PRODUCTION EFFICIENCY, ADOPTION, AND IMPACT OF WHEAT PRODUCTION TECHNOLOGY PACKAGES ON SMALLHOLDER FARMERS' FOOD SECURITY AND INCOME IN HORO GUDURU WOLLEGA ZONE, OROMIA REGION, ETHIOPIA

PhD DISSERTATION

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Production Efficiency, Adoption, and Impact of Wheat Production Technology Packages on Smallholder Farmers' Food Security and Income in Horo Guduru Wollega Zone, Oromia Region, Ethiopia

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In Partial Fulfillment of the Requirements for the Degree of DOCTOR OF PHILOSOPHY IN AGRICULTURAL ECONOMICS

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I hereby certify that I have read and evaluated the dissertation prepared by: Oliyad Sori Zenbaba, entitled "*Production Efficiency, Adoption, and Impact of Wheat Production Technology Packages on Smallholder Farmers' Food Security and Income in Horo Guduru Wollega Zone, Oromia Region, Ethiopia*" prepared under my guidance. I recommend it be submitted as fulfilling the dissertation requirement for the degree of DOCTOR OF PHILOSOPHY IN AGRICULTURAL ECONOMICS.

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DEDICATION

I dedicated my research work to innocent people in Ethiopia who lost their soul and displaced from their home.

STATEMENT OF THE AUTHOR

I declare that this dissertation is my own work which is prepared by following all ethical principles in collecting and analyzing data and hat all sources of materials used for this dissertation have been duly acknowledged. This dissertation has been submitted in partial fulfillment of the requirements for Ph.D. degree at Haramaya University and is deposited at the University Library to be made available to borrowers under rules of the Library. I solemnly declare that this dissertation is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

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BIOGRAPHICAL SKETCH

The author was born in East Wollega zone, Gobu Sayo district, Ulumayi Chala *kebele* on May 29, 1992 G.C. He completed primary school at Cheka Karu School in 2007, high school at Gudeya Jere in 2009 and preparatory school at Gudeya Bila in 2011. Then, he joined Wollega University in 2011 and graduated with a B.Sc degree in Agricultural Resource Economics and Management in June, 2014. Upon graduation, he was employed as a Graduate Assistant I (GA-I) at Wollega Universityn in July 2014.

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ABBREVIATIONS AND ACRONYMS

ADLI	Agricultural Development Led Industrialization
ATA	Agricultural Transformation Agency
ATT	Average Treatment Effects on Treated
ATU	Average Treatment Effects on Untreated
CIMMYT	International Maize and Wheat Improvement Center
CSA	Central Statistical Agency
DEA	Data Envelopment Analysis
DH	Double Hurdle
DID	Difference-in-Difference
DMU	Decision Making Units
FSIN	Food Security Information Network
FTC	Farmers Training Center
GPS	Generalized Propensity Score
HDDS	Household Dietary Diversity Score
HFCS	Household Food Consumption Score
IAP	Improved Agronomic Practices
ILO	International Labor Organization
ITA	International Trade Administration
kg	Kilogram
MESR	Multinomial Endogenous Switching Regression
MLE	Maximum Likelihood Estimation
MNL	Multinomial Logit
MoA	Ministry of Agriculture

MoARD	Ministry of Agriculture and Rural Development
MOFED	Ministry of Finance and Economic Development
NGO	Non-Governmental Organizations
NWFP	National Wheat Flagship Program
OLS	Ordinary Least Squares
OV	Omitted Variable
PSM	Propensity Score Matching
SFA	Stochastic Frontier Analysis
SFM	Stochastic Frontier Model
SNP	Safety Net Programme
USDA	United State Department of Agriculture
VIF	Variance Inflation Factors
WB	World Bank
WFP	World Food Program

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Production Efficiency, Adoption, and Impact of Wheat Production Technology Packages on Smallholder Farmers' Food Security and Income in Horo Guduru Wollega Zone, Oromia Region, Ethiopia

ABSTRACT

Wheat production is considered as a national strategic crop for serving as a main source of food, nutrition, and cash for smallholder farmers and alleviating the food insecurity problem in Ethiopia. However, its production is inefficient, and its technology packages adoption and contributions to households' food security and income are low in the country. This study is aimed at examining production efficiency, adoption, and impact of wheat production technology packages on smallholder farmers' food security and income in the study area. A multi-stage sampling procedure was used to select a representative sample and the survey data were collected from a randomly selected 302 sample households proportional to size at each sample unit. Data were analyzed by using descriptive and inferential statistics and econometric models. Parametric stochastic frontier models of Cobb- Douglas type production and cost functions revealed that the mean technical, allocative, and economic efficiencies of wheat production were 0.810, 0.881 and 0.714, respectively. The Tobit model results of determinants of efficiency differentials (technical, allocative, and economic efficiencies) revealed that education level positively and significantly and farm size negatively and significantly influenced all efficiency differentials. Soil fertility status and use of improved seed had a positive and significant effect on the technical and economic efficiency of wheat production, while farm distance negatively and significantly influenced. Family size positively and significantly affected allocative and economic efficiency, while the technical efficiency of wheat production is positively and significantly affected by the number of livestock owned. The adoption intensity of wheat technology packages was analyzed by using a two-limit Tobit model and results show that education level of household, access and purchase of improved seed, livestock owned, farm training, annual farm income and access to off/non-farm income had positive and significant effect, while distance from the nearest market had a negative and significant effect. The multinomial logit model results revealed that households' decisions to adopt wheat technology package combinations are significantly influenced by sex, education level of household head, distance to nearest market, *farm areas and training centers, ownership of telephone devices, agricultural cooperative membership farm size, livestock, and landholding size. The multinomial endogenous switching regression model results indicate that adoption of full recommended wheat technology packages has a greater positive impact of 21.71%, 11.31% and 3.38% on households' food consumption score, dietary diversity score and wheat production income, respectively. The findings of the study contribute for the National Wheat Flagship Program of wheat self-sufficiency for better food security, sustained livelihood outcomes and import substitution. Therefore, agricultural policymakers, development organizations, and qualified agricultural practitioners should engage in the improvement of wheat production efficiencies and full technology packages adoption through timely supplying improved seed and solving its access barriers, usage of recommended types and amounts of inputs, improving financial services and strengthening the extension workers' role for advising and training farmers, strengthening adult literacy programs and farm input-oriented institutions.*

Keywords: Wheat Production; Smallholder Farmers; Technology Adoption; Food Security; Income; Oromia Region

1. INTRODUCTION

1.1. Background of the Study

Agriculture contributes for subsistence, livelihood, economic growth and poverty reduction in Sub-Saharan countries (Ssozi *et al.*, 2019; Kibrom *et al*., 2021; Setsoafa *et al*., 2022). In Ethiopia also, it contributes for the national development goals, the overall livelihood of smallholder farmers, economic growth, foreign exchange, employment opportunities, and reduce food insecurity and poverty (ATA, 2018; Diriba, 2020; Gebeyanesh *et al.,* 2021; FAO, 2023). However, the sector faces limited access to production technologies, lack of finances, inefficient marketing, underdeveloped research, and poor extension services (USDA, 2023) which caused different agricultural production strategies and policies have to be formulated and developed in Ethiopia (Zewdie, 2020). Among these, the Agricultural Development Led Industrialization (ADLI) and Growth and Transformation Plans (GTP) I and II strategies were aimed at intensifying agriculture to increase its productivity (MOFED, 2010; MoARD, 2010). More specifically, Ethiopia's Development Plan identifies sustained agriculture programs to accelerate economic progress and ensure national food security by producing sufficient wheat (USDA, 2022). However, both ADLI and GTP strategies not achieved their goals due to weak structural transformation in production, less advanced with technology, agricultural production inefficiency, traditional subsistence farming, rain-fed dependency and low commercialization of agriculture (Mussie, 2019).

Cereal crops are the principal staple crops, serving as a major food crops in Ethiopia and its area coverage and volume of production are top-ranked. Ethiopia has a favorable agro-ecology for wheat production and ranked first in the volume and allotted areas for wheat production in Sub-Saharan Africa (Mulu *et al*., 2022). Wheat production is ranked third in area of production and second in volume of production next to maize, while its production shares 15.31% (1.86 million hectares) with 17.71% (5.8 million tons) among cereals grown in Ethiopia (CSA, 2022). Wheat is the most important staple crop and considered as a strategic crop to realize food self-sufficiency and serves as source of households' income in the country (Hodson *et al*., 2020; Adugnaw and Dagninet, 2020; MoA, 2023). However, its productivity is still low in Ethiopia although various strategies planned and implemented to improve its productivity (Zewdie, 2022) caused by challenges mostly related to wheat production methods, input usage, and its input costs (Hodson *et al*., 2020). Accordingly, the national wheat yield is 3.11 tons/ha, while it is 3.36 tons/ha in the Oromia region and 3.39 tons/ha in Horo Guduru Wollega zone (CSA, 2022; Wuletaw *et al*., 2022). These yield figures are too low when compared with the average yield obtained in other countries of the world, such as Ireland (10.17 ton/ha) and 6.7 ton/ha obtained in South Africa (FAOSTAT, 2017) and there is some improvement compared with sub-Saharan Africa countries which was 2.58 ton/ha. As a result, huge wheat productivity gaps exist in Ethiopia (Brasesco *et al*., 2019; Hodson, 2020). Moreover, in against to low wheat productivity, demand and consumption for wheat and its products become higher in Ethiopia due to an increased number of population, rural–urban population demographic shifts, increased urbanization, climate change, increasing food prices due to the COVID-19 pandemic and awareness of value addition (Tolesa, 2024; Kefena *et al*., 2025). To meet these demand gaps along food security, adoption of wheat technology packages profoundly got considerable attention in Ethiopia through maximizing the level of wheat production.

Food problems are the most influential challenges to the livelihood of the population of developing and undeveloped countries (Lashina *et al*., 2023). The food insecurity problem is a global challenge and got the attention of policy makers as many individuals are suffering with hunger and malnutrition (Workicho *et al*., 2023). The issue is more severe in Africa with an estimated 61.6 million food-insecure people in East Africa (WB, 2025). However, despite various efforts the populations of developing countries of Sub-Saharan Africa are facing with the continued problems of food insecurity (Cheteni *et al*., 2020). In Ethiopia, food insecurity problems are caused by both natural and human-made factors such as population growth, fragmented farmland, failed rains and droughts where substantial proportions of Ethiopian households are facing with the problems of food insecurity problems (Mohammed *et al*., 2023; Habtamu *et al*., 2024). By considering the issues of food insecurity, the production and wheat through using irrigation, adoption of improved wheat production technologies and mechanization thereby ensure wheat food security and self-sufficiency got attention (Tolesa, 2024).

In low-income countries, improved agricultural technology adoption has a substantial importance in boosting resource utilization for improving agricultural productivity, food security, consumption, and income, and reduces poverty (Mark *et al.*, 2014; de Janvry *et al*., 2017).

However, it needs dissemination and utilization of the technology (Glover *et al*., 2019). Moreover, adoption of recommended modern agricultural technology packages more improves the expected highest yield outcome (Rehman *et al*., 2016). The common packages include row planting application, seed varieties usage, weeding rate, and recommended chemicals and fertilizers application. But, the identification of these packages could be complex and needs making proactive decisions on technology package selection and usage (Teshome, 2021; Carrillo *et al*., 2022).

In Ethiopia, adoption and adoption rate of agricultural technologies is found to be low predominantly caused by adopters' internal and external production constraints, such as shortage of cropland, land tenure issues, lack of knowledge, low return, market problems, farmers' behavior, technological constraints and lack of advisory services (Gebeyanesh *et al*., 2021; Mesele *et al*., 2022). Besides, wheat production technology package adoption rate is characterized as low caused by demographic, economic, technological and resource ownership factors in Ethiopia in general and Oromia region specifically (Degefu *et al*., 2017). The low adoption rate of wheat production technologies brought stagnated productivity and low crop yields, exposing the country to recurrent food shortfalls and national food insecurity. Like other cereals, wheat technology packages also include improved varieties, seeding rates, row planting, better irrigation, weed management, application of recommended fertilizers, and the likes (Gashaw *et al*., 2018; Adhikari *et al*., 2021). Adopting these technology packages contributes to improving wheat productivity, food security consumption expenditure, income, asset per capita, and livelihood of households (Nirgude and Sonawane, 2017; Giller *et al*., 2017; Araya and Lee, 2020; Aklilu *et al*., 2022).

Horo Guduru Wollega zone is a largely populated area where larger proportions of its population subsistent on agriculture, and has sufficient rain per year required for agricultural production. The area has suitable agro-ecologies for the production of cereal crops like wheat. However, the productivity of wheat production and its adoption rate of improved production technology packages are low caused by a lack of access to wheat production technologies, a lack of awareness, and lack of supporting services (Megersa, 2021). Its technology adoption level and productivity far from expected and resulted in stagnant and high production efficiency differences. Utilizing the available and recommended wheat production technologies by

Ethiopian ministry of agriculture such as improved wheat varieties, planting in row, and agro-chemicals application could improve wheat production and income and reduce food insecurity. However, many studies did not consider the efforts of different stakeholders' engagement in producing wheat by utilizing full and recommended technology packages' adoption and its impact analysis. Therefore, this study is conducted by focusing on production efficiency, adoption of wheat production technology packages and its impact on smallholder farmers' food security and income from wheat production.

1.2. Statement of the Problem

Agriculture contributes a lion's share in improving the livelihood of smallholder farmers in agriculture-dependent poor developing countries like Ethiopia. It creates employment opportunities, improves smallholder farmers' food security, income, and the level of the economy. However, against to its contributions, smallholder farmers in Ethiopia and Horo Guduru zone are inefficient in terms of agricultural production due to production related constraints (Tolesa and Bacha, 2022). Similarly, wheat production has a potential influence on mitigating the impacts of food shortage and rising food prices and improving farm income (Tolesa, 2024). The crop is selected as strategic crop to achieve food self-sufficiency, poverty reduction and income generation in Ethiopia (Wuletaw *et al*., 2022). However, its production efficiency, adoption, and its influence on households' food security and income improvement are very low in the country. To overcome these problems, improving wheat farming practices in an efficient manner, adoption of full production technology packages, and ensuring its impact on smallholder farmers' food security and income become prioritized in Ethiopia in general and in Horo Guduru Wollega zone, specifically (MoA, 2023).

Wheat production is characterized as low productivity while its consumption demand is increasing in Ethiopia (Tolesa, 2024). Its productivity is influenced by its domination by smallholder farmers, inefficient production systems, limited use of technologies, lack of appropriate production policy and adoption of technology packages in Ethiopia. More specifically, constraints along the application of improved varieties, farming methods, irrigation services, biophysical and socio-economic challenges and the applications of agro-chemicals such as fertilizers and chemicals hinder wheat production and productivity. As a result, famine, extreme poverty, stagnated economy, and food insecurity problems happen to the livelihood of smallholder farmers (FAO, 2017; Milkessa *et al*., 2019; Neglo *et al.*, 2021; Zewdie, 2022; ITA, 2022; Mulu *et al.*, 2022).

Smallholder farmers' farming systems which are cereal-based, traditional and non-commercial oriented, could be affected by problems along agronomic practices, availability of improved varieties, irrigation facilities, recommended fertilizer per hectare, and soil fertility. Moreover, in Ethiopia, rain-fed farming systems are undertaken by subsistent farmers is challenged by the complicated constraints along with different biotic and abiotic factors, but the systems could be reversed through agricultural technology adoption (Adugnaw and Dagninet, 2020; Gebissa, 2021; Alemayehu *et al*., 2023). As a result, inefficiency in wheat production remains high, while identifying the causes of production inefficiencies creates appropriate concerns about wheat production in the country (Kaleb and Workneh, 2016). Many studies were undertaken on wheat production efficiency in different parts of Ethiopia (Mesay *et al*., 2013; Wudineh and Endrias, 2016; Kaleb and Workneh, 2016; Tekleyohannes *et al*., 2018; Moges, 2019; Birara *et al*., 2023; Woretaw and Kumar, 2023). However, most farm production efficiencies are concerned with technical efficiency and there were limited empirical studies done on the allocative and economic efficiencies. Technical efficiency analysis alone might not properly identify farm level wheat production constraints, the overall performance of wheat producers' expected benefit and may not help policy makers to design and set proper policies for improving wheat production efficiencies.

Agricultural technology adoption has prominent contributions to sustain productivity in agricultural production, improve household food security and farm income in a poor country like Ethiopia. However, the extent of agricultural technology adoption is directly influenced by the inherent factors of farmers such as their attitude and perceptions, adoption cost, technological and geographical factors (Bell *et al*., 2016; Kendall *et al*., 2022) and controlling technology adoption factors simplifies technology diffusion (Clark *et al*., 2018). More specifically, smallholder farmers' understanding, behavior, knowledge, information, and willingness about the technology significantly influence wheat production technology package adoption. However, to maximize the impact of wheat production and productivity, it needs the adoption of full recommended technology packages than adopting a few or a single technology package (Aklilu *et al*., 2022). In Ethiopia, several development actors and wheat policies were considered as a criterion to improve productivity of wheat through technology adoption for sustaining the well-being of smallholder farmers (Zewdie, 2022). However, wheat production technology package adoption rate is characterized as low caused by demographic, economic, technological and resource ownership factors in Ethiopia in general and Oromia region specifically (Degefu *et al*., 2017).

Agricultural technology packages adoption did not bring expected output improvements in Ethiopia despite many adjustments of diversity in biophysical and socioeconomics for the adoption of agricultural technology packages (Tewodros *et al*., 2020). Smallholder farmers might fail to employ and adopt integrated agricultural which need selection of production-maximizing technology packages (Teshome, 2021). Most studies undertaken on wheat technology adoption (Tesfaye *et al*., 2016; Regasa and Degye, 2019; Subedi *et al*., 2019; Gedefaw and Sisay, 2019; Milkias, 2020; Negese and Jemal, 2021; Gezahagn, 2021; Bedilu *et al*., 2021; Dawit and Girma, 2022; Gemechu and Sura, 2024) focused on a single or few technology adoption. However, there were no adequate studies on the determinant factors of smallholder farmers' simultaneous adoption of recommended wheat production technology packages such as improved wheat seed, row planting, and the application of recommended fertilizers and chemicals.

In Ethiopia, adoption of wheat production technology packages profoundly improves smallholder farmers' food security and farm income (Wuletaw *et al*., 2022; Gadisa, 2024). Food insecurity is the most influential factor to the livelihood of Ethiopian population in general and Horo Guduru Wollega zone in particular. It is primarily caused by hunger and food shortages. Moreover, the extent of food insecure proportion of households was low and which is caused by lack of resources, inability to get resources, lack of food (no availability of food), and improper use of resources (Bacha and Wandu, 2022). This indicates that the existence of food shortages and starvation in the country and in the study area. However, jointly adopting recommended technology packages can achieve realized and expected outcomes (Araya and Lee, 2020). Additionally, under-estimation or over-estimation and low outcomes could be obtained from a single or incomplete technology package(s) analysis (Ward *et al*., 2018; Wubneshe *et al.*, 2020; Ogada *et al*., 2021) and such estimation could not be an input for wheat production policymakers (Milkias, 2020).

However, most previous studies, such as Tsegaye and Bekele (2012), Bekele *et al*. (2014), Tesfaye *et al*. (2016), Chilot and Dawit (2016), Tigist (2017), Regasa and Degye (2019) Muluken *et al*. *(*2021) and Abebaw *et al*. (2022), did not focus on impact analysis of full technology packages adoption rather they discussed the adoption impact of a single agricultural technology. Although adoption of wheat technology packages contributes a key role in attaining food security level and improving farm incomes, their status and packages' selection remained challenging and limited, relying on a few technologies. Overall, identifying the impact of wheat production technology packages adoption on households' food security status and wheat production income has a vital role in implementing and intervening in agricultural policies and strategies.

The study addresses the key research gaps in the literature in fourfold: first, the study jointly considered all wheat production efficiencies (technical, allocative, and economic efficiency). Second, the study analyzed both adoption decision and intensity of recommended wheat technology packages rather than relying on a single or few packages. Third, the study evaluates impact of full wheat technology packages on households' food security and wheat production income rather than relying on a single or few technology package(s). Finally, to assess the impact of technology adoption on outcome variable and solve problems of self-selection bias created due to unobservable factors, the study employed an endogenous switching regression model.

1.3. Research Questions

This study attempts to answer the following basic research questions:

1. Are there efficiency differences among wheat producer households in the study area?
2. What are the levels of the technical, allocative and economic efficiencies of wheat-producing smallholder households?
3. What are the factors influencing wheat production efficiency (technical, allocative and economic efficiencies)?
4. What are the factors affecting wheat production technology package combinations adoption decision?
5. What are the factors affecting adoption intensity of wheat production technology packages?

6. What are the adoption impacts of wheat production technology packages on smallholder farmers' food security and wheat production income?

1.4. Objectives of the Study

1.4.1. General Objective

The general objective of the study is to investigate production efficiency, adoption and impact of wheat production technology packages on smallholder farmers' food security and wheat production income in Horo Guduru Wollega zone, Oromia region, Ethiopia.

1.4.2. Specific Objectives

The specific objectives of the study are to:

1. Estimate the level of efficiency and identify factors affecting efficiency (technical, allocative, and economic) differentials among smallholder households in wheat production;
2. Identify factors affecting adoption decision of smallholder farmers' wheat production technology package combinations;
3. Identify determinants of smallholder farmers' adoption intensity of wheat technology packages production;
4. Measure impact of adoption of wheat production technology packages on smallholder farmers' food security and wheat production income.

1.5. Significance of the Study

The majority of the Ethiopian populations rely on subsistent agriculture, which is undertaken by almost all smallholder farmers. Greater proportions of the people of the country are food insecure and living by low income. Though agricultural production methods are backward, practicing and applying agricultural technologies and their adoptions have various advantages. It contributes to the improvement of smallholder farmers' agricultural production, income and food security. Therefore, by considering the expected benefits of efficient wheat production, adoption of wheat production technology packages and its impact evaluation, identifying the areas of problems and conducting a research contributes multifold advantages.

Efficiency analysis of this study has considerable contributions in identifying farm level wheat production constraints and differentiating the level of wheat production efficiency to organize the activities could minimize its inefficiencies and improve wheat productivity. Moreover, it provides useful information for extension workers, policymakers, farmers and researchers about wheat production technical, allocative and economic efficiencies. Moreover, the findings of this study provide practical knowledge for agricultural experts about agricultural technology adoption and make them aware about complex wheat production challenges. These help them to understand to design appropriate strategies more for solving agricultural technology adoption and make farmers aware of how to further adopt agricultural technologies and produce efficiently.

The findings of this research also contribute valuable information and technical gaps that exist between farmers and agricultural service providers like extension workers, researchers, and policymakers to understand the stages, patterns, levels, and factors of production and wheat technology packages adoption and adoption impact. They become advantageous in getting information and research-based data on challenges and opportunities of wheat production, its efficiency, technology diffusion among farmers, and its feature perspectives and sustainability of technology practices adoption. Further, impact evaluation of this study contributes to the National Wheat Flagship Program (NWFP) of Ethiopia, in providing wheat production policymakers feedback about wheat production, technology adoption and is impact of households' food security and income. This research will also contribute to serve as a literature along with the current title for future researchers who interested in conducting further studies. So overall, the findings of this research will contribute as an input for farmers engaged in producing wheat by adopting technologies, researchers, Ethiopia's national development frameworks, agricultural experts (extension workers), and agricultural policymakers.

1.6. Scope and Limitations of the Study

The study is undertaken in Horo Guduru Wollega zone by focusing on wheat production efficiency, wheat production technology packages adoption, and its impact on smallholder farmers' food security and wheat production income. In the study area, producing wheat by using irrigation methods, especially during winter by creating participatory activities for increasing wheat productivity is started recently. However, this study depends on only rain-fed wheat production, as irrigated wheat production in the selected districts was negligible. So, conducting research depending on only rain-fed wheat production might create problems during data collection, as respondents may respond to questions for both rain-fed and irrigated wheat, though the quantity of wheat produced by irrigation is too low in the study area. Data regarding the dynamic nature of technology adoption and its impact analysis and production efficiency might need panel data, as they are influenced by different factors over time, and it is difficult to capture inter-temporal variations by analyzing cross-sectional data only. But, the survey was undertaken through interview to collect the required data from the selected households. Accordingly, the study properly used measures for collecting and analyzing the required and expected data for obtaining the relevant research output without being constrained by the above-mentioned limitations.

1.7. Organization of the Dissertation

This dissertation study is composed of seven chapters. The remaining chapters of the dissertation are organized as follows: The second chapter is a literature review, the third chapter is research methodology, followed by results and discussion in the fourth chapter, the fifth chapter is summary, conclusion, and recommendations, the sixth chapter is references, and the last chapter is appendices.

2. LITERATURE REVIEW

This part represents the intensely reviewed literatures on efficiency, adoption and impact evaluation by focusing on definitions of terms, theoretical framework, methodological framework, analytical framework, empirical review and conceptual framework.

2.1. Definition of Basic Concepts

2.1.1. Efficiency

The central point in describing efficiency in production is about competence. Measurement of efficiency of production could be either with respect to its desired normatively performance or with another farm performance while the observed performance and specified standard notion of performance are used for its computation. Efficiency related with production stages is assumed by neoclassical economics as farmers in the market always efficiently operate. However, it might not always true due to efficiency problems which exist with farmers caused by productive resources wastes and unforeseen exogenous shocks outside the producer's control (Kokkinou, 2010). However, productivity examines input and output relationships at a given production process which is output versus input. It does not represent the volume of output produced rather it shows output obtained in relation to resources employed (Coelli and Rao, 1998).

Efficiency represents and defined in terms of technical efficiency, allocative efficiency and economic efficiency. Technical efficiency represents the maximum possible output with a specified endowment of inputs and technology mix and environmental conditions while allocative efficiency is a combination of inputs at the least cost required to produce a given level of output. It is the possibility of producing a given level of output with less of at least one input and no more of another. Allocative inefficiency causes increment in the costs of production, and reduction in profit from production. Similarly, economic efficiency represents the ability of a firm to produce a given level of output with least cost. It represents the other components of efficiency like allocative efficiency (AE) and technical efficiency (TE) which their ratio results economic efficiency (Farrel, 1957). Production efficiency measurement gives powerful and relevant information in making designed decisions for how to utilize scarce resources, which is important for formulating development policies. Improvement of production efficiency could be realized through resource allocation and application of new technology. But these may not bring new advantages unless the existing resources and technologies remain efficient while generating and disseminating technologies used to bring higher growth. The level of production productivity obtained through utilizing the available inputs and technologies measures production efficiencies. A production is said to be economically efficient if it is technically and allocativelly efficient (Gravelle and Rees, 2004; Shanmugam and Venkataramani, 2006). Therefore, technical, allocative and economic efficiencies are considered for this study.

2.1.2. Technology Adoption

Technology is the use of knowledge and tools through employing various techniques and methods of using new or already in use technologies (Porter, 1985; Loevinsohn *et al*., 2013). Innovation-diffusion model is the principal model of technology adoption which is widely used for the decision and stages of decisions of technology adoption. It passes through different stages such as awareness, interest, evaluation, trial, and adoption stages. While spread of an innovation of adoption at the aggregate level viewed over time, diffusion of technology cumulatively measure adoption at successive time periods of different categories like innovators, early adopters, early majority, late majority and laggards (Rogers, 1962). However, the successfulness of adoption of the technology needs the creation of a new technology into the existing practices over time (Loevinsohn *et al*., 2013). As a new technology is introduced after making decision at the beginning and afterward, the rate at which the technology is diffused and adopted varies from group to group. Adoption rate slowly started to be adopted and become experienced to grow with time (Feder *et al.*, 1985). Adoption of technology can be measured by individuals' the extent of new technology utilization and time required to adopt (Sunding and Zilberman, 2001). Agricultural technology can be a broad-term that covers describing about agricultural apparatus, genetic material, farming methods, and agricultural inputs usage to improve agricultural outcome effectiveness which is related with agricultural productivity, health, welfare, and sustainability (Ruzzante *et al*., 2021). The decision to adopt agricultural technologies simulated at the farm level and described in terms of the behavior of adopters (Xie *et al.*, 2021).

Technologies are not easily accepted and adopted as a package but after adopted it could have interlinked relationship with the outcome variables and it provides proper direction for farmers to improve their production. On average, agricultural technology packages which are employed at different areas includes improved variety, fertilizers, weed management, planting methods, and etc. The agricultural technology adoption can be either in package combinations or in single package. The improvement in the adoption of the technology need time and undertaken sequentially which can grant profitability of the technology, risk reduction, uncertainty, and institutional constraints (Byerlee and Polanco, 1986). For this study, the adaptability and utilization of smallholder farmers' wheat production technology packages are considered and technology packages such as improved wheat variety, row planning and application of fertilizers and chemicals are selected and used.

2.1.3. Impact evaluation

Impact evaluation is a process of systematic and objective identification of the short and long-term effects which directly or indirectly imposes intervention on economic, social, environment and institution. It is an effect produced by intervention which can result in positive or negative probability outcomes of intended, unintended, direct and indirect while its evaluation is used to identify changes resulted after intervention. Impact evaluation can be undertaken for deciding to stop, continue and/or expand the interventions to successfully diversify the extent of impact interventions and create link with others about the advantages of intervention outcomes. It is primarily undertaken for the purpose of deciding whether or not to continue or expand an intervention, to learn how to scale up and successfully adapt a successful intervention to suit another context, and to inform intended beneficiaries about the benefits of the intervention (Rogers, 2012). Impact evaluation of wheat technology adoption on smallholders' food security and income is widely discussed by this study.

2.1.4. Food security

The concept of food security is dynamic in its nature which changes over-time while its definitions vary from scholars to organizations (WFP, 2017). Food security is a situation that exists when all people at all times have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life (FAO, 2021). It incorporates availability, food accessibility, utilization and stability of food access (Bonnard, 1999). In spite of its definition prevailed, food scarcity might prevails due to constraints relate to temporal or permanent access to food though a given country is sufficient in food. This demand for domestic food gaps caused by the above factors need to be solved for real existence of food security in a given country (Rocha, 2017). Moreover, food insecurity is inability to acquire the required enough food to meet dietary requirements for maintaining and sustaining lives (Olaniyi, 2014). It is caused by unavailability of food, insufficient purchasing power, inappropriate distribution or inadequate use of food at the household level (FAO, 2021).

Food insecurity exists when normal growth, development, and an active and healthy life are not sustained as people lack to secure access to sufficient amounts of safe and nutritious food (FAO, 2021). It inherently exists with humans, and eradicating it from its root is complex and challenging (Cordero-Ahiman *et al*., 2020). Food insecurity and malnutrition problems are mostly related with the population growth, drought, rising prices of goods and services, political instability, internal conflict and displacement, and unemployment (WFP, 2023; Tadesse and Alemayehu, 2019). These issues are caused in general by social, institutional, and technological problems that contributed the aggravation of households' food insecurity and dependency on Safety Net Programme (SNP) aid for survival (FSIN, 2017).

2.1.5. Household income

Household income is income gained from employment, production of household services for own consumption and transfers owned, and property income. It includes all receipt which members of household received annually or at frequent interval (in kind) or monetary. However, it excludes windfall gains and irregular and typically one-receipts of households. Household income receipts are used for current consumption and its reduction of its cash, disposal of its other financial or non-financial assets or an increase in its liabilities does not reduce the net worth of the household (ILO, 2004; Canberra Group, 2011).

2.2. Theoretical Framework

2.2.1. Theoretical framework of technology adoption

The theoretical framework on diffusion of technology innovation was developed by Rogers and the theories mostly focus on explaining on how a given technology emerged, adopted and diffused to the society (Rogers, 1983). Technology adoption starts from thinking about the technology through passing to learning and adopting. The acceptance and the level of adoption become complex as the adoption decision moves from conception to adoption. This is due to adopters' decision of using different inputs, heterogeneity problems in technology adoption, uncertainty of the adoption, time length, side effects of externalities on learning adoption of the technology and lack of well-organized adoption data. Frequently accepted and adopted innovations grouped to different categories of innovation packages such as materials/mechanicals, agronomic, biological, chemicals, and information related innovation. These and all other innovation packages have direct or indirect influence adoption decision and level and need innovation policy adjustments by identifying process of innovations, impacts of innovation adoption on economic development, and production related factors such as yield, cost, risks, and other external factors. Lower risk response of modern input of technology adoption and higher output price of modern input use of the technology improves optimal level of new technology/innovation usage (Sunding and Zilberman, 2001; De janvry *et al.,* 2016).

From its beginning, technology adoption might be understood from two perspectives: Fist, technology adoption focused on characteristics of adopters' perception of innovation, their adoption decision, the extent of adoption and their communication with others about the technology. Second, diffusion of adopted technology which might consider economic variables as determinants of technology adoption emerged. At the initial stage, technology could be adopted by fewer adopters of the technology and through a time, the majority starts to adopt the technology which in turn increases the rate of technology adoption before it becomes slow. The diffusion of technology adoption focused on adopters who adopt early and late, the attributes of innovation and effect of early adopters of innovation on the rate of adoption (Griliches, 1957; Sunding and Zilberman, 2001; Rogers, 2003). Moreover, the diffusion of innovation theory which regarded on innovation acceptance and adoption developed by Rogers and focused on analyzing how innovation shared between households and information about the innovation communicated overtime through certain channels (Rogers, 1995).

Time and space have great influence on the technology adoption process for diffusion of technologies. Moreover, adoption of new technologies needs the support of technological changes through identifying factors of adoption process at any time for the improvement of adoption of technologies. The sustainability of the technology adoption largely focuses on individual adopters' willingness, ability, attitude, wealth, education, land holding and characteristics of technology (CIMMYT, 1993). Determining adoption and adoption rate of the technology is based on a sample of adopters in which some members of the sample unaware about the technology. This creates a base for the underscore of the technology adoption which suffers from non-exposure bias. The outcome might be underestimating or overestimating the true population. Over-estimation of the true population of the sample adoption might result in positive population selection bias where then subpopulation is expected to be exposed first for adoption (Diagne and Demont, 2007). The dynamicity of adoption depends on learning about new technologies while the stages of time flow for adoption pass through trial, early/late adoption, partial adoption, and non-adoption. Static adoption models fail to adequately explore the effects of changes in farmers' perception and attitudes over time (Doss, 2006; Hailu, 2008).

Maximization of expected utility/profits of adopters' choices of technology in a given time period at the given level of technology/production inputs determine the adoption decisions of adopters. To maximize their expected utility from the adoption of technology/innovation, farmers should select technology from a mix of technology packages. However, the outcome of expected utility mostly regards with apparent income and or consumption and disregard about maximization of temporal expected utility. These processes of adoption of new technology need the creation of awareness about the existence of the specific technology. And then, adopter analyzes the information about the new technology and gets to understand further about features of the technology and make a trial about the technology adoption. The supposed benefits of the technology enable adopter/s about actual technology adoption and depending on benefits of technology adopted by the adopter (Feder *et al.*, 1982; Simtowe *et al.*, 2016).

