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Does the Adoption of Mobile Internet Technology Promote Wheat Productivity? Evidence from Rural Farmers

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Abstract: The adoption of mobile Internet technology (MIT) in organizational systems is rapidly increasing. MIT has developed agricultural structures and dramatically altered farming activities to improve agricultural systems. MIT is considered one of the most essential technologies because of its huge impact on agriculture, economy, and our daily lives. In this study, we utilized sample data from 460 wheat growers in the Khyber Pakhtunkhwa (KP) province of Pakistan to analyze the adoption of MIT and its impact on the promotion of wheat productivity. This study used the propensity score matching (PSM) technique to address probable self-selection bias. Existing research outcomes show that decision making, education, farm size, cooperative membership, gender, extension services, access to credit, weather forecast information, risk perception, market distance, and other factors significantly affect productivity and subsidy awareness agendas. However, outcomes signify that MIT adoption will have a significant positive impact on wheat productivity. This research concludes with a policy impact, emphasizing that it is essential to accelerate MIT adoption by wheat growers as a policy to enhance Pakistan's agriculture or wheat productivity and food security.

Keywords: mobile Internet technology; adoption; propensity score matching; wheat productivity; smart agriculture; Pakistan

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Citation: Khan, N.; Ray, R.L.; Kassem, H.S.; Khan, F.U.; Ihtisham, M.; Zhang, S. Does the Adoption of Mobile Internet Technology Promote Wheat Productivity? Evidence from Rural Farmers. *Sustainability* **2022**, *14*, 7614. https://doi.org/10.3390/su14137614

Academic Editor: Ewa Ziemba

Received: 30 May 2022
Accepted: 20 June 2022
Published: 22 June 2022

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1. Introduction

The agricultural sector remains one of the most fundamental drivers of the economy, providing food, employment opportunities, and income, especially in rural areas with large arable land [1,2]. As the main sector in most emerging countries, agriculture provides food for increasing populations, supplies crucial raw materials and products for manufacturing services, is a key connection in the input–output value chain, and provides surplus labor for industrial services [1,3]. Smallholder agriculture significantly contributes to food production livelihoods in low-income and developing countries [4,5]. While these farms only represent 12% of the world's cropland, they account for 80% of the total food production in Sub-Saharan Africa and Asia [6]. Thus, increasing their productivity can reduce poverty, improve food security and nutrition at different levels, and contribute to the achievement of several United Nations Sustainable Development Goals (SDGs). Moreover, smallholder farmers in many developing countries face challenges in accessing market information, skills, and knowledge that can increase their income [1,7–9]. These barriers include, for

instance, asymmetric information regarding importing traders and exporting consumers, high transaction expenses, insufficient agricultural services, and insufficient access to credit resources [10–13]. Especially due to information asymmetry, small growers, particularly those living in rural areas, may not be able to adopt the latest equipment such as mobile Internet technology (MIT) and inputs to increase productivity [14]. Therefore, the crop yields and incomes of these growers are low, which is not conducive to their livelihoods and rural development [15–18]. Hence, advanced methods used to reduce information asymmetry are worthwhile, especially when using MIT to improve farm performance [19].

The use of Internet technology (IT) can disseminate information quickly and at a low cost, thereby helping to reduce information asymmetry. Previous evidence has proved that the adoption/use of MIT can improve the accessibility of financial and agricultural services [20], the availability of input and output markets [16,21,22], and the promotion of income activities (such as non-agricultural commodities) for smallholder farmers. Given the significant benefits of Internet usage, many countries have implemented various Internet-based programs to improve farm performance and boost rural development [23–25]. The Internet + agriculture + finance model, rural e-commerce, and farmers' field school are instances of Internet-based agendas used in China [10,26,27]. Many researchers have observed the positive influence of the use of information communication technologies (ICTs) (e.g., mobile phones, computers, and the Internet of Things) on agriculture and rural development [23,25,28]. These studies have focused on the selection bias of ICTs used by applying various methods such as instrumental variables (IVs), endogenous therapy regression (ETR), and PSM models. By evaluating the PSM model, Issahaku et al. [29] reported that MIT usage could greatly promote agricultural growth in Ghana.

The adoption of agricultural technologies may affect the production of crops because it may influence growers' production behaviors in combining and using different inputs (e.g., labor, capital assets, fertilizers, and pesticides). Technical efficiency represents the ratio of the output observed by growers to the maximum achievable production with a given input [30–32], indicating the use efficiency of farming technology inputs. The relevant literature shows that the adoption/use of ICTs will significantly affect the behavior of growers in terms of seed and fertilizer usage [24,33,34] as well as land expansion [35]. To the best of our knowledge, in addition to the work conducted for Zambia by Mwalupaso et al. [36], sparse past findings have investigated the influence of ICT usage on crop production. Mwalupaso et al. [36] studied the impact of mobile phone access to IT on corn production in Zambia. They observed that mobile phone usage has greatly improved the technical efficiency of growers.

