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Adoption of Labour-Saving Technologies in Selected Five Southern-District of Bhutan

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Authors' contributions

This work was carried out in collaboration among all authors. Author NN designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Authors RW and BS managed the analyses of the study, literature searches, and did the proofing. All authors read and approved the final manuscript.

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Abstract

This study assessed the adoption of labour-saving agricultural technologies and the factors associated with their use across five districts in Bhutan. Data were collected in May and June 2024 from 1,142 farming households selected through a multistage sampling design. Descriptive statistics and probit regression were used to examine the adoption of power tillers, mini tillers, tractors, threshers, hullers, grass cutters, and rice millers. The pooled power tiller adoption rate was 21.9%, although adoption varied substantially among districts. Power tillers were the most widely adopted land-preparation technology, while machinery users generally preferred hiring services to individual ownership, particularly for power tillers and tractors. Reduced agricultural drudgery was the most frequently reported reason for adopting power tillers, accounting for 65% of adopter responses. High machinery costs were the principal barrier reported by non-adopters. Probit estimates indicated that cultivated area, educational attainment, family literacy, smartphone use, and the prevalence of the same technology within the local gewog were associated with adoption, although the direction and statistical significance varied across technologies. The strong association with local technology prevalence may reflect peer learning and improved access through machinery-hiring markets. The findings indicate that expanding affordable state-managed or privately managed hiring services, together with targeted financial support, operator training, and improved rural infrastructure, may facilitate broader and more inclusive access to labour-saving technologies among small-scale farming households in Bhutan.

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Keywords: Technology; adoption; probit analysis; hiring, drudgery; food security.

1. Introduction

Agriculture plays a significant role in Bhutan's economy, contributing approximately 15% of gross domestic product (GDP). The crop subsector accounts for approximately 6.81% of total GDP and 46% of agricultural GDP (National Statistics Bureau [NSB], 2023b). With regard to employment, the agricultural sector accounted for approximately 43% of employed persons (NSB, 2022). Therefore, Bhutan's economic performance in terms of output and employment remains substantially dependent on the agricultural sector.

However, agriculture in Bhutan is constrained by several production factors, of which labour shortages are among the most important. The agricultural workforce is ageing, while younger generations are increasingly moving away from traditional farming occupations, contributing to labour shortages in the sector. For example, the 2017 Population and Housing Census of Bhutan reported that 21.7% of the total population had migrated from rural areas to urban centres (NSB, 2018). The Labour Force Survey 2022 reported that approximately 43% of employed persons worked in agriculture (NSB, 2022).

Agriculture often requires increased labour during specific seasons, such as planting and harvesting. Manual labour may not be readily available during these peak periods, resulting in delays to critical farming activities and potential productivity losses. Labour costs also constitute a substantial proportion of agricultural expenditure. Increasing labour scarcity, combined with rising wages, places financial pressure on producers. Labour-saving technologies can improve economic viability by reducing dependence on manual labour and increasing overall efficiency. Although several labour-saving technologies have been introduced to farmers in Bhutan, their adoption remains limited.

Understanding agricultural technology adoption rates is important because adoption directly affects productivity, sustainability, and food security. Examining these rates can provide insights into the effectiveness of technological innovations in improving agricultural practices and outcomes (Ong et al., 2022). Evidence on technology adoption can also inform policy-making by enabling governments and stakeholders to develop targeted interventions, incentives, and support mechanisms. Such measures can promote the uptake of beneficial technologies and address barriers to adoption, thereby facilitating the integration of technological advances into agricultural practices, optimising productivity, and strengthening food security.

Recent evidence indicates that machinery-hiring services can expand smallholders' access to mechanisation without requiring individual ownership, while adoption decisions are influenced by service costs, farm characteristics, labour conditions, institutional support, and access to service providers (Lu et al., 2022; Tesema et al., 2023; Tufa et al., 2024).

Studies of custom-hiring and machinery-based technologies further identify affordability, timely availability, technical knowledge, and operational support as practical considerations affecting adoption and use (Das & Patil, 2024; Kathpalia et al., 2026).

The remainder of this paper is organised as follows. Section 2 describes the methodological framework adopted for the study. Section 3 examines the status of farm mechanisation in Bhutan. Section 4 presents the study findings and discusses their implications. The final section provides recommendations and concludes the paper.

Nevertheless, district-level evidence remains limited regarding the adoption of multiple labour-saving technologies and the associations between their use and household characteristics, education, smartphone use, cultivated area, and neighbourhood-level technology prevalence across the five selected southern districts of Bhutan.

Despite the number of agricultural technologies released for field use, comprehensive evidence on their adoption rates in Bhutan remains limited. To address this gap, the Department of Agriculture, Bhutan, through projects under the Asian Food and Agriculture Cooperation Initiative, initiated an assessment of the current adoption of labour-saving technologies in Bhutan's agricultural sector, with the following objectives:

- ➢ Assess the types and extent of labour-saving technologies adopted by farmers across the five districts.
- ➢ Identify the factors influencing technology adoption among farmers in the five districts.

2. Methodology

2.1 Study Sites

The study covered five districts comprising 51 blocks (Fig. 1), which were further subdivided into 259 units called chiwogs. These districts fall within the technical mandate of the Agriculture Research and Development Centre, Samtenling, which focuses on agricultural technology transfer and outreach programmes. The Centre collaborates with district and geog agriculture offices to disseminate agricultural technologies in farmers' fields.

