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FACTORS AFFECTING THE ADOPTION INTENSITY OF FARM MACHINERY AMONG WHEAT FARMERS IN RUPANDEHI DISTRICT, NEPAL

Jamuna Pandey[1]* and Binayak Prakash Mishra[2]
[1]Nepal Polytechnic Institute, Purbanchal University, Nepal
[2]Agriculture and Forestry University, Rampur, Chitwan, Nepal
*Corresponding author: jamunapandey15@gmail.com
Jamuna Pandey: 0009-0008-2619-0830
Binayak Prakash Mishra: 0009-0009-6526-8917

ABSTRACT

An investigation was done in 2025 to identify the factors affecting the adoption intensity of farm machinery among wheat farmers in Rupandehi district, Nepal. Using a random sampling technique, 120 farm households within the wheat zone area of the Prime Minister Agriculture Modernization Project (PMAMP) were selected. Primary data was collected through household surveys using a semi-structured interview schedule. In addition, Focus Group Discussions (FGDs) and Key Informant Interviews (KIIs) were also conducted with selected individuals. Descriptive statistics and an ordered Probit model were employed to analyze the data using STATA 17. The results revealed that both institutional and resource-related factors significantly influenced the adoption intensity of farm machinery. Specifically, membership in agricultural cooperatives, farm size, and access to government subsidies through PMAMP positively and significantly affected adoption intensity. These findings suggest that strengthening cooperative institutions, promoting land consolidation or collective use models such as group farming, and maintaining targeted subsidy programs are vital for accelerating the adoption of farm machinery in wheat production. Furthermore, mechanization policy should adopt a holistic approach that integrates institutional support, land-use planning, and financial incentives to facilitate sustainable agricultural mechanization.

Key words: *Cooperatives, mechanization, ordered probit, subsidy*

INTRODUCTION

Wheat contributed 5.88 percent to the agricultural GDP in FY 2080/81 (2023/24). Wheat ranks third in terms of cultivation area in Nepal, following paddy and maize. In 2022/23, wheat was cultivated on 697,762 hectares (ha), that achieved production of 2,098,462 metric tons (t) and yield of 3.01 t/ha. In comparison to the previous year (2021/22), both the cultivated area (716,978 ha) and production (2,144,568 t) slightly declined, although the yield increased from 2.99 t/ha to 3.01 t/ha (MoALD, 2024). This signifies the importance of wheat in Nepalese agricultural economy.

Unavailability of labors in time and higher labor costs often lead to delays in important crop management practices, leading to decrease in farm productivity and profit. These issues, along with other structural issues lowered the domestic production of major cereals and increased dependence on imports (Paudel et al., 2023). Import records of 2022/23 highlighted 59,000 kilograms of durum wheat seed, 6,571,249 kilograms of other durum wheat, 33,851 kilograms of wheat seed, and 362,380 kilograms of wheat or meslin flour (excluding maida) (MoALD, 2024), indicating that domestic production remains insufficient to meet national demand. Thus, there is a need to opt modern practices in production process.

Agricultural mechanization refers to the use of appropriate and modern machinery and equipment in farming to enhance productivity and working conditions (Zhang et al., 2024). Promoting mechanization that matches the scale of farming is recognized as an important strategy to address acute labor shortages, reduce cost of production and generate rural employment through mechanization service provision (Paudel et al., 2019a, b; Van Loon et al., 2020; Yang et al., 2013). Mechanization in smallholder farming systems is positively impacting farming by reducing production costs through alleviating labor constraints, minimizing drudgery, and subsequently enhancing productivity (Pingali, 2007; Kienzle et al., 2013; Khatiwada et al., 2021). Thus, it has potential to drive the structural transformation in agrarian economies by improving on-farm efficiency, raising agricultural productivity, and strengthening food security (Paudel et al., 2023).

The shortage of agricultural labors, along with increasing daily wages, has increased the potential for farm machinery in Nepal (Shrestha, 2022). Additionally, the flow of remittance has boosted both the commercialization and investment in farm machinery (Shrestha, 2022). Similarly, the Government of Nepal introduced the Agricultural Mechanization Promotion Policy in 2014 with the aims to improve productivity through suitable mechanization, increase access to agricultural machinery, promote women-friendly farm machinery, and strengthen institutions related to mechanization (Shrestha, 2022). Further, Agriculture Development Strategy (ADS) of Nepal (2015-2035), highlighted the importance of adopting suitable farm technologies to improve productivity. The ADS promotes a core program that provides various mechanization options for farmers. It supports this adoption through activities such as creating awareness, stimulating demand, facilitating concessionary financing arrangements, offering capacity building, and implementing suitable taxation measures (MoAD, 2016).

