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RESEARCH ARTICLE

Assessing the digital transformation efficiency of agribusiness firms: A case study in the South-Western zone of Tamil Nadu

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Abstract

The rapid pace of digitalization has transformed industries and consumer behaviour worldwide, prompting businesses to accelerate their digital transformation efforts. This study aimed to assess the efficiency of agribusiness firms in achieving digital transformation within the South-Western Zone of Tamil Nadu. Data were collected from 41 agribusiness firms and analysed using Data Envelopment analysis (DEA), a method for evaluating the efficiency of decision-making units (DMUs). The results showed that ten DMUs involved in the processing and value addition of millets and firms selling organic products, were efficient, accounting for 24% of the total agribusiness firms. The major cause of inefficiency was the decline in pure technical efficiency and the market's steadily declining returns to scale. Hence, firms must closely track their resource and scale allocations, manage their internal operations and modify their output in response to market conditions to avoid a decline in their technical efficiency. The export potential of processed foods is projected to increase by 35% during 2027-28. The export potential of processed foods is projected to increase by 35% during 2027-28. Therefore, the growth of agribusiness enterprises, especially food processing firms, provides increased value and employment opportunities. Firms should prioritize investments in recruiting a digitally skilled workforce and dedicate training hours to ensure the effective use of advanced digital technologies, thereby enhancing efficiency. Firms should prioritize investments in recruiting a digitally skilled workforce and dedicate training hours to ensure the effective use of advanced digital technologies, thereby enhancing efficiency.

Keywords

agribusiness firms; data envelopment analysis; digital technologies; export potential; processed foods

Introduction

Agriculture, a critical sector of the Indian economy, accounted for 17.80% of the nation's gross value added (GVA) in 2019-20. Around 54.60 percent of workers are employed in agriculture and allied sectors (1). In the current era, technology and data analytics seem to have huge promise for both financial success and increased production. Technology in agriculture is becoming more widespread to ensure food security worldwide. Following the green revolution, Indian agriculture has been significantly impacted by the digital agriculture revolution, which is emerging alongside the fourth industrial revolution, or "Industry 4.0," It shows that digital technologies present new opportunities to integrate smallholders into an agrifood system that is driven by technology (2). In recent years, India has developed the third-largest startup ecosystem globally, which plays an essential role in transforming the agriculture sector through innovation and digital transformation. The start-up ecosystem is crucial for driving innovation and digital transformation in the agriculture sector (3). According to Kannan (4), nearly 75% of businesses are expected to adopt big data analytics, cloud computing, e-commerce, digital trade and AI technologies between 2023 and 2027. At present, there are 1774 start-ups in food processing, 474 in organic agriculture, 130 in animal husbandry and dairying, 48 in horticulture, 22 in fisheries and 74 in the combination of all these (5). In addition to the growth in startups, Indian agricultural exports were valued at US$52.50 billion in 2022-2023. Among these sectors, the food processing industry is the largest sector in terms of output, growth, exports and consumption in India. It is projected that foreign direct investment in the food processing industry to reach Rs. 5,037 crores (608 USD million) in 2023-2024. Similarly, processed food exports are expected to reach USD 7,701.66 million in 2023-24 (6). The COVID-19 pandemic accelerated digital transformation, reshaping how businesses operate and consumers make purchases (7-9). It is anticipated that global spending on digital transformation services and technology will increase to $3.5 trillion by 2023, exceeding $2.16 trillion. This upsurge demonstrates how crucial digital transformation has been recognised as a key factor in organisational performance(10). In 2023, internet penetration in India was 48.7% while social media usage stood at 32% (11). Before the COVID-19 pandemic, micro, small and medium-sized enterprises (MSMEs) in India accounted for 11 percent of the digitalisation share in areas such as e-commerce, digital payments and online services. This has increased to 55 percent after the outbreak of COVID-19 (12,13). The digital media industry in India was estimated to be worth about Rs. 654 billion in 2023 and it is expected to grow by Rs. 955 billion by 2026 (14). The application of digital technologies has impacted the efficiency of agribusiness firms. It includes real-time information on the source, quality and handling of agricultural goods that may be accessed by supply chain stakeholders by combining blockchain technology with RFID tags and Internet of Things sensors. Indian farmers may now communicate directly with buyers and consumers due to the disruption of conventional agricultural marketing channels caused by the emergence of digital marketplaces and e-commerce platforms (15). As a result, agribusiness enterprises are compelled by the digital revolution of the marketing system to create new digital marketing abilities (DMAs) to compete in the digital age (16,17). In light of the above context, this study aims to evaluate the performance and effectiveness of agribusiness enterprises towards digital transformation.

