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Adoption process of portable digital nutrient decision-support technologies: perennial experience of Shaanxi's kiwifruit smallholders

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A B S T R A C T

Digital decision-support tools for nutrient management have offered a promising entry point to precision agriculture, yet little is known about how smallholders engage with these tools over time. This study aimed to identify the decision stages and temporal pathways through which farmers adopted three portable digital nutrient decision-support technologies (PDDSTs) - soil testers, chlorophyll meters, and agro-advisory mobile applications. Using survey data from 675 kiwifruit growers in Shaanxi Province, China, we reconstructed adoption trajectories using Sankey diagrams and examined post-adoption patterns using transition matrices. The results showed that adoption was nonlinear and cyclical, with farmers frequently moving between trial, initial use, sustained use, reduced use, discontinuation, and reuse. Trial-based learning was strongly associated with sustained adoption, whereas direct adoption without prior trial was linked to higher disengagement risks. Concurrent use of multiple complementary tools further reinforced long-term commitment to site-specific nutrient management. These findings highlighted the importance of policies that expand access to PDDSTs through trial-enabled extension and distribution channels, support structured learning opportunities, and strengthen the market and institutional mechanisms needed to promote effective and sustained adoption among smallholders.

1. Introduction

Improving nutrient use efficiency through site-specific nutrient management (SSNM) is central to achieving sustainable agricultural intensification, particularly in smallholder farming systems. In many developing countries, fertilizer application remains poorly aligned with crop nutrient demand, resulting in substantial inefficiencies and environmental externalities. Globally, nutrient use efficiency has been estimated at only 56% for nitrogen, 69% for phosphorus, and 79% for potassium, with inefficiencies most pronounced among smallholders [1]. These patterns highlight both the urgency of improving nutrient management practices and the potential role of decision-support technologies in enhancing farmers' fertilizer-related decision-making.

Recent advances in portable digital nutrient decision-support technologies (PDDSTs) have lowered the technical, financial, and operational barriers that historically constrained the adoption of precision agriculture [2,3]. Unlike capital-intensive precision agriculture systems, PDDSTs are scale-neutral and increasingly accessible to smallholders. They include field-deployable, user-facing tools that provide site-specific nutrient diagnostic or advisory information at the point of fertilizer decision-making, including in-field measurement devices (e.g., soil and crop nutrient testers) and mobile-based advisory platforms that translate such information into fertilizer recommendations [4]. As such, PDDSTs offer a practical entry point for introducing precision nutrient management in contexts where conventional precision technologies remain out of reach.

While the agronomic potential of PDDSTs is increasingly recognized, less attention has been paid to how farmers engage with these technologies over time. Much of the existing adoption literature relies on binary indicators of use and non-use, providing limited insight into the learning processes that shape farmers' decisions beyond initial uptake [5]. Adoption is not a singular event but a dynamic process involving awareness, evaluation, trial, adoption, and confirmation, as conceptualized in innovation diffusion theory. However, empirical evidence

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capturing how farmers progress through these stages - particularly for digital decision-support tools - remains scarce [6].

Learning and experimentation play a critical role in managing uncertainty during technology adoption [7]. Trialability allows farmers to assess the usefulness and compatibility of new technologies under real-world conditions before committing themselves to sustained use. Nevertheless, existing studies rarely examine how trial-based pathways differ from direct adoption routes in shaping long-term engagement, nor how post-adoption behaviors such as reduced use, discontinuation, or reuse unfold over time [8]. This gap is especially relevant for digital decision-support technologies, whose benefits may only become apparent through repeated application and experiential learning.

In this context, China provides a salient context for examining these adoption dynamics. As the world's largest consumer of chemical fertilizers, China has faced mounting environmental pressures associated with nutrient surpluses and pollution [9,10]. In response, national policies such as the “Zero Growth Action Plan for Fertilizer and Pesticide Use” have emphasized fertilizer reduction and the promotion of scale-neutral digital technologies [11,12]. These policy initiatives have accelerated the dissemination of PDDSTs, particularly in regions dominated by smallholder farming. However, policy-driven access does not necessarily translate into sustained or effective use, underscoring the need to understand farmers' technology-decision processes in greater depth.

Against this background, the objective of this study was to examine the technology-decision processes associated with the adoption of portable digital nutrient decision-support technologies for fertilizer management among kiwifruit smallholders in China. Using survey data from 675 growers in Shaanxi Province, this study reconstructed farmers’ decision stages and transitions for three widely available PDDSTs namely soil nutrient testers, chlorophyll meters, and agro-advisory mobile applications. Sankey diagrams were employed to visualize nonlinear and cyclical adoption pathways, while transition matrices were used to validate post-adoption dynamics across different adoption routes.

This study contributes to the literature by offering a temporal perspective on the adoption of digital nutrient decision-support technologies, based on a detailed case study of nutrient diagnosis and monitoring tools in perennial agriculture. By reconstructing adoption trajectories over time, the analysis demonstrates that learning in the technology-decision process for site-specific nutrient management unfolds through two distinct pathways. Trial-based engagement, typically spanning a full cropping season, is associated with a higher likelihood of sustained adoption, whereas direct adoption relies on a longer learning-by-doing process and is more prone to subsequent disengagement. As adoption stabilizes, farmers increasingly combine multiple complementary tools to support nutrient management decisions, underscoring the integrative nature of digital technology use in practice. Together, these findings extend existing adoption and diffusion frameworks by emphasizing the role of experiential learning and temporal sequencing, while also pointing to the importance of capacity-building approaches that support continued learning beyond one-off technology promotion initiatives.

2. Background

Amid rising environmental and population pressures, improved nutrient management is essential for achieving sustainable productivity growth. Historically, agricultural growth in China was accompanied by escalating pollution, largely driven by policies that encouraged intensive fertilizer use [13]. Xiao et al. [14] observed that fertilizer-intensive cultivation exacerbates non-point source pollution. Bai et al. [15] estimated that by 2010, approximately 80% of manure nitrogen and 40% of manure phosphorus were lost to the environment. Such levels of fertilizer overuse are unsustainable [16]. Clearly, Chinese farmers must strategically rationalize manure application while maintaining or enhancing output productivity. Nevertheless, the receptivity of the need for such changes among farmers remains poorly understood.

2.1. Nutrient management in kiwifruit production

Nutrient management in kiwifruit orchards is a delicate undertaking. Gentile et al. [17] draw nutrient guidelines primarily from studies conducted in New Zealand between the 1980s and early 2000s. Xiloyannis et al. [18] describe kiwifruit vine nutrient requirements based on the Italian context. In China, existing nutrient management guidelines for kiwifruit are largely derived from Ministry of Agriculture directives and industry standards. In theory, smallholders gain greater control over nutrient application when transitioning from rain-fed systems and broad-spectrum fertilizer broadcasting to fertigation technologies, which synchronize water and nutrient delivery with plant demand at specific set times [19]. For instance, to improve fruit set and weight, water and fertilizer applications can now be regulated at key growth stages [20]. However, smallholders often fail to properly align nutrient supply with the shifting nutrient demands across different phenological phases. Zhu et al. [8] observed, for example, a common misapplication of nitrogen during the early spring fruit-filling phase. Moreover, yield response to nutrient application is rarely assessed or factored into management decisions.

In most Chinese kiwifruit orchards, nutrient application is primarily guided by local officials, whose assessments are based on results from soil and leaf tissue analyses (Fig. 1). Seasonal soil sampling is conducted across representative orchards within a village, typically in spring, to address nutrient imbalance during the budbreak phase and in winter to rebuild nutrient availability for the subsequent season. Late season fertilization improves mineral reserves and flowering in kiwifruit [21]. Soil testing during these key phenological phases primarily targets nitrogen, phosphorus, and potassium, given their significant influence on kiwifruit growth and productivity. The availability of these macronutrients is critical for maintaining nutrient balance and supporting effective plant uptake [22–24]. However, broad structural imbalances persist within China's kiwifruit industry. For example, Wang et al. [25] reported widespread nitrogen surpluses in Shaanxi orchards, while Gao et al. [26] identified concurrent potassium and magnesium deficiencies alongside excessive phosphorus accumulation. In contrast, the role of micronutrients has received comparatively limited attention [27].

Following a similar sampling approach, leaf nutrient testing is conducted in late spring and summer to detect nutrient intake deficiencies. Tissue nutrient concentrations vary across phenological stages and can also be influenced by fruit development [28,29]. In China, therefore, samples are collected when leaves have reached physiological maturity. This timing ensures relatively stable nutrient concentrations, enabling more accurate diagnostic assessments. Such diagnostic information allows farmers to identify nutrient imbalances and implement targeted foliar applications for in-season nutrient correction [30,31].

