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Digital Readiness and Extension Support in Chili Farmers' Plantix Adoption for Pest Control in Indonesia

Putri Aulia Wardani*, Gunawan, and Arum Pratiwi

Department of Sustainable Agricultural Extension, Agriculture Development Polytechnic Malang, Indonesia

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CORRESPONDING AUTHOR

*E-mail: putriauliaaw0@gmail.com

ABSTRACT

Digital transformation in agriculture has encouraged the development of artificial intelligence-based applications such as Plantix, which assists farmers in diagnosing plant pests and diseases through image analysis. Although Plantix has proven technically effective, its adoption rate among Indonesian farmers remains low and is presumably influenced by internal and external factors that have not been widely studied at the local level. This study aims to analyze the factors influencing chili farmers' adoption of the Plantix application in Kayukebek Village, Indonesia. A quantitative approach was used with 58 respondents selected through purposive sampling from a population of 188 chilli farmers. Data were analyzed using multiple linear regression with two independent variables: farmer characteristics (age, education, farming experience, smartphone use frequency) and environmental support and interaction (extension support, access to information and training, social influence, internet access). The results show that the regression model explains 45.5% of the variation in Plantix adoption ($R^2 = 0.455$) and is significant simultaneously ($F = 5.118$; $p < 0.001$). Partially, smartphone use frequency, agricultural extension support, and social and environmental influence significantly affect adoption ($p < 0.05$), while age, education, farming experience, information/training access, and internet access do not. These findings indicate that adoption is driven more by digital readiness, extension assistance, and peer influence than by farmers' demographic characteristics or the availability of infrastructure alone, and provide a basis for designing more targeted extension strategies.

Contribution to Sustainable Development Goals (SDGs):

SDG 1: No Poverty

SDG 2: Zero Hunger

SDG 8: Decent Work and Economic Growth

SDG 9: Industry, Innovation and Infrastructure

SDG 12: Responsible Consumption and Production

1. INTRODUCTION

1.1. Research Background

Across the globe, agriculture is under mounting pressure from population growth, shrinking arable land, and increasingly volatile climate conditions, pushing the sector toward rapid digital transformation. Artificial intelligence (AI)-based decision support tools have become a central strategy for addressing these

pressures worldwide, with applications ranging from early pest and disease detection to precision fertilisation and yield forecasting, deployed across both developed and developing agricultural economies [1]. Despite this global momentum, the pace and pattern of digital technology adoption remain highly uneven between regions, shaped by farmers' socio-economic conditions, institutional support, and the availability of context-appropriate digital infrastructure [1].

Indonesian agriculture faces increasingly complex challenges, including rising food demand, limited natural



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resources, and the impact of climate change. Digital transformation, particularly through artificial intelligence (AI) based applications, has become one of the main strategies to improve productivity and efficiency in farming, offering features ranging from pest and disease detection to fertilization recommendations and yield prediction. High smartphone penetration among Indonesian farmers presents a considerable opportunity to use digital applications such as Plantix, iGrow, Sipindo, and Agrio as decision-support tools in farming activities. Nevertheless, the adoption of digital technology among Indonesian farmers generally remains low [1]. This is in line with Wijayanto and Puspitojati, who asserted that the transition towards digital agriculture in Indonesia necessitates technical mentoring and direct field learning, with the success of technology adoption highly contingent on farmers' readiness and local institutional support [2].

Among the available applications, Plantix has become one of the most widely adopted AI-based agricultural applications globally, with a comprehensive plant disease database developed since 2015 by PEAT GmbH, Germany [3]. Using image-based machine learning, Plantix can identify more than 780 types of disorders across 82 crop species, provide treatment recommendations, and connect users with local agricultural input suppliers. A comparative evaluation of plant disease detection applications found that Plantix performs well in identifying crops from images, detecting disease, maintaining an extensive plant database, and suggesting potential treatments [4]. However, while Plantix has been widely used by smallholder farmers in India as a primary source of farming information [5], adoption in Indonesia remains constrained by social, economic, and institutional factors, including low digital literacy, limited contextual relevance, and weak agricultural extension support [1].

