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Equity-Calibrated Technology Forecasting for Sustainable Development: A Portable ADOPT Framework Integrating Bayesian-Ising Diagnostics

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ABSTRACT

Climate-smart agriculture (CSA) is widely promoted to enhance resilience and productivity among smallholder farmers, yet its diffusion remains uneven due to structural barriers and heterogeneous adoption contexts. Existing forecasting tools, such as the Adoption and Diffusion Outcome Prediction Tool (ADOPT), estimate adoption trajectories but rely largely on expert-driven assumptions that may overlook empirical disparities in access, capability, and opportunity. This study develops an equity-calibrated forecasting framework by integrating empirical diagnostics from a Bayesian-Ising ensemble model into ADOPT. Using survey data from 569 smallholder households in Western Kenya, stratified by gender and agroecological zone, we forecast adoption trajectories for six CSA practices while accounting for structural inequalities in adoption pathways. The model predicts a peak adoption level of 84% after 19 years, with 50% of peak adoption reached by year 8.2. Sensitivity analysis identifies perceived economic benefit as the strongest determinant of adoption, followed by awareness, trialability, and relative advantage. Results reveal a pronounced asymmetry: a one-step negative shift in perceived income benefit reduces peak adoption by 19.9 percentage points, more than double the 8.9-point increase generated by an equivalent positive shift, consistent with Prospect Theory's prediction of loss aversion. Compared with an expert-only scenario, the equity-calibrated model lowers the projected adoption ceiling by 15 percentage points, highlighting the consequences of ignoring structural barriers. By linking empirical diagnostics with technology forecasting, the study provides a replicable framework for equity-sensitive innovation governance and inclusive scaling strategies.

1 | Introduction

Climate adaptation technologies—such as bundled climate-smart agricultural practices (CSA) represent critical socio-technical innovations for Sustainable Development (Devarajan et al. 2026). However, their diffusion remains low and inequitable, constrained not by technical potential but by structural barriers within innovations' ecosystems. This is despite

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CSA "triple win" potential to simultaneously enhance productivity, resilience, and mitigation (FAO 2010; Westermann et al. 2018). This study directly engages Sustainable Development Goals (SDGs) 2 (Zero Hunger), 5 (Gender Equality), 10 (Reduced Inequalities), and 13 (Climate Action) by recalibrating technology forecasting models to predict and promote equitable adoption.

We focus on Kenya's smallholder sector as a living laboratory of innovation inequality, where gendered and agroecological disparities shape access to green technologies. Moving beyond aggregate adoption curves, we develop a portable framework that diagnoses, forecasts, and prescribes interventions for inclusive technology diffusion—a model applicable to sectors from renewable energy to digital health across the Global South.

Forecasting technology adoption in the Global South is a critical challenge for innovation governance, technological foresight, and a cornerstone of rural development planning. Yet, conventional models—from classic diffusion curves (Rogers et al. 2014) to probabilistic frameworks (Bass 1969)– typically fail to account for the structural barriers (embeddedness) that perpetuate uneven uptake and inequality within socio-technical systems (Bryan et al. 2023, 2024). In agrifood systems, this gap manifests acutely, where intersectional constraints like gendered resource access and agroecological disparities necessitate granular diagnostics (Njuki et al. 2022).

Tools like the Commonwealth Scientific and Industrial Research Organization (CSIRO)'s Adoption and Diffusion Outcome Prediction Tool (ADOPT) provide a necessary foundation for forecasting, excelling at modelling aggregate adoption timelines by simulating individual farmer decision-making (Brown et al. 2019; Kuehne et al. 2017; Llewellyn and Brown 2020). Its structured, systematic approach to quantifying economic, social, and perceptual factors offers a crucial baseline for generating probabilistic timelines. As demonstrated in recent work on digital traceability (Parra-López et al. 2025), the parsimony of ADOPT can even integrate expert knowledge and produce probabilistic timelines for peak adoption, providing crucial baselines from which more nuanced, equity-sensitive models can be built.

However, its standard parameters lack mechanisms to integrate two critical realities: (1) practice complementarities (such as the synergistic bundling of soil management and agroforestry); and (2) stratified adoption pathways (such as gendered attrition in sequential adoption). This disproportionately limits its forecasting diagnostics within marginalized groups (Doherty et al. 2023).

Recent applications of ADOPT illustrate both its value and a persistent limitation. Rezgui et al. (2026) used ADOPT to evaluate diversification pathways in European cereal systems, finding that economic viability was the primary adoption determinant even when environmental and social benefits were substantial. Similarly, (Parra-López et al. 2025) employed expert elicitation to forecast digital traceability adoption in the olive sector. These studies highlight ADOPT's portability across contexts, yet they share a common constraint: inputs are derived from expert judgment, stakeholder perceptions, or ex-ante assessments rather than empirical diagnostics of observed adoption behavior. This limitation is particularly consequential in contexts of persistent gender disparities and heterogeneous agroecological conditions, where aggregate forecasts may conceal substantial differences in adoption pathways and outcomes.

Our study builds directly upon this foundation to address ADOPT's core methodological limitation. We integrate empirical, stratified data from the target population to calibrate ADOPT, transforming it from a tool that relies on perception to one grounded in diagnostic evidence. This allows us to not only predict aggregate adoption but to forecast equity gaps directly and identify nuanced, asymmetric drivers of behavior, thereby converting structural diagnostics into actionable and equitable policy foresight. A recent study grounded on a Bayesian-Ising model in Western Kenya empirically quantified these barriers using data from 569 smallholders (Momanyi et al. 2026). It identified a core co-adoption of CSA practices with strong synergies but revealed severe attrition in adoption sequences, particularly for female-headed households in marginal agroecological zones, leading to significant equity gaps. However, such diagnostic information remains siloed from the forecasting tools policymakers use for planning and resource allocation, creating a diagnostic–predictive gap.

This study bridges the diagnostic-praxis divide by calibrating the ADOPT tool with empirical Bayesian-Ising-derived thresholds for practice synergy (synergy coefficients) and stratified adoption pathways (attrition rates). This integration represents a novel methodological advance in forecasting science, moving beyond merely diagnosing barriers to generating equity-sensitive projections and identifying precise intervention points. Our analysis is designed to yield critical insights that challenge conventional scaling wisdom by addressing three research questions:

1. What is the predicted diffusion trajectory for CSA bundles in Western Kenya, and to what extent do aggregate forecasts mask adoption disparities across gender and agroecological lines?
2. Which factors are the most powerful levers for increasing the scale and accelerating the pace of equitable CSA adoption?
3. Is there an asymmetry in how positive and negative economic perceptions influence adoption outcomes, consistent with prospect theory's prediction of loss aversion?

By answering these questions, this paper provides a replicable framework for converting structural diagnostics into actionable, equitable, and efficient scaling strategies, ensuring that high-potential innovations translate into timely, just, and equitable social change—directly contributing to the 2030 Agenda for Sustainable Development. While the specific empirical findings from Western Kenya are not portable—they reflect local structural barriers—the analytical framework itself is designed to be portable. It can be deployed as a self-contained toolkit to diagnose and forecast adoption constraints in any setting where stratified adoption data are available.

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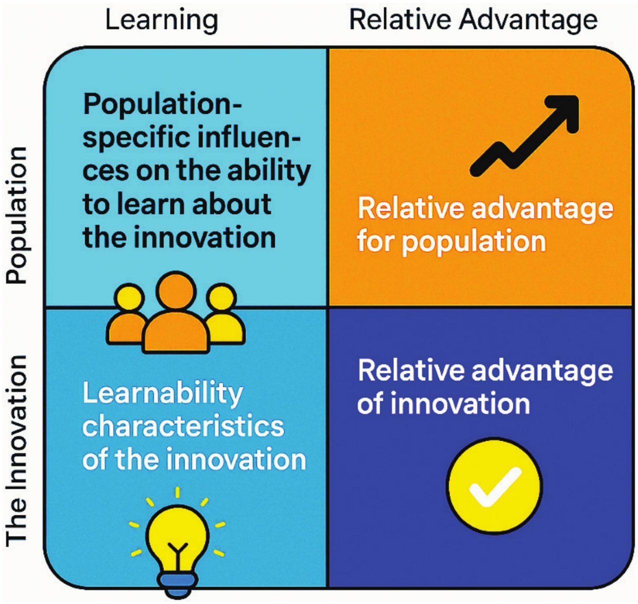

FIGURE 1 | The core conceptual model illustrates how learning, perceived benefits, the target population, and the specific practice are interconnected.

