 2016, a series of policy documents have been released to provide policy assurance for the integration of digital technologies and the food industry. A series of digital construction initiatives have been implemented, such as the High-Quality Grain Project, and the establishment of the food industry platform. These initiatives have greatly accelerated the integration of digital technology with the food industry. The integration of intelligent systems with agricultural equipment and food manufacturing, driven by the Internet of Things, cloud computing, and intelligent control, is revolutionising the traditional production and processing methods of agricultural products. As the pace of China's digital village construction continues to accelerate, digital technology is gradually penetrating into the food distribution sector.

In the future, the transformation of the grain market will evolve from a sole focus on production capacity to an integrated capacity encompassing production, distribution, and innovation. China practices the strategy of sustainable farmland use and innovative application of agricultural technology to increase farmland productivity. The deep integration of digital technology and various fields of economy and society has continuously released the value of data elements. The combination of digital technology with different sectors of the economy and society has given rise to a new paradigm. This paradigm is characterised by digital transformation, which serves as a comprehensive approach driving changes in production and management practices. This paradigm reshapes industrial patterns and economic landscapes. Therefore, driven by policy guidance, market-oriented reform of the food industry and technological progress, digital transformation has become a necessary path for high-quality development of food enterprises.

There are different views on the relationship between digitalisation and TFP. Solow (1987) famously asserted that the information technology productivity paradox, also known as the Solow paradox, refers to the fact that firms investing large amounts of information and communication technology (ICT) resources do not significantly increase productivity. At the macro level, several studies have indicated that digital technologies, such as AI, have not had a significant impact on total factor productivity (TFP) in technologically advanced developed economies (Brynjolfsson et al. 2018). However, studies conducted at the micro level have generally found a positive association between digitalisation and TFP (Acemoglu et al. 2014; Li and Tian 2023). Additionally, some research suggests an inverted U-shaped relationship between digitalisation and TFP (Sun et al. 2023). Furthermore, it has been proposed that a threshold effect exists between digital inputs and firm efficiency. Initially, efficiency declines below the threshold, but beyond that point, digital inputs and firm efficiency reveal a complex non-linear relationship (Cheng et al. 2023). It may be due to the short-term rise in transformation costs that affects TFP growth (Dong and Xu 2008). Overall, the positive effect of digital transformation on manufacturing transformation has been generally recognised by academia (Reis et al. 2018; Guo and Xu 2021). However, the effectiveness of digital transformation can be influenced by the diverse endowment characteristics and stages of digital transformation across different industries. However, the impact of digital transformation on TFP may vary across industries and over different time periods.

Most existing studies primarily focus on the role of digital transformation in the manufacturing sector (Reis et al. 2018; Guo and Xu 2021; Cirillo et al. 2023), with fewer studies examining the outcomes of digital transformation in traditional agricultural enterprises. Specifically, research on the digital transformation of food-related enterprises is particularly scarce (Cannas 2023; Maheshwari et al. 2023). Due to regional differences in the division of food production regions and the imperfect compensation mechanism of benefits between major grain production regions and non-major grain production regions, the economic development of major grain production regions has histori-

https://doi.org/10.17221/271/2023-AGRICECON

cally lagged behind (Gao et al. 2018; Wang et al. 2018; Xie et al. 2021).How to catch up with the economic development of the major grain production regions in the new era has become an important issue of concern to the government. As an important market player in food distribution, food-related enterprises build a bridge between traditional agricultural provinces and modernised economic provinces to achieve common prosperity. Hence, it is imperative to initiate research at the micro level and explore strategies to enhance the development capacity of food enterprises. In the digital era, can digital transformation become a new driving force for high-quality development of food enterprises? Can underperforming food-related enterprises enhance their capabilities through digital transformation to catch up with more advanced counterparts, and what is the mechanism for catching up? These questions remain to be empirically examined and tested.

The main marginal contributions of this paper are as follows: First, this research expands the current literature on the digital transformation of food enterprises by incorporating digital technology as a modern production factor. Second, this study analysed the factors that contribute to the varying effects of digital transformation among different grain enterprises to explain how less advanced enterprises can narrow the gap between them and their more advanced counterparts through digital transformation. Third, this study explores how the digital transformation of food enterprises affects TFP by enhancing intrinsic enterprise capacity. Its objective is to enhance our understanding of the impact of the technological revolution on the high-quality development of China's food industry. The findings offer valuable insights for policymakers in devising strategies to enhance the digitally empowered food industry.

