The AI shift: Gender roles and the changing labour market

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Abstract: Artificial intelligence (AI) is increasingly deployed to enhance decision-making in complex production environments, yet its implications for labour allocation and productivity remain incompletely understood. We study the effects of AI-enabled agronomic advice through a randomised controlled trial among smallholder farmers. The intervention increased crop yields and profits by improving the timing and coordination of input use. It also restructured on-farm labour: demand rose for skilled female workers, unskilled family members substituted for hired male labour, and participation in nonfarm employment declined. These adjustments led to a 7.5% reduction in the gender wage gap, primarily driven by increases in female wages. Our findings show that AI technologies influence labour markets not only by raising productivity, but also by reshaping household labour allocation and wage structures. These dynamics highlight the role of intelligent technologies in reallocating tasks among workers and redistributing economic benefits.

Keywords: Artificial intelligence, poverty, agriculture, experiment, India

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1. Introduction

Artificial Intelligence (AI) technologies are transforming production processes, reshaping labour markets, and prompting new debates about their broader economic implications. Recent studies have provided theoretical frameworks and macro-level evidence on AI's role in substituting for routine tasks, increasing productivity, and altering wage and employment patterns across developed economies (Acemoglu and Restrepo, 2019; Autor and Thompson, 2025; Gregory, Zierahn, and Salomons, 2022). Despite this growing literature, rigorous causal evidence on how AI affects individual productivity, labour allocation, and task structure—particularly in decentralised and labour-intensive production contexts common in low-income settings—remains scarce. This gap is especially pronounced in agriculture, a sector where decisions are complex, information is limited, and labour markets are informal, making it an ideal environment to understand AI's micro-level economic effects.

This paper provides experimental evidence on how AI-enabled decision support affects farm productivity, labour allocation, and wage dynamics. We conduct a large-scale randomised controlled trial in rural India, introducing an AI-powered extension service that offers farmers plot-specific recommendations on pest management, nutrient application, and irrigation practices. The AI component used in this study refers to an integrated decision-support system that combines image-based diagnostics with adaptive machine learning. At its core, the system employs a computer vision module powered by deep learning, particularly convolutional neural networks, to analyse crop images and detect issues such as pest infestations, disease symptoms, and nutrient deficiencies. This visual diagnostic function is complemented by a machine learning engine that continuously updates and refines its predictive accuracy through statistical learning, based on new data gathered from the field.

In addition to image inputs, the system integrates sensor-based and environmental data, such as soil moisture, temperature, and weather conditions, to support more comprehensive agronomic decision-making. By combining multiple sources of data and continually improving, the AI system not only substitutes for specific labour tasks but also enhances the overall efficiency of input use and crop management practices. This dual role—as both a productivity-enhancing technology and a substitutable input—justifies its inclusion as both an efficiency factor and an explicit input in the production function modelled in this paper.

The analysis examines how AI adoption influences the composition of labour inputs across cultivation stages, with a particular focus on gendered patterns of task allocation. Unlike traditional digital advisory services (e.g., SMS-based alerts, IVR systems), which typically provide generic or static recommendations, this integrated AI approach responds dynamically to local conditions, thereby improving farmers' ability to coordinate and optimise input use. A comparison of these systems is provided in Appendix Table A1. The AI tool's dual role—as both a decision-support input and an efficiency-enhancing technology—permits a richer analysis of its economic consequences, extending the literature on technology adoption, labour markets, and agricultural productivity.

Our analysis yields three central findings. First, the AI-driven advisory intervention significantly raised productivity, increasing crop yields by 10% and farm profits by 31%. These gains arose primarily from improved decision-making, including more precise timing of input applications and optimised resource management. Crucially, productivity improvements were achieved without raising overall production costs, demonstrating how intelligent technologies can enhance resource allocation efficiency and profitability in decentralised production environments.

Second, the intervention substantially altered labour market dynamics within treated households. Demand for female labour increased significantly, particularly for skilled agricultural tasks, while family labour increasingly substituted for previously hired male labour in response to rising male wages. Consequently, households reallocated labour internally, withdrawing from nonfarm employment and increasing the utilisation of family labour for farming operations. These adjustments resulted in a meaningful reduction in the gender wage gap by approximately 7.5%, primarily driven by rising wages for female labour due to increased market demand. This finding highlights how AI technologies can have important distributional effects, reshape gendered patterns of task allocation and influence wage structures in rural labour markets.

Third, the AI intervention led to a significant reallocation of household labour from nonfarm activities to agricultural production. This internal shift fully absorbed the household labour released from other economic activities, indicating no net reduction in overall household labour supply. This finding shows AI's role not only in boosting productivity but also in reorganising how households allocate their labour between external market activities and internal production

tasks, underscoring broader implications for labour markets in informal and flexible labour contexts.

Taken together, our results suggest that the broader economic implications of AI hinge not just on its capacity to automate tasks, but on its ability to improve decision-making quality, reshape household-level task structures, and alter labour market dynamics. These insights offer valuable lessons for understanding the potential role of intelligent technologies across a wide range of informal, task-intensive sectors beyond agriculture, including small-scale manufacturing, informal retail, and primary healthcare.[1]

This paper relates to the literature in three main ways. First, we extend the burgeoning literature on AI and labour markets (Acemoglu and Restrepo, 2019; Autor et al., 2020; Gregory, Salomons, and Zierahn, 2022; Noy and Zhang, 2023; Autor and Thompson, 2025) by providing causal evidence at the micro-level, demonstrating precisely how AI influences productivity, task allocation, and wage structures in contexts distinct from formal, capital-intensive environments typically examined in prior studies. While existing research largely employs observational macro-level data or controlled experiments in advanced economies (Brynjolfsson et al., 2018; Agrawal et al., 2019; Acemoglu and Johnson, 2024), our study directly uncovers behavioural mechanisms underlying productivity and labour-market changes in decentralised, informal, and task-intensive production settings common in developing countries.

Second, we contribute to the growing literature on digital technologies in agriculture, which has primarily focused on simpler forms of information provision, such as SMS-based extension services, farmer helplines, and interactive voice-response systems (Cole and Fernando, 2021; Fabregas, Kremer, and Schilbach, 2019; Aker and Ksoll, 2016). Unlike these earlier interventions, which offer static or generalised recommendations, our AI-powered decision-support system provides adaptive, real-time advice based on integrated data sources. This

[1] Similar labour structures are observed in sectors such as informal retail, small-scale manufacturing, and primary healthcare. In these environments, workers frequently perform multiple roles, operate with limited formal oversight, and face significant informational or diagnostic constraints. Evidence from small-scale manufacturing suggests that productivity-enhancing technologies can encounter organisational frictions but may involve internal adjustments to workflows or responsibilities, rather than job displacement (Atkin *et al*., 2017). In healthcare, early evaluations suggest that AI-assisted diagnostic tools may enhance clinical decision-making in resource-constrained settings, particularly by supporting triage and diagnosis. However, rigorous, large-scale field studies—especially those measuring effects on provider performance or labour outcomes—remain limited (Ciecierski-Holmes *et al*., 2022). In service industries, AI-based language tools have been shown to alleviate skill bottlenecks and improve productivity in communication-intensive tasks (Brynjolfsson *et al*., 2019). Studying AI in agriculture may therefore yield broader insights into how AI technologies—distinct from earlier digital tools—could shape labour markets in similarly structured, low-productivity sectors across developing countries.

enables more precise, plot-specific guidance that effectively addresses productivity constraints related to input timing, pest management, and resource utilisation. Our findings thus complement recent studies evaluating more targeted digital interventions, such as customised nutrient-management services (Arouna et al., 2021), by highlighting AI's enhanced capacity to respond to farm-level heterogeneity and improve decision-making quality dynamically.

Third, our research contributes to the literature on gendered labour market outcomes in developing economies (Doss, 2018; Klasen, 2019; Afridi et al., 2023). Prior studies document that agricultural modernisation and structural transformations frequently shift gender roles, sometimes enhancing women's economic empowerment through increased market opportunities, but often also intensifying existing inequalities due to differential technology adoption or access (Deere, 2005; Lastarria-Cornhiel, 2006). By showing how AI specifically influences labour demand in favour of female workers, narrows the gender wage gap, and reshapes household-level labour allocation, our findings illustrate a pathway through which technology-driven productivity gains can directly support greater gender equality. This is particularly relevant for policy discussions aimed at harnessing technological innovation to mitigate structural inequalities and foster inclusive economic growth.

The remainder of the paper is structured as follows. Section 2 presents the conceptual framework, Section 3 outlines the study context and experimental design discussed in Section 4, and Section 5 describes the data used and the estimation strategy employed. Section 6 is dedicated to discussing the main results of the impact of crop-specific technology. Section 7 presents the aggregate AI-powered program impact on crop incomes, nonfarm work, and labour allocation. The cost-benefits of the AI-powered program are presented in section 8. Finally, section 9 concludes.

2. Conceptual framework

This section illustrates a framework for understanding how AI integration affects farm labour allocation, production, and profitability. Crop production involves a sequence of distinct tasks, each demanding specific types of labour, knowledge, and timing. In traditional smallholder settings, these tasks are often gender-segregated and performed by both family and hired labour. The integration of AI-based advisory tools transforms task execution by improving decision-making under uncertainty and reallocating labour more efficiently.

We define the expected crop output as:

$$\mathrm{E}[Y] = \pi(AI).A.\prod_{j=1}^{J} Y_j^{w_j}$$

where:

$\pi(AI) \in [0,1]$: Probability of avoiding crop failure, increasing in AI.

A: Baseline farm productivity.

Y_j: Output contribution from task j ∈ {1, …., J}, such as sowing, irrigation, transplanting, harvesting, etc.

w_j: Share parameter for task j, with $\sum w_j$=1.

Each task-specific output function takes the CES form:

$Y_j = [\alpha_j L_{m,j}^{\rho} + \beta_j L_{hf,j}^{\rho} + \delta_j L_{ff,j}^{\rho} + \varphi_j K_j^{\rho} + \psi_j AI_j^{\rho}]^{1/\rho}$, $0 < \rho < 1$, $\sigma = 1/(1-\rho) > 1$

where:

AI_j: AI intensity applied to task j.

$L_{m,j}$: Skilled male labour (hired + family) in task j.

$L_{hf,j}$: Hired skilled female labour

$L_{ff,j}$ is Unskilled family female labour

K_j: Capital inputs (fertiliser, irrigation, mechanisation)

ρ: Substitution parameter

α_j: weight on (total) male labour $L_{m,j}$

β_j: weight on hired skilled female labour $L_{hf,j}$

δ_j: weight on unskilled family female labour $L_{ff,j}$

φ_j: weight on capital inputs K_j

ψ_j: weight on AI intensity AI_j

σ: elasticity of substitution

Unskilled labour—primarily represented by family female workers—typically does not participate in labour markets beyond their own farms and performs unpaid tasks with limited access to skill acquisition opportunities. As a result, we assume they are less productive than skilled labour. In contrast, both hired and family male labourers are treated as skilled: family male members frequently engage in paid work on other farms, thereby gaining experience and

improving their technical proficiency.[2] Given their similar skill levels and task profiles, we treat hired and family male labour as substitutes and aggregate them into a single labour category in the model.

We model AI as both an efficiency-enhancing factor and a separate input to reflect its dual role in the production process. First, AI enhances total factor productivity by improving the effectiveness of other inputs—particularly labour—through more accurate, timely, and plot-specific agronomic recommendations. This aligns with the view of AI as a task-augmenting technology that raises the marginal productivity of complementary inputs (Acemoglu and Restrepo 2019; Brynjolfsson *et al*. 2018). Second, AI requires dedicated resources to adopt and use—such as data collection, training time, and software interaction—making it a real input with costs and adoption constraints. This conceptualisation follows Agrawal *et al*. (2018), who frame AI as a "prediction input" that substitutes for human judgment. Modelling AI in both roles captures the technology's impact on labour demand, input substitution, and productivity in a way that would be incomplete if it were treated solely as an efficiency shifter or a direct input.

Crop production is a labour-intensive process involving various tasks, from land preparation to harvesting. Traditionally, these tasks are divided along gender lines, with male labour responsible for operations such as ploughing, irrigation, and chemical application, while female labour—particularly unskilled family female workers—is engaged in tasks like transplanting, weeding, and harvesting (Deolalikar and Vijverberg, 1982). However, productivity is often constrained by labour inefficiencies, as unskilled female workers have limited opportunities for skill acquisition due to cultural norms restricting access to training and professional interactions (Quisumbing and Padolfelli, 2010).

Cost considerations

Total cost:

[2] A substantial body of literature on agricultural dualism in developing countries argues that, due to limited alternative employment opportunities for family labour, its shadow price—and consequently, its marginal productivity—is lower than both the market wage rate and the marginal productivity of hired labour (Sen, 1966; Mazumdar, 1975). Additional explanations suggest that hired labour is often assigned specialised tasks critical to output or is primarily employed during peak periods of intense time pressure, such as the harvest season, when labour's marginal product is high. However, these factors seem to apply primarily to female family labour rather than male family labour. In our farm surveys, we compared the wages earned by male family labourers when working off the family farm with the wages paid to hired labourers on their own farms. Our findings indicate that farmers pay hired male workers the same wages they themselves receive when employed on other farms.

$$C = \sum_j (w_m L_{m,j} + w_{hf} L_{hf,j} + w_{ff} L_{ff,j} + c_k K_j) + c_{AI}(AI)$$

where:

w_m, w_{hf}, w_{ff} are wages for male, skilled female, and unskilled female labour, respectively. c_k is the per-unit cost of capital in each task. $C_{AI}(AI)$ is AI implementation cost, assumed to be increasing but with diminishing returns, given as:

$$C_{AI}(AI) = c_0 + c_1 AI + c_2 AI^2, c_1, c_2 > 0$$

The constant term c_0 captures fixed implementation costs such as initial installation, training, or onboarding. The linear term $c_1 AI$ represents proportional operational costs, such as platform subscriptions or field-level deployments. Most critically, the quadratic term $c_2 AI^2$ allows for increasing marginal costs of adoption. This convex structure captures the realistic notion that integrating AI becomes more complex and resource-intensive as its intensity increases, whether due to the need for greater user attention, data calibration, or managing sophisticated, time-sensitive recommendations.

The presence of the quadratic term ensures that the model yields an interior solution for optimal AI usage. In the absence of this term, marginal costs would be constant, and a profit-maximising farmer would either adopt no AI at all or use it fully, producing corner solutions that are rarely observed in practice. By contrast, the quadratic form allows AI adoption to respond smoothly to economic incentives and marginal benefits. This structure is also supported in the literature on digital technology and AI economics, including Acemoglu and Restrepo (2019) and Agrawal *et al*. (2018), who emphasise the growing costs of prediction-based automation tools and their strategic deployment. Empirically, it aligns with observed patterns in our setting, where farmers adopt AI services incrementally and adjust usage over time, especially as engagement deepens.

AI can significantly lower agricultural production costs by enhancing efficiency and minimising waste across various farming operations. Precision farming enables the targeted application of water, fertilisers, and pesticides, reducing unnecessary input expenses. Predictive analytics would allow farmers to make informed decisions about planting and harvesting by analysing weather patterns, soil conditions, and crop data, thereby minimising losses and maximising yields. Smart irrigation systems, for example, leverage AI to assess soil moisture and weather data, optimising water use while also cutting labour costs. Additionally,

AI supports more efficient labour allocation, helping to reduce operational expenses and decreasing the need for labour in specific tasks such as irrigation.

Optimisation problem: profit maximisation

The farmer's objective is to maximise profit (Π), defined as:

$$\Pi = p \,.\, E[Y] - C$$

where p is the output price (or revenue per unit of expected yield), $E[Y]$ is the expected output, and C is the total cost. The household chooses $\{L_{m,j}, L_{hf,j}, L_{ff,j}, K_j, AI\}$ to maximise π, subject to the production function above. The AI-augmented marginal-revenue price:

$$p_j \equiv \pi(\mathrm{AI})\, \mathrm{A} w_j\, Y_j^{1-\rho}$$

First-order conditions for optimal input allocation

Optimal male labour use:

The profit-maximisation condition for hired male labour in task *j* is

$$p_j \frac{\partial Y_j}{\partial L_{m,j}} = w_m,$$

where

$$Y_j = [\alpha_j L_{m,j}^{\rho} + \beta_j L_{hf,j}^{\rho} + \delta_j L_{ff,j}^{\rho} + \varphi_j K_j^{\rho} + \psi_j AI_j^{\rho}]^{1/\rho}$$

and hence

$$\frac{\partial Y_j}{\partial L_{m,j}} = Y_j^{1-\rho}\, \alpha_j L_{m,j}^{\rho-1}$$

Substituting gives the first-order condition

$$p_j\, Y_j^{1-\rho}\, \alpha_j L_{m,j}^{\rho-1} = w_m$$

The marginal product of male labour increases in tasks where α_j is high, and where AI enhances the productivity of complementary inputs. If $\rho < 1$, male labour and AI complements, and demand for male labour rises with AI (e.g., transplanting, harvesting).

Optimal hired female labour use:

The profit-maximisation condition for hired female labour in task *j* is

$$p_j \frac{\partial Y_j}{\partial L_{hf,j}} = w_{hf},$$

where

$$Y_j = [\alpha_j L_{m,j}^{\rho} + \beta_j L_{hf,j}^{\rho} + \delta_j L_{ff,j}^{\rho} + \varphi_j K_j^{\rho} + \psi_j AI_j^{\rho}]^{1/\rho},$$

and hence

$$\frac{\partial Y_j}{\partial L_{hf,j}} = Y_j^{1-\rho} \beta_j L_{hf,j}^{\rho-1}$$

Substituting gives the first-order condition

$$p_j Y_j^{1-\rho} \beta_j L_{hf,j}^{\rho-1} = w_{hf}$$

Demand for skilled female labour (hired) increases when AI enhances productivity in female-intensive tasks such as weeding and transplanting. If β_j is large and AI is complementary ($\rho < 1$), then $\frac{dL_{hf,j}}{dAL} > 0$. This is consistent with the empirical evidence presented later in the paper, which shows significant increases in the hiring of female labour for transplanting and harvesting.

Optimal family female labour use:

The profit-maximisation condition for family female labour in task j is

$$p_j \frac{\partial Y_j}{\partial L_{ff,j}} = w_{ff},$$

where

$$Y_j = [\alpha_j L_{m,j}^{\rho} + \beta_j L_{hf,j}^{\rho} + \delta_j L_{ff,j}^{\rho} + \varphi_j K_j^{\rho} + \psi_j AI_j^{\rho}]^{1/\rho},$$

and hence

$$\frac{\partial Y_j}{\partial L_{ff,j}} = Y_j^{1-\rho} \delta_j L_{ff,j}^{\rho-1}$$

Substituting gives the first-order condition

$$p_j Y_j^{1-\rho} \delta_j L_{ff,j}^{\rho-1} = w_{ff}$$

$$\frac{dL_{ff,j}}{d\mathrm{A}} = \frac{1}{1-\rho} Y_j \left(\frac{p_j \delta_j}{w_{ff}}\right)^{1/(1-\rho)} \frac{1}{A}$$

Since $\delta_j < \beta_j$ by assumption (family female labour is less productive), and in many tasks AI substitutes for unskilled labour, the demand for $L_{ff,j}$ falls behind in some tasks due to AI, while being assigned to crop care tasks such as insecticide and herbicide applications. This aligns with empirical findings on the substitution of female family labour by skilled male and female workers in tasks like transplanting and weeding.

Despite an increase in yields, evidence presented shows a decline in average labour productivity (output per worker).

Let Average Labour Productivity (ALP) = $\frac{\sum_j Y_j}{\sum_{i\in\{m,hf,ff\},j} L_{ij}}$

where Y_j is output in task j and L_{ij} is the number of workers of type i in task j. AI raises total output both through the markup term, π(AI), and by intensifying the use of high-return tasks, such as insecticide application, fertiliser use, and harvesting. However, because the CES elasticity satisfies $0 < \rho < 1$, this boost in productivity also magnifies the marginal value of labour—especially for skilled hired workers—so that total labour input expands by more than output. As a result, average labour productivity (output per worker) falls even though overall yields rise. In a capital-constrained setting, AI therefore drives labour intensification rather than mechanisation: tasks such as transplanting and weeding become more skill-sensitive, and households respond by hiring additional help, consistent with our empirical observations.

