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Impact of blockchain technology adoption in farms of FPO members

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Agriculture is the main driver for economic development and poverty reduction in Asian countries. Small and marginal farmers produce foods for rural and urban populations, as well as for income and employment generation. Realizing the importance of the agricultural sector, the government focuses on improving the quality production and productivity for enhancing food security and safety, and improving the livelihoods of small and marginal farmers. The Indian government is placing a significant emphasis on agriculture development through modernization and adoption of new technologies in agriculture. Blockchain is one such digital technology that provides transparency and traceability.

Blockchain technology (BCT) was adopted by the members of Kazhani Farmer Producer Company (FPC) in Erode district of Tamil Nadu. The objective of this study was to assess the impact of blockchain technology adoption on farm income of Kazhani FPC members using propensity score matching method. The farmers perceived that the Farmers producer organisations (FPO) provided several services to the farmers to improve the profits (Gokul *et al.* 2019, 2020). Propensity score matching (PSM) was used to estimate the outcome of the observed characteristics between the participants and non-participants. It matched each treated group with the non-treated group to generate an artificial control group (Priscilla and Chauhan 2019). PSM is used to match each treated group with the non-treated group to generate an artificial control group (Gendzwill *et al.* 2021). Cunguara and Darnhofer (2011) estimated rural household income in Mozambique using PSM approach and adoption of technology such as automated irrigation systems reduced labour costs and increased household income.

The present study was carried out in Erode district of Tamil Nadu, in which FPO members had adopted BCT in red banana cultivation for marketing their produce with traceability. Kazhani-FPO located in Erode district focuses on banana exports, smart IoT-based agriculture, blockchain-based traceability, organic farming to increase farmers' income and improve their standard of living. Madurai agribusiness incubation forum, a business incubator assists and fosters agribusiness development. Kazhani FPC has implemented BCT in red banana cultivation with support from red banana farmers. BCT adopters upload the red banana crop cultivation details, cultural practices followed by harvest details in the food sign mobile application. Kazhani FPC procured farmers' produced in bulk and sold it to retailers with QR codes. The QR codes generated information about the banana from production to consumption. Consumers with their smartphone scanner traced the information of red banana by scanning the QR codes (Fig 1).

Simple random sampling technique was employed to select the sample respondents of 120 BCT adopters from six villages from Gobichettipalayam block in Erode district. 120 non-adopters were also selected to gather information. Quantitative data were collected using an interview schedule in the year 2023. Demographic and socio economic characteristics of sample farmers were also collected. Descriptive statistics was used to represent the demographic and socio-economic profiles of sample farmers. Propensity score matching approach was employed to assess the impact of BCT adoption on farm income of sample farmers.

Rosenbaum and Rubin (1983) described the propensity score as the conditional chance of getting a treatment based on the pre-treatment variables. Thus, when a group of individuals have similar propensity scores, the distribution of observed variables between the adopters and non-adopters will be identical (Lee *et al.* 2010). The steps involved in propensity score matching (PSM) approach are variable selection, model creation, treatment effects estimation, and quality matches (Steiner and Cook 2013). The treatment effect analysis of blockchain technology adoption can be modelled as follows:

$$Yi = \alpha Xi + \beta Ti + \varepsilon i \quad (1)$$

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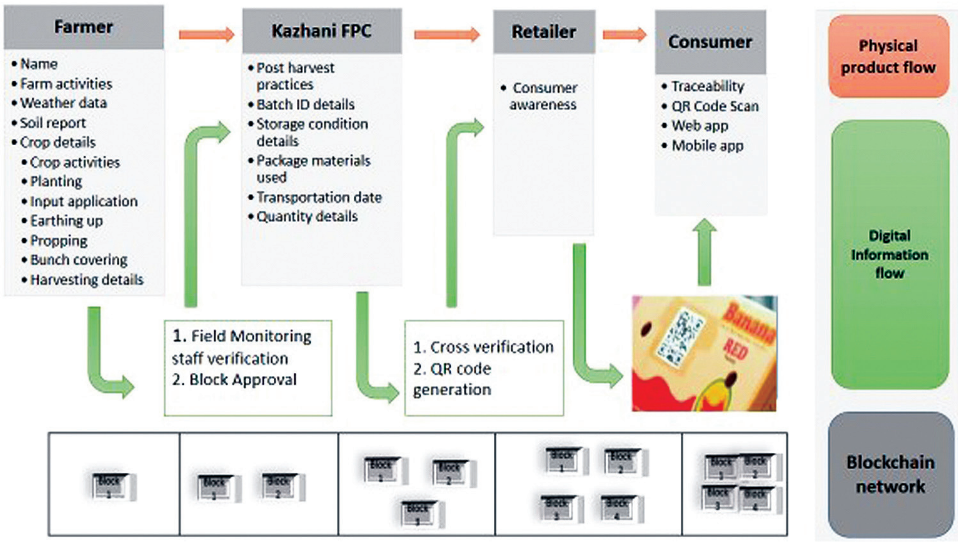

Fig 1 Blockchain integrated agricultural supply chain (Red Banana).