Chili (*Capsicum annuum* L.) is one of the horticultural commodities most relevant to Plantix's pest and disease detection capability, given its high economic value and vulnerability to organisms such as thrips, aphids, fruit flies, mites, *Fusarium* wilt, anthracnose fruit rot, and viral infections [6]. Kayukebek Village, Tutar District, Pasuruan Regency, is one of the district's productive chilli-growing centres, yet farmers frequently adopt suboptimal cultivation practices that increase the risk of pest and disease outbreaks, reducing productivity, product quality, and farm income. Given Plantix's potential to support early detection and targeted pest control recommendations, and considering that no prior study has specifically examined the factors influencing its adoption in this location, this study analyzed the factors influencing chili farmers' adoption of the Plantix application in supporting pest and disease (OPT) control decision-making in Kayukebek Village.

1.2. Literature Review

1.2.1. Innovation Diffusion Theory

According to the Diffusion of Innovations theory, the adoption of an innovation proceeds through five stages: knowledge, persuasion, decision, implementation, and confirmation [1]. Rogers further explains that individual characteristics such as age, education, and experience are not the primary determinants of adoption success; rather, adoption decisions are more strongly influenced by perceptions of relative advantage, compatibility, complexity, trialability, and the role of change agents, such as

agricultural extension workers, in accelerating the diffusion process. This framework underpins the classification of independent variables used in this study, namely farmer characteristics (internal factors) and environmental support and interaction (external factors), and the dependent variable representing the stages of Plantix adoption.

1.2.2. Technology Acceptance Model

While Diffusion of Innovations explains why an innovation spreads through a farming community over time, the Technology Acceptance Model (TAM) offers a complementary lens on why an individual farmer chooses to use a specific tool once it is available. Davis proposed that an individual's intention to use a technology is shaped by two beliefs: perceived usefulness, the degree to which the technology is believed to improve task performance, and perceived ease of use, the degree to which using it is believed to require little effort [32]. It is important to note that the present study does not measure perceived usefulness or perceived ease of use as separate constructs; the research instrument, hypotheses, and independent variables (X1, X2) were derived entirely from Rogers' Diffusion of Innovations framework, consistent with the study's multiple linear regression design. TAM is introduced here, and used later in the Discussion, purely as an interpretive lens to help explain one specific empirical pattern: why smartphone use frequency (a sub-variable of X1) shows a significant positive effect on adoption. TAM suggests a plausible mechanism: prior smartphone familiarity lowers the perceived effort of operating Plantix, a relationship that Rogers' framework identifies but does not explain at the individual cognitive level.

1.2.3. Plantix Application and Chilli Pest Management

Chilli cultivation in Indonesia is commonly affected by pest complexes, including thrips, aphids, mites, and fruit flies, as well as by diseases such as fruit rot, leaf spot, *Fusarium* wilt, and viral infections, all of which can substantially reduce yield if not managed appropriately [6]. Digital diagnostic tools such as Plantix, which combine image recognition with a treatment recommendation database, are positioned as practical decision-support tools for farmers to detect such organisms at an early stage. Realizing this potential in practice, however, depends not only on the technical quality of the application but also on farmer- and environment-level factors that determine whether the innovation is adopted and consistently applied in day-to-day farming.

1.2.4. Factors Influencing Farmers' Adoption of Digital Applications

Beyond the diffusion perspective above, adoption of agricultural mobile applications has also been explained through a broader set of determinants. These have been classified into five interrelated categories: individual factors, such as age, education, farming experience, and digital literacy; technical factors, such as diagnostic accuracy, ease of use, response speed, and data or battery consumption; social factors, including support from extension workers, peer farmers, and community norms; economic factors, such as the affordability of internet quota and the perceived cost benefit of learning a new tool; and institutional factors, including network infrastructure quality and government policy [7].

Farmer characteristics in particular have been shown to shape an individual's capacity to receive, interpret, and apply new information, since age, education, and farming experience are closely related to responsiveness to change and to the way farmers evaluate the risk and benefit of an innovation [8]. This multi-level framework underlies the classification of independent variables used in the present study, which distinguishes farmer-level characteristics (X1) from external environmental support and interaction (X2).

1.2.5. *Decision Making Theory in Pest and Disease Control*

Decisions on how to control plant pests and diseases directly affect production output, input costs, and the sustainability of a farming enterprise. According to Simon, decision-making is a rational process comprising four stages: problem identification, generation of alternatives, evaluation of alternatives, and selection of the best alternative [9]. Robbins and Judge add that such decisions are shaped jointly by rational considerations, an analysis of cost and benefit, and behavioral considerations, experience, risk perception, social values, and existing knowledge [10].