Findings of previous studies (Rai et al., 2024; GC et al., 2019; Ranabhat et al., 2025; Khadka et al., 2024) have identified some of the factors affecting the adoption of farm mechanization in Nepal. However, research on the intensity of their adoption remains largely lacking. Thus, the main objective of this study was to identify the factors affecting the adoption intensity of farm machinery. Therefore, this study aims to provide insights that will assist technology developers, policymakers, and extension workers in promoting the efficient and widespread adoption of a range of farm machinery.

MATERIALS AND METHODS

Lumbini province was purposively selected for the study as among provinces, Lumbini ranks second after Madhesh in wheat production, with production of 535,020 t in 2022/23. Within Lumbini province, Rupandehi district was purposively selected as it ranks second in wheat area (92,967 ha) after Kapilbastu, but first in production with 369,089 t (MoALD, 2024). Further, command area of PMAMP under 'wheat zone' was purposively selected, which includes Kotahimai Rural Municipality (ward 3-7), Sammarimai Rural Municipality (ward 1-4,6-7), and Marchawari Rural Municipality (ward 3-7). PMAMP is facilitating farm machinery with subsidies and technical support to farmers, while also encouraging private sector involvement in agribusiness.

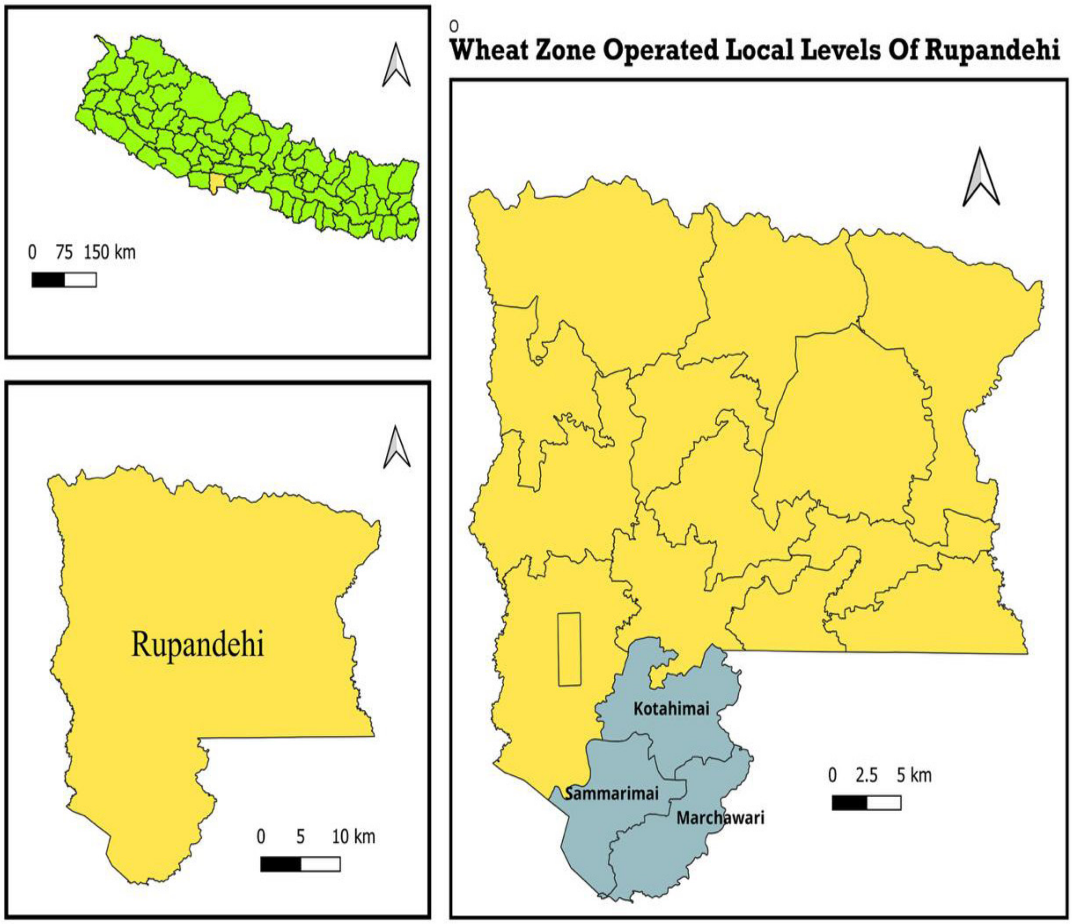

Figure 1: Map of Nepal showing study area in Rupandehi

Then, 120 farm household were randomly selected from the command area of PMAMP-wheat zone. The primary data were collected by household surveys using semi-structured interview schedule with household head. Further, 6 Focus Group Discussion (FGD) was carried out with farmers in a group of 6-8 members. Similarly, 8 Key Informants Interview (KII) was carried out with extension workers, local representatives, progressive farmers and executive officials of agricultural cooperatives and farmers groups. FGD and KII were carried out to complement the information collected through household survey.

Secondary data were collected from published journal articles, annual reports of different institutions such as PMAMP, Agriculture Knowledge Center (AKC), Ministry of Agriculture and Livestock Development (MoALD), Nepal Agricultural Research Council (NARC) and I/NGOs. Descriptive analysis and ordered probit model were employed using Stata/BE 17.0. The objective of this study is to identify the factors affecting the adoption intensity of farm machinery. The dependent variable was constructed as an ordered categorical variable reflecting discrete levels of machinery use. Consequently, the use of Ordinary Least Squares (OLS) regression was inappropriate, as it assumes a continuous, cardinal dependent variable and would yield biased and inconsistent parameter estimates (Greene, 2012). While a Multinomial Logit (MNL) model accommodates categorical outcomes, it disregards the inherent ordinality of the adoption intensity levels (e.g., High > Medium > Low), leading to a loss of statistical efficiency (Wooldridge, 2010).