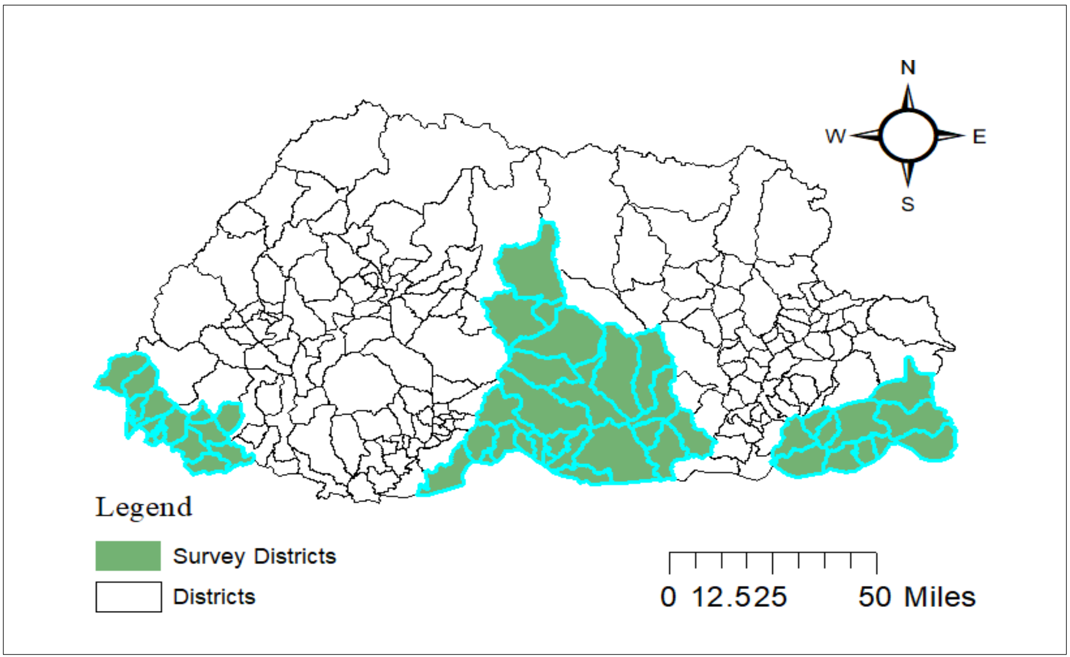

Fig. 1. Survey districts included for data collection

2.2 Study Population and Sample Selection

Data were collected in May and June 2024 from a target sample of 1,340 households across five districts. Household lists for the five districts were obtained from the Integrated Agriculture and Livestock Census of Bhutan, 2022, published by the National Statistics Bureau (NSB, 2023a). A multistage sampling design was used to select respondents. The primary sampling units (PSUs) were the 259 precincts (Chiwogs) in the study area, and the secondary sampling units (SSUs) were the 20,792 households within these Chiwogs. In the first stage, PSUs were selected using proportional simple random sampling (PSRS). A 50% sampling intensity was applied, resulting in the selection of 130 of the 259 Chiwogs.

In the second stage, households within the selected PSUs were sampled using proportional simple random sampling. The 130 selected Chiwogs contained 10,396 households. A sampling intensity of approximately 10% was applied, and 1,340 households were selected for interview.

The allocation of households across districts was proportional to the number of households in each selected PSU. Households were selected using computer-generated random numbers based on the final household lists obtained from the selected Chiwogs.

To ensure data quality during data collection, KoboToolbox, a free online data-collection platform, was used. The questionnaire comprised five sections covering household characteristics, land endowment, crop production, technology adoption rates, and determinants of technology adoption. Farmers were asked about household decision-making, particularly who made key decisions regarding technology adoption. The principal questions focused on the use of agricultural technologies and the factors affecting adoption.

The survey used both structured and semi-structured questionnaires for data collection. The approach also included measures to protect participant privacy and secure the collected data.

The survey was conducted by agricultural researchers from ARDC-Samtenling. The study process comprised questionnaire preparation, stakeholder consultation, enumerator training, mock questionnaire sessions, data collection, and data processing and analysis.

2.3 Data Analysis

Data were analysed using Microsoft 365, Stata, and R. Both descriptive and inferential analyses were conducted. Descriptive statistics included frequency distributions, means, and percentages, while inferential analysis comprised probit regression. Probit regression was used to determine the influence of sociodemographic variables (Table 1) on technology adoption. The survey findings were triangulated with administrative data to strengthen their validity and credibility.

In the probit model, the outcome (dependent) variable is the technology adoption status yi, which equals one if farm i uses the technology and zero otherwise. The aim is to estimate the effects of household characteristics on technology adoption yi. These characteristics, represented by the vector $\mathbf{x}i$, include age, education, farm size, altitude, and other variables detailed in Table 1. The probit model assumes $yi = 1$ if $\mathbf{x}i\beta + ui > 0$ and 0 otherwise, where β denotes the parameters of interest and ui is an error term following a standard normal distribution. A positive (negative) estimated parameter indicates that a higher value of the variable increases (decreases) the probability of adoption.