In kiwifruit production systems, nutrients are removed through both harvesting and pruning activities. Additional nutrient losses may also occur through leaching and runoff [32]. These processes highlight the importance of maintaining balanced nutrient replenishment in orchard systems. The use of rain-shelter systems, which is now increasingly common, helps to protect the soil surface and reduces these losses. Cover crops are another option. Such management practices can help improve soil nutrient retention and support sustained plant productivity [33].

2.2. Portable digital decision-support technology for nutrient management

“Average” fertilizer prescriptions present inherent challenges in ensuring that nutrient supplies adequately balance crop nutrient requirements and removals. Kiwifruit smallholders often lack the knowledge needed to adapt general recommendations to address the site-specific nutrient gaps of their orchards [34]. Beyond in-season nutrient uptake and removal, kiwifruit nutrient requirements are

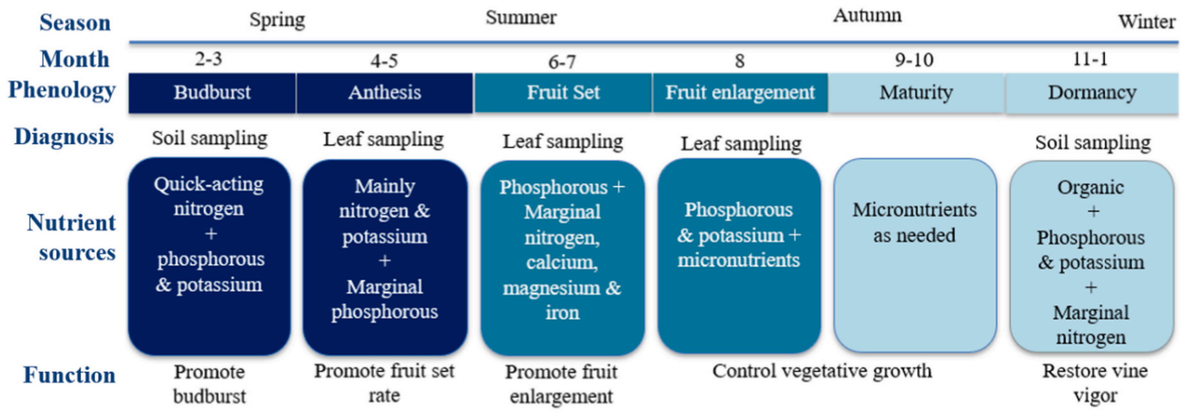

Fig. 1. Kiwifruit cropping season and nutrient management in China.

further shaped by the crop's perennial nature, especially its internal nutrient reserves and the cumulative nutrient stocks and flows from previous seasons. As a result, "average" applications often lead to asymmetric over- or under-fertilization. For example, Lu et al. [35] found that 94.3% of orchards had insufficient manure inputs while 81.8% applied excessive nitrogen fertilizer. Nutrient imbalances contribute to low kiwifruit productivity. Smith and Clark [36] observed that leaf boron concentrations exceeding 80 μg per gram were associated with yield reductions of more than 10%. Therefore, site-specific information is critical to support fertilizer decision-making processes.

Soil testers and chlorophyll meters offer rapid, *in-situ* assessments of macronutrient requirements-typically the largest component of fertilizer costs-for smallholder kiwifruit orchards. Standard soil nutrient diagnostics measure the availability of macronutrients across multiple sampling points within orchard blocks and provide additional readings on soil moisture and pH levels. Field measurements from these tools have shown moderate to high correlation with laboratory-based analyses. Chlorophyll meters evaluate chlorophyll content and nitrogen status based on nutrient concentrations in mature leaves.

Both soil and leaf nutrient status are interpreted against established critical thresholds to determine SSNM requirements. In China, these thresholds are the collective results of long-term field trials, as codified in national or provincial fertilization guidelines [25]. These tools can also be used to evaluate the effectiveness of fertilizer application. National and provincial agro-advisory mobile applications further strengthen the SSNM framework by offering phenology-specific reference values, technical support, and recommendations. These applications assist farmers in translating diagnostic data into actionable management strategies.

Importantly, soil fertility testers and chlorophyll meters offer complementary insights into plant nutrient status. For example, in orchards where soil testers indicate sufficient nitrogen availability, chlorophyll meter readings may still reveal nitrogen deficiency due to delayed root uptake or environmental constraints. Their combined use enhances the precision of nutrient management by identifying discrepancies between nutrient supply and plant uptake. Such complementarity allows farmers to integrate soil-based and plant-based diagnostics when adjusting fertilizer decisions.

However, the use of PDDSTs is not straightforward. In perennial crops, specific nutrient requirements unfold across multiple phenological phases and seasons. Kiwifruit nutrient uptake is gradual, and fertilizer effects manifest themselves only after a full cropping season [37]. For instance, yield improvements lag early-season nutrient corrections [38]. Since the utility of such tools is influenced by temporal responses [39,40], a temporal connect must be factored into decision-making. Furthermore, chlorophyll meters require a degree of agronomic literacy and adherence to strict protocols to ensure accurate diagnosis [41–43]. The effectiveness of agro-advisory mobile applications is also shaped by external factors such as smartphone penetration, stable internet connectivity, and users' digital proficiency [44]. Many of these challenges can be gradually mitigated through continued learning and accumulated user experience.

3. Methodology

At present, few studies provide *ex post* assessments of technological change related to precision agriculture. Nonetheless, it is well recognized that the ability of individual farmers to enhance their fertilizer application practices, and to strategically capitalize on potential yield improvements, largely depends on access to targeted, site-specific information in the form of actionable prescriptions. In this context, we examine the technology-decision process concerning the use of soil testers, chlorophyll meters, and agro-advisory mobile applications in kiwifruit production systems. Fig. 2 illustrates the conceptual framework guiding this investigation.

The technology adoption-decision process illustrated in Fig. 2 reflects the range of possible adoption outcomes. Rogers characterizes this process as a temporal sequence through which individuals may progress: (1) acquiring knowledge about a technology, (2) evaluating its relevance and utility, (3) deciding whether to adopt or reject it, (4) implementing the technology, and (5) seeking confirmation or reinforcement of the decision made. In practice, individual decision-making pathways may vary, often involving a combination or partial progression through these stages, depending on specific circumstances and considerations.

In this study, farm-level data recalling the timing of changes in the technology-decision process enable us to examine three key aspects: (a) the decision stages and transitional flows with respect to individual PDDSTs, (b) the average time required to reach various decision stages, and (c) the temporal patterns of integrative use across these technologies. Nuanced decision-making processes that warrant strategic emphasis going forward are subsequently considered in relation to innovation diffusion.

3.1. Study area

Shaanxi Province provides a suitable case study for examining the technology-decision process of PDDSTs in China. As the country's largest kiwifruit-producing region, it is home to nearly 150,000 farmers. In 2023, approximately 67,338 ha were under vine, generating 1.46 million tons of kiwifruit. The province accounts for almost two-thirds of China's total kiwifruit output.

However, intensive kiwifruit production in Shaanxi Province has come at significant environmental cost. Lu et al. [35] reported nitrate accumulation in the 0-100 cm and 0-200 cm soil layers of kiwifruit orchards, associated with nitrogen application rates of 466 and 793 kg of nitrogen ha^{-1} in the Yujia River catchment. Liu [46] documented

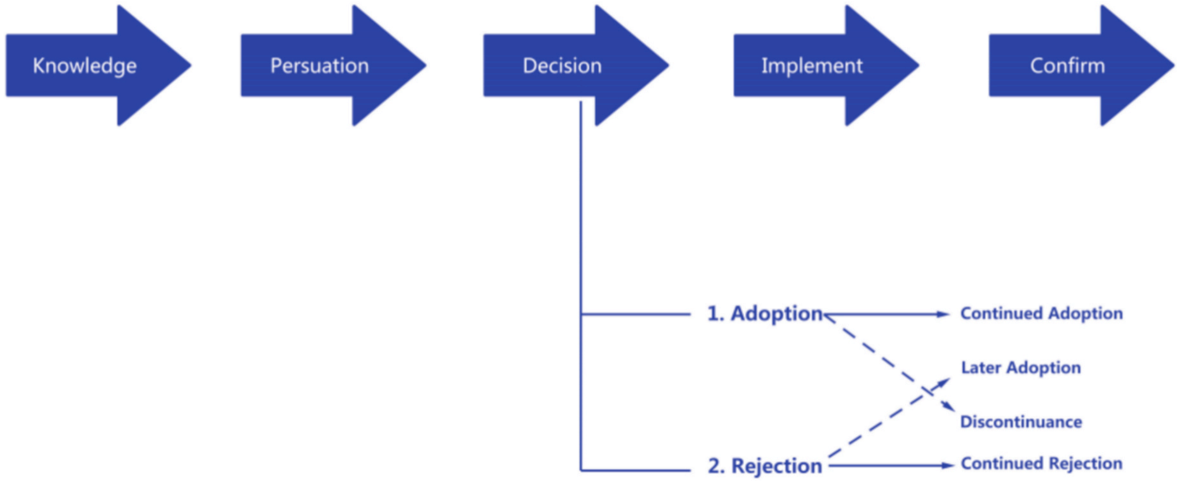

Fig. 2. Technology-decision process
Adapted from: Rogers [45].

volatilization ranging from 11.57 to 13.98 kg of ammonia hm^{-2} in the same area. Gao et al. [9] found that nitrate concentrations in nearly all groundwater samples from the local Qinling Mountains exceeded World Health Organization standards. Various evidence highlights the prevalence of suboptimal fertilization practices in Shaanxi's kiwifruit production.