Materials and Methods

Study Area

Agribusiness incubators of Tamil Nadu Agricultural University, located in Coimbatore, Mettupalayam, Madurai and Periyakulam (Theni) districts, were contacted for the study. The South-Western Zone of Tamil Nadu was chosen as the study area, focusing on agribusiness enterprises registered under these incubators. Based on purposive sampling, data was collected by conducting personal interviews with the agribusiness enterprises that adopt digital platforms for marketing and sales of their produce. Table 1 shows a detailed description of the variables selected for assessing the efficiency of agribusiness firms towards digital transformation.

Table 1. Variables selected for assessing the digital transformation of agribusiness firms Source: (18)

Variables	Statement
Inputs	
Ratio of existing digital transformation talents (RDTT)	RDTS = existing digital transformation talents/the total number of employees
Ratio of invested funds in digital transformation (RIFDT)	RIFDT = digital transformation budget/business turnover
Ratio of the training hours of digital transformation (RTHDT)	RTHDT = training hours dedicated to the digital transformation/total training hours
Outputs	
Digital transformation techniques (DTT)	The integrity of data security, information systems and information services is high.
	The degree to which the company gathers, analyses and applies information when making its business decisions is high
Organizational operations (OO)	The degree of consensus among company leadership regarding the vision and strategies of the digital transformation and the company's digital culture is high.
	The degree of understanding and application of digital skills among the company's staff, in both digital transformation and other departments, is high.
	The degree of information exchange and application between ecosystems is high.
	The degree to which the company's internal workflows (purchase orders, procurement, warehousing and interdepartmental collaborations) have been optimized and digitized is high.
Customer experiences (CE)	The degree to which the company's external workflows (supply chains, sales channels, marketing channels, customer service and after-sales support) have been optimized and digitized is high.
	The ability of the company to collect and analyse internal and external data to further understand customer patterns, demands and preferences is high.
Business models (BM)	The ability of the company to develop innovative business models to open up new markets is high.

As a general rule of thumb, the minimum number of DMUs required for DEA is n ≥ max {m×s, 3× (m+s)}, in which m is the number of inputs and s is the number of outputs (19). The study includes three input and five output variables. Hence, the minimum number of samples required is n ≥ (15, 24) = 24. Data was gathered from 41 agribusiness enterprises across various sectors. Likert scale was used to evaluate the responses of participants to the output indicators in each dimension, i.e., the opinions of respondents on the outcomes of digital transformation. In this study, a 5-point Likert scale was applied, where 1 indicates strongly disagree and 5 indicates strongly agree.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric technique to assess the relative efficiency of numerous input and output decision-making units (DMUs) (20,21). The CCR model, a linear programming technique was used to calculate the relative efficiency of various inputs and outputs. The BCC model was developed by dividing technical efficiency into pure technical efficiency and scale efficiency. It also removed the fixed-returns constraint present in the CCR model (22). There are two types of DEA: input-oriented and output-oriented. The goal of output-oriented DEA is to maximize output with a fixed input condition (23). When there is a fixed output, input-oriented DEA is used to minimize input and provide the ideal configuration. The vectors x_i (inputs) and y_i (outputs) correspond to each i unit, respectively. Equation (1) is used to estimate the technical efficiency using a binary problem.

$$\min_{\theta, \lambda} \ \theta$$

$$\text{Subject to} \quad -y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0 \qquad (1)$$

$$\lambda \geq 0$$

where the technical efficiency, denoted by θ, is between 0 and 1 ($0 \leq \theta_i < 1$). A point on the frontier is specified and a DMU is deemed technically efficient if θ = 1 (θ = 100%). If the value of θ is less than one (θ < 1), then a point below the frontier is identified and the unit (i) is said to be non-technically efficient. Equation (1) can be solved N times to determine the efficiency score (θ) for every DMU (24,25). The procedure for data envelopment analysis is given in Fig.1.