Further development of new innovation/technology needs the acceptance and confidence of the adopters about the technology where the acceptance of the technology is considered as one component of the development of technology adoption. Technology acceptance models and theories such as technology Acceptance Model, Theory of Planned Behavior, Diffusion of Innovation theory, Theory of Reasoned Action, Model of PC Utilization and etc. have been applied in a wide variety technology adoption to understand and predict users' behavior about technology adoption (Mathieson, 1991). However, the adopters' acceptance of these dynamic technologies depends on a number of factors such as availability of technology, convenience, consumers' need, security and etc. (Meuter *et al*., 2000).

2.2.2. Theoretical framework of efficiency analysis

Efficiency measurement of a farm production given a particular input of land could be represented as yield per hectare. However, as production efficiency of farm output is a function of interdependent combinations of inputs and requires econometric analysis theories to discrepancies between the level of production and values production given a set of technologies. Efficiency issues are the most influential challenge among the most factors in agricultural production economics. Given at attainable production function, actually obtained value of the objective function helps to measure efficiency of production (particularly agricultural production). Efficiency in agricultural production is aimed at improving technical, allocative and economic efficiencies to boost agricultural production by increasing optimum utilization of resources in developing counties (Burhan *et al*., 2009).

Transforming a given set of inputs to produce a given maximum level of output given the existing and available farm technology represents production function. The model is described in-terms of maximum output produced from specific combination of inputs given the available technology. In economic theory, the goal of the firm/producer is to produce at isoquant frontier to maximize its profit though it needs making helpful production decision. The firm is considered as technically efficient when its output is produced at the optimal production frontier. TE analysis is undertaken to help us to identify factors that shift production function upwards on the production frontier (Battese and Coelli, 1995). Allocative efficiency (AE) of production represents the ability of the firm to allocate different combination of inputs to produce a given produce through minimizing cost. AE is the relationship between the required total output cost and actual factor in efficient manner at optimum level (Chukwuji *et al*., 2014). It is directly related to the firms' ability to mix the existing resources for the production at the given level of output. Similarly, economic efficiency (EE) in microeconomic theory is the ratio of TE and AE. A frontier production function of a firm represents technical and allocative efficiencies in production and a firm needs to be efficient in these both efficiencies and so that they could be economically efficient. Input-output combination should on both frontier function and expansion path to produce output in economically efficient manner (Farrell, 1957).

From the following figure 1, firm use inputs X_1 and X_2 to produce a single Y output for efficiency measurement in the scheme of inputs usage if it operates under constant returns to scale and fully efficient firms' knowledge represented by SS'. Overall, the distance QP represents technical inefficiency if a firm decided to use the set of inputs given at point P and produce quantity of output Q. Technical Efficiency is formulated as: TE = OQ/ OP = 1- QP/OP where it takes the values between 0 and 1. Allocative efficiency is also the input price ratio represented by the slope of isocost line AA'. Then, the Allocative Efficiency (AE) of the firm operating at point P is defined as: AE = OR/OQ. RQ also represents production costs which is reduced and at point Q' allocative and technical efficiency occurs but at point Q it is only efficient technically but inefficient allocatively. Finally, the overall EE (Economic Efficiency) = TE *AE = OR/ OP

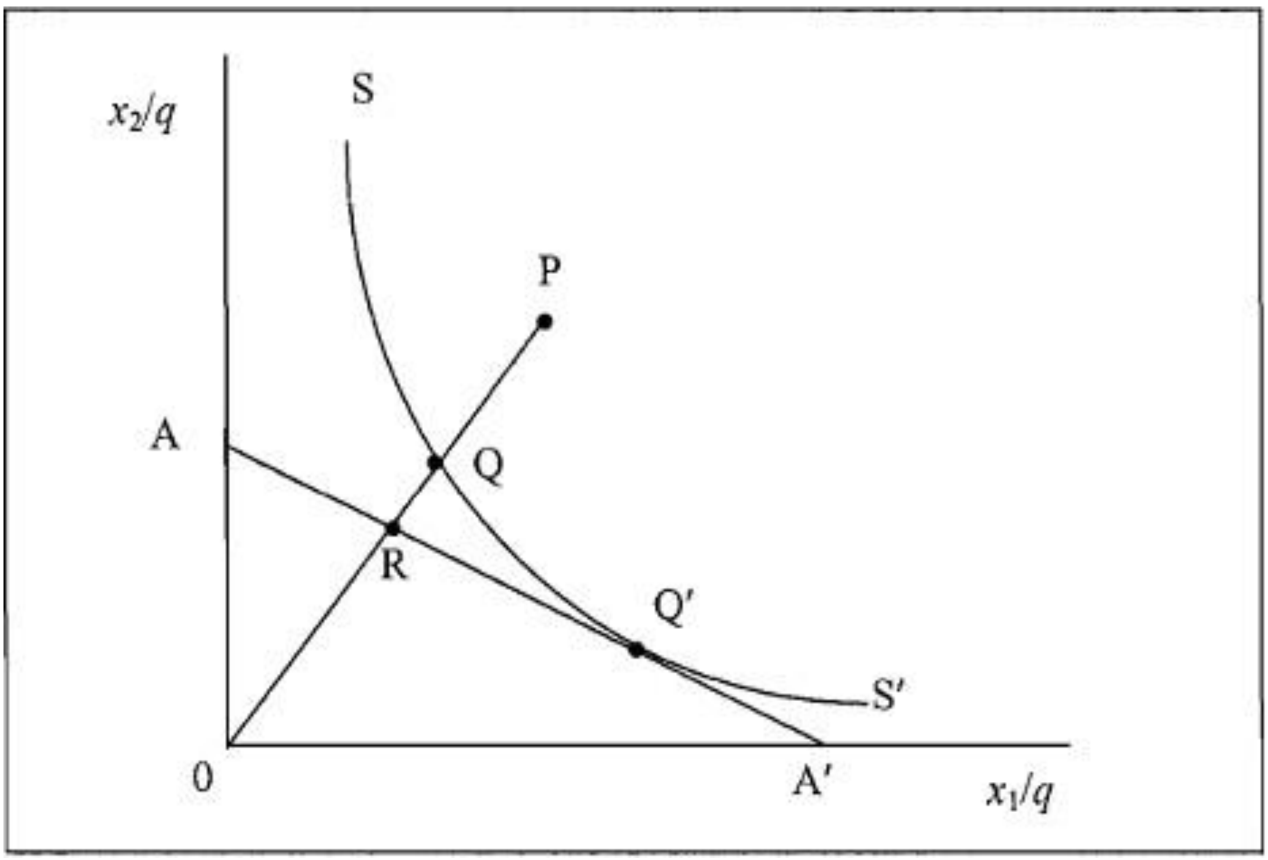

Figure 1: Input-oriented firm's technical, allocative and economic efficiencies
Source: Coelli *et al.* (2005).

However, in an output oriented scheme given by figure 2 as follows, incomplete knowledge related to technical production problems and internal inherent influential factors are challenges for not to attain frontier production stages. From the below figure 2, AP' represents the operation of firm's actual or perceived production function while at point C the firm lie on actual frontier but allocatively inefficient and at point D which is tangent to the price line and both technically and allocatively efficient which at maximum profit π_4 attained. However, π_1 the potential economic efficiency frontier of the firm cannot attained and both schemes resulted in the same outcome which calls for the application of decision making units (DMUs) which focuses on output-oriented than input-oriented.

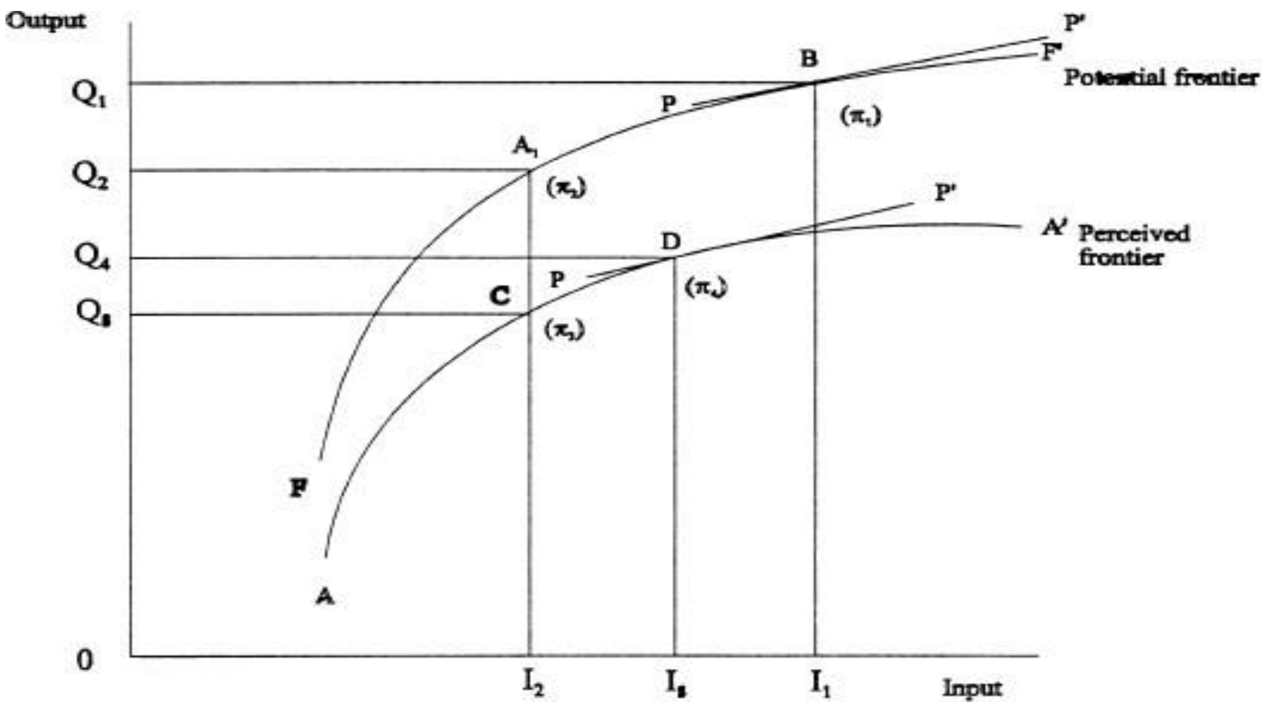

Figure 2: Output-oriented firm's technical, allocative and economic efficiencies

Source: Coelli *et al.* (2005).

2.2.3. Theoretical framework of impact evaluation

Causal effect is the vital goal of impact evaluation which brings positive feedback for routinely undertaken product development. It offers rationale for continuing effective programs, tackle problems, identify effective conditions for development policies, and create awareness on how interventions in the development policies applied and implemented. More specifically, it provides platforms for the conception of innovations to build fundamental theories for human behavior, create wisdom, and direct development toward effective progress of the development policies. So, development practitioners regularly follow the prior impact analysis undertaken for daily activities to compare their performance and to set plan activities for the future. However, the problem of selection bias is central issue of theory of impact analysis (White and Raitzer, 2017).

Measurement of longer term adoption of technology impact on improvement and diffusion of technology causes measurement problems. This is due to continuous evolution of the technology over time, availability of other technologies and un-expected changes in the users. Profit maximization is an immediate expected new technology adoption which drives households' to new agricultural production technologies adoption and provides opportunities for improving households' wellbeing. To measure households' technology adoption impact on their welfare needs measuring impact of technology adoption on poverty and expenditure (de Janvry *et al.*, 2011).

Impact analysis of technological innovation adoption is undertaken to evaluate the extent of diffusion of technology and helps to estimate the overall influence of the new technology adoption on a set of outcome variables. Estimation of the extent of adoption and the average effect of adoption on outcomes of the adopters accurately measure the impact of new technology adoption (Maredia, 2009). However, it is difficult to surely measure how technology adopters better in advantage of the technology than non-technology adopters. To minimize the effect of causal relationship between technology adoption and its impacts, it needs comparing the observed outcome with the outcome that when individual is not participated in the technology adoption. However, this can be resulted factual outcome as two outcomes cannot be observed for the same individual. Therefore, impact evaluation of technology adoption might face the problem of missing data during the analysis and conclusion (Blundell and Costa, 2000).

The robust randomization helps in controlling the group to true counterfactual of the treated group by balancing observed and unobserved confounding factors between treated and control groups of impact evaluation. This helps to minimize the problem of selection bias. To do this, randomization should follow selection of eligible participants and the sampled population to get treatment and control groups. Then, treated and control groups give consistent evaluation of obtaining outcome of interest and confirms the control group to represents the treated group's true counterfactual (Duflo *el al*., 2008). Counterfactual and non-counterfactual are another methods for impact analysis of any development projects as counterfactual method removes estimation bias through appropriately making comparison between groups though non-counterfactual systematically create bias. The applicability of the counterfactual method need to isolate participants and non-participants of the project and comparing participants with treatment group while the control group is used for non-participants. This method of impact analysis if undertaken along with quantitative approach provides appropriate impact outcome during with or without, before and after project is undertaken (ADB, 2007).

2.3. Methodological Framework

The methodological review of this study focused on achieving research objectives of the study depending on the existing methods, philosophies and the practical principles of methodological aspects. Moreover, it answers the research questions and how the study was undertaken by using the existing scientific methods.

2.3.1. Efficiency analysis

Parametric and non-parametric approaches have been employed to estimate wheat producing smallholder farmers' efficiency levels.

2.3.1. 1. Approach of non-parametric efficiency analysis

Non-parametric approach which has been integrated with Data Envelopment Analysis (DEA) was profoundly applied to analyze production efficiency. The methods of data generating mechanism, and interpretation, use of linear programming methods of DEA makes it different from other econometric models (Greene, 2007). Data envelopment analysis specifies the relationship between inputs and outputs which does not require the assumption of a functional form. Its other importance is its distributional assumption of the inefficiency term is not necessarily required and it does not require the specification of a particular functional form for the technology. This means DEA does not make any accommodation for noise, but interprets the whole deviation from the frontier as inefficiency and it is considered as deterministic estimation method (Coelli, 1995; Ajibefun, 2008). Moreover, this model is comparatively criticized due to non-statistical nature due to being deterministic, and measurement error or other noise might cause possibility of deviation from the frontier which could result in inefficiency (Grosskopf, 1996).

2.3.1. 2. Approach of parametric efficiency analysis

Parametric econometric estimation methods for efficiency measurement largely undertaken by using Stochastic Frontier Analysis (SFA) which considers random external factors of firms maximum output rather than being deterministic parametric frontier model. The model is developed by Aigner *et al*. (1977) and Meeusen and van den Broeck (1977) and assumed that stochastic production frontier model that extended other parametric approaches by incorporating a statistical noise term in the analysis. According to the model, production frontier is specified to define output as a stochastic function of a given set of inputs and it answers to the deterministic parametric frontier model. It is less vulnerable to the influence of outliers than deterministic frontier model due to the presence of stochastic elements and decomposes the stochastic term into error and inefficiency. Similarly, a stochastic frontier analyzes inefficiency while inefficiency component is observed indirectly and considers error term $\boldsymbol{\varepsilon}$ to separate into a random error and a random variable effect. Unlike SFA, statistical noise arises from the omission of relevant variables, measurement errors and approximation errors are associated with the choice of functional form for the deterministic production function (Greene, 2007). By considering the advantages and disadvantages of both parametric and non-parametric approaches of efficiency analysis, parametric efficiency analysis is selected and used for this study.

2.3.2. Adoption Analysis

Several previous literatures on adoption of agricultural technologies were progressively emerging starting from the Green Revolution which aimed at understanding the drivers and constraints for expanding new technologies. The issues were emanated from understanding factors of improved adoption of technology and ways of realizing impact improvement. However, dynamicity and complexity in adopting or not adopting the technology result from farmers optimization on utility of adoption and model behavior used in the analysis (Arslan, 2020). Potential process of adoption depends on the households' decision whether farmers to adopt or not to adopt and if they adopt, also it needs to take-up rate of agricultural technology. It is estimated by using length of time required for a certain percentage of the members of the system to adopt the technology innovation while innovations to be adopted related with its advantages, compatibility, less complexity, divisibility, and a more rapid rate of adoption (Rogers, 2010). The decision to adopt technologies directly related with the expected optimized profit and the return from adopting technology could be constrained by prices of inputs like land, technology and cost of other inputs and prospective expected price of output (Feder *et al*., 1985).

Factors of households' technology adoption could be understood depending on the behaviors and perceptions of farmers, nature, categories, spread of diffusion, and objectives of the existing technology/s. Moreover, the issues related to adoption of agricultural technologies are determined by the time variation, farmers' willingness and ability to adopt new agricultural technologies, efforts to create awareness about technology adoption, its trial procedures, and decision making on adoption of all recommended technology packages that provide the expected outcome. Availability of adoption data over longer time and its analysis could result in representing adoption status of agricultural producers if the assumed influential factors seem to change over time. Complexity in understanding attributes of adopters of interdependent agricultural technologies lasting for a long time and constraints in hindering farmers from technology adoption could easily identified with the analysis of adoption of time series data. However, unavailable of these data bound this study to solely depend on cross-sectional data using and analysis. In the current study area, smallholder farmers employ different technology packages for wheat production but the extent at which some technology packages being adopted is insignificant and difficult to be considered by this study. Among the existing packages improved variety, row planting, fertilizers and chemicals were considered to estimate the overall intensity of technology packages.

2.3.3. Impact evaluation

To analyze the impact of wheat technology packages adoption on the outcome variables, this study used household food consumption score and household dietary diversity score which outlined by WFP and wheat production income as outcome variables. Food consumption score is calculated by considering eight food items such as main staples, pulses, vegetables, fruits, meat/fish, milk, sugar and oils. Its computation was undertaken by using yes or no questions of successive previous seven days from the date of interview. Similarly, household dietary diversity score composed from cereals, roots and tubers, vegetables, fruits, meat/poultry, eggs, fish, pulses/legumes/nuts, oil/fats, sugar/honey and miscellaneous. The overall HDDS is obtained by using yes or no questions of prior 24 hours from the time of interview. Wheat farming income is also obtained by using income obtained from wheat production during 2022/2023 production season.

The effectiveness of program evaluation needs the interventions to rely on theories and evidences to achieve desired outcomes. However in the absence of treatment, it becomes difficult and challenging to construct the counterfactual outcome and impact evaluation. Unobservable characteristics of counterfactual outcome create missing data problems and could be resulted in biased estimation. Assessing impact evaluation of interventions need knowing what will happen without the same interventions applied. So, comparing outcomes of treated individuals of groups in comparison of untreated and eliminating unobserved characters solve the problems of counterfactual problems of the analyzed data. Various impact evaluation methods can be employed in order to overcome these problems and these methods can be propensity score matching, endogenous switching regression models and double-difference (Heinrich *et al*., 2010; Fredriksson and Oliveira, 2019).

Adoption of technologies under single/few technologies with indeterminate behavior of farmers and factors like institutional services, markets and policies significantly constrain adoption and adoption status. Continuously adopting agricultural technologies cannot further achieved where rain-fed agriculture is under-performing relative to its potential unless supplemented with irrigation. In this case farmers have to an opportunity to select and adopt technologies among different agricultural technologies or adopt its combination for maximizing its utility and return. However, risky rain-fed conditions and its dominancy by smallholder farmers create absence of making complex decision and create heterogeneity between farmers in adoption behavior. So, the nature of business of farmers complicated the motivation of farmers for not to fully adopt agricultural technologies (De Janvry *et al*., 2016). Randomized control trials (experimental) studies randomly assign treated groups with control groups and it provides unbiased estimates of intervention impacts. Similarly, quasi-experimental researches like experimental designs test causal hypotheses. The analysis undertaken by using both methods consider program tests intervention in which a treatment-comprising the elements of the programme being evaluated.

However, non-experimental designs depend on determinants of participation in a program and variables that are either observable or unobservable are the prior criteria for program selection (White and Sabarwal, 2014).

2.4. Analytical Framework

Analytical framework contains different tools, one or more model forms, different research techniques and methods, and accepted solution.

2.4.1. Efficiency analysis

Efficiency can be measured by input oriented (by how much output could be expanded from a given level of inputs) and output oriented (by how much can input quantities be proportionally reduced without changing the output quantity produced). Both measures will coincide when the technology exhibits constant returns to scale only (Coelli and Battese, 2005). Quadratic function of efficiency analysis form includes translog production function, flexible functional forms and the function in some aspects is less restrictive (Christensen *et al*., 1973). Different scholars argue that application of different functional forms could impose various restrictions inputs and outputs and their physical and economic relationships. Mostly, functional forms can be applied in production and cost functions when the choice of functions represents the shape of the isoquants. And also, demand and factor substitution of elasticity can be easily computed and it needs imposing a few restrictions on the functional forms. However, it relaxes the restriction on demand and substitution elasticities (Green, 2007).

At first time the initial Cobb Douglas function proposed in 1928 focusing on elasticity of both labor and capital. Theory of production was the initiation point and aimed at identifying the relationship between a series of output, capital and labor through sketching graph and the output lies between the two input variables (Douglas, 1934). Besides, factors of production, labor and capital, are determined by their marginal product (Dushko *et al*., 2011). The form of Cobb-Douglas function which is widely used in production economics is given as $AL^{\alpha}K^{\beta}$ where α and β are positive constants related with A to combine both inputs such as labor (L) and capital (K). However, instead of the Cobb-Douglas formal alternatives and generalizations have been suggested to be applied production function of economics to represent extended Cobb-Douglas form in which A, α and β are not a function of constants rather L and K (Cobb and Douglas, 1928; Chames *et al*.,1986).

Moreover, the most common functional forms include Cobb–Douglas, constant elasticity substitution and translog functions. Similarly, all the deviations from the frontier are a result of firms' inefficiency according to deterministic frontiers whereas deviation from the frontier is due to random events according to stochastic frontiers assumption and while other part is due to firm specific inefficiency. Cobb–Douglas production function could be specified to the Cobb-Douglas Production elasticities as a log linear function of the inputs is used to obtain generalized into a translog function (Battese, 1992; Coelli *et al.*, 1998). Cobb–Douglas production function allows testing reliability of the estimations by allowing hypothesis testing and confidence interval calculation. The model imposes less restriction if its functional form is flexible and it measures the marginal contribution of each input to aggregate agricultural output (Dharmasiri and Datye, 2011). Transcendental Production function was modified from Cobb-Douglas with a clearly visible three stages in the production function as it faces the problem of not extended to three stages of Cobb-Douglas production function *i.e* not possible to generalize this function to more than two inputs (Halter *et al*, 1957).

The principal advantage of Stochastic Frontier Production Function (SFPF) of parametric frontier analysis is that it provides for testing hypothesis and show for the goodness of fit of the model. Specification of technology requirement is its main disadvantage while also frontier analysis allows the possibility of calculating production efficiencies (Ajibefun, 2008). Stochastic frontier model allow the disturbance term to be symmetrically distributed. Besides, the model include the normal-half-normal, normal-gamma and normal-exponential distributions and Maximum Likelihood Estimation (MLE) (Green, 2007). SFA model includes Normal-half and exponential distributions where normal-half mostly used and applied in various stochastic frontier analyses (Murillo-Zamorano, 2004). For this study, to know whether inefficiencies exist in between wheat producer farmers or not, efficiency scores were calculated. Following Bravo-Ureta and Rieger (1990), the second step stochastic estimation of factors affecting efficiency level of households is employed for this study by using different characteristics of efficiency factors. The first steps is regarded with analysis of computing the correlation coefficient followed by two-step approach for the estimation of efficiency where its determinant factors are analyzed by using tobit model authored by Tobin (1958). The scores obtained from efficiency calculation were between 0 and 1 which calls for the application of tobit model and employing OLS may lead biased estimation (Greene, 1991; Green, 2003).

Measuring agricultural production efficiencies in developing countries where data used for undertaking research are affected by problems of measurement errors and other production related problems like weather conditions and diseases. In such phenomenon, using SFA is considered more appropriate than DEA. The model is fully applicable for estimating production efficiency of all agricultural products and method of estimating the model has been considered as interesting subject among econometric models (Coelli *et al.*, 1998). Moreover, SFA is considered more suitable than data DEA in agricultural production application where the extent of production is less performed, factors of agricultural production predominately exist and getting proper data is difficult. These situations also happen in other production of agriculture like fishing and its model analysis could be undertaken by SFA though its applicability is subject to the requirement in econometric criteria. Similarly, unlike DEA, SFA has the advantages related to stochastic nature and incorporations of statistical noise. However, robust parametric assumptions are desired to analyze the model and disentangle inefficiency from noise (Kortelainen, 2008). So in this study, Stochastic Frontier Model (SFM) is employed to examine production efficiency while its determinants of efficiency differentials were also analyzed by using Tobit model.

2.4.2. Analysis of adoption

By identifying the nature of data which is discrete variables or continuous variable in adoption, the study provides insights about data analysis by using appropriate model. If qualitative response regressand variable of agricultural technology adoption gathered, using binomial models are preferable. Qualitative nature response models takes on values which are qualitative in nature such as adopting or not adopting. Such factors assume these values are called dummy variables and takes on values 1 and 0. For these types of data linear probability models, probit model, logit model, multinomial logit and probit, and the tobit models can be employed (Greene, 2012; Gujarati, 2004). The values of qualitative nature data's non-normality and heteroscedasticity lying outside the 0 - 1 range, and low R^2 values problems can be created if we employ linear probability model in adoption study. The model consider probability value of dependent variable equal 1, given the explanatory variables, but linearly increase with the explanatory variables, implying constant marginal effect of the independent constant (Gujarati, 2004).

Data with dichotomous, binary and categorical dependent variable can be analyzed by the regression models like linear probability models, Logit, Tobit, probit, and multinomial logit models. Jointly measuring exposures, adoption and its interpretation of coefficients from these classical adoption models is inconsistent. The models assume that farmers might have two alternatives: either adopting or not adopting the technologies. They also adopt new agricultural technologies in order to maximize their expected utilities of adopting technologies which is subject to adoption constraints (Feder *et al.,* 1985; Dimara and Sakura, 2003). Exposure to agricultural technology adoption where farmers not randomly selected, applying treatment effect allows to control for both non-exposure and selection bias. This helps to estimate determinants of adoption of by true population and its extent of adoption for identifying treated and untreated (Simtowe *et al.,* 2016).

OLS regression model could be applied for explaining the decision of adopters and non-adopters but not the extent or intensity of adoption. However, the analysis may result in inconsistent outcome as it faces in-appropriate normality of disturbance, standard errors and t-ratios; produce predictions other than zero and one (Feder *et al*., 1985). For the problems happen due to OLS model is applied for categorical/dummy dependent variables, Logit or Probit model can be applied as they employ maximum likelihood estimation (MLE) procedures. This results consistent, efficient and normal estimates of all parameter. According to Gujarati (2004), binary logit and probit give standard result for discrete choice estimation and used to estimate its relationship. Besides, Adeoti (2009) analyzed adoption study by using Heckman model to analyze both adoption decision and its intensity of adoption. Besides, for the case reported as if a household adopted a given technology, household want to adopt technology but no positive adoption is reported due to adoption constraints and if no adoption is reported by households, it is argued that double hurdle model is appropriate. Several studies (Yu and Nin-Pratt, 2014; Menasbo *et al.,* 2020; Singbo *et al*., 2021) were also employed this model by considering these assumptions. Observations require a censored regression model (Two-limit Tobit model) for a dependent variable which bears a zero value a data at the limit (Tobin, 1958). This is preferable model to analyze adoption level of wheat production technology packages for the current study.

2.4.3. Impact of technology adoption

In order to analyze non-experimental causal effect variables propensity score matching (PSM), difference-in-difference (DID), generalized propensity score (GPS) and other econometric models were frequently used without considering their weakness. PSM method matches and compares adopters and non-adopters of technology to measure impact of technology adoption on household outcome variables. It is used to calculate the causal effect and based on the observed covariates; it assigns the score of the matching to each observation. It also calculates propensity score of estimated probability of being treated by matching (adopters) and untreated (non-adopters) observations to calculate the average difference in the outcome variable of adopter and non-adopter. It needs absence of baseline data while larger sample is required. If the baseline and end-line data are available and small sample sizes exist, DID is better than PSM. But both methods create selection bias since they don’t consider about unobserved factors (Gertler *et al.*, 2016).

Matching approach in impact evaluation is used to identify counterfactual of outcomes of observable treatment group factors on outcome variables. Difference in mean outcomes between the groups and matching estimators which rely on the validity of the conditional independence assumption used to assess impact (Rosenbaum and Rubin, 1985). Treatment effect can be identified by conditioning on all relevant covariates. Propensity score assumes assignment to treatment is independent of the potential outcomes (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008). Propensity score matching (PSM) method used matches participants of program with non-participants by using observable characteristics. It assumes that participant of the program and non-participant of comparison group which have similar characteristic with participating program are paired together. By using propensity scores it matches control groups to treatment groups while better match as the score close each other. PSM compares only comparable observations and parametric assumptions (Becker and Ichino, 2002).

In order to demonstrate causal evidence of the impact of an intervention on a set of outcome, quasi-experimental approaches might be highly recognized. It addresses endogeneity by exploiting variation in variables which are correlated with adoption though the model doubtful exogenous for using it for as instruments to consider for systematic difference of adopters and non-adopters (Meenakshi *et al.,* 2021). Difference-in-Difference (DD) model is applied when a need arise to compare technological adopters and non-adopters and used to control the time-invariant characteristics of individuals. The model is mostly applicable for program evaluation if the evaluation is likely planned in advance where the intervention clearly defined. Frequent use of DD for impact analysis of development policies are due to its provision for us to think about adoption decision and how adopters differ from non-adopters and their outcomes are equal (de Janvry *et al*, 2011).

Multinomial endogenous switching regression (MESR) calculates the average treatment effects on treated (ATT) and untreated (ATU). Impact analysis models like PSM ignore adoption process effects of unobservable factors of adopters and non-adopters. However, MESR use a selection correction method to correct selection bias by computing an inverse Mills ratio and use the theory of truncated normal distribution and latent factor structure (Bourguignon *et al*., 2007). MESR model enables us to analyze the impact of treatment variable with observable and unobservable variables on outcome variables (Khonje *et al*., 2018). Therefore, for analyzing impact of wheat production technology packages adoption on household food security and income, MESR model is employed.

2.5. Empirical Literature Reviews

2.5.1. Adoption analysis

Adoption of agricultural technologies is a fundamental tool for enhancing production and productivity of agricultural sector, poverty reduction and ensuring food security. But, different factors affect farmers' adoption of improved agricultural technologies, and the level of adoption is slowly developed while its aspect might not well known. However, interdependent potential constraints could hinder farmers not to adopt and use improved agricultural technologies in developing countries. Among them, the most common factors include, lack of awareness about technologies, risk aversion, institutional constraints, lack of human and financial capital and lack of infrastructure might significantly challenge agricultural technologies adoption at different levels. Moreover, it enables agricultural development workers and policy makers to profoundly engage in creating wheat technologies to amplify its contribution for economic growth, minimize wheat import and realize household food security. More specifically, farmers' demographic and socioeconomic characteristics, resource endowment, and farm attributes are factors that influence adoption intensity of agricultural technologies (Solomon, 2020; Solomon *et al.,* 2021).

The research findings of Chilot *et al*. (2013), Tolesa (2015), Ghimire *et al*. (2015), Tesfaye *et al*. (2016), Owoeye (2017), Degefu *et al*. (2017), Adebayo *et al*. (2018), Hadush *et al*. (2018), Adunea and Fekadu (2019), Djibo and Maman (2019) and Getinet *et al*. (2020) revealed that the demographic characteristics of households, such as household age, family size, and level of education, significantly influenced adoption of agricultural technologies. Similarly, adoption intensity of agricultural commodities are influenced by extension contact, access to credit, agricultural training, farmers' cooperative membership, demonstration (training) participation, and seed multiplication membership (Chilot *et al*.,2013; Ghimire *et al*.,2015; Awotide *et al*.,2016; Tesfaye *et al*.,2016; Degefu *et al*.,2017; Owoeye, 2017; Djibo and Maman, 2019; Getinet *et al*., 2020; Tewodros *et al*., 2020; Negussie *et al*.,2022; Atrsaw *et al*.,2022). Sinkie and Getasew (2024) studied adoption of improved bread wheat varieties in Ethiopia by employing binary probit and identified that educational level, family labor, oxen ownership, training access, membership in cooperatives, credit access and age are adoption associated factors. Households' distance from their residence to the main market, input market, main road, training centers, and farm areas are determinant factors affecting adoption of agricultural technology packages (Tesfaye *et al*., 2014; Degefu *et al*., 2017; Atrsaw *et al*., 2022). Agricultural technology adoption could be influenced by the interdependent activities of agriculture related institutions while improving the contributions of the agricultural institutional services requires policy, resource management, and service provisions.

Similarly, Gemechu and Sura, (2024) discussed that adoption of a single technology package (wheat row planting) by using a binary logistic regression model and revealed that age, education, farming experience, labor, annual income and extension service are influential factors of technology adoption. Both these empirical studies focused on adoption decision of a single technology and did not consider adoption of recommended technology packages and its intensity of adoption which could cause incomplete technology adoption and low wheat productivity. According to Obayelu *et al*. (2017) and Melese (2018), the decision to adopt agricultural production technology is undertaken by considering different factors, such as household characteristics (e.g., age, sex, family member size), household socioeconomic factors (e.g., educational level, farm size, livestock ownership, income, technology adoption costs), institutional factors (e.g., access to credit, extension workers' contacts, membership to social services, distance from the nearest service providers), and technological factors (e.g. information about access to new technologies).

Resource ownership such as landholding, livestock ownership, and number of oxen owned were important factors in determining the level of households' agricultural technology adoption (Ghimire *et al*., 2015; Tesfaye *et al*., 2016; Degefu *et al*., 2017; Milkias, 2020 and Negussie *et al*., 2022), while income from farm and non-farm were influential factors in determining adoption of agricultural technologies (Degefu *et al*., 2017; Hadush *et al*., 2018; Tewodros *et al*., 2020). Moreover, the location of farmers (region) had an impact on adoption of agricultural technologies (Adebayo *et al*., 2018; Tewodros *et al*., 2020), owning communication media such as radio and mobile also were influential factors of agricultural technology adoption (Negussie *et al*., 2022), and households' perception about yield significantly affected agricultural technology adoption (Hadush *et al*., 2018; Atrsaw *et al*., 2022). To improve the decision and level of adoption smallholder farmers need to control and access the key agricultural production resources either formally or informally whereas controlling the challenges of resource ownership need to be identified.

A combination of different production input technologies can be adopted jointly or disaggregated and agricultural technologies are either limited to a single, a few, or a combination of few technologies. As a result, adoption of agricultural production technologies became low and did not expand in the area allocated for agricultural production. The research findings of Menasbo *et al*. (2021) revealed that adoption of agricultural production technology packages in Ethiopia is limited, although it can contribute for many advantages in generating income, improving agricultural productivity and food security. Double-hurdle model was used to analyze three rounds of panel data collected from smallholder farms for a total sample of 1,269 households. The results indicate that agricultural technology adoption and its intensity of adoption are affected by demographic, weather, and market factors. According to the results, landholding size and access to irrigation had a positive effect on adoption, and smallholder farmers who adopted new crop technology showed a small increase in adoption over several years. Bedilu *et al*. (2021) discussed that the low adoption rate of high-yielding wheat varieties causes low wheat productivity, though the study was conducted by using a single technology package, which could be a factor in low wheat productivity. The authors employed double hurdle model and identified that seed availability, row planting, distance to the cooperative and farmland allotted determined adoption intensity of the improved wheat variety, while its adoption decision was influenced by associated factors such as farming experience, distance to the cooperative, renting a tractor and combine harvester, urea application, and wheat sale income. The adoption of all recommended wheat production technology packages realizes the expected aim of improving wheat production and productivity, and meeting domestic wheat demand through solving the barriers of full technology package adoption.