Unguided decision-making in nutrient management carries significant economic consequences. Wang et al. [34] documented the poverty prevalent among kiwifruit smallholders in Shaanxi who refused to use quality fertilizers in line with industry organizations' recommendations. The nature of poverty among these smallholders was multidimensional and more complex compared to those who adopted recommended practices. Informed nutrient management holds important potential for contributing to sustainable rural revitalization.

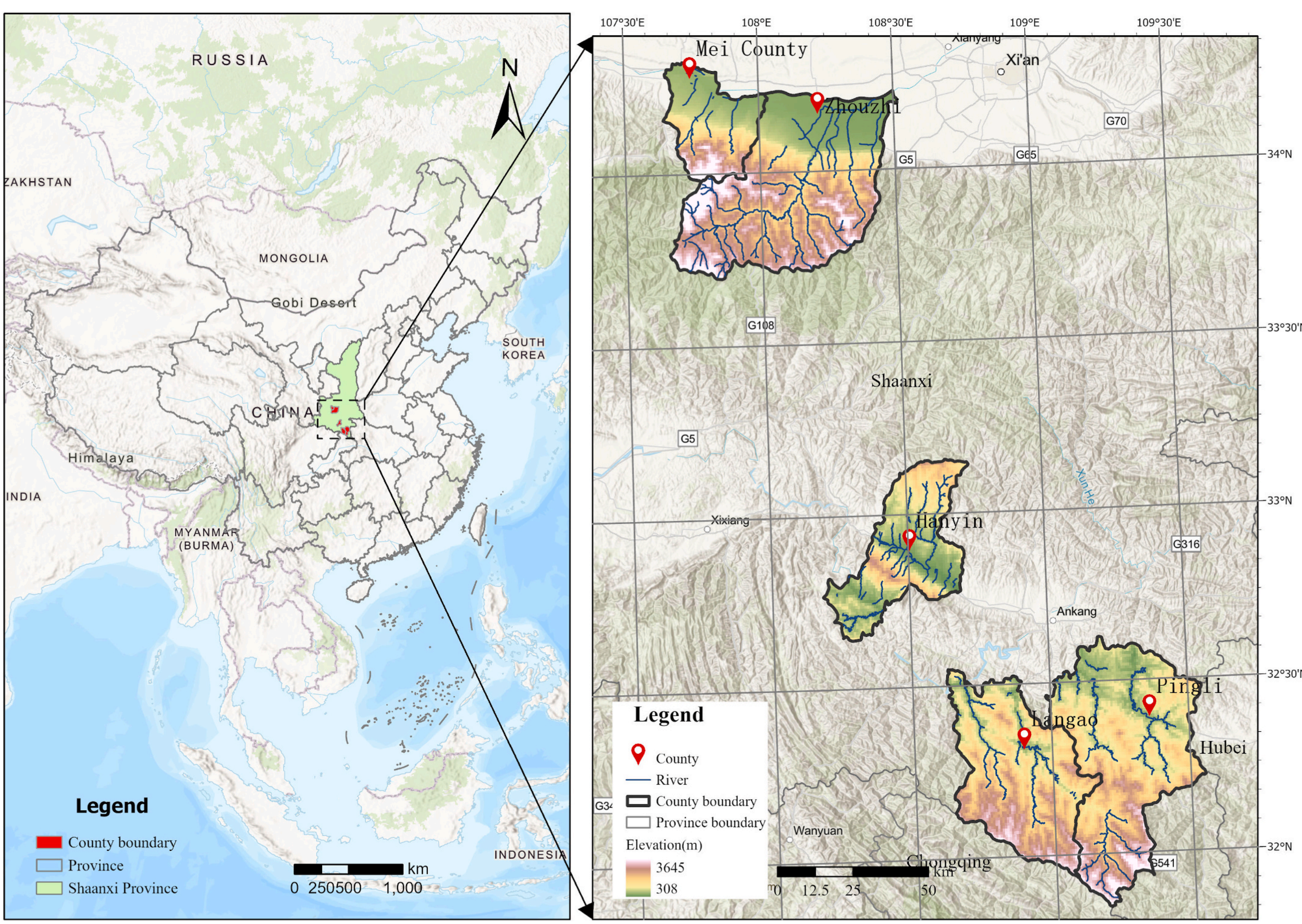

Fig. 3. Study areas in Shaanxi Province, China.

Sustainable agricultural intensification, a national priority, has been localized as a policy focus in Shaanxi Province. This subnational alignment mirrors the direction of China's Ministry of Agriculture and Rural Affairs, which has advocated the deployment PDDSTs for SSNM (Ministry of Agriculture and Rural Affairs of China, 2021). The momentum for local transition is further reinforced by the National Outline for Smart Agriculture Development (2021-2025) and Shaanxi's provincial initiatives, such as the Digital Rural Development Action Plan (2020-2025) and the Smart Agriculture Construction Implementation Plan (2019-2022) (Shaanxi Provincial Government, 2020; Shaanxi Department of Agriculture and Rural Affairs, 2019). These policies provided subsidies (up to 50% reimbursement) for PDDST acquisitions and technologically integrated demonstration sites in major fruit-producing counties, such as Zhouzhi and Mei County, which are central to the kiwifruit industry. Notably, to optimize nutrient management, the Shaanxi Kiwifruit Industry High-Quality Development Guidelines (2021) specifically recommended the integration of PDDSTs (Shaanxi Provincial Fruit Industry Center, 2021). Within this context, the uptake of one tool may plausibly catalyze the adoption of others to enhance the precision of nutrient management decisions.

3.2. Sampling and survey

Primary data were collected through 675 face-to-face interviews conducted between November 2024 and January 2025. The survey covered Zhouzhi and Meixian counties in the Guanzhong Plain, as well as Hanyin, Pingli, and Langao counties in the southern Qinba mountainous region of Shaanxi Province (see Fig. 3). The respondents were recruited using convenience sampling.

In addition to the structured survey, in-depth qualitative follow-up interviews were conducted with a subsample of respondents and local key informants. These interviews aimed to contextualize farmers' reported technology experiences, capture decision rationales not observable in structured responses, and support the interpretation of behavioral pathways reconstructed in the quantitative analysis.

Respondents were recruited through village cadres and local extension contacts who facilitated access to kiwifruit-growing households in each county. Eligible participants were required to meet two criteria: (i) being the primary household decision-maker responsible for fertilizer and nutrient management, and (ii) managing a kiwifruit orchard that had already entered the fruit-bearing stage. These criteria ensured that respondents had both decision authority and practical production experience relevant to the technologies under study.

Data collection was implemented through two complementary modes. In some villages, enumerators conducted one-to-one household interviews arranged by village cadres, allowing for in-depth recall of individual technological experiences. In addition, centralized interviews were carried out during scheduled agricultural training sessions organized by local extension services, which enabled the inclusion of growers with varying levels of market access and technical exposure. Importantly, participation was not restricted to cooperative members or training attendees, and no financial or material incentives were provided. This mixed recruitment approach was adopted to mitigate potential selection bias toward particularly technology-active farmers. To situate the representativeness of the convenience sample, and to emphasize the contextual rather than statistical nature of external validity, Appendix Table 2 provides a descriptive comparison between key sample characteristics and county-level benchmark ranges reported by local extension services and official agricultural statistics. While the sample characteristics fall within the benchmark ranges, several indicators—such as orchard area, training participation, and cooperative membership—are located near the upper end of these ranges. This pattern suggests a potential upward skew toward relatively technology-engaged growers, and therefore the observed diffusion patterns may reflect a comparatively active segment of farmers rather than the entire population.