Applied specifically to pest and disease management, farmers' control decisions have been linked to socio-economic characteristics such as age, education, and farm experience [11]; farmers are more likely to adopt digital pest and disease management technologies when they perceive them as useful, effective, and capable of reducing production risks while providing tangible agronomic benefits [8], and to the institutional and policy support available to them through farmer groups, extension programs, and government incentives [1]. Digital decision-support tools are positioned to strengthen this process by lowering the cost of searching for information and by supplying rapid, image-based identification and treatment recommendations that help farmers select a more timely and appropriate control action [12]. In the present study, Plantix is examined as such a tool for chili farmers making day-to-day OPT control decisions.

1.2.6. *Pest and Disease Complex in Chili Farming*

Chilli (*Capsicum annum* L.) is a high-value horticultural commodity that plays an important role in local economies and household nutrition [13]. When control measures are inadequate or delayed, pest and disease attacks can reduce chili yield by 25% to 100% [14]. The main pest complex comprises sap-sucking insects such as thrips, aphids, and whiteflies, which cause leaf curling, silvering, and sooty mould and also act as vectors of viral disease, together with mites and fruit flies that damage young leaves and fruit directly [15][16]. The main disease complex includes *Fusarium* wilt and bacterial wilt caused by *Ralstonia solanacearum*, both producing progressive wilting and vascular discoloration; anthracnose fruit rot, which blackens fruit under humid conditions; and Gemini virus-associated yellow leaf curl, transmitted by the whitefly *Bemisia tabaci* [16]. Because these organisms are often difficult to visually distinguish at an early stage, image-based diagnostic tools such as Plantix are particularly relevant for chilli farming, where early and accurate identification directly determines the effectiveness and cost of subsequent control actions.

Collectively, these theories provide a complementary explanation of Plantix adoption. Diffusion of Innovations

explains how farmers become aware of the application through extension services and social interaction. The Technology Acceptance Model explains how prior smartphone experience facilitates perceived ease of use, thereby strengthening acceptance of the technology. Finally, Decision-Making Theory explains how farmers evaluate available information before deciding whether to incorporate Plantix into routine pest management. Accordingly, this study combines Rogers' diffusion perspective as the principal theoretical foundation while employing TAM and Decision-Making Theory as complementary interpretive frameworks.

1.3. *Integrated Conceptual Framework*

The three theoretical perspectives reviewed above operate at different levels of analysis and serve different roles in this study. Diffusion of Innovations is adopted as the study's primary and sole operational framework: it is the basis on which the two independent variables were classified, farmer characteristics (X1) as Rogers' individual-level adopter attributes and environmental support and interaction (X2) as the external, change-agent-mediated conditions that accelerate diffusion, and on which the two hypotheses (H1 and H2) tested through multiple linear regression were formulated. The dependent variable, level of Plantix adoption (Y), is likewise measured through indicators of knowledge, attitude, intention, and actual use, corresponding to Rogers' stages of knowledge, persuasion, decision, and implementation. The Technology Acceptance Model and Decision-Making Theory are not operationalized as separate constructs or additional hypotheses in this study; no items in the research instrument measure perceived usefulness, perceived ease of use, or the discrete stages of a rational decision process independently of the Rogers-based indicators. Instead, both are used as complementary interpretive lenses in the Discussion section, TAM to help explain the individual-level mechanism behind the significant effect of smartphone use frequency, and Decision-Making Theory to help explain how farmers translate extension support and social influence into a concrete pest-control decision, so that the statistical findings from the regression model can be interpreted with greater theoretical depth without overstating what the quantitative design itself tested.

1.4. *Research Objective*

This study aims to (1) analyze chili farmers' level of knowledge and perception of the Plantix application as a decision-support tool for pest and disease control, and (2) analyze the factors influencing the level of Plantix adoption among chili farmers in Kayukebek Village, Tutar District.

2. MATERIALS AND METHODS

2.1. *Research Design, Location, and Time*

This study used a quantitative approach with a cross-sectional survey design. The research was conducted in Kayukebek Village, Tutar Sub-district, Pasuruan Regency, East Java, from January to March 2026.

