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Farmers' Participation in Messenger-Based Social Groups And Its Effects on Performance in Irrigated Areas of Kazakhstan and Uzbekistan

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ABSTRACT

The penetration of information and communication technologies (ICTs) in farming communities is increasing the use of smartphone-based instant messaging apps. Despite this, the reasons behind participation and the impact on farm productivity in developing countries remain unexplored. This study uses survey data of cotton growers in Kazakhstan and Uzbekistan to explore factors explaining participation in social media groups and its impact on farm performance. The results show that the factors and benefits differ across these two countries. Participation in social media groups has a positive effect on cotton yields in both countries, but increases revenue only in Kazakhstan. We discuss possible reasons for contrasting results and policy implications for improving agricultural extension and advisory services in Central Asia. Scaling up smartphone-based e-extension should focus on younger, more educated farmers. Emphasizing associated economic benefits and fostering decision-making autonomy among farmers will be crucial for creating conducive environment for benefiting from e-extension services.

JEL Classification: C31, C34, Q12, Q16

1 | Introduction

The penetration of information and communication technologies (ICTs), including computers, the Internet, and smartphones, has made messaging applications (e.g., WhatsApp, Telegram, IMO, Viber, Skype, and Facebook Messenger) key ICT-based tools for creating knowledge-sharing channels (Ahmed et al. 2019). These applications are increasingly popular in agriculture in developing countries, facilitating virtual groups for knowledge sharing among farmers (Fabregas, Kremer, and Schilbach 2019). Farmers can join and organize virtual communities to exchange information, ideas, personal messages, and media content related to agribusiness, engaging with peers and experts (Norton and Alwang 2020). Such virtual agricultural information-sharing group (AISG) participants can also include agricultural advisors, extension agents, researchers, policymakers, processors, and retailers. Such groups enable rapid feedback to extension agencies, informing service improvements, research agendas, and participatory technology development (Materia, Giarè, and Klerkx 2015). AISG proved vital for technology diffusion and reducing costs for both public and private extension and advisory services (Norton and Alwang 2020).

Despite the literature has largely focused on communication-enabling ICT tools, including the use of mobile phones, smartphones, mobile internet and internet services (Bounkham, Ahmad, and Yaseen 2022; Kaila and Tarp 2019; Ma, Grafton, and Renwick 2020; Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. 2020; Michels, Fecke, Feil, Musshoff, Pigisch, et al. 2020; Ogutu, Okello, and Otieno 2014; Quandt et al. 2020; Spielman et al. 2021; Van Campenhout, Spielman, Lecoutere 2021; Zhu et al. 2021), little attention has been paid to factors related to participation in social media groups in rural settings (Klerkx 2021; Faxon 2023). Only recently the focus has shifted to social media users and does not account for the new global phenomenon of farmers using social media, especially organizing online self-help groups in instant messaging applications. Within this narrow body of literature, the studies examined collective learning and thematic content of virtual communication (Agnese et al. 2023; Faxon 2023; Phillips, McEntee, and Klerkx 2021), whether virtual exchange is related to increased social capital (Phillips, McEntee, and Klerkx 2021; Lee and Suzuki 2020), and production decisions (Mills et al. 2019). Yet, there is an increasing call to understand the institutional and organizational conditions under which farmers engage in such virtual knowledge exchange and the productivity gains that result from it (Faxon 2023; Klerkx 2021; Phillips, McEntee, and Klerkx 2021). The only study that looks at this direction explicitly is by Mendes et al. (2023) who investigated determinants and income-effects of participation in AISG among cattle farmers in Brazil. To better understand the ways of harnessing communication-enabling ICT tools for improved extension services, more evidence is needed about how farmers use social media groups, what factors define their participation in such platforms, and how it affects farm business (Norton and Alwang 2020).

The paper addresses this research gap by exploring two questions: (1) Which factors explain farmers' participation in social media groups?, and (2) How does this participation affect farm performance? We examine these questions in Kazakhstan and Uzbekistan, two transition economies where agribusiness information has traditionally been communicated through centralized, top-down extension and advisory services from government and research institutions, often overlooking farmers' actual needs (Nazarov 2008; de Danieli and Shtaltovna 2016). Because a strong representation of farmers' interests is lacking, and the public organizations have targets set by the central ministry, farmers cannot communicate their knowledge needs to policymakers. Consequently, outdated knowledge, poor communication, and conflicting agendas prevent public agricultural services from fully meeting farmers' needs (de Danieli and Shtaltovna 2016). The existing extension and advisory services do not equitably serve all farmers, with those in remote areas having particularly limited access. Knowledge dissemination projects can reach only a small number of farmers and do not lead to wide adoption (Van Assche 2016). Thus, farmers seek information through alternative sources, including their peers, TV, newspapers, and radio (Kurbanov, Tadjiev, and Djanibekov 2022).

Social media messengers like WhatsApp, Telegram, and Facebook Messenger facilitate information sharing across farming communities via virtual networks, with WhatsApp favored in Kazakhstan and Telegram in Uzbekistan. Despite widespread use, including by administrative and agricultural extension organizations, their potential for professional farm extension communication has been underexplored. The widespread adoption of ICTs, such as internet-connected mobile smartphones, facilitates the expansion of social media messengers and participation in virtual groups among farmers, setting the stage for e-extension development. The challenge lies in how policymakers and extension and advisory services can leverage this digital engagement for agricultural growth. By analyzing the institutional, organizational, and demographic characteristics of participants of AISG and the productivity gains associated with participation, valuable insights can be gained for designing and expanding social media-based e-extensions in Central Asia.

To address the research question, we use survey data collected in spring 2022 from 527 managers of cotton-growing farms in irrigated areas of Kazakhstan and Uzbekistan. Cotton in Central Asia is the major crop in irrigated areas, contributing to rural livelihoods, employment and national income (Pomfret 2019). For nearly a century of cotton specialization, a strong network of traditional extension and advisory services related to its production has evolved in the region. While sharing a common origin in the Soviet agricultural production system, the two study areas have since diverged into contrasting institutional environments surrounding cotton cultivation. In Uzbekistan, unlike Kazakhstan, cotton farmers' decisions have been influenced by a top-down procurement policy, which dictates farm business priorities and ties land tenure security to the fulfillment of production targets (Kurbanov, Tadjiev, and Djanibekov 2022).