Based on the structured event-history survey module, respondents reported recalled years of awareness, trial use, adoption (with or without trial), and subsequent post-adoption adjustments for each PDDST. These raw responses were systematically mapped into analytical technology-decision states, which constitute the state space for the Sankey flow reconstruction and the transition matrices. Appendix Table 3 documents the exact survey items, response options, and operational definitions used to code each pre-adoption and post-adoption state.

Pandemic-adopter subgroup. To contextualize adoption dynamics under an exogenous shock, we additionally conduct a descriptive subgroup analysis focusing on respondents whose first recorded initial adoption of a given PDDST occurred in 2020 (the "pandemic adopters"). We compare their subsequent post-adoption states observed in 2024, distinguishing trial versus non-trial pathways. This analysis is descriptive and does not aim to identify causal effects.

Appendix Table 6 reports descriptive comparisons between pandemic adopters and other adopters to contextualize potential compositional differences between the two groups.

3.3. Recall-based reconstruction and internal validity checks

Because the timing of transitions was reconstructed retrospectively, responses may be subject to recall error, including telescoping (misplacing events earlier or later than they occurred) and heaping (reporting rounded years). To reduce cognitive burden and improve temporal consistency, interviews were conducted face-to-face using an event-history style prompt: enumerators first anchored respondents' technology experiences to salient farming and household reference points (e.g., orchard expansion, major training attendance, or notable production shocks) and then confirmed the year for each decision status sequentially (awareness → trial/adoption → post-adoption states).

We additionally conducted internal plausibility checks on the recalled timing information. First, we inspected the distribution of reported adoption and trial years for each tool and assessed potential year heaping (e.g., concentration at rounded years). While no systematic rounding to focal years such as 2015 was observed, we note a noticeable concentration of soil-tester first trials in 2020, which may reflect both pandemic-period promotion dynamics and recall salience around a memorable year. Second, we cross-checked recalled timing against locally documented program rollouts (e.g., county-level training and demonstration periods, and subsidy availability) to verify that reported uptake patterns were broadly consistent with known diffusion windows. To improve transparency, an indicative timeline summarizing PDDST-related training programs, demonstration activities, and subsidy promotion periods across the five study counties is provided in Appendix Table 7. Third, qualitative follow-up interviews and key-informant consultations were used to triangulate typical adoption narratives and timing sequences, providing contextual validation for the reconstructed trajectories. A summary of these qualitative follow-up interviews, including respondent types and key themes discussed, is provided in Appendix Table 8.

For full methodological transparency and reproducibility, we provide a dedicated Reproducibility Appendix (Appendix 7), which documents the mapping of survey items to analytical adoption states, the coding rules for individual trajectory construction, and the computational procedures (pseudocode) used to generate the Sankey diagrams and transition matrices.

3.4. Methods

Sankey diagram analysis was employed in this study to uncover the technology-decision process. A Sankey diagram is a visual representation of quantities flowing between discrete states, usually aggregated over a period. Conceptually, the Sankey diagram is a directed weighted graph, G, defined by:

$$G = (S, F) \tag{1}$$

where S is a set of nodes (decision states):

$$S = \{s_1, s_2, \ldots, s_n\} \tag{2}$$

F is a set of directed weighted edges:

$$F = \{F_{i \to j} | s_i, s_j \in S\} \tag{3}$$

where $F_{i \to j}$ represents the flow from state s_i to state s_j and its magnitude is proportional to the number of respondents making the transition. Each flow has a source i, a target j, and a share value.

The total outflow (O_i) from s_i is:

$$O_i = \sum_{j \neq i} F_{i \to j} \tag{4}$$

The total inflow (I_i) into s_i is:

$$I_i = \sum_{j \neq i} F_{j \to i} \tag{5}$$

In this cross-sectional study, when the system is conservative with no external gain or loss, then the total inflow equals total outflow:

$$\sum_i O_i = \sum_i I_i \tag{6}$$

Each edge $F_{i \to j}$ is visualized in the diagram with a width proportional to its flow value. In addition, the average time incurred to move from source i to target j was also estimated.

While the Sankey diagram provides visual intuition, it is not dynamic in time. A transition matrix was thus used to validate the dynamics of technological change. Based on Equation (2), let $P = [p_{ij}] \in R^{k*k}$ denote a transition matrix, where:

$$p_{ij} = Pr\left(s_j^{(t+1)} \middle| s_i^{(t)}\right) \tag{7}$$

That is, p_{ij}, is the probability of transitioning from state s_i at time t to state s_j at time t+1. Each row i in P must sum to 1.

If $x^{(t)} \in R^k$ be the distribution vector at time t, where $x^{(t)}$ is the proportion of individuals in state s_i at time t. Then, the state at s_i at time t+1 is:

$$x^{(t+1)} = x^{(t)} . P \tag{8}$$

This is the discrete-time Markov process equation, where P drives the evolution of states.

The flow from state s_i to s_i is:

$$f_{ij} = x_i^{(t)} . p_{ij} \tag{9}$$

where f_{ij} is the proportion of individuals transitioning from s_i to s_i, and

$$\sum_{j=1}^{k} f_{ij} = x_i^{(t)}. \tag{10}$$

4. Results

The technology decisions identified by kiwifruit smallholders were used to construct Sankey diagrams. As an initial check on the temporal data underlying this reconstruction, the distribution of recalled trial years across the three PDDSTs is summarized in Appendix Table 1, which shows no pronounced year heaping. Fig. 4 illustrates the decision-making process with soil testers, chlorophyll meters, and agro-advisory mobile applications. In these diagrams, nodes represent distinct decision states, while flows represent transitions between them. The width of each flow is proportional to the number of respondents making that transition, with thicker flows indicating larger proportions. As such, these diagrams provide an interpretable view of the technology-decision process, disaggregating the trajectories of PDDSTs through representation of decision stages and their decision flows.

Each Sankey diagram is constructed using the full survey sample (n = 675) as the base population. Both adopters and non-adopters are retained in the diagrams. Farmers who never became aware of or never used a given technology are explicitly represented as terminal nodes (e.g., "Unaware" or "Never adopted"), thereby preserving a consistent population base across tools.

Diagrams are constructed from the full survey sample (n = 675). Flows represent aggregated sequential transitions reconstructed from recalled adoption histories (each respondent may contribute multiple transitions). Flow widths are proportional to the number of respondents (see Appendix Table 4 for underlying counts). Red labels on flows indicate the mean duration (in years) between consecutive states.

4.1. Technology-decision stages

In Fig. 4, four main stages are broadly identified: *awareness*, *trial*, *initial adoption*, and *post-adoption*. Firstly, the *awareness* stage reflects farmers' recognition that PDDSTs are available for nutrient management in the local kiwifruit production landscape. Awareness was primarily shaped by formal sources such as farm equipment suppliers, training programs, agricultural extension visits, and sample farms. These channels varied in informational depth: suppliers typically promoted individual tools, while training and demonstrations offered insights across multiple technologies. Complementing these were informal sources, which contributed secondary information. These included social networks, mass media, and social media. Collectively, these formal and informal channels formed the foundation of farmers' early understanding of the tools' relevance and potential utility.

Secondly, the *trial* stage refers to the period during which farmers piloted the PDDSTs on a selected scale and for a limited duration within their kiwifruit production. Users typically evaluated the tools' ease of use and their compatibility with existing operations. Some non-participants reported observing the outcomes experienced by peers, although the benefits of improved fertilizer application are not easily distinguishable in the short term. On that basis, evaluation of the tools was often directed to the relative efficiency of diagnosis-aided decisions compared to their own heuristic methods. Such subjective assessments occurred despite fertilizers representing the most significant cost among chemical inputs.

Thirdly, the *initial adoption* stage marks the early phase of using a PDDST to inform nutrient management practices in kiwifruit production. As a rapid diagnostic toolkit, such technology is also used for ongoing monitoring and evaluation. During this stage, most farmers adopted these tools at the preferred scale. Those who implemented on a limited scale afforded a base of comparison and had room for growth in usage. Others applied the tools across all their farms, though with varying use intensity of use. To accurately reflect this variation, cases of initial adoption that already involved consistent use were reclassified as "sustained use" within the *post-adoption* stage.

Finally, the *post-adoption* stage captures the range of user experiences that either reinforced or weakened kiwifruit smallholder engagement with PDDSTs. At this stage, "sustained use" refers to an unchanged scale in the application of the tools. "Expanded use" captures a scaling-up of engagement, whereby farmers sampled more blocks and points to gauge average nutrient requirements across their farms. Conversely, some smallholders reported negative trajectories, including "reduced use" due to sporadic engagement or declining perceived utility, and "discontinued use" resulting from persistent technical challenges, particularly in obtaining appropriate samples. In some cases, disengaged users "reused" the tools following reskilling through training activities.