While these lessons did not reach similar conclusions regarding the adoption of MIT, the descriptive variables utilized are essential for understanding the process of factors that could affect farmers' decisions to adopt MIT. In addition, this series of documents can assist as a beneficial instrument for policymakers and agricultural extension officials in the advancement and strategic diffusion of MIT systems. However, there is limited evidence or information on the welfare effects of ICTs in Pakistan. Few surveys have examined ICT adoption and effectiveness, although none have attempted to evaluate MIT adoption and its influence on wheat productivity in Pakistan. Therefore, this paper enhances the importance of developing digital agriculture information. We have a strong knowledge of the key aspects that ascertain MIT adoption to accomplish the goal of effectively and efficiently increasing wheat productivity. We tested the actual influence of MIT on wheat yield by limiting the selection bias in production and adoption decisions. Therefore, the PSM method was applied to measure the impact of MIT by erecting treatment and control groups.

The key purposes of the existing research were (i) to analyze the factors that impact farmers' decision to adopt MIT and its impact on Pakistani wheat productivity; and (ii) to deliberate policy implications. In this research, we regard wheat yield as an indicator of land productivity. To achieve our primary goal, first, we utilized the logit method to assess the likelihood of MIT adoption for different farm and family attributes. The logit

method utilizes the maximum probability evaluation technique to assume the logistic dissemination of the error term. Then, we used the PSM technique to measure the MIT influence on wheat productivity.

The remainder of this article is organized as follows. Section 2 explains the literature review. Section 3 introduces the model specification, study area, sampling strategy, and data collection. Section 4 describes the results and discussion of the study hypothesis. Section 5 examines the research conclusion, recommendations, and limitations.

2. Literature Review

In recent years, the global popularity of ICTs has attracted a lot of attention from the academic community [37–39], and most studies have shown that the adoption of ICTs has a significant impact on agricultural productivity in emerging countries [40–42], which is positively coined the "Digital Dividend". Min et al. [37] reviewed studies on the impact of ICT adoption on agricultural development and summarized the possible impact mechanisms, such as better access to information, farmer knowledge, input and output supply chain management, improved delivery services, reduced transaction value, as well as farm credit and health insurance. Qiang et al. [43] pointed out that the adoption of ICT applications in the agricultural sector can facilitate agricultural development and the rapid progress of rural areas, mainly because the usage of ICTs can provide millions of farmers with access to up-to-date information, market prices, and other services.

In Africa, the adoption of ICTs in the farming sector has positively impacted economic development and poverty reduction [44]; a study of digital credit remotely providing rapid microloans via digital channels showed the enhancing use of ICT in sub-Saharan Africa [45]. Chavula [44] utilized cross-sectional data for thirty-four African countries from 2000 to 2001 and indicated that ICTs played a very important role in improving agricultural productivity. Although the widespread use of mobile phones and Internet technology in farming has not significantly impacted agricultural production, main telephone lines are still an important contributor to farming development.

In Asia, Kaushik and Singh [46] specified that the adoption of ICTs can promote wide economic growth in northern India. ICT adoption can help the poor by imparting a better education system or governmental services [47–50]. Based on a study from rural households in Southeast Asia, Hartje and Hubler [51] observed that the ownership of smartphones can upsurge labor mobility (assessed through commuters' numbers). However, Hubler and Hartje [41] realized a very substantial influence of smartphones and MIT ownership on rural household income. Hence, these studies have shown that modern mobile communication equipment can help economic enhancement.

Moreover, the equitable influence of ICTs on agriculture and economic development is ambiguous. Using data from eighty-one countries from 1995 to 2000, Lio and Liu [52] found that the level of ICT usage in rich countries was much higher than that in developing countries. The return on ICTs utilized in agricultural production in rich countries was about two times more than the rate of return in poorer countries. Additionally, the authors stated that ICTs could lead to differences in overall agricultural productivity between countries. In contrast, Min et al. [37] argued that the worldwide diffusion of ICTs could support emerging nations in narrowing the economic gap between developed and developing nations. Furthermore, Deichmann et al. [53] indicated that many hopeful examples in which farmers face no obstacles to the positive impact of ICTs' on rural livelihoods.

Although China plays an important role in the global ICTs field, there is a lack of empirical indication of the role of ICTs in the farming sector in rural areas of China according to Leng et al. [28] and Min et al. [37]. Correspondingly, the first three studies revealed the positive effects of smartphone usage on agricultural productivity and revenue, non-agricultural income, and the profit diversity of rural Chinese farmers. Khan et al. [54] examined the positive influence of MIT usage on the economic well-being of rural households in Pakistan. Nie et al. [55] observed that the use of smartphones improves subjective well-being in rural areas of China. However, these reviews did not investigate trends in the adoption of MIT by

growers or the likely influence of MIT adoption on growers' wheat productivity. Therefore, more empirical studies are needed in developing countries, including Pakistan, to measure the possible impact of MIT adoption on agricultural productivity and the economy.