MATERIAL AND METHODS

Impact of digital transformation on TFP of food-related enterprises

Existing studies generally agree that digital transformation has a significant enhancement effect on enterprises' TFPs. Digital transformation enhances the TFP of enterprises through capability building. Digital transformation improves firms' data management capabilities (Buffington et al. 2017), innovation capabilities (Li and Tian 2023), organisational management capabilities (Schneider 2018), and dynamic capabilities (Shen et al. 2022). However, TFP is improved through effectiveness management. By leveraging the transmission of information and capitalising on synergistic effects, enterprises can accelerate knowledge spillovers (Kučera and Látečková 2006). Enterprises can facilitate inter-enterprise knowledge spillover through information transmission and synergistic effects. Enterprises can also leverage technological advantages to enhance efficient information integration, computational analysis, and exchange communication. Digital investments can improve collaboration efficiency between upstream and downstream actors in the industrial chain and different entities (Zhang et al. 2022b). Various mechanisms can be employed to improve enterprise efficiency. These include the promotion of vertical specialisation (Jia and Wang 2022), optimisation of human capital structures, fostering integration between advanced manufacturing and modern service industries (Zhang et al. 2023b), as well as optimising the operating model (Lee et al. 2021). These measures aim to enhance overall operational effectiveness and productivity, resulting in higher TFP.

Digital technologies play a crucial role in improving the productivity of the food industry (Baldwin et al. 2004). With digitisation, agribusinesses are not only able to restructure their organisation but also possess the capacity for dynamic transformation (Cannas 2023). However a significant majority of Chinese food-related enterprises has yet to reach the technological efficiency frontier (Wu et al. 2017). As a market player, food enterprises, particularly state-owned enterprises, focus on ensuring national food security instead of solely prioritising profit-making. Therefore, building their capacity to ensure a smooth flow of goods takes precedence. Especially in some emergency situations, it is necessary to have emergency response capacities, such as the ability to produce large quantities of commodity foods within a short period, as well as storage and transportation capacities. The application of digital technology in the food industry will revolutionise food storage, processing and marketing, especially the ICT technology is significant in the field of sustainable food processing (Raja et al. 2022). With the wide application of digital technology and intelligent equipment, the production capacity and management efficiency of food enterprises have been improved. Digitally transforming food enterprises' scale and standardising production processes enhances productivity and boosts TFP by enhancing technology levels and technical efficiency, which ultimately enhances food security guarantee capabilities.

The mechanism of digitalisation empowering TFP in food-related enterprises

Innovation capability enhancement effect. Innovation capability is an important ability in firm devel-

https://doi.org/10.17221/271/2023-AGRICECON

opment. The promotional effect of the increase in innovation on TFP has been confirmed by endogenous growth theory (Aghion et al. 1998). Firms' innovation capability was studied by many researchers, and the relationship between innovation capability and the firm's TFP has been found (Ma et al. 2022).

Digital technologies possess the characteristics of penetration, substitution effects, and synergy of innovation channels, which can enhance enterprises' innovation capabilities and consequently improve TFP. First, digitalisation can permeate enterprises' production and management processes (Wen et al. 2022). The application of digital technology helps traditional food enterprises to deeply integrate with digital production and establish a modern food production system (Jagtap and Duong 2019; Carmela Annosi et al. 2020). By innovating digital application scenarios and utilising digital workshop construction, the production and management capabilities of food enterprises change from automation and networking to digitisation and intelligence. (Maheshwari et al. 2023).

Second, digitalisation promotes the substitution of traditional production factors in enterprises. It facilitates the optimisation of human capital structure, leads to a decrease in the proportion of production staff and an increase in technical and sales staff, and facilitates the substitution of high-skilled personnel for low-skilled workers (Izzo et al. 2022; Tao and Ding 2022). Integrating the theory of the 'smile curve', it is evident that after digital transformation, enterprises can gradually allocate more personnel and resources to high-value-added sectors. This enhances the profitability and growth potential of enterprises, thereby improving TFP.

Finally, the analysis is based on the synergy of innovation channels, including external and internal synergy. In terms of external synergy, due to the limited size of numerous agricultural firms, their internal capacities often prove inadequate to support high-quality innovation (Forsman 2008), thereby necessitating the utilisation of external resources. The adoption of digital technologies helps mitigate the disparity in innovation factors across regions (Li et al. 2017), improves the technological innovation capacity of firms, and enables their integration into global innovation networks (Rodrigo et al. 2022). This integration gives rise to a digital agricultural innovation ecosystem (Lajoie-O'Malley et al. 2020), ultimately enhancing TFP.