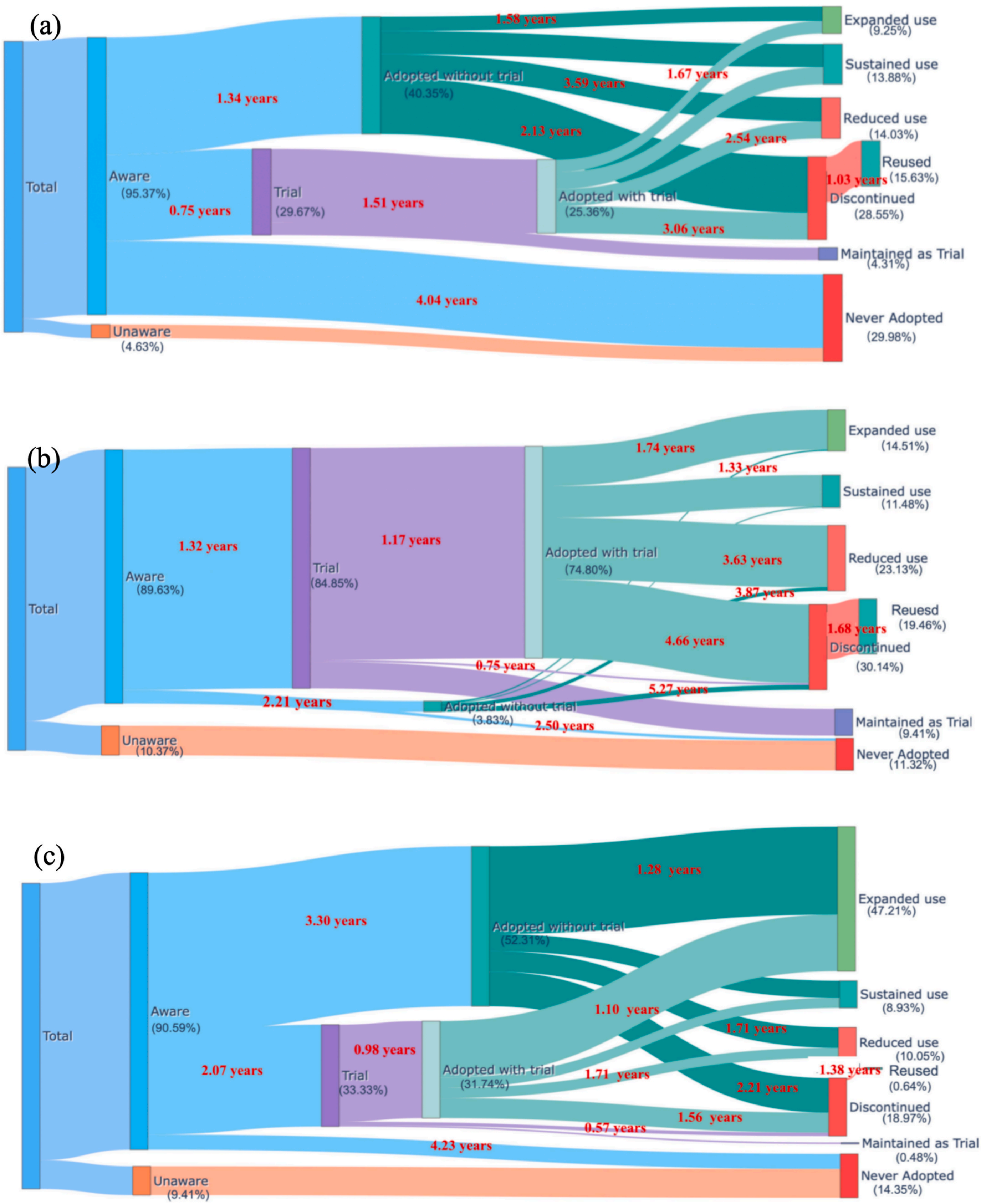

Fig. 4. Life-course Sankey diagrams of cumulative adoption trajectories (2015–2024) for (a) soil testers, (b) chlorophyll meters, and (c) agro-advisory mobile applications.

4.2. Technology-decision flows

The Sankey flows represent cumulative life-course transitions reconstructed over the full observation window (2015–2024). The underlying transition counts used to construct each diagram are reported in Appendix Table 4. Percentages are calculated relative to the full sample (n = 675) for comparability across transitions, while mass conservation across decision layers is ensured by the flow counts. Each respondent may contribute multiple sequential transitions to the diagrams as they move across technology-decision states over time (e.g., trial → adopted → reduced → reused). They therefore represent life-course cumulative trajectories rather than single-period cohort snapshots.

In Fig. 4, flows that connect distinct decision-making stages illustrate the technology-decision process. Nearly all kiwifruit smallholders became aware of the availability of PDDSTs. Smallholders posit awareness as the gateway through which they enter the decision-making pathway toward initial adoption. As such, awareness served as a critical precondition for both direct and indirect transitions.

Direct and indirect transitions are illustrated through the flows from awareness to initial adoption. In direct transitions, the initial adoption of soil testers and agro-advisory mobile applications occurred after an average of 3.30 years and 1.34 years, respectively, among nearly half of the respondents. The relatively high acquisition cost of soil testers compared to mobile applications was a key factor explaining this variable pace of adoption. In indirect transitions, nearly two-thirds of respondents waited about two years before deciding to pilot soil testers and nine months for mobile applications. An average gap of 15 months between awareness and trial was reported for chlorophyll meters by about 85 percent of respondents. Before progressing to initial adoption, the trial stage for soil testers and chlorophyll meters typically lasted close to one year, which is consistent with the annual cropping and lagged yield response characteristics of kiwifruit production. Reported transition durations are calculated as mean year differences between consecutive reported states. For respondents who have not yet experienced a subsequent state by the end of the survey period, transition durations are treated as right-censored and excluded from duration calculations, while the corresponding individuals remain included in flow counts. Counts displayed in the Sankey diagrams and in Appendix Table 4 include right-censored respondents, whereas reported transition durations are computed from uncensored spells only.

Trial participants generally demonstrated greater efficiency in decision-making during the post-adoption stage when compared to non-trial participants. This distinction was clear when looking at the flows from initial adoption to tool discontinuation: trial participants learned about negative experiences with soil testers and chlorophyll meters about eight months before non-trial participants did. The absence of a prior trial phase resulted in a longer learning curve in line with the lagged plant response to inputs. Furthermore, non-trial participants showed higher rates of reduced and discontinued use of all the hardware in question. In contrast, those who had previously participated in a trial stage were more likely to continue using these tools, notwithstanding instances of intermittent disengagement.

4.3. Descriptive subgroup analysis: pandemic adopters

In this study, pandemic adopters are defined as farmers whose first recorded initial adoption of a given PDDST occurred in 2020. To descriptively examine post-adoption trajectories under this pandemic-period context we construct a two–time-point transition matrix that maps each respondent's post-adoption state from 2020 (t) to 2024 (t+1), conditional on having first adopted the corresponding PDDST in 2020. The year 2024 is treated as the follow-up endpoint because the survey was conducted in 2024–2025 and thus captures respondents' most recent post-adoption status after the normalization of extension services and market conditions following the COVID-19 pandemic.

The time step in this matrix is therefore a four-year interval (2020 → 2024), rather than an annual Markov step. Descriptive comparisons in Appendix Table 6 show that pandemic adopters and other adopters are broadly similar in age, education, orchard scale, farming experience, training participation, cooperative membership, smartphone access, and market distance, suggesting no major compositional differences between the two groups. Individuals with no state change between 2020 and 2024 remain in the same post-adoption state (e.g., “Sustained use”) and are retained in the denominator when computing transition probabilities. While presented in a Markov notation, this matrix is used descriptively to summarize observed transition frequencies between two recalled time points, rather than to assert that farmers' decisions satisfy the Markov property.

Fig. 5 illustrates both positive and negative post-adoption trajectories following the initial use of the three PDDSTs. Positive trajectories include “sustained use,” “increased use,” and “reuse,” while negative trajectories are defined as “reduced use” and “discontinued” use. When comparing the two trajectories, the likelihood of trial participants falling into the negative trajectories was estimated to be between 10.2% and 47.2%. They were lower than those of non-trial participants, who had a 25.6% to 62.5% chance of moving into negative territories. To quantify sampling uncertainty for these comparisons, Appendix Table 5 reports exact two-sided 95% Clopper–Pearson binomial confidence intervals for the probability of entering a negative trajectory (Reduced + Discontinued), computed using the cell percentages in Fig. 5 and the corresponding sample sizes (n) displayed on the heatmaps. However, the non-trial subgroups for soil testers and chlorophyll meters are small (n = 8 in each case), resulting in wide confidence intervals that overlap substantially with those of the trial groups. This prevents statistical discrimination between the two groups for these tools. The observed trial-versus-non-trial contrast should therefore be interpreted cautiously and is best viewed as a suggestive pattern, most clearly supported by the chlorophyll meter trial group (n = 139) and the mobile app groups.