3. Methodology and Analytical Framework

3.1. Study Area Description and Data Collection

The present study was conducted in Khyber Pakhtunkhwa (KP) province, Pakistan, from January 2021 to March 2021. Four-hundred and sixty questionnaires were distributed to wheat farmers to collect the data required for this study. Basic information was collected via face-to-face interviews with wheat growers using a multistage random sampling technique. To understand the first phase of ICT adoption by wheat growers in KP province, data collection was conducted in four districts, namely Dera Ismail Khan, Charsadda, Mansehra, and Swat, based on the share of agricultural production in these regions (Figure 1 and Table 1).

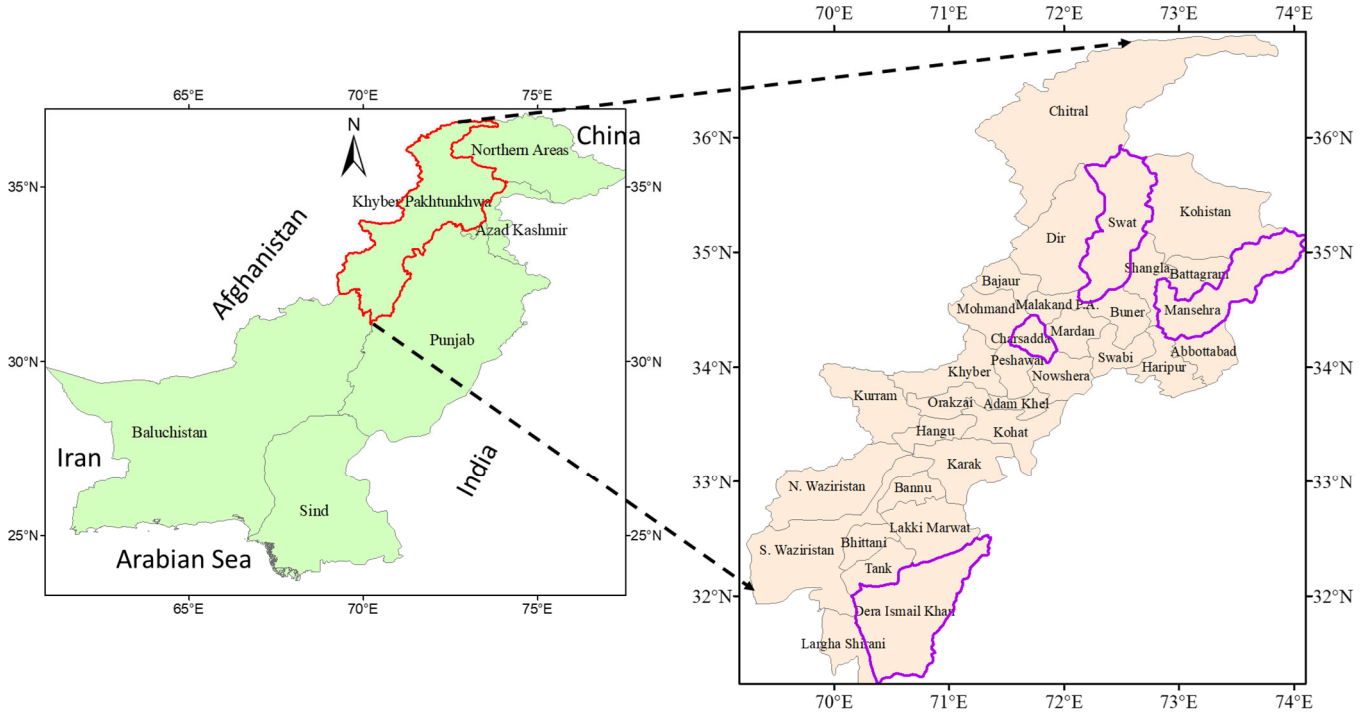


Figure 1. Map of the study area [54].

Table 1. Sample distribution.

Province	Zones	Districts	Tehsils	UC	Villages	Samples
KP	South	DIK	1	1	4	115
	West	Charsadda	1	1	4	115
	East	Mansehra	1	1	4	115
	North	Swat	1	1	4	115
Total	4	4	4	4	16	460

In the second stage, a tehsil was chosen to fill out the questionnaire, and in the third stage, a union council (UC) was selected from each tehsil. In the fourth step, each selected UC randomly followed four villages and finally collected basic data from the wheat growers in the selected villages. The questionnaire used in this study was divided into different sections. The first part of the organized questionnaire contained the demographic and socioeconomic characteristics of the respondents. The remainder of the questionnaire was designed to obtain information about MIT from wheat growers. The questionnaire

was originally written in English and later translated into Urdu for the convenience of the respondents.

Current data from wheat farmers were collected through interviewees and questionnaires. Due to the complexity of the questionnaire, we conducted in-depth interviews. To remove uncertainty, the questionnaire was pre-tested. The survey data questionnaire included information on the socioeconomic characteristics of the farmers, MIT, and other variables useful for the study. Data were edited and coded using Stata 14 to ensure accuracy, validity, uniformity, consistency, and completeness.