2.5.2. Efficiency analysis

Extensive empirical studies on agricultural production efficiency analysis have been conducted both in Ethiopia and outside of Ethiopia while most of them specifically rely on analysis of technical efficiency and some others jointly focused on all efficiency analysis (TE, AE and TE) with their levels of inefficiency analysis. The authors used Two-limit Tobit model for analyzing inefficiency effects and showed that age of household, education level, improved seed variety, extension contact services, services of rural credit, off-farm income earning, and farm size allotted were the most important factors for improving technical efficiency, allocative efficiency and economic efficiency (Alula *et al*., 2021). Sisay *et al*. (2015) investigated analysis of maize production technical, allocative, and economic efficiency of smallholder farmers in Southwestern Ethiopia by using Cobb-Douglas, SFA. The findings of the study revealed that maize farmers were inefficient in technical, allocative and economic production efficiencies and these inefficiencies were caused due to differences in a number of family sizes, education level, extension contact, membership to cooperatives, farm size owned, livestock and mobile usage. Agricultural production efficiency analysis well-identified and used as base input in production policy setting and implementing when all efficiency parts are jointly studied and causes of production inefficiency are identified. The empirical studies of various agricultural efficiency analyses suggest undertaking technical, allocative and economic efficiencies through investigating agricultural policies and other factors to it’s improve production and productive of

Kebebew *et al*. (2021) conducted wheat farm economic efficiency in Debra Libanos district Ethiopia by using a stochastic production frontier and two-limit Tobit. The authors discussed that mean technical, allocative and economic efficiencies were 78.5%, 85.6% and 66.7%, respectively. Moreover, technical efficiency of wheat production was significantly influenced by age, family size, livestock, extension service, and ploughing frequencies while allocative efficiency was significantly affected by sex, farm size and soil fertility. Similarly, economic efficiency of farmers' wheat production was significantly influenced by sex, livestock, farm size, soil fertility, extension services, and ploughing frequencies.

Sime *et al*. (2022) by their study used stochastic production frontier to analyze the technical, allocative and economic efficiency of malt barley producers in Arsi zone, Ethiopia and found that inefficiency the crop production. The inefficiency factors were estimated by using two-limit Tobit regression and showed that education level, access to credit, owned livestock size, distance from market, proximity to homestead, and soil fertility status were significant factors affecting malt barley production efficiencies. Moges (2019) analyzed factors of technical efficiency and level of technical efficiency of smallholder wheat producers of wheat-growing farmers. The model result revealed that land allocated, fertilizer, labor and number of oxen significantly determined wheat output and the mean level of technical efficiency estimated is 82%. Similarly, stochastic production frontier model was employed for estimating inefficiency parameters and significantly affected by age, education, improved seed, training, credit services and farm size. It is very essential to improve efficiency of agricultural production inputs, institutional services, implementing sustainable agricultural production practices, minimizing cost of production and using technologies.

Inefficiency of wheat production can be minimized through maximizing wheat output and efficiently using the existing inputs. Tadele *et al*. (2018) studied efficiency of technical and yield gap of smallholder wheat producers in Ethiopia by using Stochastic Frontier Analysis. The study identified the existence of wheat production technical inefficiency and the overall wheat mean production technical efficiency was 0.769. Education level of household, oxen ownership, credit services, soil fertility, tractor usage, improved seed, family labor, distance and crop rotation significantly influenced its technical efficiency level. Similarly, Birara *et al*. (2023) revealed that smallholder farmers' technical efficiency of wheat production in north western Ethiopia was

0.77. The study employed beta regression approached and identified that educational, experience, and access to price information improves technical efficiency of wheat production while dependency ratio, distance to the local wheat market, and distance to the extension office decreases wheat production technical efficiency. Cobb-Douglas functional model and quantile regression technique were employed to analyze technical efficiency and factors that affect technical efficiency, respectively. Promoting institutional, socioeconomic and biophysical and agro-ecological factors further improve wheat production (Kaleb and Workneh, 2016).

Abdulai *et al*. (2018) collected cross-sectional data and used input-oriented data development regression analysis for analyzing determinants of technical efficiency of maize production in northern Ghana. Access to agricultural mechanizations, years of education and access to extension services were significantly affected technical efficiency of maize production. The findings of the study revealed that existence of production inefficiency. Technically efficient farmers used different combination of inputs like seed, herbicide and labors to a given amount of yield. The yield outcome of maize production showed that increasing returns to scale which implies that quantities of inputs used were resulted in greater proportion of outcome. Similarly, Aschalew (2020) analyzed and identified that determinant factors which significantly affected technical inefficiency of maize were gender, age of the head of the household, income from farm, planting in row, access to credit, active labor force, farm size owned, improved seed and seed type used, and livestock. Finally, the author identified that advancing production by technology would have the possibility of raising yield per hectare. To achieve this, undertaking study on recommended efficiency analysis with their respective efficiency factors need to be prioritized as relying on a single or incomplete efficiency levels may forward imperfect policy suggestions.

Determinant factors of making technical efficiency in Pakistan were analyzed by using stochastic frontier model techniques (Ali *et al*., 2019). The analyzed data revealed that the mean technical efficiency scores were 79.2 and 89.4 of credit constrained farmers and credit unconstrained farmers, respectively and the mean technical efficiency two groups was 10.2%. Large losses caused by inefficiency in production while farmers need to maximize their production by exploiting the existing level of inputs' supply were the main issue. Different determinant variables like education of the household, family size, married family members, off-farm income, experience, tractor, irrigation through a lined course, seed, extension contact, household saving, age of household and fragmented land, interest rate and a credit services significantly affected technical efficiency of farmers' agricultural production.

Okello *et al*. (2019) in their study on the rice production in allocative efficiency in Northern Uganda found that difference in district (Gulu district), distance to the nearest trading center and number of crop enterprises, use of ox-plough had significantly and positively influenced allocative efficiency of the crop. Similarly, determinant factors such as family size, farm size, use of hired labor and access to credit services significantly and negatively influenced allocative efficiency of rice production. Perveen *et al*. (2021) analyzed allocative efficiency analysis of wheat and cotton in Pakistan and discussed that education level, experience, and family size of household head have a significant effect on wheat production. Meanwhile, access to credit, education, experience, and family size had a joint significant effect on cotton and wheat production. In agriculture dependent country, identifying the efficiency levels of agricultural production has a direct link with improving the welfare status of smallholder farmers. To minimizing yield gap, improving productivity and efficiency of agricultural production, securing and accessing land tenure, training farmers, adjusting external factors, monitoring cost of inputs, strengthening institutional capacity and expansion of agricultural researches more improve the level of agricultural production level.

2.5.3. Impact analysis

Adoption of agricultural technology has strong positive linkage with household food security and income. Agricultural technology adoption is the best strategy requirement for directly impacting food insecurity issues and improving households' capacity of producing major staple crops for food and impacts its amount, type, stability, and its incomes generation. Better and diversified agricultural production through agricultural technology adoption helps to reduce food insecurity of agriculture-dependent and non-direct agriculture-dependent households. Similarly, agricultural technology adoption significantly contributes to economic, social, and environmental development of communities through improving their livelihoods and self-sustainability (Rocha, 2017).

Impact evaluation of agricultural technology adoption helps to know the status and stages of the technology adoption at the perspective of users and development initiators. So far, many studies on the impact analysis of agricultural technology adoption have been extensively undertaken in different areas. However, among these studies, most of them focused on analyzing the impact of a single or a few technology packages, which might not achieve the real potential expected outcomes. Several studies analyzed impact evaluation by using analysis of a single technology adoption (Bekele *et al*., 2014; Khonje *et al*., 2015; Tesfaye *et al*.,2016; Musa *et al*.,2016; Regasa and Degye, 2019; Richard *et al*.,2020; Oyetunde-Usman *et al*., 2021) while some others focused on multiple or full agricultural technology adoption (Menale *et al*., 2015; Manda *et al*.,2016; Khonje *et al*., 2018; Wubneshe *et al*., 2020; Musa, 2022). These literatures helps us to understand and identify which agricultural technology has the most influential impact for fulfilling the ever-growing food needs of population through improving agricultural productivity and farm income.

The impact analysis of improved agricultural technologies on food security of households was studied by Mekonnen *et al*. (2021) and revealed that adoption of improved agricultural technologies significantly increases dietary energy supply, dietary diversity, and food consumption score. Further, they concluded that its impact is improved when technologies are adopted jointly rather than separately. Muluken *et al*. (2021) discussed that adoption of agricultural technologies profoundly increases the income of smallholder farmers and this can be improved when awareness about agricultural technology adoption is created for farmers by the university service provision, the districts' agricultural and natural resources offices, non-governmental organizations (NGOs), and model farmers. Wubneshe *et al*. (2020) revealed that impact evaluation of agricultural technology adoption is less understandable with adoption of a single or few agricultural technologies, but adoption impact on household welfare becomes high as households adopt multiple agricultural technologies. Overall, the study identified that adoption of different combinations of agricultural technologies had a greater impact on consumption, poverty, and vulnerability among smallholders than adoption of a single technology.

Mesele *et al*. (2022) studied agricultural technology adoption impact on household food consumption expenditure impact and identified more household food consumption expenditure per adult equivalent are obtained as households adopt agricultural technology, while actual and counterfactual scenario differences in outcome variables of households are observed. Musa (2022) analyzed improved seed and inorganic fertilizer on maize yield and consumption expenditure and discussed that adoption of agricultural technology combinations (improved seed and inorganic chemical fertilizer) boosts yield and consumption expenditure more than adopting single agricultural technology. Khonje *et al*. (2018) revealed that jointly adopting multiple agricultural technologies improves household welfare (poverty), yields, and household income more than adopting each technology in isolation. Impact of adoption of on-farm combination of improved agronomic practices (IAPs) on net crop income and agrochemical use in Malawi was conducted by Menale *et al*. (2015). Their findings revealed that a positive impact of adoption of a combination of technologies had on net crop income and reduced other costs of purchasing technologies compared to single technology adoption.

Oyetunde-Usman *et al*. (2021) discussed impact of organic fertilizer adoption on households' welfare in Nigeria and revealed that its adoption is influenced by per-capita total house expenditure, per-capita asset value, and per-capita food expenditure. Moti *et al*. (2018) studied the impact of improved maize variety adoption on household food security and identified that adoption of improved varieties affected food security in maize growing areas of Ethiopia. Moreover, adopting improved maize varieties improves per capita food consumption and increases the probability of smallholder farmers' to have a food surplus. Regasa and Degye (2019) showed that adoption of high yielding wheat varieties had a greater impact on the farm income of households than non-adopters. Bekele *et al*. (2014) found that access to modern wheat varieties and their usage increase food security more than who did not adopt improved wheat varieties. Khonje *et al*. (2015) conducted study on adoption and welfare impacts of improved maize varieties in eastern Zambia and revealed that adoption of improved maize improves gains in crop incomes, consumption expenditures, and food security. Tesfaye *et al*. (2016) conducted a study on the impact of improved wheat technology adoption on productivity and income and discussed that improved wheat variety adoption increases the income of adopters more than that of non-adopters. These empirical findings failed to consider the impacts of joint adoption of recommended technology packages and robust econometric models rather focused on comparing difference between the impact of adoption and non-adoption on outcome variables.

2.6. Conceptual Framework

Conceptualizing production efficiency, technology adoption and impact analysis strengths the justification needed to be identified within wheat production, adoption and impact of technology adoption problems, influential determinant factors, and key concepts of the study. These concepts can more strengthened in a justifiable manner of understanding the factors related with production efficiency factors, pattern and degree of technology adoption and impact factors. The jointly included variables such as land, fertilizer, improved seed variety, oxen, labor and chemicals with farm households' socioeconomic, resource endowment, and institutional factors determine the level of wheat production efficiency directly or indirectly, affect adoption decision and level of wheat production technology packages and its impact on smallholder farmers' food security and wheat production income. Transforming selected and combined resources in to output results in getting expected production given the existing production technology and its production efficiency (technical, allocative and economic) level is discussed in this study. Similarly, households' socioeconomic, resource endowment, and institutional factors predominantly affect wheat production efficiency which might significantly affect adoption of wheat production technologies and its impact on food security and wheat farm income.

Besides to the above mentioned production factors, adoption of full recommended technology packages influenced by households' socioeconomic, attributes, resource endowment, and institutional factors while it could also had significant impact on improving production efficiencies and contribute for improving smallholders' food security and income. Any effort from different stakeholders aimed at identifying factors influencing wheat production efficiency, adoption and its impact, could improve productivity of wheat, proper utilization of resources, and adoption of full recommended technology packages to create sustained welfare of smallholder farmers.

Therefore, this study looks at the effect of factors from socio-demographic, economic, institutional, attributes and farm specific characteristics on dependent variables such as analysis of wheat production efficiency levels (technical, allocative and economic efficiencies), adoption index (composed from different technology packages), and outcome variables (food security and wheat production income). More specifically, the socio-demographic factors include variables such as sex, age, and family members of the farm household while the economic characteristics of the households included in the analysis were owned land, livestock, annual farm income, off/non-farm income and input used for wheat production. The study used different institutional characteristic variables such as education level of the household head, access to extension services, credit services, cooperative membership and ownership of communication assets. Similarly, household perception includes household perception on wheat yield and soil fertility status for wheat production while the location of household refers to the area where households located of both agro-ecologies (midland and highland), distance from farm areas, nearest market centers and training centers (Figure 3).

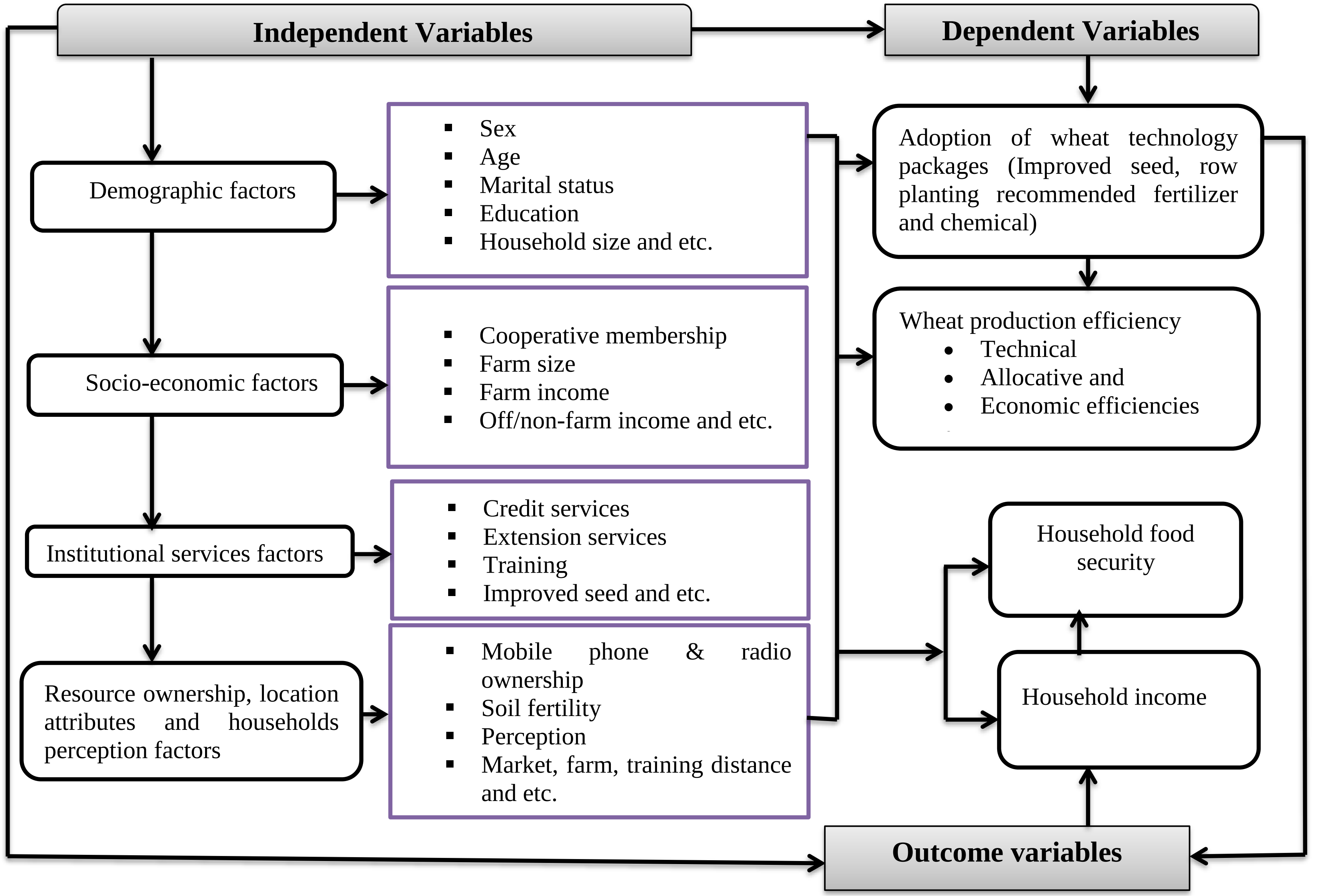

Figure 3: Conceptual Framework of the Study
Source: Own sketch

3. RESEARCH METHODOLOGY

This part focuses on the methodology of the study which includes description of the study area, types and sources of data, methods of data collection, sampling techniques, data analysis methods of dependent and independent variables, model specification and hypothesis.

3.1. Description of the Study Areas

Horo Guduru Wollega zone is one of the zones located in western Oromia region, Ethiopia. The area lies between latitude of 9° 10′ N and 9° 50′ N and longitude 36° 00′ E and 36° 50′ E direction. The zone has 576,737 while the proportion of men is 50.1% and the remaining are women (CSA, 2007). The zone has the average annual temperature of 22.1°C with 13°C and 30°C minimum and maximum temperatures, respectively while it's annual rainfall ranges from 1000 mm – 2400 mm. It is characterized by the dry and wet season with over nine months wet period. The wet season of the study area runs from May/June to August/September which is the main agricultural summer growing season. The most rainfall occurs in June, July and August. Horo Guduru Wollega zone shares border line with Amhara National Regional state in the North, West Shoa zone in the East and South, and East wollega zone in the West. The administrative Centre of the zone is Shambu town which is located to the western and far away 314 km from Addis Ababa, the capital city of Ethiopia. The zone has 12 districts and wheat is produced in all districts of the zone though the extent of the production greatly varies among the districts. The study area is suitable for crop production and the major crops grown in the area are wheat, *teff*, maize, barely, oat, nug, sesame, groundnut, fruits, vegetables, coffees, and etc. It is also well known for raring livestock such as cattle, sheep, horses, mule, donkey, poultry, and etc. Fishery production and development is also largely undertaken in the study area (HGWZAO, 2023).

Horo Guduru Wollega zone is divided into three agro-ecological zones like highland, midland and lowland. The highland agro-ecology parts of the study area characterized as cold weather condition while the midland areas of the zone are characterized as moderate weather condition. Similarly, the lowland agro-ecology parts of the study area are mostly characterized as warm weather condition. The zone is endowed with natural resources like water bodies and forests. Finca'a and Neshe lakes contribute in generating hydroelectric power for local residents and people of other areas of the country. In addition to generating power, they serve as a source of fishery production and being used as sources of irrigation. Raring local and hybrid livestock are widely undertaken in the zone by different stakeholders like farmers, government institutions (Example: Wollega University) and serve as a source for income of smallholder farmers (HGWZAO, 2023).

Finally, two districts such Ababo Guduru, and Horo, were purposively selected from each agro-ecology among the districts found in the zone. Four *kebeles* were selected from both districts (two districts from high agro-ecology and two districts from midland agro-ecology). Accordingly, Ilamu Molale and Loya Malole *kebeles* from the Ababo Guduru district and Leku Igu and Gitilo Dale *kebeles* from the Horo district were selected (Figure 4).

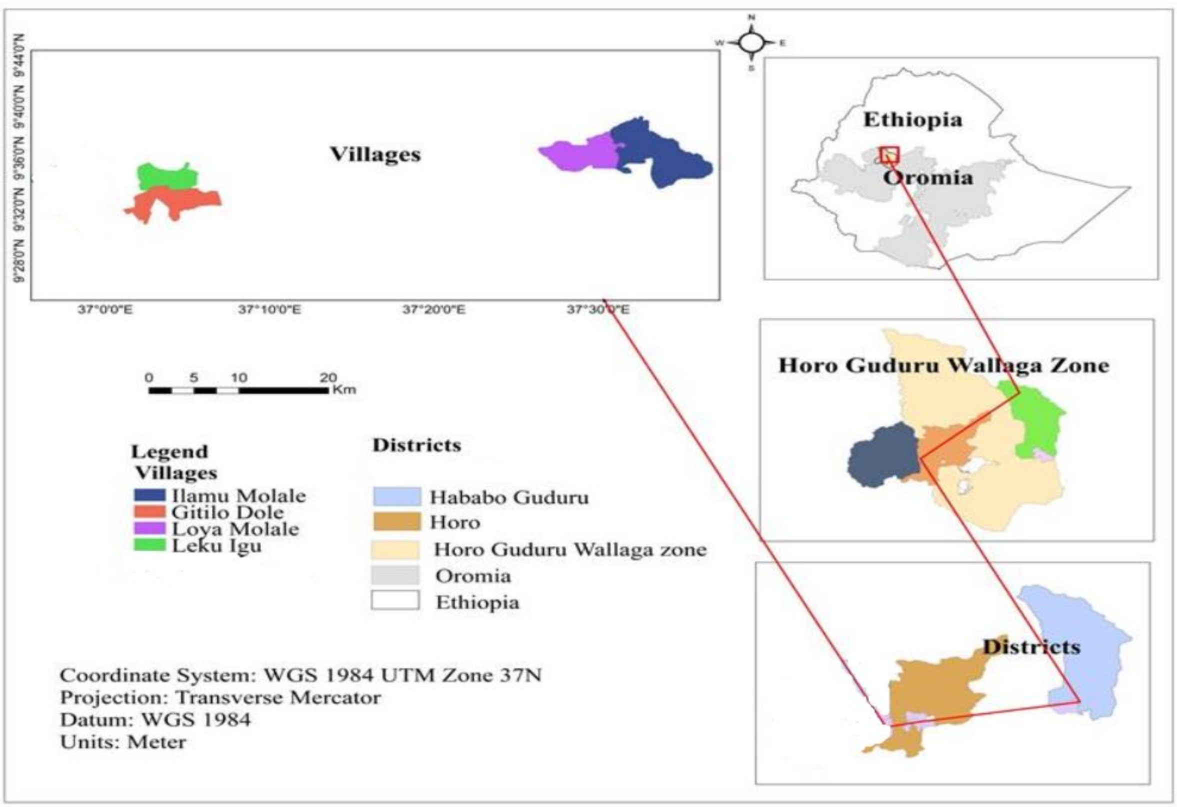

Figure 4: Administrative map of the study area
Source: Adapted from Ethiopia Map

3.2. Research Design

3.2.1. Types, sources and methods of data collection

Both qualitative and quantitative data were collected from different sources and used in this study. To collect the overall primary data, different activities, such as technology package identification, discussion with agricultural experts, site selection, preliminary activities through visiting specific study areas, and collecting data were undertaken at different times. Accordingly, to collect the required data, informal survey is used to collect preliminary information about wheat production, adoption and its impact in the stud area which helps to construct and modify the questionnaire. This stage was followed by training enumerators on the methods of data collection and how to approach to the respondents. A cross-sectional household survey method was employed to collect quantitative data from randomly selected farm households in the study area during 2022/2023 agricultural production season. These primary data were collected from households' socio-demographic, socio-economic, institutional, households' perceptions, resource factors, production inputs and its costs, level of production, technological factors, income and food security status using a structured questionnaire while these variables were selected depending on various relevant literatures. To improve the validity of the quantitative data, the study followed appropriate methodologies and designs. Questionnaires were translated to the farmers' mother tongue (from English to Afan Oromo) to avoid any misunderstandings of the questions to enable them to fully participate in the interview.

Finally, the expected data were successfully collected from the head of the households (male or female) without any delays or incompleteness. Moreover, the collected data checked for errors, incompleteness, and inconsistencies/discrepancies problems but no problem observed. Additionally, secondary data were also collected from the agricultural office of the zone, selected districts, central statistical agencies (CSA), reports, and websites. In order to collect qualitative data, key informants and members of focus group discussions (FGD) who were assumed to have in-depth knowledge about the purpose of this study and support the integrity of the results of the study were interviewed. To achieve these, qualitative data were collected from model farmers, peasant association administrators, and agricultural extension workers/experts using unstructured questionnaire.

3.2.2. Sampling techniques and sample size

A multi-stage sampling procedure was used to select a representative sample. At the first stage, the zone was stratified into highland, midland, and lowland based on its agro-ecologies and for this study, both highland and midland agro-ecologies were selected and two potential districts were purposively selected from both stratum. At the next stage, the list of all selected wheat-producing *kebeles* was taken from both districts' agricultural offices and two (2) *kebeles* (to compare differences among groups) were randomly selected from both selected districts. In the final stage of probability sampling, the list of wheat growing farmers was obtained from *kebeles*' development agents. Then from the listed number of wheat producer farmers, sample farm households were randomly selected. Kothari (2004) formula is used for sample size determination so that comparing differences among groups at each agro-ecology was considered and allocation of sample size to each *kebele* was undertaken by proportional to the family size of each *kebele* within their respective districts (Table 1).

$$n = \frac{Z^2 pqN}{e^2(N-1)+Z^2 pq} \qquad (1)$$

Where n = is the sample size drawn from total population, N = is the total population of wheat producers from which sample size was drawn, e is acceptable error, Z (1.96) = is the standard cumulative distribution that corresponds to the level of confidence, p is the proportion of population, while$q = 1 - p$.

The sample size of each district is proportionately determined as follows:

$$n_i = n\left(\frac{N_i}{N}\right) \qquad (2)$$

Where n_i = represents the sample size from each district, n= represents total sample size of the study from all districts, N_i = represents total wheat producers in each district, N = represents total wheat producers in all district.

Table 1: Sample size of households in selected districts and *kebeles*

Districts	***Kebeles***	**Household size (districts & *kebeles*)**		**Sample size (districts & *kebeles*)**	
Horo		4,253		120	
	Laku Igu		569		69
	Gitilo Dale		417		51
Ababo Guduru		6,451		182	
	Ilamu Molale		671		97
	Loya Malole		589		85
Total		**10,704**		**302**	**302**

Source: HGWZAO, 2023

3.3. Methods of Data Analysis

To estimate the values of the unknown parameters and testing of hypotheses, the study used descriptive and inferential statistics and econometric models. Descriptive statistics such as mean, standard deviation, percentage, ratios, maximum and minimum were used to analyze data on household demographic, socio-economic, attributes and institutional characteristics of wheat producer farmers. Similarly, inferential statistics like chi-square test and F-test were also employed to analyze the data and summarize household information. To analyze wheat production and cost functions, determinants of wheat production efficiencies, wheat production technology packages adoption decision and intensity and impacts of wheat production technology packages adoption on smallholder farmers' food security and wheat production income, different econometric models such as Stochastic Frontier Cobb-Douglas Production and Cost models, Tobit model, multinomial logit, two-limit Tobit, and Multinomial Endogenous Switching Regression Model were employed, respectively.

3.3.1. Analysis of production and cost efficiency

Efficiency analysis part of this study focused on model specification for the production and cost functions, and technical, allocative and economic efficiency analysis of wheat production by using analytical approach of the stochastic parametric frontier for all efficiency analysis.

The Stochastic Production Frontier (SPF) function are parametric in nature and have useful substantive interpretations, with the advantage of being able to offer superior parameter estimates compared to non-parametric approaches such as Data Envelopment Analysis (DEA), Farrell (1957). The stochastic frontier approach is considered more appropriate than the Data Envelopment Analysis (DEA) approach in the analysis of data on agricultural production efficiencies, which are affected by systematic uncertainty errors (Dang, 2017). Stochastic production frontier (SPF) model was developed by Meeusen and van den Broeck (1977) and Aigner *et al*. (1977) profoundly used to estimate technical, allocative, and economic efficiency scores. According to Coelli *et al*. (2005) the stochastic frontier method assumes that deviation from the frontier random errors and firm-specific inefficiency are used to estimate production and cost functions and their respective levels of efficiencies such as technical, allocative and economic efficiencies. However, with respect to the choice of functional form, Stochastic Production Frontier Cobb-Douglas and translog models are mostly employed in the literature. Comparatively, Cobb-Douglas production function has various advantages over translog models with respect to the data fitness, feasibility in computation and simplicity features shape of the isoquants, interpretation of values of elasticities and factor substitution (Coelli *et al*., 1998; Greene, 1993). Similarly, according to Taylor *et al*. (1986), if the aim of the study specifically focuses on efficiency analysis and measurement rather than about overall production stages of agricultural production technology the Cobb-Douglas production function is selected over translog models. Therefore, depending on the test result, Cobb–Douglas functional form is selected for this study.

Hence, the stochastic frontier production function and its specification of this study are represented as follows:

$$\ln Y_i = \beta_0 + \ln \sum_{k=1}^{6} \beta_k X_{ik} + e_i \tag{3}$$

Where: ln is the natural logarithm; $\mathbf{Y_i}$ is the total quantity of wheat produced, $\mathbf{X_{ik}}$ is the farm input variables of the ith farmer; $\boldsymbol{\beta_0}$ is intercept; $\boldsymbol{\beta_k}$ is a vector of estimated production function parameters, $\mathbf{e_i = v_i - u_i}$, $\mathbf{v_i}$ is disturbance term and capture components beyond the control of the household and, $\mathbf{u_i}$ is non-negative random variable which capture the technical inefficiency effects in the production of wheat.

Moreover, Eq. 3 is specified as follows:

$$\ln Y_i = \beta_0 + \beta_1 \ln \text{land} + \beta_2 \ln \text{labor} + \beta_3 \ln \text{oxen} + \beta_4 \ln \text{fertilizer} + \beta_5 \ln \text{seed} + \beta_6 \ln \text{chemical} + \varepsilon_I \quad (4)$$

Where: $\boldsymbol{ln}$ is natural logarithm, $\boldsymbol{Y_i}$ is total wheat output of i^th^ farmer; $\boldsymbol{\beta_0}$ is constant and $\boldsymbol{\beta'}$s are coefficients of input variables and $\boldsymbol{\varepsilon_i}$ is the error term.

A dual cost frontier of the Cobb–Douglas production function in Eq. 3 is specified as follows:

$$\ln C_i = \alpha_0 + \ln \sum_{k=1}^{6} \alpha_k Z_{ik} + \alpha_6 Y_i^* \quad (5)$$

Where: $\mathbf{ln}$ is natural logarithm; $\mathbf{C_i}$ is minimum cost of wheat production for the i^{th} household; $\mathbf{Z_i}$ is a price of inputs; $\mathbf{Y_i^*}$ is total wheat output adjusted for noise v_i; $\boldsymbol{\alpha}$s are parameters.

More specifically, Eq. 5 is specified as follows:

$$\ln C_i = \alpha_0 + \alpha_1 \ln Z_R + \alpha_2 \ln Z_W + \alpha_3 \ln Z_O + \alpha_4 \ln Z_F + \alpha_5 \ln Z_S + \alpha_5 \ln Z_c + \alpha_6 \ln Y_i^* + (u_i + v_i) \quad (6)$$

Where: $\mathbf{Z_R}$, $\mathbf{Z_W}$, $\mathbf{Z_O}$, $\mathbf{Z_F}$, $\mathbf{Z_S}$, and $\mathbf{Z_C}$ are cost of land rent, labor wage, oxen, fertilizer, seed and chemical, respectively.

By solving the above Eq. 3, and the observed input ratios $\frac{X_1}{X_i} = m_i (i > 1)$, the technically efficient input vector of the i^{th} farm X_{it}, derived for a given level of output Y_i^* following Kopp and Diewert (1982) and Bravo-Ureta and Reiger (1991). Assuming production function stated by Eq.5 is self-dual, the algebraically derived dual cost frontier is represented as follows:

$$C_i = C(Z_i,; Y_i^*; \alpha) \quad (7)$$

Where $\mathbf{C_i}$ is minimum cost of the i^{th} households for producing adjusted output $\mathbf{Y_i^*}$, $\boldsymbol{Z_i}$ a vector of input prices, $\boldsymbol{\alpha}$ is a vector of parameters to be estimated. The following Eq. 8 represented the economically efficient input vector of household i, X_{ie}, which is obtained by using Shephard's Lemma and by substituting the households' input prices and adjusted output level into the resulting system of input demand equations.

$$\frac{\partial C_i}{\partial Z_n} = X_i^e(Z_i, Y_i^*; \alpha) \tag{8}$$

Where **n**-is the total number of inputs used and $\mathbf{Z_i'X_i}$, $\mathbf{Z_i'X_{it}}$ and $\mathbf{Z_i'\,X_{ie}}$ represent the observed, technically and economically efficient costs of production of the *i*th household, respectively. Depending on these values, the efficiency indices can be given as follows:

$$TE_i = \frac{Z_i'X_{it}}{Z_i'X_i} \tag{9}$$

$$EE_i = \frac{Z_i'X_{ie}}{Z_i'X_i} \tag{10}$$

$$AE_i = \frac{Z_i'X_{ie}}{Z_i'X_{it}} \tag{11}$$

Determinants of production efficiency analysis can be estimated by using either one-stage procedure or two-stage procedure. One-stage estimation is mostly applied for the simultaneous estimation of the frontier production function parameters and an inefficiency model. But, it fails to accommodate the analysis of all efficiency factors, such as allocative and economic efficiency (Battese and Coelli, 1995; Bravo-Ureta and Reiger, 1991). However, the two-stage procedure of efficiency score analysis besides analyzing the one-stage procedure, it also estimates the determinants of efficiency scores of all efficiencies by using other econometric models such as tobit model. For these reasons, this study applied two-stage estimation for such as the stochastic production function, to obtain efficiency scores and a Tobit model is used to identify determinants of efficiency scores. Most studies also used this estimation procedure (Sime *et al*., 2022; Sisay *et al*., 2015). Analyzing determinants of all efficiency levels (scores) has profound significance in identifying smallholder farmers' production challenges, supporting and forwarding wheat production strategies and policies, and recommending further future researches for improving agricultural production. Using a Tobit model, a second-stage procedure was employed to analyze the effects of demographic, socioeconomic, farm attributes, and institutional variables on each efficiency scores of wheat production. Therefore, a Tobit model consistently estimates unknown parameters and it is best suited for such analysis, where the dependent variable (efficiency score in this case) bears values between zero and one (Maddala, 1986). Accordingly, we specify the two-limit Tobit model as follows:

$$Y_k^* = X_{ki}\,\beta_i' + \mu_k \tag{12}$$

The censored observed dependent variable (Y_k), the Tobit model is represented as follows:

$$Y_k = \begin{Bmatrix} 0 & if\ Y_k^* \leq 0 \\ Y_k^* if & 0 < Y_k^* < 1 \\ 1 & if\ Y_k^* \geq 1 \end{Bmatrix} \tag{13}$$

Where $\boldsymbol{Y_k}$ is the observed dependent variable; $\boldsymbol{X_{ki}}'s$ are vectors of independent variables used; $\boldsymbol{\beta_i}$ are vectors of unknown parameters; $\mu_{\boldsymbol{k}}$ is a normally and independently distributed error term.