2.2. *Population and Sample*

The population consisted of 188 chili farmers in Kayukebek Village. The sample was selected using purposive sampling, a non-probability sampling method that allows researchers to

recruit participants who meet predetermined criteria relevant to the research objectives [17]. The selection criteria included chili farmers aged 18-40 years, with at least a junior high school education, at least 5 years of farming experience, and owning an Android-based smartphone. Based on these criteria, 58 farmers were selected as respondents. The selected sample was deemed appropriate for achieving the research objectives, as all respondents met the predetermined inclusion criteria and possessed the characteristics necessary to evaluate the adoption of the Plantix application as a digital decision-support tool for pest and disease management in chilli cultivation.

It is acknowledged that purposive sampling is a non-probability method, and the resulting sample is therefore not statistically representative of the full population of 188 chili farmers in Kayukebek Village; the age, education, experience, and smartphone-ownership criteria used to select respondents mean that the findings describe adoption patterns among digitally reachable, relatively younger farmers and should not be generalized to older or non-smartphone-owning farmers without further study. This design choice was made deliberately, since evaluating Plantix adoption requires respondents who already own an Android-based smartphone and are therefore able to engage with the application; a probability sample drawn from the full population would have included many farmers structurally unable to use Plantix, which would have limited rather than strengthened the validity of the adoption analysis [17]. The purposive criteria are nonetheless reported in full above to make the boundaries of generalizability transparent to readers.

2.3. Variables and Measurement

This study used two independent variables and one dependent variable [18]. The Farmer Characteristics variable (X1) includes age, education level, farming experience, and smartphone use frequency as internal factors that affect farmers' ability to adopt and use digital technology. The Environmental Support and Interaction variable (X2) encompasses extension support, access to information and training, social and environmental influence, and internet access availability as external factors that support the adoption process. The dependent variable (Y) is the level of adoption of the Plantix application for supporting pest control decision-making, measured using indicators of knowledge, attitude, intention to use, and actual use of Plantix in chili cultivation. All indicators were measured on a five-point Likert scale (1 = strongly disagree/very low to 5 = strongly agree/very high). For each sub-variable, item scores were summed and then converted into a composite index using the formula $\text{Index} = (\text{Total score obtained} / \text{Maximum possible score}) \times 100$, so that every sub-variable, and the higher-order variables X1, X2, and Y computed as the mean of their respective sub-variable indices, was expressed on a common 0-100 scale regardless of the number of items it contained. This composite index, rather than the raw Likert scores, was used in the multiple linear regression analysis and also served as the basis for the category cut-offs (e.g., low, moderate, high) reported in Table 1.

2.4. Hypotheses

Based on the research objectives and conceptual framework, two sets of hypotheses were formulated prior to data analysis. The first hypothesis examined the influence of farmer characteristics on Plantix adoption, while the second examined the influence of environmental support and interactions on Plantix adoption.

These were then tested using multiple linear regression analysis [19]. The following are the hypotheses in this study:

H0₁: Farmer characteristics do not significantly affect the level of Plantix adoption.

H1₁: Farmer characteristics significantly affect the level of Plantix adoption.

H0₂: Environmental support and interaction do not significantly affect the level of Plantix adoption.

H1₂: Environmental support and interaction significantly affect the level of Plantix adoption.

2.5. Data Analysis

Data were analyzed using IBM SPSS Statistics version 25. The analytical procedure included validity and reliability testing of the research instrument, followed by classical assumption tests comprising normality, multicollinearity, and heteroscedasticity tests before conducting multiple linear regression analysis. The goodness of fit of the regression model was evaluated using the coefficient of determination (R^2), the simultaneous F-test, and the partial t-test to determine the explanatory power and significance of the proposed model [20][21].

3. RESULT AND DISCUSSION

3.1. Respondent Characteristics

The majority of respondents (41%) were in the early-adult category (30–35 years), most had completed senior secondary education (SMA/SMK, 72%), 47% had 5–10 years of farming experience, and smartphone use frequency was fairly evenly distributed across 2 to more than 4 hours per day. Regarding environmental support, extension support was perceived as moderate to low by 91% of respondents, while information/training access, social influence, and internet access were mostly in the moderate-to-high categories (74–90%). Overall, farmers' internal characteristics and environmental conditions were relatively supportive of digital technology adoption, except for the still-limited extension assistance.