The introduction of AI-powered agricultural software transforms how farms allocate their workforce. By providing real-time insights on soil conditions, pest and disease detection, nutrient management, water optimisation, and yield forecasting, these tools shift technically demanding or time-sensitive tasks away from unskilled female family labour and toward skilled hired workers guided by AI recommendations. Meanwhile, unskilled family labour is redeployed to less complex crop-care activities—those requiring manual effort and attention but not precise timing or specialist expertise. In this way, AI acts as a truly labour-augmenting technology in smallholder agriculture.[3]

[3] While herbicide application is typically a skilled task requiring technical precision, empirical data reveal that a small share of unskilled family female labour performs herbicide spraying, particularly in low-volume follow-up applications. In our setting, AI treatment via the eSAP platform is associated with a decline in herbicide use, although the effect is statistically insignificant. This suggests that AI's guidance may lead to more targeted or restrained chemical use, potentially substituting not just decision-making labour, but also reducing unnecessary applications. The direction of the effect is consistent with the theoretical prediction that AI enhances input efficiency, particularly in areas where overuse or mistiming is common.

Some key insights from the above model:

(a) Under CES technology with $\rho < 1$ (so elasticity of substitution $\sigma=1/(1-\rho) <1$), AI acts as a gross complement to all labour inputs, implying $\frac{\partial L_{ff}}{\partial AI} > 0$. However, since the share parameter on family female labour is strictly smaller than that on skilled hired labour, the semi-elasticity of unskilled family labour demand to AI-driven productivity gains is appreciably lower than for skilled inputs. In equilibrium, AI therefore increases the absolute level of female family labour, reflecting redeployment into routine crop-care tasks, but by less than it boosts skilled labour demand in precision-sensitive activities. This differential response captures why, even as overall labour input rises, we observe a relative displacement of unskilled family workers from high-precision tasks toward broad-coverage chores, such as pesticide and herbicide applications.

(b) AI enhances productivity beyond simple labour substitution. In the conceptual framework, AI enters both as a "prediction-input" and multiplicatively as an efficiency shifter, raising the marginal product of all complementary inputs through more accurate, timely agronomic recommendations.

(c) Cost of AI adoption affects its optimal level. The cost function $C_{AI}(AI) = c_0 + c_1 AI + c_2 AI^2$ (with $c_2 > 0$) ensures an interior solution. Higher linear (c_1) or quadratic (c_2) costs raise the marginal cost curve, reducing the optimal AI intensity.

(d) Labour costs dictate hiring decisions. Because output is CES in hired male, hired female, family female and AI inputs, a rise in the hired male wage w_m makes male labour relatively more expensive. Cost minimisation then reallocates usage along the CES isoquant toward all other inputs–family male labour, skilled female labour and AI–according to the common elasticity of substitution ($\sigma=1/(1-\rho) <1$).

AI transforms labour dynamics in the agricultural sector by moving away from traditional gendered roles in favour of skill-based deployment. Instead of assigning tasks based on physical ability or social norms, AI promotes a merit-driven workforce where efficiency is prioritised. Skilled labour benefits from AI-driven precision tools, data analysis, and predictive technologies, enabling workers to assume higher-value roles. At the same time, AI simplifies tasks such as crop monitoring and pest and disease management, making them more accessible to less-skilled workers and reducing barriers to entry.

By enhancing both efficiency and inclusivity, AI supports the development of a labour market where individuals succeed based on their skills rather than gender-based roles. This

transformation ultimately boosts productivity in crop cultivation. Higher productivity, in turn, drives increased demand for labour, particularly during harvest periods. Additionally, favourable weather conditions that intensify pest pressure further raise the need for specific labour to carry out insecticide applications. The framework above illustrates AI's dual role as both a labour-substituting and labour-augmenting force, showing how AI-driven agricultural systems can enhance productivity by reallocating tasks to skilled workers and optimising overall farm management.

3. Study context

3.1. AI-powered Extension Program

Developed by Tene Agricultural Solutions (TAS), a leading Indian agri-tech firm, the Electronic Solutions Against Agricultural Pests (eSAP) seamlessly integrates AI into crop production. By leveraging advanced algorithms, eSAP software analyses farm data to identify growth patterns and predict crop health, providing early insights into potential economic impacts and enabling farmers to make informed decisions. Originally designed as a diagnostic tool for identifying pests and diseases, the software has evolved into a comprehensive crop management system. With its ability to autonomously learn patterns, detect anomalies, and deliver real-time solutions, it enhances precision, efficiency, and sustainability in modern agriculture.

The primary objective of eSAP is to leverage cutting-edge agricultural technology to maximise farm productivity through innovative, data-driven approaches. By utilising its vast crop-level database, which encompasses technology insights, pest and disease profiles, and farmer responses, eSAP benchmarks each farmer's initial practices to provide a customised roadmap for improvement. Its dynamically personalised content adapts to the farmer's experience level, rate of progress, and specific farm conditions, ensuring tailored guidance.

Research has consistently demonstrated that localised, individualised advice is significantly more effective than broad, centrally planned recommendations (Krishnan and Patnam, 2014; Arouna *et al*., 2021). To maximise accessibility, eSAP delivers information through multiple channels, including on-farm consultations, call centres, and self-guided animations, and is deployable both online and offline via computers, tablets, and smartphones.

At the time of the study, eSAP supported over 100,000 farmers in the neighbouring districts of Karnataka and deployed them to provide information for only a few crops. With the rollout of

our project, TAS began expanding its crop pests and disease information database to include over 26 major crops widely grown in the state. According to FAO (2017), plant pests and diseases are the foremost emergencies responsible for 20-40% of global food production losses. It poses a significant threat to the livelihoods of vulnerable farmers in developing countries and global food security. Although farmers face constraints such as access to credit, insurance, and input and output markets, this study focuses on access to information on crop cultivation practices, considering all other constraints.

3.2. eSAP software: The interactive software features continuous crop assessment alongside instructional videos and animations, through which farmers learn through explanations and feedback. Here, we highlight four critical design features of the software and provide a more detailed pictorial description, along with examples, in the Online Appendix C.

First, despite the numerous pest management options available, identifying problems and finding solutions is challenging for the various pests and issues that harm crops, including insects, viruses, fungi, bacteria, weeds, and nutrient deficiencies. All of these reduce crop yields and affect farmers' well-being. The AI-powered content incorporates the latest research on effective crop and soil health management, as well as real-time field monitoring, with built-in intelligence that supports informed decision-making based on accurate and verifiable data.

Second, the eSAP system employs an adaptive framework, delivering tailored solutions based on each farmer's crop performance. This dynamic adaptation process is initiated at the onset of the crop cycle through a comprehensive diagnostic assessment and continues to refine its recommendations with each subsequent agricultural activity. The pest identification module utilises an advanced image-based branching model integrated with a machine learning system that continuously improves through statistical learning. A key software innovation lies in its ability to provide precise, pest-specific diagnoses, enabling farmers to accurately quantify damage and determine the economic threshold for optimal pest management. By delivering targeted advisory support through its "Extension at the Right Level" approach, eSAP effectively mitigates the diverse pest and disease challenges encountered in Karnataka's major crops, enhancing resilience and productivity.

Third, eSAP enables real-time monitoring of the crop field by integrating the spatial coordinates of the field into the GIS map along with the severity of the problem. The application is built on a platform that opens a gateway for the two-way dissemination of information in real-time. It features substantial built-in intelligence for on-field decision

support and protocols for conducting intelligent surveys to gather crop growth-related information, which can be viewed through the GIS platform. As surveillance entails capturing multiple images by the field device, a set of close-ups and field images, along with data on the crop, crop age, pest damage, and the field's geo-coordinates, are transmitted to the cloud for further use by researchers and policymakers.

Finally, high-quality images that depict crops at various stages are used to guide users in identifying concerns related to crop health in an intuitive manner. Audio assistance in the local language is provided at every step; the user does not need to be literate. The interactive user interface, combined with the individualisation of material for each farmer, facilitates the farmer's continuous engagement with the prevailing crop health management strategies. This approach aims to boost farmer attention and engagement, provide feedback at the level of each intermediate step in solving a problem, and shorten the feedback loop between farmers facing similar pests and diseases.

4. Experimental design

4.1. Study sample

Our sample comprises farmers from two districts in different agroclimatic zones of Karnataka, a southwestern state in India. The two districts are Tumkur in the south and Bellary in the north. To randomise farmers into treatment, we followed a three-stage procedure (Figure 1). In the first stage, we stratified the 58 *Gram Panchayat* (GP, an administrative unit smaller than the district) with 205 villages into the farm and nonfarm based on the primary sources of income to guarantee the desired heterogeneity in terms of sectors of activity.[4]

After the GP was stratified in the second stage, we randomly allocated the villages to treatment and control within each stratum. We assigned 102 villages to the treatment group and 103 to the control group. In the third stage, we identified farmers who had cultivated paddy over the last three years. Over the course of the program, we randomly selected 300 households from each of the treatment and control villages.[5] We randomise at the village rather than the

[4] We conducted focus group discussions with the village elders (progressive farmers, retired government servants, elected representatives) in each village to identify the primary sources of household income. A village is categorised as nonfarm if there is a consensus among village elders that the main source of household income collectively is not from crop cultivation. Departing from our pre-analysis plan, we increased the number of villages from 160 to 205 to better capture crop diversity and nonfarm economic activities (Subramanian, 2025).

[5] Our power calculation, based on paddy crop yield outcomes, indicated a required sample size of 300 households for both the control and treatment groups (Subramanian, 2025). Additionally, we randomly selected 60 households from the treatment villages as a spillover group, though this was not part of the power calculations. The number of spillover households was determined solely by budget constraints, rather than any methodological rationale.

household level to mitigate spillovers between treatment and control households through markets or eSAP delivery agents.

Six households from the treatment group were lost during the second visit to the selected households for the baseline survey. Twenty-four months after the project commencement, one control household and three treatment households were lost to follow-up. After thirty-six months, forty control households and nineteen treatment households were lost to follow-up. Since we had oversampled the households at the baseline, we randomly added additional households in the following order: 30 to the control group and 26 to the treatment group. As indicated in Figure 1, we successfully traced back some households that experienced attrition for the endline survey. Thirteen treatment households that had previously experienced attrition during the 2015-16 intervention period were re-traced. Additionally, all twenty-two re-traced households had been lost to follow-up during the second midline survey.

As shown in Figure 1, we successfully traced some previously attrited households for the endline survey. Among them, thirteen treatment households had missed the 2015–16 intervention, while all twenty-two traced households were unavailable for the second midline survey. Figure 1 provides a complete overview of both treated and control households.

4.2. Experimental groups

Control Group: Print Information, Awareness and Conventional Extension

Farmers in the study were aware that they were part of an experiment; that is, the awareness (control) group did not receive any visits from eSAP delivery agents but were conscious of their crop productivity being monitored. We developed an informational brochure and a wall calendar that summarises solutions to common agricultural pests and diseases, supporting farmers. All households in the control villages of the study received a printed copy of the information brochure in their local language. Additionally, these households continued to receive occasional visits from the government's conventional agricultural extension agents. They retained access to pre-existing public agricultural support services, including the farmer helpline, the Kisan Call Centre, and the local Krishi Vigyan Kendra (KVK).[6]

Consequently, we were unable to include spillover households in some treated clusters and did not select a comparable spillover group from control villages. As a result, these households are excluded from the analysis in this paper.

[6] Our baseline survey revealed that only 12% of households reported receiving visits from government extension workers. This finding aligns closely with state-level data from the NSSO 77th round, as reported by Sahu *et al*. (2024), which shows that just 10% of households had access to public extension services—encompassing

Treatment Group: Print Information and AI-powered eSAP Extension

Households in the treatment group also received the same printed information described above. Farmers in the program receive 60-minute sessions fortnightly from a delivery agent, who uses the eSAP software on a handheld Android tablet.[7] These sessions, conducted over three agricultural years, involve inspecting the crop field and taking photos from all four coordinates. Once the eSAP software completes its diagnosis, it initiates a video dialogue addressing the crop's health, identifying pests and diseases, nutritional deficiencies, and weed issues. The delivery agent then hands the tablet to the farmer, who watches the video in their local language to understand the crop's progress. If any potential problem is identified, the software recommends solutions to the farmers.

The services were provided at no cost to the treatment group of farmers, utilising an in-person targeting strategy to deliver AI-powered agricultural extension. This intervention served as a proof of concept, with farmers receiving fortnightly access to the eSAP software. However, the scalability of this approach presents potential challenges. To enhance cost-effectiveness and facilitate broader implementation, alternative delivery mechanisms—such as downloadable applications for tablets or mobile devices with regularly updated information on pests and diseases—should be explored.

5. Data and estimation strategy

5.1. Data

The data used in this paper come from two primary sources over a five-year period. Trained research assistants, different from the eSAP delivery agents' team, visited the sample households at their homes and farms to administer a baseline survey. The baseline round took place before households received the printed information on brochures and wall calendars. First, we collected farm-level survey data in April 2013 (baseline), April 2014 (first follow-up), April 2016 (second follow-up), and April 2017 (third follow-up). Second, we collected household-level survey data for all the rounds mentioned above, except for the first follow-up (2014).

Farm surveys

government extension agents, Krishi Vigyan Kendras, agricultural universities and colleges, and veterinary departments.

[7] According to the pre-analysis plan, visits were initially scheduled on a weekly and bi-weekly basis. However, over time, the delivery agents determined that fortnightly visits were more suitable, as more frequent visits did not yield additional benefits, and fortnightly scheduling offered a more efficient balance between monitoring needs and logistical feasibility (Subramanian, 2025).

These surveys were conducted on a four-monthly basis during on-farm eSAP monitoring over a four-year period spanning the agricultural seasons (Figure 2).[8] The farm survey comprised a plot roster that recorded the output of crops in each plot for the months preceding the interview. We collected plot-level information on the type of crop produced, planted area, output quantity and prices, and the duration of the crop produced. We collected operation-specific labour hours for each type of labour, labour cost (including family labour), input quantity and prices, and revenues in the cost module. This information was recorded for each crop plot and all eleven farming operations.

Household surveys

Annual household surveys were conducted to collect data on household and demographic characteristics. The individual roster documented member-specific details, including age, sex, education, occupation, salary, and wage income from both agricultural and non-agricultural employment. It also recorded information on asset ownership and livestock activities. Additionally, we gathered data on information exchange beyond village connections, tracking the receipt and transmission of agricultural-related communications. Farmers were asked to list individuals, both within and outside the village, whom they would consult for advice when making farming decisions.

5.2. Balance and attrition

Baseline balance. Table A2 in the online Appendix A shows the balance of pre-program characteristics using the baseline sample. The first column indicates the estimation unit, column 2 displays the total number of observations, and columns 3-5 show the treatment means, the difference in means between treatment and control, and the corresponding p-values. Baseline balance checks across the groups revealed no statistically significant difference between the groups. Since randomisation was stratified to account for variations in the primary source of income, we evaluate effects in different strata, reporting heterogeneous results for the sector of activity.

Attrition. We tested the differential attrition across the different survey rounds. The results in online Appendix Table A3, column 1, show an 8% attrition rate in the control group. Examining the differential attrition reveals that the experimental group is less likely to attrit than the control group in the baseline and first follow-up, whereas the opposite is observed in

[8] The agricultural seasons are *kharif* (from June to September), *rabi* (from October to January), and summer.

the second and third follow-ups. However, for the differential attrition in the second and third follow-up outcomes, we bound our main treatment effects using the bounding approach of Lee (2009) to construct upper and lower bounds, as reported in Table A4.

Compliance. To interpret the results, it is essential to verify whether participants adhered to the assigned treatment protocol. Table A5 presents the regression estimates for households receiving the treatment. Overall, participation in the program was high, at 96%.

5.3. Empirical strategy

Using the Analysis of Covariance (ANCOVA) specification, we regress different outcomes on treatment status using the specification[9]:

$$O_{ivt} = \propto + \beta_1 Treatment_{ivt} + \gamma O_{ivo} + Y_t + \theta_{gp} + \epsilon_{ivt} \qquad (1)$$

The subscripts denote household i residing in village v in time t, O_{ivt} is the outcome of interest. $Treatment_{ivt}$ is a dichotomous variable equal to 1 if the household received the eSAP intervention. O_{ivo} is the value of the dependent variable at the baseline, Y_t is the year fixed effects, θ_{gp} is the strata fixed effects and are included to improve efficiency because the randomization is stratified by GP. The error term ϵ_{ivt} is clustered by village, the unit of randomization. We also report unadjusted p-values that control for the false discovery rate alongside p-values to correct our standard errors for multiple hypothesis testing.

6. Results

6.1. Program effects for paddy: unpacking the impact

In this section, we unpack the ITT effect based on Equation 1 of the AI-powered eSAP program in paddy. On average, the experimental households owned and managed at least one paddy plot at the baseline, in addition to plots growing 33 other crops. Since we tracked each plot over the program period, we reported results using the plot-level data. We use Equation 1 to estimate the performance of each crop plot for household *i* in village *v* at time t as the outcome variable. Since household crop choices are endogenous, we report later in the paper the results of the impact of eSAP on aggregate household crop income to alleviate any strategic considerations

[9] For experimental design, ANCOVA is preferred over difference-in-difference estimators with a large improvement in power for noisy and less autocorrelated outcomes such as farm profits, household incomes and expenditures (McKenzie, 2012).

in the choice of the plot. Of course, we consider that no land was purchased or sold during the study period.

Table 1 presents regression results for several outcomes across the entire program, illustrating its long-term impact. In the first column, we report crop yield (a measure of agricultural productivity) since the program started. In the subsequent columns, we report crop profits in column 3. In the remaining columns, we report labour allocations by gender across both extensive (columns 3 and 4) and intensive margins (columns 5 and 6). Additional results distinguishing hired and family labour are also reported in the online Appendix Table A6.

6.1.1. Crop productivity and profits

The eSAP program has demonstrated substantial success, with the potential to increase crop yields by 284 kilograms per acre—a 10% increase ($p = 0.000$) over the program's duration (column 1) compared to the control group, which had an average yield of 2,662 kilograms per acre. The program's direct impact peaked in its first year of implementation with a yield increase of 490 kilograms per acre compared to the control group (online Appendix, Table A7). However, this impact diminished in subsequent years despite ongoing farmer engagement and re-treatment efforts.

Over time, the diminishing impact of AI-driven interventions highlights the challenge of sustaining long-term productivity gains. This decline may be attributed to improved agronomic conditions, which can narrow the yield gap between treated and control households, diminishing marginal returns on investment (fade-out effects) for treated households, or a combination of both. Another possible explanation is that control households gradually gained access to information from treated households. However, this scenario was unlikely, as spillover effects were intentionally minimised by selecting villages rather than households, thereby keeping the control and treatment groups apart (see Section 4.1). Additionally, household survey responses indicated that control households did not report treatment farmers as sources of agricultural information. Nonetheless, the study was not designed to isolate the precise cause of the decline.

Despite this, eSAP's primary contribution to crop productivity, as noted below, remains in its ability to optimise comprehensive crop management—enhancing pest and disease control, improving input efficiency (including water and labour), and minimising yield losses at a minimal cost.

Next, we analyse profit—revenue minus cost—over the program years. The cost of cultivation comprises both material inputs and wage expenditures, with wage costs encompassing payments to hired labour as well as imputed wages for family labour. The imputed wage cost was estimated by multiplying the number of family members engaged in each agricultural operation by the corresponding gender- and operation-specific market wage rate. Since family members earn wages when working on other farms, their labour on their own farm is valued at the same market rate. This approach ensures an accurate estimation of imputed wage costs, reflecting the true economic value of their contribution. However, female family members (unskilled labour) working only on their own farms are assigned an operation-specific wage rate that is 20% lower than that of hired female labourers (skilled labour). This difference reflects their relatively lower skill levels and accounts for the time they would otherwise spend commuting to work.[10]

The regression results presented in Table 1, column 2, reveal a significant 31% increase in profit ($p = 0.000$) for treatment households over the program's duration compared to the control group.[11] Several factors contributed to this increase in profitability. First, farmers in treatment villages experienced higher crop yields, as shown in column 1 of Table 1. Second, cultivation costs remained stable—and even declined during the program's final two years (columns 4–6, Online Appendix Table A8)—which helped sustain profitability even as yield gains began to level off (columns 1–3, Online Appendix Table A7). Additionally, evidence that treatment farmers received higher prices for their paddy crop in the final year (column 3, Online Appendix Table A9) suggests that improved market access or enhanced crop quality may have contributed to sustained income gains. Although our study was not designed to precisely disentangle these mechanisms, the combined effect clearly indicates lasting economic benefits for treated households.