Therefore, an ordered probit model was selected as the most suitable analytical framework. This model is specifically designed for ordinal dependent variables by assuming an underlying, unobserved continuous propensity that maps to the observed categories. It is a robust and widely used method in technology adoption studies for analyzing intensity and extent of use (Aryal et al., 2018; Upendram et al., 2023).

Construction of the dependent variable

The dependent variable for the model was Adoption Intensity (Y). This variable was constructed based on the number of farm machinery used by a farmer in wheat production, out of a total of seven key machinery identified in the study area. To categorize farmers into distinct, ordered groups, the Mean and Standard Deviation classification method was employed. This statistical approach provides an objective and reproducible basis for segmentation.

Let *M* be the sample mean of machinery adopted and *SD* be the sample standard deviation. The three categories for the dependent variable (Y_i) for the *i*th farmer are defined as follows:

Category 1 (Low Intensity): Farmers who adopted machinery less than (M - 0.5 * SD). This group represents minimal engagement with mechanization.

$Y_i = 1$

Category 2 (Medium Intensity): Farmers who adopted machinery between (M - 0.5 * SD) and (M + 0.5 * SD), inclusive. This group represents a moderate level of mechanization.

$Y_i = 2$

Category 3 (High Intensity): Farmers who adopted machinery greater than (M + 0.5 * SD). This group represents significant integration of machinery in their farming practices.

$Y_i = 3$

The ordered probit model framework

The ordered probit model is based on a latent variable, Y_i*, which represents the unobserved propensity or utility of the i^{th} farmer to adopt a higher intensity of machinery.

The latent variable is expressed as a linear function of explanatory variables:

$Y_i = \beta' X_i + \varepsilon_i$* (Equation 1)

Where:

Y_i* is the unobserved latent adoption propensity.

X_i is a vector of explanatory variables (socio-economic, institutional, and farm-specific factors).

β is the vector of parameters to be estimated.

$\boldsymbol{\varepsilon_i}$ is the random error term, assumed to be independently and identically distributed following a standard normal distribution, $\varepsilon_i \sim N(0, 1)$.

The observed categorical outcome, Y_i, is determined by the value of the latent variable Y_i* relative to a set of unknown threshold parameters, or “cut points” (μ), which are estimated alongside the β coefficients.

The relationship is specified as:

$Y_i =$

1 (Low Intensity) if $Y_i \leq \mu_1$*

2 (Medium Intensity) if $\mu_1 < Y_i \leq \mu_2$*

3 (High Intensity) if $Y_i > \mu_2$*

Where μ_1 and μ_2 are the thresholds that partition the continuous latent variable into the three observed ordered categories.