Here, Yi represents the outcome for household i; where, Yi (1) for adopters and Yi (0) for non-adopters. Xi is a set of selected observed variables of the individual household i; Ti is the dummy equal to 1 for adopters and 0 for non-adopters. εi is an error term reflecting unobserved characteristics that affects Yi. For individual households, the difference (δi) between the treated and untreated results determined the unobserved treatment effect and it was expressed as follows:

$$\delta i = Yi(1) - Yi(0)$$

Here, ATT is the average treatment effect or average gain in outcomes of treated groups (adopters) relative to non-treated groups (non-adopters). It can be introduced as:

$$ATT = E\left(\frac{Yi(1)}{T}=1\right) - E\left(\frac{Yi(0)}{T}=1\right)$$

Where, Yi refers to the outcome for an individual and; T refers to the treated dummy variable. Yi (1) represents an outcome of i^{th} individual under treated (adopters) and Yi (0) represents an outcome of an untreated individual (non-adopters). Thus, in simple, the average treatment effect on the treated (ATT) can be estimated as follows:

$$ATT = E\left(\frac{Yi(1) - Yi(0)}{T} = 1\right)$$

The empirical model used in the present study is given as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon i$$

Where, X_1 (age), X_2 (gender), X_3 (family type), X_4 (educational status), X_5 (farming experience), X_6 (farm size), X_7 (asset value), X_8 (extension agency contact), X_9 (training programme attended), X_{10} (access to technological information). The causal effect of blockchain technology adoption on farm income was estimated using the nearest neighbour matching principle using psmatch2 command on STATA16.

The demographic and socio-economic profile of sample farmers provided an idea about the improved technological adoption in agriculture by farmers. The results indicated that the majority of the BCT adopters (38.00%) belonged to the age group of 41–50 years, and non-adopters were more than 50 years (34.00%) of age. Since, the majority of BCT adopters belong to the nuclear family category, they have high decision making power regarding technology adoption. Most of the adopters were well educated compared to non-adopters and the level of education was higher among the adopter farmers, which would have helped them in adopting new technology in farming. It has been observed that the majority of sample farmers (both adopters and non-adopters) had more than 20 years of farming experience and most of them were medium farmers with 2–5 ha of land holdings. The result concluded that most of the sample farmers were small and marginal farmers. BCT adopters had frequent extension agency contact with state department officials and university scientists, and participated in many training programmes organized by the extension officials (Fig 2). In addition, access to technological information related to agriculture, skill upgradation and easy access to market related information through farmer producer companies were found to be higher among adopters than non-adopters.

The basic idea of propensity score matching was to match each identical adopter with non-adopters and to measure the difference among them (Aditya and Kishore 2018). The probit model was used for the estimation of propensity scores to quantify the impact of BCT adoption on farm income. The log pseudo-likelihood ratio obtained has a value of 71.01% which indicates that the included explanatory variables satisfy the adequate propensity scores. The model has a pseudo R^2 value of 0.21 which was considerable (Table 1).

The results in the Table 1 showed that farming experience, farm income, training programme and access to technological information were statistically significant at 1% level of significance. Educational status, farm size, extension agency contact were significant at 5% level of significance. The findings revealed that educational status positively influenced the technology adoption at 5% level of significance indicating that educated farmers were more likely to adopt BCT. Farming experience was found to be significant at 1% level of significance. It indicates that farming experience of individual helps in strong decision making with various alternatives to earn better farm income.

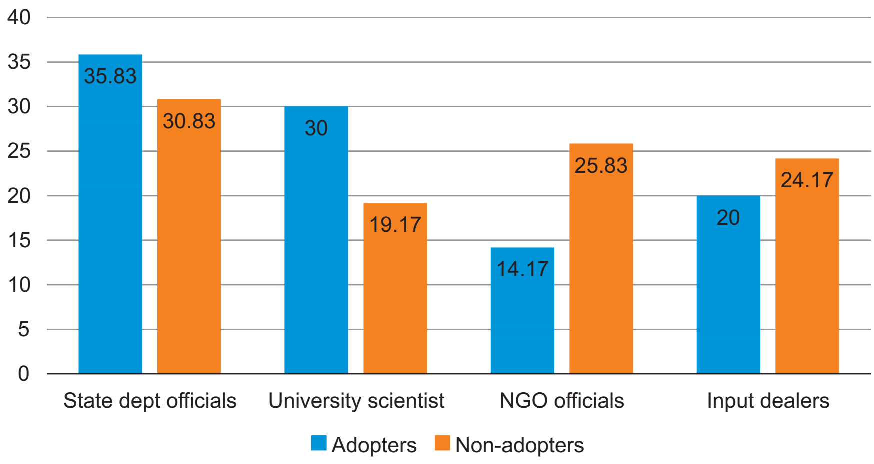

Fig 2 Extension agency contact.