In terms of internal synergy, the digital synergy of innovation resources and production management has expanded the transmission of data and knowledge elements between departments within the enterprise (Forman and Van Zeebroeck 2019), allowing sectors of one firm form a vertically integrated organisation (Karantininis et al. 2010). This approach serves to enhance management effectiveness and innovate with data, significantly augmenting their capacity to make data-driven decisions. Thus, the internal coordination of digitalisation-induced innovations facilitates the improvement innovation capacity of firms and promote TFP.

Cost reduction effect. Digital transformation has a cost reduction effect on enterprises, particularly in the food industry. The adoption of digital technologies enables the optimisation of production processes and improves production efficiency. This is especially important for food enterprises facing low profitability. By promoting intensive production or utilising advanced agricultural machinery, labour costs can be effectively reduced (Acemoglu and Restrepo 2018). The use of digital technologies, such as the Internet, also lowers marketing costs and minimises food waste. Precise control over processing levels through digital machinery helps minimise losses (Benyam et al. 2021). Through the utilisation of intelligent programs, real-time monitoring of production conditions enables timely and effective detection of hidden machine issues, consequently reducing maintenance costs and time expenditures (Peng and Tao 2022). Additionally, digital management facilitates scientific production scheduling, synergy between production and marketing, and precise cost control. Streamlining operations, optimising grain purchase and settlement mechanisms, automating warehouse processes, and enhancing grain purchase efficiency all contribute to improved productivity and TFP for food enterprises.

Based on the analysis above, three research questions were proposed: First, does digital transformation improve the TFP of food-related enterprises? Second, how does digital transformation contribute positively to TFP? Third, does it occur through enhancing firms' innovation capabilities or reducing costs?

Data source

This research was based on panel data from 2010 to 2020 of 151 A-share-listed food-related enterprises in China. The selected food-related listed companies represented various sectors, including cereal processing, edible vegetable oil processing, feed processing, soybean products processing, as well as condiment processing and distribution enterprises. These companies were primarily engaged in the production, wholesale, and retail of grain and manufactured food products. The data of firm-level variables were mainly

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collected from the China Stock Market & Accounting Research (CSMAR 2019) database and the RESSET database (RESSET/DB 2011–2019). The city-level data, such as the number of post offices and landline phones, were collected from the China City Statistical Yearbook by the National Bureau of Statistics of China (2020).

In this paper, the research data were processed as follows: First, the data of enterprises whose listing status was special treatment (ST) or *ST were excluded; second, the data of enterprises with missing data or abnormal data were excluded; third, all continuous variables were winsorised at the 1st and 99th percentiles to mitigate the potential impact of outliers. The final sample included 1 231 firm-year observations for 151 food-related listed firms.

Methods

Model specification and variable description. To investigate the impact of digitalisation on the TFP of Chinese food enterprises, we refered to the study of Li and Tian (2023), which established the following panel model for empirical research:

$$tfp_{it} = \alpha_0 + \alpha_1 digi_{it} + \beta_i \Sigma X_{it} + ind + year + \varepsilon_{it} \quad (1)$$

where: i – firms; t – year; tfp_{it} – dependent variable, total factor productivity of firm; $digi_{it}$ – core explanatory variable, enterprise digitisation index; X_{it} – control variable, vector of characteristics correlated with corporate TFP; *ind* – industry fixed effect; *year* – year fixed effect; ε_{it} – error term.

The variables were defined as follows:

(1) Dependent variable**:** total factor productivity (*tfp*). This study builds upon existing research and utilises the OP method (Olley and Pakes 1996) to quantify the TFP of enterprises. The data for measuring corporate TFP using the OP method are as follows:

i) Firm output was assessed using business revenue as the indicator.

ii) Labor input was evaluated by considering the number of employees.

iii) Capital input was measured through the assessment of fixed capital stock.

In this paper, the OP method (Olley and Pakes 1996) was used in the baseline regression results, while the LP method (Levinsohn and Petrin 2003), OLS (ordinary least squares) method and FE (fixed effects) method were used as robustness tests. The reasons were as follows: the phenomenon of firm withdrawal exists in the sample sampling process, but the LP method does not consider the sample withdrawal problem, and the OP method can better solve the problem of sample selectivity bias caused by unbalanced panel data and firm withdrawal.