The probability that a farmer falls into each category, conditional on the explanatory variables X_i, is derived from the cumulative distribution function (CDF) of the standard normal distribution, denoted by $\Phi(\cdot)$.

$P(Y_i = 1 \mid X_i) = \Phi(\mu_1 - \beta' X_i)$ (Equation 2) $P(Y_i = 2 \mid X_i) = \Phi(\mu_2 - \beta' X_i) - \Phi(\mu_1 - \beta' X_i)$ (Equation 3) $P(Y_i = 3 \mid X_i) = 1 - \Phi(\mu_2 - \beta' X_i)$ (Equation 4)

The model parameters (β and μ) are estimated using the method of Maximum Likelihood Estimation (MLE).

RESULTS AND DISCUSSION

Descriptive statistics

The socio-economic and institutional characteristics of the respondents are presented in Table (1). The results revealed that 79.16% of the respondents were male with an average age of 47.53 years. The mean years of schooling was 6.70, while the average farming experience was 28.5 years. The average family members involved in farming was 5.95. The average household annual income was NPR 195,583.30. The mean farm size was 22.11 katha under wheat cultivation. Regarding institutional and resource access, 73.3% of the farmers cultivated wheat commercially, 67.5% had regular contact with extension workers, and 65% were members of cooperatives. Access to credit (10%), labor (33.3%), and PMAMP support (25%) was relatively low among respondents (Table 1).

Table 1: Descriptive statistics of the variables used in the study, Rupandehi, Nepal

Variables	Description	Mean	Standard Deviation (SD)
Gender	Gender of the respondents (=1 if male, 0 if female)	0.7916	0.407
Age	Age of the respondents (year)	47.53	16.63
Education	Formal schooling of the respondents (year)	6.70	5.53
Involvement	Number of family members involved in farming (number)	5.958	3.506
Income	Annual income of household (NPR)	195583.3	174600.6
Production	Nature of production (1= if commercial, 0 subsistence)	0.733	0.4440
Contact	1= if regular contact with extension workers, 0 otherwise	0.675	0.4703
Membership	1= if member in agricultural cooperatives, 0 otherwise	0.65	0.4789
Credit	=1 if access to credit, 0 otherwise	0.10	0.3012
Labor	=1 if access to labor, 0 otherwise	0.333	0.4733
Farm size	Farm size (katha)	22.11	24.26
Experience	Farming experience of the respondents (year)	28.52	14.98
Subsidy	=1 if access to subsidies support from PMAMP, 0 otherwise	0.25	0.4348

Source: Field survey, 2025

Adoption status of farm machinery

The adoption status of farm machinery by the respondents is presented in Table (2). The results revealed that the 92.5% of the respondents had adopted rotavators. Similarly, 70% had adopted pump sets and 68.33% had adopted harvesters. Also, 52.5% of the respondents had adopted threshers, 20% had adopted reapers, 5.8% had adopted seed drills and 5% had adopted power tillers. On average, the number of farm machinery adopted by farmers ranged from 1 to 6. The average adoption was 3.14, with a standard deviation of 0.81. Based on Mean and SD, farmers were grouped into three categories of adoption intensity. Low intensity represents adoption of 1-2 machinery, medium intensity (3 machinery) and high intensity (4 to 6 machinery). In the study, 18.33% of the respondents fell under low intensity, 54.17% under medium intensity, and 27.50% under high intensity.

Table 2: Adoption status of farm machinery, Rupandehi, Nepal

Machinery	Description	Mean	SD
Rotavator	=1 if adoption, 0 otherwise	0.925	0.2644
Seed drill	=1 if adoption, 0 otherwise	0.058	0.2353
Reaper	=1 if adoption, 0 otherwise	0.20	0.4016
Thresher	=1 if adoption, 0 otherwise	0.525	0.5014
Harvester	=1 if adoption, 0 otherwise	0.6833	0.4671
Power tiller	=1 if adoption, 0 otherwise	0.05	0.2188
Pump set	=1 if adoption, 0 otherwise	0.70	0.4601

Source: Field survey, 2025

Factors affecting the adoption intensity of farm machinery

The factors affecting the adoption intensity of machinery and its marginal effects is presented in Table (3) and Table (4). The significant variables are discussed below. Cooperatives membership: Membership in agricultural cooperatives positively affected the adoption intensity (β= 1.187, p = 0.007), indicating that cooperative members will adopt more machinery intensively. In specific, membership in cooperatives increases the likelihood by 25.2%. Result is similar to the finding of previous studies (Burman et al., 2025; Zhang et al., 2020; Jena & Tanti, 2023; Zhong et al., 2023), which reported membership facilitates improved access to shared resources and collective bargaining power promoting adoption.