3.2. Analytical Framework

3.2.1. Modeling the Adoption Decision and Influencing Problems

MIT adoption in many emerging nations is often limited by constrained economic resources, imperfect markets, weak rural area infrastructure, and the absence of information [56,57]. Despite these limitations, Aker et al. [58] suppose that growers would adopt new technology, provided that its usage could increase their utility in terms of net revenues. Therefore, following Aker et al. [58], the random utility framework was applied to simulate MIT adoption. We presume that growers are risk-neutral and choose modern technologies that maximize their utility function under input expenses and further restraints. Furthermore, let us describe U_{iA} as the utility obtained by growers i from the adoption of MIT and U_{iN} as the utility obtained from not adopting. Under this assumption, if the utility obtained from adopting the technology is larger than the utility of not adopting it, $D_i^* = U_{iA} - U_{iN} > 0$, and farmers usually adopt the technology [59–63]. Meanwhile, as these two utility values are unobservable, we could articulate them as function factors such as technical and farmer attributes in the latent variable model, as shown below:

$$D_i^* = X_i a + \varepsilon_i \text{ With } D_i = \begin{cases} 1 \; if \;\; D_i^* > 0 \\ 0 \; otherwise \end{cases} \quad (1)$$

Among them, D_i^* is a binary variable, and the value is 1 for growers who adopt MIT and 0 otherwise. X_i is the vector of technical and household attributes; α is the vector of parameters to be assessed; and ε_i is the error term, where $\varepsilon_i \sim N(0, \sigma)$.

$$Y_i = X_i' + \delta D_i + \mu_i \quad (2)$$

Estimating equation two can indicate the direct impact of MIT adoption on outcome variables (that is, wheat productive). Moreover, this method may produce unreliable evaluations because it believes that MIT adoption is almost unaffected by exogenous factors. In addition, due to personal self-selection and purposeful planning, treatment allocation is not random. Specifically, when the unobserved variables correlate with the error term ε_i of the adopted description and the error term μ_i of the outcome model, the selection bias issue occurs. In this argument, the OLS method will tend to produce biased assessments [57].

In order to address the selection bias issue, past analyses have used various econometric models, such as the IV, Heckman's two-stage, the difference in difference (DID), and PSM methods. In addition, Heckman's two steps rely on the restrictive hypothesis that unobserved variables are generally distributed [11,64,65]. The IV technique is constrained by the complexity of the outcome of at least one variable in its choice model as a suitable tool for result estimation. Furthermore, the IV technique relies on the functional form used to estimate the outcome equation [1]. The DID matching technique is another estimator that can produce consistent and unbiased estimates for selection bias. Although the DID technique is only appropriate for surveys using panel data [11,66], these data have not been utilized in existing research. In order to overwhelm the limitations of the above methods, we applied the PSM technique suggested by Rosenbaum and Rubin [67] to solve the selection bias issue in cross-sectional data sets. The PSM technique eases the operating form and distributional expectations employed in the outcome model description [65,68].

3.2.2. Estimates of PSM Technique

To evaluate the influence of MIT, we compared the outcome variables achieved when growers received and did not obtain treatment. The structure of such counterfactual findings constitutes a major challenge in assessing the impact of emerging technology adoption. According to Rosenbaum and Rubin [67], the average treatment effect (ATE) in the counterfactual context is measured as:

$$ATE = E\left(Y_i^1 - Y_i^0\right) \tag{3}$$

where Y_i^1 and Y_i^0, respectively, signify the outcomes of farmers i who adopt MIT and farmers i who do not adopt MIT (that is, wheat productivity). However, in the description of equation three, because it is difficult to assign growers to the treatment group and control group, misleading estimates may be provided [69]. Usually, for each farmer i, only the result Y_i^1 or Y_i^0 is remarked at a provided point in period. Let D signify a dummy variable, equivalent to 1 for the adopter and 0 for non. Therefore, the detected result Y_i is provided by:

$$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0 \tag{4}$$

Presuming that there is no selection bias, we determine the influence of MIT on the families that adopt them as the ATT [2,36]:

$$\begin{array}{c} ATT = E(\triangle | X, D = 1) \\ = \mathrm{E}(Y_i^1 - Y_i^0 | X,\ D = 1) \\ = E(Y_i^1 | X,\ D = 1) - E(Y_i^0 | X,\ D = 1) \end{array} \tag{5}$$

where X is the family feature vector and $E\left(Y_i^0 \middle|\ X, D = 1\right)$ is the counterfactual result. Because no counterfactual results are observed, the ATT in the equation is estimated, and there might be bias in Equation (5) [70,71].

We apply the PSM technique to match individuals who adopt the MIT with non-adopters who have parallel disseminations on numerous studied covariates [70]. The PSM is also called the likelihood of MIT adoption, and it is centered on dual hypotheses. First is the conditional individuality hypothesis, which states that for a set of specified observable covariates X, the adopted state variables and outcome variables are independent [72]. The second hypothesis is the common support condition, which shows that the probability of adopters and non-adopters using a similar covariate is positive, so $0 < \Pr(D = 1\ X) < 1$ is an overlapping condition.