The likelihood function of the Tobit model is expressed and represented as follows:

$$L(\beta, \frac{\delta}{y_k}, X_k L_{1k}, L_{2k} = \prod_{y\,=\,L_{1k}} \phi\left(\frac{L_{1k} - \beta' X_k}{\delta}\right) \prod_{y_k\,=\,y_k^*} \frac{1}{\delta}\psi\left(\frac{Y_k - \beta' X_k}{\delta}\right) \prod_{y_k\,=\,L_{2k}} 1 - \phi\left(\frac{L_{2k} - \beta' X_k}{\delta}\right) \tag{14}$$

Where $\boldsymbol{L_{Ik}}$ and $\boldsymbol{L_{2k}}$ are lower limit and upper limit, respectively; $\boldsymbol{\phi}(.)$ is normal density function and $\boldsymbol{\psi}(.)$ is standard density function.

Marginal effects of a Tobit model include the probability of explained variable falling in the uncensored part of the distribution and the expected value of the dependent variable which is conditionally larger than the lower bound caused due to the influence of explanatory variables. Following McDonald and Moffitt (1980), the total marginal effect of the Tobit model is divided into the following three marginal effects based on the above Eq. 14 of the likelihood function.

1. The unconditional expected value of the dependent variable:

$$\frac{\partial E(Y^*)}{\partial X_K} = [\ \phi(Z_U) - \phi(Z_L]\frac{\partial E(Y^*)}{\partial X_K} + \frac{\partial[\phi(Z_U) - \phi(Z_L)]}{\partial X_K} + \frac{\partial(1 - \phi(Z_U)}{\partial X_K} \tag{15}$$

2. The expected value of the dependent variable conditional upon being between the limits:

$$\frac{\partial E(Y^*)}{\partial X_K} = \beta_i\left[1 + \frac{\{Z_L\phi(Z_L) - Z_U\phi(Z_U)\}}{\{\phi(Z_U) - \phi(Z_L)\}}\right] - \left[\frac{\{\psi(Z_L) - \psi(Z_U)\}^2}{\{\phi(Z_U) - \phi(Z_L)\}^2}\right] \tag{16}$$

3. The probability of being between the limits:

$$\frac{\partial[\phi(Z_U) - \phi(Z_L)]}{\partial X_K} = \frac{\beta_i}{\delta}[\psi(Z_L) - \psi(Z_U)] \tag{17}$$

Where: $\boldsymbol{\phi}(.)$ is is the cumulative normal distribution, $\boldsymbol{\psi}(.)$ is the normal density function, $\boldsymbol{Z_L} = \frac{-\boldsymbol{\beta}'\boldsymbol{X}}{\boldsymbol{\delta}}$ and $\boldsymbol{Z_U} = \frac{\boldsymbol{1-\beta X}}{\boldsymbol{\delta}}$ are standardized variables obtained from the likelihood function given the limits of $\boldsymbol{Y}^*$ and $\boldsymbol{\delta}$ is the standard deviation.

3.3.2. Analysis of technology adoption

Intensity of adoption (adoption index)

In many adoption studies, different econometric models such as double hurdle (DH) model (Obayelu *et al.*, 2017; Bedilu *et al*., 2021; Dejene and Workalemahu, 2023) Heckpoisson regression model (Miine *et al*., 2023), tobit model (Aklilu *et al*., 2022; Midamba *et al*., 2023), and a two-limit tobit model (Degefu *et al*., 2017; Tewodros *et al*., 2020) have been employed to analyze and identify the factors influencing the intensity (level) of agricultural technology adoption. The selection of an appropriate econometric model depends on the nature of the data, objectives/s, and type of dependent variable of the study (Wooldridge, 2020). According to Cragg (1977), to analyze adoption intensity and factors affecting adoption decisions, the DH model is preferably selected over other models when farmers' access to agricultural inputs is constrained. For example, Atrsaw *et al*. (2022), Negussie *et al*. (2022), Dejene and Workalemahu (2023) used the DH model to analyze factors influencing agricultural technology adoption. It is not possible to employ the Ordinary Least Square (OLS) model for a categorical or qualitative analysis, as the parameter estimates obtained become inefficient and heteroscedastic problems occur (Greene, 2012).

If the dependent variable bears continuous values below and above the limits (0 and 1), simultaneously censored from above and below, a two-limit Tobit model (censored regression model) can be used (Tobin, 1958; Maddala, 1986). In this study, the dependent variable was computed from different wheat production technology packages (indexed) commonly adopted by farmers in the study area. It bears the values either between 0 and 1, or outside of the range. Therefore, this study employed a two-limit Tobit model to analyze the determinants of wheat production technology packages adoption. Some authors, such as Degefu *et al*. (2017) and Tewodros *et al*. (2020) also employed a two-limit Tobit model to assess factors affecting adoption of technology packages.

The index function of general formulation of two-limit Tobit model is given as follows:

$$Y^{*} = X'B + e \tag{18}$$

$$Y_i = \begin{Bmatrix} 0 & if\ Y_i^* \le 0 \\ Y_i^* if\ 0 < Y_i^* < 1 \\ 1 & if\ Y_i^* > 1 \end{Bmatrix} \tag{19}$$

where Y^* - is limited dependent variable, which is the intensity of adoption of wheat production technologies, X'-explanatory variables and the later two equations represent a censored distribution of the data. The expected value of Y_i as a function of a set of explanatory variables (X) weighted by the probability that $Y_i > 0$ can be estimated by Tobit model (Tobin, 1958).

$$E(Y) = X\beta F(z) + \sigma f(z) \text{ and } z = X\beta / \sigma \tag{20}$$

Where: F(z)- cumulative normal distribution of z; f(z)- value of the derivative of the normal curve; z- score for the area under the normal curve, and s - standard error of the error term. Depending on wheat production technology packages such as improved wheat varieties, wheat row planting, and application of agro-chemical fertilizers (NPS, UREA, and herbicides/pesticide) in the study area, intensity of adoption of the wheat technology packages of adopters is computed following Maddala (1983) as follows:

$$AI_i = \sum_{i=1}^{n} \frac{\frac{AIT_i}{RIT_i}}{NP} \tag{21}$$

Where AI_i= is adoption index of i^{th} household; i= 1, 2, 3,…; AIT_i= actually applied quantity of inputs; RIT_i= is recommended quantity of input; NP= number of practice; n= is total number of households.

Depending on Eq. 21 above, adoption index is fixed at below or 1% or above or 100% and all the elements of the packages specified as follows:

$$AI_i = \sum_{i=1}^{n} \frac{\frac{AW_i}{AT_i} + \frac{ARP_i}{RRP_i} + \frac{AFA_i}{AFR_i} + \frac{ACA_i}{ACR_i}}{NP} \tag{22}$$

Where, i=1, 2, 3… n; n= total number of households; AI_i= adoption index of the i^{th} household; AW= area under improved variety of wheat of the i^{th} household; AT= total area covered by wheat production (all seed types if any); ARP= area under wheat row planting in hectare; RRP=

total area of wheat planted both through row planting and broadcasting; AFR=recommended amount of fertilizers; AFA= applied amount of fertilizers; ACR=recommended amount of chemicals; ACA= applied amount of chemicals and NP= number of practices.

3.3.3. Analysis of impact of technology adoption

Decision making for multiple agricultural technologies adoption could enable smallholder farmers to respond to factors outside of farmers' control such as diseases, drought, plant pests, erosion, and soil infertility. Additionally, their decision to select one or more interdependent agricultural technology packages could be affected by observed factors like demographic, institutional, and economic factors and/or unobserved factors that represent innovation and ability of farmers (Ehiakpor *et al*., 2021; Setsoafa *et al*., 2022). Adoption of agricultural technologies is exposed to self-selection problems by their nature, especially when farmers are categorized as non-adopters, single technology adopters, and two or more full package adopters. In this case, if methods are not appropriately carried out the end result of the impact analysis would be biased and inconsistent (Setsoafa *et al*., 2022). However, some empirical studies employed different econometric models such as PSM, OLS, and logit models (Berihun *et al*., 2014; Musa *et al*., 2016; John *et al*., 2020; Wang *et al*.,2020; Yilma *et al*.,2021; Chanyalew *et al.*, 2021; Muluken *et al*., 2021) which may ignore observable selection bias. Besides, some studies used endogenous switching regression model (Moti *et al*., 2018; Workineh *et al*., 2020; Ngomi *et al*., 2020; Mekonnen *et al*., 2021; Abebaw *et al*., 2022).

However, most empirical studies used MESR (multinomial endogenous switching regression) model if smallholder farmers have two or more probability of willingness to adopt technologies as a package. The model estimates average treatment influence of adoption of technology packages on outcome variables. By applying this model, the issues of farmers' self-selection bias among the technology packages could be addressed as observable and unobservable factors of outcome variables which might affect farmers' interest. Accordingly, some studies (Menale *et al*., 2015; Danso-Abbeam and Baiyegunhi, 2018; Mesele and Read, 2021; Ali *et al*., 2022; Musa, 2022; Setsoafa *et al*., 2022; Ngango *et al*., 2022; Kindineh, 2024) used the MESR model. The model considers both observed and unobserved factors of impact analysis and comparatively solves the issue of selection bias when alternative technology adoption options exist.

Multinomial logit selection model

At this stage, MNL model is employed to analyze determinant factors affecting smallholder farmers' decisions to adopt technology package combinations. The estimation of multinomial logit (MNL) model accounts for unobserved heterogeneity by generating inverse Mills ratios. At the second stage, the computed inverse Mills ratio is used as independent variable to address selection bias problems, and the outcome equations are estimated.

The expected utility, U_{im}^{*}, household derives from adopting **m** package technology is specified as follows:

$$U_{im}^{*} = X_i \beta_m + \varepsilon_{im} \tag{23}$$

Where U_{im}^{*} is a latent variable, X_i is observed exogenous variables, ε_{im} is an error term that accounts for the characteristics of unobserved. If **M** represents index of farmer's technology package selection and M is given as follows:

$$\begin{cases} 1 \text{ if } U_{n1}^{*} > \max\limits_{j \neq m}(U_{nj}^{*}) \text{ or } \eta_{n1<0} \\ \cdot \qquad\qquad \cdot \\ \cdot \qquad\qquad \cdot \\ \cdot \qquad\qquad \cdot \\ M \text{ if } U_{nm}^{*} > \max\limits_{j \neq m}(U_{nj}^{*}) \text{ or } \eta_{nm<0} \end{cases} \tag{24}$$

Smallholder farmers adopt technology packages in isolation or combinations M if they expect more utility from technology package(s) adoption M than any other package $j \neq M$ (Bourguignon *et al*., 2007).

According to Mc-Fadden (1973), the probability that farmer ***i***, select technology package ***m*** given exogenous variable $\mathbf{x_i}$, by assuming that the error terms are identical and independently Gumbel distributed is specified as follows:

$$\text{Prob}\ (m|X_i) = \frac{\exp(\sigma_m + X_i\beta_m)}{\sum_{n=1}^{m} \exp(\sigma_n + X\beta_n} \tag{25}$$

Where Prob $(m|x_i)$ is the probability that a given farmer i selects to adopt technology packages m, σ_m is constant term of technology packages m, β_m is vector of parameters to be estimated and X_i is a set of observed exogenous variables.

Multinomial endogenous switching regression

Multinomial endogenous switching regression model is employed to analyze adoption impacts of different combinations of technology packages on households' food security (HFCS and HDDS) and wheat production income. Under this subsection, the current study used wheat technology packages that are widely applied in the study area, such as improved wheat seed, application of row planting, and inorganic fertilizers application. Farmers could have the possibility of using these technologies in eight (2^3) possible combinations, depending on their selection interests. These possible combinations are none of the packages adopted ($I_0R_0F_0$) which is used as a base category, improved seed only ($I_1R_0F_0$), row planting only ($I_0R_1F_0$), fertilizer only ($I_0R_0F_1$), improved seed and row planting only ($I_1R_1F_0$), improved seed and fertilizer only ($I_1R_0F_1$), row planting and fertilizer only ($I_0R_1F_1$) and improved seed, row planting and fertilizer only ($I_1R_1F_1$).

At second stage of the model equation, which shows the relationship between outcome variables (food security and wheat production income) and a set of endogenous variables given as A for the selected technology package(s), is separately estimated for both non-adopters and adopters of the technology packages. Accordingly, adoption of combinations of technology packages is represented as $(m = 2 \dots n)$ and while non-adoption is given as $m = 1$ which serves as a reference category and the overall equation is specified as follows:

$$\begin{cases} \text{Regime 1: } Q_{i1} = A_{i\alpha 1} + u_{i1} \text{ if } I = 1 & (26a) \\ \qquad \vdots \qquad\qquad\qquad \vdots & \\ \text{Regime M: } Q_{iM} = A_{i\alpha M} + u_{iM} \text{ if } I = M & (26b) \end{cases}$$

Where: Q_i is i^{th} farmer's outcome variables with and without adoption of technology packages M; I is an index which represent farmer i's selection of technology package/s; A_i is a set of exogenous variables; α_1 and α_M are estimated parameters; u_{i1} and u_{iM} are error terms.

The MESR framework estimates and calculates the selectivity correction terms under Eq. 23 and to mitigate unobserved selection bias included the corrections under Eq. 26a and 27b. The observed selection bias problems given by these equations were solved by using vector of observed covariates given under A_i. But, if farmers' decision to adopt technology packages and outcome variables are simultaneously affected by the same unobserved factors, the error terms given under the above Eq. 23 and 26a and 26b would be correlated and unobserved selection bias occurs which resulted in biased estimate. Using these assumptions, the above Eq. 26a & 26b could be rewritten as follows:

$$
\begin{cases}
\text{Regime 1: } Q_{i1} = A_{i\alpha 1} + \lambda_1 \sigma_1 + \omega_{i1} \;\; \text{if } I = 1 & (27a) \\
\qquad\qquad\qquad\qquad \vdots \qquad\qquad \vdots & \\
\text{Regime M: } Q_{iM} = A_{i\alpha M} + \lambda_M \sigma_M + \omega_{iM} \; \text{if } I = M & (27b)
\end{cases}
$$

Where Q_i are i^{th} farmer's outcome variables with and without adoption technology packages M; A_i is a set of exogenous variables; λ_1 & λ_M are selectivity correction terms applied for solving selection bias issues computed from the estimated probabilities in Eq. (25) where in this model it is given as M-1 for each technology package; σ_1 & σ_M are covariance between error terms given in Eq 23, Eq 26a & 26b. To solve for the heteroscedasticity created from the generated regressor, standard errors are bootstrapped and given by Eq. (27).

According to Menale *et al*. (2015), it is possible to identify the parameters of a multinomial ESR model even though selection and outcome equations have the same regressors. This means that to identify multinomial treatment effects' parameter model, inclusion of instrumental variables in the selection equation is not strictly necessary. However, Menale *et al*. (2018) and Musa (2022) included the selection instrument to improve the consistency of the model but excluded it from outcome equations. For the validity of the MESR model, proper and consistent estimation of appropriate selection instruments were included in exogenous variables but not in outcome equations (A_i). Following Bekele *et al*. (2014), Menale *et al*. (2015) and Kindineh (2024), input market distance and distance from the training center (measured in minutes) were used as selection instruments, and these variables were not expected to directly influence outcome variables but rather through package combination adoption. A simple test concerning to confirm the admissibility of these instruments falsification was performed following Di Falco *et al*. (2011). Accordingly, the selected instruments were valid and jointly affected wheat technology package combinations adoption decisions but not affected non-adopter outcome variables such as food security (FCS and HDDS) and wheat production income (Appendix Table 14).

Average treatment effects estimation

The multinomial endogenous switching regression (MESR) method computes the average treatment effects on treated and untreated (ATTs and ATUs). The equations represent the expected outcomes of food security and wheat production income for adopters and non-adopters of technology packages. Following studies undertaken by Menale *et al*. (2018), Setsoafa *et al*. (2022) and Musa (2022), the average treatment effect on the treated (ATT) estimation for actual and counterfactual scenarios is given by using equations. Adopters with adoption (actual) are given by Eq. 28a & 28b.

$$\begin{cases} E(Q_{i2}|I = 2) = A_{i\alpha 2} + \lambda_2 \sigma_2 & (28a) \\ \quad\vdots \\ E(Q_{iM}|I = M) = A_{i\alpha M} + \lambda_M \sigma_M & (28b) \end{cases}$$

Adopters had they decided not to adopt (counterfactual) is given by Eq. 29a & 29b

$$\begin{cases} E(Q_{i1}|I = 2) = A_{i\alpha 1} + \lambda_2 \sigma_1 & (29a) \\ \quad\vdots \\ E(Q_{i1}|I = M) = A_{i\alpha 1} + \lambda_M \sigma_1 & (29b) \end{cases}$$

So, ATT is calculated by using the differences of the above actual and counterfactual equations (27a & 29a or 27b & 29b). By using Eq. 28a & 29a, ATT is presented as follows:

$$ATT = E(Q_{i2}|I = 2) - E(Q_{i1}|I = 2) = A_{i\alpha 2} + \lambda_2 \sigma_2 - A_{i\alpha 1} - \lambda_2 \sigma_1 = A_i(\alpha 2 - \alpha 1) + \lambda_2(\sigma_2 - \sigma_1) \quad (30)$$

3.4. Measurement of Outcome Variables

Food security measurement is not easy and no fixed method is employed to identify its status and impact, as it might be calculated through methods with different unobservable characteristics. The challenges with food security measurement were along with its level of measurement, with its ability to assess, quantify, and qualify food security (Jones *et al*., 2013; Webb *et al*., 2006). However, according to Maxwell (1996), Maxwell *et al*. (2014), Cafiero *et al*. (2014), Ogundari (2017) and Izraelov and Silber (2019), different indicators of food security measurements are developed and being used to measure the status of food security in households. This study used the household food consumption score and household dietary diversity scores developed by WFP and mostly used as proxies for the main food access indicators of food security (WFP, 2008).

The Food Consumption Score (FCS) is an index that aggregates dietary diversity, food consumption frequency, and the nutritional importance of food groups consumed. The family members who make food were asked yes-or-no questions about how many days at least one member of the family consumed at least one food group during the preceding seven days of the interview. It is calculated by multiplying the frequency of food groups consumed over the previous seven days by the weighted relative nutritional value (WFP, 2008). The weighting value of each food type varies depending on the nutritional density of the food group classified by WFP (INDDEX Project, 2018). The eight types of food items include: main staples, pulse, vegetables, fruit, meat/fish, milk, sugar and oil.

HDDS measures the quantity and quality of food access for 12 food groups consumed by a household over a given reference period. It relies on food or food items consumed within the last 24 hours and households' ability to access food (Hoddinott and Yohannes, 2002; Kennedy *et al*., 2011). DDS is aimed at identifying whether a family member consumed at least one food group from each of the 12 food categories over the preceding 24 hours at interview time (Swindale and Bilinsky, 2006). The procedure follows mostly by asking a household member who prepares food using 'yes' or 'no' questions and counting down the list of food items consumed, which may range from 0 to 12, with 0 for none of the food groups consumed and 12 for all food groups consumed within the last 24 hours. These twelve food groups included in this study are: cereals, roots/tubers, vegetables, fruits, meat/poultry, eggs, fish, pulses/legumes/nuts, milk/milk products, oil/fats, sugar/ honey and miscellaneous. By the two methods, this study did not consider food consumed occasionally; rather, it depends on food consumed regularly to reduce estimation bias Wheat production income represents smallholders' annual wheat production income and measured in Ethiopian Birr (ETB). It is obtained by valuing wheat product (quintal) at market price and deducting the costs of all variable inputs during last production seasons of when survey was undertaken.

3.5. Definitions of Variables and Hypothesis for Efficiency Analysis

3.5.1. Efficiency analysis of stochastic frontier production and cost

Dependent Variables

In the study area, production and productivity of wheat are highly dependent on a mix of different production inputs such as land, oxen, labor, agrochemicals (fertilizers and chemicals), and seed. The dependent variables represented are analysis of production efficiency, which is the total wheat output measured in kilogram (kg), and analysis of cost efficiency, which is the total cost used for the production of a given amount of wheat. The effect of these influential variables and their respective costs was analyzed by using stochastic frontier Cobb-Douglas production and cost functions, respectively. All data on production and cost function variables were transformed into natural logarithms before fitting the Cobb-Douglas both functions to linearize them to easily estimate the model.

Independent variables of frontier functions

Land: It is the size of land allocated for wheat production and measured in hectares. It is the most important factor among inputs required for the production of a given level agricultural commodity and is expected to directly affect the quantity of wheat produced. As the size of land allocated for wheat production increased, a larger quantity of wheat is expected.

Labor: It is the availability and number of total labor, which can be either from family members or hired or both. They participate in farming of wheat production activities like ploughing, sowing seed, fertilizer application, weeding, harvesting and threshing output. Labor is an essential and the most important input required for agricultural production when the amount employed determines the amount to be produced. It is measured in man-days (MDs) of eight hours. So, the quantity of wheat produced is directly related to the labor used in the production processes.

Oxen: In agriculture-dependent livelihoods where the applicability of agricultural mechanization is low, oxen labor contributes to ploughing and threshing services. It is used in pairs, and the amount of oxen in pairs is employed in farming activities of wheat cultivation to improve its productivity. Therefore, the amount of oxen labor used directly influences wheat production and is measured in oxen-days.

Seed: It is the basic element required for ongoing production of agricultural products and measured by kg. Farmers might suffer low agricultural productivity by using local seed, but utilizing the right amount of improved seed per hectare enhances the level of production. So, seed, when used optimally as recommended, and production levels are directly related.

Fertilizers: It is chemical fertilizers like NPS and UREA that are used to maximize agricultural productivity through improving soil fertility. The amount of fertilizers used directly determines the amount of agricultural products produced and lower amounts of its usage brings low levels of output, while optimum amounts at the right time maximize the level of its production. Its unit of measurement is kg.

Chemicals: It includes chemicals such as herbicide and pesticide applied for wheat production in the study area and measured in liter (L). Weeds and diseases are the most commonly seen challenges in agricultural production, starting from sowing seed and harvesting products. Using herbicides and pesticides can solve or minimize these production challenges and help to improve the production of the output. Therefore, using chemicals and the level of wheat production are directly related. Table 2 represented the variables used in determining wheat production and cost of production of stochastic frontier Cobb-Douglas production and cost function.

Table 2: Variables, definitions and measurements of production and cost functions

Variables	Descriptions	Measurements
ln (output)	Natural logarithm of wheat output	Kilogram
Independent Variables		
ln(land)	Natural logarithm of land under wheat production	Hectare
ln(labor)	Natural logarithm of labor	Man-days
Ln(oxen)	Natural logarithm of oxen days	Oxen-days
ln(fertilizers)	Natural logarithm of fertilizers	Kilogram
ln(seed)	Natural logarithm of improved wheat seed	Kilogram
Ln(chemical)	Natural logarithm of chemicals	Liter
ln (total cost)	Natural logarithm of total wheat production cost	Ethiopian Birr
ln(land cost)	Natural logarithm of cost of land under wheat production	Ethiopian Birr

ln(labor cost)	Natural logarithm of wage of labor	Ethiopian Birr
Ln(oxen cost)	Natural logarithm of cost of oxen labor	Ethiopian Birr
ln(fertilizers cost)	Natural logarithm of cost fertilizers	Ethiopian Birr
ln(seed cost)	Natural logarithm of cost of wheat seed	Ethiopian Birr
ln(chemical cost)	Natural logarithm of cost of chemicals	Ethiopian Birr

3.5.2. Determinants of production efficiency scores (technical, allocative and economic)

Determinant factors such as demographic, economic, institutional, and farm attributes influenced technical, allocative, and economic efficiency of wheat farmer households. Under this sub-section, the dependent variables are technical efficiency scores (TE), allocative efficiency scores (AE), and economic efficiency scores (EE). Hence, the set of explanatory variables, their definitions, measurements, and their influential effect hypothesis are presented as follows:

Independent variables of efficiency scores (TE, AE and EE):

Agro-ecology: It is a dummy variable and represented by 1 if households located in highland agro-ecology and 0 if households located in midland agro-ecology. The location of households have an influential impact on households' access production inputs, institutional services, market access and locational influence which could have direct or indirect effect on the production and productive of agriculture. If famers are located in appropriate agro-ecology for wheat production they might have fertile and good whether condition for wheat production which might no expose hem for extra cost of production. Households who are found in appropriate agro-ecology might be efficient in wheat production of wheat than others. There it is expected that appropriate agro-ecology positively influence wheat production efficiency.

Educational level of household head: It represents the level of education households attended and is measured by year. Education is the base for improving knowledge and ability of farmers to produce agricultural products and help them to be efficient. Educated farmers can easily make decisions on how to choose and combine different inputs to produce and maximize their products by adopting production technologies. Milkessa *et al*. (2019), Gidey *et al.* (2021) and Sime *et al*. (2022) discussed that education level is directly related to the efficiency of malt barley, wheat, and sesame production, respectively. So, the educational level of households is expected to positively affect wheat production efficiency of farmers.

Family Size: It is a continuous variable and represents the number of household members who live under one roof and are involved in wheat farming. It is the number of persons engaged in agricultural activities such as land preparation, plowing, planting, weeding, hoeing, harvesting, threshing, and storing that contributes to improving the level of agricultural output. The labors may be from household members like children, women, and men. However, there may be the possibility that a larger number of family sizes involved in production, which is greater than the farm activities required, negatively affect production efficiencies. Families with a larger number of dependent members also reduce efficiency in agricultural production. Ali *et al*. (2019), Tolesa *et al*. (2019), Yadeta and Guta (2019) and Sime *et al*. (2022) discussed that family size improves malt barley, maize, and malt barley production efficiency, respectively. But Anang *et al.* (2022) identified that family size negatively affected the technical efficiency of maize production. So, it is expected that the size of a family engaged in wheat production directly or indirectly affects wheat production efficiency.

Farm distance: It is a walking distance for households to travel to reach their farm area from their home residence. It is obvious that farm households located near their farm area more efficient than those located far away. As they are near to their farm site, farmers do not spend more time reaching their farm in order to engage in their work; they frequently observe the farm for supervision and monitoring of any damage to their farm. Moreover, those farmers living near their farm site can easily transport the production inputs to the site and do not have to be exposed to the higher transportation cost of supplying inputs. The research findings of Sime *et al*. (2022) identified that households' farm distance negatively influenced malt barley production efficiency. Hence, a negative effect of farm distance on wheat production efficiency is expected.

Farm size: It is a continuous variable that represents the total area covered by crops managed by farmers and measured by hectare. Identification of efficiency of production of farmers with larger or less farm size has great implications for the production of crops. In most cases, as the size of a farm increases, the probability of farmers being efficient becomes less, and his/her managing ability of larger farm sizes also decreases. In some cases there might be the possibility that the larger size improves wheat production efficiencies. Hussien *et al*. (2019) and Tolesa *et al*. (2019) showed the number of farm size increases production efficiency. Empirical efficiency studies Kebebew *et al*. (2021), Alula *et al*. (2021), and Fisseha *et al*. (2022) revealed that farm size negatively and significantly affected the allocative efficiency of farmers. Hence, it is expected that farm size negatively or positively affects wheat production efficiency of farmers.

Livestock: It is the number of livestock household owned and measured in tropical livestock units (TLU). It serves as a source of traction power and income for purchasing input, tillage, harvesting, organic fertilizer, and used as transporting inputs from market to the farm sites. Kaleb and Workneh (2016) and Kebebew *et al*. (2021) discussed that livestock ownership had a positive effect on the efficiency of wheat producers. Hence, a positive effect of livestock on the production efficiency of wheat is expected.

Access to credit: It is a dummy variable and represented by 1 if household access to credit services and 0 if not access to credit services. Credit helps farmers as a source of finance required to purchase different production inputs like improved seed, pesticide, herbicide, fertilizers, hired labor, and etc. It significantly plays a central role in improving and maximizing production output if used for its purposes. However, if the financial institutions have limited financial capacity and farmers use the borrowed money for other purposes rather than farming, the quantity of output produced becomes low and farmers less efficient in wheat production. Tolesa *et al*. (2019) identified that those farmers who accessed credit services were less inefficient in maize production. Hence, access to credit is expected to be directly related to wheat production efficiency.

Access to extension services: It is a dummy variable and is represented as 1 if household head access to extension services and 0 otherwise. Development agents of extension workers help farmers to be aware and advised on production methods, application and amount of inputs recommended, technology adoption, and willingness to change production methods according to the changing circumstances, etc. However, there is a condition when extension workers contact farmers for other purposes other than agricultural production. Getachew *et al*. (2018) discussed the positive relationship between extension contact and the production efficiency of malt barley. But, Musa *et al*. (2015) revealed that extension contact negatively affected the efficiency of maize production. Therefore, access to extension services of farmers is hypothesized to affect wheat production efficiency either positively or negatively.

Mobile phone ownership: It is a dummy variable and is represented as 1 if a farm household head have own mobile phone and 0 otherwise. Communication with other farmers, model farmers, and agricultural experts through exchanging information by using mobile phones about the availability of agricultural production inputs and costs, technology adoption, production methods, harvesting, and its marketing has inevitable advantages in improving households' wheat production and minimizing its respective costs. Therefore, a direct relationship between owning and using a mobile phone and wheat production efficiency is expected.

Cooperative membership: It is agricultural cooperative membership and represented as 1 if household farmers are members of the cooperative and 0 otherwise. Agricultural cooperatives are the organizations that aim at training, advising, providing an easy way of access to credit, and arranging methods for how farmers can access and purchase improved seed. Sisay *et al*. (2015) and Adugna *et al*. (2019) discussed that being cooperative members positively affected maize and sesame production efficiency, respectively. Hence, it is expected that cooperative membership of households positively affects wheat production efficiency.

Improved seed: It is a dummy variable and represented by 1 if household access to and use of improved seed and 0 otherwise. Farmers prefer improved seed over local seed when only they perceive the final output produced by using both seeds. However, improved seed predominately maximizes the expected production level as it is adaptive and resistant to environmental changes. The research findings of Adino and Tessema (2020) and Zinabu *et al*. (2021) identified that farmers who used improved seed were less inefficient in agricultural production. Therefore, access to improved seed is hypothesized to positively affect wheat production efficiency.

Soil fertility status: It is the status of households' soil fertility and allocation of fertile land for wheat production. It is represented as 1 if households assume their soil is fertile and allocated for wheat production and 0 otherwise. Producing wheat on fertile soil, preventing soil erosion, improving soil organic matter, and enhancing soil aggregation improves wheat yield. It also reduces the need for extra use of inputs such as fertilizer and herbicides, and wheat production through these methods improves its output and its efficiency. Getachew *et al*. (2018) and Milkessa *et al*. (2019) showed that allocating fertile soil for wheat production improves its production efficiency. Therefore, allocating fertile soil for wheat production is expected to positively influence its production efficiency.

Off/non-farm income: It is a dummy variable that takes a value of 1 if the household gets income from off/non-farm activities and 0 otherwise. Households that participate in income-generating activities and non-farming activities might improve their financial capacity and purchase additional inputs of agricultural production and improve the production level of the output. Similarly, the probability of shifting the business from agriculture to others may occur after participating in off-farm income which might negatively affect the agricultural production efficiency. According to Adugna *et al*. (2019), off/non-farm income participation had a positive effect on the production efficiency of sesame, while Wai and Hong (2020) discussed the negative effect of off-farm income on the efficiency of rice production. So, participation in off/non-farm income is expected to positively or negatively affect wheat production efficiency.

Table 3: Variables, measurements and hypothesis for determinants of efficiency differentials

Independent variables	**Measurement unit**	**Expected effect on TE, AE and EE**
Agro-ecology	Dummy (1=highland; 0=midland)	+ve
Education of household head	Years	+ve
Family size of household head	Numbers	+ve/-ve
Farm distance	Walking minute	-ve
Farm size	Hectare	+ve/-ve
Number of livestock owned	TLU	+ve
Access to credit services	Dummy (yes=1; no=0)	+ve
Access to extension services	Dummy (yes=1; no=0)	+ve/-ve
Purchased and used improved seed	Dummy (yes=1; no=0)	+ve
Cooperative membership	Dummy (yes=1; no=0)	+ve
Mobile ownership	Dummy (yes=1; no=0)	+ve
Soil fertility status	Dummy (yes=1; no=0)	+ve
Off/non-farm income	Dummy (yes=1; no=0)	+ve/-ve

3.6. Definitions of Variables and Hypothesis for Adoption and Impact Analysis

Different explanatory variables from demographic characteristics, socioeconomic factors, farm attributes, and technological factors were expected to explain households' wheat production technology packages adoption decisions and intensity and its influence for improvement in smallholders' food security status and income.

3.6.1. Dependent variables

3.6.1.1. Technology packages adoption choice (adoption decision)

It is a dependent variable which is categorical and it is the probability of the household head adopting different production technology package combinations composed of improved wheat seed, row planting, and application of recommended fertilizers (NPS and UREA). In this study, seven possible technology packages combinations such as no adoption ($I_0R_0F_0$), adoption of all packages ($I_1R_1F_1$), adoption of improved wheat seed and row planting only ($I_1R_1F_0$), adoption of improved seed and chemical fertilizers only ($I_1R_0F_1$), adoption of row planting and chemical fertilizers only ($I_0R_1F_1$), adoption of improved seed only ($I_1R_0F_0$), and adoption of chemical fertilizer only ($I_0R_0F_1$), packages combinations were selected from eight possible combinations.

3.6.1.2. Adoption Index (adoption intensity)

It is adoption index of wheat technology packages used in the model and computed from the use and use intensity of wheat production technology packages. These technology packages include improved wheat varieties, wheat row planting, fertilizers (NPS & UREA), and chemicals as specified by equation 21.

3.6.2. Outcome variables

It represents household food security status measured by Food Consumption Scores (FCS) and Household Dietary Diversity Scores (HDDS) and smallholder farmers' annual wheat production income (in ETB).

3.6.2.1. Food Consumption Score (FCS)

It is measured from the consumption of nutrient-rich food groups of households based on the food type and frequency of food consumed over the continuous previous seven days prior to the survey. Based on food consumed, a food security score is assigned for each household (minimum 0 and maximum 112 scores), and depending on weighted values, different thresholds classify households' food security status. It is expected that adopters of recommended wheat technology packages have greater FCS than adopters of a few or single technology package/s.

3.6.2.2. Household Dietary Diversity (HDDS)

The HDDS is used to measure households' status of food security and represents the total number of food groups eaten in the previous 24 hours when the survey was conducted. The values of HDDS vary from 0 to 12, with 0 for none of the food groups consumed and 12 for all food groups consumed within the last 24 hours. It is assumed that adopters of full recommended wheat technology packages have more diversified diets than adopters of a few or single technology package/s.