Table 1. Variables used for probit analysis

	Unit	Mean	SD	Min	Max
Dependent variable (y)					
Power tiller	Yes = 1, No = 0	0.219	0.414	0	1
Mini tiller	Yes = 1, No = 0	0.075	0.264	0	1
Tractor	Yes = 1, No = 0	0.106	0.308	0	1
Thresher	Yes = 1, No = 0	0.039	0.195	0	1
Huller	Yes = 1, No = 0	0.104	0.306	0	1
Grass cutter	Yes = 1, No = 0	0.294	0.456	0	1
Rice miller	Yes = 1, No = 0	0.250	0.433	0	1
Independent variables (x)					
Cultivated area (owned + leased – fallow. The sum of wetland, dryland and orchard)	Acre	3.216	3.947	0	81.5
Altitude	Meter	856.8	516.2	68.6	2642
Actual no. of family member working on farm		2.408	1.185	0	9
Share of literate family labour	share (0-1)	0.474	0.660	0	1
No. of season road is unusable		0.224	0.417	0	1
Wage rate	BTN/day	426.5	138.6	0	1000
Wage rate	BTN/day	426.5	138.6	0	1000
Decision maker is head of family	Yes = 1, No = 0	0.784	0.412	0	1
Decision maker is head of family	Yes = 1, No = 0	0.784	0.412	0	1
Decision maker is male	Yes = 1, No = 0	0.567	0.496	0	1
Education of decision maker: Primary or Monk	Yes = 1, No = 0	0.184	0.388	0	1
Education of decision makers: Secondary or higher	Yes = 1, No = 0	0.060	0.238	0	1
Decision makers use the smart phone	Yes = 1, No = 0	0.602	0.490	0	1
Decision maker is 40s	Yes = 1, No = 0	0.206	0.404	0	1
Decision maker is 50s	Yes = 1, No = 0	0.187	0.390	0	1
Decision maker is 60s	Yes = 1, No = 0	0.167	0.373	0	1
Decision maker is > 70	Yes = 1, No = 0	0.100	0.300	0	1

A total of 1,142 households completed the survey. The regression analysis included 1,122 observations; the difference resulted from excluding records with incomplete information for one or more model variables.

Regression analyses were therefore conducted using complete-case observations. The excluded records represented 1.75% of surveyed households.

2.4 Survey Weighting and Clustering

Because the study employed a multistage probability sampling design, survey weights were incorporated into all descriptive and regression analyses. The probability of selecting each household was calculated as the product of the probability of selecting the Chiwog (primary sampling unit) and the probability of selecting the household within that Chiwog. The household sampling weight was therefore computed as:

$$Wi = \frac{259}{130} * \frac{Nh}{nh}$$

where Nh is the total number of households in Chiwog h and nh is the number of sampled households in that Chiwog. The final weight was the inverse of the overall selection probability and was applied to obtain population-representative estimates.

To account for the clustered sampling design, standard errors were adjusted for clustering at the Chiwog (PSU) level using survey-design-based estimation procedures. District was specified as a stratification variable in the survey design. All descriptive statistics, bivariate analyses, and regression models were estimated using weighted survey procedures.

3. Farm Mechanisation in Bhutan

In Bhutan, the transition to mechanisation began in 1964, when the Japanese expert Dasho Keiji Nishioka introduced modern farming techniques. Farm equipment obtained through Japanese grants was sold to farmers or provided through government hiring services at subsidised rates of 55–73%. Bhutan received two rounds of Kennedy Round (KR) grant aid over more than 25 years, beginning in 1984, as well as General Grants in 2016 and 2019 and Japanese Non-Project Grant Aid in 2008 and 2010. Through these grants, approximately 3,423 power tillers and 5,078 other machines were acquired (Upreti et al., 2024).

However, the limited use of modern agricultural technologies and machinery poses a substantial challenge to the sector’s productivity, commercialisation, and competitiveness (Pingali, 2007). Only approximately 22.5% of the total operational area (Policy and Planning Division, 2019) is under some form of farm mechanisation, while the remainder continues to be farmed using traditional practices. The total potential area for farm mechanisation has not been assessed.

The Agriculture Machinery and Technology Centre is responsible for testing, standardisation, and certification of agricultural machinery for use in Bhutan (Lhendup, 2023). These machines are sold to farmers by FMCL and private firms within the country. Separate registration data for tractors and power tillers were obtained from the Bhutan Construction and Transport Authority (BCTA, 2024). The first power tiller (Kubota) in the country was owned by an individual, Namgay Zangmo, in 1970, followed by Tshering Dorji in 1988. Similarly, the first Ford tractor in the country, also privately owned, was registered in 1989 (BCTA, 2024). Over the past five decades, imports of power tillers and tractors have steadily increased (Fig. 2). In particular, the number of active power tillers increased sharply from 26 in 2014 to 153 in 2015. However, the number declined substantially in 2019, a pattern also observed for tractors.

The decline in imports in 2019 may be attributed to the COVID-19 pandemic, which disrupted international trade (Ngawang et al., 2022). As of June 2024, Bhutan had 1,661 active power tillers and 743 active tractors out of 3,945 and 933 registered units, respectively. According to BCTA records, the remaining machines were cancelled, disposed of, exported, or outstanding (BCTA, 2024). The active machines are owned and utilised by individuals and organisations, primarily to support agricultural activities across Bhutan.

The allocation of substantial public funds by governments to agricultural technology research and development highlights the importance of such investment in streamlining processes and increasing production (Romanelli et al., 2022).