4.4. Aggregated adoption

The results show that kiwifruit smallholders' technology-decision processes took place concurrently across the three PDDSTs. They distinguish adoption from “trial use” and conceptualize adoption as a spectrum that includes “sustained use,” “increased use,” “reuse,” and “reduced use.” This broader conceptualization aggregates the nuanced technology engagement beyond initial uptake. Highlighting both singular and combined use of the PDDSTs over time, Fig. 6 presents the aggregated adoption patterns across individual smallholders.

The findings indicate an increasing incidence in the integrative use of PDDSTs among kiwifruit smallholders. In the early years following their introduction, adoption was largely limited to individual tools, primarily soil testers or chlorophyll meters. Agro-advisory mobile applications, which involve minimal barriers to entry or exit, began to see uptake only in 2017. By 2018-2019, the adoption of singular technologies had largely plateaued, paving the way for sustained growth in their combined use. By 2024, nearly one-quarter of respondents reported to be concurrently using both soil testers and chlorophyll meters, or all three PDDSTs.

These adoption patterns reflect an incremental trajectory. Many smallholders began with a single tool, only to later adopt additional technologies after recognizing the limitations of individual instruments. The transition toward integrated use was motivated by the pursuit of synergistic benefits. Rather than being mutually exclusive, the tools are functionally complementary, addressing the complex nature of nutrient cycling and plant-specific requirements. Respondents consistently emphasized the added value of more accurate diagnosis, data triangulation, and the improved decision-making afforded by technology integration.

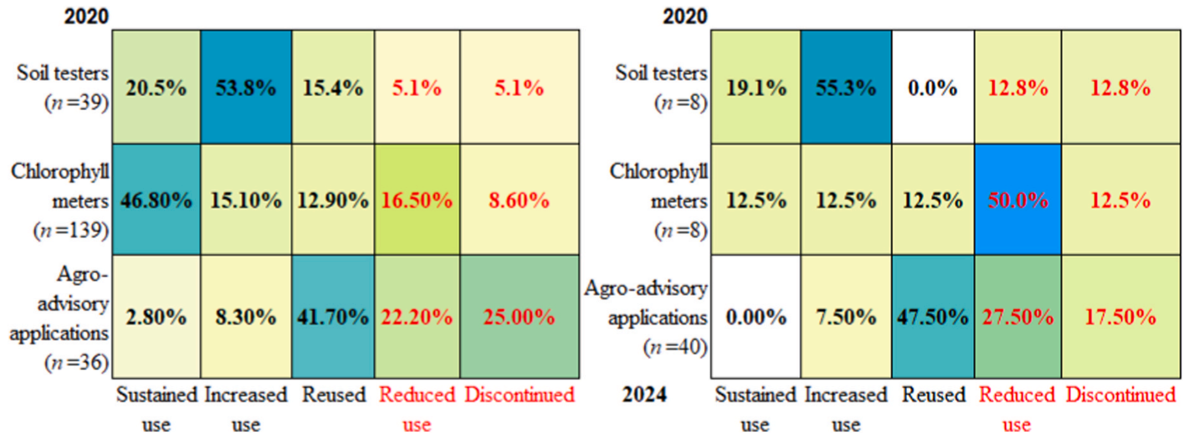

Fig. 5. Transition probabilities from initial adoption in 2020 to post-adoption states in 2024 for (a) trial groups and (b) non-trial groups across three PDDSTs among kiwifruit farmers. Exact two-sided 95% Clopper–Pearson confidence intervals for negative transition probabilities (Reduced + Discontinued) are reported in Appendix Table 5.

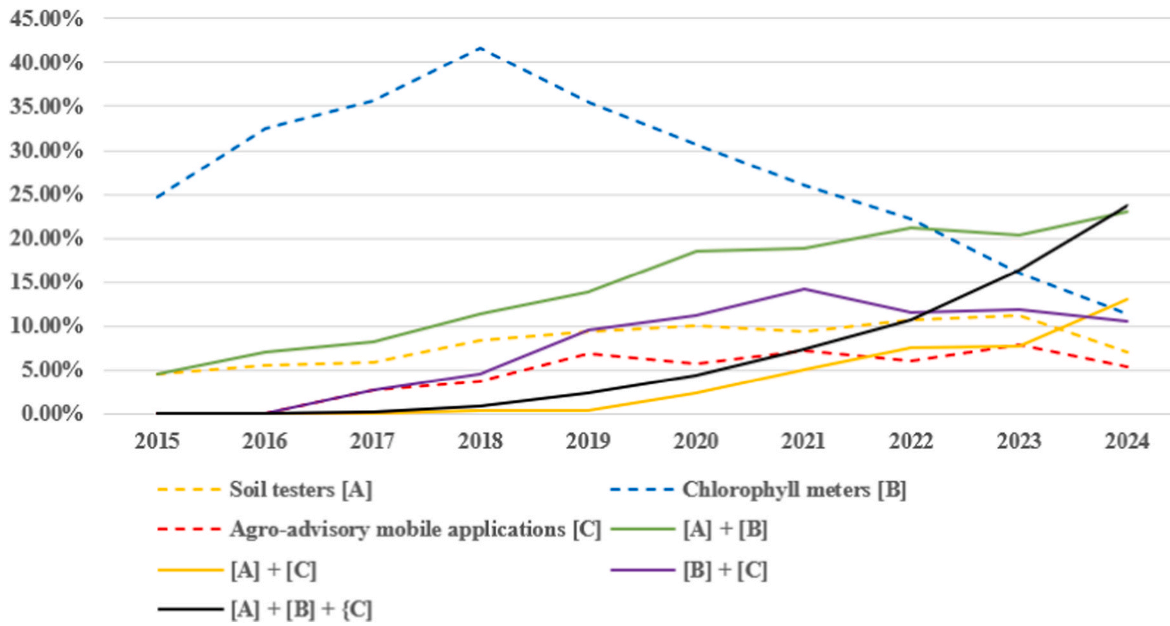

Fig. 6. Aggregated adoption of portable digital decision-support technologies in Shaanxi's kiwifruit production, 2015-2024.

5. Discussion

The diversity of decision stages and transitional flows associated with the adoption of PDDSTs highlights the complex learning dynamics underlying precise nutrient management in perennial production systems. The technological change pathways identified in this study closely align with Rogers' technology-decision framework, which conceptualizes adoption as a multistage process shaped by evolving information, experience, and feedback rather than a single discrete choice [45]. Consistent with this framework, adoption in our study includes both progressive states - such as initial, sustained, and expanded use - and iterative states, including reuse following periods of reduced or discontinued use. As farmers accumulate experience through use, they update their beliefs about expected benefits and risks, which may lead to changes in adoption intensity or temporary disengagement. Importantly, our results indicate that disengagement may still occur even when SSNM contributes to productivity improvements, echoing prior evidence that economic or agronomic gains alone are often insufficient to ensure sustained adoption [47]. These patterns suggest that reducing uncertainty through continuous learning and feedback mechanisms may be important for sustaining engagement with digital nutrient decision-support tools in perennial farming systems.

Providing structured learning opportunities is particularly important in cropping contexts, where delayed yield responses make experimentation and experiential learning essential. As evidenced in this study, the varied decision flows - particularly where trialability is present - reveal several insights. First, farmers' adoption decisions, whether direct or indirect, appear to be shaped by different learning strategies. In crops, the effects of nutrient management interventions often become visible only after a full production cycle, meaning that learning-by-doing unfolds across multiple seasons rather than within a single growing period [48,49]. Second, trialability allows farmers to evaluate technologies more rapidly and may reduce perceived risk during the early adoption stages. This finding is consistent with prior research suggesting that trial-based learning can facilitate confidence formation when farmers adopt information-intensive agricultural technologies [50]. Third, sustained engagement with PDDSTs appears more common among farmers who participated in trials, suggesting that structured learning opportunities may help reinforce continued use. However, it should be noted that the non-trial subgroups for soil testers and chlorophyll meters are small (n = 8 in each case), resulting in wide confidence intervals that overlap with those of the corresponding trial groups. Consequently, the trial-versus-non-trial contrast for these tools should be interpreted cautiously and viewed as a suggestive pattern rather than a statistically distinguishable difference. Even so, the observed pattern remains consistent with the broader literature recognizing trialability as a factor facilitating learning and behavioral adjustment in technology adoption processes [51].