6.1.2. Impact on labour allocation

We collected granular data on person-workdays and hours worked, disaggregated by gender and by hired versus family labour, for each cultivation task. Consistent with longstanding evidence on gender segmentation in agriculture (Laufer, 1985; Doss, 2018), women in our sample at the baseline predominantly performed labour-intensive tasks—such as transplanting,

[10] In the farm surveys, household heads reported that the labour cost of female family members working on their farms was typically 20% to 25% lower than that of hired labour.

[11] The survey results on paddy profits, presented in columns 4 to 6 of Online Appendix Table A7, show a decline from 43% in the first round to 24% in the third round relative to the control group, despite a 6.89% increase in paddy prices occurring only in the program's final year (column 3, Online Appendix Table A9).

weeding, and harvesting—while men handled tasks like land preparation, irrigation, and the application of agrochemicals. Harvesting and threshing emerged as the most labour-intensive operations, with a heavy reliance on hired labour. In contrast, crop-care activities (e.g., manure and nutrient application) were largely undertaken by male family members, reflecting their greater access to training and supervisory roles (Quisumbing and Padolfelli, 2010).

Gendered Shifts in Labour Demand. Table 1 (columns 3–6) shows that the AI advisory drove significant increases in both extensive (person-workdays) and intensive (hours per worker) margins of labour demand. Remarkably, female labour demand rose by 104% on the extensive margin—more than double the 43% increase for male labour—while hours per employed worker grew by 136% for women versus 69% for men.[12] These disproportionate gains echo findings in other sectors where productivity-enhancing technologies can inadvertently amplify existing segmentation, boosting demand for certain groups even as they improve overall output (Atkin et al., 2017; Autor and Salomons, 2018).

Hired versus Family Labour. Disaggregating further (Table 2), female family workdays surged by 128% (column 3, Panel B), and hired female workdays by 86% (column 3, Panel A). On the intensive margin, hours worked per employed female rose by 114% (hired) and 92% (family). By contrast, male labour gains were limited to family members: there was no change in hired male workdays (Panel A, column 1), but family male labour increased by 41% on the extensive margin and 30% on the intensive margin (Panel B, columns 1 and 2). This substitution of family for hired male workers was driven by a 20% rise in male wage rates for tasks like pesticide application (column 4, Online Appendix Table A10 and also Figure A1), aligning with theoretical predictions that higher wages encourage within-household substitution (Mazumdar, 1975).

Constraints on Family Female Labour. Although wages for hired female workers increased (columns 1-3 in Online Appendix Table A10 and Figure A2), the lack of available female family substitutes meant that farms relied more on hired female labour for time-sensitive, skill-intensive tasks—such as sowing and transplanting—where AI-guided precision was most valuable. Female family labour, facing both time and mobility constraints, could not fill these

[12] To account for multiple hypothesis testing, the family-wise p-values presented in braces in Table 1 were adjusted using the Romano and Wolf procedure, reflecting tests across ten hypotheses for five outcomes within Panel A.

roles, leading to greater hiring rather than reallocation within the household (Quisumbing and Padolfelli, 2010).

Implications for Labour Productivity. Overall labour input grew faster than output, producing a measured decline in average labour productivity (Online Appendix Figure A3). Under CES with $\rho < 1$, output gains amplify the marginal value of complementary inputs more than average productivity, leading to an expansion of labour input that outpaces output growth—a dynamic our data and model both capture.

This "efficiency yet intensity" pattern—where a technology augments productivity while increasing total labour use—reflects coordination gains from adaptive, data-driven recommendations that reshape task sequencing and resource allocation, even as they may raise aggregate labour requirements. Our findings thus demonstrate how AI's precision-tailored guidance simultaneously drives efficiency improvements and reconfigures task-level labour shares based on CES predictions about complementarity and substitution.

6.1.3**.** Impact on the gender wage gap

Table 3 reports estimated real daily wages by gender and treatment status, based on the OLS specification in Online Appendix B1. We regress individual real wages on treatment, a female indicator, and their interaction, controlling for baseline wages, GP fixed effects, and year fixed effects, with robust standard errors clustered at the village level. In control villages, women earn on average ₹109.41 per day less than men. In treatment villages, the gender gap narrows to ₹101.22—a statistically significant reduction of ₹8.19 ($p < 0.001$), equivalent to a 7.5% decline in the wage differential.

This narrowing appears to be driven by gains in female wages relative to those of their male counterparts (Figure 3). Estimates are based on predictive margins from the regression model, allowing for interpretation net of covariates. Our findings align with evidence that technological interventions can alter gender wage disparities by shifting labour demand toward tasks in which women have comparative advantages (Moorthy, 2024). They also resonate with theoretical models of task-based technology adoption, which predict that AI, by augmenting the productivity of complementary inputs, can raise wages for those inputs (Acemoglu and Restrepo, 2019; Agrawal, Gans and Goldfarb, 2018). In our context, AI's plot-specific advisories increased demand for skilled female labour (high share parameter β in our CES

framework), thereby boosting female wage rates relative to male rates and contributing to the observed compression of the gender wage gap.

6.2. Impact on production cost

This section examines how the eSAP intervention altered the cost structure of paddy cultivation—an essential channel through which productivity gains translate into higher profits and influence labour allocations. Drawing on detailed input-cost data for each farming operation, Table 4 reports control-group means (first column) alongside treatment impacts from separate ANCOVA regressions that include baseline controls, year fixed effects, and strata fixed effects. Each cell in columns 2 and 3, based on separate regressions, shows the impact of the eSAP on the cost of input use in farming operations.[13]

Seed and Transplanting. Following our CES framework (Section 2), AI's plot-specific recommendations enhance the efficiency of seed use ($\nu = 1/\rho$). Adopting the eSAP recommendation of seed priming and its associated practices improved germination and emergence rates, reducing the need for high seeding rates (see online Appendix B). Treatment households, guided by eSAP's germination diagnostics, reduced seed requirements by 116% (Table 4, column 2), while adopting direct-seeding eliminated nursery transplanting. Transplanting operations fell by 6.98%, delivering labour and water savings without increasing weeding costs—consistent with the framework's prediction that AI raises the marginal product of complementary inputs (α for male labour in transplanting tasks) and lowers redundant operations.

Weed Management. While reduced transplanting might be expected to raise weeding needs, eSAP's targeted recommendations kept herbicide costs virtually unchanged. By prescribing pre-emergence applications within two days of sowing, the system avoided unnecessary over-application—demonstrating how precision advisories can trim agrochemical use without sacrificing yields. In our CES framework, this reflects AI's dual role as both an efficiency shifter (raising the productivity of chemical inputs) and a direct "prediction" input (ψ) that optimises timing and dosage.

Crop-Care Inputs. Alongside stable herbicide costs, treatment households increased insecticide application by 26.9% and micronutrient use by 24% (Table 4, column 2). In our CES framework (Section 2), these crop-care operations carry large share parameters, so AI intensity

[13] In Online Appendix Table A11, we report input costs categorized into non-labour input costs (columns 1 and 2) and labour costs (columns 3 and 4) for each agricultural operation.

(ψ) raises their marginal productivity and leads to greater usage precisely where and when it matters most.

Irrigation Costs and Water Productivity. By integrating real-time soil-moisture and weather data, the AI system optimised water productivity with irrigation timing and volume, cutting labour costs for water management by 90% (Table 4, column 2). Because water itself is not traded (Online Appendix Table A11, column 4), this saving reflects a reduction in predominantly male family labour devoted to irrigation (online Appendix Table A13, column 2 for extensive margins and Table A14 for intensive margins). In our profit-maximisation model (Section 2), AI recommendations increase the marginal productivity of water and its complementary male labour input, allowing agronomic water needs to be met with substantially less effort. Thus, lower sowing costs (116%) and irrigation costs (90%) limit the overall production cost across all program years (see online Appendix Table A8, columns 4-6).

Harvesting. Higher yields and optimal harvest timing—improved by AI's predictive guidance on crop maturity—raised harvesting costs by 23%, met by increased engagement of family male labour (online Appendix Table A13, column 2), as well as both hired females (online Appendix Table A13, column 3) and family workers (online Appendix Table A13, column 4) in harvesting operations. This aligns with the model's implication that AI augments demand for complementary labour in peak tasks (Section 2).

Labour allocation by crop operation. Labour allocation in agriculture follows a gender-specific division of tasks, with men and women working together but assuming distinct roles. Skill levels also differ between hired and family female workers, particularly in specialised activities such as transplanting, weeding, and harvesting. Limited access to skill development and training opportunities can result in lower marginal productivity among female family workers compared to their hired counterparts. However, with the eSAP intervention, their workload in transplanting and weeding decreases as these essential, skill-intensive tasks are reassigned to skilled male labour or hired female workers.[14] Instead, female family workers take on more crop care responsibilities, including applying manure, fertilisers, micronutrients, herbicides, and even insecticide spraying—a task traditionally performed by men (online Appendix Table

[14] Online Appendix Table A12, which details the transplanting operation by gender, shows a 36% increase along extensive margins in female labour (column 2), driven mainly by hired female workers (online Appendix Table A13, column 3). However, the intensive margins show a decrease (online Appendix Tables A14 and A15). Similarly, fertiliser application increased by 249%, but this operation was exclusively driven by female family labour (online Appendix Table A13, column 4).

A13, column 4). AI guidance facilitates these operations (see online Appendix B2), making them more accessible to unskilled workers.

6.3. Cultivation practices

We next examine whether the above practices are affected by the treatment status. Although we previously demonstrated the lower production cost resulting from reduced water and male family labour use, here we elaborate further on the two modifying features of the changed practices. With AI deployment, direct seeding significantly reduces labour demand, as rice seeds are sown directly in wet fields, eliminating the need for nursery bed preparation and transplanting.

Table 5 summarises these effects across program years. Panel A shows a decline in the frequency of transplanting and irrigation over time. Panel B examines the impact of the eSAP intervention on the number of family workdays per acre allocated to these activities, revealing a significant reduction. Notably, the treatment group experienced a significantly larger decline compared to the control group. Online Appendix Table A13 highlights that male family members exclusively perform irrigation, whereas transplanting involves both male and female workers. A substantial reduction in male family labour (337%) is partially offset by a modest increase in hired male labour (65%) relative to the control group, while a decline in female family labour (255%) is similarly compensated by an increase in hired female labour (42%).

Pests and diseases intensify under water-limited conditions (Bonman, 1992), disrupting the soil's macro- and micronutrient balance (Geo *et al*., 2006). This imbalance significantly raises production costs by increasing the need for micronutrient and insecticide applications (online Appendix B2). In response, the eSAP intervention resulted in only a 24% increase in micronutrient applications among treatment households (column 2, Table 4). Insecticide use also saw a significant increase, with treatment households incurring an additional ₹647 per acre—a 26% rise (column 2, Table 4)—which, in turn, drove higher demand for hired male workers (online Appendix Table A13, column 1). Meanwhile, female family members took on the role of substituting for hired female labourers in this crop care operation (online Appendix Table A13, columns 3 and 4).[15]

[15] Although herbicide application is typically classified as a skilled task, a small subset of unskilled family female workers in our sample report performing it (online Appendix Table A13, Column 4). The overall decline in herbicide use among treated households—though statistically insignificant (Table 4, Column 2)—is directionally consistent with the AI tool's guidance promoting more targeted and timely input application.

6.4. Impact on nonfarm activities

In this section, we examine the extent to which the reallocation of family labour into farming affects household incomes and labour opportunities in nonfarm sectors. Using Equation (1) for household *i* at the individual member level, we analyse the impact of the eSAP intervention on nonfarm activity, which encompasses both non-agricultural employment and self-employment.[16] Non-agricultural activities include roles such as welders, carpenters, building contractors, and drivers, both within and beyond the village. These activities primarily involve the production of local non-tradable goods. Meanwhile, self-employed nonfarm activities involve running shops, renting out agricultural machinery and livestock, and earning interest from money lending or bank deposits.

As shown in Table 6, the AI-powered extension program resulted in a decline of ₹9,211 (Panel C, column 1) in male household income and ₹1,490 (Panel C, column 4) in female household income from nonfarm activities in the treatment group compared to the control group. This reduction was primarily driven by a substantial shift in family household labour away from nonfarm work. This is reflected in an annual decline of 9 person-workdays for male family labour (Panel C, column 2) and 6 person-workdays for female family labour (Panel C, column 5) over the course of the program. These findings highlight the program's substantial impact in redirecting family labour away from nonfarm sectors, leading to a fundamental shift in household income structures. A similar decline can also be observed at the intensive margin (Panel C, columns 3 and 6), primarily driven by the reallocation of family labour to the agricultural sector. This trend persists across the second (Panel A) and third (Panel B) follow-up surveys. Fink *et al*. (2020) also report a decrease in labour reallocation from the market to the family farm in different contexts in response to increased agricultural output resulting from a subsidised loan intervention.

The decline in household nonfarm income is closely tied to the rising demand for both male and female family labour in crop cultivation on family farms under the eSAP intervention. These findings underscore the transformative impact of AI-driven agricultural technology in reshaping household labour dynamics, pulling workers away from nonfarm employment and ultimately reducing household nonfarm earnings.

[16] Since household members work on farm and nonfarm activities at different times of the year, we do not classify a worker as agricultural or non-agricultural. Thus, we work with the number of workdays each household member spends in each sector.

7. Farm income, nonfarm work and labour allocation

Since the eSAP platform supports 33 additional crops, this section evaluates its overall impact across all 34 crops cultivated by households. Rural households typically manage risk by diversifying their livelihoods, engaging in various activities such as crop cultivation, livestock rearing, off-farm work, and nonfarm occupations like carpentry, tailoring, and construction.

As shown in Table 7, households in our program rely on four primary sources of income: crop cultivation, livestock rearing, off-farm wage labour, and nonfarm work. At baseline, crop cultivation accounted for 63% of total household income, while off-farm wage labour and nonfarm work contributed 10% and 23%, respectively (see the bottom of Table 7).

In this section, we evaluate the impact of our intervention on various household income sources and explore the underlying mechanisms driving these changes.

7.1. Household incomes

Figure 4 illustrates the trends in aggregate crop incomes across treatment groups. Households receiving eSAP support saw an increase in crop incomes compared to the control group, with earnings reflecting profits from the 34 crops supported by the intervention. In the program's first year, the intervention resulted in a notable increase in crop income. While this gain was not sustained in the following year, the final year saw the largest increase in crop income for the treatment group relative to the control.

Table 7 presents the regression results for household income across all four income sources, controlling for year and strata fixed effects, as well as the value of the dependent variable at baseline. In this table, we aggregate incomes from all crops the households cultivate (column 1), various livestock activities (column 2), and agricultural (column 3) and nonfarm (column 4) wage incomes each family member earns. To ensure comparable estimates across columns, we restrict the regression analysis for crop profits to the last two years of the program. This restriction is necessary because the second follow-up survey, as previously noted, only collected data related to crop cultivation, allowing for consistent comparison.

Crop profits from eSAP intervention increased by 36% for the treatment group compared to the control group over the program period (Table 7, Panel A, column 1).[17] However, the increase in crop incomes from the agricultural sector comes at the cost of the nonfarm sector

[17] In the Online Appendix, Table A16 presents the results for each survey round in Panels A and B.

(Panel A, column 4), with earnings declining by 65% (p = 0.001) for treatment households relative to control households. Given the income substitution reported above in response to eSAP support, we now examine its likely impact on the total household income. Aggregating incomes across all four activities (Panel A, column 5), we observe a net positive effect of 32% relative to the control, or ₹68,767 per annum (p = 0.046), on total household incomes for treated households during the program.[18]

7.2. Mechanism

7.2.1. Crop cultivation

A structured follow-up survey was administered to 318 treatment farmers who received access to the AI-powered eSAP advisory tool in April 2016, before the second follow-up survey. The goal was to assess user experiences and perceived impacts of the technology on various aspects of crop production. The survey reveals that farmers perceive the eSAP tool as a highly valuable input into their farming operations, particularly for its ability to offer tailored and timely agronomic guidance. Online Appendix D Figure D1 highlights the features farmers found most useful during the last season. The most frequently cited was autonomy—farmers valued being able to make independent decisions without waiting for extension workers. This was followed closely by perceived benefits from input savings and personalised advice, underscoring how AI helped optimise resource use. Visual diagnosis also scored high, indicating that the image-based diagnostic interface was both accessible and trusted.

Online Appendix D, Figure D2, further elaborates on the aspects of the tool that shaped actual decisions. The top responses were "Saved cost on fertiliser" and "Helped identify pests early", which confirms that AI recommendations directly influenced key input and pest management decisions. Farmers also found that the advice matched their crop condition, reinforcing the strength of field-specific personalisation. Additionally, the tool helped with fertiliser timing and irrigation planning, pointing to improvements in intertemporal decisions.

[18] In online Appendix A, Figures A5-A7, we investigate whether the analysis overlooks important heterogeneity in response to the intervention, although with the caveat that our sampling design did not account for differential land size holdings, which could confound the interpretation. We note two points: (a) Receiving eSAP intervention relative to the control is more profitable on large farms, decreases nonfarm incomes, and increases total household incomes. (b) For farms with less than 5 acres, receipt of eSAP intervention is regressive (except for nonfarm incomes) relative to control. The economies of scale may be the most likely candidate for explaining the observed impact. Although we cannot fully explain why this is the case, future studies can design interventions to investigate the causal effect, considering the heterogeneity impact within their research design.

Turning to actual behavioural change, Online Appendix D Figure D3 shows a range of modifications in farming practices prompted by the tool. A significant share of farmers reported using less fertiliser**,** starting pest scouting earlier, and altering the timing of pesticide application. Interestingly, farmers also mentioned that they no longer rely on neighbours' advice, which suggests a shift from informal, socially mediated guidance toward data-driven decisions. Other adjustments included monitoring leaf colour before applying nutrients and reducing pesticide and irrigation use, which pointed to both cost efficiency and more environmentally sustainable practices.

Finally, Online Appendix D, Figure D4, examines how farmers perceive the AI tool relative to traditional sources of advice. The strongest endorsements were for the tool's ability to reduce the need to travel, provide faster responses, and offer advice when it was most needed. Farmers also felt that visuals were easier to understand, and the information provided involved less guesswork than advice from extension agents or dealers. The tool was seen as more timely and more accurate, confirming that AI can outperform conventional extension channels in both responsiveness and precision.

Taken together, these findings suggest that the AI tool is valued not only for its novelty but also for its substantive role in enhancing farmer autonomy, optimising input use, and replacing unreliable advice networks. The results validate the theoretical framework's assumptions that AI acts both as a labour-augmenting and efficiency-enhancing input, particularly through better timing, pest detection, and input management.

7.2.2. Labour allocation

In Table 7, Panel B, we examine the impact of AI-powered extension intervention on the labour market.[19] We report the number of person-workdays employed (on an extensive margin) in the household activity sector. We found a 19% increase in the number of person-workdays for farm workers (14 person-workdays) over the program period. In response to the increase in labour demand from the eSAP program, labour working in the livestock sector was withdrawn in the second follow-up survey. Family labourers engaged in nonfarm work responded to the program by reducing their person-workdays by 28% (69 person-workdays) relative to the control (Table 7, Panel B, column 4). These are family members working in the urban informal sectors (e.g., auto drivers, welders, carpenters, electricians, construction labourers, low-skill manufacturing

[19] In the Online Appendix, Table A17 presents the results for each survey round in Panels A and B.

workers, etc.).[20] Still, individuals working in the formal sector, such as teachers and state transport drivers, did not reallocate to crop cultivation.