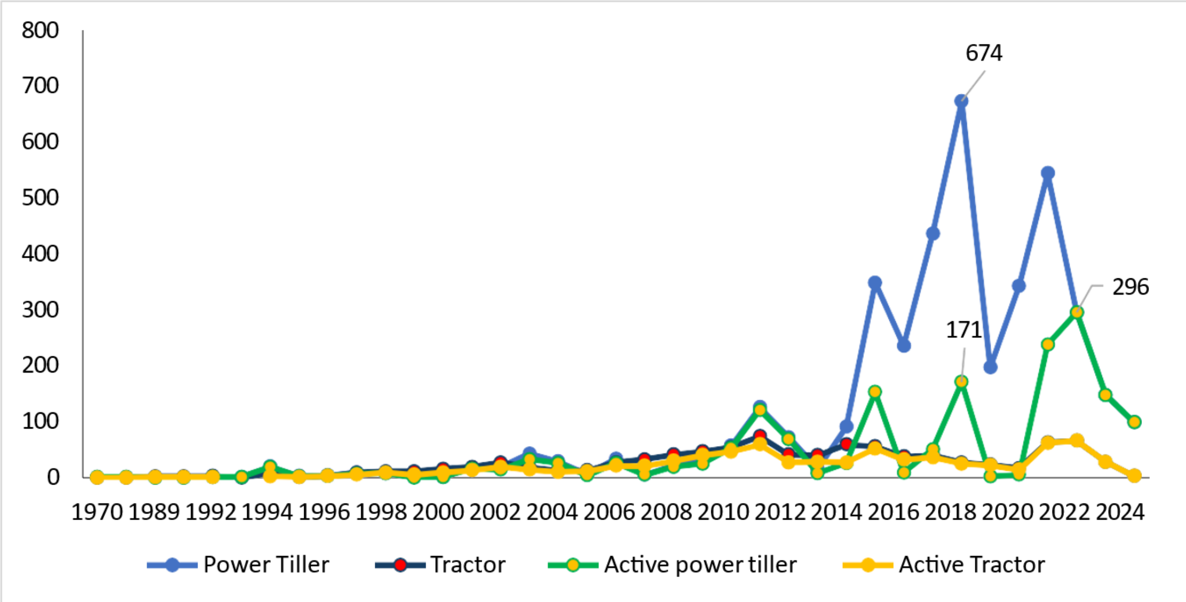

Fig. 2. Trend in Tractor and Power Tiller Numbers in Bhutan (1970–June 2024)
Source: BCTA (2024)

Table 2. Lists of technologies included for survey

# Type of technology		Technology
1. Labour-saving technologies	1.	Power tiller
	2.	Tractor
	3.	Mini tiller
	4.	Thrashers
	5.	Hullers
	6.	Grass cutters
	7.	Rice millers

4. Results and Discussion

4.1 Demographic Information and Socio-Economics Features

The descriptive analysis showed that 1,142 households participated, representing 85.2% of the targeted sample of 1,340 and a non-response rate of 14.8%. Among the five districts, Samtse had the highest participation rate, accounting for 36.6% of respondents, followed by Sarpang (24.0%), Samdrup Jongkhar (22.1%), Zhemgang (9.9%), and Trongsa (7.4%) (Table 3). The proportional sampling strategy allocated more participants to districts with larger household populations.

Regarding age distribution, most respondents (84.6%) were aged 19–64 years, 15.3% were older than 65 years, and only 0.1% were younger than 18 years. In terms of gender, 58.9% of respondents were male and 41.1% were female.

Regarding educational attainment, 61.3% of respondents had received no formal education, compared with 1.0% who had university-level education. Most households (94.9%) had 1–4 family members working on the farm, while 4.4% had 5–8 members. Regarding literacy, 58.2% of households had 1–4 members who could read or write, 40.0% had none, and 1.8% had 5–8 literate members. The respondent group included 58.9% males and 41.1% females.

Technology adoption decisions were primarily made by the household head (78.4%), a pattern consistent with Bhutanese cultural practices (Sariyev et al., 2020). Family consensus determined 20.8% of decisions, while any household member could decide in only 0.8% of cases.

Table 3. Distribution of sample size among 5 districts and socio-economic characteristics of the household

Variable		No. of HHs	Proportions (%)
District	S/jongkhar	252	22.1
	Samtse	418	36.6
	Sarpang	274	24.0
	Trongsa	85	7.4
	Zhemgang	113	9.9
Total		1142	100
Age	<18	1	0.1
	19-64	966	84.6
	>65	175	15.3
Gender	Male	673	58.9
	Female	469	41.1
Qualification	Not Studied	700	61.3
	Nonformal – Primary Level	250	21.9
	High School - Higher	151	13.2
	University Level	11	1.0
	Lay Monk	30	2.6
Family member working on farm?	0	6	0.5
	1-4	1084	94.9
	5-8	50	4.4
	Above 8	2	0.2
How many of them can read or write?	0	457	40
	1-4	665	58
	5-8	20	1.8
	Above 8	0	0.0
Who takes decision on tech adoption?	Head of the family	895	78
	Family consensus	238	20.8
	Anyone	9	0.8

4.2 Association of Households' Characteristics and Adoption of Labour-Saving Technologies

The probit model estimates (Table 4) suggest that the adoption of labour-saving technologies is influenced particularly by farm size, knowledge, and neighbours.