1.1 | The ADOPT Concept

The Adoption and Diffusion Outcome Prediction Tool (ADOPT), developed by Kuehne et al. (2017), predicts the adoption rates of socio-technical (agricultural) innovations within specified target populations by modelling diffusion dynamics (Figure 1), including peak adoption levels and timeframes.

It accounts for population heterogeneity by integrating factors such as relative advantage, learning requirements, and social influence, though it assumes static conditions unless manually adjusted (such as policy changes or cost reductions must be user-defined). ADOPT is designed for group consensus-building in workshops and can evaluate multi-component innovations, but it requires a clear characterization of sub-populations to address varying adoption pathways. Bridging innovation studies and technology forecasting, we integrate empirical Bayesian-Ising diagnostics (Momanyi et al. 2026)—which quantify social and structural barriers—into the established ADOPT tool.

This methodological fusion enables us to move beyond expert-driven forecasts toward evidence-based, equity-calibrated projections. While originally developed for agricultural contexts, its structure is generalizable to any innovation requiring behavioral change and capacity building. Our approach treats technology adoption not as binary uptake but as a pathway shaped by skill gaps, network disparities, and perceived risks—factors generalizable to off-grid energy, telemedicine, or fintech adoption in similar contexts.

While validated against broadacre agricultural case studies, its projections are probabilistic and less suited to innovations with unpredictable dynamic factors (such as rapidly evolving costs). The tool outputs a "near-peak" adoption metric (99% of peak) to avoid overemphasizing tail-end adoption delays. Notably, ADOPT can operate without primary survey data, relying instead on structured expert input, though PDF backups of project settings are recommended for archival purposes. However, ADOPT does not automatically model external shocks, fine-grained regional heterogeneity, or time-dependent variables (such as innovation cost trajectories), and its validation remains largely confined to specific agricultural contexts.

Building on these insights, we adapt ADOPT's standard diffusion framework by incorporating two equity-sensitive calibrations:

1. Stratified adoption probabilities based on Bayesian-Ising-observed attrition rates.
2. Synergy-driven bundling rules derived from empirical practice complementarities

1.2 | Prospect Theory and Asymmetric Adoption Behavior

Prospect theory posits that individuals evaluate outcomes relative to a reference point rather than in absolute terms, and that losses loom larger than equivalent gains—a cognitive bias termed loss aversion (Kahneman and Tversky 2013). In agricultural technology adoption, this asymmetry implies that farmers' decisions are disproportionately shaped by fear of negative outcomes (crop failure, indebtedness, foregone income) rather than by the prospect of equivalent gains. A single failed adoption experience or negative testimonial can therefore collapse scaling efforts more readily than a positive demonstration can accelerate them.

We integrate prospect theory into our analytical framework at three levels. First, as a theoretical foundation, it motivates our expectation that ADOPT parameters capturing perceived economic benefit (Question 16) and risk exposure (Question 21) will exhibit asymmetric sensitivity: negative shifts will reduce peak adoption more sharply than equivalent positive shifts will increase it. Second, as an analytical lens, it shapes how we interpret the sensitivity analysis results. Third, as a policy heuristic, it reframes intervention design: de-risking adoption becomes strategically more important than promoting benefits. This theoretical grounding directly informs our third research question and provides interpretive architecture for Section 4.2.

2 | Methodology

The ADOPT tool is designed to be flexible, allowing researchers to populate its parameters from various sources, including expert elicitation—as demonstrated in the olive traceability study (Parra-López et al. 2025)—literature reviews, and, crucially, existing empirical diagnostics from prior studies. This section outlines how the tool can leverage pre-existing, stratified data for calibration, establishing a framework for the current application.

2.1 | Contextual Inputs From Prior Research

A key strength of ADOPT is its ability to integrate rich, pre-existing datasets, reducing the need for *de novo* primary

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surveys (Kuehne et al. 2017). This approach is exemplified in several studies:

- *Household surveys and agricultural statistics:* Swamila et al. (2020) calibrated ADOPT using prior household survey data and regional statistics to predict agroforestry technology adoption in Tanzania, setting realistic baselines for farmer stratification
- *On-farm and on-station trial data:* Dogra et al. (2022) used empirical data from agricultural trials in India to parameterize ADOPT for silvopastoral systems, providing robust evidence on relative advantage (fodder yields) and complexity.
- *Extension reports and feasibility studies:* Lumenyela et al. (2023) drew upon diagnostic assessments from local reports and NGO studies in Zanzibar to populate ADOPT factors related to constraints and learning capacity for seaweed farming
- *Expert elicitation and literature synthesis:* Foundational ADOPT guidance promotes using expert opinion and literature synthesis to inform parameters where specific local data are scarce (Kuehne et al. 2017; Llewellyn and Brown 2020). This approach is validated by the tool's use in diverse contexts, from traceability systems (Parra-López et al. 2025) to soil management.

This study follows the established precedent. It leverages a prior empirical study applying Bayesian-Ising analysis (Momanyi et al. 2026) as a sophisticated diagnostic to provide stratified, empirical data for calibration, moving beyond expert opinion to data-driven parameterization.

2.2 | Empirical Calibration: A Case Study in Western Kenya Agrifood Systems

To demonstrate the framework's application, we calibrated it using a stratified diagnostic dataset from Kenya's agrifood sector—a context where gender and agroecological disparities create clear structural barriers. The data come from a survey of 569 smallholder households conducted between September and October 2023 in Kakamega and Bungoma counties, Western Kenya (Momanyi et al. 2026). Sampling followed a multi-stage stratified design, explicitly stratifying by gender of the household head (female-headed, FHH; male-headed, MHH) and agroecological zone (Lower Midlands, LMZ; Upper Midlands, UMZ) (Table 1 in Momanyi et al. 2026). The LMZ (81% of the sample) has less reliable rainfall and higher temperatures, while the UMZ enjoys more consistent precipitation and cooler conditions.

The Bayesian-Ising ensemble framework (Momanyi et al. 2026) was applied to these data to quantify practice synergies and stratified adoption pathways using two complementary models:

1. *Low-rank Ising network (LRIN)*—captures simultaneous co-adoption patterns. Nodewise logistic regression with Laplace priors (scale $b = 0.5$) was used, and the optimal rank ($r = 3$) was selected via Pareto-smoothed leave-one-out cross-validation (PSIS-LOO). The resulting pairwise interaction energies (J) are reported with 95% credible intervals in (Momanyi et al. 2026).
   Key synergy output: A "resilience triad" of practices—soil management (CSA1), resilient crops/varieties (CSA3) and productive agroforestry (CSA4) - showed strong complementarities only in the most advantaged stratum (MHH-UMZ), e.g., CSA3-CSA4 $J = 0.460$ (95% CI: 0.114–0.798) and CSA4-CSA5 $J = 0.686$ (0.250–1.151). By contrast, in FHH-LMZ a strong negative interaction was found between water harvesting (CSA2) and energy efficiency (CSA5): $J = -0.727$ (−1.386 to −0.203).
2. *Bayesian Chain Analysis (BCA)*—models sequential adoption pathways using score-based Bayesian networks with Dirichlet-multinomial conditional probability tables (CPTs) (Heckerman et al. 1995). An order constraint (CSA1 → CSA2 → …) was imposed, and the BDeu score ($\alpha = 1$) with an edge penalty of 1.2 was used.
   Key attrition output: The transition from CSA1 (soil management) to CSA2 (water harvesting) was the most critical bottleneck. For FHH-LMZ, the conditional probability of this transition was $p = 0.136$ (95% CI: 0.190–0.353), whereas for MHH-UMZ it was $p = 0.247$ (0.161–0.347). The cumulative probability of reaching CSA4 through the modelled sequence was only 0.039 (0.024–0.059) for FHH-LMZ and 0.035 (0.026–0.045) for MHH-LMZ, compared to 0.056 (0.032–0.091) for MHH-UMZ.