(2) Core explanatory variable: First, the digital transformation index was constructed using the text analysis method. Similar to Li et al. (2013) and Wu et al. (2021), this article selected the Management Discussion & Analysis (MD&A) section of each annual report as the corpus, based on the information of MD& A of food-related listed companies, the precise frequencies of digital keywords in the corpus were defined as the degree of digital transformation (*digi*). A robustness test was conducted to use the proportion of digital keyword frequency in MD& A to the total word frequency of MD& A (*Dig*) as a proxy variable.

Second, unlike existing studies that construct digital transformation indicators only by textual analysis, this study considered both subjective and objective factors. Both subjective strategic planning and objective inputs of firms facing digital transformation can have a significant impact on the degree of digital transformation. In terms of subjective strategic planning, the Term Frequency-Inverse Document Frequency (TF-IDF) method can overcome the problem of overestimation of enterprise digitisation caused by the high frequency of keywords in text analysis. Therefore, the TF-IDF of keywords' frequencies in the texts of annual reports of listed companies was used as a subjective weight in this study. In terms of objective inputs, refer to Xiao et al. (2022) and Fang et al. (2022), we use digital intangible asset inputs and the amount of actual digital hardware investment as objective inputs. For example, the proportion of intangible assets related to digital transformation and the proportion of digital hardware investments. The entropy weighting method was used to construct a comprehensive digitisation level index (*digit_w*) with both subjective and objective data.

(3) Mechanism variables:

i) Innovation capability (*inno*). Improving technology level and factor allocation efficiency are two important ways for firms to improve TFP. The technological progress of enterprises mainly includes the innovation of new technologies and the improvement of the efficiency of existing technologies. In academia, it is commonplace to use the number of patents as a significant output of technological innovation in order to gauge the technological progress of a company (Liu et al. 2022). Considering the lengthy review process for patent grants (Gans et al. 2008), the number of patent applications more accurately reflects the intensity and efficien-

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Table 1. Descriptive statistics

Variable	Definition	Observations	Mean	P50	SD	Min	Max
tfp_op	total factor productivity	1 231	6.688	6.601	0.943	3.454	11.440
digi	digital transformation	1 231	2.561	2.639	0.918	0.000	5.106
lev	leverage ratio	1 231	0.413	0.397	0.213	0.008	1.290
size	ln(gross asset)	1 231	21.970	21.810	1.020	19.240	25.910
listage	listed years	1 231	10.520	10.000	7.368	0.000	28.000
board	board	1 231	11.460	10.000	4.000	4.000	33.000
indep	independent director / board × 100	1 231	36.980	36.840	10.330	10.000	80.000
dual	duality of COB and CEO (yes = 1, no = 0)	1 231	0.261	0.000	0.439	0.000	1.000
soe	state-owned enterprises (yes = 1, no = 0)	1 231	0.340	0.000	0.474	0.000	1.000
roa	return on total assets	1 231	0.047	0.040	0.080	–0.600	0.675
lnL	ln(employee)	1 231	7.717	7.639	1.273	3.219	11.710
inno	number of patents	1 231	16.910	4.000	36.520	0.000	308.000
cost	operation cost/revenue	1 231	1.030	0.964	1.404	0.404	47.220

COB – Chair of the Board; CEO – Chief Executive Officer; P50 – 50^{th} percentile
Source: Authors' own elaboration

cy of a company's input and utilisation of factor resources. Given the relatively low number of patents in grain enterprises (Zhang et al. 2023a) and the innovation spillover effect enjoyed by subsidiaries from their parent companies (Gong et al. 2022), this paper measured the innovation capacity of enterprises using the number of patents applied for independently by the companies themselves and jointly with their parent companies.

ii) Cost control (*cost*) plays a crucial role in open-source initiatives and cost reduction strategies. It directly contributes to improving company performance and indirectly supports the enhancement of TFP through rational resource allocation. Given the intense competition in the food product market, there is limited opportunity to increase profits solely by reducing absolute costs. Therefore, this study used a relative measure, namely the operating cost-to-revenue ratio, to assess the efficiency of cost-saving efforts within enterprises. A smaller ratio indicated higher cost-saving efficiency for the enterprise.