The probit estimates indicate that cultivated area (log) was positively associated with the probability of adopting each technology, although the magnitude and statistical significance of the association varied across models. The association was strongest for grass cutter ($p < 0.01$), rice miller ($p < 0.01$), huller ($p < 0.01$), and power tiller ($p < 0.01$) adoption. Mini tiller adoption was also positively and significantly associated with cultivated area ($p < 0.01$). In contrast, thresher adoption showed a weaker but statistically significant association ($p < 0.05$), while the evidence for tractor adoption was comparatively weak ($p < 0.10$). These findings suggest that a larger cultivated area is associated with a higher likelihood of adopting agricultural mechanisation technologies, although the strength of the association is not uniform across technologies. This pattern is consistent with Ruzzante et al. (2021), who reported that larger landholdings and secure land tenure were positively associated with the adoption of various agricultural technologies.

Knowledge was also important. Education was divided into three categories: 'Primary or Monk', 'Secondary or higher', and no formal education. Compared with farmers without formal education, those with primary or monastic education or secondary or higher education were more likely to adopt technologies. Greater literacy among family labour also significantly favoured the adoption of power tillers, tractors, grass cutters, and rice millers. Similar findings were reported by Quayum and Ali (2012), Chang and Tsai (2015), and Zhou et al. (2008). Smartphone use also positively affected the adoption of some technologies. Overall, these results suggest that knowledge is an important driver of technology adoption.

Finally, technology adoption was strongly associated with the prevalence of the same technology among farmers within the gewog. For example, in the power tiller model, the variable 'share of farmers using the same machine in the gewog' represented the proportion of farms using power tillers in the respondent's gewog. The probit coefficient for this variable was positive and highly statistically significant ($Z = 12.44$, $P < 0.01$), indicating that households in gewogs with higher power tiller use were more likely to adopt power tillers. Similar positive and statistically significant associations were observed for mini tillers, tractors, threshers, hullers, grass cutters, and rice millers.

These findings are consistent with theories of social learning, peer effects, and technology diffusion. Farmers often learn about machinery performance, costs, and benefits by observing neighbouring farmers and interacting within local social networks (Nyambo et al., 2022; Zhou et al., 2008). Higher local use rates may also improve access to machinery through rental and hiring markets, thereby reducing transaction costs and facilitating adoption. Understanding these local diffusion mechanisms is important for designing interventions that promote the widespread and equitable adoption of agricultural mechanisation technologies.

The positive associations may reflect greater access to machine-hiring services in gewogs with higher user rates. Understanding these factors is important for designing effective interventions to promote the widespread and equitable adoption of technologies that support production (Thuijsman et al., 2022).

Apart from farm size, knowledge, and neighbours, the other variables showed non-significant or mixed effects in most models. For example, age was hypothesised to negatively affect technology adoption; however, this was not observed in the study. Older farmers were not necessarily more reluctant than younger farmers to adopt new technologies. These results may reflect severe labour shortages in Bhutan, which encourage farmers of all ages to adopt labour-saving technologies.

4.3 Adoption of Power Tiller, Mini-Tiller and Tractors Technologies among the Districts

Trend analysis showed that the adoption of power tillers and mini tillers increased substantially over time, with power tiller adoption peaking between 2016 and 2020 before declining slightly (Fig. 3). Tractor adoption increased steadily before declining substantially in the most recent period, while mini tiller adoption continued to rise.

From 1990 to 1995, adoption of the three types of machinery was either one or zero. Adoption increased slightly during 1996–2000. A substantial increase occurred during 2011–2015, when power tiller adoption rose to 38, tractor adoption remained at 22, and mini tiller adoption increased to 2. This upward trend continued during 2016–2020, when power tillers reached a peak of 105 adopters across the five districts. Tractor adoption increased to 57, while mini tiller adoption rose to 15. These findings are consistent with the registration data maintained by BCTA under the Ministry of Infrastructure and Transport. The increases may be associated with government policies, subsidies, and project incentives intended to encourage farm mechanisation. The factors reported by adopters are discussed later in this section.

Survey data from the five districts—Samdrup Jongkhar, Samtse, Sarpang, Trongsa, and Zhemgang—showed variation in adoption rates. Overall, the pooled power tiller adoption rate was 21.9%, while the unweighted mean across the five districts was approximately 33%. Based on unweighted district means, power tillers were the most widely adopted machinery, compared with tractors (10%) and mini tillers (8%) (Table 5). Trongsa had the highest proportion of power tiller users (76.5%), while Samtse had the lowest.

The absence of tractor use among Trongsa respondents may reflect the district's landscape, as most farmers used power tillers and mini tillers. Records indicate that Trongsa lies at elevations of 1,203–2,642 m above sea level and that much of its agricultural land is sloping, potentially reducing the feasibility of tractor use. By contrast, Sarpang respondents used all three machine types, with tractors showing the highest adoption rate (28.5%), followed by power tillers (20.8%) and mini tillers (15.3%).

By contrast, Samtse, which has a landscape similar to that of Sarpang, had the lowest use of the three machines. Farmers reported that the machines were expensive and unaffordable. Respondents also reported that much of the agricultural land was stony and that draught animals remained preferred.

Power tillers were used most frequently, possibly because of land suitability and the typical size of farmers' holdings. The factors influencing adoption are discussed later in this section. The average farm size was approximately 3.2 acres per household, for which power tillers may be suitable, including in some sloping areas, whereas tractors may be more appropriate for a limited number of larger, flatter areas.