We employ an endogenous switching regression model to address endogeneity and sample selection bias in impact assessments (Heckman 1979; Abdulai 2016) as farmers can self-select themselves into participants and nonparticipants of AISG. The endogenous switching regression model can mitigate self-selection bias issues arising from observable factors such as farmer's age, education, and farm size, and unobservable factors such as farmers' abilities and motivations to improve land productivity (Abdulai 2016, Jaleta et al. 2016). This paper makes three key contributions. First, it adds to the limited global empirical literature on farmers' participation in AISG, where only few studies exist. Second, it provides systematic evidence on the impact of ICT-based advisory services, specifically through social media group-based e-extension, on financial performance and crop yields, addressing the gap in the existing literature (Schroeder, Lampietti, and Elabed 2021; Mendes et al. 2023). Third, by using an example of two Central Asian countries, our study is among the first empirical investigations to inform the development of e-extension services in transition economies.

2 | Data and Descriptive Statistics

2.1 | Data

We use a data set that originates from a survey of farm managers conducted as part of the Structured Doctoral Programme on Sustainable Agricultural Development in Central Asia (SUSADICA) project in Turkistan (Kazakhstan) and Samarkand (Uzbekistan) provinces from April to May 2022. The farm survey data in the Turkistan province were collected employing stratified two-step sampling. First, three villages (locally named "Aul") were sampled from each district that was part of the Institutional Change in Land and Labour Relations in Central Asia's Irrigated Agriculture (AGRICHANGE) farm survey in 2019. Second, 50 farm managers were randomly chosen from each Aul's farm lists. In Samarkand, farm managers were randomly chosen from the district farm list. Maktaaral and Shardara districts in Turkistan and Pastdargam and Payarik districts in Samarkand were chosen because of their long-standing specialization in cotton cultivation. Sariagash district in Turkistan and Jomboy district in Samarkand were selected for their diversified crop cultivation systems. The data set consists of 901 individual farmers (451 in Kazakhstan and 450 in Uzbekistan) registered as owner-operator or fixed tenants specializing in crop production.

Farmers were surveyed using a detailed questionnaire that included socio-demographic, behavioral, institutional, farm, field, and geographical information. The survey explored attitudes towards the usefulness of mobile internet and participation in social groups, focusing on autonomy in crop selection, agronomic practices, and marketing. Farmers using smartphones were specifically asked about their participation in social media groups in instant messenger apps to find out information relevant for their farm business.

As cotton is the predominant crop in Central Asia's irrigated areas and has been intensively cultivated for over a century, our analysis focuses on a more homogeneous subgroup of cotton-growing farmers. Cotton growers have distinct agronomic information and knowledge demands, including pest control, cultivation methods, and marketing strategies, compared to non-cotton growers, such as those specializing in horticulture. Focus on a single type of producer allows us to minimize the potential heterogeneous demand and productivity impacts from participation in social media groups. Cotton growers, armed with their extensive local knowledge of cultivation and production, can share insights among their peers, enhancing comparability and reducing the need to control for various confounders that may arise among more diversified farmers. Moreover, the diversity and the number of observed crops, ranging from vegetables and beans to melons and potatoes, cultivated by non-cotton growers representing less than 30% of total sample do not support a separate impact analysis for this subgroup.

Based on their responses, we categorized cotton-growing farmers, a total of 527 respondents, into participants and non-participants of AISG. 107 farmers in Turkistan province and 145 farmers from Samarkand province responded "yes" about participation in AISG to find out information relevant for their farm business. Of the total sample 139 farmers in Turkistan and 136 farmers from Samarkand responded as non-participants of AISG.

2.2 | Descriptive Statistics

Table 1 provides descriptive statistics for social media group participants and non-participants in AISG in both settings. In Kazakhstan and Uzbekistan, participants were 3–6 years younger than non-participants. The share of farmers with specialized agricultural education is larger among social media participants than among non-participants, especially in Kazakhstan. In both countries, participants allocated a larger area to cotton than non-participants. Both participants and non-participants in each setting grew a similar number of crops, but Uzbekistan farmers cultivated twice as many crops as their counterparts in Kazakhstan. Our sample indicates that in both settings, participants in social media groups dedicated more time to off-farm employment than non-participants. Notably, in Kazakhstan, farmers spent six times more hours on off-farm work compared to those in Uzbekistan, likely due to the smaller farm sizes in Kazakhstan, which create a greater need for supplementary income.

In Uzbekistan, social media group participants reported greater autonomy in crop selection compared to non-participants, indicating that those with more decision-making freedom were more active in these groups due to their ability to apply peer-shared knowledge more autonomously. Moreover, among Uzbekistan farmers the participants reported to be less caring about the opinions of other farmers compared to non-participants. However, this trend did not hold for Kazakhstan, where participants and non-participants were similarly concerned about the opinions of other farmers. Across both countries, a higher proportion of participants felt more open to new ideas compared to non-participants.

In Uzbekistan the average farm size among participants was significantly larger (107 ha) than that in Kazakhstan (12 ha), leading to a greater reliance on external agronomy experts among Uzbekistan respondents. In contrast, nearly all respondents in Kazakhstan relied on own agronomy knowledge. The proportion of farmers relying on own agronomy knowledge in Uzbekistan was half that of Kazakhstan. Participation in training during the last 3 years was higher among AISG participants in Kazakhstan (36%) compared to non-participants (10%). In Uzbekistan, 82% of farmers in both groups attended training, reflecting the state's emphasis on cotton cultivation as a strategic crop. In both settings, approximately two-thirds of both participants and non-participants received information from media such as newspapers, radio, TV, and the internet.

In Kazakhstan, the larger share of AISG participants tend to have daily phone talks about their farm business with more than four people compared to non-participants. However, in Uzbekistan the share of farmers making such telephone exchange among both participants and non-participants is far more than in Kazakhstan. This increased communication in Uzbekistan may be attributed to larger farm sizes and corresponding production management needs (i.e., a more diversified crop portfolio among Uzbekistan farmers compared to Kazakhstan farmers).

In terms of physical characteristics of farms and surrounding infrastructure, in Kazakhstan a higher share of non-participants than participants in AISG reported having good quality land (68% against 49%). In Uzbekistan, about equal share of respondents in both farm groups reported having good quality land. In Kazakhstan, a significantly larger proportion of non-participants in AISG had fields near irrigation canals and were

TABLE 1 | Descriptive statistics of variables across AISG participants and non-participants.