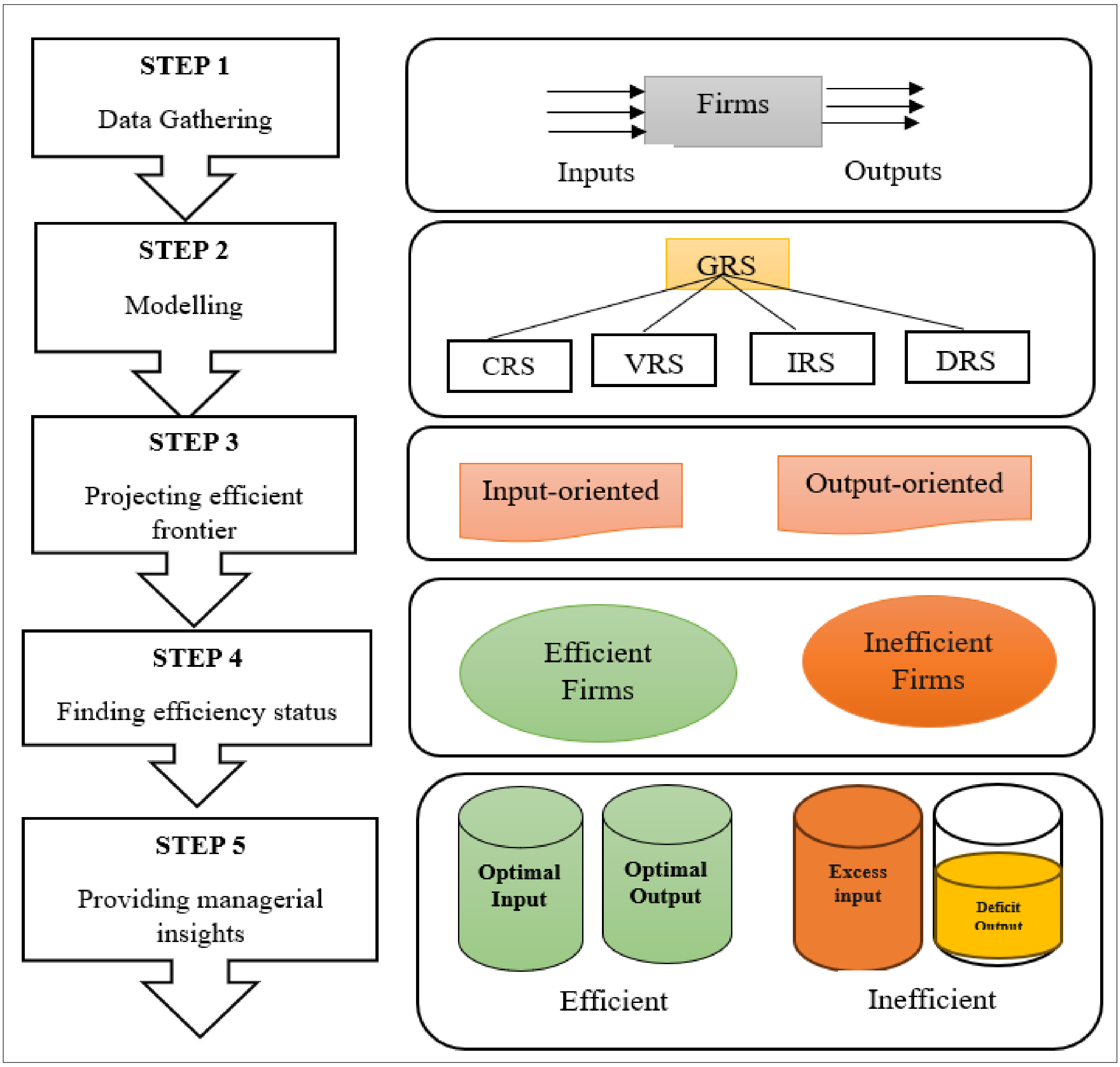

Fig. 1. Procedure of Data Envelopment Analysis, Source: (24)