(4) Control variables: Following the prior literature, this paper controlled for factors that affected productivity at the firm level. Specifically, firm size (*size*), leverage (*lev*), return on assets (*roa*), board size (*board*), board independence (*indep*), the dual role of the board chairman (*dual*), state-owned enterprise (*soe*), firm age (*listage*) and number of employee (ln*L*). The description and descriptive statistics of each variable are shown in Table 1.

Descriptive statistics indicated that the TFP of most enterprises is below the average level in the sample period. We found that most of the food-related enterprises had carried out digital transformation, but the digital transformation level of some food-related enterprises needed to be improved. The innovation capability of food-related enterprises was generally weak and there was a large gap between food-related enterprises. We also found that some food-related enterprises had serious cost control management problems. Therefore, the following section will empirically test the effect of digital transformation of food enterprises on TFP and conduct a mechanism analysis for the innovation and cost control capabilities of food enterprises.

RESULTS AND DISCUSSION

Baseline regression results

Table 2 reports the results of the baseline regression. The estimated coefficient of *digi* exhibited a significant positive relationship to *tfp_op* at the 1% level. Moreover, the coefficient of *digi* decreased in magnitude after incorporating control variables. This suggests that digital transformation played a role in improving TFP within food-related enterprises. These results remained statistically significant even after controlling for industry and year fixed effects. Taking into account industry and year fixed effects, as well as other firm

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Table 2. Baseline regression results (N = 1 231)

OLS	Model(1)	Model (2)	Model (3)	Model (4)
	tfp_op			
digi	0.204*** (0.029)	0.183*** (0.034)	0.121*** (0.027)	0.073*** (0.026)
lev	–	–	0.944*** (0.117)	1.080*** (0.114)
size	–	–	0.674*** (0.032)	0.631*** (0.030)
listage	–	–	–0.001 (0.004)	–0.005 (0.004)
board	–	–	–0.002 (0.006)	–0.004 (0.006)
indep	–	–	–0.004* (0.002)	–0.004* (0.002)
dual	–	–	0.056 (0.050)	0.039 (0.047)
soe	–	–	–0.069 (0.047)	–0.051 (0.046)
roa	–	–	2.669*** (0.292)	2.817*** (0.270)
lnL	–	–	–0.223*** (0.023)	–0.185*** (0.022)
cons	6.165*** (0.078)	6.219*** (0.091)	–7.023*** (0.563)	–6.272*** (0.545)
Year FE	no	no	no	yes
Industry FE	no	yes	yes	yes
R^2	0.040	0.048	0.475	0.576

*,**,*** P < 0.10, P < 0.05, P < 0.01; SE in parentheses; OLS – ordinary least squares; *tfp_op* – total factor productivity; *digi* – digital transformation; *lev* – leverage ratio; *size* – ln(gross asset); *listage* – listed years; *board* – board; *indep* – independent director / board × 100; *dual* – duality of COB and CEO; *soe* – state-owned enterprises; *roa* – return on total assets; *lnL* – ln(employee); *cons* – costant term; *FE* – fixed effect

Source: Authors' own elaboration

characteristics, the results in column (4) indicate that a 1% increase in the level of digital transformation led to a 0.073 unit rise in TFP. This corresponds to approximately 1.09% of the sample mean (0.073/6.688). Both statistically and economically, digital transformation significantly contributed to the enhancement of TFP in food-related enterprises.

Endogeneity

There might have been an endogeneity problem due to reverse causality in the empirical study of this paper. The digital transformation might have increased the TFP, and at the same time, firms with higher productivity might have a stronger willingness to adopt digital technologies and actively promote digital transformation themselves, leading to endogeneity problems. In addition, problems such as model setting bias or omitted variables may also lead to endogeneity problems. To mitigate the endogeneity problems, this section controls not only for a set of firm-level characteristics in the benchmark model but also for industry and year fixed effects to better absorb the effects of industry and time-varying unobservable factors in order to mitigate the omitted variable problem.