The landholding size was found to be negatively significant, which indicates that decreased land area could reduce the chance of BCT adoption. The institutional variables such as extension agency contact, training programme and access to technological information positively influenced the sample farmers for BCT adoption. This indicates that 1% increase in these institutional variables may increase the chance of adopting BCT among sample farmers. The results are in consistent with results of Leng *et al.* (2020). They concluded that promotion of improved agricultural technologies enhanced household food and nutrition security. Aweke *et al.* (2021) highlighted that adoption of improved agricultural technologies were more likely to have higher food security compared to non-adopters of the technology. Quality and nutrient content were major product traits influencing consumers for purchasing the FPO food products (Malarkodi *et al.* 2023).

The three groups in the nearest neighbour matching principle consisted of outcome variable (farm income), independent variables (demographic, socio-economic and institutional variables) and the treatment dependent variable (dummy adopters'1'and non-adopters'0'), respectively (Table 2).

The results showed a significant increase in the farm income as a result of BCT adoption among sample farmers. BCT can complement the adoption of good agricultural practices through the authentication process. This resulted in increased yield and price for red banana produce with traceability. Hence, BCT adopters earned higher farm income of ₹25829.16/ha compared to non-adopters of BCT. Hence it has been proven that the adoption of BCT enhanced the farm income. The result obtained was consistent with the previous empirical results of Habtemariam *et al.* (2019), who indicated a positive income effect of adopting BCT in grape wine cultivation.

The present study assessed the impact of BCT adoption on farm income through propensity score matching estimation procedure. The results showed that BCT adopters had a positive effect on farm income. Thus the study found that blockchain technology adopters benefitted with increased farm income of ₹25829.16 compared to non-adopters. Based on the findings, the following suggestions can be made to enhance the technological adoption in agriculture. Awareness creation campaigns regarding the importance of blockchain technology can improve adoption among small and marginal farmers. In particular, it is essential to encourage young farmers to adopt the best farming practices and innovative technologies to increase farm profit. Furthermore, new technology adoption experience encourages the farmers towards adoption of improved technologies in agriculture. A multi-stakeholder involvement to develop, disseminate and scale up technologies need to be encouraged through the

Table 1 Estimates of probit model for BCT adoption

Variable	Coefficient	Standard error	P-value
Demographic variables			
Age	-0.098^{NS}	0.022	0.208
Gender	0.670^{NS}	0.427	0.116
Family type	-0.036^{NS}	0.326	0.911
Educational status	0.465**	0.208	0.026
Farming experience	0.166***	0.028	0.001
Economic variables			
Farm income	0.000***	0.000	0.001
Farm size	-0.063**	0.064	0.034
Asset value	0.000^{NS}	0.000	0.372
Institutional variables			
Extension agency contact	0.437**	0.193	0.024
Training programme attended	1.813***	0.296	0.004
Access to technological information	1.271***	0.323	0.001
No. of observations = 240			
LR $chi^2(11)$ = 238.69			
Prob > chi^2 = 0.0000			
Log likelihood = 74.012			
Pseudo R^2 = 0.21			

*** 1% level of significance; ** 5% level of significance; NS, Non-significant.

Table 2 Impact estimates of BCT adoption on farm income

Matching algorithm	Outcome variable	Average treatment effect (ATE)	Standard error	P-value
Nearest neighbour matching	Farm income	25829.16	3.23	0.001

*** 1 % level of significance.

university's research and extension services. As blockchain based traceability can help ensure food safety and security, agricultural universities can boost up the innovation process and develop a new business model for FPOs for the commercialization and export of FPO products through blockchain based traceability systems.

SUMMARY

BCT adoption remains to be a promising way to achieve food security and safety in many developing countries. This paper explores the impact of blockchain technology adoption on household farm income. Based on a simple random sampling method, a cross sectional survey was conducted in the year 2023 to collect data from 240 sample farmers including 120 BCT adopters and 120 non-adopters in Erode district of Tamil Nadu. The information regarding socio-economic profiles like age, gender, educational status, farming experience, farm size, extension agency contact, training programmes attended, access to technological information were collected from sample farmers through personal interviews. The present research used a treatment effect analysis with propensity score matching approach to assess the impact of blockchain technology adoption on household's farm income. Results showed a significant increase in farm income as a result of blockchain technology adoption among sample farmers. PSM approach estimated that the blockchain technology adopters earned higher farm income of ₹25829.16 as compared to non-adopters. Hence the findings provide empirical evidence that blockchain technology adoption in agriculture can contribute to improve quality food production and enhance farm income.

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