Scale efficiency (SE) was calculated by

$$SEi = \theta i^{CRS} / \theta i^{VRS}$$

where θi^{VRS} denotes the efficiency under the VRS and θi^{CRS} denotes the efficiency under the CRS hypothesis (26). If scale efficiency equals one (100%), the DMU operates under the constant returns to scale assumption. Otherwise, the unit may exhibit increasing (IRS) or decreasing returns to scale (DRS) (27). If a percentage change in the factors of production results in a greater change in the output, then there is an "increasing" return to scale. When there is a percentage change in the factors of production, but the change in output is less, it is known as the "decreasing" returns to scale (28).

Overall Technical Efficiency = Pure Technical Efficiency × Scale Efficiency

$$TE\ (CRS) = TE\ (VRS) \times SE$$

Support Vector Regression (SVR)

To predict the export status of processed foods for the next four years, Support Vector Regression (SVR) was employed. It is used in the construction of a Support Vector Machine (SVM), which is a popular AI-based technique (29,30). The reliability of SVR performance is largely determined by the kernel function and the characteristics of data used in constructing SVR (31,32). In this context, the export value of processed food is predicted by Support Vector Regression using the linear kernel and the parameters are optimized through hyperparameter tuning with the grid search method. The grid search technique is applied to the training dataset by inputting various kernel functions and parameters (33-35).

Results

General Characteristics of the Agribusiness Firms (n = 41)

The general profile of the agribusiness firms selected for the study in the south-western zone of Tamil Nadu is presented in Table 2-5 and Fig.2.

Table 2. Type of Business Organization

Type of business	Frequency	Percentage
Sole Proprietorship	17	42.00
Private Organization	14	34.00
Venture Capital	1	2.00
FPO	2	5.00
Partnership	5	12.00
FPC	2	5.00
Total	41	100.00

Table 3. Type of Agribusiness sector

Industry type	Frequency	Percentage
Processing & Value addition	17	41.00
Production	5	12.00
Services	8	19.00
Inputs	2	5.00
Organic fruits & vegetables	7	17.00
Retail	2	5.00
Total	41	100.00

Table 4. Duration of the existence of organization

Year	Frequency	Percentage
Less than 1 year	3	7.00
1-2 years	13	32.00
2-4 years	9	22.00
More than 4 years	16	39.00
Total	41	100.00

Table 5. Duration of adoption of digital marketing platforms

Year	Frequency	Percentage
Less than 1 year	5	12.00
1-2 years	21	51.00
2-4 years	10	25.00
More than 4 years	5	12.00
Total	41	100.00

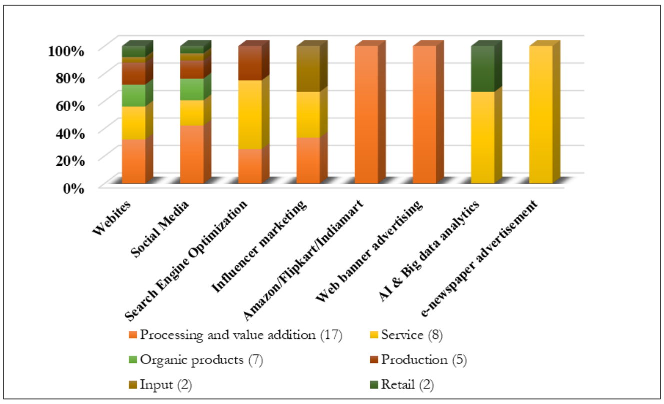

Fig. 2. Digital Platforms adopted by business organization.