The PSM for MIT adoption is assessed by applying the logit model. We then used three matching algorithms to match the treatment and control groups. These algorithms are commonly used to estimate the average effect of a specific treatment when utilizing cross-sectional data: namely kernel-based matching (KBM), nearest neighbor matching (NNM), and radius matching (RM) methods. The NNM estimator is constructed to coordinate each processed individual with the control individual through the closest PSM [10,35]. Under the KBM, each processed individual corresponds with the weighted average of the entire control individual in the common support area [35,73]. On the other hand, the RM algorithm matches the processed observations corresponding to the control observations within the specified PSM range (calipers) [74]. After using the matching method, it is essential to examine whether PSM estimation can stabilize the distribution of the variable between the treatment group and the control group.

The evidence behind the balance test confirms that there are no residual variances in the covariates between the treatment and control groups [74]. In this case, Sianesi [75] projected a comparison technique of pseudo R^2 values accomplished before and after matching to present these diagnostic statistics. The pseudo R^2 indicates the impact degree of the independent variable on the likelihood of joining the program. After matching, there would be no systematic variance in the distribution of the variable of interest between the adopter and non-adopter groups so that the pseudo R^2 would be below [76]. The

additional balancing test frequently utilized in the literature includes calculating a standardized average deviation to verify whether the observed deviation is condensed after corresponding. In addition, the covariate balance hypothesis requires the rejection of the combined significance of entire independent variables after corresponding [77]. However, eliminating systematic differences, that is, when there is no observed bias in the distribution of covariates between the treatment group and control group, does not certify the estimator robustness or hidden bias absence. Therefore, a compassion examination of the assessed ATE is essential to accomplish the hidden bias problem. Therefore, we used the bounding method to check whether the impact of unobserved covariates' on the outcome variable is sufficient to disrupt the matching procedure.

4. Results and Discussion

4.1. Description of Variables and Summary Statistics

The summary statistics of the variables in Table 2 show that approximately 41% of farmers in the study area adopted MIT. The average age of the sample households was approximately 48 years old, and approximately 70% of the surveyed households were the male heads of families. The average education level in the sample area was approximately 7 years of primary school education. The average family size was approximately 7 people, and the average figure of livestock held by the family was about 1.37 tropical livestock units. On average, each family grew wheat on 1.7 ha of land, yielding 1995 kg.

Table 2. Variables description and descriptive statistics.

Variables Name	Description	Mean (S.D)
Outcomes		
Wheat yield	Wheat yield (kg/ha)	1995.5 (293.5)
Treatment		
MIT	1 if the farmers adopts mobile Internet technology; 0 otherwise	0.41 (0.49)
Independent		
Gender	1 if the respondent is male; 0 if the respondent is female	0.69 (0.46)
Age	Age of the respondents (years)	47.91 (11.50)
Education	Education of the respondents (years)	6.93 (5.04)
Household size	Household size (number)	6.69 (1.65)
Farm size	The area under wheat production (ha)	1.7 (0.90)
Cooperative	1 if the respondent is a member of the farmers' cooperative membership; 0 otherwise	0.50 (0.50)
Access to credit	1 if the respondent has access to credit; 0 otherwise	0.49 (0.50)
Agri-Extension facilities	Contacts with agri-extension workers (No/year)	30.84 (7.89)
Weather information	1 if the respondent has access to the weather forecast information; 0 otherwise	0.50 (0.50)
Market distance	Distance between farm and market (km)	6.65 (6.05)
Risk perceptions	1 if the respondent is willing to attempt new technology; 0 otherwise	0.50 (0.50)
Subsidy awareness	1 if the respondent of the subsidy program on ICT; 0 otherwise	0.53 (0.50)
Livestock ownership	Livestock amount held in tropical livestock units	1.38 (1.14)
Districts dummies		
Dera Ismail khan	1 if the respondent is located in DIK; 0 otherwise	0.33 (0.47)
Charsadda	1 if the respondent is located Charsadda; 0 otherwise	0.35 (0.46)
Swat	1 if the respondent is located in Swat; 0 otherwise	0.23 (0.42)
Mansehra	1 if the respondent is located in Mansehra; 0 otherwise	0.32 (0.47)

4.2. Variances in Household Attributes via Adopting Category

The results presented in Table 3 indicate that adopters and non-adopter growers are very different in terms of farm-level and socio-economic attributes. In particular, the average wheat yield of the MIT adopters (2250.30 kg) is much higher than that of non-adopters (1810.48 kg). Moreover, growers who adopted are highly differentiated in terms of asset ownership, that is, they own further livestock and land area than growers who

did not adopt MIT. Considering the demographic characteristics of household information, for instance, gender, age, family size, and level of education, our findings show that the average number of MIT-adopted farmers is higher than that of non-adopted farmers. We also found that there is a substantial variance in the share of male-headed families between the MIT adopter and non-adopters. The descriptive data in Table 3 show that MIT adopters have easier contact with agri-extension facilities, weather forecast information, credit access, and reliable information resources than non-adopters.