These empirical outputs directly informed the ADOPT calibration in two ways:

1. *Bundling definition:* The innovation was defined as the synergistic CSA1–CSA3–CSA4 bundle, justified by the high synergy coefficients ($J \geq 0.15$) observed in MHH-UMZ (the only stratum where positive complementarities reached statistical significance).
2. *Parameterization of learning and reversibility:* The observed attrition rates, especially the low transition probability for FHH-LMZ from CSA1 to CSA2, were used to calibrate ADOPT's "relevant existing skills and knowledge" (Q12). Following the rule in Table 1 (see main ADOPT paper), an attrition rate < 0.2 triggered the response "Almost all will need new skills" for the FHH-LMZ subgroup. Similarly, the irreversible nature of agroforestry (perennial trees) and biogas infrastructure, documented in the Bayesian-Ising discussion, informed the "reversibility" parameter (Q15) set to "Difficult to reverse".

The calibration logic is summarized in Table 1 below. The full set of calibrated input values for all ADOPT parameters, by stratum, is provided in the Supporting Information: Three and (Momanyi et al. 2026).

2.3 | Rationale and Calibration for This Study

Following the established precedent and methodology of ADOPT, the present study leverages the empirical diagnostics described in Section 2.2 (Momanyi et al. 2026) to calibrate the tool's equity-sensitive parameters. The prior study identified critical

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TABLE 1 | Calibration logic for integrating Bayesian-Ising diagnostics into the ADOPT framework.

Bayesian-Ising diagnostic output from (Momanyi et al. 2026)	ADOPT parameter informed	Calibration logic/mapping rule	Final calibrated input (FHH-LMZ)	Source in Bayesian-Ising paper
High attrition rate in sequential adoption				
Transition CSA1 → CSA2: FHH-LMZ: $P = 0.136$ (95% CI: 0.190–0.353) MHH-UMZ: $p = 0.247$ (0.161–0.347)	Q12: Relevant existing skills and knowledge	Attrition rate < 0.2 → "Almost all will need new skills" Attrition rate 0.2–0.3 → "A majority will need new skills" Attrition rate > 0.3 → "About half will need new skills"	"Almost all will need new skills" for FHH-LMZ	(transition probabilities)
Strong practice synergies				
CSA3–CSA4 in MHH-UMZ: $\hat{J} = 0.460$ (0.114–0.798) CSA4–CSA5 in MHH-UMZ: $\hat{J} = 0.686$ (0.250–1.151) CSA1–CSA3 in pooled: $\hat{J} = -0.385$ (−0.577 to −0.199)	Innovation definition (bundling)	Practices with pairwise synergy coefficient $\hat{J} \geq 0.15$ and 95% CI excluding zero are defined as a synergistic bundle.	Innovation modelled as CSA1–CSA3–CSA4 bundle (the "resilience triad")	(transition probabilities)
Marginal adoption probabilities				
CSA4 adoption: FHH-LMZ: 1.1% (0.8%–1.4%) MHH-UMZ: 26.6% (22.1%–31.1%)	Baseline conditions (starting adoption level) and population stratification	Use observed marginal probabilities to set initial adoption level for each stratum in the model. Baseline for disadvantaged groups set to reflect observed inequity.	FHH-LMZ baseline CSA4 adoption = 1.1% MHH-UMZ baseline CSA4 adoption = 26.6%	(marginal probabilities by stratum)
Intersectional equity gap				
IAEI for FHH-LMZ: 0.747 (0.349–1.384) IAEI for MHH-LMZ: 0.666 (0.361–1.154)	Multiple ADOPT parameters (e.g., Q14 upfront cost, Q16 income benefit, Q21 risk exposure)	Large disparities in IAEI signal that multiple structural barriers are at play. Use to cross-check and adjust a cluster of parameters for disadvantaged groups (e.g., set Q14 to "Large investment", Q16 to "Moderate advantage", Q21 to "Large reduction in risk").	For FHH-LMZ: Q14 = Large initial investment Q16 = Moderate advantage Q21 = Large reduction in risk	Intersectional Adoption Equity Index (IAEI)
Intersectional equity gap				
P(CSA4) through modelled sequence: FHH-LMZ: 0.039 (0.024–0.059) MHH-LMZ: 0.035 (0.026–0.045) MHH-UMZ: 0.056 (0.032–0.091)	Q5: Management horizon Q6: Short-term constraints	Very low cumulative probability (< 5%) indicates that farmers cannot plan beyond the immediate season and face severe liquidity constraints.	Q5 = 1%–20% have > 10-year horizon Q6 = 80%–99% have severe short-term financial constraint	(cumulative P(CSA4))
Negative practice interactions				
FHH-LMZ: CSA2–CSA5 $\hat{J} = -0.727$ (−1.386 to −0.203) MHH-LMZ: CSA1–CSA6 $\hat{J} = -0.649$ (−1.267 to −0.080)	Q7: Trialable Q15: Reversibility	Strong negative interactions suggest that practices are mutually exclusive or trade-offs exist. This is used to justify "Moderately trialable" (Q7) and "Difficult to reverse" (Q15) for the bundle.	Q7 = Moderately trialable Q15 = Difficult to reverse	(stratified Ising edges)

Note: (1) All confidence intervals are 95% credible intervals from the Bayesian-Ising posterior distributions. (2) The calibration rules are derived from the observed distribution of attrition rates and synergy coefficients across strata. (3) The final calibrated inputs shown are for the FHH-LMZ (female-headed households in the Lower Midland zone) as the most disadvantaged stratum. Similar mappings were applied to MHH-LMZ and MHH-UMZ. (4) Full details of the Bayesian-Ising model specification, robustness checks, and uncertainty propagation are provided in the Supporting Information of (Momanyi et al. 2026).

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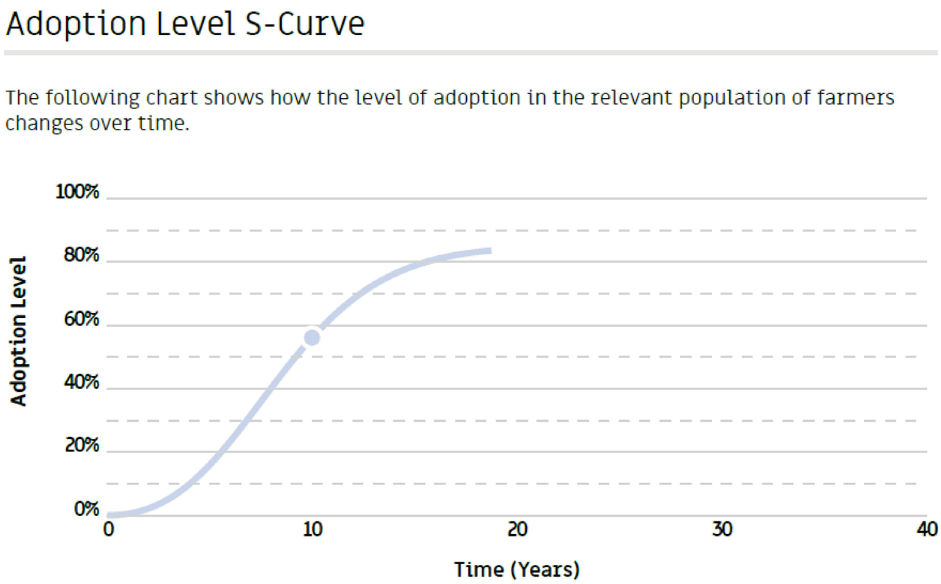

FIGURE 2 | Predicted adoption S-curve for CSA bundles over a 40-year horizon, based on the yearly adoption levels detailed in Table 2. The trajectory shows a slow initial uptake, a period of rapid acceleration, and a final plateau near the 84% ceiling.

strata that determine adoption inequities. Key contextual inputs are:

1. *Geographic and demographic scope:* The target population comprises smallholder farmers in Kakamega and Bungoma counties, stratified by gender (FHH vs. MHH) and agroecological zone (LMZ marginal vs. UMZ high-potential).