Next, the instrumental variable approach was also used to further mitigate the negative impact of endogeneity issues on the study findings. As an important digital infrastructure, Internet broadband access ports lay the foundation for the digital transformation of enterprises, and their number represents the degree of digital economy development. The year 2006 was the beginning of China's 11$^{\text{th}}$ Five-Year Plan, after which significant advancements in information networks were achieved. In the same year, the Chinese government released several important policy documents on digital development. After that, China's economic and social development entered a new stage, with an accelerated transformation of the economic growth mode, vigorous development of digital infrastructure construction, and a strong digital economy driving industrial transformation and upgrading. This paper aims to construct instrumental variables based on ideas presented in existing literature (Nunn and Qian 2014; Goldsmith-Pinkham et al. 2020). Similar to Acemoglu et al. (2022), we calculated the average of the degree of digital transformation of other companies in the sample company's industry at the two-digit level defined by SITC (Standard International Trade Classification) in 2006 (*digital*_2006), and we mulitplied it with the number of Internet broadband access ports nationwide (excluding the province in which the focus firm is located), which as the instrumental variable (*IV1*). For the correlation criterion, the degree of digital transformation of firms was correlated with the industry in which they were located. For the exclusion criterion, the exclusion was enhanced by using industry data from the first four years of the sample rather than the whole sample period. The number of Internet broadband access ports for which focal provincial data were excluded was multiplied with *digital*_2006 to make the instrumental variable change over time.

https://doi.org/10.17221/271/2023-AGRICECON

This paper refers to the study of Huang et al. (2019). We selected the interaction term between the number of urban post offices and landline phones in 1984 and the number of Internet broadband access ports in the previous year as an instrumental variable (*IV*2) for robustness testing.

Table 3 reports the two-stage least squares (2SLS) regression results for the instrumental variables. The results showed that the instrumental variables were selected effectively, and the digital transformation had a significant effect on TFP of food-related enterprises.

Heterogeneity analysis

The impact of digital transformation on TFP varied, depending on property rights, industry characteristics, and regional differences. State-owned food enterprises have advantages over non-SOEs due to their market power (Dai and Li 2020), financing dominance (Jin et al. 2019), and policy support (Austin et al. 1987). Differences in factor inputs and attributes among industries may also affect the impact of digitalisation on TFP between SOEs and non-SOEs (Zhang et al. 2022a). Additionally, regions with varying levels of economic development and digital infrastructure may experience heterogeneous gains from digital transformation. Therefore, this section aims to analyse the heterogeneity impact of digitisation on TFP through the nature of property rights, industry characteristics and regional characteristics.

Table 3. Instrumental variables approach (N = 1 231)

2SLS	Model (1)		Model (2)	
	1st stage *digi*	2nd stage *tfp_op*	1st stage *digi*	2nd stage *tfp_op*
digi	–	0.436** (0.180)	–	1.902*** (0.558)
*IV*1	0.048*** (0.000)	–	–	–
*IV*2	–	–	0.006*** (0.002)	–
Control variables	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
F statistics	41.060	90.370	13.840	18.120
Kleibergen-Paap rk *LM* statistics	16.901	–	13.207	–
Cragg-Donald Wald *F* statistics	49.484	–	14.280	–
Kleibergen-Paap rk Wald *F* statistics	27.652	–	13.842	–

*,**,*** P < 0.10, P < 0.05, P < 0.01; SE in parentheses; 2SLS – two stage least square; *tfp_op* – total factor productivity; *digi* – digital transformation; *IV* – instrumental variables; FE – fixed effect

Source: Authors' own elaboration

i) Property rights heterogeneity. The results in columns (1) and (2) of Table 4 show that digital transformation significantly improves the TFP in both SOEs and non-SOEs. The regression results of the sub-groups show that digital transformation had a relatively greater effect on TFP of SOEs. Possible reasons for this result are that the digital transformation of enterprises required large-scale application of digital technologies, large-scale investment in digital factories and modern workshops, and construction of modern information systems. State-owned enterprises benefiting from advantages in capital, scale, R&D, and policies can effectively leverage their own characteristics by implementing digital transformation. This allows for the organic integration of digital strategies with the comparative advantages of the enterprises, effectively compensating for any efficiency losses in SOEs, and promoting high-quality development. Additionally, this outcome provided valuable insights for future reforms of grain SOEs.

ii) Industry heterogeneity. Referring to the study of Fang et al. (2022), the industries were classified into labour-intensive and capital-technology-intensive according to the method of Lu and Dang (2014). The results are shown in columns (3) and (4) of Table 4, where digital transformation increased TFP in labour-intensive industries, but did not increase TFP in capital-technology-intensive industries. This findings were similar to the previous discussion of the 'productivity paradox'. This paper found new evidence of a digital technology 'crowding effect' (Graetz and Michaels 2015) at the firm level, using market players in the modern food industry. Interestingly, it was observed that capital-intensive and technology-intensive food-related enterprises were not significantly influenced by digital transformation. This may be due to these enterprises already having adopted and implemented digital technologies prior to the sample period, leading to diminished marginal utility and less noticeable increases in TFP. In contrast, less developed food-related enterprises experienced a catch-up effect, resulting in more considerable benefits from digitalisation.