Table 3. Variances in household attributes via adopting type.

Variables Name	Adopt (n = 198)	Non-Adopt (n = 262)	Mean Variance	t-Value
Wheat yield	2250.30	1810.48	441.83 ***	21.82
Gender	078	0.64	0.15 ***	2.82
Age	48.95	45.48	3.46 ***	3.08
Education	7.48	4.66	2.83 ***	12.40
Household size	7.09	6.41	0.69 ***	3.95
Farm size	2.29	1.29	1.01 ***	12.42
Agri-extension facilities	35.45	27.62	7.84 ***	10.65
Cooperative	0.66	0.39	0.26 ***	4.77
Access to credit	0.63	0.41	0.23 ***	4.13
Weather information	0.60	0.45	0.16 ***	0.82
Market distance	0.70	0.36	0.35 ***	6.78
Risk perceptions	0.59	0.44	0.16 ***	2.87
Subsidy awareness	0.57	0.49	0.08	1.48
Livestock ownership	2.05	0.89	1.15 ***	10.95

Note: *** indicates statistical significance at the level of 1%.

It is worth noting that growers who adopt MIT are more conscious of new technologies and more eager to try modern technologies than growers who do not. However, there does not seem to be a statistically substantial variance between the growers that did and did not adopt in terms of subsidy policy awareness. The results also indicate that 62% of growers who adopted MIT managed agricultural advancements, which is the best for advanced farming systems. The adopters are also different in terms of membership of farmers' associations. The number of adopters in farmers' associations is greater than the number of adopters without them.

4.3. Determinants of MIT Adoption

Table 4 reports the maximum probability assessment finding of the logit model for the considerations of MIT adoption. The results show that most variables are statistically substantial in affecting the likelihood of MIT adoption. High-level schooling substantially upsurges the probability of MIT adoption. This result is similar to Yang et al. [15] regarding MIT adoption in China. It reproduces the fact that education enables growers to examine the adoption of modern technology and make appropriate decisions [15,78,79]. In terms of gender, it is found that female-headed families are less probable to adopt MIT than male-headed households [25]. However, the study by Zheng et al. [80] and Nahayo et al. [81] pointed out that because women have limited interaction and control over assets, female-headed families are unlikely to adopt modern farming technologies. In addition, land area has a substantial positive influence on the possibility of MIT adoption.

Table 4. Logit model estimation for determinants of MIT adoption.

Variables Name	Coeff. Estimates	Marginal Effects
	Coeff. (S.E)	Coeff. (S.E)
Gender	−0.919 ** (0.440)	−0.204 ** (0.097)
Age	−0.005 (0.015)	−0.001 (0.003)
Education	0.408 *** (0.029)	0.090 *** (0.008)
Household size	0.014 (0.096)	0.003 (0.022)
Farm size	1.269 *** (0.478)	0.281 *** (0.107)
Agri-extension facilities	0.057 * (0.009)	0.013 * (0.003)
Cooperative	1.693 *** (0.504)	0.380 *** (0.109)
Access to credit	2.024 *** (0.516)	0.447 *** (0.112)
Weather information	1.701 *** (0.698)	0.376 *** (0.153)
Market distance	2.759 *** (0.781)	0.609 *** (0.170)
Risk perceptions	1.877 *** (0.372)	0.414 *** (0.080)
Subsidy awareness	0.780 ** (0.510)	0.173 ** (0.113)
Livestock ownership	−0.314 (0.288)	−0.069 (0.064)
District dummies		
Dera Ismail Khan	1.04 3 *** (0.513)	0.207 *** (0.325)
Charsadda	−0.248 (0.930)	−0.059 (0.105)
Constant	−12.047 *** (1.733)	
Model diagnosis		
Log-likelihood	−106.865	
LR chi^2	276.89	
Prob > chi^2	0.000	
Pseudo R^2	0.5659	
N	460	460

Note: ***, **, and * show statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors (S.E) are in parentheses.

As expected, we found that the members of farmers' cooperatives are more likely to adopt MIT than non-members, which is consistent with previous research and shows the significance of social capital in expanding the rate of technology adoption. With regard to the influence of agri-extension facilities on adoption choices, our findings show that families often visited by agricultural extension workers are more likely to adopt modern technology than families not often visited. As a reasonable description, agri-extension systems support growers in obtaining up-to-date knowledge and practical information about agricultural systems [74]. In addition, access to credit is considered an important factor in increasing the probability of MIT adoption. In fact, this verdict confirmed the outcomes of Kim et al. [82], who acknowledged the importance of credit in serving growers to accrue sufficient capital to afford these modern technologies.