Aggregating across household labour activities (Table 7, Panel B, column 5), there are no significant net effects on the total number of person-workdays. This suggests that all withdrawals from nonfarm activities are fully deployed with no idle work capacity. It is worth noting that the decrease in extensive margins in nonfarm work occurs despite twice the average wages paid compared to farm wages (Table 7, one above the bottom row, and online Appendix A, Figure A4).

The eSAP program's impact on labour market allocation across all 34 cultivated crops reveals a substantial shift in workforce dynamics, as shown in Table 8. The hiring of female workers increased by 52% (column 3, Panel A) relative to the control group, while male family workers previously engaged in nonfarm sectors were reallocated to crop cultivation, increasing person workdays by 23% (column 1, Panel B), with their hours worked rising by 16% (column 2, Panel B). Due to rising wages for male harvesters (online Appendix Figure A1), no additional male labourers were hired, nor were the working hours of existing employees increased (Table 8, Panel A, columns 1 and 2). Although no additional female family members entered farm work, those already working on the family farm significantly increased their working hours by 37% (column 4, Panel B) compared to the control group. These findings highlight the program's role in reshaping labour allocation, drawing workers—particularly women—further into agricultural activities.

To employ additional hired female labour in crop cultivation (Table 8, Panel A, column 3), wages were set above the village equilibrium (see also online Appendix A, Figure A2). However, the potential for substitution was limited, unlike male labourers, who could be replaced by other skilled workers when male wages increased (online Appendix A, Figure A1). As most casual labour transactions occur within the village, wages are determined endogenously through case-by-case negotiations.

8. Cost-benefit of eSAP program

Using nominal monetary measures of profit and cost, we conduct a back-of-the-envelope cost-benefit analysis of our eSAP support. We conservatively assume that the full research cost we

[20] The focus group did not highlight any industrial or manufacturing work that was unpleasant or posed any health risk, including work in agri-food processing units and agricultural machinery manufacturing.

incurred is required to implement such a treatment. The eSAP program, as delivered, had an unsubsidized cost of about ₹455 per household per month. This included payments made by the project to TAS for providing eSAP support (although services to farmers were provided free of charge), covering hardware costs (₹130), staffing for bi-monthly visits (two hours of salary, ₹250), and pro-rated fees for software development (₹75).[21]

Our ITT estimates indicate that the annual average treated household experienced an annual income gain of ₹5,731 per month from eSAP support (Panel A, column 5 in Table 7). This estimate captures all sources of income, including potential reductions in nonfarm earnings. Even under conservative assumptions—high fixed costs, no economies of scale, and no spillover effects—the intervention yields a benefit-cost ratio of 12.61. These results suggest that the eSAP program has significant potential value. Preliminary cost-benefit calculations indicate that eSAP could be a highly promising policy tool. It offers a scalable and cost-effective intervention that enhances the welfare of poor farmers.

9. Conclusion

Technological change—from early mechanisation to today's AI—has long been feared as a threat to employment, framing a zero-sum struggle of "labour versus machine." Economic models warn that routine-replacing innovations can shrink overall employment unless balanced by lower prices, higher demand, or the creation of new tasks and sectors. Yet we lack rigorous, field-based studies of AI's effects outside formal firms. Instead, most research uses reduced-form methods or examines single technologies (for example, industrial robots). Nevertheless, comprehensive, causal evidence on AI's net labour-displacing versus labour-augmenting impacts in decentralised, informal settings remains scarce.

This paper fills that gap by integrating a labour-allocation lens tailored to smallholder agriculture with a large-scale randomised controlled trial of an AI-powered extension service in India. Our findings parallel work on routine-replacing technologies in manufacturing and services (Gregory, Salomons and Zierahn, 2022), but uniquely provide causal evidence from an AI advisory system deployed at scale across individual farm plots.

[21] This includes both the cost of the technology, and the expenses associated with eSAP workers supporting farmers, including transportation. Extensive training for field staff is not necessary, as the eSAP application is menu-driven and can be deployed directly to farmers' smartphones without requiring in-person assistance. The cost of eSAP workers was estimated based on the number of visits made by delivery agents.

We document three main results. First, the AI intervention boosted paddy yields by 10% and per-acre profits by 31%, driven by more precise input timing, coordinated pest and nutrient management, and lower cultivation costs. In static terms, these productivity gains reduced the labour required per unit of output—akin to a displacement effect in task-based models—and led to substitution of family labour for hired male workers in routine crop care tasks.

Second, countervailing labour-creating channels more than outweighed these labour-saving effects. By raising farm profits, the intervention increased overall demand for farm-related labour: skilled female workers saw sharply higher employment, and family members reallocated from nonfarm activities into crop cultivation. As a result, total household labour supply remained fully absorbed in agriculture, with no idle capacity and no net loss of income—even though nonfarm earnings declined.

Third, the net employment impact depends critically on the distribution of gains from technological progress. We show that the narrowing of the gender wage gap by 7.5%—driven by higher female wages—amplified labour demand for women, while rising farm mark-ups would have otherwise dampened employment growth. These findings mirror insights from studies on the ownership of technological capital (Freeman, 2015) and on labour's share in national income (Autor et al., 2017).

Taken together, our results underscore that AI in agriculture functions not merely as a labour-replacing force, but as a driver of both productivity enhancement and internal labour reorganisation. By explicitly modelling and measuring the behavioural channels—task substitution, price-induced demand effects, and income distribution—this paper bridges the micro-level evidence gap and complements macro studies of routine-replacing technologies (Acemoglu and Restrepo, 2019; Autor and Thompson, 2025).

Looking forward, two avenues merit further attention. First, extending our framework to general-equilibrium settings could capture spillovers across labour markets as AI advisories scale. Second, integrating credit, insurance, and market-access interventions would clarify how complementary policies shape the distributional and employment effects of AI. Addressing these questions will be crucial for comprehending the comprehensive economic impact of intelligent technologies in agriculture and beyond.

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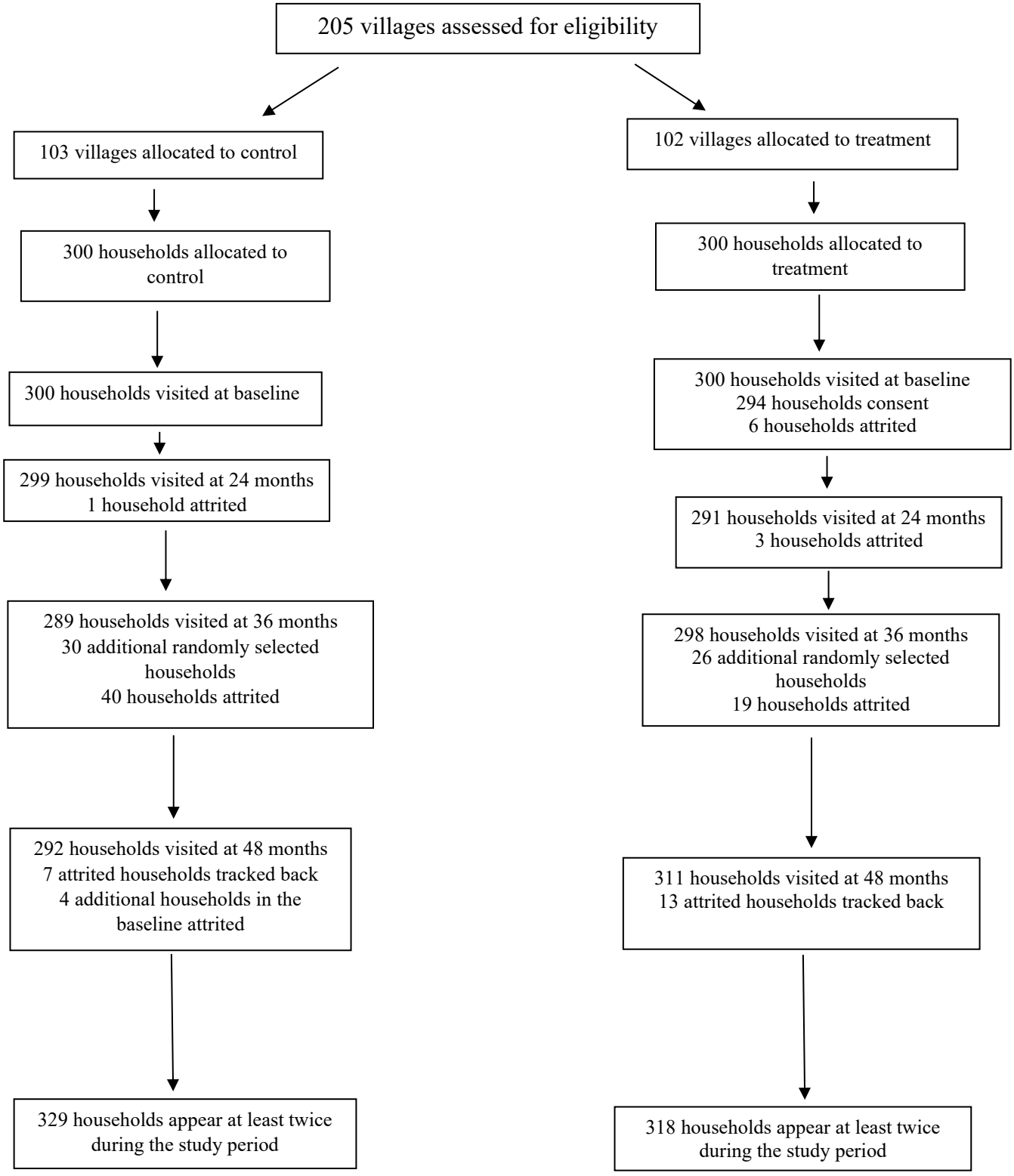


Figure 1: Experimental design

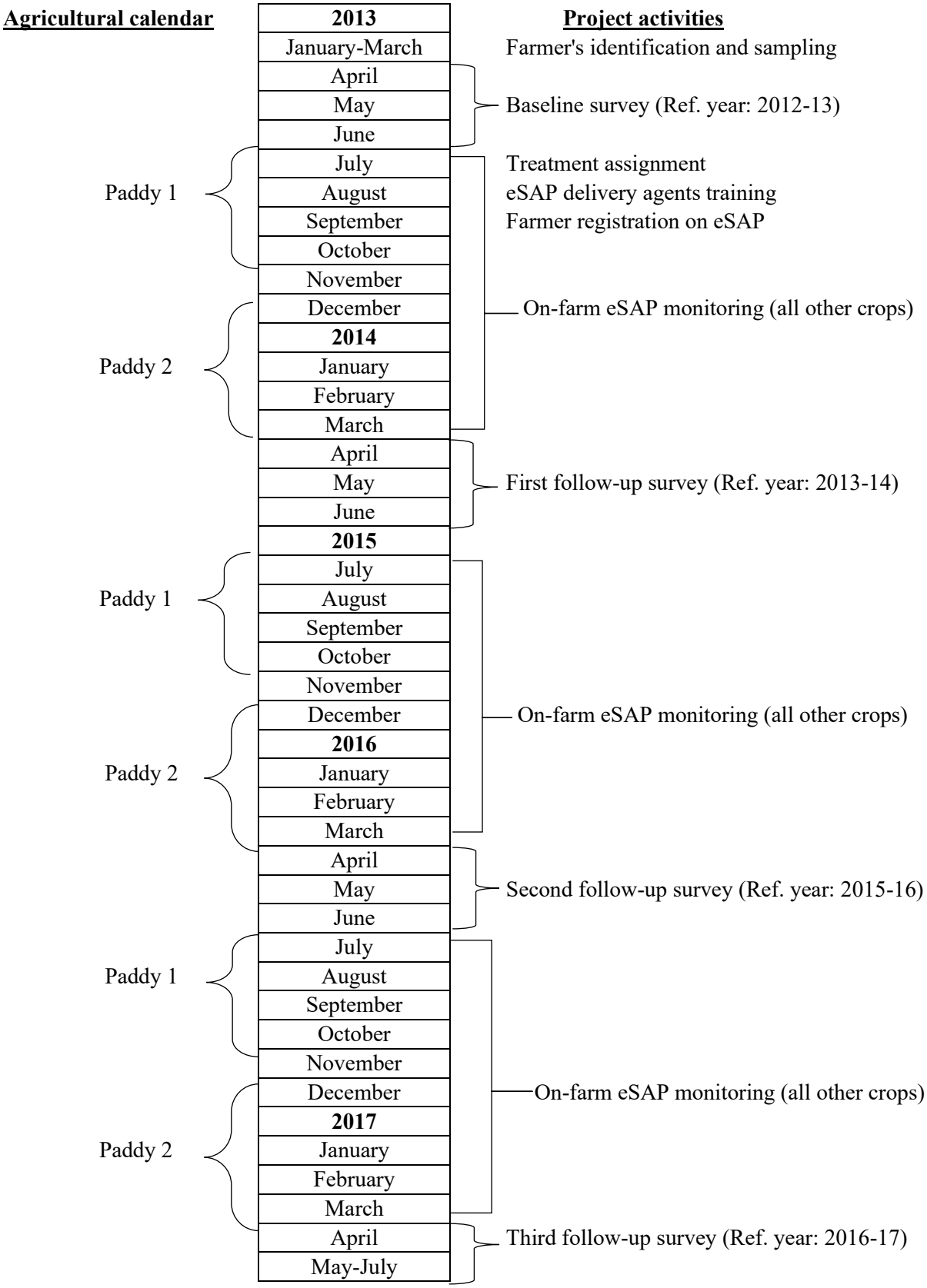


Figure 2: Project timeline

Notes: We did not conduct on-farm eSAP monitoring between July 2014 and June 2015. During the first follow-up survey, we did not carry out household surveys. Not all farmers grow paddy every season, which depends on water availability. No plots were sold or taken out of production for the entire year over the study period.

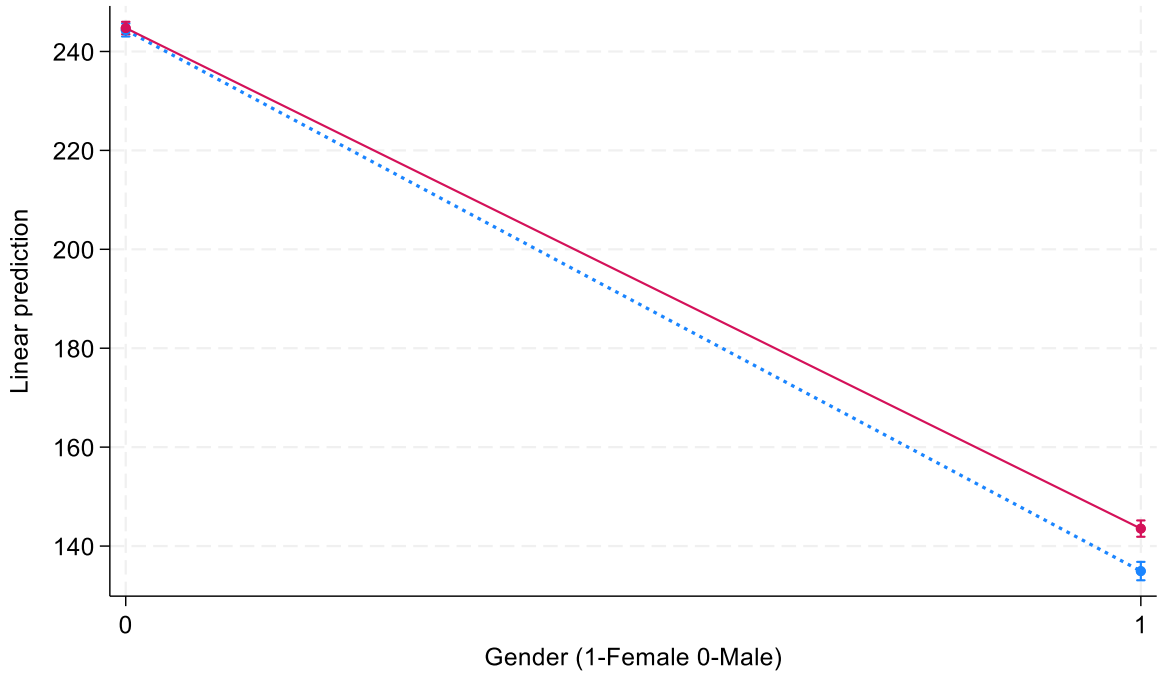


Figure 3: Predicted real wages by gender and treatment (dashed line-Control group, smooth line-Treatment group)

Notes: The x-axis represents worker gender, with 0 indicating male and 1 indicating female. The y-axis shows predicted real wages in Indian Rupees (₹) per day, derived from an OLS regression that controls for baseline wages, GP fixed effects, and year fixed effects (online Appendix B1). Two lines are plotted: the blue dashed line represents the control group (no eSAP intervention), and the red smooth line corresponds to the treatment group (households receiving the eSAP intervention). Each point includes 95% confidence intervals around the predicted wage estimates.

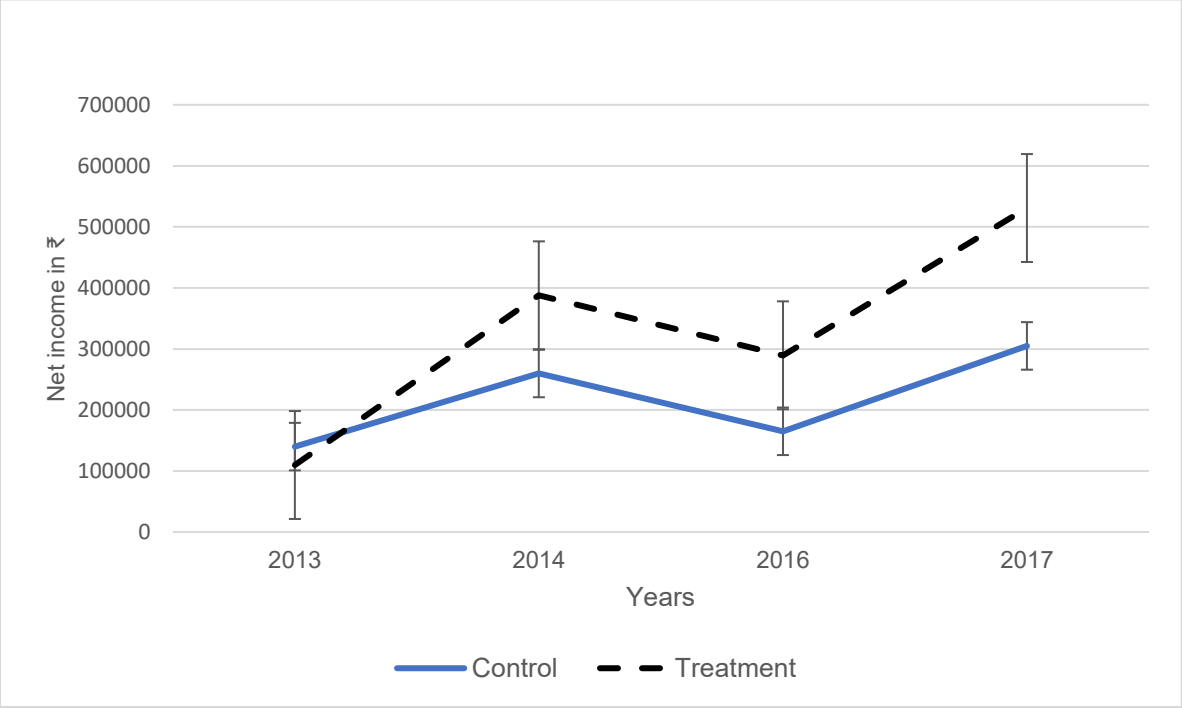


Figure 4: Trends in aggregate crop income by treatment groups

Notes: Crop income is the aggregate of profits across treatment groups from each of the 34 crops grown and calculated as revenue minus the cost of cultivation, including hired and family labour. The crops grown are paddy, cotton, chili, pearl millet, bengal gram, horse gram, maize, red gram, sugarcane, sunflower, cowpea, barley, groundnut, castor, green gram, sorghum, ten different types of vegetables and a combination of several crops raised together.