	Kazakhstan			Uzbekistan		
Variables	**Participants ($N = 107$)**	**Non-participants ($N = 139$)**	**Mean diff**	**Participants ($N = 145$)**	**Non-participants ($N = 136$)**	**Mean diff**
Farmer's age (years)	47.477 (12.742)	53.180 (13.688)	−5.703***	46.075 (10.054)	49.532 (9.597)	−3.458***
Farmer has a special education in agriculture (1/0)	0.206 (0.406)	0.079 (0.271)	0.126***	0.537 (0.500)	0.525 (0.501)	0.012
Amount of time that farmer spends for off-farm work (hours/week)	13.271 (19.699)	8.489 (16.258)	4.782**	2.816 (8.869)	0.705 (3.904)	2.111**
Total currently available land (ha)	12.871 (13.007)	10.804 (14.299)	2.067	107.155 (84.935)	79.896 (38.365)	27.260***
Number of cultivated crops	1.140 (0.375)	1.187 (0.533)	−0.047	2.231 (0.574)	2.144 (0.475)	0.087
Farmer's opinion about own decisions in crop cultivation (categorical: 1 = not free at all… 5 = completely free)	4.692 (0.895)	4.712 (0.662)	−0.021	3.170 (1.559)	2.475 (1.656)	0.695***
Farmer has own knowledge in agronomy (1/0)	0.925 (0.264)	0.935 (0.247)	−0.010	0.435 (0.498)	0.381 (0.487)	0.054
Farmer is open to new things (1/0)	0.645 (0.481)	0.439 (0.498)	0.206***	0.755 (0.432)	0.489 (0.502)	0.266***
Farmer cares about opinion of other farmers (1/0)	0.794 (0.406)	0.748 (0.436)	0.046	0.497 (0.502)	0.705 (0.458)	−0.208***
Farmer participated in at least one training during last 3 years (1/0)	0.364 (0.483)	0.101 (0.302)	0.264***	0.823 (0.383)	0.820	0.003
Share of good soils in farmland (0–1)	0.488 (0.498)	0.672 (0.459)	−0.184***	0.668 (0.361)	0.649 (0.417)	0.019
Distance from farm fields to dwellings (km)	7.740 (8.375)	5.926 (5.238)	1.815*	4.086 (4.781)	3.663 (5.099)	0.423
Distance from farm fields to a district center (km)	46.262 (27.226)	37.460 (26.908)	8.801**	15.255 (6.512)	15.683 (6.656)	−0.428
Farmer with fields near irrigation canal and satisfied with quality of irrigation and drainage infrastructure (1/0)	0.131 (0.339)	0.266 (0.444)	−0.135***	0.145 (0.353)	0.199 (0.400)	−0.054
Farmer receives information on agronomy from newspaper, radio, TV, internet (1/0)	0.645 (0.481)	0.604 (0.491)	0.040	0.571 (0.497)	0.554 (0.499)	0.017
Number of people farmer talks daily on telephone about farm business (1/0, 1 = more than 4 people)	0.654 (0.478)	0.496 (0.502)	0.158**	0.939 (0.241)	0.942 (0.233)	−0.004
Farmer's perception about quality of local mobile internet connection (1/0, 1 = very good)	0.299 (0.460)	0.223 (0.418)	0.076	0.429 (0.497)	0.245 (0.431)	0.184***
Using mobile internet fits farm business (categorical: 1 = doesn't fit at all… 5 = completely fits)	2.804 (0.829)	2.957 (0.806)	−0.153	4.109 (0.922)	3.727 (0.841)	0.382***

(Continues)

TABLE 1 | (Continued)

Variables	Kazakhstan			Uzbekistan		
	Participants ($N = 107$)	Non-participants ($N = 139$)	Mean diff	Participants ($N = 145$)	Non-participants ($N = 136$)	Mean diff
Cotton area (ha)	11.615 (11.194)	9.604 (13.091)	2.011	45.624 (33.858)	35.925 (16.834)	9.699***
Labor cost per ha (US$/ha)	145.439 (161.751)	157.481 (179.984)	−12.040	280.551 (294.196)	303.257 (225.310)	−22.710
Fertilizer costs in cotton cultivation (US$/ha)	99.779 (43.537)	112.840 (55.526)	−13.060**	232.532 (63.819)	220.853 (50.048)	11.680*
Cotton seed costs (US$/ha)	34.495 (16.354)	29.578 (18.813)	4.917**	64.213 (23.217)	59.899 (20.737)	4.315*
Cotton yield (t/ha)	2.312 (0.715)	2.286 (0.685)	0.025	2.804 (0.596)	2.780 (0.560)	0.025
Cotton net returns (US$/ha)	1401.917 (570.866)	1372.575 (622.476)	29.340	1132.638 (509.803)	1060.319 (458.746)	72.320

Note: Standard deviation in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

more satisfied with the irrigation and drainage system compared to participants. In both countries, non-participants slightly more often reported having fields near the sources of irrigation water. Additionally, in Kazakhstan, fields of AISG participants were farther from district centers than those of non-participants. In both countries, fields belonging to AISG participants were located farther from their homes compared to those of non-participants. In both countries, the participants in social media groups also reported better quality of mobile internet connection than non-participants.

Figure 1 describes the types of instant messaging apps used among smartphone users in the two settings. It is apparent that WhatsApp and Telegram are the most widely used messaging apps among farmers in Kazakhstan and Uzbekistan, respectively. Fewer than 20% of farmers use other messaging apps such as IMO, Facebook Messenger, Viber, and Skype.