3.6.2.3. Wheat production income

It represents smallholders' wheat production annual income and is measured in Ethiopian Birr (ETB). It is obtained by valuing wheat products (quintals) by using market price and deducting the costs of all production input variables during the last production season when the survey was undertaken.

3.6.3. Independent Variables of adoption

Agro-ecology: It is a dummy variable and is represented as 1 if the household is located in highland agro-ecology and 0 if the household is located in midland agro-ecology. Agro-ecology predominantly influences the production of wheat by affecting the interest of smallholder farmers in adoption of recommended agricultural technologies. If households are located in suitable climatic conditions for wheat production and it is assumed that they can easily adopt the existing and new agricultural technologies. However, they might fear the cost of adopting these technologies if they are producing wheat in less preferable agro-ecology. A study undertaken by Degefu *et al*. (2017) indicates that agro-ecology is an influential factor in determining adoption intensity of wheat production technology packages. Therefore, it is expected that location of households in appropriate agro-ecology are positively affect adoption intensity.

Sex of household head: It is a dummy variable and takes the value of 1 if the household head is male and 0 otherwise. Being male increases the ability to withstand with the risks of agricultural production technologies and constraints confidentially. While being female might limit the probability of deciding to adopt improved wheat production technologies, as female households lack the experience of agricultural production and its technology adoption. Tesfaye *et al*. (2016) and Melese (2018) discussed that being male favors adoption of agricultural technologies as a whole and improved wheat varieties technology adoption, respectively. But Simtowe *et al*. (2016) identified that being male decreases the probability of adopting pigeonpea varieties. Therefore, it is expected that being male-headed households' increases or decreases adoption of improved wheat production technologies.

Age of household head: It is a continuous variable and measured by year. Aged households either decide to generate and fully adopt wheat production technology packages or fear to exploit the existing technologies. As households experienced the use and advantages of technology adoption through age, their decision to adopt technologies can be improved. But older farmers who grew up with no or less experience of technology adoption have low decision-making ability regarding technology adoption. Chilot *et al.* (2013), Sikhulumile (2019), Getinet *et al*. (2020) and Ogada *et al*. (2021) discussed that as the age of the household increased, adoption of improved maize, inorganic fertilizers, and improved wheat varieties technologies decreased, respectively. But against to this, Richard *et al*. (2020) discussed the positive effect of households' age on rice technology intensity of adoption. So, it is assumed that the age of households had a positive or negative influence on the households' adoption decision and intensity of wheat production technology packages.

Educational level of household head: It is a continuous variable and measured by a year of education households attended. Education provides bases for acquiring, processing, sharing, using, and disseminating knowledge and information of wheat production technologies. Educated farmers are eager to create agricultural production technologies and adopt the existing technologies. Moti *et al*. (2018), Hadush *et al*. (2018), and Teshome (2021) revealed that increased levels of household education increases the probability of adopting improved maize varieties, rice technologies, and garden coffee production technology package adoption, respectively. Hence, it is expected that education level positively affects the households' adoption of wheat production technologies.

Family size: It is a number of households' family members, and used in the model as a continuous variable. The existence of larger family members either enhances the decision to adopt agricultural production technologies or hinders it. Larger family members can jointly decide their technology adoption, and the existing labor in the family is used to implement improved wheat production technologies. In contrast to this, a member of the family may convert and use the existing resources for personal consumption purposes and reduce their decision of adopting wheat production technologies. Moti *et al*. (2018) identified a direct relationship between family size of households and adoption decisions of improved maize varieties. Hence, family size of households is expected to positively or negatively affect wheat production technology packages.

Market distance: It is a continuous variable that represents distance from the main market and is measured in walking minutes. Adoption decision probabilities and its extent of smallholder farmers' decrease as farmers located far from the nearest market. Market centers are a source where farmers get access to purchase production inputs for agricultural production and supply their harvested crops to the market but they could get challenged to access to these inputs if they far located from the nearest market. Their far location from the nearest markets expose them to incur other additional costs especially cost of transportations and it might hinder them not to adopt the technology they want and it declines their adoption extent. The research findings of Aklilu *et al*. (2022) identified that distance from market and adoption decision probability and its level are inversely related. Therefore, negative relation between market distance and adoption probability and extent of adoption is expected.

Farm distance: It is the walking distance households walk to reach their farm area from their home residence. It is obvious that farm households located near their farm area are more eager to adopt recommended technology packages than those located far away. As they are near to their farm site, farmers do not spend more time reaching their farm in order to engage in their work; they frequently observe the farm for supervision and monitoring of any damage to their farm. This enables them to adopt more. Moreover, those farmers living near their farm site can easily transport the production inputs to the site and do not have to be exposed to the higher transportation cost of supplying inputs. Hence, a negative effect of farm distance on wheat production technology packages is expected.

Distance from training centers: It represents the distance between households' residences and agricultural training centers and is measured in walking minutes. Regular agricultural farm training through advisory services provided by agricultural experts at the agricultural centers, such as FTC, improves households' decision to adopt agricultural technologies. However, if households located far from these centers, they couldn't get updated information about the technologies, and their closeness to the centers positively influences adoption of the technologies. Therefore, it is assumed that an indirect relationship is expected between training distance centers and wheat technology packages adoption.

Access to credit services: It is a dummy variable and is used as 1 if the household has access to credit services and 0 otherwise. Access to credit services enables farmers to solve the problems of finances required for purchasing wheat production inputs. It helps them to apply recommended production technologies and be capable of buying them on time through minimizing constraints of inputs' availability. Hadush *et al*. (2018), Ullah *et al*. (2018) and Ogada *et al*. (2021) identified a positive impact of access to credit on households' adoption of upland rice, inorganic fertilizer technologies, and improved cultivars, respectively. So, access to credit services is hypothesized to positively affect adoption of wheat production technologies.

Access to extension services: It is a categorical variable and represents households' frequency of extension contacts per year. Agricultural extension workers provide information and training about input usage, production, agricultural production innovations, creation and adoption of improved agricultural production. They have a key important role in overcoming the problems of information and knowledge gaps of agricultural production, improved technologies and adoption of improved technologies. Atrsaw *et al*. (2022) identified that extension contact positively and significantly affected adoption and adoption intensity of tef production technology packages. Sikhulumile (2019) and Adunea and Fekadu (2019) also identified that extension contact improves adoption decision of improved maize variety technology and adoption and intensity of use of row planting for wheat production technology, respectively. Hence, it is expected that access to extension services would increase households' adoption of wheat production technology packages.

Farmers' cooperative membership: It is a dummy variable that takes a value of 1 if households' membership to cooperatives and 0 otherwise. Farmers who participate in multi-purpose farmers' cooperatives share transferred and diffused knowledge from their cooperatives' members and become aware, eager, and likely to adopt modern agricultural technologies. The cooperative may provide information for farmers on input, production, marketing, and cooperation between farmers. Tewodros *et al*. (2020) discussed that being a member of cooperative organizations increases adoption of tef, maize, wheat, barley, sorghum, and potato technology. Salazar and Rand (2016) and Degefu *et al*. (2017) also discussed how farm households being members of cooperatives increases the probability of adopting agricultural and wheat production technology packages, respectively. Hence, it is expected that households' cooperative membership increases adoption decisions and adoption level of wheat production technology packages.

Mobile ownership: It is a dummy variable that takes a value of 1 if respondents' get information from mobile and 0 otherwise. Mobile phones help households as an instrument in searching for information on newly implemented agricultural technologies and getting agricultural input price information from different sources and their availabilities. Households who own and use mobile phones might improve their adoption of improved wheat technology packages more than those who did not own and use mobile phones. The research findings of Abebaw *et al*. (2023) revealed that owning a mobile phone positively influenced the likelihood of households' adoption of improved rice seed. Therefore, it is assumed that mobile ownership is expected to positively affect households' adoption of wheat technology packages.

Radio ownership: It is a dummy variable that takes a value of 1 if respondents' use radio to get information about agricultural technology packages from radio and 0 otherwise. Through listening to the radio, farmers get information and improve their understanding about the benefits of joint adoption of agricultural technology packages rather than adopting incomplete packages. Farmers who have radios or listen to the radio about agricultural production information could adopt all the recommended technology packages, while those who do not own radios and listen. So, it is expected that access to information about agricultural production from radio positively affects households' adoption of wheat technology packages.

Farm size: It is a continuous variable and measured by hectare. It represented the size of land households owned that is mostly assumed as wealth status which is a proxy households' status. Owning larger land can conceivably encourage farmers to adopt improved wheat production technologies and produce more for maximizing their return. Large farm size allocated for agricultural production has a significant role in technology adoption and thereby solving households' food security problems and income. Chilot *et al.* (2013), Manda *et al*. (2016) and Menasbo *et al*. (2020) discussed that farm size owned is directly related to adoption of cash crops, SAP technologies, and improved wheat varieties, respectively. However, Luchia and Hadush (2018) discussed the negative influence of farm size on the intensity of wheat technology package adoption. Hence, it is hypothesized that larger farm size would be positively or negatively related to adoption of improved wheat production technology packages.

Access and purchase of improved seed: It is a dummy variable that takes a value of 1 if household purchased wheat improved seed at the right time and in the right quantity and 0 otherwise. Purchasing available improved wheat seed at the right time with the required quantity enables farmers to adopt different wheat production technology packages. Lack of access to inputs and imperfection of seed markets can limit adoption of agricultural technology. Adunea and Fekadu (2019) revealed access to that improved variety at the right time and quantity improves the farmer's adoption probabilities of wheat production row planting. So, improved seed purchased is expected to positively affect adoption of wheat production technology packages.

Livestock size: It is a continuous variable and represents the number of livestock household head owned and measured in TLU (Tropical Livestock Unit). Livestock contribute to either the production of agricultural products or their sale, which can serve as a source of income for purchasing agricultural inputs. The research findings of Tesfaye *et al*. (2016), Ullah *et al*. (2018) and Sikhulumile (2019) discussed that the number of livestock households owned positively affected adoption of improved cultivars and improved wheat varieties production technologies, respectively. So, it is expected that the number of livestock owned is expected to affect adoption of wheat production technology packages positively.

Farmers' perception: It is a dummy variable that takes a value of 1 if respondents' perception towards wheat yield is positive and 0 otherwise. Farmers who have a better perception of wheat yield than other crops are more likely to adopt improved wheat technology packages, while if not, they don't assume; they become reluctant to adopt. They evaluate their perception about different agricultural yield which they produce and depending on their perception they decided their willingness technology adoption by expecting with higher outcome than other low yield crops. Hadush *et al*. (2018) discussed that positive perception of farmers' rice yield significantly and positively affected rice production technology adoption. Hence, positive farmers' perception towards wheat yield is expected to positively affect wheat technology package adoption.

Participation in farming training: It is a dummy variable that takes a value of 1 if a household attends specific training related to wheat production and technology adoption and 0 otherwise. Training helps farmers to be aware of innovative and new ideas about input usage, improve their knowledge and insight for productivity maximization, and technology adoption. Atrsaw *et al*. (2022) identified that agricultural training positively and significantly affected adoption and adoption intensity of *tef* production technology packages. Musa *et al*. (2016) discussed that a positive relationship between training and groundnut improved seed technology adoption. Therefore, it is hypothesized that participation in wheat production training directly affects wheat technology package adoption.

Annual farm income: It is a continuous variable that represents annual income obtained from farm production, measured in Ethiopian Birr (ETB), and it is the proxy measure of wealth. Farm income enables farmers to invest in technology adoption through supporting financial services and timely use of wheat technology packages. Farmers who have higher annual income from farm production may be less constrained by technology adoption factors to adopt than farmers with low annual farm income. Aklilu *et al*. (2022) and Negussie *et al*. (2022) revealed that annual farm income positively affected adoption and intensity of adoption of improved wheat and bread wheat technologies, respectively. Therefore, annual farm income is expected to positively affect adoption of wheat production technology packages.

Off/non-farm income: It is a dummy variable and takes a value of 1 if farmers participate in off/non-farm income and 0 otherwise. It is additional income-generating activities that are obtained both from off-farm (outside-farm) and non-farm (outside-agriculture). It enables farmers to improve their capacity of purchasing agricultural production inputs and be willing to easily adopt agricultural technologies, while farmers who did not access t off/non-farm income may be less engaged in farm income. Hadush *et al*. (2018) discussed the positive relationship between off-farm income and rice technology adoption. Hence, it is expected that off/non-farm income is positively or negatively affect adoption of wheat production technology packages.

Table 4: Variables, measurements and hypotheses for adoption and impact analysis

Outcome Variables		**Units**	
Food Consumption Score		Number	
Household Dietary Diversity		Number	
Wheat production income		Ethiopian Birr	
Variables	**Units**	**Expected sign**	
		Effect on dependent variables	
Explanatory variables		**Adoption decision** ($I_0R_0F_0$, $I_1R_1F_0$, $I_1R_0F_1$, $I_0R_1F_0$, $I_1R_0F_0$, $I_0R_0F_1$, $I_1R_1F_1$)	**Adoption Index**
Agro-ecology	Dummy (1=Highland 0= Midland)	*	+ve/-ve
Age of household head	Continuous (Years)	+ve/-ve	+ve/-ve
Sex of Household head	Dummy (Male=1, Female=0)	+ve/-ve	+ve/-ve
Education of household	Continuous (Years)	+ve	+ve
Family size	Continuous (Numbers)	*	+ve
Market distance	Continuous (Minutes)	-ve	-ve
Training distance	Continuous (Minutes)	-ve	*
Farm distance	Continuous (Minutes)	-ve	*
Mobile ownership	Dummy (Yes=1, No=0)	+ve	*
Radio ownership	Dummy (Yes=1, No=0)	+ve	*
Farm size	Continuous (Hectare)	+ve/-ve	+ve/-ve
Improved seed purchased	Dummy (Yes=1, No=0)	*	+ve
Livestock size	Continuous (TLU)	+ve	+ve
Access to credit services	Dummy (Yes=1, No=0)	+ve	+ve
Access to extension services	Dummy (Yes=1, No=0)	+ve	+ve
Cooperative membership	Dummy (Yes=1, No=0)	+ve	+ve
Farmers' perception	Dummy (Yes=1, No=0)	*	+ve
Farm training	Dummy (Yes=1, No=0)	+ve	+ve
Annual farm income	Continuous (Ethiopian Birr)	*	+ve
Off/non-farm income	Dummy (Yes=1, No=0)	+ve	+ve/-ve

4. RESULTS AND DISCUSSION

This chapter represents analyses results of the cross-sectional data collected through a survey to obtain the findings and discussion of this study. The chapter includes four sections, such as descriptive statistics, production and cost efficiency and determinants of TE, AE, and EE analysis, determinants of intensity of adoption of wheat technology packages, factors of adoption decision of wheat production technology packages combinations, and finally, impact analysis of wheat technology packages adoption on households' food security and wheat production income.

4.1. Descriptive Results

4.1.1. Demographic and socio-economic characteristics of households

The demographic and socioeconomic characteristic of sample households were analyzed and represented by descriptive statistics such as mean, frequency, maximum, minimum, percentage, and standard deviation. Among the demographic and socioeconomic characteristic variables discussed, the set of continuous variables include age of household, education level of household head, family size, farm size, number of livestock, wheat yield and farm income while dummy variables were sex and marital status of household head and access to off/non-farm income (Table 5).

Age of the household head can influence wheat production efficiency in determining activities required from land preparation to harvesting time. And also it could determine adoption of various agricultural technology packages. The mean age of the wheat producer sample household head in all agro-ecology was 39.54 years. The mean age of household head was lower in the midland agro-ecology (39.36 years) and higher in highland agro-ecology (39.81 years). The t-test of the mean difference statistics showed that, there is no statistically significant difference between the locations of households in terms of the variable.

Both male and female households participated in the production of wheat and its adoption of production technologies, although the number of female participants was low when compared with their male counterparts. On average, 86.75% of the sampled wheat producers were male household head. The proportion of male household head that produce and adopt wheat production technology packages is higher in Horo district (89.17%) when compared with Hababo

Guduru district which was 85.16%. This difference among both districts of both agro-ecologies was not statistically significant ($\chi2$=1.01). About 95.36% of the total sampled households were married while the others are single, divorced and widowed (Table 5). Education helps farmers in equipping them with knowledge and understandings about agricultural input usage, production methods, harvesting and selling of the products. The average education level of household head in both agro-ecologies of the study area was 3.97 years of schooling. Specifically, the average education level attended in highland agro-ecology was 4.8 years) and it was 3.4 years in the midland agro-ecology. There is a statistically significant mean difference at 1% among the location of households in terms of the level of education households attended.

The presence of larger family size contributes for improving the efficiency of wheat production and agricultural technology adoption by serving as a source of labor during the stages from the first start of farming activities to final harvesting. In addition, the shared knowledge in between family members contributes for adoption of improved wheat technology packages. Farmers in highland agro-ecology had the larger average family size (4.5) when compared with midland agro-ecology (4.37). On average, the sample households had 4.42 family members and the t- test results showed that no statistically significant difference among the locations of the households in-terms of their family members. The size of farm households has a direct or indirect effect on farmers' wheat production efficiency and adoption of agricultural technologies. Greater landholding size could be an input for an improvement of agricultural production if wisely used, and could also be a reason for bringing inefficiency of production. Similarly, if efficiently used and supported by new technologies, larger farm sizes enable farmers to produce wheat efficiently, but this may not be practically seen in less performing agricultural production systems. In the study area for both districts in combination, the average size of farm areas was 1.98 ha, with a standard deviation of 0.84. The mean farm size of highland and midland were 1.95 ha and 2.00 ha, respectively. The t-test result shows that there is no a statistically significant mean difference between the locations of household head in terms of their farm size ownership (Table 5).

In the study area, households engage in production of different crops such as cereals (teff, wheat, maize, barley, and sorghum, etc.), pulses (pea, bean, and haricot, etc.), vegetables (potato, tomato, onion, carrot, *etc*.), fruits, oil crops (groundnut, nug, sesame, etc), coffee, and etc.

Moreover, the average land under cereals, pulses, others crops (such as oil crops, fruits and vegetables) and coffee and grazing land were 1.22 hectare, 0.50 hectare, 0.21 hectare and 0.05 hectare, respectively. For wheat production households possessed land from their own, share cropping and rent contact for a year or few years while most of land was owned.

The number of average livestock owned by sampled households in both districts was 6.38 measured in TLU with a standard deviation of 1.79. The average TLU of highland and midland agro-ecologies were 7.25 and 5.81, respectively, while the t- test showed that the difference in the number livestock owned in both locations was statistically significant at 1% significance level. In the study area, the types of livestock owned by households include cows, oxen, calves, heifer, horse, donkey, sheep, goats, mule, and chicken. Livestock is the source of various wheat production activities in the areas where agricultural production machinery rarely exists. It serves for traction power, farming manure, transportation services, and etc. It also serves as a source of income through sales for purchasing production inputs which improve wheat production (Table 5). The average wheat production in the study area is 2397.02 kg per hectare and the higher amount (2566.75 kg) was produced in the midland agro-ecology (Ababo Guduru district) while the average wheat production in the highland agro-ecology (Horo district) was 2139.58 kg. The t-test shows there exist is a statistically significant mean difference in average annual wheat production of households across both agro-ecologies at 1% significance level.

In the study area, in addition to serving for consumption purposes, wheat production also helps farmers as a source of income. Accordingly, during the production season of 2022/2023, about 23129.8 ETB on average and 21517.5 ETB and 24192.86 ETB were earned from wheat production in Horo and Ababo Guduru districts, respectively. The average income which sampled households obtain from annual farm activities (agricultural production, livestock, beekeeping and etc) for all the districts was 56745.36 ETB. The income obtained from farm activities in Horo district was 53572.5 ETB while it was 58837.36 ETB in Ababo Guduru district. The t-test for households' average wheat production income and annual farm income from both locations are statistically significant at 10% significance level (Table 5).

In addition to engaging in farming activities, some proportion of the sampled households were participating in non-farm income generating activities such as local trading (include buying and selling animals, and temporal grain trade), labor wage, and etc. Accordingly, about 46.35% of households engaged in non-farm income-generating activities in addition to agricultural production, while the difference in household location did not show a significant influence ($\chi2$ = 0.73) on households' engagement in non-farm activities. On average, sample households get 6797.24 ETB from engaging in off-farm income, while on average 5197.80 ETB off-farm income was obtained in Ababo Guduru district, and on average about 4,725.00 ETB obtained in Horo district. Similarly on average, households in the study area annually earns 61755.3 ETB income from both farm and non-farm income and higher income was obtained in Ababo Guduru district (64,035.16 ETB) while in Horo district on average, 58,297.50 ETB was obtained. The t-test for households' average annual total income from both locations is statistically significant at 5% significance level (Table 5).

Table 5: Descriptive statistics of demographic and socio-economic characteristics of wheat farmer households

Variables	Highland District (n=120)		Midland District (n=182)		Total (n=302)		t-test
	Mean	**Sd.Dev**	**Mean**	**Sd.Dev**	**Mean**	**Sd.Dev**	
Age of household head	39.81	8.42	39.36	8.28	39.54	8.33	0.45
Education of household head	4.80	2.41	3.42	2.10	3.97	2.32	5.25***
Family size	4.50	1.37	4.37	1.34	4.42	1.35	0.84
Farm Size J	1.95	0.81	2.00	0.86	1.98	0.84	-0.46
Wheat area	0.60	0.39	0.74	0.39	0.69	0.40	-2.92***
Cereal area (including wheat)	1.06	0.51	1.32	0.57	1.22	0.56	-3.98***
Pulses area	0.58	0.33	0.44	0.29	0.50	0.32	3.75***
Oil crops, fruits and vegetables areas	0.23	0.15	0.19	0.13	0.21	0.14	2.27**
Others (coffee, grazing area, etc)	0.07	0.09	0.04	0.08	0.05	0.09	2.75
Livestock	7.25	1.79	5.81	1.54	6.38	1.79	7.40***
Wheat Output	2139.58	1013.41	2566.75	1021.18	2397.02	1037.763	-3.56***
Wheat Income	21517.5	11351.56	24192.86	13710.69	23129.8	12872.57	-1.77*
Non-farm income	4725.00	6272.47	5197.80	7132.86	5009.93	6797.24	-0.59
Farm income (with wheat)	53572.5	21426.05	58837.36	24084.63	56745.36	23172.55	-1.94*
Total income	58297.5	22772.74	64035.16	2485.62	61755.3	24174.55	-2.02**

	Category	**Highland District (n=120)**	**Midland District (n=182)**	**Total (n=302)**	**χ2-Value**
Sex of household	Dummy, 1= Male	89.17	85.16	86.75	1.01
Marital status of household	Dummy, 1= Married	95.00	95.60	95.36	0.17
Access to off/non-farm income	Dummy, 1=Yes	43.33	48.35	46.35	0.73

Source: Source: Own survey result, 2023

4.1.2. Institutional and farm attribute characteristics of farm household head

Various institutional variables such as access to extension services, access to credit services, cooperative membership, farm training, households' distance from the nearest market, distance between households' homestead to farm areas, distance between households' residence to training center, ownership of communication services such as mobile phones and radio, and households' perception about wheat yield, were discussed and presented (Table 6).

On average for all districts in the study area, 57.28% of the sampled households accessed credit services from different financial institutions located in both districts' main town, while the difference in access to credit services across the district was statistically significant at the 5% level, with $\chi 2$ =3.85. Comparing each district, access to extension services was statistically significant at 5% significance level with a value of $\chi 2$ =3.91, implying that there is a difference in access to extension services in both districts. In both districts, about 44.70% of the sampled households had access to extension services on average, which indicates that for both district, low access to extension services occurred. Among the sampled households, lower proportions were members of different agricultural cooperatives which might support them in producing and adopting wheat production technologies. About 48.67% of households were members of agricultural cooperatives while the difference in households' location in both agro-ecologies (districts) in terms cooperative membership was not statistically significant ($\chi 2$ =0.009) (Table 6).

Households selected as a sample from both districts travel 33.02 minutes on average to reach the nearest input market and travel 19.35 minutes to arrive at farmers' training center (FTC) from their residential areas. Regarding with time taken to travel to the nearest market of households, t-test shows that there exist significant difference between both agro-ecologies at 5% significance level while no significant difference was seen in-terms of households' distance from their home to farmers' training centers. The average walking distance between farmers' residence and farming area was 13.24 minutes, and it was higher in midland agro-ecology (13.87 minutes) and in average, it was 12.29 minutes in midland agro-ecology. Among the sampled households, 46.68% had received training on how to improve agricultural production capacity and technology adoption. The differences in participating in different agricultural training given in each district were not statistically significant ($\chi 2$ =0.05). Among the total sampled households, 50.66% had a good perception of their subsequent year's wheat production, which enabled them to produce and adopt wheat production technology packages, while the difference across each district was statistically significant at 5% significance level with $\chi 2$ = 4.27. This implies that the difference in the location of households did cause a difference in their good perception about wheat yield (Table 6).

Producing wheat on fertile land had significant effect in improving wheat output and initiating households' adoption of recommended agricultural technologies. Soil fertility has also a potential influence in affecting households' wheat production efficiency and improving households' willingness to adopt agricultural technologies. The group chi-square test statistics showed that there was a significant difference among the groups in households' location with respect to the difference in household perception on soil fertility status at 1% significance level with $\chi 2$ = 14.73 implying that farmer' difference in location with respect to soil fertility had difference in wheat production and technology packages adoption. Among sampled households, only 40.39% had mobile phone and accessed information exchanged from different sources such as peers and agricultural experts through phone. The difference in household's location to different agro-ecologies (districts) regarding owning mobile phone ownership was not statistically significant as $\chi 2$=1.15. Radio is also a source of information for farmers broadcasted from different sources to enable them to understand about agricultural information especially in acquiring knowledge about input usage, input costs, time, methods of production and agricultural technology packages. In the study area, about 34.10% of households had information from radio and there is a statistically significant difference at 1% significance level with $\chi 2$=24.43 among the location of households in terms of radio ownership (Table 6).

Table 6: Descriptive statistics of institutional and farm attributes characteristics of wheat farmer households

Variables	Highland district (n=120)		Midland district (n=182)		Total (n=302)		t-test
	Mean	**Sd.Dev**	Mean	**Sd.Dev**	Mean	**Sd.Dev**	
Market distance	35.20	12.37	31.59	14.14	33.02	13.56	2.28**
Farm distance	12.29	9.11	13.87	7.61	13.24	8.26	-1.63
Training distance	19.08	8.62	19.53	10.65	19.35	9.88	-0.38
	Category	**Highland district** (n=120)		**Midland district** (n=182)	**Total** (n=302)		**χ2-Value**
Access to credit services	Dummy, 1=Yes	64.16		52.74	57.28		3.85**
Access to extension services	Dummy, 1=Yes	51.66		40.10	44.70		3.91**
Cooperative membership	Dummy, 1=Yes	48.33		48.90	48.67		0.009
Improved seed	Dummy, 1=Yes	18.33		26.92	23.50		2.96*
Training received	Dummy, 1=Yes	47.50		46.15	46.68		0.05
Soil fertility status	Dummy, 1=Yes	76.66		54.94	63.57		14.73***
Good perception on wheat yield	Dummy, 1=Yes	43.33		55.49	50.66		4.27**
Mobile phone ownership	Dummy, 1=Yes	36.66		42.85	40.39		1.15
Radio ownership	Dummy, 1=Yes	17.50		40.05	34.10		24.43***

Where ***, ** & * represent the significance at 1%, 5% and10% probability levels, respectively.
Source: Own survey result, 2023

4.2. Wheat production agronomic practices and input use of the farm households

In the study area, different agronomic practices of wheat production were undertaken by households during the 2022/2023 production season. Among these agronomic practices, the major practices include wheat row planting and/or broadcasting, crop rotation, planting on time, ploughing frequency, weeding frequency, and harvesting on time. Similarly, different types of input mixes were employed for wheat production in the study area. These major inputs include seed (improved and local seed), labor, oxen, agrochemical fertilizers (NPS and UREA), and the use of chemicals such as herbicides and pesticides (Table 7).

With regard to wheat planting methods, about 48.34% of sampled households used wheat row planting only, while the remaining followed both row planting and wheat broadcasting methods or broadcasting only. Row planting has various advantages in wheat production in the study area in reducing inefficiency of input costs and improving production efficiency. There was no significant difference between wheat producer households' location (agro-ecology) in terms of applying row planting ($\chi2$=0.89). The crop rotation method is a well-known sustainable agricultural practice in order to improve soil fertility and efficiency of wheat production. In the study area, about 76.49% of households follow crop rotation on their land. There was a significant difference between wheat producer households' location (agro-ecology) in terms of applying row planting at a 1% significance level with $\chi2$=7.36 (Table 7).

Among the sampled households, 74.50% of households followed recommended plough frequency times, and about 97.01% of sampled households planted wheat at the right time during the expected time of sowing seed. Similarly, about 89.07% of households weeded wheat on time, and there was no significant difference in terms of the proportion of weeding on time. About 95.03% of the sampled household harvested wheat produce timely without exposure to pre- and post-harvest loss, and there was no significant difference in terms of harvesting on time with respect to households' location. The utilization of the water resources for irrigation purposes is not well-practiced and negligible in the study area. In terms of irrigation usage, the chi-square test statistics showed that there is no significant difference among respondents of both locations (agro-ecologies) of the study area. Only 5.62% of the population of the sample households started to use irrigation services, and the area of land covered by the irrigation is too low and difficult to measure. The reasons for the ineligibility of irrigation practices might be lack of experience and understanding, difficulties in accessing water bodies, its applicability during off-farm seasons, and low adoption practices of irrigated wheat production technology packages (Table 7).

The efficiency of wheat production directly relies on the amount of seed used. However, in the study area, households failed to apply the recommended quantity of wheat seed, mostly due to lack of availability of seed, high prices of seed, and the involvement of illegal traders in retailing seed. Among the sampled households, only 65.23% used the recommended amount of fertilizer (NPS and UREA). Among both district of the study area, about 64.16% and 65.93% of sampled household head used the recommended amount of fertilizer for wheat production in Horo and Ababo Guduru districts, respectively. However, only 51.98% of sampled households get access to the right quantity of fertilizer at the right price. With regard to using recommended fertilizer for wheat production, no significant difference was seen between households' locations (districts). In the study area, access, price, and purchase of fertilizer input are more complicated than at any time, and these factors might be the cause for households not to apply recommended amounts of fertilizer input. Differences in households' location at both agro-ecologies with respect to access to improved wheat seed were statistically significant at the 10% significance level with the value of $\chi 2 = 2.96$, showing that the difference in district influences access to improved seeds. Overall, only 23.50% of farmers have accessed and purchased the required quantity of improved wheat seeds in the study area. Similarly, only 56.62% of the sampled households in the study area applied the recommended amount of wheat seed per hectare, which might be caused by the absence of getting the required amount of wheat seed at the right time and price (Table 7).

In the study area, access, price, and purchase of chemicals are more complicated than at any time before, and these factors might be the cause for households not to apply recommended amounts of chemical inputs. Applying the recommended amount of chemicals (herbicides and pesticides) for weeding, clearing land, and controlling wheat diseases has more profound importance in improving wheat production efficiency than using manual labor. In the study area, only 45.69% of sampled households used the recommended amount of chemicals. The application of recommended chemicals such as herbicides and pesticides for wheat production during the 2022/2023 production season mismatched with the required amount. This could be caused by the unavailability of the chemical on time, its high price, the presence of illegal traders, and lack of farmers' awareness about the usage of chemical. The descriptive statistics result showed that only about 559.16% and 36.81% of household farmers applied the recommended amount of chemicals for wheat production in Horo and Ababo Guduru districts, respectively. The mean difference statistics showed that there is a significant difference at the 1% significance level with the value of $\chi 2 = 14.56$ among the households' location in terms of using the recommended amount of chemicals (Table 7).

Table 7: Summary statistics of agronomic practices of the smallholder wheat farmers

Variables	Category	Highland district (n=120)	Midland district (n=182)	Total (n=302)	χ2-Value
Use crop rotation	Dummy, 1=Yes	68.33	81.86	76.49	7.36***
Used row planting	Dummy, 1=Yes	45.00	50.54	48.34	0.89
Ploughed as recommended	Dummy, 1=Yes	68.33	78.57	74.50	3.99**
Access and purchase of fertilizers	Dummy, 1=Yes	54.16	50.54	51.98	0.37
Applied recommended fertilizers	Dummy, 1=Yes	64.16	65.93	65.23	0.09
Applied recommended chemicals	Dummy, 1=Yes	59.16	36.81	45.69	14.56***
Access and purchase of improved seed	Dummy, 1=Yes	18.33	26.92	23.50	2.96*
Applied recommended improved seed	Dummy, 1=Yes	60.00	54.39	56.62	0.92
Planted timely	Dummy, 1=Yes	96.66	97.25	97.01	0.08
Weeded timely	Dummy, 1=Yes	86.66	90.65	89.07	1.18
Harvested timely	Dummy, 1=Yes	93.33	96.15	95.03	1.21
Used recommended storages	Dummy, 1=Yes	59.16	76.37	65.62	10.10***
Irrigation usage	Dummy, 1=Yes	5.83	5.49	5.62	0.01

Where ***, ** & * represent the significance at 1%, 5% and 10% probability levels, respectively
Source: Own survey result, 2023.

In the study area, wheat production activities start from land preparation and, among others, include wheat planting, cultivation, weeding, harvesting, and threshing. To achieve these, households in the study area employed a total of 93 man-days of labor on average, where a larger proportion of man-days of labor were employed in Ababo Guduru district (102 man-days) and 80 man-days in Horo district. The sources of these households' labors that engage in wheat farming in the study area were own labor, hired labor, and others such as '*dabo*.' The application of inorganic fertilizer in wheat farming is widely undertaken in the study area. However, the common problem in the usage of inorganic fertilizer in the study area is that farmers did not follow the recommended amount of fertilizers to be used per hectare, which had an influential impact on wheat production efficiency. Overall on average, 84.99 kg of inorganic fertilizer (NPS and UREA) was used for wheat production in the study area, where a larger proportion of fertilizer was utilized in Ababo Guduru district (94.53 kg) and 70.53 kg used Horo district. Similarly, on average, about 0.49 liters of chemicals (herbicide and pesticide) per hectare were used for wheat production, which is below the recommended amount of chemicals per hectare.

On average, 75.70 kg of wheat seed (improved and local) is used for wheat production in the study area. Depending on the proportion of seed used in the study area, on average 67.86 kg and 80.86 kg of wheat seed were used in Horo and Ababo Guduru districts, respectively. Applying the recommended amount of inorganic fertilizer (such as NPS and UREA), wheat seed, and chemicals used per hectare could result in a higher amount of wheat production quantity. However, farm households failed to use the recommended amount of these inputs due to its availability problems and its increased and unstable prices. The t-test shows that there exit statistical differences between the locations (agro-ecologies) of households and the use of these inputs except application of chemical at 1% significance level (Table 8).