Beyond the descriptive patterns documented in this study, the observed diversity of adoption trajectories and the correlated adoption of multiple diagnostic tools suggest that complementary technologies may play an important role in farmers' learning processes. Prior studies have noted that stand-alone decision-support tools often fail to generate sustained benefits when users lack complementary information or capabilities [52]. In contrast, the incremental adoption of multiple PDDSTs may allow farmers to gradually integrate diagnostic information from soil and plant indicators, enabling iterative adjustments in nutrient management practices [53,54]. While the present survey did not directly measure institutional arrangements, market viability, or distribution constraints, these findings suggest that future research could examine how such factors influence the accessibility and joint diffusion of digital nutrient decision-support technologies among smallholders. Understanding how complementary tools become available and useable in local agricultural systems may help explain how site-specific nutrient management practices scale beyond pilot contexts.

Several limitations should be acknowledged when interpreting these findings. First, the reconstruction of technology-decision trajectories relies on respondents' retrospective recall of the timing at which they transitioned across decision stages. As with any recall-based data, this approach may be subject to telescoping and heaping, whereby events are misdated or clustered around rounded years. Such recall errors could bias estimates of the duration between stages, potentially understating or overstating the pace of adoption and post-adoption transitions. To mitigate these concerns, several internal validation steps were undertaken. The distribution of reported trial and adoption years was examined to assess potential heaping patterns, and recalled timing was cross-checked against locally documented diffusion windows, including training and demonstration activities. In addition, qualitative follow-up interviews and key-informant consultations were used to triangulate typical adoption narratives and assess the plausibility of reported transition sequences. While these measures do not eliminate recall bias, they suggest that the reconstructed trajectories are broadly consistent with observed diffusion processes and farmers' experiential accounts. Accordingly, the temporal estimates presented in this study should be interpreted as approximations of decision dynamics rather than precise event timings.

6. Conclusion

Blanket fertilizer applications are increasingly recognized as detrimental to agroecosystem health and constitute a constraint to sustainable agricultural intensification. In response, PDDSTs have been developed to enhance the precision of SSNM, particularly among smallholder farmers. These tools represent a relatively novel class of entrée technologies to precision agriculture for perennial crops, and understanding the decision-making process associated with their adoption adds a valuable dimension to the existing literature, which, heretofore has largely focused on overcoming user capacity barriers. This study leverages the case of China's kiwifruit production industry, which is widely cited for its significant nutrient excesses It traces the stepwise progression toward PDDST adoption. Within this specific perennial and smallholder-dominated context, this study seeks, as part of a sustainable intensification strategy, to generate more user-oriented policy insights for promoting the broader implementation of SSNM.

Given its diffusion desirability, a critical task is to uncover the decision stages and transitional flows undertaken by farmers. Trialability emerges as a key stage, informing and sustaining the use of PDDSTs over time. In parallel, awareness can lead directly to initial adoption, a stage where learning begins by doing. Disengagement is thus more likely among adopters who bypass the trial phase. While it is tempting to define adoption solely because of initial uptake, temporal analyses of soil testers, chlorophyll meters, and agro-advisory mobile applications reveal nuanced adoption trajectories, including sustained use, expanded use, reduced use, and eventual reuse. Aggregated analysis of these states suggests that the integrative use of PDDSTs tends to occur incrementally. Future work will build on this descriptive process mapping by explicitly modeling the correlations of trajectory types (e.g., sustained/expanded versus reduced/discontinued use) using farm, human-capital, and market-access variables collected in this survey. Such analyses are beyond the scope of the present paper, which is intentionally focused on reconstructing and visualizing adoption pathways rather than estimating their causal determinants.

The findings highlight the importance of continued, structured learning opportunities and invite further policy deliberation, particularly around mitigating negative post-adoption trajectories. Importantly, they also point to a more fundamental issue: many smallholders may lack a basic understanding of crop growth, nutrient cycles, and nutrient balances. Nutrient accumulation and lagged crop responses present additional layers of complexity in perennial agriculture. This knowledge gap makes it unrealistic to expect that a single tool can address the multifaceted challenges inherent in SSNM or accommodate the diverse capacities of smallholders. These limitations are especially pronounced in underdeveloped areas. To address these barriers, institutional innovations are essential to promote complementary technologies. In practical terms, this implies prioritizing coordinated deployment strategies, such as embedding PDDST use within extension-led training programs, supporting trial-based access through co-operatives or demonstration orchards, and sequencing tool introduction to match farmers' learning capacities. These policy directions should be interpreted as context-specific implications consistent with the observed adoption patterns and existing literature, rather than as causal effects directly estimated from the present dataset.

A fundamental limiting factor in the effectiveness of SSNM lies in the potential continued use of substandard fertilizers. The adoption of PDDSTs offers a promising pathway by enabling more precise, targeted application of single-nutrient sources, which are generally less susceptible to quality manipulation, when compared with blended fertilizers. However, adoption research has seldom incorporated fertilizer quality as a variable influencing technology effectiveness, despite its potential to undermine the utility of decision-support tools. From a policy perspective, this suggests that digital decision-support initiatives should be aligned with fertilizer quality regulation and input market supervision. This implication is drawn from the consistency between the present findings and existing evidence on fertilizer quality heterogeneity, rather than from direct measurement within the survey. Strengthening quality inspection mechanisms for single-nutrient fertilizers, while simultaneously promoting diagnostic-based fertilizer recommendations, can help ensure that the informational gains provided by PDDSTs translate into agronomic and environmental outcomes. The value of decision-support technologies thus extends beyond nutrient management to reinforcing the broader integrity of sustainable agricultural intensification.

CRediT authorship contribution statement

Xia Li: Writing – original draft, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Ahmad Hanis Izani Abdul Hadi:** Writing – review & editing, Validation, Supervision, Methodology. **Yeong Sheng Tey:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Shaufique Fahmi Sidique:** Writing – review & editing, Supervision, Conceptualization. **Nolila Mohd Nawi:** Validation, Methodology, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2026.102836.

Appendix

Appendix Table 1
Distribution of recalled trial years across PDDSTs (2014-2024)

Year	Soil tester (%)	Chlorophyll meter (%)	Agro-advisory app (%)
2014	2.39	26.32	0.00
2015	8.61	24.62	0.00
2016	6.70	13.91	0.00
2017	5.26	8.65	12.90
2018	11.96	8.27	16.13
2019	5.74	3.57	16.67
2020	19.62	2.82	9.14
2021	9.09	1.13	4.84
2022	8.13	6.20	17.20
2023	13.40	2.82	13.98
2024	9.09	1.69	9.14

Note: Percentages refer to the share of respondents reporting the corresponding year as their first trial use of each technology. The distributions do not suggest systematic rounding to focal years such as 2015. We nevertheless observe a notable concentration of soil-tester first trials in 2020 (19.62%), which may reflect genuine pandemic-period promotion and uptake, but could also partly capture recall salience around a memorable year. Accordingly, we interpret the recalled timing patterns as broadly plausible while acknowledging residual recall uncertainty.

Appendix Table 2
Descriptive comparison between sample characteristics and county benchmarks

Indicator	Sample (n = 675)	County benchmark
Mean orchard area (ha)	4.19	2.67-5.33
Education ≧ high school (%)	73.7	60-80
Training participation (%)	82.3	65-85
Cooperative membership (%)	72.7	55-75
Mean farming experience (yrs)	12.0	10-15

Note: County benchmark ranges are based on aggregated information from local extension officers, county-level agricultural bureaus, and publicly available agricultural development reports, reflecting typical distributions of orchard scale, education attainment, training participation, cooperative membership, and farming experience among kiwifruit smallholders in the study areas. These benchmarks are intended to provide a contextual reference rather than exact population parameters.

Appendix Table 3
Operational definitions of technology-decision states

Analytical state	Event-history item (survey module B01)	Response option	Operationalization in analysis
Unaware	*Year become aware but not used*	Blank	Farmer had no prior awareness of the technology.
Aware	*Year become aware but not used*	Year reported	Farmer was aware of the technology but had not yet used it.
Trial	*Year of trialing*	Year reported	Farmer engaged in limited-scale experimental use (typically $\leq$20–30% of orchard area) for evaluation purposes, without integrating the technology into routine fertilizer decision-making.
Adopted (after trial)	*Year of used, after trial*	Year reported	Farmer began regular use of the technology for fertilizer decision-making following a prior trial stage.
Adopted (without trial)	*Year of used, without trial*	Year reported	Farmer began regular use of the technology for fertilizer decision-making without prior trial.
Expanded use	*Year of increased use*	Year reported	Farmer increased the scale, frequency, or coverage of technology use after adoption.