Table 1. Summary of respondent characteristics and environmental support (n = 58)

Variable	Category	n	%
Age	Early adult (30–35 yrs)	24	41
Education	Senior secondary	42	72
Farming experience	5–10 years	27	47
Smartphone use	3–4 hours/day	30	52
Extension support	Moderate–Low	53	91
Info & training access	Moderate–High	43	74
Social & environmental infl.	Moderate–High	52	90
Internet access	Moderate–High	49	85

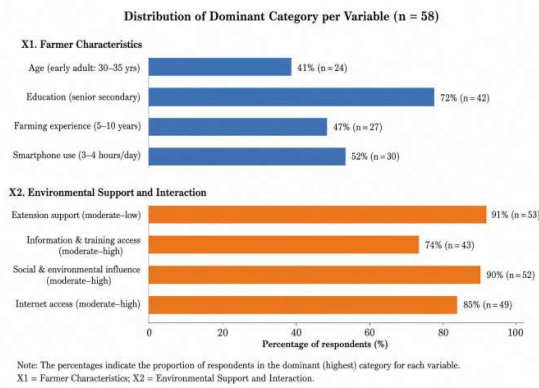


Figure 1. Distribution of respondent characteristics and environmental support by dominant category (n = 58)

Figure 1 visualizes the proportions reported in Table 1. It shows that extension support is the variable with the highest concentration in a single (low to moderate) category, at 91% of respondents. In contrast, information/training access, social and environmental influence, and internet access are each concentrated in the moderate-to-high category at 74–90%. The farmer-characteristic variables (age, education, farming experience, smartphone use) show a comparatively more even spread across categories.

3.2. Validity and Reliability

The research instrument underwent validity and reliability testing before data collection. Of the 50 questionnaire items initially developed, 45 were declared valid based on the Pearson product-moment correlation test, with calculated correlation coefficients exceeding the critical value at the 5% significance level. Reliability analysis showed that the Cronbach's Alpha coefficients were 0.940 for the independent variables (28 items) and 0.932 for the dependent variable (22 items), both exceeding the recommended minimum threshold of 0.70, indicating that the instrument demonstrated excellent internal consistency and was suitable for subsequent statistical analysis [20].

3.3. Classical Assumption Tests

The Kolmogorov–Smirnov test yielded a p-value of 0.200 (> 0.05), indicating that the regression residuals were normally distributed. The multicollinearity test showed that Tolerance values were > 0.10 and VIF values were < 10 for all independent variables, indicating no multicollinearity. The Glejser test showed significance values > 0.05 for all variables, confirmed by a random scatterplot pattern, indicating the model was free from heteroscedasticity [21], [22]. The model therefore satisfied the requirements for a Best Linear Unbiased Estimator (BLUE) for further hypothesis testing.

3.4. Model Fit, Simultaneous Test, and Partial Test

The coefficient of determination test yielded an R value of 0.675 and an R^2 of 0.455, indicating that the independent variables jointly explained 45.5% of the variation in Plantix adoption, with the remaining 54.5% attributable to other factors outside the model. The Adjusted R^2 of 0.366 indicated the model remained adequate after adjusting for the number of predictors.

Table 2. Coefficient of determination

Model	R	R Square	Adjusted R Square
1	0.675	0.455	0.366

The simultaneous F-test produced $F = 5.118$ with a significance value < 0.001 (< 0.05), indicating that age, education, farming experience, smartphone use frequency, extension support, information and training access, social influence, and internet access jointly and significantly affect Plantix adoption. The partial t-test results and the resulting multiple linear regression equation are presented in Table 3.