Table 8: Summary statistics of input use of the smallholder wheat farmers

Variables	**Highland**	**Midland**	**All**	**t-test**
	Mean(**Sd.Dev**)	Mean(**Sd.Dev**)	Mean(**Sd.Dev**)	
Land (Hectare)	0.60(0.39)	0.74(0.39)	0.69(0.40)	-2.92***
Labor (Man-days)	80.92(24.91)	102.12(33.85)	93.69(32.28)	-5.88***
Oxen (Oxen days)	18.20(9.53)	21.85(9.42)	20.40(9.62)	-3.27***
Fertilizer (Kilogram)	70.53(44.78)	94.53(57.84)	84.99(54.25)	-3.84***
Seed (Kilogram)	67.86(31.18)	80.86(35.17)	75.70(34.19)	-3.28***
Chemicals (herbicide & pesticides) (Liter)	0.45(0.35)	0.52(0.40)	0.49(0.38)	-1.42

Where *** represents the significance at 1% probability level

Source: Own survey result, 2023

4.3. Econometric Results

This sub-section includes the estimation of wheat production and cost efficiency levels, determinants of technical, allocative, and economic efficiencies analysis of wheat production, adoption decision and intensity of wheat technology packages, and impact of adoption of wheat production technology packages on household food security and wheat production income.

4.3.1. Efficiency Analysis

Stochastic frontier analysis of efficiency mostly employs Cobb-Douglas and translog functional forms and both are interchangeably used. However, the model specification- hypothesis was undertaken in this study and the hypothesis is about that all interaction term and square specification coefficients are equal to zero in Translog functional forms that $H_0: \beta_{ij} = 0$. The test result showed that Cobb–Douglas production function adequately matches the data and favored the selection of Cobb–Douglas production function over the translog specification (Appendix Table, 2). As a result, the Cobb-Douglas functional model is superiorly selected over translog functional forms. Hence, this study used parametric stochastic frontier (normal/half-normal) of Cobb-Douglas production and cost functions.

4.3.1.1. Estimation of production function

The comparison results of the maximum likelihood (ML) parameter estimates of the Cobb–Douglas stochastic production frontier function and the standard ordinary least squares (OLS) estimate are presented in Table 9. The model specification result of Cobb–Douglas stochastic production frontier function is significant at the 1% significance level ($Wald\ chi^2 = 834.28; \mathrm{prob} > chi^2 = 0.0000$) which reflects rejection of null hypothesis that all slope coefficients are equally to zero. The coefficient of gamma calculated by using $\gamma = \frac{\boldsymbol{\sigma}_u^2}{\boldsymbol{\sigma}^2}$ and it was 0.771 which implies that about 77.1% of disparity in wheat yied caused by technical inefficiency while the remaining was created by the factors beyond the control of farmers. Additionally, the value of lambda is greater than 1, which shows the effect of technical inefficiency on the variation in the observed yield ($\lambda = 1.836$). Similarly, the model has no multicollinearity problem as the mean value of VIF is less than 10 (VIF=2.56) (Appendix Table 3).

Table 9: Maximum-likelihood and Ordinary Least Squares estimates of production function

Variables	Maximum likelihood estimate		Ordinary Least Square estimate	
	Coefficient	Sd.Dev	Coefficient	Sd.Dev
ln(land)	0.233***	0.039	0.215***	0.041
ln(labor)	0.484***	0.061	0.404***	0.064
ln(oxen)	0.084*	0.049	0.088*	0.051
ln(fertilizer)	0.111***	0.023	0.098***	0.025
ln(seed)	0.093**	0.045	0.128***	0.046
Ln(chemical)	0.036*	0.020	0.033	0.021
Constant	5.232***	0.275	4.799***	0.279
Wald χ^2 (6)	834.28***			
Prob χ^2	0.0000			
Log likelihood	19.88739			
sigma^2	0.103			
Gamma	0.771			
Lambda	1.836			

Where ***, **&* represent the significance at 1%, 5% and 10% probability levels, respectively.
Source: Own survey data, 2023

Production inputs, such as land area under wheat (ha), oxen (oxen-days), labor (man-days), fertilizer (kg), seed (kg) and chemicals (L) were used to composite the dependent variable (quantity of wheat harvested during the 2022/2023 production season). Depending on these inputs, the fitted model is given as follows:

$$\mathbf{lnOutput(kg)= \underset{(0.275)}{5.232}+\underset{(0.039)}{0.233}lnLand(ha)+\underset{(0.061)}{0.484}lnLabor(man\text{-}days)+\underset{(0.049)}{0.084}lnOxen(oxen\text{-}days)+}$$

$$\mathbf{\underset{(0.023)}{0.111}lnfertilizer(kg) +\underset{(0.045)}{0.093}lnseed(kg) +\underset{(0.020)}{0.036}lnchemical}$$

All the input variables used in the model significantly affected the dependent variable (wheat output). This shows that wheat production directly depends on a combination of different inputs. The coefficients of all production function variables are positive and significant, which implies that they are different from zero and that these variables significantly explain wheat production. Land allotted for wheat production, labor employed, and quantity of fertilizer applied significantly influenced wheat output at the 1% significance level, whereas the use of oxen and chemicals had an effect at the 10% significance level while the application of wheat seed significantly affected wheat output at the 5% significance level. This shows that wheat yield in the study area could be increased by increasing the level of these inputs. Accordingly, a 1%

increase in land, labor, oxen, fertilizer, seed, and chemicals increased wheat production by 0.233, 0.484, 0.084, 0.111, 0.093, and 0.036, respectively, keeping other factors constant. This implies that jointly improving these factors of production and minimizing its access barriers enhance the level of wheat production in the study area (Table 9).

The production elasticity is explained in terms of the coefficient of each production inputs used during the study, and the sum of the elasticity of all factors of wheat production was 1.041 (Table, 9). The returns to scale (RTS) is greater than 1, indicating that wheat production in the study area exhibited increasing returns to scale in the first-stage economic region of the production function. This shows that a proportionate increase in all inputs used to influence wheat yield results in a greater than proportionate increase in wheat output and the potentiality of farmers in wheat production through improved and coordinated management of the existing input resources. Therefore, both farmers and agricultural policymakers need to be motivated in improving the level of application of these wheat production input combinations through solving its access challenges and usage of modern wheat production technologies to further improve the extent of wheat production in the study area. This result is consistent with the research results of Kebebew *et al*. (2021), Sime *et al*. (2022), Sisay *et al*. (2015), and Adugna *et al*. (2019).

4.3.1.2. Determinants of households' technical wheat production efficiency differentials

A tobit model is employed to analyze factors affecting farmers' wheat production technical efficiency after the existence of efficiency variations among wheat producer farmers is identified. The VIF test of the model also indicated that there was absence of multicollinearity problem. The overall VIF value is 1.15, with minimum and maximum values of 1.05 and 1.35, respectively (Appendix table 4). According to the tobit model result represented below, the technical efficiency of wheat production was positively and significantly affected by the educational level of household head, the number of livestock owned, soil fertility status, and access to and purchase of improved seed, while it was negatively and significantly affected by the distance between farmers' residences and their farm sites. The result of the tobit result analysis of determinants of technical efficiency and marginal effects are represented by Table 10.

Education level: The level of education households attended had a positive and significant influence on wheat production technical efficiency at a 5% significance level. Farm households who attended formal education have the knowledge and ability to improve their resource use efficiencies and tend to produce agricultural products more effectively than those who attended less formal education. Education helps farmers to acquire information and knowledge about farming methods, types of agricultural technologies, and innovation that needs to be adopted and proper application of production inputs. The marginal effect of education level of household head indicates that as the education of the household head increased by 1 year, the mean wheat production technical efficiency of farmers increased by 0.4 percent. The result is consistent with the research findings of Sisay *et al*. (2015), Getachew *et al*. (2018) and Milkessa *et al*. (2019).

Farm distance: As hypothesized, distance from households' residences and farm sites negatively and significantly affected the technical efficiency of wheat production at 10% significance level. One minute walking distance increase in households' residence to their farm site decreases the mean level of technical efficiency by 0.1 percent. This implies that farm households located near to their farm are more efficient than those located far away. As they are located near to their farm site, farmers do not spend more time to reach their farm in order to engage in their work; they frequently observe the farm for supervision and monitoring of any damage to their farm. Moreover, those farmers living near their farm site can easily transport the production inputs to the farm site. The result is consistent with the research findings of Sime *et al*. (2022).

Livestock: The number of livestock owned positively and significantly affected wheat production technical efficiency at 5% significance level. This shows that households who owned more livestock efficiently produced wheat than those who owned less. A country in which agriculture is the dominant activity of livelihood, livestock helps with land ploughing, threshing, and transport inputs and outputs and serves as a draft power for weeding and improving soil fertility through the application of manure preparation. Similarly, it serves as a source of income for purchasing agricultural inputs to access farm technologies. A one-unit increase in the number of livestock owned increases the mean technical efficiency by 0.5 percent. Kaleb and Workneh (2016), Kebebew *et al*. (2021), and Tadesse *et al*. (2022), also found similar findings.

Soil fertility: Wheat farming on the fertile soil positively and significantly affected the technical efficiency of wheat production at 1% significance level. This implies that households who produce wheat on fertile soil could increase the level of wheat production technical efficiency more than households who use infertile land for wheat production. Wheat production output and its efficiency could be improved, and its' extra use of inputs such as fertilizer and herbicides is reduced when it is produced by using improved fertile soil through preventing soil erosion, improving soil organic matter, and enhancing soil aggregation. The mean technical efficiency of farmers who allocated fertile soil for wheat production increases by 3.1 percent compared to those who did not. The result is consistent with the research findings of Getachew *et al*. (2018) and Milkessa *al*. (2019).

Access and purchase of improved seed: Access and purchase of improved seed affected wheat production technical efficiency at 1% significance level. This shows that household farmers who access and use improved wheat seed are more efficient in wheat production than those who use local wheat seed. Accessing and purchasing improved wheat seed for wheat production profoundly influences its production and productivity. Improved seed is more adaptive to various risks such as climate, diseases, and pests than local seed and considerably improves productivity of wheat production. Therefore, the availability of the preferred type and quality of wheat seed at the right time, at a fair price, and the required quantity improves the wheat production efficiency level of smallholder farmers. Households who access and purchase improved wheat seed can increase the technical efficiency of wheat production by 2.5 percent more than those who did not. Similar to these findings, Moges (2019) and Zinabu *et al*. (2021) identified that usage of improved wheat seed improves its production rather than using local seed.

Table 10: Determinants and marginal effects of technical efficiency of wheat production

Variables	**Coefficients**	**Sd.Dev**	**Marginal Effects**		
			Pr(0<y<1)	Exp(0<Y<1)	Unc. Exp
Agro-ecology	0.0146	0.0110	0.01394	0.01197	0.01620
Education level of household	0.0051**	0.0407	0.00491	0.00422	0.00570
Farm Distance	-0.0011*	0.0006	-0.00110	-0.00094	-0.00127
Family size of household	0.0040	0.0037	0.00385	0.00330	0.00447
Land holding size	-0.0087	0.0063	-0.00833	-0.00715	-0.00968
Access to extension services	-0.0014	0.0107	-0.00143	-0.00122	-0.00165
Access to credit services	-0.0008	0.0024	-0.00078	-0.00067	-0.00090
Mobile ownership	0.0165	0.0104	0.01576	0.01349	0.01898
Cooperative membership	0.0017	0.0101	0.00170	0.00146	0.00198
Livestock	0.0062**	0.0031	0.00597	0.00513	0.00694
Soil fertility status	0.0382***	0.0113	0.03664	0.03182	0.03887
Access and purchase of improved seed	0.0322***	0.0123	0.03038	0.02560	0.04234
Access to off/non-farm income	0.0066	0.0102	0.00636	0.00546	0.00743
Constant	0.6995***	0.0104			
Log likelihood	309.94351				
Prob χ^2	0.0000				
Pseudo R2	-0.1070				
Number of observations	302				

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey data, 2023

4.3.1.3. Estimation of production cost function

Analysis results of stochastic cost frontier Cobb-Douglas estimation are represented by Table 11. The overall fitness of the model from the significant Wald test statistics shows that the dependent variable is explained by the explanatory power of the independent variables included in the model. Multicollinearity problems among the independent variables were checked by using VIF, and the result revealed that no problem of multicollinearity exists in the model, as overall the VIF result is 2.04 with a minimum value of 1.12 and 2.65 maximum values (Appendix Table 5). Wheat production output positively and significantly determined the cost of wheat production at 1% significance level. According to the results, a 1% increase in wheat production increases wheat production total cost by 0.78. The research outcomes of Okello *et al*. (2019) identified that increase in the quantity of production increases its related total costs. The cost of land under wheat production also significantly and positively affected the total cost of wheat production at

5% significance level. This shows that 1% increase in the price of rent of land increase the total cost of wheat production by 0.044. The result is consistent with Sime *et al*. (2022).

On the other hand, labor, seed and chemical costs had no significant effect on wheat production costs. The cost of oxen used for wheat production significantly and positively affected the total cost of wheat production at 5% significance level. This indicates that increasing the number of oxen in wheat production, increases wheat production total cost by 0.026. In the area where tractors are not employed for land plough and trace, oxen play a significant role in wheat production. Additionally, the cost of fertilizer used significantly and positively influenced total cost at 1% significance level. This shows a 1% increase in fertilizer cost increases the total cost of wheat production by 0.05. Perveen *et al*. (2021) discussed consistent result with the findings of this study.

Table 11**:** Cobb-Douglas stochastic cost frontier estimation results

Cost variables	**Coefficient**	**Sd.Dev**
ln(total cost of wheat production)		
ln(wheat output)	0.780***	0.016
ln(land)	0.044**	0.017
ln(labor)	-0.009	0.022
ln(oxen)	0.026**	0.012
ln(fertilizer)	0.050***	0.012
ln(seed)	0.019	0.015
ln(chemical)	-0.001	0.003
Constant	4.507***	0.135
Wald χ^2 (7)	6529.80***	
Prob χ^2	0.0000	
Log likelihood	287.16215	
sigma^2	0.029	
Lambda	7.561	

Where ***&** represent the significance at 1% and 5% probability levels, respectively.

Source: Own survey data, 2023

Depending on the result of stochastic production frontier from Table 11, the respective dual-cost frontier function parameters are estimated and presented as follows:

$$\mathbf{lnC_i = \underset{(0.135)}{4.507} + \underset{(0.017)}{0.044}lnZ_{land} - \underset{(0.022)}{0.009}lnZ_{labor} + \underset{(0.012)}{0.026}lnZ_{oxen} + \underset{(0.012)}{0.05}lnZ_{fertilizer} + \underset{(0.015)}{0.019}lnZ_{seed}}$$

$$\mathbf{- \underset{(0.003)}{0.001}lnZ_{chemical} + \underset{(0.016)}{0.780}lnY_i^*}$$

Where: $\mathbf{C_i}$ is total wheat production cost of i$^{\mathbf{th}}$ household farmer, $\mathbf{Z_i}'s$ are input prices; $\mathbf{Y_i^*}$ is total wheat output adjusted for noise.

4.3.1.4.Determinants of households' allocative wheat production efficiency differentials

A tobit model is used to analyze determinants of wheat production allocative efficiency, and the model fits well. The model was tested for multicollinearity problem, and no multicollinearity problem happened as the VIF value is 1.14 (Appendix Table 6). The model result of the study revealed that the allocative efficiency of wheat production is significantly and positively influenced by the educational level of the household and household family size and negatively and significantly affected by agro-ecology and landholding size.

Agro-ecology: The outcome of the econometric model showed that, households' location (agro-ecology) negatively and significantly influenced allocative efficiency of wheat production at 10% significance level. This implies that household location contributes for differences in households' allocation efficiency of their wheat production and the change in their locations decreases wheat production allusive efficiency by 1.35 percent. These differences might be attributed due to district's production potentiality, appropriate agro-ecology, availability of production inputs, and access and utilization awareness of district's households.

Educational level of household head: The educational level of the household significantly and positively influenced the allocative efficiency of wheat production at 5% significance level. Educated farmers can easily make decisions on how to choose and combine different inputs to produce and maximize their wheat production. Education helps farmers to properly allocate their cost of production in order to improve wheat production efficiency than less educated farmers. One year increase in the level of households' education increases allocative efficiency by 0.4 percent. The result is in line with the research findings of Getachew *et al*. (2018) and Sime *et al*. (2022) who revealed that education positively affected allocative efficiency of malt barely and barely production, respectively.

Family size: Allocative efficiency of wheat production is positively and significantly affected by the number of family size at the 5% significance level. This implies that households that have larger family size are more efficient in cost minimization than those that have lower family size.

This might be due to larger family sizes being able to use their own labor to engage in farm activities such as plowing, weeding, harvesting, and accomplishing their work on time. They can easily deploy their own labor on farming activities rather than employing people from outside, who are immensely required during production uncertainty time, as agricultural production is weather sensitive. This can reduce extra costs that occurred due to crop loss and damages. Additionally, having larger family size reduces the probability of searching for and employing labor and minimizes costs incurred for labor employment for farming activities. One unit increase in households' family members increases allocative efficiency by 0.5 percent. Hussien *et al*. (2019), Tolesa *et al*. (2019), Yadeta and Guta (2019), and Sime *et al*. (2022) discussed that family size improve maize, malt barley, maize and malt barley production efficiency, respectively.

Farm size: Farm size negatively and significantly influenced the allocative efficiency of wheat production at 1% significance level. Larger farm size requires frequent supervision and more labor to be employed, which can create inefficiency of resource allocation. One unit increase in households' landholding size decreases allocative efficiency of wheat production by 0.8 percent. The result is consistent with the findings of Kebebew *et al*. (2021) and Fisseha *et al*. (2022) revealed that farm size negatively and significantly affected allocative efficiency of farmers' wheat and *teff* production, respectively.

Table 12: Determinants and marginal effects of allocative efficiency of wheat production

Variables	Coefficients	Sd.Dev	Marginal Effects		
			Pr(0<y<1)	Exp(0<Y<1)	Unc. Exp
Agro-ecology	-0.0190*	0.0110	-0.01729	-0.01354	-0.03701
Education level of household	0.0059**	0.0023	0.00536	0.00420	0.01148
Farm Distance	-0.0004	0.0006	-0.00036	-0.00028	-0.00078
Family size of household	0.0072**	0.0035	0.00653	0.00512	0.01398
Land holding size	-0.0125**	0.0060	-0.01141	-0.00893	-0.02442
Access to extension services	0.0096	0.0101	0.00870	0.00680	0.01882
Access to credit services	0.0044	0.0099	0.00404	0.00317	0.00860
Mobile ownership	-0.0081	0.0099	-0.00738	-0.00579	-0.01556
Cooperative membership	0.0045	0.0096	0.00408	0.00320	0.00876
Livestock	-0.0059	0.0030	-0.00539	-0.00422	-0.01154
Soil fertility status	-0.0107	0.0107	-0.00975	-0.00761	-0.02150
Access and purchase of improved seed	0.0079	0.0117	0.00718	0.00560	0.01603
Access to off/non-farm income	-0.0035	0.0097	-0.00321	-0.00251	-0.00685
Constant	0.9256***	0.0386			
Log likelihood	325.46244				
Prob χ^2	0.0050				
Pseudo R2	-0.0481				
Number of observations	302				

Where ***, **& * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey result, 2023

4.3.1.5. Determinants of households' economic wheat production efficiency differentials

Determinants of wheat production economic efficiency differentials were analyzed by the tobit econometric model. No multicollinearity problem exists in the model as the overall mean VIF value is 1.13 (Appendix Table 7). Economic efficiency of wheat production is positively and significantly influenced by the level of education, family size, soil fertility, and access to and purchase of improved seed and negatively and significantly influenced by farm distance and landholding size.

Educational level of household head: The educational level of household head positively and significantly influenced the economic efficiency of wheat production at 1% significance level. Educated farmers can easily acquire and get production information and easily make decisions on farming methods and types of agricultural technologies to adopt; innovation needs to be adopted and proper application of production inputs and related costs of production. A one-unit increase in the level of households' education increases the economic efficiency of wheat production by 0.8 percent. The result of the study is consistent with the research findings of Sisay *et al*. (2015), Getachew *et al*. (2018), Milkessa *et al*. (2019) and Sime *et al*. (2022).

Farm distance: Economic efficiency of wheat production is negatively and significantly affected by households' location from their farm area at 10% significance level. It is obvious that farm households located near their farm are more efficient than those located far away. As they are near to their farm site, farmers do not spend more time reaching their farm in order to engage in their work; they frequently observe the farm for supervision and monitoring of any damage to their farm. Moreover, those farmers living near to their farm site can easily transport the production inputs to the site and do not have to be exposed to the higher transportation cost of supplying inputs. One unit increase in the distance from households' residence to their farm decreases the mean economic efficiency by 0.1 percent. The result is similar with the research findings of Sime *et al*. (2022) who identified that households' farm distance negatively influenced malt barely production efficiency.

Family size: The number of households' family members significantly and positively influenced the economic efficiency of wheat production at 5% significance level. The presence of larger members of the household family can easily deploy their own labor and might not need the extra cost of labor and reduce the effort of searching for labor for employment on production activities such as land preparation, plowing, planting, weeding, hoeing, harvesting, threshing, and storing. One unit increase in the number of household member increases wheat production economic efficiency by 0.8 percent. The result is in line with Hussien *et al*. (2019), Tolesa *et al*. (2019) and Sime *et al*. (2022).

Land holding size: Economic efficiency of wheat production is negatively and significantly influenced by the size of land households owned at the 5% significance level. The size of a farm decreases the probability of farmers being efficient and affects the managing ability of farm households to regularly supervise their farm sites. Larger farm size needs higher cost of production input and the ability to make decisions on how to allocate land to different production of agricultural commodities. One unit increase in landholding size of households decreases economic efficiency of wheat production by 1.5 percent. Empirical research findings of Sisay *et al*. (2015), Alula *et al*. (2021) and Kebebew *et al*. (2021) also found similar results.

Soil fertility status: Using fertile land for wheat production had positively and significantly affected wheat production efficiency at 5% significance level. Reducing soil erosion, improving soil organic matter, and enhancing soil aggregation of land under wheat production can improve soil fertility and thereby improve wheat yield. These methods also reduce the need for extra use of inputs such as fertilizer and herbicides employed for improving soil fertility. Wheat production through these methods improves its output and production efficiency. Households that produce wheat on fertile land produce 2.6 percent more in level of economic efficiency than those who produce wheat on infertile land. Getachew *et al*. (2018), Milkessa *et al*. (2019) and Alula *et al*. (2021) found similar findings and showed that allocating fertile soil for agricultural production improves its production efficiency.

Access and purchase of improved seed: Economic efficiency of wheat production is positively and significantly influenced by access to and purchase of improved seed at 5% significance level. Improved seed predominately maximizes the expected production level as it is adaptive and resistant to environmental changes. Households who used improved seed for wheat production had 3.1 percent more in level of EE than those who did not use improved seed. The result is consistent with the research findings of Sisay *et al*. (2015), Alula *et al*. (2021) and Zinabu *et al*. (2021).

Table 13**:** Determinants and marginal effects of economic efficiency of wheat production

Variables	**Coefficients**	**Sd.Dev**	**Marginal Effects**		
			Pr(0<y<1)	Exp(0<Y<1)	Unc. Exp
Agro-ecology	-0.0019	0.0135	-0.0019	-0.00180	-0.00839
Education level of household	0.0094***	0.0029	0.00927	0.00855	0.00397
Farm Distance	-0.0013*	0.0007	-0.00131	-0.00120	-0.00056
Family size of household	0.0094**	0.0038	0.00925	0.00853	0.00396
Land holding size	-0.0176**	0.0074	-0.01734	-0.01599	-0.00742
Access to extension services	0.0057	0.0125	0.00563	0.00519	0.00243
Access to credit services	0.0064	0.0122	0.00635	0.00586	0.00269
Mobile ownership	0.0069	0.0122	0.00679	0.00625	0.00295
Cooperative membership	0.0045	0.0118	0.00445	0.00410	0.00190
Livestock	-0.0004	0.0037	-0.00045	-0.00041	-0.00019
Soil fertility status	0.0293**	0.0131	0.02889	0.02677	0.01149
Access and purchase of improved seed	0.0349**	0.0144	0.03417	0.03108	0.01803
Access to off/non-farm income	0.0041	0.0119	0.00403	0.00317	0.00173
Constant	0.6540***	0.0475			
Log likelihood	263.21513				
Prob χ^2	0.0000				
Pseudo R2	-0.1343				
Number of observations	302				

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey result, 2023

4.3.1.6. Production efficiency scores and their distributions

The mean technical efficiency of wheat production was 0.810, with minimum and maximum technical efficiencies of 0.423 and 0.952, respectively. This implies that with a given current input mix and technologies, it is possible to increase wheat production quantity by 0.190. Furthermore, the mean technical efficiency was higher in highland agro-ecology (0.814) while it was 0.806 in midland agro-ecology. Similarly, the estimated mean allocative efficiency is 0.881 which indicates that wheat growers in the study area can attain a more efficient level and reduce their production costs by 0.119. The mean allocative efficiencies in highland and midland agro-ecologies were 0.893 and 0.873, respectively. The t-test for the mean allocative efficiency of household among the agro-ecologies is statistically significant at 5% probability level. The overall mean economic efficiency in both agro-ecologies was 0.714, and it was higher in the highland agro-ecology (0.728) and it was 0.705 in the midland agro-ecology. The t-test for the mean economic efficiency of household among the agro-ecologies is statistically significant at 10% probability level (Tables 14 and 15).

Table 14**:** Technical, allocative and economic efficiency and the distributions of wheat producers

Efficiency score ranges	**Technical Efficiency**		**Allocative Efficiency**		**Economic Efficiency**	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
0.91–1.00	45	14.90	165	54.64	3	0.99
0.81–0.90	145	48.01	73	24.17	70	23.18
0.71–0.80	73	24.17	50	16.56	108	35.76
0.61–0.70	27	8.94	14	4.64	70	23.18
0.51–0.60	9	2.98			39	12.91
0.41–0.50	3	0.99			9	2.98
0.31–0.40					2	0.66
0.21-0.30					1	0.33
Total	302		302		302	
Mean	0.810		0.881		0.714	
Std. Dev.	0.095		0.086		0.112	
Minimum	0.416		0.638		0.271	
Maximum	0.956		0.990		0.928	

Source: Own survey data, 2023

The efficiency distribution of wheat production showed the existence of efficiency differentials in the technical, allocative, and economic aspects of wheat production among the study area's agro-ecologies. Agazhi *et al*. (2024) discussed consistent results that the discrepancies in efficiency of wheat production exist among the agro-ecologies, and wheat production efficiency shows disparities across ecologies. It is known that mostly wheat is produced in highland and midland agro-ecological areas where suitable weather conditions, fertile soil, and adequate soil moisture exist for its production. However, farmers might not be adapted for producing wheat in lowland agro-ecology. These issues call agricultural policymakers to create awareness of farmers, focus on agro-ecological factors, subsidize, and support farmers through providing modern agricultural technology inputs to improve wheat production efficiency in lowland agro-ecology and minimize production efficiency discrepancies among the agro-ecologies.

Similarly, only about 48.01%, 24.17% and 35.76% of sample households' efficiency scores in the study area lie within the range of the mean efficiency scores of technical efficiency, allocative efficiency and economic efficiency, respectively. But, about 14.90%, 54.64% and 24.17% sample households' efficiency scores in the study area lie above the range of the mean efficiency scores of technical efficiency, allocative efficiency and economic efficiency, respectively. However, about 37.08%, 21.20% and 40.06% sample households' efficiency scores in the study area lie below the range of the mean efficiency scores of technical efficiency, allocative efficiency and economic efficiency, respectively (Table 15). These justify that it is also possible to improve wheat production efficiency without altering the existing mix of wheat production inputs through proper management of these factors of production.

Table 15**:** Summary statistics of efficiencies (technical, allocative and economic efficiency) scores

Variables	**Highland district** (n=120)		**Midland district** (n=182)		**Total** (n=302)		**t-test**
	Mean	**Sd.Dev**	Mean	**Sd.Dev**	Mean	**Sd.Dev**	
Technical Efficiency	0.814	0.086	0.806	0.101	0.810	0.095	0.721
Allocative Efficiency	0.893	0.075	0.873	0.092	0.881	0.086	1.984**
Economic Efficiency	0.728	0.099	0.705	0.119	0.714	0.112	1.718*

Source: Own survey data, 2023

4.3.2. Adoption analysis of intensity of wheat production technology packages

Table 16 presents the empirical findings of the two-limit Tobit econometric model. Prior to running a two-limit Tobit model, independent variables were tested for multicollinearity problem using Variance Inflation Factors (VIFs), and no problem was observed in these variables. The mean VIF was 1.17 with 1.06 and 1.37 minimum and maximum, respectively (Appendix Table 8). The omitted variable (OV) test given in Appendix Table 9, shows that there was no problem with explanatory variable omission, as its P value is insignificant (0.5204). Similarly, the data were tested for the existence of heteroscedasticity, and the model has no heteroscedasticity problem as the significance value from the Breusch–Pagan/Cook-Weisberg test was 0.1325, which is insignificant (Appendix Table 9).

Seventeen explanatory variables were hypothesized to influence adoption intensity of wheat production technology packages. Among the independent variables included in a two-limit model to affect the adoption intensity, the educational level of the household, the household's location from the nearest market, access and utilization of improved seed, the number of livestock owned, household participation in farm training, income from farm production, and access to off/non-farm income significantly affected adoption intensity of wheat production technology packages at different significance levels.

Unlike expected, differences in households' locations due to different agro-ecologies had no significant influence on farmers' adoption intensity of wheat technology packages, which implies that households' locations did not contribute to differences in technology adoption rate. Farmers' distance from their farm areas also had no effect on the adoption intensity of wheat technology packages. Theoretically, services provided for farmers by extension workers are assumed to influence adoption intensity of wheat technology package, but unlike expected, access to extension services was not significant, and its influential coefficient was negative. All other insignificant variables like landholding size, age, sex, family size, cooperative membership, and access to off/non-farm income were also assumed to affect wheat technology package adoption intensity but had no significant effect.

Educational level of household head: The educational level of households significantly affected adoption of technology packages at the 5% significance level, as expected. As the educational level of households increased by one year, the likelihood of wheat production package adoption increased by 1.68%, keeping other factors constant. This implies that educated farmers can easily be aware of the importance of technology adoption to adopt new technologies, easily get information about technologies and utilize them, be technically capable of getting training from agricultural experts, and apply the offered training on the ground. Overall, education provides the basis for acquiring, processing, sharing, using, and disseminating knowledge and information about wheat production technologies. In line with these findings, Moti *et al*. (2018), Hadush *et al*. (2018), Teshome (2021) and Aklilu *et al*. (2022) revealed an increased level of household education increased adoption of improved maize variety, rice technologies, garden coffee production technology packages, and wheat production technology packages, respectively.

Distance from the nearest market: The econometric model results showed that households' distance to the nearest market significantly and negatively influenced adoption of wheat production technology packages at the 1% significance level. The results show that, as households' walking to the nearest market increases by one minute, the likelihood of adopting wheat production technology decreases by 0.46%, keeping other factors constant. As market distance increases, farmers' probability and the extent of adoption of wheat technology packages decrease. This is because market centers enable farmers to access agricultural production inputs and supply their produce to the market; however, if they are found far from the market, they become constrained to obtain these services. Similarly, as they are far from the market, they spend more time and incur greater costs in obtaining services that prevent them from adopting wheat production technology packages. This result is consistent with the findings of Aklilu *et al*. (2022) who showed that market distance and the probability of adoption and intensity of adoption of wheat production technology are negatively related.

Access to and purchase of improved seed: Access to and purchase of improved wheat seed positively and significantly affected households' adoption intensity of wheat production technology packages at 5% significance level. Access and purchase of improved wheat seed increase adoption intensity of wheat production technology packages by 10.14%, keeping other factors constant. Accordingly, access to and purchase of available improved wheat seeds at the right time with the required quantity enables farmers to adopt different wheat production packages. The lack of access to inputs and imperfections in seed markets can limit adoption of agricultural technology. The findings of this study are in line with those of Adunea and Fekadu (2019), who revealed that supplying improved seed at the right time with the required quantity increases the farmer's probability of adopting row planting of wheat production.

Number of livestock owned: The number of livestock owned significantly and positively affected adoption of wheat production technology packages at the 1% significance level. The results revealed that an increase in the number of livestock increased adoption intensity of technology packages by 2.94%, keeping other factors constant. The results revealed that farmers who have a larger number of livestock can easily produce agricultural products and use them as a source of income to purchase agricultural inputs through their sales. This result is in line with the research findings of Ullah *et al*. (2018), who discussed that the number of livestock households owned positively affects adoption of improved cultivars.

Participation on farm training: As expected, households' participation in farm training had a positive effect on adoption of production technology. The coefficient of participation in farm training is statistically significant at the 10% level of significance, and it increases adoption intensity by 6.33%. The results suggest that training helps farmers to be aware of innovation and new ideas for input usage and improves their knowledge and insight for productivity maximization and technology adoption. This result is consistent with the findings of Musa *et al*. (2016) and Atrsaw *et al*. (2022) who revealed that agricultural training had a positive effect on adoption of *teff* and groundnut-improved seed technologies, respectively.

Annual farm income: Similar to the hypothesis, annual farm income positively and significantly affected adoption of wheat production technology packages at the 5% significance level. The results showed that, as the annual farm income of households increased by one birr wheat production technology, adoption increased by 7.71%, keeping other factors constant. This implies that households with higher annual farm income are more likely to adopt wheat technology packages than households with lower annual farm income. Moreover, it is the fact that income obtained from agricultural production enables farmers to improve their capacity to purchase agricultural production inputs and to be willing to adopt agricultural technologies easily. This result is in line with the research findings of Aklilu *et al*. (2022) and Negussie *et al*. (2022), who revealed that annual farm income positively affected adoption and intensity of adoption of improved wheat technologies.

Access to off/non-farm income: Access to off/non-farm income also positively influenced households' adoption intensity of wheat technology packages at 10% significance level as expected. The result of study identified that as households engage in off/non-farm income generating activities, their adoption intensities increased by 5.55% keeping other variables constant. This is due to the fact that income generated from engaging in non/non-farm activities enables farmers to improve their capacity of purchasing agricultural production inputs and willing to easily adopt agricultural technologies while farmers with higher off/non-farm income may less engage in farm income. The result is in line with the findings of Hadush *et al*. (2018) who discussed positive relationship between off-farm income and rice technology adoption.