2. *Practice-specific parameters:* Baseline adoption rates are derived from the Bayesian-Ising model's marginal probabilities (Figure 2a/b in Momanyi et al. 2026). For example, CSA1 (soil management) is adopted by 75.9%–83.6% of households across strata, whereas CSA4 (productive agroforestry) is adopted by only 1.1% of FHH-LMZ but 26.6% of MHH-UMZ.

3. *Pathway dynamics:* Complementarity thresholds ($J \geq 0.15$ for the CSA1-CSA3-CSA4 bundle) guide bundling priorities. Attrition points identified in Bayesian chain sequences (such as the CSA1 → CSA2 drop-off for FHH-LMZ) directly inform ADOPT's parameters related to reversibility (Q15) and learning challenges (Q12).

4. *Contextual cross-checks:* Publicly available data, such as Kenya's AEZ classifications (Jaetzold 2010), are used to contextualize zone-specific risks. National surveys (such as the Kenya Agricultural Observatory Platform) on CSA awareness cross-validate the Bayesian-Ising findings.

The calibration process follows a transparent, replicable three-step workflow. All inputs are empirically grounded—for instance, the synergy thresholds are taken directly from the Ising network posterior means—fulfilling ADOPT's requirement for transparent assumptions. The stratification mirrors the focus of Kenya's County Integrated Development Plans (CIDPs), ensuring that the model's outputs align with policy-making scales.

To ensure that the calibration is defensible, we systematically cross-referenced every ADOPT parameter against the corresponding Bayesian-Ising output. Supporting Information: Three—derived directly from the ADOPT module/template—maps each of the 22 ADOPT questions to the exact findings in Momanyi et al. (2026) from which the responses were derived. For example:

1. Q6 (Short-term constraints) → derived from the finding that 81% of the sample resides in the LMZ and that even initial adopters face severe liquidity barriers (Section 3.1 and Table 2 in Momanyi et al. 2026).

2. Q16 (Income benefit in years used) → derived from the moderate yield advantages reported for CSA1–CSA3 bundles (Table 2 in Momanyi et al. (2026)) and the documented positive but moderate synergy coefficients.

2.4 | Validation Strategy

To ensure the robustness of this equity-adjusted ADOPT framework, a multi-tiered validation strategy is employed, consistent with rigorous applications of the tool (Kuehne et al. 2017; Parra-López et al. 2025) and with the extensive sensitivity checks reported in the Bayesian-Ising supplement.

1. *Cross-validation against the Bayesian-Ising diagnostics:* ADOPT predictions are compared with the observed transition probabilities from the Bayesian Chain Analysis. For instance, the predicted cumulative adoption of CSA4 for FHH-LMZ under the baseline scenario is cross-checked against the observed product of transition probabilities: $P(CSA1) \times P(CSA2|CSA1) \times P(CSA3 \mid CSA1, CSA2) \times P(CSA4 \mid CSA1, CSA3) = 0.0392$ (Momanyi et al. 2026). Any large discrepancy would trigger a recalibration.

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TABLE 2 | Yearly predicted adoption levels (%) for CSA bundles, forming the basis of the adoption S-curve.

Year	Adoption %
1	0
2	2
3	5
4	10
5	16
6	23
7	32
8	40
9	48
10	56
11	63
12	68
13	73
14	76
15	79
16	81
17	82
18	83
19	84
(Peak Adoption)	

2. *Sensitivity analysis of ADOPT parameters:* Following the approach used in the Bayesian-Ising paper (Momanyi et al. 2026), we conduct a systematic sensitivity analysis of the 22 ADOPT factors. For each factor, we compute the change in peak adoption (%) and time to peak (years) resulting from a one-step increase or decrease in the response, while holding all other factors constant. The results (presented in Section 3.0, Tables 3 and 4) identify the most influential levers (e.g., Q16: income benefit; Q12: skills and knowledge) and are benchmarked against the sensitivity analysis of the Bayesian-Ising model (e.g., edge stability across sample splits, latent confounder perturbations).
3. *Robustness checks against key assumptions:* The Bayesian-Ising paper includes an extensive battery of robustness checks (Momanyi et al. 2026) that directly inform the credibility of our ADOPT calibration:
   - *Temporal stability:* Split-sample re-estimation of the Ising network showed that the sign of key edges remained consistent ($\Delta J \leq 0.02$) for most edges (Momanyi et al. 2026).
   - *Latent confounder sensitivity:* Perturbing the posterior mean interaction matrix with multiplicative normal noise (mean 1, SD 0.05) resulted in 100% sign consistency for all 15 edges tested (Momanyi et al. 2026).
   - *Ordinal versus binary coding:* Using a stricter adoption definition (practice adopted only if the household's total adoption count exceeded the median) preserved the qualitative structure of the core triad (Momanyi et al. 2026).
   - *Dirichlet pooling for sparse strata:* CPT variance for FHH-LMZ and FHH-UMZ was reduced by 57%–59% without altering substantive interpretation (Momanyi et al. 2026).

These checks demonstrate that the observed adoption disparities are not artifacts of a single modelling choice, thereby strengthening confidence in the ADOPT calibration.

4. *Benchmarking against classical adoption models:* Where possible, ADOPT's projections are compared with forecasts from a Bass diffusion model (Bass 1969) using the same stratified adoption rates. The Bass model yields a similar S-curve shape but lacks the equity-sensitive parameters; the comparison is used to highlight the added value of the equity-calibrated ADOPT framework.

This multi-tiered validation strategy ensures that the ADOPT forecasts are not only statistically robust but also operationally actionable for policymakers seeking to address adoption inequities. All data and code for replicating the validation are provided in the Supporting Information.

3 | Results: Proof-Of-Concept From Kenya's Agrifood Sector

This section presents findings from the equity-calibrated ADOPT model, demonstrating how structural barriers constrain diffusion timelines. The Kenyan agrifood case reveals a pattern likely generalizable to other sectors when equity is ignored. We forecast the diffusion trajectory of Climate-Smart Agriculture (CSA) technology bundles in Western Kenya and identify the critical leverage points that govern the scale and pace of adoption.

3.1 | Overall Adoption Forecast

The equity-calibrated ADOPT model predicts a peak adoption level of 84%, reached after 19 years, with 50% of peak adoption achieved by year 8.2, 16% adoption by year 5, and 56% by year 10 (see Figures S1 and S2 and Table S2 for the original ADOPT dashboard outputs). Table 2 details the annual progression underlying this adoption S-curve.

Table 2 details the annual progression underlying the adoption S-curve. Adoption starts slowly, with only 2% of the target population adopting by year 2, then accelerates to 16% by year 5, 56% by year 10, and finally plateaus at 84% in year 19.

This S-curve (Figure 2) visualizes a classic diffusion pattern: a slow "pioneer" phase, a period of rapid acceleration as social learning and perceived benefits spread, and a final plateau as the remaining non-adopters face insurmountable constraints (e.g., extreme liquidity shortages, land tenure insecurity, or advanced skill requirements). The 19-year timeline is notably longer than the 15-year horizon often assumed for simpler agronomic practices, underscoring the complexity of the bundled innovation.

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TABLE 3 | Comprehensive sensitivity analysis: Quantified impact of a one-step improvement (Step Up) or decline (Step Down) for each ADOPT parameter on predicted peak adoption level (%) and time to peak adoption (years).