Table 1: Impact on farm activity from paddy cultivation

Unit of estimation:	Plot					
Household activity:	Paddy cultivation (per acre)					
	Crop yield (kilogram)	Crop profit (amount in ₹)	Male workdays	Female workdays	Male hours worked to total employed	Female hours worked to total employed
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	284.489***	7,045.757***	81.374***	82.183**	100.482***	64.088***
	(71.513)	(1406.302)	(24.052)	(36.242)	(30.172)	(13.362)
	{0.002,0.004}	{0.001,0.002}	{0.001, 0.002}	{0.003, 0.005}	{0.000, 0.001}	{0.001, 0.002}
Control means (in levels)	2,662	22,396	188	79	145	47
R-squared	0.2347	0.2436	0.1281	0.0466	0.1365	0.0790
Observations	2,316	2,316	2,316	2,316	2,316	2,316

Notes: Treatment is the impact of the eSAP intervention. All farmers cultivate paddy 1 in the first season (a few in multiple plots), but the choice of cultivation of paddy 2 in the second season varies every year depending on water availability. Since crop cultivation is an endogenous choice, we also estimate using data for only the first season. The estimates from these regressions are not very different from the results in the above table. Incomes from off-farm labour include wages earned by household members working on others' farms across all three agricultural seasons. Workdays are calculated by multiplying the number of times an agricultural operation was performed by the number of days it took and the number of hours worked per day. This total is then divided by 8, assuming a standard 8-hour workday, to convert total hours into equivalent workdays. This approach standardises labour input across individuals and tasks before summing it to obtain the total labour input. Since each agricultural operation can range from a few hours to several days, it is important to account for each operation separately to ensure accurate measurement of labour effort. All regressions include a constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). We report unadjusted p-values (left) and p-values adjusted (right) for multiple hypothesis testing in braces. These are computed using the Romano-Wolf multiple hypothesis testing (Clarke, Romano and Wolf, 2019). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 2: Impact of the program on the labour market by gender type in paddy

Unit of estimation	Plot			
	Male labour		Female labour	
	Workdays per acre	Hours worked per acre to total employed	Workdays per acre	Hours worked per acre to total employed
	(1)	(2)	(3)	(4)
Panel A: Hired labour				
Treatment	29.149	48.688	56.515**	32.544**
	(24.207)	(31.137)	(29.568)	(13.602)
Control means (in levels)	119.175	87.972	65.489	28.388
R-squared	0.1014	0.1048	0.0603	0.0859
Observations	2,316	2,316	2,316	2,316
Panel B: Family labour				
Treatment	28.920***	57.348***	17.607***	41.111***
	(9.074)	(15.043)	(6.029)	(5.971)
Control means (in levels)	69.553	185.847	13.668	44.567
R-squared	0.1140	0.0906	0.0405	0.0409
Observations	2,316	2,316	2,316	2,316
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included

Notes: Treatment is the impact of eSAP intervention in paddy cultivation. The observations include data from all three follow-up surveys. All regressions include constant, strata-fixed effects, time-fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 3: Treatment effects on real wages – regression, predicted means, and gender gap decomposition

	All workers	Male workers	Female workers
	(1)	(2)	(3)
Panel A: Real wages per day			
Treatment	−100.820***	2.466**	9.497***
	(1.067)	(0.863)	(1.235)
Female	−109.410***		
	(1.161)		
Treatment X Female	101.218***		
	(1.041)		
Baseline wage	0.158***	0.053***	0.374***
	(0.003)	(0.003)	(0.008)
R-squared	0.5065	0.1435	0.2189
Observation	21,517	11,105	10,412
Strata FE	Included	Included	Included
Year FE	Included	Included	Included
Robust SE	Included	Included	Included
Panel B: Predicted real wages per day			
Control Male	244.349***		
	(0.673)		
Treated Male	244.746***		
	(0.639)		
Control Female	134.939***		
	(0.948)		
Treated Female	143.528***		
	(0.841)		
Panel C: Gender wage gaps			
Gap (Control)	-109.409***		
	(1.160)		
Gap (Treatment)	-101.218***		
	(1.041)		
Difference-in-Gaps	-8.191***		
	(1.597)		

Notes: Wages refer to daily earnings paid to agricultural labour in paddy cultivation, disaggregated by gender and type of agricultural operation, and estimated using a pooled regression model. Columns (2) and (3) restrict the sample to male and female workers, respectively. Estimates in Panel B report predictive margins from a regression controlling for baseline wages, GP fixed effects, and year fixed effects. Robust standard errors are used throughout.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 4: Impact on components of input costs by agricultural operations in paddy

Unit of estimation:	Plot		
Dependent variable:	Cost of input use (amount in ₹ per acre)		
	Control mean (SD)	Treatment (SE)	Bootstrap p-values for multiple hypothesis test (unadjusted; Romano-Wolf)
Agricultural operations	(1)	(2)	(3)
Plowing	894.956	-129.200	(0.115,0.199)
	(603.197)	(121.085)	{0.464,0.940}
Harrowing	872.059	93.979	(0.017,0.099)
	(726.389)	(157.176)	{0.570,0.940}
Sowing	1381.288	-1606.805**	(0.100,0.069)
	(1526.517)	(675.861)	{0.053,0.336}
Transplanting	1813.567	-126.640***	(-,0.009)
	(825.487)	(66.654)	{-,0.009}
Weeding	1931.455	-62.635	(0.000,0.029)
	(3270.457)	(253.245)	{0.233,0.841}
Fertiliser application	6624.472	1007.697	(0.000,0.009)
	(4174.271)	(1100.365)	{0.434,0.940}
Micro-nutrient application	339.663	81.610***	(0.013,0.099)
	(407.653)	(20.332)	{0.740,0.940}
Irrigation	84.288	-76.070***	(0.019,0.099)
	(125.876)	(12.553)	{0.010,0.069}
Insecticide application	2409.194	647.599***	(0.001,0.029)
	(1677.366)	(149.565)	{0.620,0.940}
Herbicide application	212.391	-8.666	(0.063,0.118)
	(248.109)	(30.822)	{0.038,0.217}
Harvesting	2349.978	541.927**	(0.073,0.218)
	(1425.561)	(215.539)	{0.046,0.316}

Strata FE	Included
Year FE	Included
Cluster SE	Included
Observations	2316

Notes: The observations include data from all three follow-up surveys. The figures in parenthesis in column (1) are the standard deviation (SD), and figures in columns (2) and (3) are clustered standard errors (SE). Standard errors are clustered at the village level (in parentheses). Each cell in columns (2) and (3) is based on separate regressions showing the impact of eSAP intervention on the cost of input use in each agricultural operation. Input costs across all operations include the use of machinery, animal, and human labour. If a machine or an animal is owned, we use the year-wise going hire price to quantify the value of their services. Human labour includes the cost of both hired and family labour. We use the year-wise going wage rate to quantify the value of family labour. In column (5), we report unadjusted p-values (left) and p-values adjusted (right) for multiple hypothesis testing. These are computed using the Romano-Wolf multiple hypothesis testing (Clarke, Romano and Wolf, 2019). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5: Impact on farming practices in paddy cultivation

Unit of estimation	Plot					
	First follow-up survey		Second follow-up survey		Third follow-up survey	
	Transplanting	Irrigation	Transplanting	Irrigation	Transplanting	Irrigation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of times in each operation per acre						
Treatment	-0.483***	-16.928***	-0.169**	-5.852**	-0.222**	-14.045***
	(0.147)	(4.724)	(0.081)	(2.565)	(0.076)	(3.297)
Control means (in levels)	0.318	9.256	0.307	10.103	0.289	7.632
R-squared	0.4166	0.4191	0.427	0.308	0.5288	0.5231
Observations	1,420	1,420	1,139	1,139	1,079	1,079
Panel B: Family workdays per acre						
Treatment	-0.258	-13.162***	-0.667**	-9.978***	-0.806**	-19.216***
	(0.226)	(2.967)	(0.279)	(2.910)	(0.334)	(5.298)
Control means (in levels)	0.069	12.876	0.219	15.471	0.235	14.743
R-squared	0.039	0.3526	0.0531	0.4334	0.0524	0.4736
Observations	1,420	1,420	1,139	1,139	1,079	1,079

Notes: Treatment is the impact of eSAP intervention. All regressions include constant, strata fixed effects, time fixed effects, and value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 6: Impact on nonfarm activity from crop cultivation

Unit of estimation:	Individual					
Household activity:	Male			Female		
	Income (amount in ₹)	Person workdays	Hours worked to total labour	Income (amount in ₹)	Person workdays	Hours worked to total labour
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impacts in the second follow-up survey						
Treatment	-7785.832***	-15.469**	-94.970***	-1070.204***	-8.959***	-26.486***
	(1910.852)	(7.810)	(22.247)	(313.217)	(3.161)	(2.792)
Control means (in levels)	10,558	54	219	1,088	26	32
R-squared	0.3011	0.5293	0.5539	0.1616	0.4330	0.3932
Observations	2,791	2,791	2,791	2,604	2,604	2,604
Panel B: Impacts in the third follow-up survey						
Treatment	-6460.257***	-5.866**	-69.064***	-1256.346***	-5.262	-25.570**
	(1864.696)	(2.098)	(14.321)	(463.811)	(3.318)	(9.886)
Control mean (in levels)	9,418	51	195	865	24	26
R-squared	0.2978	0.5643	0.5867	0.2784	0.4345	0.3690
Observations	2,815	2,815	2,815	2,585	2,585	2,585
Panel C: Second and third follow-up surveys						
Treatment	-9211.317***	-9.610***	-102.915***	-1490.769***	-6.090**	-35.187***
	(2476.478)	(3.192)	(24.229)	(462.310)	(2.974)	(7.871)
Control mean (in levels)	11,082	46	212	1,067	19	28
R-squared	0.2087	0.3852	0.4499	0.1251	0.2983	0.2492
Observations	4,230	4,230	4,230	3,902	3,902	3,902

Notes: Treatment is the impact of eSAP intervention. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). The number of workdays is calculated as the number of days multiplied by the number of hours multiplied by the number of family and household labour divided by 8 working hours per day. Hours worked to total labour reflects how long (hours) each labour worked in any nonfarm work. All regressions include constant, strata fixed effects, time fixed effects, and value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 7: Impact on rural household earnings (₹ per annum) and labour market over the program

	Sector of household activity				Activity across all sectors
	Crop cultivation	Livestock	Off-farm labour	Nonfarm work	
Unit of estimation	Household				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Income				
Treatment	73,706***	8,247	-990	-18,142***	68,767**
	(23246.61)	(10300)	(917)	(5500)	(32732)
Control means (₹ in levels)	201,374	-31,062	13,816	27,742	211,870
R-squared	0.3282	0.3052	0.4958	0.2348	0.3069
Observations	1,784	1,784	1,784	1,784	1,784
	Panel B: labour workdays				
Treatment	14.195***	19.634	53.045	-69.592**	1740
	(3.986)	(23.259)	(87.656)	(30.603)	(1430)
Control means (in levels)	71	157	881	245	7581
R-squared	0.5659	0.3530	0.3818	0.1007	0.0266
Observations	1,784	1,784	1,784	1,784	1,784
Nominal wage per person per day (₹)	178	174	231	320	
Share in household income at baseline	63%	-	10%	23%	100%

Notes: Treatment is the impact of eSAP intervention across all 34 crops. Estimates are based on data from the last two years and a base year to make it comparable across the various income sources. The detailed data collected for the first follow-up only included crop cultivation. The share (%) in total household income does not include receipts from land leased out (4%). Crop profits include 34 crops – paddy, cotton, sorghum, chili, bengal gram, horse gram, maize, red gram, sugarcane, sunflower, cowpea, barley, groundnut, castor, green gram, and a combination of several crops raised together. Livestock includes milk production, meat, poultry, and hire, sale and purchase of animals. Incomes from off-farm labour include wages earned by household members working on other's farms pooling across all three agricultural seasons. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table 8: Labour market impact of the program by gender type in crop cultivation

Unit of estimation	Plot			
	Male labour		Female labour	
	Workdays per acre	Hours worked per acre to total employed	Workdays per acre	Hours worked per acre to total employed
	(1)	(2)	(3)	(4)
Panel A: Hired labour				
Treatment	11.643	20.782	119.863***	6.921
	(15.029)	(16.809)	(40.301)	(6.227)
Control means (in levels)	77.548	60.007	227.978	25.693
R-squared	0.1093	0.1272	0.1264	0.0818
Observations	3,852	3,852	3,852	3,852
Panel B: Family labour				
Treatment	12.836**	23.515**	2.519	20.549**
	(6.488)	(11.349)	(5.172)	(10.487)
Control means (in levels)	53.542	140.736	23.848	54.188
R-squared	0.0986	0.1296	0.0250	0.0354
Observations	3,852	3,852	3,852	3,852
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included

Notes: Treatment is the impact of eSAP intervention across all 34 crops. The observations include data from all three follow-up surveys. All regressions include constant, strata-fixed effects, time-fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

ONLINE SUPPLEMENTARY APPENDICES

SUPPLEMENT TO

The AI shift: Gender roles and the changing labour market

Arjunan Subramanian and Parmod Kumar

22 July 2025

Appendix A. Online Supplementary data

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Appendix B

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Appendix C

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Appendix D

Figure D1: Important features of the AI tool during the last farming season
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Online Appendix A

Table A1: Comparative features of traditional digital extension tools vs. AI-driven agricultural decision support systems

Feature	Traditional digital tools	AI-drive tool
Personalization	Generic or localised recommendation	Plot-specific real-time
Adaptiveness	Static rules	Learns continuously using a machine learning
Data sources	Single-source information	Multi-model (image + sensor + weather)
Labour Implications	Informational only	Substitutes and reallocates labour
Economic modelling	External to production	Internal costed input + efficiency
Outcome monitoring	Rare	Feedback enabled, evidence-based, iterative learning

Notes: Traditional digital tools for agricultural extension include Short Message Service (SMS), Interactive Voice Response (IVR) systems, video-enabled platforms, call centres, community radio with mobile feedback, and Unstructured Supplementary Service Data (USSD-based) services offering general or static advice. Under labour implications, AI tools are capable of substituting for diagnostic labour, such as identifying diseases without agronomist visits. Also enhances the productivity of family labour, especially in tasks requiring attention and judgement (e.g., targeted plant care), thus directly influencing labour demand and allocation. For economic modelling, traditional tools are rarely modelled explicitly as economic inputs; they are seen as information add-ons. AI tools are modelled as both a capital-like investment and an efficiency multiplier, allowing optimisation of AI adoption alongside labour and capital. This is similar to human capital modelling, as it improves labour productivity (efficiency-enhancing) and is also accumulated through costly investments. Similarly, energy efficiency technologies reduce overall energy usage per unit output (efficiency), but the equipment still costs money and requires investment (input).

Table A2: Sample description and observable balance

	Unit of estimation	Total Observation	Treatment (T) Mean	Difference in means	P-value
	(1)	(2)	(3)	(4)	(5)
Panel A: Demographic characteristics					
Age (years)	Individual	4073	27.6483	0.0100	0.9901
Gender (0-female; 1-male)	Individual	4073	0.5094	0.0128	0.4352
Farming experience (years)	Household	594	20.139	1.123	0.4517
Panel B: Occupation					
Off-farm wage income (₹ per annum)	Individual	4073	25.6361	0.7621	0.8235
Livestock income (₹ per annum)	Household	594	-4.1e+04	1.6e+03	0.8917
Nonfarm income (₹ per annum)	Individual	4073	6.8068	-1.6733	0.4453
Panel C: Crop					
Production cost (₹ per acre)	Plot	1020	2.3e+04	-8.7e+02	0.8576
Revenue (₹ per acre)	Plot	1020	2.6e+04	3.5e+03	0.1740
Profit (₹ per acre)	Plot	1020	2.8e+03	4.3e+03	0.3518
Panel D: Labour use					
Number of days in farm wages	Individual	4073	12.0913	-1.9351	0.1352
Number of days in livestock (family male)	Household	594	165	-37	0.1091
Number of days in livestock (family female)	Household	594	165	-20	0.4981
Number of days in nonfarm	Individual	4073	9.1143	-3.5804	0.1583
Male agricultural wage paid per day (₹)	Plot	1020	36.238	-8.560	0.4966
Female agricultural wage paid per day (₹)	Plot	1020	41.020	-4.992	0.7500
Labour productivity (kilogram)	Plot	1020	53.446	-0.108	0.9834
Panel E: Land use					
Owned (acre)	Household	594	10.0231	-2.1142	0.1329
Rented (acre)	Household	594	1.6828	-0.5862	0.5286
Fallow (acre)	Household	594	0.3495	0.0272	0.8995

Notes: There are two treated groups: Treatment (T) and Control (C) groups. Column (4) is the difference in mean between treatment (T) and the mean of the other two groups (group S and group C). The daily wages for male and female agricultural workers are for the sowing operation. A negative livestock income indicates that the costs associated with the livestock activity exceed the revenue generated.

Table A3: Sample attrition across survey round

	Survey round			
	Baseline	First follow-up	Second follow-up	Third follow-up
	(1)	(2)	(3)	(4)
Treatment	-0.0133	-0.0329	-0.0514**	-0.0668**
	(0.0291)	(0.0293)	(0.0235)	(0.0216)
R squared	0.0018	0.0094	0.0146	0.0234
Mean of control	0.088	0.088	0.085	0.085
No. of observations	647	647	647	647

Notes: The results are based on regressions of a dependent variable for attrition (dummy one if household is missing, 0 otherwise) on a binary variable for treatment. All regressions include GP fixed effects and robust standard errors clustered at the village level, which are reported in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A4: Lee bounds

	Second follow-up survey		Third follow-up survey	
Dependent variable	Lower bound	Upper bound	Lower bound	Upper bound
Crop yield (kilogram per acre)	-0.534	2.702***	1.144	3.727**
	(0.862)	(0.848)	(1.515)	(1.550
Crop profit (amount in ₹)	1523.83	8762.782***	10119.58***	14729.31***
	(1937.027)	(1630.092)	(2301.612)	(2132.36)
Hired labour workdays per acre	65.178	201.663***	36.148	137.178***
	(57.485)	(47.075)	(31.162)	(23.111)
Family labour workdays per acre	-27.172***	7.402	-12.288	39.741**
	(8.170)	(4.431)	(18.078)	(14.729)

Notes: Each row reports the results using Lee bounds to estimate the lower and upper bounds with dependent variables on a binary variable for treatment for the second follow-up survey (2016) and the third follow-up survey or endline (2017). We report bootstrapped standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A5: Treatment compliance

	Household received eSAP
Treatment	0.9676***
	(0.0106)
R squared	0.9382
No of observations	2,374
Mean in control	0.00

Notes: The result is based on a regression of a dependent variable with binary outcome for receiving eSAP treatment (1 or 0 otherwise) on a binary variable for being in the treatment group (1 or o otherwise). Regression also includes GP fixed effects and robust standard errors clustered at the village level, which are reported in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A6: Labour market impact of the program in paddy cultivation

Unit of estimation	Plot			
	Workdays per acre	Hours worked per acre to total employed	Workdays per acre	Hours worked per acre to total employed
	(1)	(2)	(3)	(4)
	Hired labour		Family labour	
Treatment	87.206**	21.782**	30.088***	38.862**
	(44.380)	(10.834)	(9.919)	(16.635)
Control means (in levels)	183.046	83.095	69.553	173.296
R-squared	0.0658	0.1615	0.1102	0.0860
Observations	2,316	2,316	2,316	2,316
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included

Notes: Treatment is the impact of eSAP intervention in paddy cultivation. The observations include data from all three follow-up surveys. All regressions include constant, strata-fixed effects, time-fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A7: Impact on crop yield and profit for paddy

Unit of estimation:	Plot					
Dependent variable:	Crop yield (kilogram)			Crop profit (amount ₹ per acre)		
	First follow-up survey	Second follow-up survey	Third follow-up survey	First follow-up survey	Second follow-up survey	Third follow-up survey
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	490.152***	344.515**	79.712	8,270.758***	8,140.727***	5,745.608**
	(130.133)	(133.848)	(124.240)	(2166.867)	(2398.44)	(2262.213)
Control means (in levels)	2,605	2,543	2,659	19,101	20,087	23,670
R-squared	0.2380	0.2109	0.2495	0.1864	0.2194	0.3536
Observations	1,420	1,139	1,079	1,420	1,139	1,079
Strata FE	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included	Included	Included