Table 3. Partial test (t-test) results

Variable	B	t	Sig.	Result
(Constant)	19.291	2.388	.021	—
Age (X1.1)	.458	1.768	.083	Not significant
Education (X1.2)	.651	.490	.627	Not significant
Farming experience (X1.3)	-.498	-1.827	.074	Not significant
Smartphone frequency (X1.4)	1.478	2.901	.006	Significant
Extension support (X2.1)	.417	2.308	.025	Significant
Info & training access (X2.2)	.187	1.421	.162	Not significant
Social & environ. infl. (X2.3)	.578	3.515	<.001	Significant
Internet access (X2.4)	.096	.612	.544	Not significant

$$Y = 19.291 + 0.458 X1.1 + 0.651 X1.2 - 0.498 X1.3 + 1.478 X1.4 + 0.417 X2.1 + 0.187 X2.2 + 0.578 X2.3 + 0.096 X2.4$$

The equation indicates that when all independent variables are held constant, the baseline adoption score is 19.291. Among the eight sub-variables, four significantly affected adoption: smartphone use frequency, extension support, and social/environmental influence (all positive), while age, education, farming experience, information/training access, and internet access were not statistically significant.

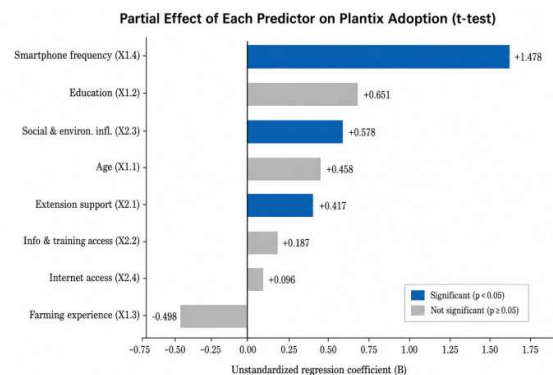


Figure 2. Unstandardized partial regression coefficients (B) of each predictor on Plantix adoption

Figure 2 visualizes the unstandardized coefficients (B) from Table 3, ordered from smallest to largest. The three significant predictors ($p < 0.05$) smartphone use frequency, extension

support, and social/environmental influence are shown in green, while the five non-significant predictors are shown in grey, illustrating both the direction and the relative magnitude of each variable's partial contribution to the regression equation.

3.5. Factors Influencing Plantix Adoption

Age, education, and farming experience did not significantly affect Plantix adoption. This is consistent with Rogers' theory that individual demographic characteristics are not the primary determinant of adoption success, and with prior findings that adoption of digital agricultural technology after farmers gain smartphone access is shaped more by digital literacy, perceived benefit, and extension support than by age or formal education [21][22]. Recent studies have demonstrated that the influence of age on digital technology adoption is inconsistent across agricultural contexts. Instead, farmers' adoption decisions are more strongly driven by access to extension services, institutional support, peer learning, and perceived usefulness of digital technologies, which collectively facilitate the transition toward digital agriculture [23][24]. The negative, non-significant coefficient for farming experience further suggests that farmers with longer cultivation experience tend to rely more on empirical judgment in identifying pest and disease symptoms, whereas less experienced farmers are relatively more open to digital decision support tools, in line with evidence that farming experience shapes technology evaluation but does not by itself drive adoption [25][26].

This relationship warrants closer attention because, at $p = 0.074$, it falls just outside the conventional 5% significance threshold and is the largest coefficient among the five non-significant predictors, suggesting a substantive pattern rather than random noise. A plausible explanation is that farmers with many years of chili cultivation have accumulated tacit, field-based diagnostic heuristics, recognizing early symptoms of thrips, Fusarium wilt, or anthracnose from visual cues built up over repeated seasons, that function as a low-cost substitute for an app-based diagnosis, and switching to a new tool carries a perceived opportunity cost that less experienced farmers, who lack this heuristic base, do not face. If this pattern is confirmed in a larger sample, it implies that extension messaging cannot rely on a single generic pitch about Plantix's accuracy; rather, more experienced farmers may need to be approached with a complementary framing, positioning Plantix as a second opinion or faster confirmation tool for ambiguous cases rather than a replacement for their existing judgment, while younger and less experienced farmers can be engaged more directly as primary adopters and, per the discussion above, as potential peer change agents.

Smartphone use frequency had a significant positive effect, indicating that farmers accustomed to frequent smartphone use found it easier to operate and adopt the Plantix application. This finding is consistent with the Technology Acceptance Model, which suggests that greater familiarity with digital devices enhances users' perceived ease of use and perceived usefulness, thereby increasing their willingness to adopt new technologies [27]. It also supports previous findings that farmers with greater exposure to digital technologies and more positive perceptions of their benefits are more likely to adopt agricultural innovations [8]. Similar conclusions have been reported in a systematic review, which identified prior smartphone experience, digital competence, extension support, and perceived usefulness as the

most consistent determinants of mobile agricultural technology adoption across developing countries [28].