It could be inferred from Table 2, that majority of the agribusiness firms were sole proprietorships (42%), followed by private organisations (34%) and partnerships (12%). Regarding the sector-wise distribution of the firms. Table 3 shows that most firms were involved in processing and value addition, particularly in products such as millets, masala products and pickles (41%). This was followed by the service sector (20%) and firms selling organic and eco-friendly products, including fruits and vegetables, millets, honey and cosmetics (17%). Table 4 shows that 39% of agribusiness firms had existed for more than four years while Table 5 reveals that 51% had adopted digital platforms for 1 to 2 years. The limited adoption of digital platforms was primarily attributed to a lack of awareness about digital tools, high investment costs and a shortage of digitally skilled employees. Figure 5 shows that websites, web portals and social media were adopted by all the sectors due to their low cost and easy maintenance. Artificial intelligence and big data analytics were adopted only in the retail and service sectors. Organisations involved in processing and value addition used SEO, influencer marketing and web banner advertising. Social media usage was high, which included WhatsApp (73 percent), Instagram (71 percent) and Facebook (54 percent). Around 63 percent of the firms had their own websites or web portals. Only 10% of respondents adopted SEO due to its high initial investment. Influencer marketing, AI, big data analytics, web banners and newspaper advertisements were the least adopted strategies among agribusiness firms. Only firms related to processing and value addition have adopted various digital platforms, including influencer marketing, web banner advertising, search engine optimisation and using e-commerce platforms like Amazon and Flipkart.

The efficiency of 41 agribusiness firms regarding their digital transformation activities was assessed using DEA, through DEAP software, in which an input-oriented model was used (36). The main aim of this study was to examine the overall efficiency of sample agribusiness firms and identify the reasons for their inefficiencies. The summary statistics of the selected variables are presented in Table 6.

Table 6. Summary statistics of variables (n = 41)

Variables	Mean	Std. Dev	Min.	Max.
RDTT (x1)	0.614	0.325	0.00	1.00
RIFDT (x2)	0.008	0.015	0.00	0.10
RTHDT (x3)	0.472	0.155	0.14	1.00
DTT (y1)	3.792	0.661	3.00	4.50
OO (y2)	3.665	0.627	2.60	5.00
PO (y3)	3.621	0.713	1.50	5.00
CE (y4)	4.292	0.642	3.00	5.00
BM (y5)	4.048	0.835	2.00	5.00

Table 6 shows that the variance of some input and output variables is large, indicating a significant deviation from the mean. This included the ratio of existing digital transformation talents (RDTT) and the business model (BM). With these illustrations, the total efficiency values were calculated using the CCR model and the technical efficiency values using the BCC model. Finally, scale efficiency (SE) was evaluated using a two-stage model to assess both technical and scale efficiencies. The descriptive data of the model are presented in Table 7.

Table 7 shows that the average overall technical efficiency of 41 agribusiness firms was 0.768. This indicated that for the firms to become more efficient, the inputs need to be decreased by 23.20 percent for a given level of output. Additionally, 10 firms (24.40%) were found to be efficient, indicating that they used inputs optimally and should maintain a constant size. Furthermore, the average pure technical efficiency was relatively high at 0.842. This indicated that the firms had to reduce their inputs by 15.80 percent to be efficient. A scale efficiency of 1 (SE = 1), shows that 24% of the firms operate at optimal size. In contrast, 76 percent of the firms were found to be operating inefficiently by using more inputs than necessary for their size (37). It was noteworthy that ten firms exhibited full technical and scale efficiency, which makes clear that these firms must maintain a steady level of inputs to be efficient since they are subject to constant returns to scale. These firms can serve as operating models for the remaining 31 firms. Table 8 shows the efficiency values of 41 agribusiness firms.