Farm size: Farm size had a positive and highly significant effect (β = 0.040, p = 0.001), showing that farmers with comparatively larger wheat-growing areas tend to adopt machinery more intensively. In specific, farm size increases the likelihood by 0.8%. This result is similar to the findings of previous studies (Mohammed et al., 2023; Dhakal et al., 2024; Ruzzante et al., 2021; Liu et al., 2025; Qiu et al., 2025; Quan & Doluschitz, 2021; Ranabhat et al., 2025), which reported farms benefit more from economies of scale, making machinery investments more cost-effective.

Table 3: Ordered probit model estimation on the intensity of farm machinery, Rupandehi, Nepal

Variables	Coefficient	Std. Err.	Z	p value
Gender	-0.276	0.325	-0.85	0.395
Age	0.004	0.010	0.43	0.666
Education	0.020	0.027	0.76	0.446
Involvement	0.029	0.367	0.79	0.430
Log(income)	0.327	0.419	0.78	0.435
Production	-0.131	0.328	-0.40	0.689
Contact	-0.610	0.452	-1.35	0.177
Membership	1.187***	0.444	2.67	0.007
Credit	-0.390	0.394	-0.99	0.323
Labor	-0.317	0.318	-1.00	0.320
Farm size	0.040***	0.012	3.24	0.001
Experience	-0.007	0.010	-0.70	0.486
Subsidy	0.650**	0.301	2.15	0.031
/cut1	1.597	2.022		
/cut2	3.680	2.047		

Number of obs=120; LR chi2(13) = 62.96;prob>chi2=0.0000;Pseudo R2=0.2628;Log likelihood=-88.298.
*Note: **, *** indicate significant at 5%,1% level of significance, respectively.*

Subsidy: Subsidies support from the Prime Minister Agriculture Modernization Project (PMAMP) was also positively associated with adoption intensity (β = 0.650, p = 0.031), highlighting the importance of government programs in promoting mechanization. In specific, access to subsidies increase the likelihood by 13.8%. Result is similar to the finding of previous studies (Mohammed et al., 2023; Dhakal et al., 2024; Jena & Tanti, 2023; Burman et al., 2025; Wu et al., 2025; Meng et al., 2024; Quan & Doluschitz, 2021), which reported subsidies reduce the high initial costs of machinery, making it more accessible.

Table 4: Ordered probit model estimation on marginal effects, Rupandehi, Nepal

Variables	Pr(1)		Pr(2)		Pr(3)	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Gender	0.0572	0.0669	0.0014	0.0093	-0.0587	0.0693
Age	-0.0009	0.0021	-0.00002	0.0001	0.0009	0.0021
Education	-0.0042	0.0055	-0.0001	0.0006	0.004	0.005
Involvement	-0.006	0.007	-0.0001	0.0009	0.006	0.007
Log(income)	-0.0677	0.086	-0.00175	0.0111	0.069	0.089
Production	0.0271	0.068	0.0007	0.004	-0.0278	0.069
Contact	0.1263	0.092	0.003	0.020	-0.129	0.095
Membership	-0.245***	0.088	-0.006	0.038	0.252***	0.936
Credit	0.080	0.081	0.002	0.012	-0.328	0.083
Labor	0.065	0.065	0.001	0.010	-0.0673	0.067
Farm size	-0.0083***	0.002	-0.0002	0.001	0.008***	0.0023
Experience	0.0014	0.002	0.00003	0.0002	-0.001	0.0021
Subsidy	-0.134**	0.0622	-0.003	0.0211	0.138**	0.062

*Note: **, *** indicate significant at 5%,1% level of significance, respectively.*

CONCLUSION

The results revealed that adoption intensity of farm machinery is primarily affected by institutional and resource factors. Like, membership in agricultural cooperatives, larger farm sizes and access to government subsidies through Prime Minister Agriculture Modernization Project (PMAMP). Overall, these findings advocate for the need to strengthen cooperative institutions, encourage land consolidation or collective use models like group-based farming, and maintain well-targeted subsidy programs to accelerate the range of farm machinery in wheat farming. National farm mechanization policy should focus on integrated approach that combine support from institutions, land-use planning, and financial incentives to promote agricultural mechanization.

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