3 | Analytical Framework and Estimation Technique

Assessing participation in AISG using non-experimental cross-sectional data necessitates correcting for self-selection bias, identifying appropriate counterfactuals, and controlling for unobservable farm characteristics (Asfaw et al. 2012; Jaleta et al. 2016). To determine the impact of AISG participation on farm outcomes, we utilized a two-stage estimation method, following standard protocols established in existing literature (e.g., Abdulai and Huffman 2014; Amadu, McNamara, and Miller 2020; Jaleta et al. 2016; Läpple, Hennessy, and Newman 2013). We denote participation in AISG as a binary variable (D_i). While we acknowledge that farmers' decisions to use social media groups may be partly driven by non-pecuniary motivations, such as maintaining professional networks, it is reasonable to assume that these decisions are also influenced by expected farm profitability and the potential for yield increases. We represent this latent variable with D_i^*. Further participants and non-participants are labeled as D_1^* and D_0^*, respectively. While the perceived benefits of participation remain unknown, the farmer's characteristics are observable during the survey. With this as the basis, participation decision (D_i) is treated as a dichotomous choice, namely $D_i = 1$ if $D_1^* > D_0^*$ and $D_i = 0$ if $D_1^* < D_0^*$. Thus, farmers' decision to participate in social media groups is related to their perception of increased net returns from participating. Based on the latent variable model, the first stage involves analyzing the determinants of participation in a social media group using the following probit model:

$$D_i^* = \delta K_i + \varepsilon_i \text{ with } D_i = \begin{cases} 1 \ if \, D_i^* > 0 \\ 0 \ otherwise \end{cases} \quad (1)$$

here, D_i is a dummy variable indicating whether farmer i participates in AISG or not. K_i is a vector of determinants of decision to participate ($n \times m$). δ is a vector of parameters to be estimated $m \times 1$, ε_i is a vector of error term ($n \times 1$) that is normally and independently distributed with a mean of 0 and a variance of σ^2.

In the second stage, to better understand the impact of AISG participation, we model cotton yield and net returns function in a $\ln(Y)$ form, which can be defined as:

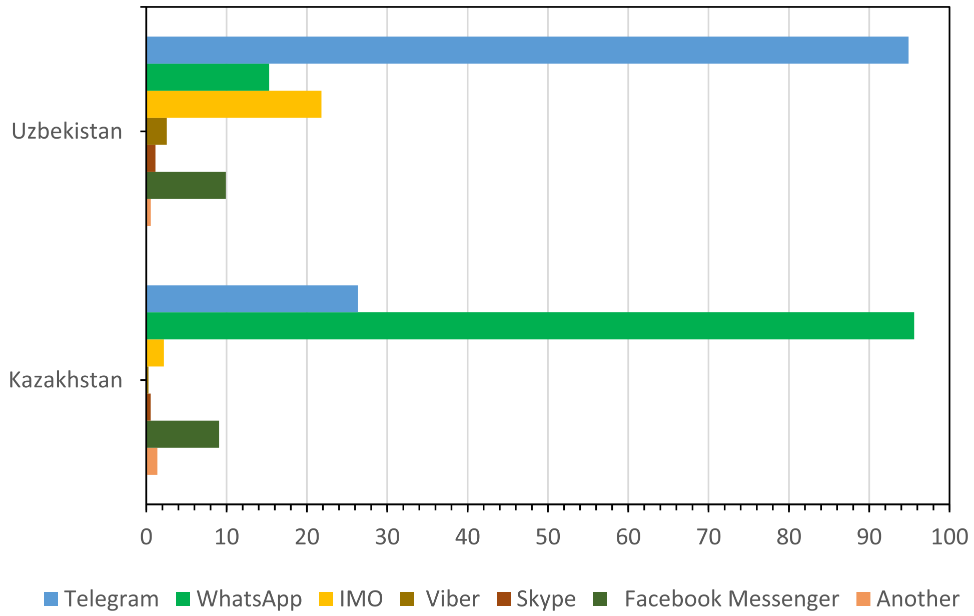

FIGURE 1 | Instant messaging apps used by farmers, % of smartphone users. In Kazakhstan $N = 349$, in Uzbekistan $N = 337$.

$$Y_i = \alpha_0 + \beta X_i + \mu D_i + u_i \tag{2}$$

where Y_i is a vector of outcome variables of farmer$i$, X_i is vectors of determinants of the outcome variables (including production inputs which are cotton area (ha), labor use (US$ per ha), seed use (US$ per ha) and fertilizer use (US$ per ha). Those input variables are given in natural logarithmic form), D_i is social media group participation of farmer$i$, where D_i take a value of 1 if a farmer participates and 0 otherwise. α_0 is a constant, β and μ are vectors of estimated parameters, and u_i is an error term.

The impact of participation in social media groups on cotton yield and net returns is estimated through the parameter μ. However, this method may yield biased estimates since it treats group participation as exogenous, whereas it may actually be endogenous (Di Falco, Veronesi, and Yesuf 2011). Farmers' participation decisions can be influenced by individual self-selection and other factors, such as technology preferences, which might vary among different groups like younger and older farmers. Participants in AISG may also have distinct characteristics from non-participants and may decide to participate based on expected benefits, which can vary due to individual differences in expectations. Recognizing that selection bias may arise from observable and unobservable attributes affecting both participation in groups and outcome variables simultaneously, using Ordinary Least Squares (OLS) may result in biased and inconsistent estimates. We apply an endogenous switching regression model to correct for endogeneity and sample selection bias by dividing farmers into participants and non-participants. The probit model in Equation 1 provides crucial information to examine and correct the potentially resulting bias (Maddala 1983: 223). To test selection bias, the Inverse Mills Ratio (IMR) can be calculated from the probit model's results (Heckman 1979) as follows:

$$\lambda_{1i} = \frac{\varphi(\delta K_i)}{\Phi(\delta K_i)}\ \lambda_{2i} = \frac{-\varphi(\delta K_i)}{1 - \Phi(\delta K_i)} \tag{3}$$

where $\varphi(.)$ and $\Phi(.)$ indicate probability density function and cumulative density function of the standard normal distribution respectively. λ_{1i} and λ_{2i} represent IMR for participants and non-participants, respectively. Thus, in our model the outcome equations in two regimes stand for:

$$\begin{aligned}&\text{Regime1 (participants in AISG)} : y_{1i}\\&= X_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} + \eta_{1i}\ \text{ if }\ D_i = 1\end{aligned} \tag{4a}$$

$$\begin{aligned}&\text{Regime2 (non−participants in AISG)} : y_{2i}\\&= X_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} + \eta_{2i}\ \text{ if }\ D_i = 0\end{aligned} \tag{4b}$$

where $\sigma_{1\varepsilon}$ and $\sigma_{2\varepsilon}$ are parameters to be estimated, η_{1i} and η_{2i} are normally distributed error terms with mean zero and constant variance.