Table 8 shows that ten DMUs (DMU_6, DMU_{16}, DMU_{24}, DMU_{25}, DMU_{27}, DMU_{29}, DMU_{30}, DMU_{31}, DMU_{36}, DMU_{40}) were found to be efficient, accounting for 24% of the total agribusiness firms. Of these, the majority of the firms were involved in processing and value addition of millet and organic products. The estimates of returns to scale (RTS) aligned with beneficial investments in a productive workforce and training hours dedicated to digital transformation. Additionally, it was apparent that an enterprise with decreasing returns to scale (DRS) does not optimally use its investment, whereas an enterprise with increasing returns to scale (IRS) would be expected to produce greater and faster digital transformation outputs. As a result of this DRS inefficiency, other firms may be able to decrease their input usage and still obtain the same or greater amounts of output. It applies in the areas of digital transformation technologies (DTT), organisational operations (OO), process optimisation (PO), customer experiences (CE) and business models (BM). Table 8 also shows that DMU_9, DMU_{17}, DMU_{20}, DMU_{26}, DMU_{33}, DMU_{37} and DMU_{41} exhibited increasing returns to scale (IRS). The presence of the IRS suggests that these DMUs achieve better returns on investments in recruiting personnel for digital transformation and in training and education.

Table 7. Descriptive statistics of Data Envelopment Analysis results

Model	Average	Minimum value	Maximum value	No. of efficient firms	Percentage of efficient firms
CRS	0.768	0.354	1.000	10	24.40
VRS	0.842	0.418	1.000	21	51.21
SE	0.918	0.447	1.000	10	24.40

Table 8. Efficiency value of each Agribusiness Firms

DMUs	OTT	TE	SE	RTS	DMUs	OTT	TE	SE	RTS
1	0.811	0.940	0.863	DRS	**22.**	0.663	0.670	0.988	DRS
2	0.685	0.888	0.772	DRS	**23.**	0.753	0.763	0.986	DRS
3	0.911	1.000	0.911	DRS	**24.**	1.000	1.000	1.000	-
4	0.988	1.000	0.988	DRS	**25.**	1.000	1.000	1.000	-
5	0.970	1.000	0.970	DRS	**26.**	0.876	0.909	0.964	IRS
6	1.000	1.000	1.000	-	**27.**	1.000	1.000	1.000	-
7	0.901	1.000	0.901	DRS	**28.**	0.668	0.719	0.929	DRS
8	0.588	0.593	0.990	DRS	**29.**	1.000	1.000	1.000	-
9	0.522	0.527	0.990	IRS	**30.**	1.000	1.000	1.000	-
10	0.648	0.650	0.997	DRS	**31.**	1.000	1.000	1.000	-
11	0.930	1.000	0.930	DRS	**32.**	0.700	1.000	0.700	DRS
12	0.801	1.000	0.801	DRS	**33.**	0.354	0.418	0.848	IRS
13	0.701	1.000	0.701	DRS	**34.**	0.666	0.718	0.928	DRS
14	0.447	1.000	0.447	DRS	**35.**	0.812	0.883	0.919	DRS
15	0.660	1.000	0.660	DRS	**36.**	1.000	1.000	1.000	-
16	1.000	1.000	1.000	-	**37.**	0.542	0.573	0.946	IRS
17	0.533	0.541	0.986	IRS	**38.**	0.793	0.936	0.847	DRS
18	0.896	1.000	0.896	DRS	**39.**	0.706	0.747	0.946	DRS
19	0.497	0.506	0.980	DRS	**40.**	1.000	1.000	1.000	-
20	0.437	0.442	0.987	IRS	**41.**	0.498	0.524	0.950	IRS
21	0.523	0.571	0.915	DRS					

Firms related to processing and value addition, especially masala and pickles (DMU_{13}, DMU_{14}, $DMU_{15}$and DMU_{32}), showed suboptimal scale efficiency. Therefore, these firms should align their digital transformation investments with actual market conditions, as arbitrary increases may reduce efficiency. Additionally, DMU_{19}, DMU_{20}, DMU_{14}, DMU_{33} and $DMU_{41}$from the service and production sectors had overall technical efficiency scores below 1, which was attributed to poor technical efficiency. These firms should strengthen their internal audits of the budgets for digital transformation and the employees assigned to them to figure out any errors that were made and the reasons behind them.