Question	Peak level (%)		Time to peak (years)	
	Impact of 1 step up	Impact of 1 step down	Impact of 1 step up	Impact of 1 step down
1. Income or productivity orientation	3.51	−4.57	0	0.08
2. Local community benefit orientation	0.96	−1.00	0	0
3. Risk orientation	n/a	0	n/a	0
4. Enterprise scale	5.34	−8.15	−0.08	0.08
5. Management horizon	1.2	−1.24	0	0
6. Short-term constraints	0	0	−0.42	0.42
7. Trialable	0	0	−1.17	1.17
8. Innovation complexity	0	0	−1.17	1.17
9. Observability	0	0	−0.42	0.42
10. Advisory support	0	0	−0.83	0.42
11. Group involvement	0	0	−0.58	0.67
12. Relevant existing skills and knowledge	0	0	−1.42	0.75
13. Innovation awareness	0	0	−0.42	0.42
14. Relative upfront cost of innovation	4.04	−5.38	−0.83	0.83
15. Reversibility of innovation	2.83	−3.43	0	0.08
16. Income or productivity benefit in the years that it is used	8.94	−19.93	−0.17	0.17
17. Future income or productivity benefit	7.17	−12.85	−0.08	0.17
18. Time until any future income or productivity benefits are likely to be realized	4.62	−10.89	−0.08	0.17
19. Local village or community costs and benefits	6.18	−9.99	−0.08	0.08
20. Time to the local village or community benefit	0.70	−1.3	0	0
21. Risk exposure	8.64	−18.47	−0.17	0.17
22. Ease and convenience	7.21	−12.98	−0.08	0.17

Note: This table is the policy dashboard. It tells us exactly where to invest limited resources for the biggest return in adoption scale (peak) or speed (time to peak). The numbers are not arbitrary—they come from the ADOPT model's internal algorithms, which are based on decades of adoption research. We use them to prioritize interventions.

3.2 | Sensitivity Analysis: Levers for Peak Adoption Level

To identify which factors most strongly influence the ultimate scale of adoption, we conducted a systematic sensitivity analysis. For each of the 22 ADOPT factors, we computed the change in peak adoption (%) resulting from a one-step improvement ("step up") or worsening ("step down") of that factor, while holding all other factors at their baseline values (Table 3).

The most striking result is the dominant sensitivity of the adoption ceiling to perceived income and productivity benefit in the years the practice is used (Question 16). A one-step improvement—from "moderate advantage" to "large advantage"—raises the peak adoption by +8.94 percentage points. Conversely, a one-step decline—from "moderate" to "small advantage"—reduces the peak by −19.93 percentage points. This asymmetry (the negative effect is more than twice as large as the positive effect) is a critical insight: negative economic perceptions are far more damaging to scaling than positive perceptions are beneficial.

Other factors that strongly influence the peak level include risk exposure (Question 21)—improving risk reduction from "large" to "very large" adds +8.64 points, while worsening it to "moderate" subtracts 18.47 points—and ease and convenience (Question 22) and future income benefit (Question 17), each with step-up effects above +7 points and step-down effects below −12 points. Interestingly, factors related to learning and trialability (Questions 7, 8, 12) have zero impact on the peak level; they affect only the speed of adoption, not the ultimate ceiling.

Figure 3 visually summarizes these sensitivities, confirming that Question 16 (income benefit) is the most sensitive lever for peak adoption, followed by risk exposure (Q21) and ease/convenience (Q22).

3.3 | Sensitivity Analysis: Levers for Time to Peak Adoption

The speed of diffusion—measured as the number of years to reach the peak adoption level—is governed by a different set of

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TABLE 4 | Key leverage points for adoption scale and speed: Baseline values, one-step impacts, and resulting changes.

Quiz	Variable affected	Baseline	Action	Impact (from table)	New value	Change (in points/years)
Q16	Peak adoption (%)	84%	1 step up (moderate → large advantage)	+8.94	92.94%	+8.94 ppt
Q16	Peak adoption (%)	84%	1 step down (moderate → small advantage)	−19.93	64.07%	−19.93 ppt
Q21	Peak adoption (%)	84%	1 step up (moderate → large risk reduction)	+8.64	92.64%	+8.64 ppt
Q21	Peak adoption (%)	84%	1 step down (moderate → small risk reduction)	−18.47	65.53%	−18.47 ppt
Q22	Peak adoption (%)	84%	1 step up (small decrease → no change in ease)	+7.21	91.21%	+7.21 ppt
Q22	Peak adoption (%)	84%	1 step down (small decrease → moderate decrease)	−12.98	71.02%	−12.98 ppt
Q17	Peak adoption (%)	84%	1 step up (large → very large future benefit)	+7.17	91.17%	+7.17 ppt
Q17	Peak adoption (%)	84%	1 step down (large → moderate future benefit)	−12.85	71.15%	−12.85 ppt
Q14	Peak adoption (%)	84%	1 step up (large → moderate upfront cost)	+4.04	88.04%	+4.04 ppt
Q14	Peak adoption (%)	84%	1 step down (large → very large upfront cost)	−5.38	78.62%	−5.38 ppt
Q12	Time to peak (years)	19.0	1 step up (60%–80% → 40%–60% need new skills)	−1.42	17.58 yrs	−1.42 yrs. (faster)
Q12	Time to peak (years)	19.0	1 step down (60%–80% → 80%–99% need new skills)	+0.75	19.75 yrs	+0.75 yrs. (slower)
Q7	Time to peak (years)	19.0	1 step up (moderately → easily trialable)	−1.17	17.83 yrs	−1.17 yrs. (faster)
Q7	Time to peak (years)	19.0	1 step down (moderately → difficult to trial)	+1.17	20.17 yrs	+1.17 yrs. (slower)
Q8	Time to peak (years)	19.0	1 step up (moderately difficult → slightly difficult to evaluate)	−1.17	17.83 yrs	−1.17 yrs. (faster)
Q8	Time to peak (years)	19.0	1 step down (moderately difficult → difficult to evaluate)	+1.17	20.17 yrs	+1.17 yrs. (slower)
Q10	Time to peak (years)	19.0	1 step up (20%–40% → 40%–60% use relevant advisor)	−0.83	18.17 yrs	−0.83 yrs. (faster)
Q10	Time to peak (years)	19.0	1 step down (20%–40% → 1%–20% use relevant advisor)	+0.42	19.42 yrs	+0.42 yrs. (slower)
Q6	Time to peak (years)	19.0	1 step up (80%–99% → 60%–80% with severe constraints)	−0.42	18.58 yrs	−0.42 yrs. (faster)
Q6	Time to peak (years)	19.0	1 step down (80%–99% → almost all with severe constraints)	+0.42	19.42 yrs	+0.42 yrs. (slower)

Note: "Step up" means improving the factor (e.g., higher income benefit, lower cost, better skills). "Step down" means worsening the factor. Baseline values (84% peak, 19 years) are from the corrected ADOPT run (Smallholder Agriculture PRO). The table highlights the largest impacts: Q16 and Q21 dominate peak adoption; Q12, Q7, Q8 dominate time to peak. This table serves as a policy dashboard: it tells decision-makers exactly where to invest limited resources for the biggest return in adoption scale (peak) or speed (time to peak). The numbers are not arbitrary—they come from the ADOPT model's internal algorithms, which are based on decades of adoption research.

Abbreviations: ppt = percentage points; yrs. = years.

factors. Table 3 also reports the impact of each factor on the time to peak. The most powerful accelerator is relevant existing skills and knowledge (Question 12). Reducing the proportion of farmers who need substantial new skills from 60%–80% (baseline) to 40%–60% (a one-step improvement) shortens the time to peak by −1.42 years (from 19.0 to 17.6 years). Conversely, worsening the skill gap to 80%–99% delays the peak by +0.75 years.

Trialability (Question 7) and innovation complexity (Question 8) are equally important: a one-step improvement in either reduces the time to peak by −1.17 years, while a worsening adds +1.17 years. Advisory support (Question 10) and short-term financial constraints (Question 6) have smaller but still meaningful effects (−0.83 and −0.42 years, respectively, for step-up improvements).

Figure 4 Panel A (top) and B (bottom) illustrate these relationships, highlighting that capacity building (skills) and making the innovation easy—to try and evaluate—are the primary levers for accelerating diffusion, even though they do not raise the ultimate adoption ceiling.

3.4 | Granular Policy Dashboard

To translate the sensitivity analysis into actionable policy guidance, Table 4 presents a granular summary of the most influential factors, showing baseline values, the impact of a one-step change, and the resulting new value.

3.5 | Narrative Summary

Using the ADOPT model calibrated with Bayesian-Ising diagnostics, we generate an equity-sensitive forecast for CSA bundle uptake among 569 smallholders in Western Kenya. The model predicts an ultimate adoption ceiling of 84%, reached after 19 years (Table 2; Figure S1). The predicted S-curve (Figure 2) shows a slow start, accelerating to 56% adoption by Year 10 before plateauing.