Existing studies, such as Abdulai and Huffman (2014), Di Falco, Veronesi, Yesuf (2011), and Jaleta et al. (2016), explain that for a more robust identification it is important to select instrumental variables (IV) that affect $D_i$in Equation 1 and do not appear as explanatory variables in the outcome equation. In Kazakhstan, farmers primarily acquire farm-related information through visits to local administrative bodies or extension agents, typically located in district centers. Given the distances between farm fields and district centers, as indicated in Table 1, farmers living farther from these centers are likely to turn to AISG as a source of information relevant to their farm business. We selected "Distance from farm fields to a district center" and "Mobile internet quality" as IVs for Kazakhstan farmers because it influences farmers' decision to participate in AISG, but does not exert direct influence on cotton yields and farm revenues. In Kazakhstan, public extension agencies that provide knowledge and information on farm business, such as procedures related to credit and subsidy applications, are based in district centers, while input suppliers are primarily located in rural areas, close to farmers. Therefore, as farms locate away from city districts, there is increased need to join virtual groups and seek out relevant information. Furthermore, in Kazakhstan, the cotton sector enjoys relatively lower transportation costs. According to Shtaltovna and Hornidge (2014), the cost of post-harvest transportation constitutes less than 4% of total costs. Relatedly, the vast geographic area in Kazakhstan makes the quality and coverage of mobile internet connections crucial for farmers' decisions to participate in social media groups. The quality of mobile internet, while crucial for social media engagement, does not directly influence access to agricultural inputs or the market prices of inputs and outputs, which are largely determined by broader economic conditions. Therefore, for Kazakhstan farmers, we use both "Distance from farm fields to a district center" and "Mobile internet quality" as IVs.

In contrast, we cannot use the same IVs for the Uzbekistan setting because they can be correlated with farm yields and revenues. Economic and social significance of cotton in Uzbekistan makes cotton growers potential target group for agricultural development projects, for example, irrigation projects and farm support services, initiated both by the local government and international organizations. These initiatives are often selected based on how proximate farms are to a district center with sufficient infrastructure. Apart from alleviating logistical issues, better infrastructure also implies a better mobile internet quality. As such, unlike in Kazakhstan, we expect a direct pathway in Uzbekistan through which mobile internet quality affects cotton yields and revenues, even for non-participants of AISG, thereby compromising the validity of this instrument. In Uzbekistan, rural settlements ("mahalla"), which host farmers' dwellings, serve as venues for information exchange among farmers. Greater distance between farm fields and farmers' homes in the settlements reduces the likelihood of face-to-face knowledge exchanges with peers in the same mahalla. This prompts these farmers to explore other options like AISG for communicating with peers about farm business. We believe these three IVs directly affect farmers' decisions to participate in AISG, but do not affect cotton yields and farm revenues. We checked the suitability of these instruments through a simple falsification test (Di Falco, Veronesi, Yesuf 2011). The falsification tests for IVs in Supporting Information S1: Table A of Appendix show that the selected variables can be considered as valid instruments: they are jointly statistically significant drivers of the decision to participate in social media groups, but not of cotton yields and revenues of non-participants.

The impact of AISG participation on farmer's outcome can be tested through the comparison of expected outcomes of participants and non-participants in actual and counterfactual scenarios based on Equations 4a and 4b as follows:

$$E(y_{1i}|X, D_i = 1) = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} \tag{5a}$$

$$E(y_{2i}|X, D_i = 0) = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} \tag{5b}$$

$$E(y_{2i}|X, D_i = 1) = X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i} \tag{5c}$$

$$E(y_{1i}|X, D_i = 0) = X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i} \tag{5d}$$

Here, Equations 5a and 5b are observed in the sample. In contrast, Equations 5c and 5d consider counterfactuals: Equation 5c is for participants who would have decided not to participate, and Equation 5 d is for non-participants who would have decided to participate. The differences between Equations 5a and 5c can be formulated as Equation 6 which explains the comparisons of the expected outcomes (net returns in US $/ha, and cotton yield in t/ha), and allows us to calculate the average treatment effect on the treated (ATT) as follows:

$$\begin{aligned} \text{ATT} = (5a) - (5c) = E(y_{1i}|X, D_i = 1) \\ - E(y_{2i}|X, D_i = 1) = X_{1i}(\beta_1 - \beta_2) \\ + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{6}$$

The differences between Equations 5b and 5d can be formulated as Equation 7 which is the average treatment effect on the untreated (ATU):

$$\begin{aligned} \text{ATU} = (5b) - (5d) = E(y_{2i}|X, D_i = 0) \\ - E(y_{1i}|X, D_i = 0) = X_{2i}(\beta_1 - \beta_2) \\ + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{7}$$

Farmers who participated in AISG could achieve higher production levels than those who did not participate for reasons other than social media use. For example, unobservable baseline characteristics like inherent abilities or motivation can influence farm outcomes, even before policy interventions take place or researcher includes all theoretically relevant variables. This is known as "base heterogeneity" (BH), meaning at the baseline there are already differences between two groups other than the role of AISG. Additionally, outcomes for two groups may differ due to unobserved factors, as groups can vary in their responses to stimuli over time. This variability is known as "transition heterogeneity" (TH), meaning post-participation outcomes are different among groups. We calculate them based on standard method (e.g., Carter and Milon 2005; Di Falco, Veronesi, and Yesuf 2011; Jaleta et al. 2016). Accordingly, the difference between Equations 5a and 5d (BH_1) represents BH for participants, and the difference between Equations 5c and 5b (BH_2) represents for the non-participants. Last but not least, the difference between Equations (6) and (7) provides TH.

4 | Results and Discussion

4.1 | Farmers' Participation in Social Media Groups

Table 2 presents the probit model estimation results for factors related to the decision to participate in social media groups among sampled cotton-growing farmers in the two study areas. We first present estimation results for Kazakhstan and then for Uzbekistan. In Kazakhstan, among two ICT variables, "Using mobile internet fits farm business" and "Farmer's perception about quality of local mobile internet connection," only the latter is significantly associated with farmers' decision to participate in AISG. Particularly, among farmers with high assessment of internet quality the likelihood of participation in

TABLE 2 | Probit model estimation of factors related to farmers' participation in AISG.