Notes: Treatment is the impact of eSAP intervention. Results in each column show the program year relative to the baseline. The estimation unit is the plot-wise output produced and the price sold in the market. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A8: Impact on revenue and cost of production for paddy

Unit of estimation:	Plot					
Dependent variable:	Revenue in ₹ per acre			Cost of production in ₹ per acre		
	First follow-up survey	Second follow-up survey	Third follow-up survey	First follow-up survey	Second follow-up survey	Third follow-up survey
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	9,665***	6,703***	6802***	96.366	-2974.06***	-1283.255**
	(2223)	(1635)	(1806)	(1647.47)	(717.496)	(666.019)
Control means (in levels)	35,433	37,166	38,888	18,294	19,382	17,895
R-squared	0.2505	0.3089	0.4034	0.1132	0.1891	0.1259
Observations	1,420	1,139	1,079	1,420	1,139	1,079
Strata FE	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included	Included	Included

Notes: Treatment is the impact of eSAP intervention. Results in each column show the program year relative to the baseline. The estimation unit is the plot-wise output produced and the price sold in the market. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A9: Impact on the price of paddy sold over program years

Unit of estimation:	Household		
Dependent variable:	Output price (₹) per quintal		
	First follow-up survey	Second follow-up survey	Third follow-up survey
	(1)	(2)	(3)
Treatment	72.143	57.861	194.525**
	(91.912)	(82.419)	(91.634)
Control means (in levels)	2408	2710	2820
R-squared	0.1114	0.2538	0.2559
Observations	1,420	1,139	1,079
Strata FE	Included	Included	Included
Year FE	Included	Included	Included
Clustered SE	Included	Included	Included

Notes: The estimation unit is the household-wise output produced, and the price sold in the market. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A10: Impact on agricultural wages in paddy cultivation

Unit of estimation:	Plot			
Dependent variable:	Wages per person per day (amount in ₹)			
	Female			Male
Agricultural operation:	Sowing	Weeding	Harvesting	Insecticide application
	(1)	(2)	(3)	(4)
Treatment	13.535**	22.500***	43.001***	45.588**
	(4.828)	(6.407)	(7.281)	(14.530)
Control means (in levels)	135	136	129	218
R-squared	0.0574	0.1220	0.1509	0.1895
Observations	2,316	2,316	2,316	2,316
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included

Notes: The estimation unit is plot-wise use of labour and agricultural operation-specific wages paid. The observations include data from all three follow-up surveys. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A11: Impact on input costs split by labour and non-labour use for Paddy

Unit of estimation:	Plot			
Dependent variable:	Non-labour input cost (₹ per acre)		Labour cost (₹ per acre)	
	Control mean (SD)	Treatment	Control mean (SD)	Treatment
Agricultural operations	(1)	(2)	(3)	(4)
Sowing	1381	-1585**	108	54**
	(1526)	(683)	(383)	(22)
Transplanting	1.59	-1.27	1902	-10.25
	(31.720)	(0.974)	(847)	(60.90)
Weeding			1931	358
			(3270)	(389)
Fertiliser application	6040	464	588	189**
	(4016)	(1063)	(635)	(72)
Micro-nutrients application	321	130**	18	6*
	(392)	(55)	(64)	(3)
Irrigation			84	-67***
			(125)	(10)
Insecticide application	1638	204*	771	341***
	(1355)	(115)	(839)	(56)
Herbicide application	175	4	37	14**
	(208)	(22)	(66)	(6)
Harvesting	2188	414*	161	72*
	(1376)	(220)	(481)	(42)
Transport	172	-109**		
	(246)	(51)		
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Cluster FE	Included	Included	Included	Included
Observations	2,316	2,316	2,316	2,316

Notes: Treatment is the impact of eSAP intervention. The observations include data from all three follow-up surveys. The estimation unit is the plot-wise output produced and the price sold in the market. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A12: Impact of the program on workdays per acre by gender in paddy

Unit of estimation	Plot	
	Male labour	Female labour
	(1)	(2)
Sowing		
Treatment	0.188** (0.102)	0.162** (0.083)
Control means	0.275	0.166
R-squared	0.1102	0.0246
Transplanting		
Treatment		3.00*** (0.969)
Control means		8.329
R-squared		0.6545
Weeding		
Treatment	0.496** (0.196)	
Control means	0.775	
R-squared	0.0690	
Manure application		
Treatment		
Control means		
R-squared		
Fertiliser application		
Treatment		0.576*** (0.110)
Control means		0.231
R-squared		0.0330
Micro-nutrient application		
Treatment	0.027* (0.015)	0.015*** (0.005)
Control means	0.058	0.014

R-squared	0.0976	0.0378
Irrigation	-10.183** (3.692)	
Treatment	10.855	
Control means	0.2309	
R-squared		
Insecticide application		
Treatment	1.312*** (0.320)	0.305** (0.134)
Control means	3.203	0.306
R-squared	0.0987	0.0470
Herbicide application		
Treatment		
Control means		
R-squared		
Harvesting		
Treatment	63.480** (22.023)	100.913** (34.986)
Control means	170.586	57.948
R-squared	0.1351	0.0551
Observations	2,316	2,316
Strata FE	Included	Included
Year FE	Included	Included
Cluster SE	Included	Included

Notes: The observations include data from all three follow-up surveys. Standard errors are clustered at the village level (in parentheses). Each cell in columns (1) and (2) is based on separate regressions estimating the impact of eSAP intervention on the cost of input use in each agricultural operation. Empty cells indicate either the absence of labour use or a null impact. We use the year-wise going wage rate to quantify the value of family labour. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A13: Impact of the program on workdays per acre across hired and family labour by gender in paddy

Unit of estimation	Plot			
	Male labour		Female labour	
	Hired	Family	Hired	Family
	(1)	(2)	(3)	(4)
Sowing				
Treatment	0.208** (0.098)		0.231** (0.084)	
Control means	0.127		0.104	
R-squared	0.0721		0.0248	
Transplanting				
Treatment	0.128*** (0.039)	-0.327* (0.172)	3.513*** (0.754)	-0.253*** (0.061)
Control means	0.195	0.097	8.230	0.099
R-squared	0.3070	0.1513	0.6590	0.0918
Weeding				
Treatment	0.106** (0.039)	0.511** (0.171)		-3.641*** (1.010)
Control means	0.125	0.649		1.680
R-squared	0.0110	0.0970		0.1240
Manure				
Treatment		-0.145*** (0.036)		0.015*** (0.003)
Control means		0.079		0.011
R-squared		0.0717		0.1151
Fertiliser application				
Treatment	0.432* (0.250)			0.540** (0.115)
Control means	1.120			0.213
R-squared	0.0813			0.0374
Micro-nutrient application				
Treatment		0.024** (0.012)		0.015** (0.005)

Control means		0.042		0.013
R-squared		0.0836		0.0164
Irrigation				
Treatment		-8.671*** (1.914)		
Control means		9.94		
R-squared		0.2080		
Insecticide application				
Treatment	1.210*** (0.354)		-0.029* (0.016)	0.332** (0.143)
Control means	1.685		0.009	0.297
R-squared	0.0779		0.0219	0.0481
Herbicide application				
Treatment			-0.023** (0.010)	0.015** (0.007)
Control means			0.001	0.010
R-squared			0.1916	0.0078
Harvesting				
Treatment		31.077*** (8.443)	83.508** (36.548)	15.115*** (5.039)
Control means		55.787	46.668	11.28
R-squared		0.1258	0.0485	0.0569
Observation	2,316	2,316	2,316	2,316
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Cluster SE	Included	Included	Included	Included

Notes: The observations include data from all three follow-up surveys. Standard errors are clustered at the village level (in parentheses). Each cell in the columns represents a separate regression estimating the impact of the eSAP intervention on input costs for each agricultural operation. Empty cells indicate either the absence of labour use or a null impact. We use the year-wise going wage rate to quantify the value of family labour. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A14: Impact of the program on hours worked per acre to total employed across hired and family labour by gender in paddy

Unit of estimation	Plot			
	Male labour		Female labour	
	Hired	Family	Hired	Family
	(1)	(2)	(3)	(4)
Sowing				
Treatment			0.123** (0.043)	
Control means			0.090	
R-squared			0.0162	
Transplanting				
Treatment			-0.545** (0.210)	-0.279** (0.134)
Control means			0.675	0.204
R-squared			0.3537	0.0877
Weeding				
Treatment	0.494*** (0.176)	1.968*** (0.425)		-3.620*** (0.469)
Control means	0.188	2.007		4.697
R-squared	0.1353	0.1156		0.2006
Manure				
Treatment		-0.457** (0.223)		0.103*** (0.027)
Control means		0.244		0.027
R-squared		0.0901		0.0396
Fertiliser application				
Treatment			-0.541* (0.305)	1.705*** (0.349)
Control means			0.033	0.844
R-squared			0.0229	0.0842
Micro-nutrient application				

Treatment	0.023* (0.014)	0.202*** (0.046)		0.117*** (0.038)
Control means	0.036	0.169		0.057
R-squared	0.0768	0.1007		0.0306
Irrigation				
Treatment		-90.652*** (13.289)		
Control means		45.604		
R-squared		0.2272		
Insecticide application				
Treatment		-1.978** (0.971)	-0.211** (0.116)	
Control means		4.424	0.049	
R-squared		0.1799	0.0319	
Herbicide application				
Treatment		0.187** (0.076)	-0.263** (0.130)	0.126** (0.054)
Control means		0.365	0.010	0.070
R-squared		0.0492	0.0311	0.0188
Harvesting				
Treatment		86.969*** (18.159)	45.689*** (14.990)	52.967*** (9.273)
Control means		128.768	25.379	37.365
R-squared		0.1206	0.0856	0.0446
Observations	2,316	2,316	2,316	2,316
Strata FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Clustered SE	Included	Included	Included	Included

Notes: The observations include data from all three follow-up surveys. Standard errors are clustered at the village level (in parentheses). Each cell in columns is based on separate regressions showing the impact of eSAP intervention on the cost of input use in each agricultural operation. Empty cells indicate either the absence of labour use or a null impact. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A15: Impact of the program on hours worked per acre to total employed by gender in paddy

Unit of estimation	Plot	
	Male labour	Female labour
	(1)	(2)
Sowing		
Treatment		
Control means		
R-squared		
Transplanting		
Treatment		-0.920*** (0.143)
Control means		0.678
R-squared		0.3771
Weeding		
Treatment	1.689*** (0.476)	-1.464*** (0.417)
Control means	2.007	2.032
R-squared	0.1116	0.1536
Manure application		
Treatment	-0.284** (0.123)	0.082** (0.030)
Control means	0.201	0.063
R-squared	0.1178	0.0572
Fertiliser application		
Treatment		1.157** (0.497)
Control means		0.861
R-squared		0.0869
Micro-nutrient application		
Treatment	0.174*** (0.047)	0.118*** (0.038)
Control means	0.170	0.059

R-squared	0.1188	0.0312
Irrigation		
Treatment	-81.170*** (10.940)	
Control means	46.003	
R-squared	0.2336	
Insecticide application		
Treatment	-1.051** (0.524)	
Control means	3.213	
R-squared	0.2201	
Herbicide application		
Treatment		
Control means		
R-squared		
Harvesting		
Treatment	136.140*** (30.548)	89.181*** (14.974)
Control means	90.173	43.597
R-squared	0.1722	0.0889
Observations	2,316	2,316
Strata FE	Included	Included
Year FE	Included	Included
Clustered SE	Included	Included

Notes: The observations include data from all three follow-up surveys. Standard errors are clustered at the village level (in parentheses). Each cell in columns (1) and (2) is based on separate regressions estimating the impact of eSAP intervention on the cost of input use in each agricultural operation. Empty cells indicate either the absence of labour use or a null impact. We use the year-wise going wage rate to quantify the value of family labour. *p < 0.10, **p < 0.05, ***p < 0.01.

Table A16: Impact on rural household earnings (₹ per annum) over the program

	Sector of household activity				Activity across all sectors
	Crop cultivation	Livestock	Off-farm labour	Nonfarm work	
Unit of estimation	Household				
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Crop profit	Livestock profits	Off-farm wage income	Nonfarm income	Total Income
Panel A: Second follow-up survey					
Treatment	50,171**	-3,435	786	-13,281***	36,975
	(17320)	(6033)	(904)	(2913)	(22510)
Control means (₹ in levels)	150,014	-28,203	17,342	26,867	166,021
R-squared	0.3774	0.4926	0.6217	0.3217	0.3698
Observations	1,181	1,181	1,181	1,181	1,181
Panel B: Third follow-up survey					
Treatment	60,910*	16,055	-2,476**	-15,021**	65,747**
	(23606)	(12668)	(791)	(4988)	(31380)
Control means (₹ in levels)	219,071	-38,312	17,735	23,665	222,160
R-squared	0.4081	0.3754	0.6041	0.3357	0.3816
Observations	1,197	1,197	1,197	1,197	1,197
Share in household income at baseline	63%	-	10%	23%	100%

Notes: Treatment is the impact of eSAP intervention across all 34 crops. Estimates are based on data from the last two years and a base year to make it comparable across the various income sources. The detailed data collected for the first follow-up only included crop cultivation. The share (%) in total household income does not include receipts from land leased out (4%). Crop profits include 34 crops – paddy, cotton, sorghum, chili, bengal gram, horse gram, maize, red gram, sugarcane, sunflower, cowpea, barley, groundnut, castor, green gram, and a combination of several crops raised together. Livestock includes milk production, meat, poultry, and hire, sale and purchase of animals. Incomes from off-farm labour include wages earned by household members working on other's farms pooling across all three agricultural seasons. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A17: Impact on household participation in labour market over the program

	Sector of household activity				Activity across all sectors
	Crop cultivation	Livestock	Off-farm labour	Nonfarm work	
Unit of estimation	Household				
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Workdays				
Panel A: Second follow-up survey					
Treatment	10.673***	41.964	94.831	-63.149***	986.876
	(2.919)	(33.597)	(136.871)	(21.032)	(1491.876)
Control means (in levels)	77	143	1195	299	7823
R-squared	0.6342	0.4864	0.5327	0.2051	0.0307
Observations	1,181	1,181	1,181	1,181	1,181
Panel B: Third follow-up survey					
Treatment	14.013***	-12.200	-13.687	-50.003*	1669.774
	(4.019)	(13.227)	(77.335)	(26.707)	(1088.528)
Control means (in levels)	73	182	1159	208	7761
R-squared	0.6914	0.4639	0.5301	0.2223	0.3197
Observations	1,197	1,197	1,197	1,197	1,197
Nominal wage per person per day (₹)	178	174	231	320	

Notes: Treatment is the impact of eSAP intervention across all 34 crops. Estimates are based on data from the last two program years and a base year. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). The number of workdays is calculated as the number of times the operation was completed multiplied by the number of days multiplied by the number of hours multiplied by the number of family and household labour divided by 8 working hours per day. We work with workdays (not days) since some agricultural operations are completed in a few hours while others take many hours. Thus, we asked the farmers for the number of hours worked and the number of days to complete each operation, which is then standardized by 8 working hours. All regressions include constant, strata-fixed effects, time-fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). *p < 0.10, **p < 0.05, ***p < 0.01.

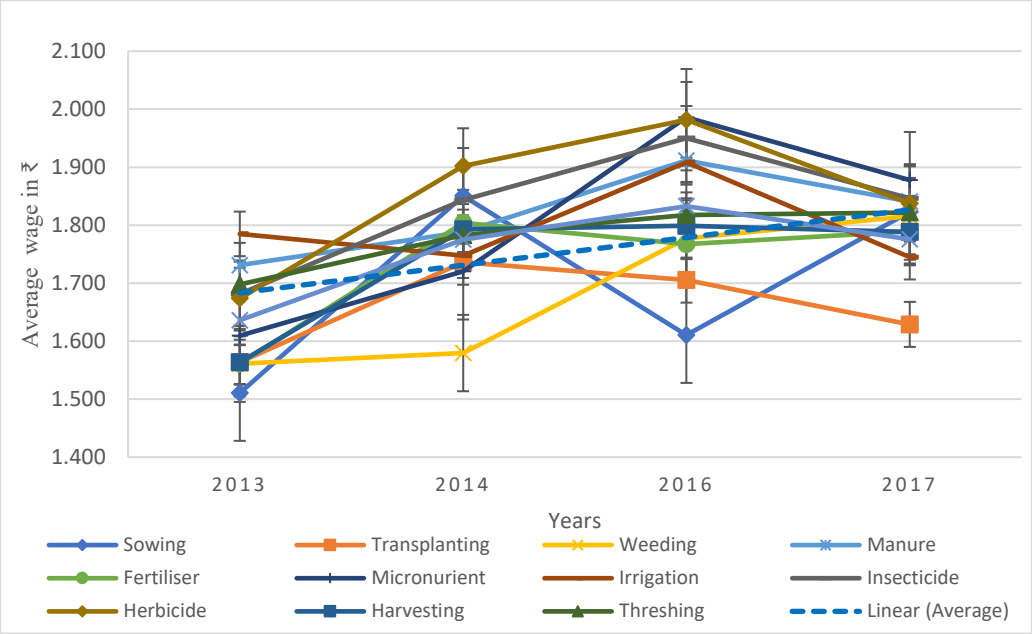


Figure A1: Average real wage for male workers by agriculture operations paid by treatment households

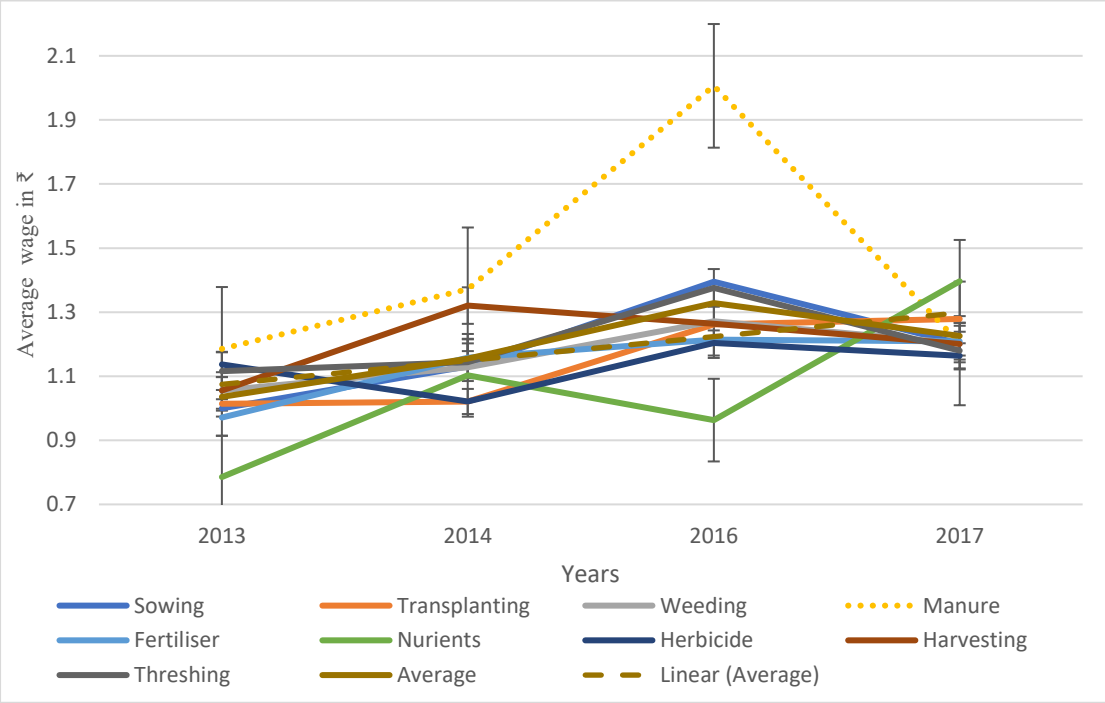


Figure A2: Average real wage for female workers by agriculture operations paid by treatment households