Sensitivity analysis (Figures 3 and 4; Tables 3 and 4) reveals that the peak adoption level is most sensitive to perceived income/productivity benefits (Question 16). Crucially, a one-step

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FIGURE 3 | Sensitivity of the peak adoption level (top panel) and time to peak adoption (bottom panel) to individual ADOPT model parameters. Green bars show the impact of a one-step improvement (Step Up); red bars show the impact of a one-step decline (Step Down). Question 16 (Income or productivity benefit) dominates peak level sensitivity, while Question 12 (Relevant existing skills and knowledge) and Question 7 (Trialable) govern time to peak.

decrease in this perception lowers the adoption ceiling by 19.9 percentage points—more than double the 8.9-point gain from an equivalent improvement—highlighting a critical asymmetry in socio-technical drivers of adoption. The tempo of diffusion is primarily governed by existing skills and knowledge (Question 12); reducing the proportion of farmers needing substantial new skills shortens the time-to-peak by 1.4 years (from 19.0 to 17.6 years).

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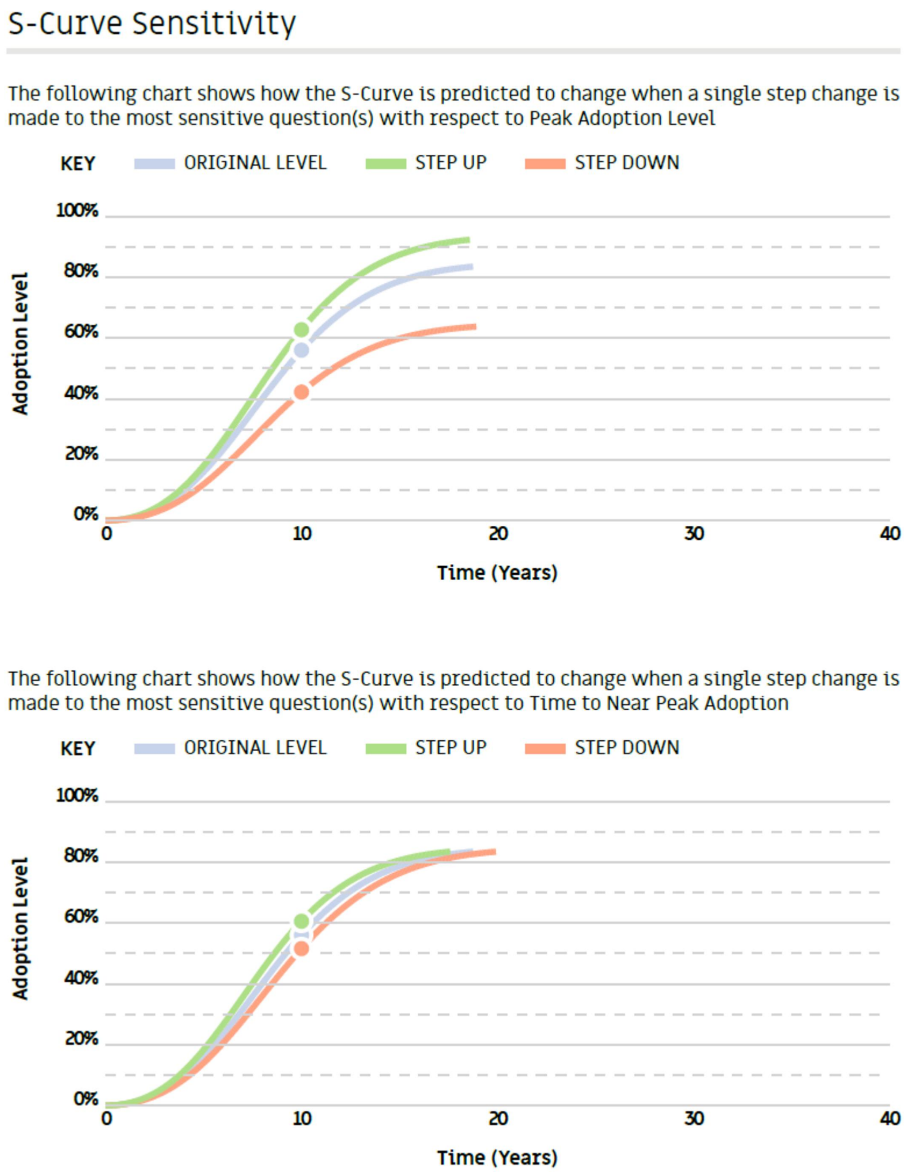

FIGURE 4 | Panel A (top), Panel B (bottom): Shift in the adoption S-curve in response to a one-step change in perceived income/productivity benefit (Question 16). An improved perception (Step Up) raises the peak to 92.9%, while a diminished perception (Step Down) lowers it to 64.1%, illustrating the strong asymmetry.

These findings corroborate a key meta-pattern in technology adoption forecasting: while profit perception defines the potential scale, the learning burden dictates the pace of achieving it. The asymmetry in risk perception aligns with prospect theory and signals that de-risking adoption is more strategic than simply promoting benefits.

Figure 5 illustrates how changing the most sensitive factor for time to peak—trialability (Q7) – alters the entire adoption trajectory.

4 | Discussion

Our study set out to move from diagnostic precision to equitable diffusion, offering a portable framework for forecasting inclusivity in technology adoption. By integrating empirical Bayesian-Ising diagnostics into CSIRO's ADOPT tool, we showcase that innovation equity is not an add-on but a calibration input. The results paint a clear picture: a high but not universal adoption ceiling (84%), a protracted diffusion timeline (19 years), a striking asymmetry in how farmers respond to economic perceptions, and the primacy of skills and trialability as accelerators of adoption speed. These findings have profound implications for innovation governance, climate finance, and Sustainable Development.

4.1 | The Diffusion Trajectory: High Potential Constrained by Structural Barriers

The forecasted peak adoption of 84% affirms the intrinsic value of the CSA bundle identified through synergy analysis. This ceiling is substantially higher than the 19% peak predicted for

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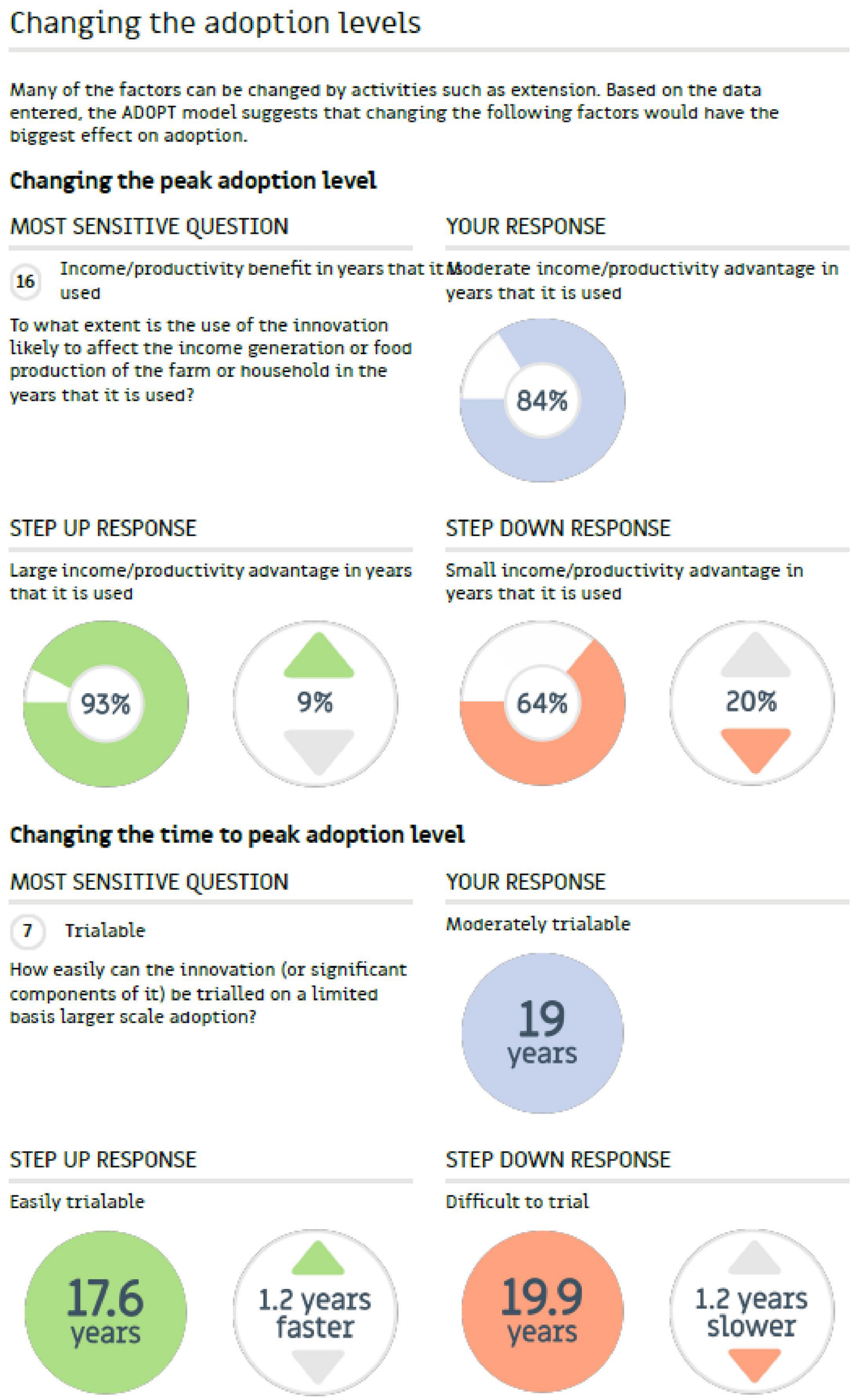