Dependent variable Decision to participate in social media groups	Kazakhstan Marginal effect	Uzbekistan Marginal effect
ICT characteristics		
Using mobile internet fits farm business (categorical: 1 = doesn't fit at all 5 = completely fits)	−0.008 (0.034)	0.101*** (0.030)
Farmer characteristics		
Farmer's age (years)	−0.005*** (0.002)	−0.004 (0.003)
Farmer has a special education in agriculture (1/0)	0.185** (0.091)	− 0.014 (0.051)
Farmer has own knowledge in agronomy (1/0)	−0.042 (0.129)	0.103* (0.057)
Farmer is open to new things (1/0)	0.081 (0.060)	0.213*** (0.070)
Farmer cares about opinion of other farmers (1/0)	0.077 (0.066)	−0.254*** (0.053)
Farm business characteristics		
Total currently available land (ha) (ln)	0.049 (0.041)	0.060 (0.060)
Number of people farmer talks daily on telephone about farm business (1/0, 1 = more than four people)	0.077 (0.055)	−0.106 (0.120)
Number of cultivated crops	−0.138** (0.062)	0.020 (0.051)
Farmer's opinion about own decisions in crop cultivation (categorical: 1 = not free at all… 5 = completely free)	−0.017 (0.034)	0.035* (0.020)
Amount of time that farmer spends for off-farm work (hours/week)	0.0004 (0.002)	0.008 (0.005)
Farmer receives information on agronomy from newspaper, radio, TV, internet (1/0)	0.046 (0.061)	−0.057 (0.059)
Farmer participated in at least one training during last 3 years (1/0)	0.195*** (0.068)	−0.068 (0.077)
Farm infrastructure		
Share of good soils in farmland (0–1)	−0.146** (0.058)	0.060 (0.072)
Farmer with fields near irrigation canal and satisfied with quality of irrigation & drainage infrastructure (1/0)	−0.168** (0.075)	−0.144** (0.073)
Instrumental variables		
Farmer's perception about quality of local mobile internet connection (1/0, 1 = very good)	0.064* (0.035)	−0.031 (0.035)
Distance from farm fields to a district center (km)	0.001** (0.001)	−0.004 (0.004)
Distance from farm fields to dwellings (km)	0.006 (0.005)	0.012* (0.006)
Model diagnosis		
No. of observations	*246*	*281*
Wald χ2 (18)	*71.710****	*60.060****
Pseudo R2	*0.215*	*0.194*
Log likelihood	*−132.300*	*−156.884*

Note: Standard errors in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

social media groups is 6.4% higher than among farmers with low assessment. Next, age is negatively associated with the likelihood of participation in such groups, whereas agricultural education is positively associated with an increased likelihood of participation. Particularly, among sampled farmers In Kazakhstan, having special agricultural education increases the likelihood of participation by almost 19%.

In Kazakhstan, among farm business characteristics number of crops and participation in trainings are significantly related to participation decision. Particularly, each additional crop being cultivated by farmers is associated with 13.8% lower likelihood of social media use. Participation in trainings tends to increase the likelihood of social media use by 19.5%. Among farm infrastructure variables, soil fertility and access to irrigation water are negatively related to the participation decisions. Specifically, better soil and better access to irrigation water are associated with a 15–17% lower likelihood of participating in AISG. Lastly, in the Kazakhstan setting there is a positive association between distance from farms to nearest district center and the likelihood of participation in online groups. Together, this suggests that physical constraints urge farmers to seek out online peer communities as a way to overcome local challenges.

In Uzbekistan among ICT variables, only 'Using mobile internet fits farm business' is associated with increased participation in AISG (Table 2). This suggests that the relevance of technology to farm business is an important factor to consider. Next, among farmer-specific variables, farmers having own agronomy knowledge, being open to new things and caring about the opinion of other farmers are significantly associated with likelihood of participation in AISG. Particularly, having own knowledge and being open about new things relate to the likelihood of participation by 10% and 21%, respectively. Notably, the coefficient for openness is twice as large as that for having own knowledge. Contrary, the opinion of other farmers tends to be negatively related to the likelihood of participating in AISG, with a 25% decrease in likelihood.

In Uzbekistan, among farm business characteristics, more autonomy in crop choices is related to increased participation in AISG. Specifically, a shift in perceived freedom for crop choice is associated with 3.5% increase in likelihood of participation. Similar to Kazakhstan, among Uzbekistan farmers farm infrastructure variables are significantly associated with participation decision. Particularly, a better access to irrigation water is associated with a 14.4% decrease in the likelihood of participating in AISG whereas a distance from fields to farmers' dwellings is positively associated with participation.

In summary, in Kazakhstan, those who are younger, have agricultural education and better mobile internet access, cultivate fewer crops, and own lands with poor quality of soil and access to irrigation, and located remotely from district centers tend to participate in AISG. In Uzbekistan, those who value mobile internet for farm business, possess agronomy knowledge, are open to new ideas, care less about others' opinions, have greater autonomy in crop choice, are located further from their dwellings, and with poor irrigation water access tend to participate in AISG.

4.2 | Impact of Farmers' Participation in Social Media Groups on Cotton Yield And Net Returns

The impact of participation in social media groups on farmers' expected outcome under actual and counterfactual conditions is measured by ATT and ATU estimated by the endogenous switching regression model. Table 3 presents the results from the endogenous switching regression treatment effect model for Kazakhstan and Uzbekistan. The last column of Table 3 presents the treatment effects of participation in social media groups. The second-stage regression estimates (Equation 5) are not discussed due to space limitation, but presented in Supporting Information S1: Table A2 in Appendix.

The obtained results reveal that in Kazakhstan the participation in AISG significantly impacts net returns and cotton yields of cotton growing farmers. The participation increases cotton net returns by 11.3% and cotton yield by 5.3%. In other words, interviewed farmers in Kazakhstan who actually participate in AISG would have obtained around 11.3% less net returns or 5.3% lower cotton yields had they not engaged in social media groups (ATT). In Uzbekistan, on the other hand, the results suggest participation positively impacts only cotton yields but not net returns (7.3% and statistically not significant). Farmers who actually participate in AISG would have obtained around

TABLE 3 | Average expected net returns and cotton yield for AISG participants and non-participants.