Agricultural extension support showed a significant positive effect on the adoption of the Plantix application. This finding reinforces the role of extension workers not only as information disseminators but also as facilitators who strengthen farmers' participation in technology adoption. Participatory technology approaches combined with active farmer-group institutions significantly improve farmers' capacity to adopt innovations because knowledge exchange occurs continuously through interactions among farmers and extension workers [29][30]. In addition, practical and participatory extension activities have been shown to improve farmers' knowledge, attitudes, and skills in pest management, thereby increasing their readiness to adopt agricultural innovations. These findings suggest that extension programs emphasising hands-on learning and continuous mentoring can enhance farmers' confidence in using digital decision-support tools, such as the Plantix application [31]. Therefore, increasing the intensity of participatory extension activities can accelerate the adoption of Plantix among chilli farmers. Descriptively, however, 91% of respondents rated extension support as only low to moderate, reflecting that one extension officer currently serves more than 200 farmers across nine farmer groups an imbalance that likely constrains the pace of Plantix adoption in the village. A ratio of roughly one extension officer to more than 200 farmers spread across nine farmer groups leaves little room for the kind of repeated, hands-on contact that both Diffusion of Innovations and TAM identify as necessary for moving a farmer from awareness to confident use, since a single officer visiting nine groups in rotation can realistically reach any one group only intermittently, long after the persuasion stage has already lost momentum. This administrative constraint is unlikely to be resolved simply by adding general digital-literacy content to existing visits; it points instead to a structural staffing gap that extension agencies and local government would need to address, for instance by training farmer-group leaders or already-adopting farmers as auxiliary change agents who can sustain day-to-day mentoring between an officer's visits, a strategy discussed further below.

Social and environmental influences were the strongest significant predictors, indicating that peer farmers, farmer groups, and family strongly shape individual decisions to adopt Plantix. This corroborates evidence that social influence and social capital are key determinants of smart-farming technology adoption, as recommendations and shared experience within the farming community increase trust in digital innovation [32][33][34].

Information/training access and internet availability did not have a significant partial effect, even though both were descriptively rated moderate-to-high by most respondents (74% and 85%, respectively, as shown in Table 3). This suggests that once a reasonably adequate level of access is available, further improvements in infrastructure alone are not sufficient to drive adoption; perceived usefulness, hands-on experience, and social encouragement play a comparatively larger role, consistent with findings that internet access functions mainly as an enabling rather than a determining factor in digital agricultural technology adoption [25][15]

3.6. Practical Implications for Agricultural Extension

These findings have direct implications for the design of extension programs to accelerate Plantix adoption among chilli farmers in Kayukebek Village. Because extension support and social/environmental influence emerged as the strongest predictors of adoption, interventions should prioritise strengthening farmer group-based demonstrations and increasing the frequency of extension visits, rather than relying solely on infrastructure such as internet access, which this study found mainly enabled rather than determined adoption.

A structured extension program that combines a clear farmer-group dissemination target, hands-on Plantix demonstration sessions, and periodic follow-up mentoring is likely to be more effective than a generic digital-literacy campaign, particularly given that the village's nine farmer groups currently rely on a single extension officer. Farmers who already show high adoption levels could also be positioned as local change agents, using the social networks identified in this study as an influential pathway to accelerate diffusion of Plantix among their peers.

4. CONCLUSION

This study found that the level of adoption of the Plantix application by chili farmers in Kayukebek Village is jointly and significantly influenced by farmer characteristics and environmental support/interaction factors ($R^2 = 0.455$; $F = 5.118$; $p < 0.001$). Partially, only smartphone use frequency, agricultural extension support, and social/environmental influence significantly affect adoption, while age, education, farming experience, information/training access, and internet access availability do not. These findings indicate that the main barrier to Plantix adoption is not farmers' demographic profile or infrastructure availability, but rather the limited intensity of extension assistance and the need to strengthen peer-based diffusion channels. Extension programs aimed at increasing Plantix adoption should therefore prioritize interactive, hands-on demonstration methods delivered through farmer groups, supported by continuous post-training mentoring from agricultural extension workers.

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