(*continued on next page*)

Appendix Table 3 (*continued*)

Analytical state	Event-history item (survey module B01)	Response option	Operationalization in analysis
Sustained use	*Year of used, after trial* or *Year of used, without trial* with no subsequent change	Year reported, no later change	Farmer reported consistent routine use at full operational scale for at least one complete cropping season.
Reduced use	*Year of decreased use*	Year reported	Farmer reduced the scale or frequency of technology use after having adopted it.
Discontinued use	*Year of discarded*	Year reported	Farmer completely stopped using the technology after adoption.
Reused	*Year of re-adoption*	Year reported	Farmer re-entered use after a period of discontinuation, indicating renewed engagement rather than repeated trial behavior.
Maintained as trial	*Year of re-adoption*	Trial reported, adoption blank	Farmer continued limited-scale experimental use without ever integrating the technology into routine fertilizer decision-making.

Note: Adoption states were derived from a structured event-history survey module (B01), in which respondents reported recalled years of awareness, trial, adoption (with or without trial), and subsequent post-adoption adjustments.

Appendix Table 4
Underlying flow counts for Sankey diagrams (n = 675)

From state	To state	Share (%)	Count (n)
(a) Soil tester (2015-2024)			
From state	To state	Share (%)	Count (n)
Total	Aware	95.41	644
Total	Unaware	4.59	31
Aware	Trial	29.63	200
Aware	Adopted without trial	40.30	272
Aware	Never adopted	25.48	172
Trial	Adopted with trial	25.33	171
Trial	Maintained as trial	4.30	29
Adopted without trial	Expanded use	4.89	33
Adopted without trial	Sustained use	8.00	54
Adopted without trial	Reduced use	8.15	55
Adopted without trial	Discontinued use	19.26	130
Adopted with trial	Expanded use	4.30	29
Adopted with trial	Sustained use	5.93	40
Adopted with trial	Reduced use	5.93	40
Adopted with trial	Discontinued use	9.19	62
Discontinued use	Reused	15.70	106
(b) Chlorophyll meter (2015–2024)			
From state	**To state**	**Share (%)**	**Count (n)**
Total	Aware	89.63	605
Total	Unaware	10.37	70
Aware	Trial	84.89	573
Aware	Adopted without trial	3.85	26
Aware	Never adopted	0.89	6
Trial	Adopted with trial	74.81	505
Trial	Maintained as trial	9.48	64
Trial	Discontinued use	0.59	4
Adopted without trial	Expanded use	0.44	3
Adopted without trial	Sustained use	0.30	2
Adopted without trial	Reduced use	1.33	9
Adopted without trial	Discontinued use	1.78	12
Adopted with trial	Expanded use	14.07	95
Adopted with trial	Sustained use	11.11	75
Adopted with trial	Reduced use	21.93	148
Adopted with trial	Discontinued use	27.70	187
Discontinued use	Reused	19.41	131
(c) Agro-advisory mobile app (2015–2024)			
From state	**To state**	**Share (%)**	**Count (n)**
Total	Aware	90.52	611
Total	Unaware	9.48	64
Aware	Trial	33.33	225
Aware	Adopted without trial	52.30	353
Aware	Never adopted	4.89	33
Trial	Adopted with trial	31.70	214
Trial	Maintained as trial	0.44	3
Trial	Discontinued use	1.19	8
Adopted without trial	Expanded use	28.74	194
Adopted without trial	Sustained use	5.63	38
Adopted without trial	Reduced use	6.67	45
Adopted without trial	Discontinued use	11.26	76
Adopted with trial	Expanded use	18.37	124
Adopted with trial	Sustained use	3.41	23
Adopted with trial	Reduced use	3.41	23
Adopted with trial	Discontinued use	6.52	44
Discontinued use	Reused	0.59	4

Note: Flow counts represent the number of respondents contributing to each transition. Percentages are calculated relative to the full sample (n = 675) to facilitate comparability across transitions. For each Sankey layer, the sum of outgoing flows equals the size of the corresponding origin-state population. Flows represent cumulative life-course transitions reconstructed from recalled event-history data during 2015–2024. Right-censored observations (i.e., respondents who had not yet experienced a subsequent transition by the survey date) are retained in node counts but excluded from duration calculations.

Appendix Table 5
95% confidence intervals for negative post-adoption trajectories in Fig. 5

PDDST tool	Group	N	K (Reduced + Discontinued)	P (Negative)	95% CI
Soil tester	Trial	39	4	10.3%	【2.9%, 24.2%】
Soil tester	Non-trial	8	2	25.6%	【3.2%, 65.1%】
Chlorophyll meter	Trial	139	35	25.1%	【18.2%, 33.2%】
Chlorophyll meter	Non-trial	8	5	62.5%	【24.5%, 91.5%】
Agro-advisory app	Trial	36	17	47.2%	【30.4%, 64.5%】
Agro-advisory app	Non-trial	40	18	45.0%	【29.3%, 61.5%】

Note: Negative trajectory is defined as “Reduced use” + “Discontinued use” in Fig. 5. Counts (k) are derived from the corresponding cell percentages in Fig. 5 and sample sizes (n) shown on the heatmaps. Confidence intervals are exact two-sided 95% Clopper–Pearson binomial intervals for k/n. Trial groups correspond to panel (a) in Fig. 5 and non-trial groups correspond to panel (b).

Appendix Table 6
Descriptive comparison between pandemic adopters (first adoption in 2020) and other adopters

Variable	Pandemic adopters (N1 = 133)	Other adopters (N2 = 542)	Definition
Age (years)	51.3 ± 9.4	52.1 ± 10.1	Respondent age
Education (0-2)	1.18 ± 0.63	1.15 ± 0.61	0 = Primary, 1 = High school, 2 = College+
Orchard area (ha)	3.11 ± 2.12	2.99 ± 1.97	Total orchard area in hectares
Years of experience	13.6 ± 7.1	14.2 ± 7.4	Years in kiwifruit farming
Training received (%)	63.4	59.8	1 = Yes
Cooperative member (%)	48.9%	45.6%	1 = Yes
Smartphone access (%)	94.7	93.1	1 = Yes
Distance to supplier (km)	5.3 ± 2.8	5.7 ± 3.1	Travel distance to input suppliers

Note: Pandemic adopters are defined as respondents whose first recorded initial adoption of a given PDDST occurred in 2020.

Appendix Table 7
Indicative rollout timeline of PDDST-related training, demonstrations, and subsidy programs in the study counties

County	Approximate period	Activity type	Technology focus	Information source
Zhouzhi	2016–2018	Demonstration orchards and training sessions	Soil testers, chlorophyll meters	County extension officers; farmer interviews
Zhouzhi	2019–2021	Equipment promotion and subsidy support	Soil testers	Local agricultural bureau reports; key informants
Meixian	2017–2020	Training programs on nutrient diagnosis	Soil testers, chlorophyll meters	Extension agents; farmer interviews
Hanyin	2018–2022	Technical training and orchard demonstrations	Soil testers	Village cadres; extension services
Pingli	2018–2023	Farmer training sessions and advisory support	Agro-advisory mobile applications	Extension officers; farmer interviews
Langao	2019–2023	Digital agriculture promotion activities	Mobile apps, soil testing	Key informants; farmer interviews

Note: The timeline summarizes approximate diffusion windows reconstructed from key-informant interviews (extension officers, village cadres) and farmer recall during fieldwork. The purpose is not to provide a precise program chronology but to verify that recalled adoption years broadly coincide with known periods of technology promotion.

Appendix Table 8
Qualitative follow-up interviews used for triangulating adoption timing narratives

Respondent type	Number of interviews	Main themes discussed	Illustrative observations
Kiwifruit farmers	18	Technology awareness sources; reasons for trial adoption; discontinuation experiences	Farmers often associated first exposure to soil testers with local training or demonstration activities
Extension officers	4	Timing of training programs and equipment promotion	Extension staff confirmed that promotion of soil testing devices intensified after 2018
Village cadres/ cooperative leaders	3	Diffusion channels and peer learning	Local leaders reported that farmers frequently learned about technologies through demonstration orchards and training sessions
Total	**25**	—	—

Note: These follow-up interviews were conducted with a subsample of respondents and local key informants during fieldwork to contextualize adoption narratives and validate the plausibility of recalled timing patterns. The summaries present thematic patterns rather than verbatim quotations.

Data availability

Data will be made available on request.

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