Outcome variables	Category	Decision to participate in social media group	Decision not to participate in social media group	Treatment effect
Cotton net returns (US$/ha) (ln)	Farmer decision in Kazakhstan			
	ATT	(a) 7.455 (0.014)	(c) 7.342 (0.037)	0.113** (0.040)
	ATU	(d) 7.429 (0.015)	(b) 7.373 (0.030)	0.055 (0.036)
	HE	$BH_1 = 0.026$	$BH_2 = -0.031$	$TH = 0.058$
	Farmer decision in Uzbekistan			
	ATT	(a) 7.380 (0.022)	(c) 7.307 (0.059)	0.073 (0.063)
	ATU	(d) 7.375 (0.017)	(b) 7.306 (0.040)	0.068 (0.042)
	HE	$BH_1 = 0.005$	$BH_2 = 0.001$	$TH = 0.005$
Cotton yield (ton/ha) (ln)	Farmer decision in Kazakhstan			
	ATT	(a) 0.778 (0.017)	(c) 0.725 (0.016)	0.053** (0.024)
	ATU	(d) 0.732 (0.019)	(b) 0.773 (0.012)	−0.041* (0.022)
	HE	$BH_1 = 0.046$	$BH_2 = -0.048$	$TH = 0.094$***
	Farmer decision in Uzbekistan			
	ATT	(a) 1.010 (0.007)	(c) 0.986 (0.012)	0.024* (0.013)
	ATU	(d) 0.978 (0.008)	(b) 1.002 (0.007)	−0.024** (0.011)
	HE	$BH_1 = 0.032$	$BH_2 = -0.016$	$TH = 0.048$***

Note: Standard errors are in parenthesis.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Here (a), (b), (c), and (d) refer to respective equations 5a, 5b, 5c, and 5d.

2.4% lower cotton yields had they not engaged in social media groups (ATT).

TH effects help us understand that the benefits of AISG participation are not the same for every farmer, and some farmers gain more from participation than others. Positive and statistically significant TH effect for cotton yields in Kazakhstan and Uzbekistan indicates that the benefits of participating in AISG, in terms of yields, are not uniform across all farmers. Instead, those who participate in AISG tend to experience higher yields compared to those who do not participate. TH for cotton net returns is also positive but statistically insignificant.

5 | Discussion

The findings presented above show that the determinants of participation decisions in social media groups and associated productivity gains remarkably differ in the two study areas. In this section, we interpret our findings and clarify the significant between-country differences in the results, considering existing relevant literature and the institutional backgrounds of the two study settings.

Technology characteristics are important for the adoption of ICTs and traditional farming practices and equipment. In the selected settings of Kazakhstan and Uzbekistan, farmers' decision to join AISG increased with access to the mobile internet and relevance of such online groups for farm business. Both results are in line with findings in existing literature. A study by Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. (2020) about mobile internet adoption among German farmers confirms that farmers located in regions with poor digital infrastructure tend to inhibit mobile internet adoption. Perceived usefulness of technology is a factor in farmers decisions to use AISG in the Uzbekistan setting. According to Caffaro et al. (2020), there is a strong positive correlation between perceived usefulness and farm productivity. Our results from Uzbekistan show that only farmers who see tangible productivity gains from social media groups are more likely to join AISG.

Farmer-specific characteristics can be another dimension of ICT use in general and AISG in particular. The negative relationship between age and motivation to use ICTs has been documented by many empirical studies (Hoang 2020; Mendes et al. 2023; Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. 2020; Poushter 2016; Smith et al. 2004). Older farmers often are not only less acquainted with new technologies as the main barrier for adoption but also have lower drive to expand farm business than their younger counterparts (Gale 1994). Younger farmers engage more actively in information-sharing networks and are more acquainted with smartphones and associated apps (Michels, Fecke, Feil, Musshoff, Pigisch, et al. 2020). In the context of Kazakhstan, possessing specialized agricultural education emerges as a significant factor, indicating that farmers with formal education in agricultural disciplines are more inclined to harness emerging AISG. This trend may stem from the nature of WhatsApp messenger groups, which are prevalent in Kazakhstan and tend to be smaller than Telegram groups, thus creating an environment that particularly appeals to farmers with agricultural education.

In Uzbekistan, having own agronomic knowledge, being open to new things, caring less about the opinion of other farmers were positively related to farmers participation in social media groups. Being open to experience new things makes farmers more willing to learn and probe with new information or technology. Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. (2020) showed that among German farming community more innovative farmers were more likely to adopt mobile internet. Further, the results from the Uzbekistan setting also indicate that farmers who care about the opinion of other farmers are less likely to participate in AISG. Research shows that farmers adjust their inputs to align with those of their neighbors who were successful in previous periods (Conley and Udry 2010). Learning about others' success is more likely to be based on one-to-one interaction where tangible farm outcomes are visible and mutual trust exists. In such cases gaining especially new information and knowledge from online social group can be a preferred mode of learning. Besides, because cotton production in both settings has a long history and is economically relevant, state agencies also run such online social groups to exchange information with farmers. Research suggests that farmers trust traditional "experts" less, in particular agricultural researchers from academic and government institutions, who they believe are not empathetic towards farmers' needs (Rust et al. 2022). Hence, when the opinion of fellow farmers is important enough to trust and learn from, farmers are likely to reduce participation in AISG.

Our result also show that organization of agricultural production is another crucial factor for farmers' motivation to use social media groups. Larger farms and farms with more diverse production portfolio tend to have more complex organization of production. Multiple production purposes and information gathering should increase demand for mobile internet and social media groups (Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. 2020). However, the results from Kazakhstan suggest otherwise—cultivating more crops reduces the use of social media groups. Generally, empirical evidence in literature is mixed (Hitt 1999; Mishra and Park 2005; Briggeman and Whitacre 2010). For example, Michels, Fecke, Feil, Musshoff, Lülfs-Baden, et al. (2020) did not find evidence to support hypothesis that cultivating more crops increase mobile internet adoption. In our case, social media groups in Kazakhstan seem to offer solutions to less complex issues that attract farmers with simple production portfolio. From another side, using smartphone-based instant messaging apps does not require large initial investment that would prevent smaller farms from participating in AISG.

Lower autonomy due to land tenure insecurity can be an important institutional constraint that inhibits farmers' decisions (Feder and Nishio 1998). Evidence from Uzbekistan showed that farmers with higher perceived autonomy to choose crops have higher likelihood of participating in AISG than those who have lower perceived autonomy. Higher decision-making autonomy in cultivating crops beyond cotton facilitates crop diversification which in turn increases farmers demand for new information on production and marketing.

Lastly, favorable bio-physical conditions such as soil fertility and irrigation water access are vital for farm business. Our findings indicate that in both settings, participation in AISG decreases with improved access to irrigation water. Additionally, in Kazakhstan, the decision to participate diminishes with higher soil fertility. Cotton farmers in the two study areas thus seem to respond to natural resource constraints by joining AISG. They may access information on ongoing or future public investments in farm infrastructure such as roads and irrigation facilities or other nongovernment initiatives. Distances from the farm field to district centers and to dwellings were positively associated with the likelihood of participation in social media groups among farmers in Kazakhstan. Hoang (2020) found that farmers who live far from local markets tend to be mobile phone users for fruit marketing in Vietnam. As large geographic area in Kazakhstan increases transaction cost associated with transportation of inputs and outputs, farmers may seek ways to reduce these costs by participating in AISG.