The outcomes presented in Table 4 indicate that obtaining weather conditions forecasting data will substantially enhance the possibility of MIT adoption. The accessibility of weather information allows growers to make more proper choices in their agricultural operations. This finding is supported by the early adoption of agricultural technology in Nigeria [83]. In addition, the risk perception coefficient is positive and significant, which means that growers who are eager to try modern technologies show an enhanced possibility of accepting the latest technology. The outcome encourages the results of Koundouri et al. [84] regarding the use of modern technology in Greece. It is pointed out that farmers who do not avoid risks may utilize new technology to manage production risks and uncertainties. Instead, Mariano et al. [85] observed that profit-oriented and risk-averse growers are often attracted by modern high-yield instruments compared with others in the Philippines.

4.4. The Impact of MIT on Wheat Production

As described in the methodology section, we applied the PSM method to evaluate the influence of MIT on wheat production. The PSM method balances the delivery of

independent variables between MIT adopters and non-adopters. Figure 2 shows the distribution of the PSM technique and areas of common aid for both groups. Caliendo and Kopeinig [86] proposed that the density distribution of the assessed PSM method of adopters and non-adopters would meet the common support situations. Therefore, twenty-seven processed observations that were obtained to be unsupported must be excluded from the examination to confirm that the observable family characteristics of adopters and non-adopters are appropriately matched.

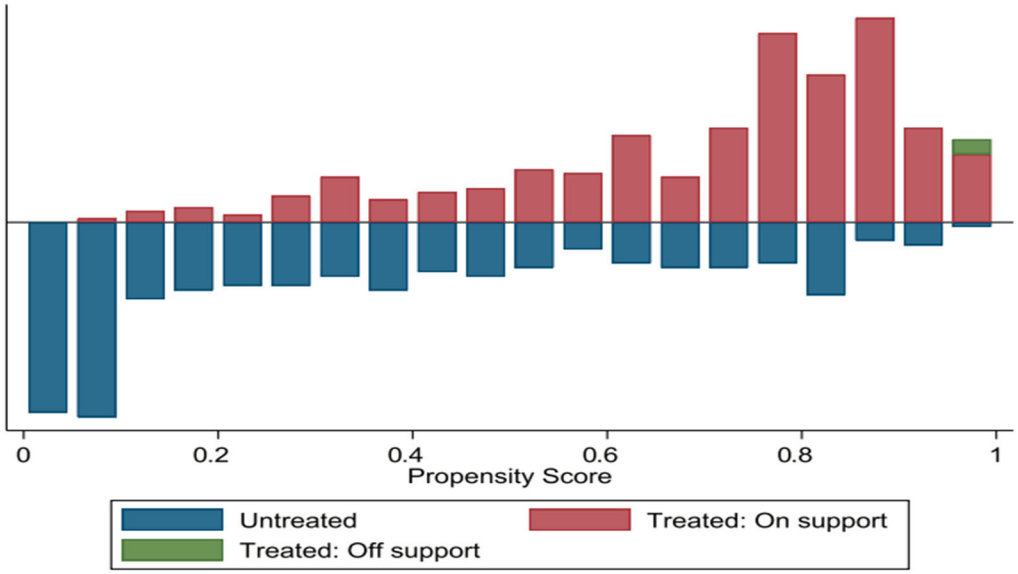


Figure 2. The estimated PSM technique distribution by treatment and common support area. "Untreated" denotes the non-adopters group; "Treated: on support" denotes the individual observations of the adoption group, revealing the corresponding match in the non-adopted group; "Treated: off-support" denotes the individual observation of the adoption group. No corresponding matches were shown in the non-adopted group.

Table 5 shows the ATT, which illustrates the impact of MIT usage on wheat yield. The ATT value is assessed using three PSM algorithms frequently used in empirical studies: namely, KBM, NNM, and RM. The outcomes of the three corresponding algorithms show that, on average, the adoption of MIT has a significant influence on wheat production. Particularly, when utilizing KBM, the MIT adoption increased average wheat production by approximately 197 kg. When utilizing NNM, it was increased by 193 kg, and when utilizing RM, it was increased by 200 kg. This means that, on average, growers who adopt MIT have a higher wheat yield by approximately 193–200 kg than farmers who do not. This finding is aligned with Kim [46], who reported that MIT adoption had a substantial positive influence on agricultural production.

Table 5. PSM estimation of ICT impact on wheat productivity and the sensitivity analysis results.

Algorithms	Outcomes Variables	ATT	S.E	*p*-Value	Critical Level of Hidden Bias
KBM	Wheat yield (kg)	197.14 ***	32.99	0.000	3.75
NNM	Wheat yield (kg)	193.38 ***	21.30	0.000	2.50
RM	Wheat yield (kg)	199.79 ***	16.58	0.000	3.75

Note: *** represents statistical significance at the level of 1%.