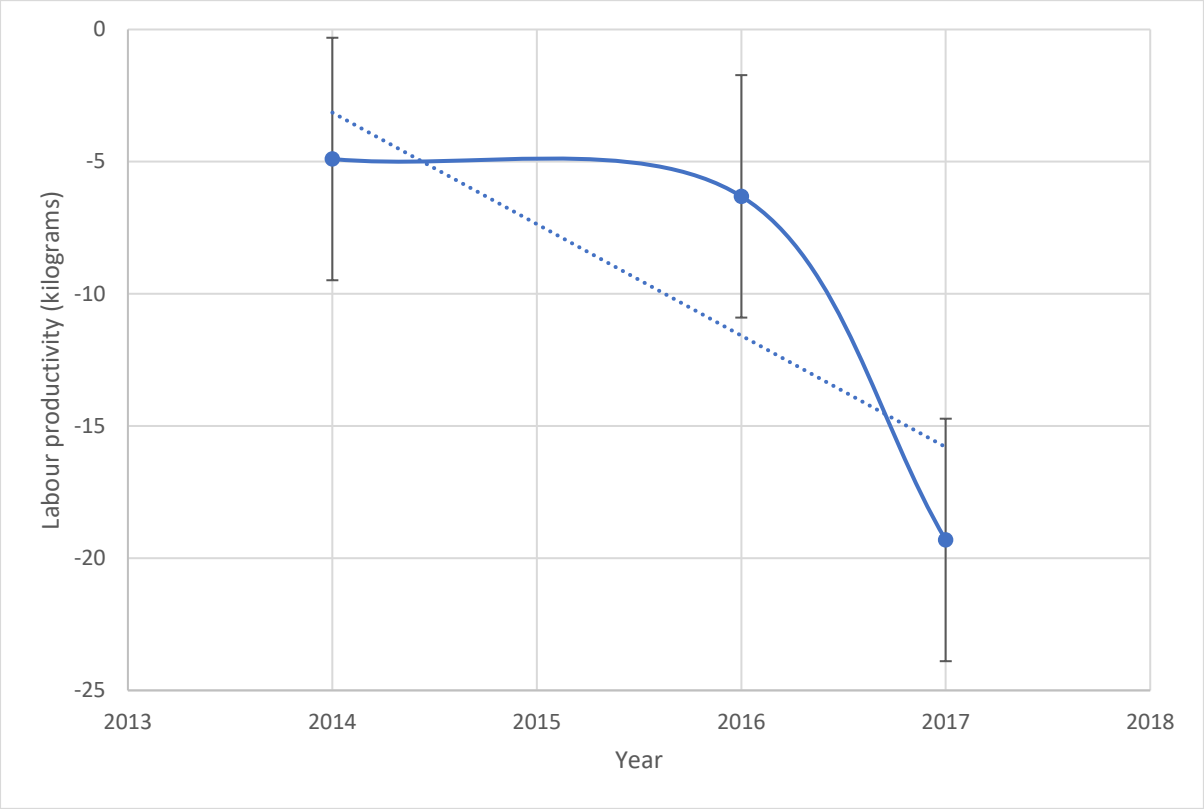


Figure A3: Labour productivity in paddy over the program years

Notes: Labour productivity is calculated as the total agricultural output divided by the total labour input. Output is measured in kilograms, and labour input is recorded in workdays, including both hired and family labour from males and females. To examine changes over time, separate regressions are run for each year, where output per workday (in kilograms) is regressed on baseline labour productivity and village fixed effects, using the same base year for comparison across all years. Each regression includes a constant term, and standard errors are clustered at the village level to account for within-village correlation. The coefficients from these yearly regressions are then plotted to illustrate how labour productivity evolves relative to the common base year.

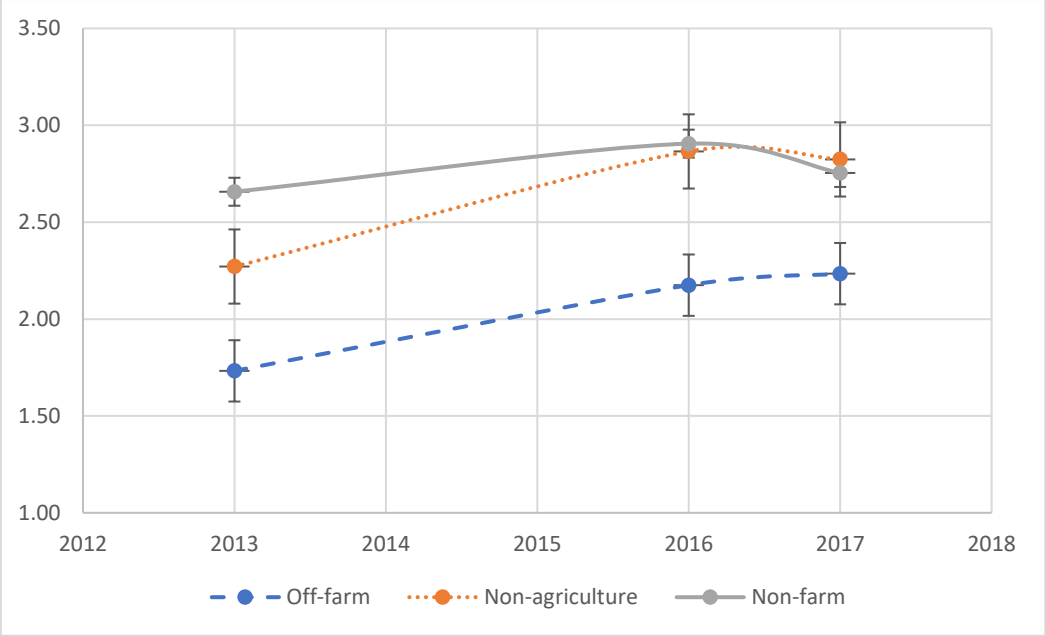


Figure A4: Average real wage across occupations

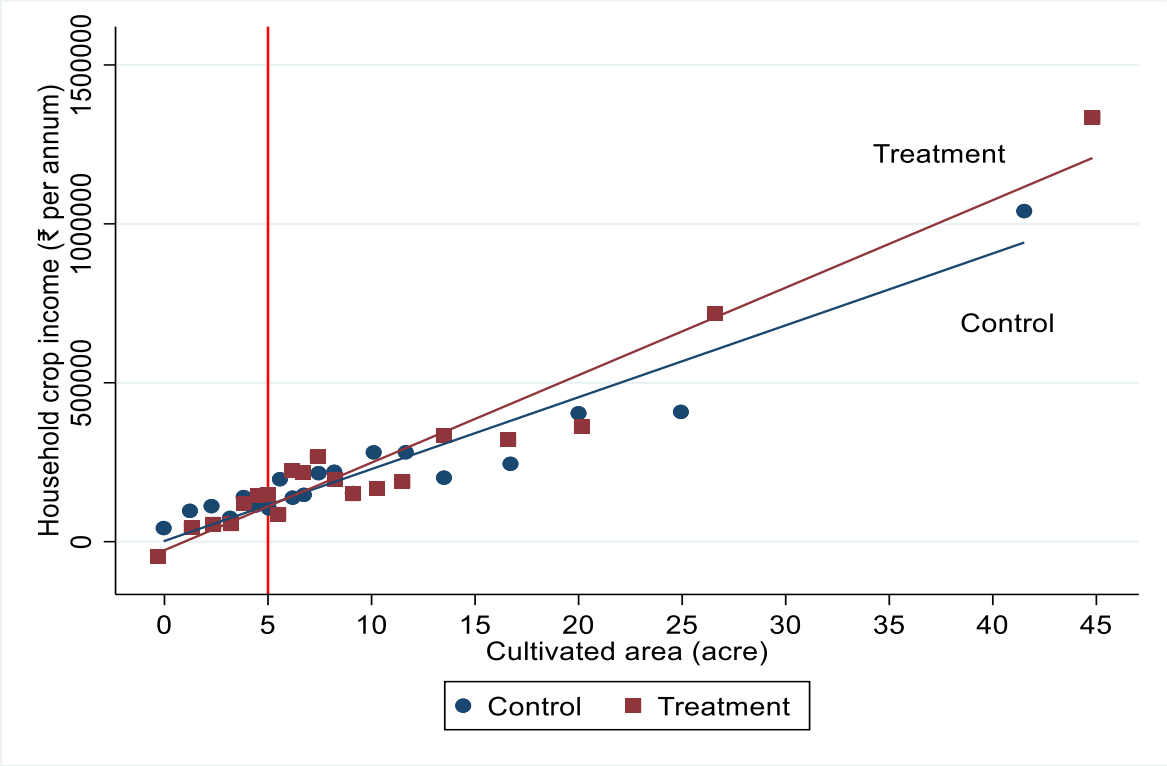


Figure A5: Crop income across the distribution of land size holdings

Notes: We split the observations into twenty equal-sized bins based on the land size holding in acres of cultivated land area in the household's crop income cell. Within each bin, we then calculate the mean change in household crop income and plot this mean change against the cultivated crop area. We estimate the best-fit lines for each treatment group using an OLS regression of the change in crop income on the cultivated area in the household data, with

standard errors clustered at the village level and year and GP fixed effects. The dashed line and the square are for the treatment group.

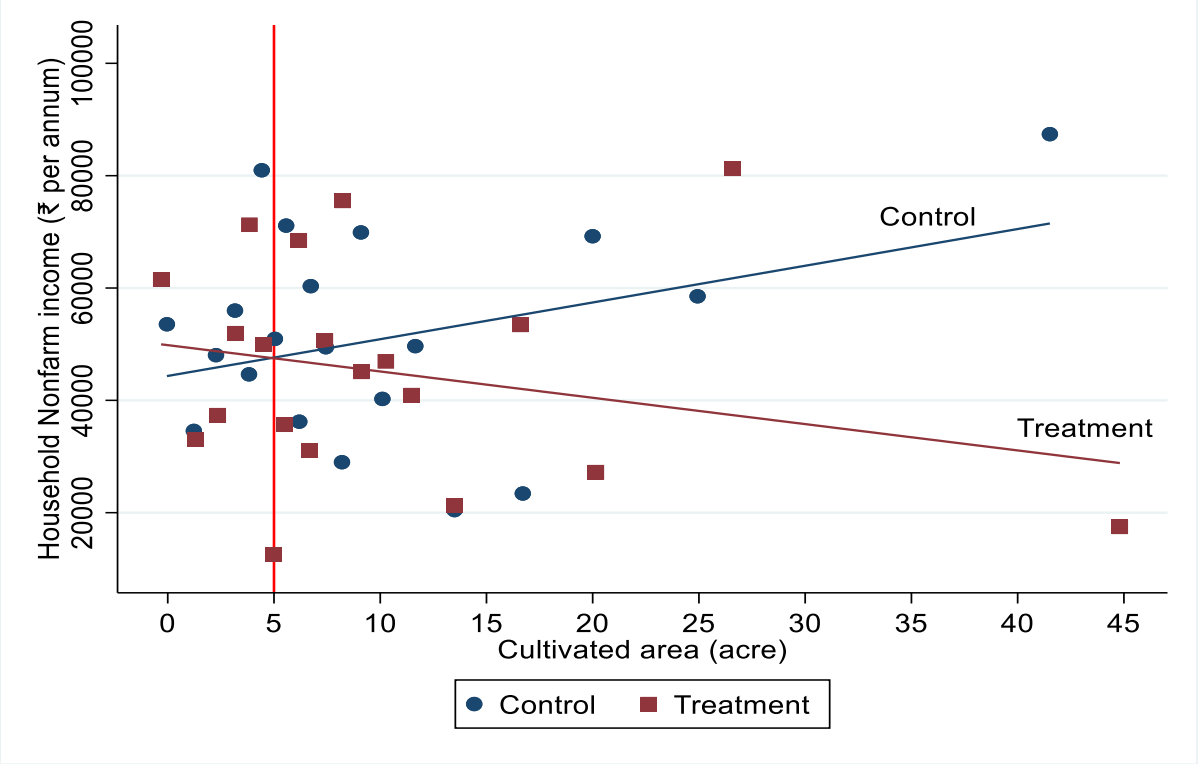


Figure A6: Nonfarm income across the distribution of land size holdings

Notes: We split the observations into twenty equal-sized bins based on the land size holding in acres of cultivated land area in the household's nonfarm income cell. Within each bin, we then calculate the mean change in household nonfarm income and plot this mean change against the cultivated crop area. We estimate the best-fit lines for each treatment group using an OLS regression of the change in nonfarm income on the cultivated area in the household data, with standard errors clustered at the village level and year and GP fixed effects. The dashed line and the square are for the treatment group.

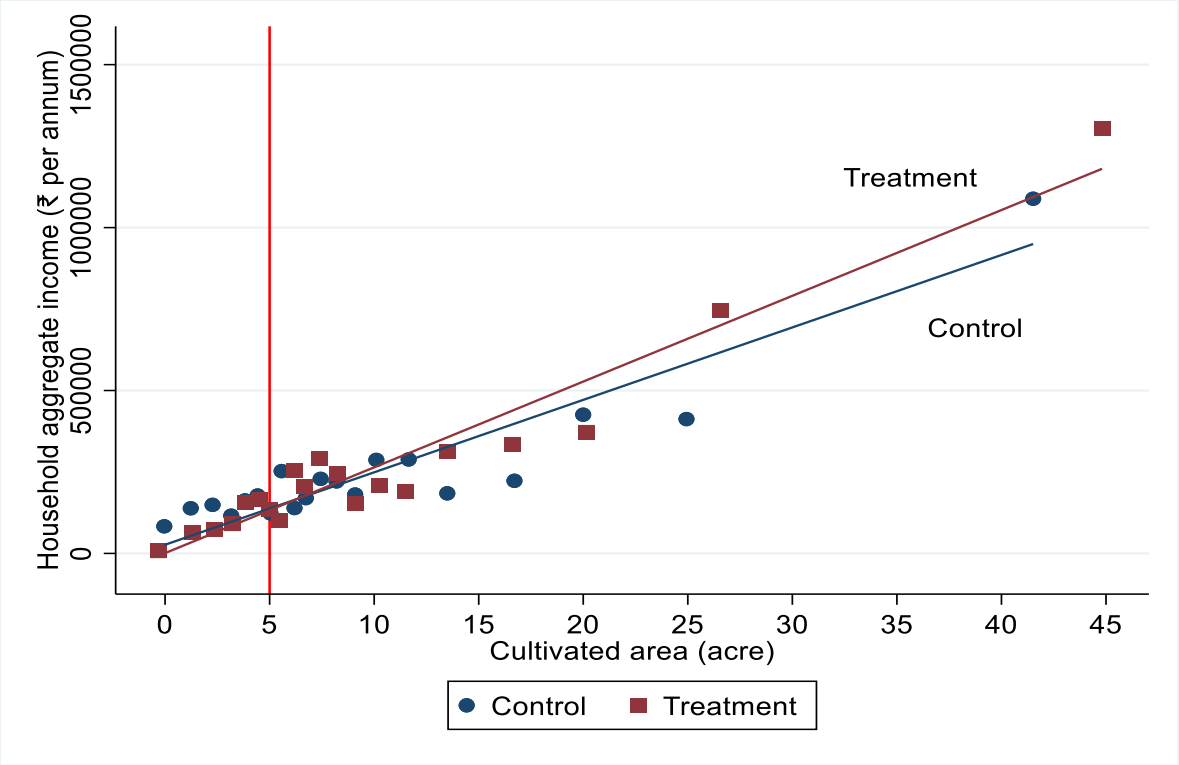


Figure A7: Total income (farm and nonfarm) across the distribution of land size holdings

Notes: We split the observations into twenty equal-sized bins based on the land size holding in acres of cultivated land area in the household's total income cell. Within each bin, we then calculate the mean change in household total income and plot this mean change against the cultivated crop area. We estimate the best-fit lines for each treatment group using an OLS regression of the change in total income on the cultivated area in the household data, with standard errors clustered at the village level and year and GP fixed effects. The dashed line and the square are for the treatment group.

Online Appendix B

B1: Impact of AI treatment on real wages and gender wage gap

Panel A is estimated using an OLS regression of real wages on treatment, gender, and their interaction, controlling for baseline wages, GP fixed effects, and year dummies.

$$RealWage_i = \beta_0 + \beta_1 Treatment_i + \beta_2 Female_i + \beta_3 (Treatment_i X\ Female_i) + \beta_4\, RealWage_{i0} + \gamma_t + \emptyset_{gp} + \epsilon_i$$

where $RealWage_i$ paid to labour i, Treatment equal to 1 if the household that hired labourer iii received the eSAP intervention, gender dummy 1 if the labourer is female, $RealWage_{i0}$ is the baseline real wage, $\gamma_t$is the year fixed effects, $\emptyset_{gp}$is the strata fixed effects and are included to improve efficiency because the randomization is stratified by GP. The $\epsilon_i$is the error term. Standard errors are estimated using heteroskedasticity-robust estimators.

Panel B is estimated using the margins after the above regression. It predicts the mean real wage for each group:

$$\widehat{RealWage} = E[RealWage\ |Treatment, Female]$$

This yields four group means:

Control Male, Control Female, Treatment Male and Treatment Female

These are conditional means controlling for covariates in the regression.

Panel C uses differences in predicted margins and computes the interaction effect in terms of gender wage gaps:

$$Gap_{control} = \widehat{Wage}_{Male,Control} - \widehat{Wage}_{Female,Control}$$

$$Gap_{treated} = \widehat{Wage}_{Male,Treated} - \widehat{Wage}_{Female,Treated}$$

$$Gender\ wage\ gap = Gap_{control} - Gap_{treated}$$

The gender wage gap illustrates how the wage difference between males and females changes in response to AI-based interventions.

B2: Impact of AI on cultivation practices

A unique trial-based seed-to-seed information using eSAP is delivered to farmers on their own farms.

Puddling and Water Management

Puddling creates a hardpan beneath the plough zone, reducing soil permeability and leading to significant water losses through surface evaporation, percolation, and puddling. With surface and groundwater resources declining, water has become a critical limiting factor in paddy production (Farooq *et al*., 2011). In control household cultivation, transplanting requires substantial labour for tasks such as uprooting nursery seedlings, puddling fields, and transplanting seedlings.

Traditionally, the widespread presence of weeds, along with ample water and labour availability, has favoured the use of puddling. This technique offers benefits such as increased nutrient availability and effective weed suppression (Singh *et al*., 2001). However, eSAP offers an opportunity to modernize production practices, increase plant density, and improve water productivity.

Weed and Pest Management

Weeds pose a significant threat to paddy cultivation by competing for essential resources, including nutrients, light, space, and moisture, throughout the growing season. An integrated weed management approach, including cultural practices, crop rotation, stale seedbed techniques, the selection of suitable seed varieties, and the strategic use of herbicide mixtures, is essential for managing shifts in weed community structure (Maity and Mukherjee, 2008).

eSAP management practices incorporate seed priming to reduce the need for high seeding rates and enhance weed control through the stale seedbed technique. This is combined with the application of the pre-emergence herbicide pendimethalin within two days of seeding. When crops experience water-limited conditions, they become more susceptible to various pests and diseases, which thrive in stressed environments. These adverse conditions disrupt the natural balance of macro- and micronutrients in the soil, leading to deficiencies or toxicities that further weaken plant health. As a result, farmers often need to apply additional micronutrients to compensate for these imbalances and use insecticides to manage the increased pest pressure. However, the implementation of eSAP helps mitigate these challenges.

By enhancing soil health, improving water retention, and fostering beneficial microbial activity, eSAP management practices reduce the severity of nutrient imbalances and pest infestations. Consequently, the reliance on excessive micronutrient supplements and insecticide

applications is significantly reduced, promoting a more sustainable and ecologically friendly approach to farming.

While paddy crops are susceptible to various diseases, rice blast is one of the most devastating, particularly in water-limited conditions. Poor water management can result in soil that is either too dry or too moist rather than properly flooded, promoting dew deposition and creating an environment conducive to host susceptibility and blast development (Savary *et al*., 2005).