Table 4. Probit analysis on HH characteristics and adoption patterns

	Power tiller	Mini tiller	Tractor	Thresher	Huller	Grass cutter	Rice miller
Cultivated Area (log)	0.259	0.210	0.142	0.175	0.378	0.313	0.373
	[4.16]***	[2.74]***	[1.71]*	[1.98]**	[4.41]***	[5.53]***	[5.88]***
Education of decision makers (no formal education = 0)							
Primary or Monk	0.259	0.312	0.538	0.648	-0.088	0.400	0.154
	[1.72]*	[1.81]*	[2.54]**	[2.96]***	[-0.43]	[3.14]***	[1.09]
Secondary or higher	0.653	0.013	0.283	0.343	0.240	0.775	0.117
	[3.01]**	[0.04]	[0.90]	[1.11]	[0.88]	[3.93]***	[0.53]
Share of literate family labour	0.168	0.094	0.203	0.025	-0.024	0.142	0.171
	[2.09]**	[1.06]	[2.21]**	[0.28]	[-0.15]	[1.94]*	[2.23]**
Decision maker uses the smart phone	-0.072	0.268	0.503	-0.103	-0.024	0.323	0.148
	[-0.44]	[1.30]	[2.02]**	[-0.45]	[-0.12]	[2.23]**	[1.05]
Share of farms who use the technology in the same gewog	3.82	5.63	4.03	7.21	5.96	3.34	4.08
	[12.44]***	[8.59]***	[9.25]***	[6.51]***	[10.49]***	[10.89]***	[13.79]***
Age of decision maker (< 30s = 0)							
Decision maker is 40s	0.132	-0.066	-0.098	-0.339	0.355	0.067	0.286
	[0.71]	[-0.28]	[-0.31]	[-1.06]	[1.72]*	[0.40]	[1.50]
Decision maker is 50s	0.0911	0.145	-0.317	0.113	0.219	0.233	0.292
	[0.46]	[0.61]	[-0.95]	[0.39]	[0.95]	[1.36]	[1.52]
Decision maker is 60s	0.054	0.112	0.131	-0.317	0.008	0.226	0.178
	[0.26]	[0.45]	[0.39]	[-1.01]	[0.03]	[1.24]	[0.88]
Decision maker is > 70	-0.087	0.433	0.702	0.295	-0.121	0.177	0.421
	[-0.35]	[1.52]	[1.82]*	[1.03]	[-0.41]	[0.84]	[1.83]*
Altitude	2.1E-05	4.2E-05	-7.4E-04	-1.0E-04	1.4E-04	4.7E-06	-1.9E-04
	[0.15]	[0.26]	[-2.10]**	[-0.45]	[0.81]	[0.04]	[-1.47]
Actual no. of family member working on farm	0.036	-0.012	0.097	-0.105	-0.038	0.057	-0.025
	[-0.80]	[-0.23]	[1.87]*	[-1.75]*	[-0.69]	[1.49]	[-0.59]
No. of season road is unusable	0.144	-0.359	-0.248	-0.026	-0.399	-0.039	0.389
	[1.04]	[-1.85]*	[-1.02]	[-0.12]	[-1.87]*	[-0.33]	[3.11***
Wage rate (BTN/day)	0.0011	0.0000	0.0013	0.0012	-0.0001	0.0001	-0.0010
	[2.14]**	[0.08]	[1.62]	[1.51]	[-0.18]	[0.34]	[-2.09]**

	Power tiller	Mini tiller	Tractor	Thresher	Huller	Grass cutter	Rice miller
Decision maker is head of family	0.002	-0.738	-0.548	-0.567	0.161	-0.622	-0.369
	[0.01]	[-2.32]**	[-1.34]	[-1.47]	[0.47]	[-2.63]**	[-1.43]
Decision maker is male	0.226	0.197	-0.007	0.585	-0.253	-0.157	-0.049
	[-1.66]*	[1.12]	[-0.03]	[2.17]**	[-1.41]	[-1.33]	[-0.37]
Observations	1122	1122	1122	1122	1122	1122	1122

*Significant results are shown in bold. z-statistics computed from robust standard errors in brackets. *** P<0.01, ** P<0.05, * P<0.1. The model includes the constant and Districts dummies*