As discussed in Section 2, a covariate balance test and sensitivity examination were needed to evaluate the matching process quality and the robustness of the findings. The outcomes presented in Table 6 reveal that excellent matching was achieved. Table 6 indicates the significant decrease in deviation caused by the corresponding method. Evaluations suggest that the bias level was significantly reduced from 63% before matching to approxi-

mately 9–13% after matching, which is consistent with an entire bias reduction of 79–86%. Additionally, the difference of the pseudo R^2 values in the second and third columns of Table 6 reveals that R^2 after matching is lower than before matching for all matching algorithms. This shows no systematic difference in the distribution of independent variables between adopters and non-adopters after matching. In addition, the *p*-value of the likelihood ratio test after matching is excessive, which means that the combined significance of the descriptive variables after matching is refused. Generally, the findings of the entire covariate balance tests used in existing research show that adopters and non-adopters have no systematic differences in the distribution of covariates after matching. Therefore, we can approve that the suggested design of the PSM assessment method is positive in balancing the attributes of adopters and non-adopters.

Table 6. Covariate balance test before matching and after matching (BM and AM).

Algorithms	Pseudo R^2 BM & (AM)	LR ch^2 (*p*-Value) BM	LR ch^2 (*p*-Value) AM	Mean Std. Bias BM & (AM)	(%) Bias Reduction
KBM	0.571 (0.033)	278.43 ($p = 0.000$)	8.12 ($p = 0.919$)	63.30 (10.9)	82.78
NNM	0.571 (0.042)	278.43 ($p = 0.000$)	8.80 ($p = 0.888$)	63.30 (8.80)	86.09
RM	0.571 (0.046)	278.43 ($p = 0.000$)	11.95 ($p = 0.683$)	63.30 (12.90)	79.62

The Rosenbaum boundary sensitivity analysis method further examines the hidden bias caused by unobservable variables. The sixth column of Table 5 displays the hidden bias critical level outcomes for the three corresponding estimators. The consequences obtained from KBM and RM show that the assessed hidden bias value was 3.75 at the 5% statistical significance level. This value specifies that the use of MITT to estimate the ATE of wheat productivity is not sensitive to unobserved deviations, which can triple the chance of MIT usage. In short, the research results are robust to hidden bias and satisfy the conditional fairness hypothesis of the PSM method.

5. Conclusions, Recommendations, and Limitations

In order to reduce poverty in Pakistan and improve agricultural productivity, the Pakistani government is committed to the promotion and dissemination of agricultural technology. Hence, it is essential to evaluate the influence of using such modern technologies in expanding agricultural production. This article analyzes the factors that influence farmers' decision making with regard to MIT adoption and the impact of MIT adoption on land yields (namely, wheat yield per hectare). The present research is based on cross-sectional data gathered from 460 wheat growers. We used the logit model to evaluate the determinants of MIT adoption. The survey results show MIT adoption in function of gender, education, farm size, agricultural extension services, membership of cooperatives, access to weather forecast information, credit, awareness of subsidy programs, and risk awareness. The PSM technique was used to assess the impact of MIT usage on wheat production. The research results show that the adoption of MIT significantly increased wheat production.

These results indicate that government and agricultural extension department intervention will focus on helping farmers with mobility impairments to easily obtain credit. The outcomes also emphasized the need to promote farmers' access to information associated with agricultural technology, as well as subsidies for new technologies that encourage MIT adoption. In fact, policy dealings, for instance, supporting successful agricultural extension services and farmer cooperatives, can support growers in overcoming information obstacles, thereby promoting the adoption of MIT. Moreover, efforts to enhance the education level of growers can expand MIT adoption rate. There is an urgent need for strategies and policies to prevent growers from obtaining a consistent source of digital technology near each village. In addition, our results on the adoption of MIT influence on wheat yield

emphasize the essence of promoting MIT usage, which is a strategic involvement that requires public and private cooperation. Since growers privately own MIT, governments and non-government and extension organizations can still perform an essential role in improving the adoption rate and disseminating MIT development.

This study also has some limitations. First, due to funding and concerns over the COVID-19 pandemic, this study was only conducted in four districts in KP province, Pakistan. Second, because of unobserved heterogeneity issues, the data limited the expansion of our outcomes within one year and limited control for selection bias. Hence, it is believed that upcoming studies should use panel data to extend our analysis to better determine the influence of MIT over time. In addition, the future study must specifically consider MIT's impact on different key outcome variables, such as food security, poverty, consumer expenditure, and agricultural productivity income.

Author Contributions: N.K., R.L.R., H.S.K., F.U.K., M.I. and S.Z. developed and outlined this concept, including the method and employed approach; N.K., R.L.R. and S.Z. developed and outlined the manuscript; N.K. and S.Z. contributed to the methodology and revision of this manuscript; N.K., R.L.R. and S.Z. wrote the article. All authors have read and agreed to the published version of the manuscript.

Funding: This work was partly supported by the Evans-Allen project of the United States Department of Agriculture (USDA), National Institute of Food and Agriculture. Also, the authors extend their appreciation to the researchers for partly supported from the project of (No: RSP-2021/403) King Saud University, Riyadh, Saudi Arabia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support our research findings are available from the corresponding author on request.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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