Slack Variable Analysis

The efficiency of digital transformation tasks and the resource allocation among agribusiness firms can be improved through projection analysis using slack variables and overall efficiency values from the CCR models. The management and control targets of each firm, or the recommended input quantity (X^*_{ik}), were determined by using the equation $X^*_{ik} = \Theta^* X_{ik} - s_i^{-*}$. Here, the original input variable is X_{ik}, the slack variable is s_i^{-*} and the total efficiency of the DMU is denoted by θ*. The slack variable indicated the number of inputs that had to be reduced by the inefficient firms to increase their relative efficiency (38). The target number of inputs for the inefficient firms is given in Table 9.

Export prediction of processed foods from India

The linear model is trained with the training dataset where the actual and SVR prediction of processed food products is depicted in Fig. 3.

Year	2023-24	2024-25	2025-26	2026-27	2027-28
Export value (Rs. Crore)	4294.95	4994.87	5517.07	5741.94	5794.43

Fig. 4 shows that the export value of processed foods from India has steadily increased over the years. In 2019-20, there was a sharp increase in exports, largely due to the effects of the Covid-19 pandemic. The export value of processed foods which stood at Rs. 4294.95 crores in 2023-24, is projected to increase by 35 per cent to Rs. 5794.43 crores by 2027-28. These figures indicate that the diversification of India's food sector and growing global demand for Indian foods create a strong need for large-scale food processing, product branding and export-oriented strategy to enhance value and generate employment.

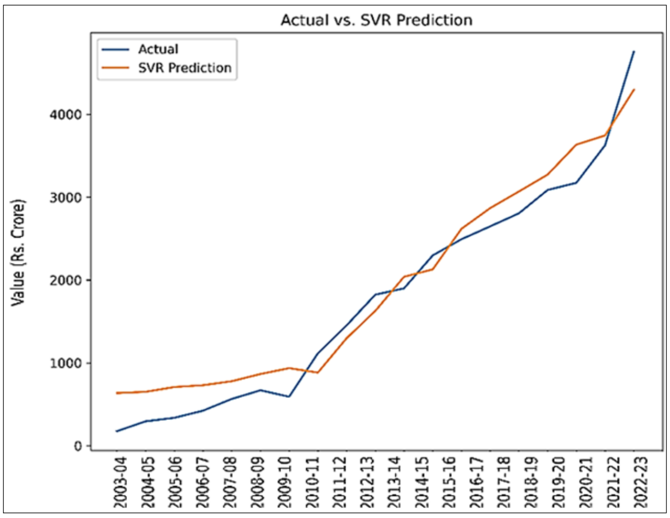

Fig. 3. Training of SVR model.

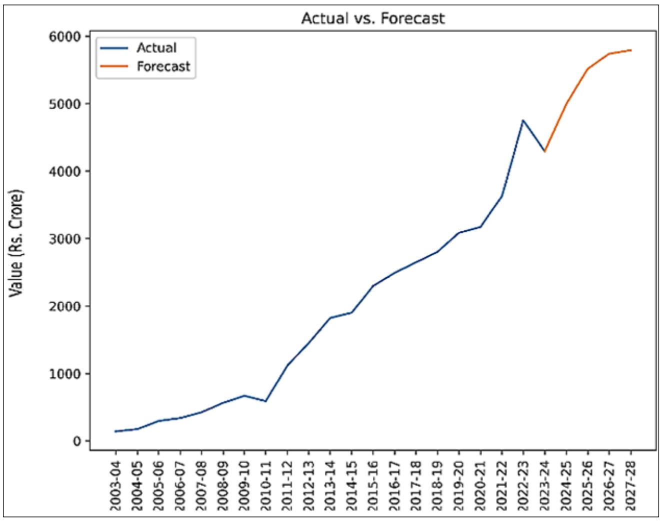

Fig. 4. Forecasted export of processed foods (2023-2028).