iii) Regional heterogeneity. Food products have unique characteristics due to their biological properties and different suitability for cultivation in various regions. Based on the geographical resource endowment,

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Table 4. Heterogeneity analysis

OLS	(1) SOE	(2) Non-SOE	(3) Labor intensive	(4) Cap-tech intensive	(5) Major	(6) Non-major
digi	0.131** (0.056)	0.063** (0.030)	0.060** (0.030)	0.318 (0.109)	0.122*** (0.039)	0.093*** (0.034)
Control variables	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
N	419	812	1 153	78	555	676
R^2	0.463	0.659	0.570	0.568	0.665	0.580
Boostrap	0.003***	–	0.036**	–	0.071*	–

*,**,*** $P < 0.10$, $P < 0.05$, $P < 0.01$; SE in parentheses; OLS – ordinary least squares; *digi* – digital transformation; FE – fixed effect; between-group difference P-values were used to test the significance of differences in *digi* coefficients between subgroups, obtained by boostrap (1 000 times)

Source: Authors' own elaboration

grain production areas can be classified as major grain production regions or non-major grain production regions. As a result, food-related enterprises tend to be located closer to major grain production regions. Historically, major grain production regions have lagged behind in economic development compared to non-major grain production regions, leading to differences in the digital development environment for enterprises. Therefore, there is a need to examine whether there are differences in the impact of digital transformation on the productivity of firms in different production regions.

The results are shown in columns (5) and (6) of Table 4, which show that the digital transformation of food-related enterprises had a significant contribution to the TFP of enterprises in all regions. The impact of digital transformation on TFP was greater for food-related enterprises in the main production areas compared to those in non-major grain production regions. This result may arise from several factors, including weaker economic development in major grain production regions, a tendency for agricultural labour to move to developed areas, and a long-term outflow of talent, capital, and other resources from major grain production regions, leading to a loss of benefits in grain production. Furthermore, the compensation mechanism in major grain production regions is not yet perfect, which constrains the TFP improvement of food-related enterprises. Furthermore, digital technology has mitigated some of these constraints by improving accessibility to production factors for food-related enterprises while enhancing governance and innovation capabilities. Thus, digital transformation has brought a catch-up effect to food-related enterprises in the major grain production regions.

Mechanism analysis

To examine the cost-saving effect and the micro-mechanical role of the firm's innovative capacity to perform, this paper refers to the four-step method of Niu et al. (2023) for mechanism analysis. In view of the possible obvious shortcomings of the three-stage test for mediating effects, the four-step method adds a test for the relationship between mechanism variables and explanatory variables, which enhances the completeness of the empirical chain (Jiang 2022). The bootstrap method was also used to relax the assumption that the product of coefficients of the Sobel test (Sobel 1982) was normally distributed. Based on this, the following tests were conducted in this section to verify the micro-level influence mechanism of this paper.

Improve innovation effects. Combined with Equation (1), the model for mechanism testing using the four-step approach was set as follows:

$$inno_{it} = \alpha_0 + \alpha_1 digi_{it} + \beta_i \Sigma X_{it} + ind + year + \varepsilon_{it} \quad (2)$$

$$tfp_{it} = \alpha_0 + \alpha_1 inno_{it} + \beta_i \Sigma X_{it} + ind + year + \varepsilon_{it} \quad (3)$$

$$tfp_{it} = \alpha_0 + \alpha_1 digi_{it} + \alpha_2 inno_{it} + \beta_i \Sigma X_{it} + ind + year + \varepsilon_{it} \quad (4)$$

where: *inno* – innovation effects; *digi* – digital transformation; *tfp* – total factor productivity.