In both settings, farmers who participated in social media groups benefited from joining AISG as of the survey period. The productivity gains in terms of both higher net returns (11.3%) and yields (5.3%) are visible in the Kazakhstan setting, but only higher yields (2.4%) in the Uzbekistan setting. These findings align with Mendes et al. (2023), who reported a positive impact of AISG participation on farm income by about 20% in Brazil.

Our findings show that institutional characteristics can define farmers' participation and associated gains from knowledge exchange platforms (Norton and Alwang 2020). Compared to Kazakhstan cotton growers, farmers in Uzbekistan make production decisions that are closely tied to top-down procurement policy (Kurbanov, Tadjiev, and Djanibekov 2022). This policy essentially restrains or gives priority areas that farmers must focus regarding learning, business planning and marketing. Farmers' land tenure security is tied to the success to meet state-imposed production targets. The failure can result in the termination of land lease contract. Under such punitive environment, farmers interpret and evaluate new information even if it brings productivity gains. Farmers' skepticism shows up in our results as well. Uzbekistan cotton growers pay more attention to perceived benefits from social media, perceived knowledge and openness. Furthermore, the differences in institutional environments also explain why productivity gains between the two study settings differ. The production targets imposed on cotton producers in Uzbekistan do not allow to convert the social media group participation into increased farm net revenues. Although farmers can increase their cotton yields from AISG participation, they do not face proper input and output prices that would translate the physical output gains into monetary gains. This suggests that to promote ICT tools among cotton growers in Uzbekistan, economic incentives should be considered along with cotton yields.

6 | Conclusion and Policy Implications

Our study contributes to an emerging research area that relates farmers' participation in social media groups to enhanced farm performance through knowledge sharing, problem solving and broader forms of distant (online) collaboration with other farmers. First, we examined the determinants of participation in social messaging groups such as WhatsApp and Telegram using farm survey data collected among farmers in the irrigated areas of Kazakhstan and Uzbekistan. Following this, we looked at the impact of participation in social media groups on farm performance measured in terms of cotton yields and net revenues. Since farmer's decision whether or not to participate in smartphone-based AISG is voluntary, we used an endogenous switching regression model to correct for possible sample selection bias stemming from observed and unobserved factors.

Our findings indicate that the determinants of farmers' participation in social media groups vary between two countries. In Kazakhstan, participants in AISG are those who have better access to mobile internet connection, are younger, have agriculture-related education, cultivate fewer crops, participate in farm trainings, have lower soil quality and irrigation water access, as well as fields further from district centers. In Uzbekistan, however, the participation decisions are made by those who see the relevance of mobile internet for their farm business, have agronomy knowledge, are open to new things, care less about the opinion of other farmers, free to choose crops, have poor access to irrigation water and fields further from dwellings. These findings suggest that farmers' use and adoption of information and communication technologies are influenced less by the type of crops and more by the local environment in which they operate such as socioeconomic, institutional, and regulatory conditions.

Our findings indicate that participation in social media groups has a positive and statistically significant effect on both outcome variables of cotton-growing farmers in Kazakhstan. The estimation results reveal that participation in social media groups increases cotton yields and net revenues by almost 12% and 5% respectively. In Uzbekistan, the participation in agricultural knowledge-sharing groups brings smaller increase in cotton yields, namely by approximately 2.5%. However, similar positive impact of social media group participation does not hold for net revenues of cotton growers in Uzbekistan. This can be explained by the institutional context of cotton production in Uzbekistan where farmers' decisions over crop choice and marketing are restrained. Thus, the regulation imposed on cotton farmers in Uzbekistan does not allow to convert the participation in AISG into higher net revenues. Although farmers can increase their cotton yields from participating in AISG, they do not face proper input and output prices that would translate the physical output gains into monetary gains. This suggests that to promote ICT tools among cotton growers in Uzbekistan, economic outcomes should be considered, not pure physical harvest quantities.

We draw the following policy implications which should be considered when designing policies and private strategies for spreading digital technologies in agriculture. In Kazakhstan where farmers produce under more liberal and secure tenure conditions, the focus could be given to improve internet connection to stimulate farmers' participation in AISG. Introducing smartphone-based e-extension should start with younger and more educated farmers. For creating conducive environment for using and benefiting from messaging apps, the priority should be given to information farmers care most such as yields, prices and costs. Specifically, a practical approach should involve specific knowledge required within a given context, such as about crop cultivation methods, access to input and output markets, and climate adaptation. Where farmers' production decisions are closely tied to top-down production arrangement, the focus should be first on showing the economic usefulness of participation in AISG. Explaining how farm business benefits from online social groups is a vital step to encourage further participation. Making farmers self-reliant entrepreneurs will reduce their tendency to follow top-down recommendations and encourage them to make more nuanced decisions that align with their needs and capacities. Higher decision-making autonomy is thus crucial for converting digitalization processes in agricultural sector into economic benefits for farmers.

The study has some limitations. First, from the data we cannot tell how long farmers have been using or how long they intend to participate in WhatsApp and Telegram groups. Thus, the determinants we estimated should be interpreted as underlying factors for current or short-term participation in AISG rather than continuous use. Secondly, the limited sample size and the variety of crops cultivated by non-cotton growers constrain our study's focus primarily to cotton producers. Incorporating non-cotton farmers could yield different insights into the impact of social media use on farmers' net revenues, especially in Uzbekistan where non-cotton (e.g., horticulture) farmers possess greater decision-making autonomy than cotton growers. Finally, because our study is based on cross-sectional data, the conclusions drawn from the model should be approached with caution due to the reliance on single-season production data. Additional empirical research will be promising once panel data is available.

Author Contributions

Zafar Kurbanov: conceptualization; writing–original draft; methodology; visualization; writing–review and editing. **Abdusame Tadjiev:** data curation; software; writing–review and editing; methodology; conceptualization; writing–original draft; investigation; validation; formal analysis. **Nodir Djanibekov:** writing–original draft; investigation; conceptualization; funding acquisition; methodology; project administration; supervision. **Ajit Govind:** validation; writing–review and editing; resources. **Akmal Akramkhanov:** validation; writing–review and editing; resources.

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Ethics Statement

The author has nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.