Table 16: Adoption of wheat technology packages (Application of two-limit Tobit model)

Variables	Coefficient	Sd. Dev	t-value
Agro-ecology	0.0173	0.0375	0.46
Age of household head	0.0002	0.0020	0.14
Sex of household head	0.0751	0.0478	1.57
Education level of household head	0.0168**	0.0077	2.17
Distance from nearest market	-0.0046***	0.0012	-3.83
Farm distance	-0.0030	0.0021	-1.41
Household size	0.0006	0.0124	0.05
Access to credit services	0.0434	0.0330	1.31
Access to extension services	- 0.0405	0.0345	-1.17
Cooperative membership	0.0069	0.0324	0.21
Farm size	-0.0119	0.0201	-0.59
Improved seed	0.1014**	0.0394	2.57
TLU	0.0294***	0.0102	2.86
Household perception	0.0432	0.0326	1.32
Access to training	0.0633*	0.0327	1.94
Farm income (log)	0.0771**	0.0366	2.10
Off/non-farm income	0.0555*	0.0322	1.72
Constant	-0.4928	0.4328	-1.14
Wald $chi^2(17)$	79.82***		
Pseudo R^2	0.3773		
Log likelihood	-65.884		
Left-censored	12		
Right censored	21		
Number of observations	302		

Where ***, **& * represent the significance at 1%, 5% and 10% probability levels, respectively.
Source: Own survey result, 2023

4.3.3. Impact analysis of effect of wheat production technology packages adoption

This part of the study depends on adoption of different categories of recommended wheat technology packages, such as improved wheat seed, row planting, and the application of recommended quantities of chemical fertilizers (Table 17). The selected three technology packages generated eight possible combinations of the packages in a single or combinations of the packages. In this study, a package or combinations of packages of 18 observations and greater were selected, and an ineligible package of zero observations was dropped. Accordingly, among the combinations of the packages, 18.54% (56) of the sampled households did not adopt any technology package ($I_0R_0F_0$), 5.96% (18) of sampled households adopted improved seed and row planting only ($I_1R_1F_0$), about 9.60% (29) farmers adopted improved seed and chemical fertilizers only ($I_1R_0F_1$), and none of them adopted wheat row planting only ($I_0R_1F_0$).

Among the packages, 8.61% (26) of households adopted improved seed only ($I_1R_0F_0$) and 14.24% (43) adopted improved chemical fertilizers only ($I_0R_0F_1$). About 32.78% (99) farmers jointly adopted all the recommended wheat technology packages, such as improved seed, row planting, and the recommended amount of chemical fertilizers ($I_1R_1F_1$). So for this study, among the total combinations of technology package(s) such as no adoption ($I_0R_0F_0$), adoption of full technology packages ($I_1R_1F_1$), adoption of improved wheat seed and row planting only ($I_1R_1F_0$), adoption of improved seed and chemical fertilizers only ($I_1R_0F_1$), adoption of row planting and chemical fertilizers only ($I_0R_1F_1$), adoption of improved seed only ($I_1R_0F_0$) and adoption of chemical fertilizer only ($I_0R_0F_1$) package combinations were selected, while no adoption technology package ($I_0R_0F_0$) is used as a reference category (Table 17). Descriptive statistics of explanatory variables, outcome variables and their comparison with respect to different categories of wheat technology packages are given by Appendix Table 10.

Table 17: Combinations of wheat production technology packages

Packages	**Packages descriptions**	**Frequency**	**Percentage**
$I_0R_0F_0$	No adoption (base category)	56	18.54
$I_1R_1F_1$	Improved seed, row planting, and fertilizer	99	32.78
$I_1R_1F_0$	Improved seed and row planting only	18	5.96
$I_1R_0F_1$	Improved seed and fertilizer only	29	9.60
$I_0R_1F_1$	Row planting and fertilizer only	31	10.26
$I_1R_0F_0$	Improved seed only	26	8.61
$I_0R_1F_0$	Row planting only	0	0.00
$I_0R_0F_1$	Fertilizer only	43	14.24

Source: Own survey result, 2023.

4.3.3.1. Factors affecting adoption decision of technology package combinations

The first stage of the multinomial endogenous treatment effect model is estimated by using the multinomial logit model. To compare the technology package or combination, non-adoption of any technology package ($I_0R_0F_0$) is used as a base category. The model fits the data substantially well with the Wald chi2 (96) = 2685.98, $\chi^2 = 0.000$ which shows that the rejection of the null hypothesis that assumed all the regression coefficients is jointly equal to zero (Table 18). The model has been checked for multicollinearity problems by using VIF, and no multicollinearity problems were seen, as given in Appendix Table 11. Similarly, the model has no problems of heteroscedasticity and omitted variables (Appendix Table 12) and the marginal effect of the probability of wheat production technology packages is given by Appendix Table 13.

The location of the household head negatively influenced the likelihood of adoption of the recommended improved seed combination ($I_1R_0F_0$) only at 1% significance level. However, the location of household farmers had no significant effect on adoption of other technology package combinations, which implies that farmers' location may not influence their knowledge about the importance of adopting all the recommended technology packages but a single and incomplete technology packages, but rather location not matter if farmers educated, trained, decision and idea makers, risk takers, and eager to adopt recommended and timely diffused technologies. Sex of household positively influenced the probability of adopting improved seed and row planting technology packages ($I_1R_1F_0$) only at 1% significance level. Compared with female farmers, male households mostly engage in income-generating activities and get higher income and are eager to participate in farm trainings, which may help them to purchase improved wheat seed and adopt row planting. Male farmers may withstand with the risks of finding improved seed at far distances when the availability of these inputs is not sufficient, which influences female farmers using the recommended amount of inputs. The result is in line with the research findings of Mekonnen *et al*. (2021).

The educational level of households had a significant and direct relationship with adoption of combinations of all technology packages, such as improved seed, row planting, and chemical fertilizer ($I_1R_1F_1$) and improved seed and row planting combinations ($I_1R_1F_0$) only at 10% significance level, while having no significant effect on other single or combinations of technology package(s). This implies that educated farmers have knowledge and awareness about the importance of new agricultural technologies and the effect of adopting all the recommended technologies for improving their welfare rather than adopting a single or few package combinations. Educated farmers easily access information through collecting, analyzing, and using it for adoption of all the recommended improved technology packages compared to those who were less educated. This result is consistent with the research findings of Manda *et al*. (2016).

Distance from the nearest market significantly and negatively influenced the probability of households adopting $I_1R_1F_1$ (improved seed, row planting, and chemical fertilizer) technology combinations, $I_1R_1F_0$ (improved seed and row planting) technology combinations only, $I_1R_0F_1$ (improved seed and chemical fertilizer) technology combinations only, $I_0R_1F_1$ (row planting and chemical fertilizer) technology combinations only, and $I_1R_0F_0$ (improved seed) technology combinations only and $I_0R_0F_1$ (chemical fertilizer) technology combinations only. This shows that farmer households who are located far from input markets are constrained to get and purchase agricultural inputs, which might be due to lack of information, high cost of transportation, lack of roads, and being forced to purchase easily transportable inputs such as chemicals. The result is in line with the research findings of Ali *et al*. (2023). Similarly, distance from training centers like farmers' training centers, such as FTC, negatively and significantly influenced farmers' adoption of full wheat technology package combinations such as $I_1R_1F_1$, $I_1R_1F_0$, $I_1R_0F_1$, $I_0R_1F_1$, $I_1R_0F_0$ and $I_0R_0F_1$. This shows that as households are located far from training centers, they might lack understanding about technology adoption, and their probability of adopting technology packages has decreased. Moreover, farm distance negatively and significantly influenced households' adoption decisions of all recommended wheat production technology package combinations ($I_1R_1F_1$) at 5% significance level. As farmers are far from their homestead, they may face the problems of regularly supervising their land and the higher cost of production, which can hinder their decision to adopt wheat technology packages.

Mobile phones are found to have a positive and significant influence on households' decisions to adopt wheat technology packages ($I_1R_1F_1$ and $I_1R_0F_1$). Mobile phones are a key resource for farmers to exchange information about the importance, methods, availability, price, and sources of agricultural inputs, which further contributes to farmers' adoption of all or nearly all recommended technology packages. Farmers' agricultural cooperative membership positively and significantly influenced adoption of combination of recommended row planting and fertilizer application ($I_1R_1F_0$) combination only. Agricultural cooperative membership enables farmers to easily access to agricultural production inputs, access to credit, share knowledge and experience which could improve their adoption decision of combination of wheat row planting and application of improved seed. The size of farmland owned also negatively and significantly influenced the probability of adopting improved seed ($I_1R_0F_0$) technology package only. Larger farm size needs efficient management, and farmers are less efficient in applying recommended improved wheat seed as they own a large size of land.

The presence of a larger number of livestock owners has positively and significantly affected the probability of adopting $I_1R_1F_1$ (improved seed, row planting, chemical fertilizer) technology package combinations only. This shows that farmers who have more livestock adopted full technology packages than those who have less. Livestock helps farmers to generate income for purchasing agricultural inputs and improves soil fertility through the provision of manure and the preparation of compost. The result is consistent with Mesele *et al*. (2022) and Ali *et al*. (2023) who discussed that livestock had a positive effect on the recommended technology package.

Table 18: Factors affecting farmers' wheat technology package combinations adoption decision

Variables	Categories of technology package combinations					
	$I_0R_0F_1$	$I_1R_0F_0$	$I_0R_1F_1$	$I_1R_0F_1$	$I_1R_1F_0$	$I_1R_1F_1$
Agro-ecology	0.050	-1.752***	0.182	-0.171	0.549	0.265
	(0.491)	(0.653)	(0.552)	(0.592)	(0.692)	(0.455)
Age	0.035	-0.008	-0.025	0.020	-0.041	-0.014
	(0.024)	(0.032)	(0.033)	(0.035)	(0.037)	(0.025)
Sex	1.410*	0.651	-0.225	1.088	14.539***	0.114
	(0.816)	(0.703)	(0.637)	(0.850)	(0.520)	(0.535)
Education	0.068	0.074	-0.074	-0.070	0.252*	0.170*
	(0.112)	(0.115)	(0.144)	(0.128)	(0.148)	(0.097)
Market distance	-0.032**	-0.042**	-0.029*	-0.036*	-0.012	-0.052***
	(0.015)	(0.018)	(0.017)	(0.020)	(0.026)	(0.014)
Training distance	-0.048**	-0.065***	-0.055**	-0.048**	-0.051*	-0.069***
	(0.021)	(0.024)	(0.022)	(0.023)	(0.028)	(0.021)
Farm distance	-0.007	-0.031	-0.004	-0.035	-0.025	-0.050**
	(0.023)	(0.037)	(0.025)	(0.036)	(0.028)	(0.025)
Mobile ownership	0.710	0.120	0.259	1.418***	1.018	1.040***
	(0.476)	(0.541)	(0.533)	(0.531)	(0.621)	(0.417)
Radio ownership	0.011	0.443	-0.654	-0.768	-0.284	-0.028
	(0.465)	(0.605)	(0.533)	(0.591)	(0.707)	(0.426)
Credit services	0.795	-0.664	-0.342	-0.215	-0.477	0.307
	(0.499)	(0.547)	(0.519)	(0.528)	(0.629)	(0.410)
Extension	-0.417	-0.436	0.347	-0.081	-0.098	-0.381
services	(0.488)	(0.613)	(0.511)	(0.569)	(0.577)	(0.410)
Cooperative	0.436	-0.139	0.659	0.557	1.031*	0.045
membership	(0.428)	(0.551)	(0.523)	(0.508)	(0.577)	(0.400)
Farm size	0.166	-1.083***	-0.527	-0.405	0.030	-0.084
	(0.282)	(0.375)	(0.332)	(0.354)	(0.370)	(0.256)
Livestock	0.123	-0.264	0.106	0.173	0.105	0.225*
	(0.134)	(0.166)	(0.147)	(0.151)	(0.176)	(0.116)
Farm training	0.727	-0.122	0.142	0.466	0.772	0.660
	(0.470)	(0.633)	(0.490)	(0.542)	(0.616)	(0.404)
Off/non-farm	0.460	0.723	0.823	0.212	0.076	0.506
income	(0.463)	(0.531)	(0.501)	(0.527)	(0.639)	(0.399)
Constant	-3.435*	8.280***	2.574	-0.126	-15.571***	1.587
	(1.962)	(2.106)	(2.190)	(2.338)	(2.563)	(1.736)
Wald chi2(96) = 2685.98		Log likelihood = -462.21548			Pseudo R^2= 0.1466	
Number of observation = 302		Prob > chi2 = 0.0000				

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively. Independence of Irrelevant Alternatives of MNL assumption is checked by the Stata command "modern hausman mlogtest iia" and confirms the validity of the model.

Source: Own survey result, 2023.

4.3.3.2. Average treatment effects of wheat technology packages adoption

The second stage of impact analysis, multinomial endogenous switching regression model is used to estimate determinants of food consumption score (Appendix Table 15), household dietary diversity score (Appendix Table 16), and wheat production income (Appendix Table 17). After identifying determinants of adoption of wheat technology package combinations, the treatment effects of wheat technology package adoption on household food security (measured by household food consumption score and household dietary diversity score) and wheat production income are estimated and represented (Table 19). The findings of the study identified that joint adoption of the technology packages more improves outcome variables (household food security and wheat production income) than adopting a single or a few combinations of technology packages.

According to ATT estimation, adoption of full recommended technology packages, such as improved seed, row planting, and application of recommended fertilizer ($I_1R_1F_1$) increases household food consumption score by 21.71 percent. This implies that jointly adopting technology packages improves FCS more than adopting them in a few combinations or in isolation. In support of this finding, Chanyalew *et al*. (2021) and Mekonnen *et al*. (2021) discussed that the joint adoption of improved agricultural technology packages resulted in a higher food consumption score than when adopted in isolation. Similarly, jointly adopting the full recommended technology packages had a significant and positive impact on the probability of households to diversify their diets. Households can improve their diversity of food by 11.31 percent as they jointly adopt all the three wheat production technology packages ($I_1R_1F_1$). The result is in line with the research findings of Mekonnen *et al*. (2021), and Chanyalew *et al*. (2021), Setsoafia *et al*. (2022). Also, the results revealed that adopting full technology packages, such as improved seed, row planting, and application of recommended fertilizer ($I_1R_1F_1$) increases wheat production income (Birr/hectare) by 3.38 percent. This implies that adoption of these packages more improves the households' wheat production income than adopting the technologies in isolation. Previous studies such as Manda *et al*. (2016), Menale *et al*. (2018), Marenya *et al*. (2020), Muluken *et al*. (2021) and Setsoafia *et al*. (2022) showed that adoption of full recommended technology packages more improves farm income than adopting a few or single technology.

Moreover, the findings of the study show that households' adoption of improved seed only ($I_1R_0F_0$) resulted in a significant and positive impact on households' food consumption score and wheat production income. It increases households' food consumption score and wheat production income (Birr/hectare) by 13.72 percent and 1.83 percent, respectively. The study also revealed that households that adopted only fertilizer ($I_0R_0F_1$) increase their income (Birr/hectare) from wheat production by 1.52 percent. The result of the study also showed that adoption of the combination of improved seed and row planting ($I_1R_1F_0$) increases food consumption score and wheat production income (Birr/hectare) by 18.08 percent and 2.44 percent, respectively. Households who adopted the package by combining row planting with chemical fertilizer ($I_0R_1F_1$) could improve HDDS, HFCS, and wheat production income (Birr/hectare) by 10.96 percent, 16.05 percent and 1.83 percent, respectively. A farm household that adopted the combination of improved seed and chemical fertilizers ($I_1R_0F_1$) improves their level of income obtained from wheat production in ETB by 2.95 percent.

Table 19: Treatment effect estimation of impact of wheat technology packages adoption on FCS, HDDS and income

Outcome Variables	**Technology packages**	**Adopting (Actual)(A_1)**	**Non-adopting (Counterfactual)(A_0)**	**ATT (B) (A_1-A_0)**	$(\frac{B}{A_0})$***100**
FCS	$I_1R_1F_1$	50.96(1.77)	41.87(1.51)	9.09(2.33)***	21.71
	$I_1R_1F_0$	52.36(3.93)	44.34(1.24)	8.02(4.13)*	18.08
	$I_1R_0F_1$	50.55(3.34)	44.21(1.23)	6.34(4.54)	14.34
	$I_0R_1F_1$	51.17(2.89)	44.09(1.28)	7.08(3.16)**	16.05
	$I_1R_0F_0$	50.38(3.15)	44.30(1.27)	6.08(3.40)*	13.72
	$I_0R_0F_1$	45.38(3.69)	44.73(1.25)	0.65(3.90)	1.45
HDD	$I_1R_1F_1$	6.79(0.17)	6.10(0.14)	0.69(0.22)***	11.31
	$I_1R_1F_0$	6.38(0.58)	6.32(0.11)	0.06 (0.59)	0.95
	$I_1R_0F_1$	6.72(0.38)	6.28(0.11)	0.44(0.40)	7.00
	$I_0R_1F_1$	6.93(0.33)	6.11(0.11)	0.67(0.35)*	10.96
	$I_1R_0F_0$	6.73(0.33)	6.28(0.11)	0.45(0.35)	7.16
	$I_0R_0F_1$	6.55(0.30)	6.28(0.12)	0.27(0.33)	4.30
Wheat production income	$I_1R_1F_1$	10.08(0.05)	9.75(0.04)	0.33(0.07)***	3.38
	$I_1R_1F_0$	10.08(0.07)	9.84(0.04)	0.24(0.08)***	2.44
	$I_1R_0F_1$	10.12(0.10)	9.83(0.04)	0.29(0.11)**	2.95
	$I_0R_1F_1$	10.02(0.09)	9.84(0.04)	0.18(0.10)*	1.83
	$I_1R_0F_0$	10.02(0.08)	9.84(0.04)	0.18(0.09)*	1.83
	$I_0R_0F_1$	9.99(0.06)	9.84(0.04)	0.15(0.07)*	1.52

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey result, 2023

5. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Summary

Overall, the study aimed at examining production efficiency, adoption, and the impact of wheat production technology packages on smallholder farmers' food security and income in the Horo Guduru Wollega zone of Oromia region, Ethiopia. More specifically, the study is conducted to estimate the level of technical, allocative, and economic efficiencies of smallholder households in wheat production; identify determinant factors affecting the efficiency differentials among smallholder farmers in wheat production; identify determinants of adoption decision and intensity of wheat production technology packages; and measure the impact of wheat production technology package adoption on smallholder farmers' food security and wheat production income. The potentiality of producing wheat was used as a criterion to purposively select Horo Guduru Wollega zone and to select a sample unit from each agro-ecology. A multi-stage sampling technique was used to select the representative sample from the study area. At the first stage, two (2) potential districts, one (1) district from highland agro-ecology and one district from the midland agro-ecology were selected purposively. Then, at the next stage, the list of all selected wheat-producing *kebeles* was taken from districts' agricultural offices, and two (2) *kebeles* (for comparing differences among groups) were randomly selected from both selected district. In the final stages of probability sampling, from the listed number of wheat producer farmers, 302 sample farm households were randomly selected.

To achieve the objectives of this study, descriptive and inferential statistics and econometric models such as the parametric stochastic frontier model of Cobb-Douglas production and cost function (for the estimation of technical and allocative efficiency scores), the Tobit model (to analyze determinants of technical, allocative, and economic efficiency differentials), the two-limit Tobit model (for analyzing determinants of adoption intensity), the multinomial logit (to analyze adoption decisions), and the multinomial endogenous switching regression model (to estimate the impact of technology adoption) were employed. These models were used to analyze cross-sectional data collected from households' demographic and socioeconomic characteristics, institutional variables, farm attributes, production inputs and outputs, and agronomic practices.

The analyzed data results showed that the mean technical efficiency of wheat production for highland and midland agro-ecologies were 0.814 and 0.806, respectively, while the overall mean technical efficiency of the study area was 0.810, which ranged from 0.416 to 0.956. The mean allocative efficiency of wheat production in the study area was 0.881, and it was higher in highland (0.893), while it was 0.873 in midland. The mean economic efficiency of highland and midland agro-ecologies were 0.728 and 0.705, respectively, and the mean EE of wheat production in the study area was 0.714, varying from 0.271 to 0.928. Production elasticity is explained in terms of the coefficient of each production input used in the study area, and the sum of the elasticity coefficients of all factors of wheat production function was greater than one, which shows an increasing return to scale. The sum of the elasticity coefficients of all factors of wheat cost function was less than one, which shows that economies of scale.

Efficiency of wheat production was significantly influenced by explanatory variables from demographic, socio-economic, farm characteristics, attributes, and institutional factors. Technical efficiency of wheat production was positively and significantly affected by the educational level of households, number of livestock owned, soil fertility status, and access and purchase of improved seed while negatively affected by distance between farmers' residences and their farm sites. Allocative efficiency of wheat production is significantly and positively influenced by the educational level of households and household family size and negatively affected by agro-ecology and landholding size. Economic efficiency of wheat production is significantly and positively influenced by the level of households' education, family size, soil fertility, and access and purchase of improved seed, while landholding size and farm distance had a negative and significant effect on the economic efficiency of wheat production. Adoption intensity of wheat production technology packages was significantly and positively influenced by the educational level of the household, access and utilization of improved seed, the number of livestock owned, household participation on farm training, annual income from farm production and access to off/non-farm income, and negatively affected by households' location from the nearest market.

The adoption decision of recommended wheat technology package combinations was positively and significantly affected by sex of household head, educational level of household head, mobile phones, agricultural cooperative membership, and number of livestock and negatively influenced by distance from the nearest market, farm distance, distance from training centers, and landholding size. The multinomial endogenous switching regression model revealed that adoption of full recommended technology package $I_1R_1F_1$ (improved seed, row planting, and chemical fertilizer) has a positive and significant impact on households' food consumption score, dietary diversity score, and wheat production income. The coefficients of the outcome variables used in this study show that adoption of full technology packages had a higher effect than when the packages were adopted in isolation or in a few combinations.

5.2. Conclusion and Recommendation

Efficiency in production resource allocation with the existing inputs and technology mix contributes to attaining the expected level of wheat production. Wheat production inputs used for this study were positive and statistically significant, indicating that the importance of these inputs for wheat production in the study area. The availability of these inputs and their access at the right price, quantity, and time help agricultural farmers engage in wheat production and produce the expected output. Therefore to improve wheat production efficiency, the proper usages of the mix of production inputs needs the formulation of agricultural policies for sufficient supply wheat inputs. However, wheat production in the study area is inefficient in terms of technical, allocative, and economic efficiencies, and in order to improve the level of wheat production quantity, famers should give proper consideration with the improvement of its joint production efficiencies. Inefficiencies in all wheat production (technical, allocative, and economic) were caused by factors from educational level related to production knowledge, livestock-owned base for farm activities, soil fertility status to maximize wheat output and improved seed, which reduce production loss, family size, which serves as a source of labor, total landholding size, and distance between farmers' residences and their farm site.

Among both agro-ecologies selected for this study, there exist disparities in wheat production efficiencies across the area. From the inputs used in the model, the elasticity of output indicates increasing the level of inputs used further improves wheat production inputs. The results of this study suggest that to attain the required amount of wheat production in both agro-ecologies, the concerned bodies should regard with improving wheat production efficiencies (technical, allocative, and economic) and it's demographic, socioeconomic, and farm attributes.

The results also showed that wheat production efficiency was significantly influenced by agro-ecologies, educational level, farm distance, family size, landholding size, livestock ownership, soil fertility, and improved seed. These suggest that agricultural development policymakers should focus on the determinants of wheat production efficiency by creating and developing suitable agricultural production strategies. More specifically, it is recommended that in order to improve wheat production efficiency, government bodies and farmers should engage in improvements in education, farm infrastructure, land use efficiency, livestock production, and improving soil fertility through the use of the application of compost and by growing crops in rotation. Farmers also need to consider the cost of applying these methods and agriculture-oriented institutions should subsidize subsistence farmers to help them to attain the expected level of production efficiency. In the study area, the service provided by the agricultural extension agents is not as expected, and it had no significant influence on smallholder farmers' wheat production efficiencies. This calls the government to rearrange extension workers to engage them in the farms of the households, and farmers need to frequently contact these professionals. Moreover, farmers need to purchase and use the required amount of seed, whereas the government should make these agricultural inputs accessible to farmers to improve the efficiency of wheat production.

Adoption intensity of wheat technology packages adoption was influenced by households' demographic, socioeconomic, institutional, farm attribute, and locational characteristics. Specifically, educational level, access and utilization of improved seed, livestock owned, households' participation on farm training, annual income from farm production and access to off/non-farm income significantly and positively affected adoption intensity of wheat production technology packages and were negatively influenced by households' location from the nearest market. The study identified that scaling up adoption of wheat technology packages needs adoption of all recommended wheat technology packages in combination rather than adopting a single or few packages to bring the desired outcome of technology adoption. These suggest that farmers may face the problem of the high cost of adopting the packages, such as the cost of fertilizer (NPS and urea), seed, and chemicals, and they need practical advice on how to apply wheat row planting, usage of improved seed, and application of other technology packages. To achieve these, agriculture-oriented institutions should organize and strengthen institutions that provide regular services for the household farmers and train them on how to solve their production inputs usages and methods and improve their understanding of technology adoption. Therefore, to promote wheat production technology package adoption in the study area, any stakeholders who directly or indirectly engage in farmers' institutional issues should provide advisory services for farmers. Additionally, farmers' participation in farm training profoundly improves their awareness and willingness to adopt technology packages. Hence, government and non-government bodies should prepare regular training for farmers to improve their skills and knowledge on technology adoption. The availability of improved wheat variety and households' purchasing power were another challenge in enhancing adoption of wheat technology package, and the concerned institutions should solve the accessibility of the input and provide it for farmers at affordable prices.

The multinomial logit model result of the study also showed that farmers' decision to adopt wheat technology package/s combinations such as $I_0R_0F_1$, $I_1R_0F_0$, $I_0R_1F_1$, $I_1R_0F_1$, $I_1R_1F_0$, and $I_1R_1F_1$ was significantly influenced by sex, education of the household head, distance to market, training centers and farm area, mobile phone, agricultural cooperative membership, livestock and farm size. The effect of all these factors is clearly identified when all households jointly adopt full technology package combinations ($I_1R_1F_1$), which needs further improvement of all these significant factors for farmers to fully adopt these technology packages. Hence, the study recommends all the concerned bodies should strengthen the provision of adoption-enhancing services and encouraging smallholders' farmers to adopt packages technologies for better food security and livelihood outcomes.

The result findings of the study from the multinomial endogenous switching regression model identified that adoption of all recommended technology package combinations greatly contributes to the improvement of household food security and wheat income compared to packages adopted in isolation or in a few combinations. Therefore, to maximize the expected outcome of technology package adoption, farmers need to adopt all the recommended technology package combinations rather than adopting incomplete packages. Besides, it is suggested that agricultural policies and strategies that aim to include farmers in participatory agricultural activities and make farmers aware of the joint adoption of all the packages to improve the expected returns of adoption effects should be designed. Overall, farmers, government, and agricultural service providers should focus on opportunities and challenges of wheat production, adoption of technology packages through providing training services, and intervening in production and adoption constraints profoundly improves adoption of wheat technology packages and achieves households' expected maximum potential in productivity of wheat production and its production income. These achievements could contribute to tackle households' long-lasting food insecurity problems and enable them to expand their own sources of income generation, which will play an important role in improving smallholder farmers' welfare in the region.

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7. APPENDICES

I. Appendix Tables

Appendix Table 1: Conversion factors used to compute tropical livestock units (TLU)

Livestock Category	Conversion factor
Calf	0.25
Weaned calf	0.34
Heifer	0.75
Cow or ox	1.00
Horse/mule	1.10
Donkey adult	0.70
Donkey young	0.35
Camel	1.25
Sheep or goat adult	0.13
Sheep or goat young	0.06
Chicken	0.013
Bull	0.75

Source: Storck *et al*., 1991.

Appendix Table 2: Tests for model specification and hypotheses

Null hypothesis	Degree of freedom	λ	Critical value	Decision
$H_0: \beta_{ij} = 0$	21	29.56	32.67	Accept H_0

Source: Own survey result, 2023

Appendix Table 3: Multicollinearity test result Stochastic Cobb-Douglas production function

Variables	VIF	1/VIF
lnland	3.08	0.325061
lnlabor	2.54	0.394368
lnoxen	3.71	0.269209
lnfertilizer	1.71	0.585485
Lnseed	2.99	0.334102
Lnchemical	1.31	0.765684
Mean VIF	**2.56**	

Source: Own survey result, 2023

Appendix Table 4: Multicollinearity test result for determinants of TE

Variables	VIF	1/VIF
Agro-ecology	1.30	0.768030
Education level of household	1.35	0.740645
Farm Distance	1.18	0.845990
Family size of household	1.04	0.965634
Land holding size	1.14	0.875972
Access to extension services	1.14	0.875028
Access to credit services	1.08	0.925881
Mobile ownership	1.06	0.941835
Cooperative membership	1.04	0.965539
Livestock	1.30	0.771341
Soil fertility status	1.19	0.840759
Access and purchase of improved seed	1.10	0.909128
Access to off/non-farm income	1.05	0.954203
Mean VIF	**1.15**	

Source: Own survey result, 2023

Appendix Table 5: Multicollinearity test result Stochastic Cobb-Douglas cost function

Variables	VIF	1/VIF
lnland cost	2.65	0.377997
lnlabor cost	2.14	0.466504
lnoxen cost	1.51	0.662178
lnfertilizer cost	2.41	0.415116
lnseed cost	2.34	0.427023
lnwheat output	2.08	0.480876
lnchemical cost	1.12	0.891205
Mean VIF	**2.04**	

Source: Own survey result, 2023

Appendix Table 6: Multicollinearity test result for determinants of AE

Variables	VIF	1/VIF
Agro-ecology	1.30	0.768030
Education level of household	1.35	0.740645
Farm Distance	1.18	0.845990
Family size of household	1.04	0.965634
Land holding size	1.14	0.875972
Access to extension services	1.14	0.875028
Access to credit services	1.08	0.925881
Mobile ownership	1.06	0.941835
Cooperative membership	1.04	0.965539
Livestock	1.30	0.771341
Soil fertility status	1.19	0.840759
Access and purchase of improved seed	1.10	0.909128

Access to off/non-farm income	1.05	0.954203
Mean VIF	**1.14**	

Source: Own survey result, 2023

Appendix Table 7: Multicollinearity test result for determinants of EE

Variables	VIF	1/VIF
Agro-ecology	1.30	0.768030
Education level of household	1.35	0.740645
Farm Distance	1.18	0.845990
Family size of household	1.04	0.965634
Land holding size	1.14	0.875972
Access to extension services	1.14	0.875028
Access to credit services	1.08	0.925881
Mobile ownership	1.06	0.941835
Cooperative membership	1.04	0.965539
Livestock	1.30	0.771341
Soil fertility status	1.19	0.840759
Access and purchase of improved seed	1.10	0.909128
Access to off/non-farm income	1.05	0.954203
Mean VIF		**1.13**

Source: Own survey result, 2023

Appendix Table 8: Multicollinearity test for determinants of wheat production adoption intensity

Variables	VIF	1/VIF
Agro-ecology	1.37	0.731473
Age of household head	1.16	0.869975
Sex of household head	1.08	0.928955
Education level of household head	1.30	0.771289
Distance from nearest market	1.11	0.899884
Farm distance	1.30	0.777214
Family size	1.15	0.870805
Access to credit services	1.09	0.913828
Access to extension services	1.19	0.837801
Cooperative membership	1.07	0.934157
Farm size	1.16	0.859517
Improved seed	1.13	0.888637
TLU	1.35	0.740381
Household perception	1.09	0.918669
Access to training	1.08	0.925333
Annual income (log)	1.28	0.783678
Off/non-farm income	1.06	0.946897
Mean VIF	**1.17**	

Source: Own survey result, 2023

Appendix Table 9: Model diagnosis test of adoption intensity

Types of tests	Test name	Statistics	Prob
hettest(Breusch–Pagan/Cook–Weisberg (Chi2) (1)	Heteroscedasticity	1.43	0.1325
ovtest (Ramsey RESET test (F(3, 351))	Omitted Variables	0.75	0.5204

Source: Own survey result, 2023

Appendix Table 10: Summary of outcome variables of by adoption categories

Variables	**$I_1R_1F_1$**		**$I_1R_1F_0$**		**$I_1R_0F_1$**		**$I_0R_1F_1$**		**$I_1R_0F_0$**		**$I_0R_0F_1$**		**$I_0R_0F_0$**	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
FCS	52.36	17.7	50.76	17.2	50.55	23.9	51.17	16.3	50.38	16.4	45.38	24.5	22.41	7.9
HDDS	6.93	1.8	6.38	2.5	6.72	2.1	6.75	1.7	6.73	1.7	6.55	2.0	4.64	1.2
Wheat income	2682	1246	2538	8522	2907	1552	2582	1314	2458	1128	2393	9899	1000	5665
	6.26	6.08	3.33	.58	5.86	3.59	4.19	0.04	0.76	8.36	3.72	.83	8.92	.27

Note: **$I_1R_1F_1$** represents adoption all of improved seed, row planting, and chemical fertilizer; **$I_1R_1F_0$** represents adoption of improved seed and row planting only; **$I_1R_0F_1$** represents adoption of improved seed and chemical fertilizer only; **$I_0R_1F_1$** represents adoption of row planting and chemical fertilizer; **$I_1R_0F_0$** represents adoption all of improved seed only; **$I_0R_0F_1$** represents adoption of chemical fertilizer only

Source: Own survey result, 2023

Appendix Table 11: Multicollinearity test for determinants of technology adoption decision

Variables	**VIF**	**1/VIF**
Agro-ecology	1.38	0.726339
Age of household head	1.07	0.933267
Sex of household head	1.06	0.942419
Education of household head	1.27	0.787472
Market distance	1.07	0.938507
Training distance	1.08	0.923440
Farm distance	1.20	0.834303
Mobile ownership	1.08	0.922407
Radio ownership	1.15	0.859982
Access to credit services	1.11	0.897430
Access to extension services	1.16	0.859982
Cooperative membership	1.07	0.938490
Farm size	1.16	0.859947
Livestock	1.34	0.746648
Access to farm training	1.08	0.923392
Access to off/non-farm income	1.05	0.955829
Mean VIF	**1.15**	

Source: Own survey result, 2023

Appendix Table 12: Model diagnosis test of adoption decision

Types of tests	**Test name**	**Statistics**	**Prob**
hettest(Breusch–Pagan/Cook–Weisberg (Chi2) (1)	Heteroscedasticity	1.48	0.2231
ovtest (Ramsey RESET test (F(3, 353))	Omitted Variables	0.16	0.9239

Source: Own survey result, 2023

Appendix Table 13: Marginal effects of wheat technology packages adoption decision

Variables	dy/dx	Std. dev	z-value
Agro-ecology	-0.465	0.292	-1.59
Age of household head	0.027	0.015	1.78
Sex of household head*	0.431	0.370	1.16
Education of household head	-0.053	0.059	-0.90
Market distance	-0.010	0.009	-1.11
Training distance	-0.017	0.012	-1.39
Farm distance	0.013	0.016	0.84
Mobile ownership*	0.009	0.258	0.04
Radio ownership*	-0.014	0.275	-0.05
Access to credit services*	0.084	0.260	0.32
Access to extension services*	-0.088	0.264	-0.33
Cooperative membership*	0.273	0.252	1.09
Farm size	-0.157	0.156	-1.01
Livestock	-0.069	0.079	-0.88
Farm training *	0.070	0.254	0.28
Access to off/non-farm income*	0.262	0.250	1.05

Source: Own survey result, 2023

Appendix Table 14: Validity test of the selection instrument based on non-adopter households