FIGURE 5 | Shift in the adoption S-curve in response to a one-step change in trialability (Question 7). Making the innovation easily trialable (Step Up) accelerates peak adoption to 17.6 years; making it difficult to trial (Step Down) delays the peak to 20.2 years. Similar patterns hold for skills (Q12) and complexity (Q8).

digital traceability in the olive sector (Parra-López et al. 2025) and the 2%–28% peaks for diversified cereal rotations in Europe (Rezgui et al. 2026), reflecting the strong agronomic and economic rationale for bundled CSA practices in high-rainfall smallholder systems. However, the 19-year timeline is considerably longer than the 15-year horizon for digital traceability or the 8–17 years for crop diversification. This protracted diffusion is characteristic of complex innovations that require new knowledge, management shifts, and upfront investment (Kuehne et al. 2017; Llewellyn and Brown 2020).

Crucially, the 84% ceiling is lower than the 96% forecast in an earlier expert-based scenario (not reported here), underscoring that empirical calibration with stratified data reveals binding

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structural constraints that expert opinion tends to underestimate. This aligns with the capability approach (Cohen et al. 2016; Dang 2014; Drèze and Sen 1990; Sen 1999), which distinguishes between access to resources and the capability to convert those resources into valued outcomes. Our Bayesian-Ising diagnostics quantified exactly such conversion failures: female-headed households in marginal zones had cumulative adoption probabilities of only 3.9% for CSA4, despite high uptake of entry-level practices (Momanyi et al. 2026). The ADOPT forecast thus makes visible what aggregate curves conceal.

4.2 | The Primacy of Economic Perception and the Asymmetry of Risk: A Prospect Theory Lens

As hypothesized in Section 1.2, the sensitivity analysis reveals a profound asymmetry in how economic perceptions shape the adoption ceiling. A one-step negative shift in perceived income benefit (Question 16)—from "moderate" to "small advantage"—reduces peak adoption by 19.9 percentage points, more than double the 8.9-point gain from an equivalent positive shift (Table 3; Figure 3). This 2.2:1 loss-to-gain ratio is consistent with prospect theory's prediction of loss aversion (Bocquého et al. 2014; Kahneman and Tversky 1979, 2013), confirming that farmers weight potential losses approximately twice as heavily as equivalent gains in their adoption calculus.

This asymmetry moves beyond simply confirming that economic returns matter—a widely documented fact (Barrett 2008; Feder et al. 1985; Jack 2013)—to reveal that the risk of negative perceptions is a far greater threat to scaling than the opportunity that positive perceptions present. Interpreted through prospect theory, a perception of "small advantage" signals high risk or uncertain returns, triggering widespread aversion that can disproportionately collapse adoption ceilings. Our results add a quantitative, asymmetric measure: the penalty for failing to prove economic gain is 2.2 times (in absolute terms) the reward for proving it (Section 1.2).

Extension strategies must therefore prioritize robust, demonstrable, and localized proof of economic gain—not merely to promote adoption, but to prevent the collapse of the entire scaling effort. This finding aligns with the capability approach (Drèze and Sen 1990; Sen 1999), which distinguishes between access to resources and the capability to convert them into valued outcomes. For female-headed households in marginal zones, low cumulative adoption of CSA4 (3.9%) may reflect not only limited access but also a rational loss-averse response to high uncertainty and weak institutional support.

4.3 | Skills, Trialability, and Complexity: Accelerating the Pace

The speed of diffusion is most sensitive to existing skills and knowledge (Q12). Reducing the proportion of farmers needing substantial new skills from 60%–80% to 40%–60% accelerates time-to-peak by 1.4 years. Trialability (Q7) and complexity (Q8) have similarly large effects (−1.17 years each). These findings corroborate a meta-pattern from other ADOPT and technology diffusion/scaling applications: the "learning burden" consistently governs the pace of adoption across diverse agricultural contexts (Akzar et al. 2023; Bandura 1969; Bandura and Walters 1977; Chavas and Nauges 2020; Lybbert and Bell 2010; Uy et al. 2025).

Importantly, these factors have negligible impact on the peak adoption level—they affect only how fast the ceiling is reached. This has a direct policy implication: capacity building, demonstration plots, and simplified user interfaces will not raise the maximum number of adopters, but they will dramatically shorten the time vulnerable populations are exposed to climate risk without resilience-building practices. The 1.4-year acceleration is not merely a statistical output; it represents a meaningful reduction in the period during which households remain locked into less resilient farming systems. This repositions capacity building from a "soft extra" to a core infrastructure investment—a theme echoed in the technology governance literature (Foster and Heeks 2013; Heeks et al. 2014).

4.4 | Equity Implications: Beyond Aggregate Forecasts

The aggregate forecast of 84% masks severe disparities identified in the Bayesian-Ising diagnostics, particularly for female-headed households in the Lower Midlands (FHH-LMZ) (Momanyi et al. 2026). The ADOPT model's structure, which incorporates equity parameters directly, explains the overall ceiling through higher adoption rates among more advantaged groups (MHH-UMZ), while the sensitivity analysis reveals universal levers that could close these gaps.

The fact that skills (Q12) and income benefits (Q16) are the key levers is highly significant for equity. It implies that the barriers for marginalized groups are not necessarily different in kind but are vastly greater in degree. For FHH-LMZ, the "skills gap" is exacerbated by reduced access to extension and higher labor constraints; the "perception of low benefits" is often a rational response to the lack of resources (e.g., land tenure for agroforestry) needed to capture those very benefits (Addaney et al. 2022; Doss and Meinzen-Dick 2020; Place 2009). Therefore, equity-focused scaling requires proactive, targeted interventions that address these amplified barriers—not generic, untargeted extension that will likely reinforce existing disparities (Bryan et al. 2023, 2024; Njuki et al. 2022).

This framework operationalizes the concept of "elite capture" (Persha and Andersson 2014; Poulton and Kanyinga 2014) by quantifying how synergistic complementarities are concentrated in the most advantaged stratum. The counterfactual simulations show that even when MHH-UMZ transition probabilities are applied to disadvantaged groups, the gains are modest and uncertain—indicating that structural dependency is not easily remedied by simply copying "best practices". This aligns with the Precision Justice heuristic developed in our companion paper (Momanyi et al. 2026), which distinguishes between strategic advantage (contingent) and structural dependency (locked-in).