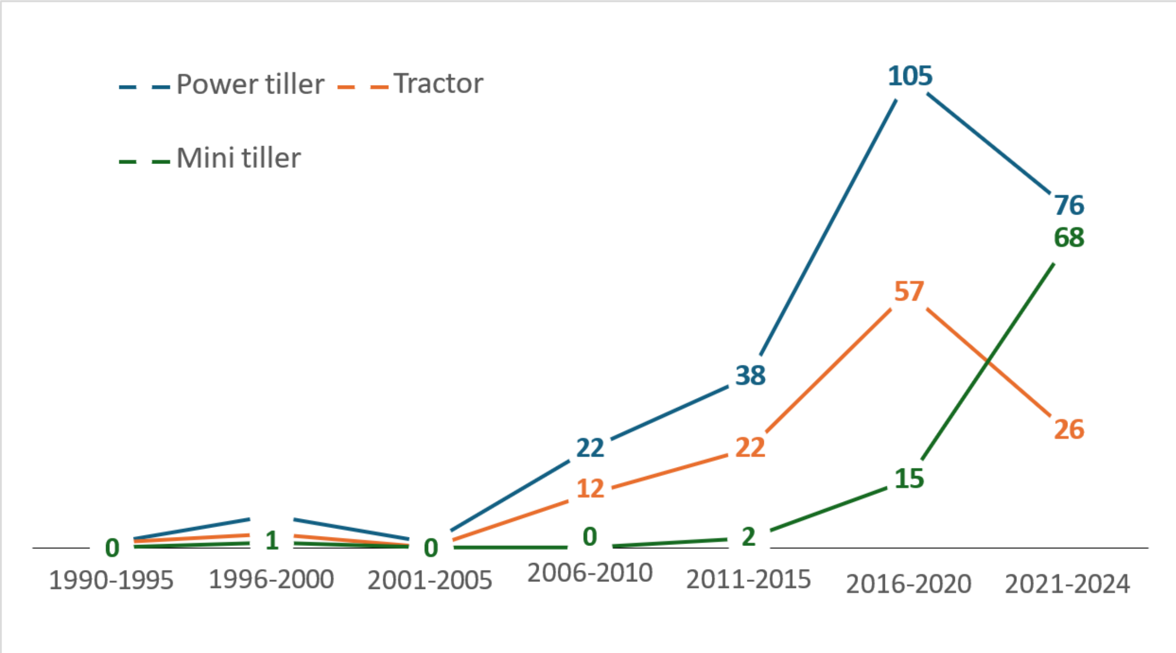

Fig. 3. Trend of power tiller, tractor and mini tiller adoption numbers over the 34 years *(data source: BCTA, 2024)*

Table 5. Adoption rate of power tiller, mini tiller and tractor by household in 5 districts (n = 1142)

		Adoption rate		
District	**Observation (nos.)**	**Power tiller (%)**	**Mini tiller (%)**	**Tractor (%)**
Samdrup Jongkhar	252	23.4	3.57	13.9
Samtse	418	6.5	3.83	1.0
Sarpang	274	20.8	15.33	28.5
Trongsa	85	76.5	9.41	0.0
Zhemgang	113	37.2	9.73	3.5
Unweighted mean		33%	8%	10%

4.4 Source of Power Tillers, Mini Tillers, and Tractors: Self-Owned or Hired

Farmers who used the three machines were asked whether they owned or hired them. In Samdrup Jongkhar, among 59 household users, 40% owned power tillers and 60% hired them (Table 6). For mini tillers, 44% were self-owned and 56% were hired. Tractors were predominantly hired, with 94.3% hired and only 5.7% self-owned.

This pattern was similar across districts, with most users hiring machinery services. Power tillers and tractors were more commonly hired than owned in most districts. However, mini tillers had higher rates of self-ownership in several districts, particularly Samtse and Trongsa. Overall, the data indicate a preference for hiring machinery rather than owning it. This pattern suggests that a higher prevalence of power tillers within the community may have a positive spillover effect on adoption among neighbouring farmers.

Table 6. Source of farm machines for use

District	**Power tiller (%)**		**Mini tiller (%)**		**Tractor (%)**	
	Self-own	**Hiring**	**Self-own**	**Hiring**	**Self-own**	**Hiring**
Samdrup Jongkhar	40	60	44	56	5.7	94.3
Samtse	26	74	63	38	75	25.0
Sarpang	23	77	52	48	1.3	98.7
Trongsa	17	83	63	38	0	0.0
Zhemgang	21	79	64	36	0	100

4.5 Determinant of the Power Tiller Adoption Revealed by Adopters

Among the three machines, the power tiller was the most widely used in Bhutan and had the highest number of privately imported units (2,985) between 1970 and 2 June 2024 (BCTA, 2024). Survey data also showed the highest unweighted mean adoption rate (33%) for power tillers across the five districts. Detailed analysis indicated that reduced drudgery was the main reported factor influencing adoption, accounting for 65% of responses (Table 7). Basavaraj et al. (2022) similarly reported that mechanisation reduced the workload associated with various farming operations by 40–64.3%. This pattern was observed across respondents in all five districts and is relevant to the Bhutanese context. The Department of Agriculture (2023) reported that paddy production is highly labour-intensive, requiring approximately 78 person-days per acre. Substitution of capital for labour may therefore be an important reason for adoption.

Affordability and income generation were also important factors, reported by 14% and 13% of adopters, respectively. Government incentives and peer influence were each reported by 4% of adopters. These data suggest that farmers may not consciously recognise peer influence as a primary motivation; however, the statistical analysis (Table 4) indicates that the local prevalence of a technology is a highly significant driver of adoption.

4.6 Factors that Hinder the Adoption Rate of the Power Tiller

Among non-adopters of power tillers in the five districts, cost was the most frequently cited reason for non-adoption across all districts. Accessibility and feasibility were also concerns, while awareness and perceived technology efficiency were more district-specific issues (Fig. 4).

Table 7. Factors influencing adoption rate of power tiller

District	No. of adopter	Government incentives	Peer Influence	Income generation	Affordable	Reduce drudgery
S/Jongkhar	59	4 (5%)	5 (6%)	12 (14%)	10 (12%)	55 (64%)
Samtse	27	0 (0%)	1 (3%)	6 (16%)	8 (22%)	22 (59%)
Sarpang	57	4 (5%)	4 (5%)	8 (10%)	9 (11%)	55 (69%)
Trongsa	65	5 (6%)	2 (2%)	7 (8%)	13 (14%)	63 (70%)
Zhemgang	42	2 (3%)	3 (5%)	11 (17%)	8 (12%)	41 (63%)
Total	250	15 (4%)	15 (4%)	44 (13%)	48 (14%)	236 (65%)

The factors influencing the adoption and non-adoption of mini tillers and tractors were similar to those affecting power tillers.