Moreover, the sector would offer a dynamic and attractive environment propelled by the country's agricultural resources, shifting consumer tastes and government assistance. Hence, the food processing industry would flourish and make a substantial contribution to the economic prosperity of the nation owing to its wide range of food products, innovative technology and rising export potential.

Table 9. Input target for the inefficient agribusiness firms

DMUs	RDTT	RIFDT	RTHDT	DMUs	RDTT	RIFDT	RTHDT
1.	0.310	0.001	0.375	**19.**	0.506	0.004	0.314
2.	0.440	0.002	0.444	**20.**	0.252	0.003	0.332
3.	0.500	0.002	0.400	**21.**	0.229	0.002	0.451
4.	0.400	0.001	0.400	**22.**	0.503	0.007	0.295
5.	1.000	0.002	0.350	**23.**	0.191	0.002	0.382
7.	0.330	0.020	0.500	**26.**	0.182	0.002	0.382
8.	0.392	0.011	0.297	**28.**	0.288	0.003	0.360
9.	0.348	0.003	0.316	**32.**	0.500	0.010	0.570
10.	0.976	0.001	0.325	**33.**	0.418	0.002	0.251
11.	0.700	0.003	0.330	**34.**	0.359	0.004	0.359
12.	0.660	0.001	0.500	**35.**	0.860	0.002	0.371
13.	1.000	0.002	0.350	**37.**	0.286	0.003	0.286
14.	1.000	0.100	0.850	**38.**	0.702	0.002	0.371
15.	0.300	0.003	0.500	**39.**	0.246	0.002	0.373
17.	0.541	0.004	0.227	**41.**	0.262	0.004	0.299
18.	0.250	0.006	0.500				

Discussion

In assessing the efficiency of agribusiness enterprises towards digital transformation, data was collected from 41 agribusiness enterprises, for which Data Envelopment Analysis was employed. Although these enterprises had been operating for more than four years, they only adopted digital platforms two to three years ago, primarily due to the COVID-19 pandemic. The pandemic situation compelled both enterprises and consumers to switch to digital platforms. The most common digital platforms used by agribusiness enterprises were websites, web portals and social media. Artificial intelligence and big data analytics were adopted mainly in the retail and service sectors. Enterprises involved in processing and value addition used SEO, influencer marketing and web banner advertising. Social media usage increased among organisations, mainly WhatsApp, Instagram and Facebook. The other digital platforms preferred by the organisations include influencer marketing, AI, big data analytics, web banners and e-newspaper advertisements. In the DEA analysis, it was found that the firms that belonged to processing and value addition of millets and the firms selling organic products were efficient. Further, it was identified that some of the firms related to processing and value addition of masala and pickles were inefficient due to poor scale efficiency. Whereas, the firms that belonged to the production and service sectors performed poorly due to their technical efficiency. A decline in pure technical efficiency, coupled with the market steadily decreasing returns to scale, contributed to the firm's poor performance. Therefore, firms must closely track their resource and scale allocations, manage their internal operations and modify their output in response to market conditions to avoid a decline in their technical efficiency. Regarding the export potential of processed foods, it was predicted that there would be a 35 percent increase in exports during 2027-28.

Conclusion

To meet the growing global demand and increase export potential, large-scale food processing, effective product branding and an export-focused strategy are critical for driving value and employment. Moreover, agribusiness firms must embrace advanced digital technologies to optimize efficiency and stay competitive in the evolving market., In the current scenario, through capacity building programs, conducting expos, buyer-seller meets, financing and facilitating the marketing of products, Agri entrepreneurs could flourish under the support of Technology Business Incubator-TNAU. With policies favouring digital transformation along with business incubation activities, the climate for agribusiness entrepreneurs is favourable. Now, if they get exposed to digital transformations then their growth remains sustained in the future competitive world.

Authors' contributions

All authors have contributed to preparing the manuscript and they have read and approved for final submission

Compliance with ethical standards

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