Variables	**FCS**	**HDDS**	**lnIncome**
Agro-ecology	-5.892(3.154)*	-0.012(0.578)	0.079(0.229)
Age of household head	0.135(0.149)	-0.008(0.027)	-0.013(0.010)
Sex of household head	0.512(2.857)	-0.615(0.523)	0.165(0.207)
Education of household head	-0.503(0.592)	-0.127(0.108)	0.077(0.043)*
Market distance	-0.134(0.087)	0.002(0.016)	0.002(0.006)
Training Distance	0.140(0.088)	-0.006(0.016)	0.008(0.006)
Farm distance	-0.260(0.155)	0.001(0.028)	-0.012(0.011)
Mobile ownership	0.556(3.016)	0.028(0.552)	-0.681(0.219)***
Radio ownership	-3.864(2.394)	-0.578(0.438)	0.684(0.173)***
Credit service	2.720(2.589)	0.276(0.474)	-0.009(0.188)
Extension service	-1.835(2.253)	-0.388(0.413)	-0.337(0.163)**
Cooperative membership	0.840(2.229)	0.136(0.408)	0.560(0.161)***
Farm size	-0.877(1.612)	0.058(0.295)	0.292(0.117)**
Livestock	-1.268(0.810)	0.096(0.148)	-0.044(0.058)
Training received	-4.199(2.269)*	0.254(0.416)	-0.112(0.164)
Off/non-farm income	-2.020(2.519)	-0.304(0.461)	-0.034(0.183)
Constant	46.054(12.947)***	5.507(2.373)**	8.465(0.940)***
R-squared	0.3761	0.1898	0.5153

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey result, 2023

Appendix Table 15: Second stage estimates of MESR for food consumption score (FCS)

Variables	**$I_0R_0F_0$**		**$I_1R_1F_1$**		**$I_1R_1F_0$**		**$I_1R_0F_1$**		**$I_0R_1F_1$**		**$I_1R_0F_0$**		**$I_0R_0F_1$**	
	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev
Location	-5.973	3.820	-8.05***	1.840	-22.78***	6.208	2.778	72.21	-39.894	47.57	102.74	68.59	-13.425	35.40
Age	-0.028	0.634	-0.284	1.131	5.300*	3.059	-0.798	11.29	-1.625	1.655	1.672	3.689	3.388	3.240
Sex	-3.710	5.023	-10.02	15.66	-4.576	5.980	-8.254	230.6	-21.901	152.8	-188.2***	35.58	51.153	223.1
Education	1.127	2.887	-4.71***	1.680	-11.22***	3.999	-15.19	55.60	-7.752	18.09	2.619	3.099	-10.476	9.867
Market distance	-0.561	0.460	-0.160	0.313	2.171**	0.880	0.488	8.602	-0.761	3.369	3.447***	0.765	3.455	4.379
Training distance	-0.339	0.495	-0.216	0.354	-2.429	1.592	-0.436	9.441	-2.11	6.099	4.124***	1.284	4.830	6.977
Farm distance	-0.68***	0.129	-0.698	0.561	0.784	1.805	-1.432	8.034	1.675	3.043	4.962***	1.475	3.209	4.805
Mobile ownership	2.494	8.965	4.536	12.41	-16.657	25.27	27.45	474.4	-37.34	51.02	-146.8***	25.46	-20.526	47.76
Radio ownership	-0.343	5.937	-13.579	10.70	56.718***	12.89	-65.52	344.1	-2.526	63.86	63.467	49.90	-39.2**	18.64
Credit services	5.637	6.394	-10.736	7.267	27.497	8.591	-60.29	74.92	-28.203	41.46	138.8***	36.49	-25.117	72.87
Extension services	-5.444	13.33	10.46**	5.144	8.303	31.31	31.78	107.4	26.953	79.25	27.998	35.10	74.6***	28.04
Cooperative membership	-1.04	5.51	19.543	12.19	-70.94***	11.88	51.69	357.9	8.100	35.54	-48.704*	28.24	61.613	38.69
Land size	0.259	4.669	-8.801	10.15	-26.292	16.47	-32.46	58.19	-47.568	73.72	81.7***	13.76	0.532	26.53
Livestock	-0.651	1.313	2.441	1.642	-2.969	8.860	2.212	23.49	-3.322	6.82	15.21***	3.909	-12.44	55.45
Off/non-farm income	1.457	2.837	3.232	7.779	-11.633	12.18	14.73	53.01	54.5**	22.77	-16.264	16.17	-53.43*	27.47
Ancillary														
σ^2	162.2	349.8	887	772	489***	275.5	991	125	295.7	287.6	749.2***	351.1	243.3	325.9
λ_0			-0.734	0.606	0.761	0.509	-0.321	0.530	-1.04**	0.501	0.52***	0.143	0.424	0.537
λ_1	1.198**	0.524			0.282	0.553	-0.488	1.066	-0.038	0.576	0.157	1.306	-1.119*	0.648
λ_2	-0.494	0.407	-0.078	0.794			0.074	0.660	-0.799	0.705	-0.110	0.070	0.485	0.390
λ_3	-0.814	0.733	0.935	0.733	0.296	0.515			-0.079	0.627	-1.419*	0.830	0.672	0.633
λ_4	0.215	0.688	0.955	1.145	0.183	1.059	1.3***	0.255			0.415	0.443	-0.163	0.887
λ_5	0.176	0.629	-0.407	0.399	0.671	0.891	-0.174	0.817	0.8***	0.120			-0.281	0.631
λ_6	-0.021	0.629	-0.497	0.757	-0.528	0.948	-0.632	0.569	0.556	1.129	0.493**	0.204		
No of observation	56		99		18		29		31		26		43	

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.

Source: Own survey result, 2023

Appendix Table 16: Second stage estimates of MESR for household dietary diversity score (HDDS)

Variables	**$I_0R_0F_0$**		**$I_1R_1F_1$**		**$I_1R_1F_0$**		**$I_1R_0F_1$**		**$I_0R_1F_1$**		**$I_1R_0F_0$**		**$I_0R_0F_1$**	
	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev
Location	-0.129	0.801	-0.736	0.955	1.198	0.830	-1.146	4.172	-3.058	3.813	1.291	25.00	1.226	0.961
Age	0.016	0.154	-0.045	0.040	0.055	0.641	0.166	0.392	-0.217*	0.129	1.291	0.654	0.0006	.095
Sex	-2.105	2.99	-1.819*	1.055	3.678	2.768	8.061	7.677	-4.604	5.343	-0.956	10.25	1.685	6.197
Education	-0.63**	0.280	-0.506**	0.214	0.430	1.332	-2.00**	0.772	-0.80**	0.403	-0.620	1.230	-0.097	0.638
Market distance	-0.033	0.101	0.003	0.042	0.198	0.146	-0.026	0.264	-0.072	0.056	-0.051	0.341	0.001	0.182
Training distance	-0.023	0.084	-0.038	0.039	-0.062	0.282	0.235	0.251	-0.056	0.121	-0.031	0.489	-0.097	0.244
Farm distance	-0.052	0.112	0.061	0.038	-0.037	0.376	-0.261	0.954	0.029	0.305	-0.251	0.430	-0.017	0.246
Mobile ownership	1.810	2.31	-1.35***	0.471	-2.659*	1.413	6.962	4.775	-6.437	5.886	-3.049	7.281	1.484	5.226
Radio ownership	-2.287	1.97	-0.815	0.952	0.957	1.662	-9.6***	2.716	-1.351	4.448	-1.606	12.03	-2.530	4.335
Credit services	-0.102	1.20	-1.12***	0.207	-1.73	1.872	-5.960	3.950	-2.329	2.541	-4.053	8.304	-1.009	2.650
Extension services	0.405	1.08	1.45***	0.493	1.73***	1.652	2.694	2.479	3.006	4.302	0.310	10.91	2.427	4.836
Cooperative membership	0.749	1.20	2.34***	0.171	-0.211	1.914	3.533	4.171	-1.807	1.504	-2.894	6.162	2.932	2.323
Land size	-0.795	1.08	-0.911**	0.358	-1.05	2.290	-5.554	3.745	-3.714	2.887	-1.085	9.284	-0.283	3.104
Livestock	0.398	0.431	0.253*	0.135	-0.218	1.075	0.504	1.286	-1.020	0.769	-0.372	4.741	0.366	0.669
Off-farm income	0.004	2.07	1.32***	0.267	1.896*	1.128	-1.857	2.089	3.698	2.771	1.506	2.678	0.555	3.164
Ancillary														
σ^2	200***	12.8	196.9***	8.927	457.3***	2.022	197.2	436.3	365.6	455.5	896.6	416.9	184.35	373.0
λ_0			-0.600	0.714	0.826	0.739	0.376	0.970	-0.033	0.981	0.429	.640	-0.552	0.655
λ_1	0.042	0.507			0.273	0.134	-0.468	0.430	0.059	0.466	0.472	1.888	-0.424	0.712
λ_2	-0.937	0.640	-0.080	0.964			-0.522	0.586	-1.4***	0.178	0.080	0.357	0.621	0.815
λ_3	1.364	0.989	-0.243	0.900	-1.320	0.840			-0.028	0.799	-0.472	0.759	0.330	0.579
λ_4	0.370	1.03	1.542**	0.677	0.434	0.276	-0.228	0.385			0.6***	0.165	1.059	1.132
λ_5	-0.469	0.699	-0.292	0.538	0.169	0.952	0.822	0.577	1.177**	0.518			-0.9***	0.174
λ_6	-0.306	0.549	-0.124	0.388	0.374	0.934	-1.112*	0.587	-0.099	0.829	-1.206	0.775		
No observations	56		99		18		29		31		26		43	

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.
Source: Own survey result, 2023

Appendix Table 17: Second stage estimates of MESR for household wheat production income (lnIncome)

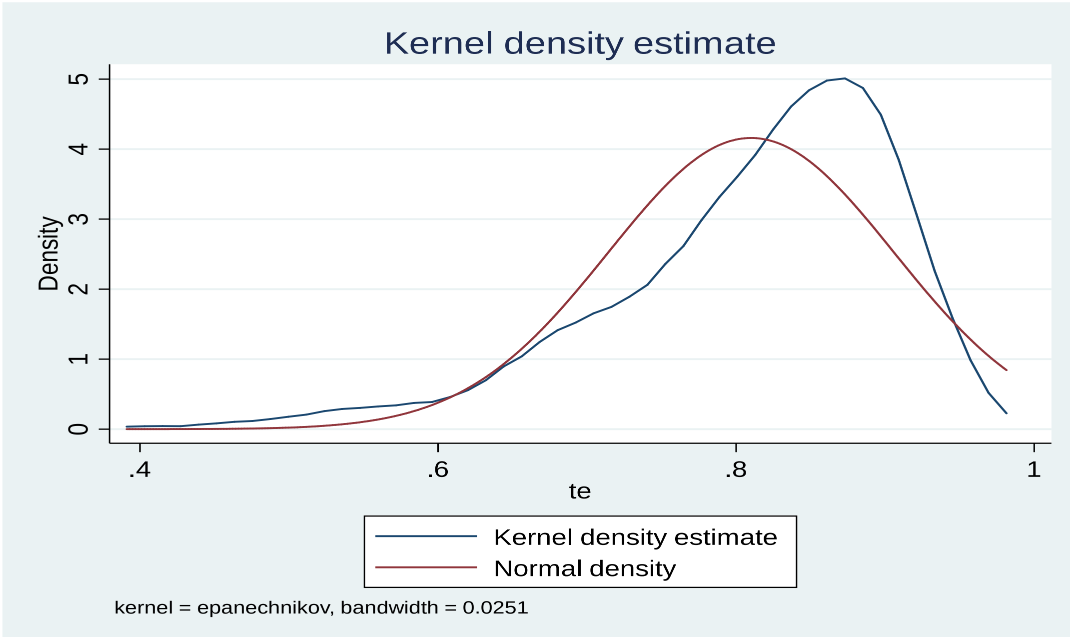
Variables	$I_0R_0F_0$		$I_1R_1F_1$		$I_1R_1F_0$		$I_1R_0F_1$		$I_0R_1F_1$		$I_1R_0F_0$		$I_0R_0F_1$	
	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev	Coef	Std. Dev
Location	0.110	0.190	0.103	0.222	-0.159	0.360	0.326	1.832	-0.519	1.107	1.107	1.171	0.257	0.494
Age	-0.058	0.036	-0.038***	0.012	-0.101	0.070	-0.006	0.048	-0.047	0.050	0.16***	0.014	0.006	0.064
Sex	-0.089	0.459	-0.358*	0.189	0.125	0.152	2.930	1.799	-1.086	0.745	-4.6***	0.799	0.125	2.018
Education	0.364***	0.116	0.074	0.059	-0.006	0.236	0.056	0.406	-0.045	0.212	0.87***	0.234	-0.007	0.112
Market distance	-0.012	0.015	-0.004	0.011	-0.033	0.039	0.068	0.120	-0.030	0.055	0.11***	0.026	0.041	0.032
Training distance	-0.012	0.034	-0.021	0.020	0.033	0.038	0.055	0.136	-0.074	0.057	0.18***	0.051	0.029	0.042
Farm distance	-0.030	0.021	0.002	0.019	0.002	0.064	0.010	0.315	-0.022	0.074	0.14***	0.047	0.021	0.066
Mobile ownership	-1.012	0.675	-0.586***	0.193	- 0.78**	0.377	0.971	4.143	-0.060	0.409	-4.7***	0.882	-0.646	1.093
Radio ownership	1.411***	0.196	0.255	0.326	-0.760	0.478	-0.782	1.529	-0.060	0.421	6.14***	0.295	-0.114	0.551
Credit services	0.014	0.514	-0.036	0.467	0.433	0.430	-1.488	2.660	-0.333	0.375	6.97***	0.417	-0.119	0.832
Extension services	-0.715	0.525	-0.144	0.177	-0.405	0.410	0.227	5.832	0.300	0.439	0.014	1.321	0.521	1.182
Cooperative membership	0.109	0.242	-0.052	0.225	0.216	0.143	0.488	1.559	0.194	0.446	-3.3***	0.338	0.241	0.718
Land size	0.681**	0.310	-0.041	0.258	0.533	0.365	-0.177	2.704	-0.901	0.603	3.60***	0.879	0.224	0.772
Livestock	-0.071	0.103	0.020	0.054	-0.208	0.309	-0.309	0.963	-0.132	0.345	-0.14	0.201	-0.173	0.522
Off-farm income	0.026	0.249	0.514***	0.165	0.249	0.192	-1.616	3.215	0.826	0.554	-0.09	0.504	-0.505	0.520
Ancillary														
σ^2	38.71***	11.93	14.677	6.380	18.6***	0.166	139.**	54.89	12.78	43.73	136***	11.19	14.802	39.91
λ_0			-0.314**	.449	-0.493	0.740	0.298	0.635	-1.09*	0.597	0.476	0.498	0.741	0.622
λ_1	0.807**	0.315			0.636	0.548	-0.7***	0.297	0.063	1.014	0.30***	1.254	-0.982	0.902
λ_2	0.698*	0.386	0.372	.624			1.189	1.144	0.023	0.385	-0.211	0.097	0.825	0.937
λ_3	-1.252**	0.544	-1.338***	.284	0-.918	0.275			-0.50*	0.272	-1.277	0.893	-0.158	0.359
λ_4	-0.168	0.523	0.846	.838	1.281	0.648	-0.756	0.764			-0.131	0.094	-0.396	0809
λ_5	0.184	0.434	0.295	.526	1.054	0.189	0.098	0.389	1.04*	0.631			0.009	0.664
λ_6	-0.271	0.610	0.034	.329	1.182	0.279	-0.171	1.010	0.101	0.801	0.837	0.549		
No observations	56		99		18		29		31		26		43	

Where ***, ** & * represent the significance at 1%, 5% & 10% probability levels, respectively.

Source: Own survey result, 2023

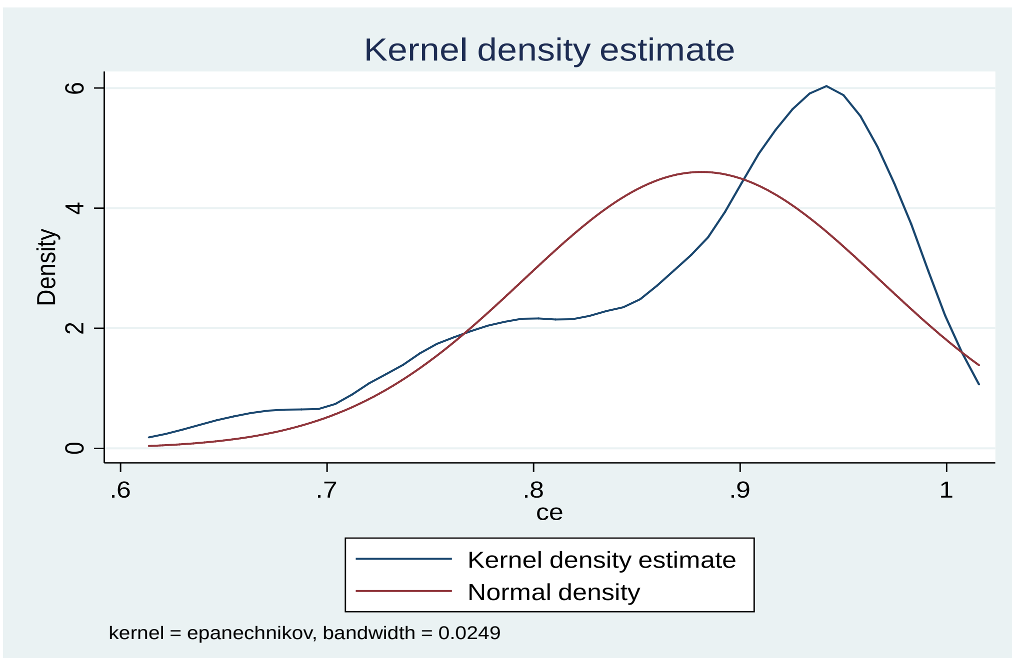
II. Appendix Figures

Appendix Figure 1: Kernel density graph of technical efficiency of wheat production



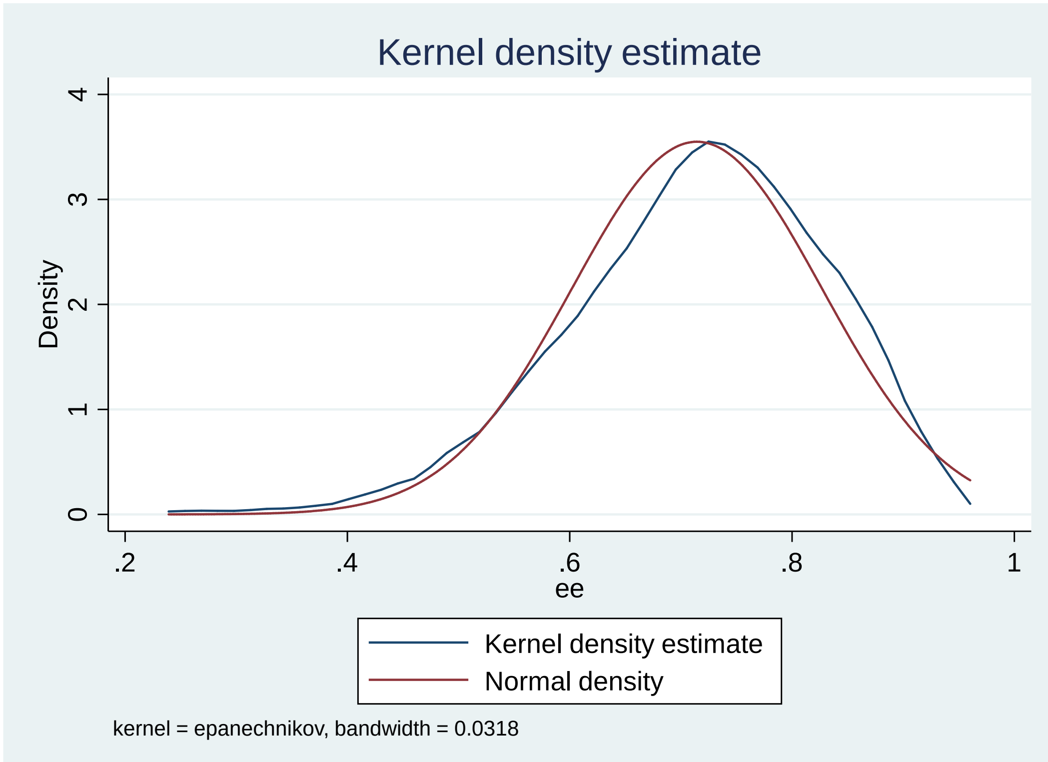
Source: Own survey result, 2023

Appendix Figure 2**:** Kernel density graph of allocative efficiency of wheat production



Source: Own survey result, 2023

Appendix Figure 3**:** Kernel density graph of economic efficiency of wheat production



Source: Own survey result, 2023

III. Appendix Survey Questionnaires Used for the Study

Questionnaire developed for farm households' survey questionnaire for wheat production efficiency, technology packages adoption and its impact on smallholder food security and income in Horo Guduru Wollega zone, Ethiopia

General instructions for enumerators:

1. Before starting the interview, please try to introduce you self to the respondents and clearly discus for them about the purpose collecting these data
2. Complete all the questions carefully without any missing
3. If you are facing the problems of difficulty in the values of the responses during the interview, try to you approaching value/s.

4. Try to take the responses from wheat producers and don't turn to other next respondent/s before filling all the questions of what you started.

General information

4.1.Name of the enumerator____

4.2.Name of the household head____

4.3. Respondent identity number______________

4.4. Date of interview: Day ____ Month _____ Year _______

4.5. Name of district ______________________________

4.6. Name of *kebele* ______________________________

4.7. Agro-ecological setting of district:

i. Highland [ ] **ii.** Midland [ ]

1. Characteristics of the household head

The head of family member is responsible for responding these questions and if the family head is not available after repeated attempt of contacting, collecting data from the spouse or older family member is possible.

1.1.Sex of the respondent: [1] Male [0] Female

1.2.Age of the respondent (in year): _______

1.3.Marital status:

[1] Single [2] Married [3] Widowed [4] Divorced

1.4. Religion of the respondents:

[1] Protestant [2] Orthodox [3] Muslim [4] Waaqeffataa/ttuu

[5] Others, specify if any:________________________________

1.5. Ethnic category of households:

[1] Oromo [2] Amhara [3] Tigray [4] Other (specify): ______________

1.6. Education level of the respondent (grade attended in year): ________

1.7. Among the overall members the family, how many people have attended school and able to read and write? ________________________________

1.8.Family members of household head

Age class (year)	Male	Female	Total
<10			
10-13			
14-16			
17-50			
>50			
Total			

1.9. Main occupation of the household head: [1] Farming [2] Non-farming [3] Others Specify:_____________________________

1.10. Age structure and engagement in farming of household member:

Age class (year)	Male	Female	Total
<10			
10-13			
14-16			
17-50			
>50			
Total			

Age class (year)	No of Males		No of Females	
	Full time	Part-time	Full time	Part-time
<10				
10-13				
14-16				
17-50				
>50				
Total				

1.11. Households' farming experience in production of:

i. Cereals:____________________ and wheat:______________

ii. Pulses:_____________________

iii. Vegetables and fruits:__________

iv. Oil crops and coffee:__________

v. Others: specify:______________

1.12. Do you own livestock? [1] Yes [0] No

1.12.1. Do you have your own oxen for plowing? [1] Yes [0] No

1.12.2. If yes, how many oxen do you have? [______]

1.13. If question 1.13 is yes, fill the following table

No.	Types of animal	Total number of animals owned
1	Cows	
2	Oxen	
3	Bull	
4	Heifer	
5	Calf	
6	Horse	
7	Donkey	
8	Mule	
9	Sheep	
10	Goat	
11	Chicken	
12	Others	

1.14. Do you have access to off/non-farm income?

[1] Yes [2] No

1.15. If yes, what are the sources of the income?

No	Sources	Annual income (in ETB)
1	Off-farm activities	

2	Sale of livestock and livestock product	
3	Farm activity for other individual	
4	Social work	
5	Sale of firewood	
6	Remittances	
7	Aid and gifts	
8	Salary/wage	
9	Others	

2. Wheat production technology packages adoption

2.1. Do you use wheat improved varieties

[1] Yes [0] No

2.2. If yes which and how much variety/ies used?

[1].________________kg________________[2]________________kg_______________

[3]________________kg________________[4]________________kg________________

[5]________________kg________________,[6]Others________________kg_________

2.3. Did you use local wheat seed?

[1] Yes [0] No

2.4. If yes which local wheat seed?

[1].________________kg________________[2]________________kg________________[3]
________________kg________________[4]________________kg________________[5]__
______________kg________________,[6]Others________________kg_____________

2.5. Area under improved wheat variety in hectare [______________ha]

2.6.Area under local wheat variety in hectare [__________________ha]

2.7.Source/s of wheat improved varieties?

[1] Stock from previous harvest [2] Local market [3] Agricultural cooperatives [4] Left from last year

2.8. Did you get improved wheat seed of the right quantity?

[1] Yes [0] No

2.9. Did you get improved wheat seed of the right price?

[1] Yes [0] No

2.10. How much you paid for purchasing 100 Kg of improved wheat seed?____________ETB

2.11. Did you perceive a better yield of using wheat improved varieties?

[1] Yes [0] No

2.12. Do you expect good price for wheat produce?

[1] Yes [0] No

2.13. Do you use fertilizers in wheat field? [1] Yes [0] No

2.14. If yes, what type/s of fertilizer and how much did you use per hectare?

[a] Compost [______kg] [b] DAP [______kg] [c] Urea [______kg]

[d] Others, specify ____

2.15. Do you get fertilizer of the right quantity?

[1] Yes [0] No

2.16. Do you get fertilizer at the right price?

[1] Yes [0] No

2.17. Do you use chemical in wheat field?

[1] Yes [0] No

2.18. If yes, what type and how much did you use per hectare?

[1]________(_____L) [2]________(_____L) [3]________(_____L)

[4]________(_____L)

2.19. Do you get chemical of the right quantity?

[1] Yes [0] No

2.20. Did you get chemical at the right price?

[1] Yes [0] No

2.21. Did you plant wheat by using row planting?

[1] Yes [0] No

2.22. If yes, area under row planting for wheat production in hectare [____________ ha]

2.23. Area under broadcasting for wheat production in hectare [____________]

2.24. How many time/s did you plough your land under wheat production? [__________]

2.25. Have you ever attended a field day or demonstration trial on wheat production and technology adoption?

[1] Yes [0] No

2.26. Have you ever attended training related to crop production in the last five years?

[1] Yes [0] No

2.28. If yes, the type of training? ____

2.29. Have you attended trainings on wheat production and technology adoption?

[1] Yes [0] No

2.30.Do you need agricultural extension services? [1] Yes [0] No

2.31.If yes, have you accessed and contacted extension workers regarding adoption of wheat technology packages?

[1] Yes [0] No

2.32. When did you start getting extension service? [________year]

2.33. Are you a member of agricultural cooperatives for agricultural technology adoption?

[1] Yes [0] No

2.34.Do you need credit services for agricultural production purposes? [1] Yes [0] No

2.35.If yes, have you accessed for production and adoption wheat technology packages?

[1] Yes [0] No

2.36. Did you take credit for wheat production and technology packages adoption?

[1] Yes [0] No

3.37. If yes, from whom did you get credit for wheat production? (√) (Multiple responses are possible)

[1] Relative [2] Bank [3] Micro finance institution [4] Friends [5] Traders [6] NGO [7] Peasant association [8] Others (specify) ______________________________

2.38. If yes how much you received? __________________________ETB

2.39. Did you irrigation for wheat production in addition to rain-fed?

[1] Yes [0] No

2.40. How many minutes/hours you travel to purchase wheat production inputs?_______________ minutes/hour

2.41. How far you travel to reach to training centers such as FTC in minute?__________

2.42. How you rate the status of soil fertility under wheat production?

[1] Fertile [0] Infertile

2.43. Do you own mobile phone? [1] Yes [0] No

2.44. Do you own radio? [1] Yes [0] No

2.45. Do you have any information about recommended rate of fertilizer application per hectare?

[1] Yes [0] No

2.46. If yes do you applied recommended amount of improved wheat seed per hectare?

[1] Yes [0] No

2.47. If yes, do you apply recommended rate of fertilizers?

[1] Yes [0] No

2.48. Do you use recommended amount of chemicals such as herbicide and pesticide per hectare?

[1] Yes [0] No

3. Wheat Production Efficiency

3.1. How many hectares of land you allocated for wheat production?____________________

3.2. Number of plots of under wheat production:_______________

3.3. How do you get the land?

[1] Own _________________________ha

[2] Share cropping: _________________________ha

[3] Rented ________________ha and its price per hectare:___________________ETB

[4] Others, specify________________(_________________________ha)

3.4. How many kg of fertilizers is used for wheat production per hectare?

[1] DAP________________ [2] NPS:_________________ [3]UREA_____________

3.5. How much you paid for purchasing 1 quintal of fertilizer

[1] DAP___________ETB [2] NPS:_________ETB [3]UREA_____________ ETB

3.6. How many oxen labor is used for wheat production?____________________

3.7. For how many days you used oxen for wheat production during ploughing?____________days

3.8. For how many days you used oxen for wheat production during other activities?____________days

3.9. Estimate cost of oxen labor per day?_________________ETB

3.10. How many human days these labors spent for wheat production in total?

3.11. Estimate cost of labor per day?_________________ETB

3.12. Sources of labor used for wheat production? [1] Family labor [2] Hired labor [3] Exchange labor [4] Others

Activities	Sources of labor			
	Family labor	Hired labor	Exchange labor	Others if any
Land preparation and plowing at all stages				
Sowing				
Cultivation and weeding at all stages				
Harvesting				
Threshing				
Others				

3.13. Estimate total labor days used for wheat production?

	Sources of labor			
	Family labor	Hired labor	Exchange labor	Others if any
No. of days spent for land preparation and plowing at all stages				
No. of days spent for sowing				
No. of days spent for cultivation and weeding at all stages				
No. of days spent for harvesting				
No. of days spent for threshing				
No. of days spent for others				

3.14. How many chemicals (herbicide and pesticide) used for wheat production in liters__________________?

3.15. How much you paid for 1 Liters of chemicals for wheat production?_______________ETB

3.16. Have you used other fertilizers like compost?

[1] Yes [0] No

3.17. If yes how many kg of compost is used for wheat production per hectare? ______kg

3.18. Do you apply recommended ploughing frequency?

[1] Yes [0] No

3.19. Do you follow timely planting?

[1] Yes [0] No

3.20. If yes, which month?__________________

3.21. Do you harvest wheat produce on time? [1] Yes [0] No

3.22. Do have appropriate store for wheat produce? [1] Yes [0] No

3.23. Do you apply recommended timely weeding?

[1] Yes [0] No

3.24. Do you apply activities for soil conservation?

[1] Yes [0] No

3.25. Do you follow crop rotation? [1] Yes [0] No

3.26. How far you travel to reach to farm sites in minute?_______

3.27. Do you have any information about wheat production in 2022/3 by using phones and radio?

[1] Yes [0] No

3.28. If yes, what type of information did you get? (√) [1]Input information [2] Input price information [3] Product information [4] Other (specify) ____________________

3.29. If yes, from whom did you get the information? (√)

[1] DAs [2] *Kebele* administration [3] *Woreda* experts [4] Radio/Television [5] Cooperatives [6] Others (specify) __________________________________

3.34.At what time interval do you get the information?

[1] Daily [2] Weekly [3] Monthly [4] Annually

3.35.For how long you were producing wheat? ___________years

3.36.How much quantity of wheat you produced in 2022/2023?__________________quintal

3.37.Last year how many quintals of wheat yield produced? _______quintal

3.38.How is the trend of wheat yield in the past five years?

A. Increasing, why? ____

B. Decreasing, why? ____

C. Constant, why? ____

3.35. Do you want to expand wheat production? [1] Yes [0] No

3.36. What opportunities will help you to expand wheat production? ____

3.36. List wheat production constraints____

3.37. What is your expectation about wheat productivity in the next year?

[1] Increase [2] Decrease [3] The same [4] No expectation

4. Impact analysis data

4.1. For what you produce wheat?

[1] Consumption [2] Sale [3] Both

4.2. How much quantity of wheat you sold in 2022/2023?__________________quintal and its price _____________ETB per quintal

4.3. How much quantity of wheat you consumed in 2022/2023?__________________quintal

4.4. Annual farm income of household head

No.	Sources of income	Quantity	Unit price	Revenue	Total cost	Income
1	Crops (exclude wheat)					
2	Wheat production only					
3	Livestock					
4	Others non-crops					
5	Others if any					
6	Total					

4.5. Fill the table depending on food groups consumed by each household member/s within 24 hours periods of time (put 1 for yes, 0 otherwise) (Data for household dietary diversity score).

No	**Food groups and items**	**1 or 0**
1	Cereals (Any food made from wheat, maize, teff, sorghum, barely, etc.?)	
2	Vegetables (Any vegetable food like onion, tomato, cabbage, lettuce, squash, and other vegetables?	
3	Fruits (Any fruits like papaya, mango, apple, avocado and other fruits?	
4	Meat (Any beef, goat, lamb, wild game, chicken, duck, or other birds, liver, kidney, heart, or other organ meats?	
5	Eggs (Any egg from chicken and others?)	
6	Fish (Any fresh or dried fish or shellfish?)	
7	Legumes, nuts and seeds (Any foods made from peas, beans, haricot bean,	

	cowpeas, pigeon peas nuts, chickpea, soybean, lentil and vetch?	
8	Milk and its products (Any cheese, yogurt, milk or other milk products?	
9	Oils and Fats (Any food made with oil, fat, or butter	
10	Sweets (Any sugar or honey and their products?	
11	Root and tubers (Any potatoes, yams, manioc, cassava or any other foods made from roots or tubers?	
12	Others (Any other foods, such as condiments, salt, spice, coffee, tea, ginger, carmine, and other alcoholic beverage?)	

4.6. Fill the following table depending on frequency of the food group eaten for breakfast, lunch, and dinner for the past 7 days only (data for household food consumption score)

No	**Food groups and items**	**1st day**	**2nd day**	**3rd day**	**4th day**	**5th day**	**6th day**	**7th day**
1	Cereals (Any food made from wheat, maize, teff, sorghum, Barely, etc.?)							
2	Vegetables (Any vegetable food like onion, tomato, cabbage, lettuce, squash, and other vegetables?							
3	Fruits (Any fruits like papaya, mango, apple, avocado and other fruits?							
4	Meat (Any beef, goat, lamb, wild game, chicken, duck, or other birds, liver, kidney, heart, or other organ meats?							
5	Eggs (Any egg from chicken and others?)							
6	Fish (Any fresh or dried fish or shellfish?)							
7	Legumes, nuts and seeds (Any foods made from peas, beans, haricot bean, cowpeas, pigeon peas nuts, chickpea, soybean, lentil and vetch?							
8	Milk and its products (Any cheese, yogurt, milk or other milk products?							
9	Oils and Fats (Any food made with oil, fat, or butter							
10	Sweets (Any sugar or honey and their products?							
11	Root and tubers (Any potatoes, yams, manioc, cassava or any other foods made from roots or tubers?							
12	Others (Any other foods, such as condiments, salt, spice, coffee, tea, ginger, carmine, and other alcoholic beverage?)							