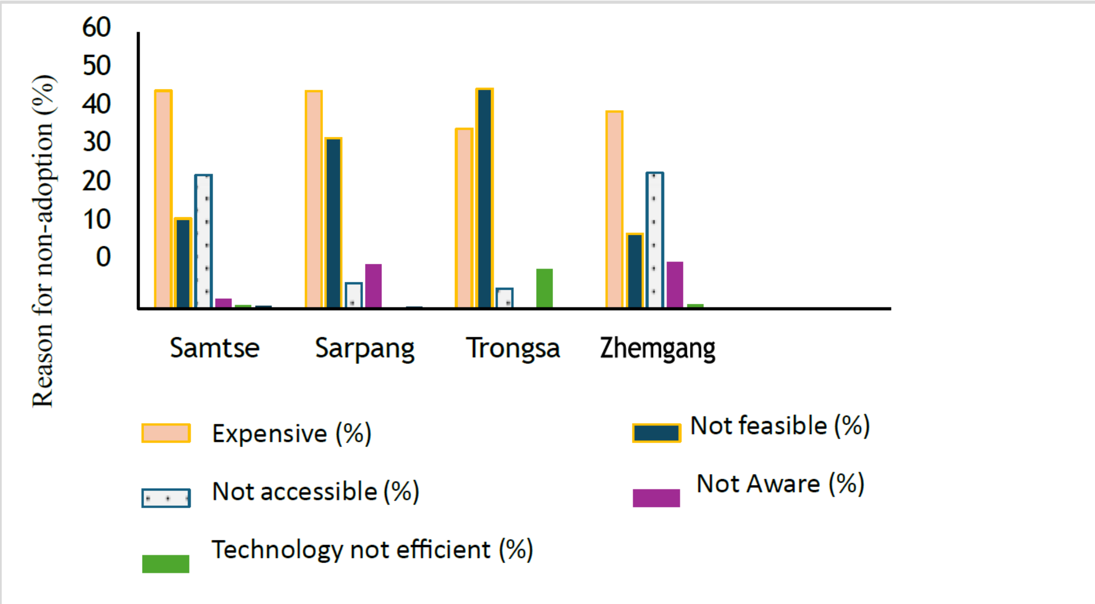

Fig. 4. Reasons for not adopting power tiller (n = 892)

5. Conclusion

The findings indicate that labour-saving technology adoption in the five surveyed districts is uneven and remains strongly shaped by access conditions. Power tillers were the most widely adopted machinery, while hiring was generally preferred to ownership, particularly for power tillers and tractors. Reduced drudgery was the leading reported motivation for adoption, whereas high machinery costs were the main barrier. Adoption was associated with cultivated area, education, family literacy, smartphone use, and the prevalence of the same technology within the gewog, although these relationships differed across technologies. The strong local prevalence effect suggests that peer learning and access to machinery-hiring services may support adoption. Accordingly, policies should prioritise affordable and timely machinery-hiring services rather than relying solely on individual ownership. Targeted financial assistance, operator training, maintenance support, and improvements in rural access infrastructure may further reduce barriers for small-scale and resource-constrained farmers. These measures could support a gradual and inclusive transition towards farm mechanisation while recognising the substantial variation in geography, farm size, and technology use across the surveyed districts.

6. Limitations

The cross-sectional design does not permit causal inference. The realised sample included 1,142 of 1,340 targeted households, and potential non-response bias was not assessed. Although survey weighting and clustering procedures were described, the manuscript does not present marginal effects, full model diagnostics, or multicollinearity assessments. The gewog-level technology prevalence variable may be endogenous and may also capture shared access to hiring services. Historical adoption trends rely on respondent recall and may be affected by recall and survivorship bias. The findings are therefore limited to the five surveyed districts and the 2024 study period.

Ethics Statement

This study adhered to established ethical principles for research involving human participants. Ethical approval for the household survey was obtained from Ministry of Agriculture and Livestock. Prior to data collection, all participants were informed about the objectives of the study, the nature of their participation, and the intended use of the collected information. Participation was entirely voluntary, and respondents were informed that they could decline to answer any question or withdraw from the interview at any stage without penalty. Verbal informed consent was obtained from all participants before the interviews commenced. To protect participant privacy and confidentiality, no personally identifiable information was included in the analytical dataset, and all survey responses were anonymized prior to analysis.

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Disclaimer

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This manuscript was prepared through the combined contributions of all author(s), including contributions to the study design, data, content development, results, interpretation, and related scholarly work. The author(s) acknowledge the use of Grammarly and ChatGPT to assist with grammar checking, language refinement, reference formatting. These AI-assisted tools were not used as authors and did not replace the intellectual contributions or scholarly judgment of the author(s). All AI-assisted outputs, including content, references, and interpretations, were carefully reviewed, revised, verified, and approved by the author(s). The author(s) accept full responsibility for the accuracy, integrity, and final content of the manuscript.

Competing Interests

Authors have declared that no competing interests exist.

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