Nutrient Dynamics and Management

Puddling in continuously flooded fields helps minimise percolation losses, maintaining a saturated soil profile that suppresses weed growth (Sahid and Hossain, 1995) and improves nutrient availability (Wade *et al*., 1998). However, in the absence of puddling, land preparation and water management play a crucial role in regulating nutrient dynamics, making nutrient deficiencies a key concern.

eSAP enables the assessment of macro- and micronutrient dynamics, facilitating the development of targeted management strategies to maximise crop yields sustainably. To enhance paddy productivity, nutrient management techniques such as deep placement and controlled-release fertilisers have been implemented. Additionally, the split application of nitrogen fertiliser improves nitrogen-use efficiency, reduces denitrification losses, aligns nutrient availability with plant demand, and enhances both straw and grain yield, as well as the harvest index. By integrating AI-driven eSAP strategies, farmers can improve crop yields, strengthen weed and pest control, and reduce overall cultivation costs, ensuring more sustainable and efficient paddy production.

The eSAP system functions as a **crop-optimisation smart platform** that integrates multiple AI capabilities designed for real-world farm use:

- **Computer vision and deep learning models** for accurate **pest and disease diagnosis**, based on field images captured via mobile devices.
- **Sensor-augmented AI analytics** (incorporating IoT soil moisture, weather data, nutrient sensors) to optimise irrigation, fertilisation**, and micro-nutrient treatments**.
- **Predictive growth modelling, which analyses** plant phenology to issue **timing alerts** for optimal sowing, transplanting, and harvesting windows.

- **Decision-support systems** driven by ensemble models and time-series analyses to recommend **insecticide and herbicide application**, minimising input costs and environmental impact.

These components illustrate how the eSAP AI tool works at two levels:

1. **AI as a decision engine across vital plant-care tasks**, enhancing precision and reducing uncertainty in on-farm operations.
2. **AI as a technological input,** requiring investment in software development, data integration, and model training, aligned with the model's treatment of AI as a priced production factor with its own costs and diminishing returns.

References

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Maity, Swapan Kumar and Pijush Kanti Mukherjee (2008) Integrated weed management in dry direct-seeded rainy season rice (Oryza sativa). *Indian Journal of Agronomy* 53(2): 116-120.

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Online Appendix C

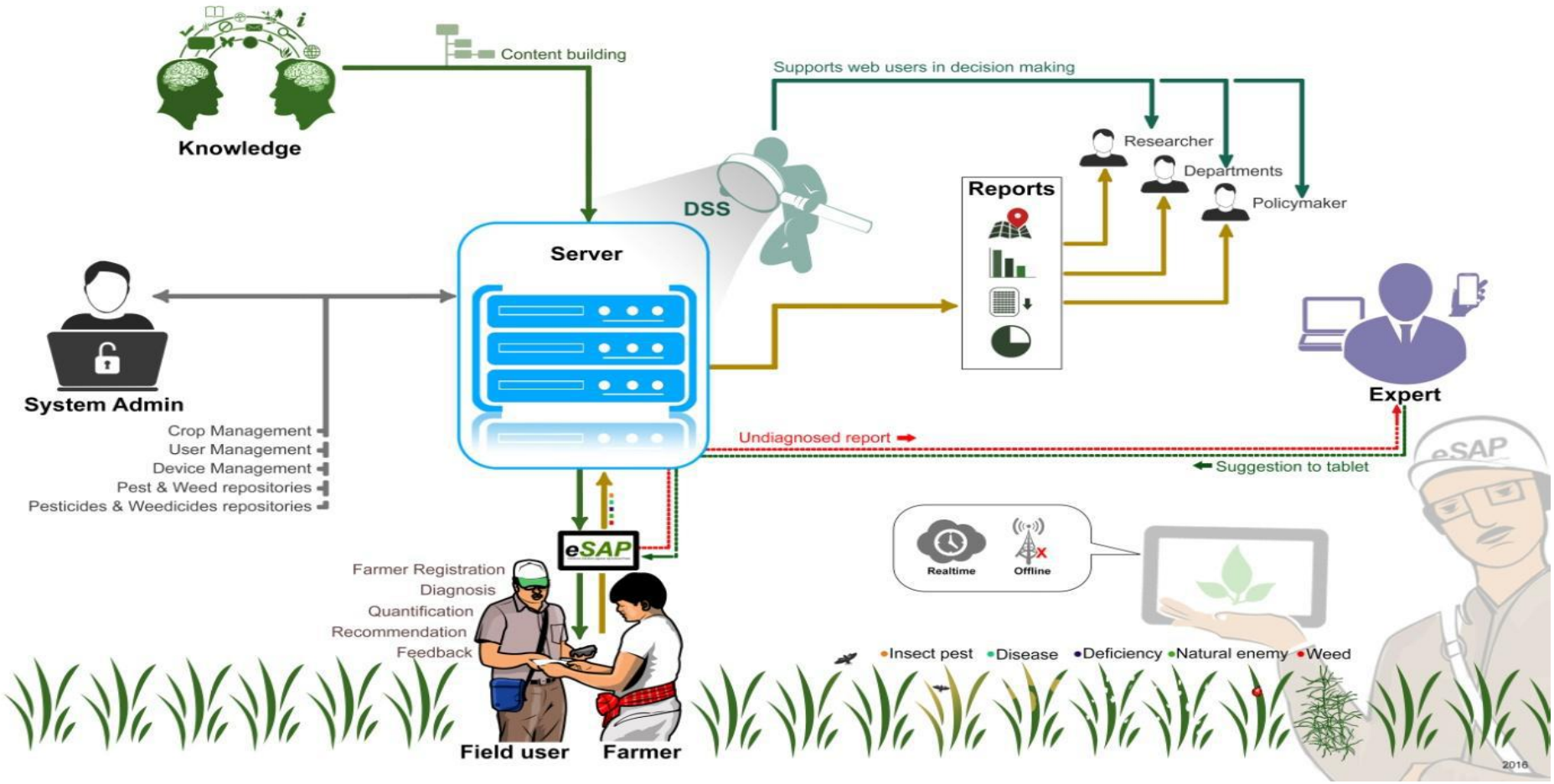


Figure C1: e-SAP workflow



Figure C2: Field captured images of paddy crop

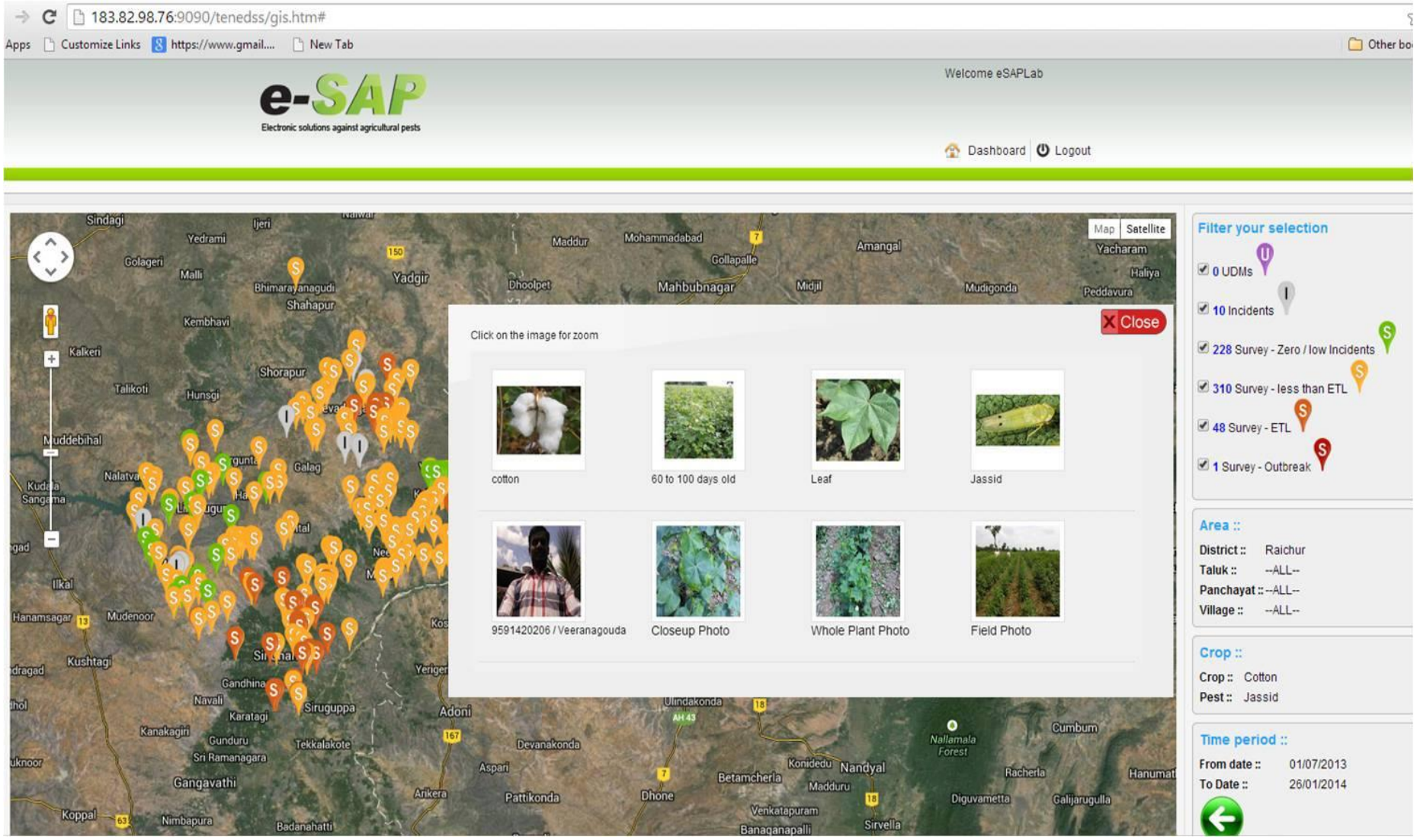


Figure C3: Expert virtual laboratory for diagnostics and solutions

Online Appendix D

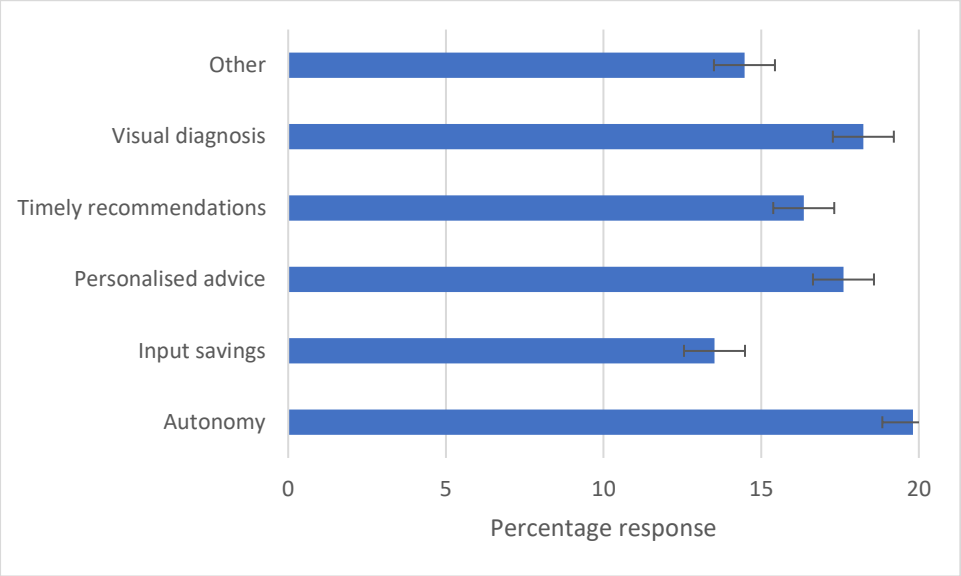


Figure D1: Important features of the AI tool during the last farming season

Notes: The response is based on the open-ended question to treatment farmers: Which feature of the AI tool did you find most useful in the previous farming season? Here 'other' includes ‘Reminders for follow-up actions, Learning how to use tech tools, Satisfaction from trying new technology’.

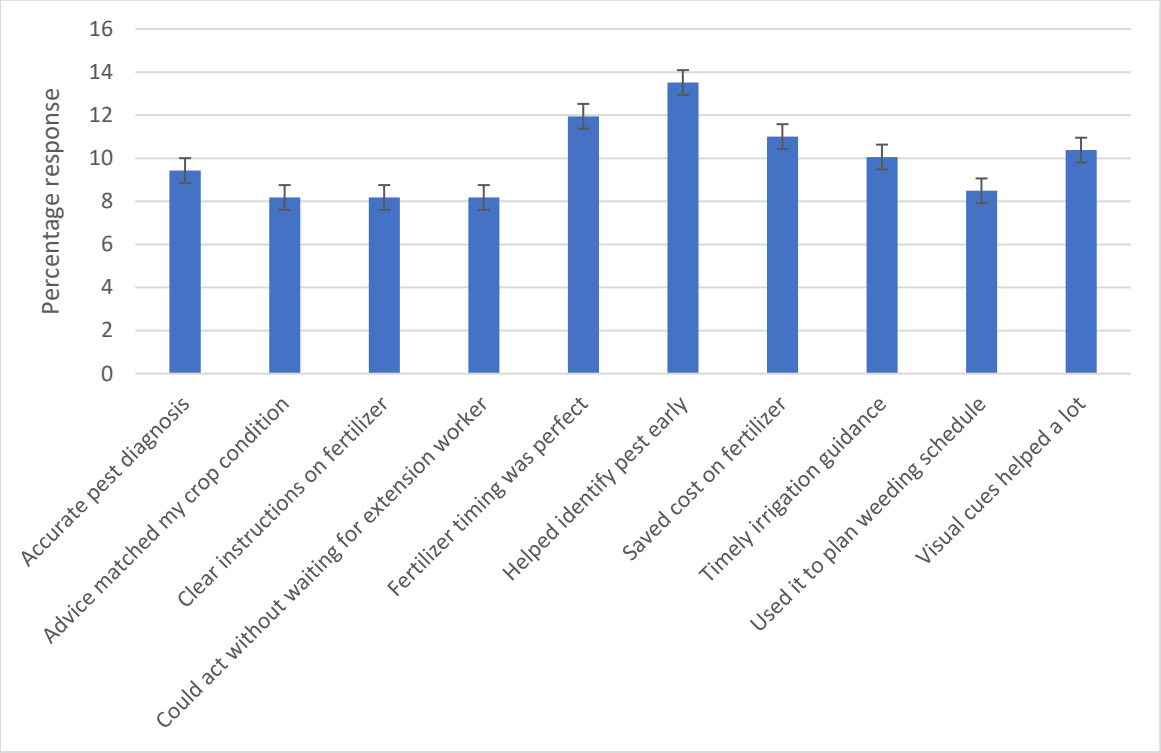


Figure D2: Most useful part of the AI tool for your farming decisions

Notes: Based on the open-ended question to treatment farmers: What was the most helpful part of the tool for your farming decisions?

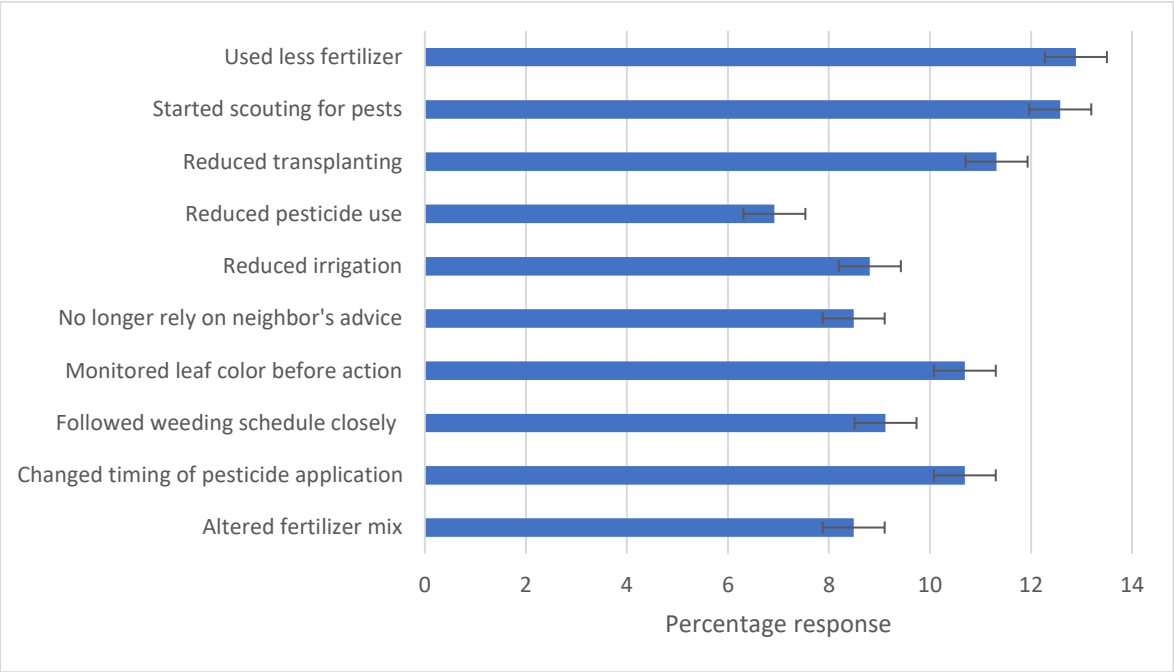


Figure D3: Change in farming practices from the recommendation of the AI tool

Notes: Based on the open-ended question to treatment farmers: Did you change any farming practices because of something the tool recommended?

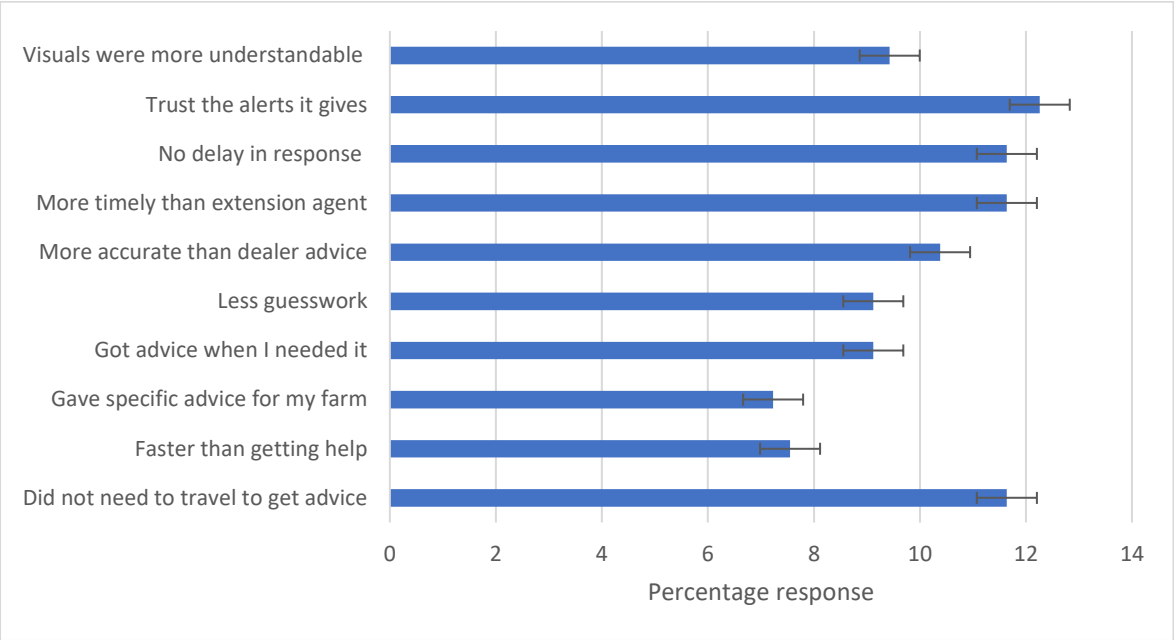


Figure D4: Farmer perception of AI tool relative to other sources of advice

Notes: Based on the open-ended question to treatment farmers: Why was the tool better or worse than other advice sources you used?