The results are shown in Table 5. The coefficients of *inno* in columns (3) and (4) were positive and significant at the 5% and 1% levels, indicating that the innovation capacity enhancement effect played a mechanism

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Table 5. Mechanism analysis (N = 1 231)

OLS	Improve innovation				Cost reduction		
	(1) *tfp_op*	(2) *inno*	(3) *tfp_op*	(4) *tfp_op*	(5) *cost*	(6) *tfp_op*	(7) *tfp_op*
digi	0.073*** (0.026)	5.034*** (1.259)	–	0.068** (0.026)	–0.145** (0.058)	–	0.062** (0.026)
inno	–	–	0.001** (0.001)	0.001* (0.001)	–	–	–
cost	–	–	–	–	–	–0.083*** (0.013)	–0.081*** (0.013)
Control variables	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes
Sobel Z		1.657*				2.323**	
Bootstrap		[0.0017, 0.0098]				[0.0019, 0.0177]	
R^2	0.576	0.348	0.575	0.577	0.063	0.588	0.589

*,**,*** $P < 0.10$, $P < 0.05$, $P < 0.01$; SE in parentheses; OLS – ordinary least squares; *tfp_op* – total factor productivity; *inno* – innovation effects; *cost* – cost reduction effects; *digi* – digital transformation; FE – fixed effects
Source: Authors' own elaboration

role. The reason might be, as mentioned in the analysis above, that digitisation can enhance a firm's innovation capability, thereby increasing TFP.

Cost reduction effects. The cost reduction mechanism model was set up in the same way as before, only the mechanism variable $inno_{it}$ was replaced with $cost_{it}$. The regression results of the mechanism test are shown in Table 5. The result indicated that the cost saving effect played the role of an intermediate mechanism. The reason might be, as mentioned above, that the increase in TFP had the potential for cost reduction, which enabled firms to allocate more resources towards research and development (R&D) and human capital investment, thereby increasing TFP.

CONCLUSION

This paper explores the food enterprises' transformation and upgrading from the perspective of digital transformation, enriching the research on the digitalisation of food enterprises. We produced three main results. First, the baseline regression result indicated that digital transformation can improve the TFP of food-related enterprises. Second, the mechanism analysis result indicated that digital transformation positively affected TFP by enhancing firms' innovation capabilities and reducing costs. The possible reason is that the adoption of digital technologies by firms enhances innovation efficiency and optimises innovation channels, thereby bolstering innovation capabilities. Additionally, the integration of digital technologies in food enterprises resulted in reduced operational costs, consequently augmenting the overall profits. Third, the heterogeneity analysis result indicated that digital transformation had a more pronounced impact on enhancing TFP in state-owned enterprises compared to non-state-owned enterprises. Meanwhile, capital-intensive and technology-intensive food-related enterprises face the 'productivity paradox' trap, which presents catching-up opportunities for labour-intensive food-related enterprises and major grain production regions. This may be because the advanced and state-owned food enterprises implementing digital technologies had already experienced the advantages of digital development. As a result, the marginal utility from further development for these firms were smaller relative to lagging regional firms and labor-intensive firms.

Previous studies paid little attention to the digital elements in food enterprises. Consistent with previous research (Zhou et al. 2022; Huang and Nik Azman 2023; Nakatani 2024), our research confirmed the positive impact of digitalisation on TFP in food enterprises. In contrast to previous research, our findings indicated that capital-intensive and technology-intensive food-related enterprises were facing the 'productivity paradox' trap. Our study revealed that the impact of participating in digital transformation on TFP differed across regions and the characteristics of food enterprises. Additionally, we explored how digitalisation acted as a catalyst for narrowing the gap among food enter-

https://doi.org/10.17221/271/2023-AGRICECON

prises.Based on these findings, this paper provides the following recommendations. First, food-related enterprises should adopt digital transformation to enhance innovation capabilities and efficiency. Governments should provide policy incentives to facilitate this transformation. Second, food enterprises should make use of cost-saving effects to allocate resources strategically and increase R&D in digitalisation. The government should invest in digital infrastructure and provide subsidies for hardware and software to help mitigate costs. Third, state-owned enterprises should lead in promoting and implementing digital transformation to help transform and upgrade private food enterprises. Fourth, governments should formulate policies that suit different types of enterprises and improve China's intellectual property rights system to encourage and support innovation in core areas of the food industry. Lastly, less competitive food-related enterprises should receive support to achieve orderly transformation and upgrading.

Acknowledgement: Author contributions: conceptualization: L.P.L. and Y.X.; methodology and formal analysis: L.P.L.; investigation and data curation: L.P.L.; writing, original draft preparation: L.P.L.; writing, review and editing: L.P.L. and Y.X.; supervision: Y.X.; funding acquisition: L.P.L. All authors have read and agreed to the published version of the manuscript.

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Received: August 16, 2023
Accepted: February 8, 2024