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4.4.1 | How These Matter in Kenya Specifically

These omissions are particularly consequential in the Kenyan context due to three compounding dynamics. First, Western Kenya's 'hydroclimate whiplash'—the increasingly rapid oscillation between extreme drought and catastrophic flooding (RFI 2025, 2026)—invalidates the assumption of stable climatic baselines. From 2020 to early 2023, the region experienced five consecutive failed rainy seasons in the longest and most severe drought in 40 years (Kimutai et al. 2025).

This led to widespread harvest failures, livestock losses, and water scarcity, pushing an estimated 4.35 million people into humanitarian need across the Horn of Africa (Kimutai et al. 2025). Just as recovery was nascent, the 2023–2024 El Niño triggered rainfall up to 140% above average, causing floods that destroyed crops, washed away livestock, and displaced over 1.2 million people (United Nations Children's Fund [UNICEF] 2023; International Federation of Red Cross and Red Crescent Societies [IFRC] 2025). This whiplash dynamic—from no water to too much water—is precisely the kind of sequential shock that static models cannot capture.

The 2020–2023 drought likely accelerated adoption of water-harvesting practices (CSA2) while depressing long-gestation agroforestry investments (CSA4), and the subsequent 2024 floods may have further reset adoption trajectories by destroying infrastructure and eroding household asset bases. A static forecast calibrated on pre-whiplash conditions cannot simulate how such shock sequences might compress or extend the 19-year adoption timeline.

Second, within-zone heterogeneity remains unmodelled, despite well-documented evidence of high biophysical and socio-economic variation across Western Kenya. Research by (Tittonell et al. 2005) demonstrates that smallholder farms exhibit steep soil fertility gradients, both between regions and within individual farms, resulting in grain yield gaps of 0.5–3 $\mathrm{t\,ha^{-1}\,season^{-1}}$ depending on field type and management. Nutrient use efficiencies vary enormously, with apparent recovery rates ranging from 0% to 70% for nitrogen and 0% to 15% for phosphorus (Tittonell et al. 2008).

This heterogeneity means that households near Kakamega town—with better access to markets, extension services, and input supply—face fundamentally different adoption conditions than those in remote Bungoma sub-counties. Our LMZ/UMZ stratification captures coarse agroecological gradients but cannot account for this fine-grained variation, which may explain some of the wide credible intervals in the Bayesian-Ising diagnostics and underscores the need for county-level or finer-scale ADOPT runs.

Third, Kenya's dynamic policy and market environment renders static cost assumptions increasingly untenable. The voluntary carbon market in Kenya is rapidly evolving, with at least 12 active carbon farming projects operating under four distinct funding models (donor-financed, investor-financed with forward purchase agreements, private-sector led with equity financing, and buyer-led). Recent carbon credit initiatives aim to provide loans to smallholder farmers specifically for transitioning to agroforestry and monetizing carbon stored in trees (Schilling 2026).

In eastern Kenya, over 21,500 farmers have already generated income from carbon credits through agroforestry, with 80% of revenue flowing directly to farmers and documented co-benefits including yield increases, reduced fertilizer use (20%–40%), and a 30%–50% boost in soil organic matter (Farm Africa, n.d.). The Western Kenya Soil Carbon Project has issued carbon credits to over 30,000 smallholder farmers, creating direct financial incentives for adopting sustainable farming practices (First Climate 2023).

These emerging markets could substantially lower the effective cost of CSA4 (productive agroforestry) through payment-for-ecosystem-services schemes (Mayr et al. 2026), potentially raising the 84% adoption ceiling or compressing the 19-year timeline. However, our sensitivity analysis captures only static one-step changes in cost perception (Q14); it cannot model dynamic cost reduction curves or the complex feedback between carbon finance availability, adoption decisions, and market maturation. Policymakers should therefore treat the 19-year timeline as contingent on current cost structures and revisit calibration as market conditions evolve.

4.5 | Policy Implications for Inclusive Innovation Governance

These findings provide actionable policy levers for Sustainable Development, directly supporting SDG 2 (Zero Hunger), SDG 5 (Gender Equality), SDG 10 (Reduced Inequalities), and SDG 13 (Climate Action). Three core implications emerge:

1. *De-risk adoption through economic proof, not just promotion:* The asymmetry in Q16 implies that a single failed story of low returns can collapse adoption. Extension programs should frontload demonstrable, localized evidence of economic gain—using pilot demonstrations, farmer testimonials, and transparent cost–benefit analyses tailored to marginalized subgroups. Messaging should frame technologies within "loss-avoidance" scenarios ("prevent soil depletion") rather than solely emphasizing potential gains, aligning with prospect theory.
2. *Treat capacity building as infrastructure, not a soft extra:* The 1.4-year acceleration from improving skills (Q12) positions training and education as primary diffusion accelerators. Policy should co-design skill-development modules with target users, embed skill-building into technology rollout plans from the outset, and leverage local peer-learning hubs (such as women's collectives, farmer groups). This is consistent with the literature on human capital as a foundation for adopting technologies (Adger 2010; Cohen et al. 2016; Hunecke et al. 2017; Lang et al. 2023).
3. *Use equity-calibrated forecasting for targeted intervention design:* Our framework provides a replicable blueprint for converting stratified diagnostic data into adoption forecasts. Policymakers can apply this to other sectors—renewable energy, digital health, financial inclusion—by first conducting stratified diagnostic analyses (for instance,

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gender-disaggregated surveys), then calibrating ADOPT to forecast subgroup-specific adoption ceilings and timelines. This moves equity from a normative goal to a quantifiable, optimizable parameter in technology policy (Ortega and Serna 2020).

4.6 | Limitations and Future Research

4.6.1 | Sensitivity to Choice of Estimator

While ADOPT provides a powerful forecasting tool, its output is contingent on input quality. The equity-calibration parameters are derived from a separate diagnostic study (Momanyi et al. 2026); future work should unify diagnostic and forecasting analyses within a single longitudinal framework. The calibration rules (Table 1) rely on empirical thresholds (such as attrition rate <0.2) specific to our context; generalizability depends on the availability of similarly rich stratified data. The model assumes static socio-economic conditions and does not dynamically account for exogenous shocks (for instance, policy upheavals, climate extremes). Longitudinal validation against observed adoption data is urgently needed.

Despite these limitations, this work demonstrates that ADOPT—when empirically calibrated—can convert structural diagnostics into policy-ready equity-sensitive projections. The calibration table and replicable steps provide a transparent foundation for others to build upon.

4.6.2 | A Note on Intersectional Calibration and Stratification

We acknowledge that our calibration of ADOPT using Bayesian-Ising diagnostics was not performed in a fully intersectional, strict sense. Ideally, one would estimate separate ADOPT parameter sets for each intersectional stratum (e.g., FHH-LMZ, MHH-LMZ, MHH-UMZ) using stratum-specific empirical data for all 22 factors. However, small sample sizes—particularly for FHH-UMZ ($n = 29$)—and the inherent sparsity of stratified adoption data prevented such a granular approach. Instead, we used a heuristic mapping (Table 1) that translated key diagnostic outputs (attrition rates, synergy coefficients, marginal probabilities) into a subset of ADOPT factors (Q12, Q14, Q16, Q21), while leaving other factors (such as Q1 profit orientation, Q3 risk orientation) at stratum-aggregated values derived from the full sample. This is a pragmatic compromise, not a statistically rigorous calibration.

Future work should develop formal statistical models that link diagnostic outputs directly to ADOPT parameters, enabling true intersectional calibration even with sparse data—for instance, using hierarchical Bayesian models that borrow strength across strata. Additionally, larger, purpose-designed surveys with adequate sample sizes per intersectional cell would allow fully stratified ADOPT runs.

Nevertheless, the current approach remains useful and defensible for three reasons. First, the heuristic mapping was explicitly derived from empirical thresholds observed in the data (e.g., attrition rate <0.2 → "almost all need new skills"), making it transparent and replicable. Second, the most influential ADOPT factors for equity outcomes—skills (Q12), income benefit (Q16), risk exposure (Q21), and upfront cost (Q14)—were precisely the ones informed by stratum-specific diagnostics, while less sensitive factors were safely left at aggregated values. Third, the resulting forecasts (84% peak, 19 years, strong asymmetry) align more closely with the observed structural barriers than any expert-only or fully aggregated ADOPT run, providing a proof-of-concept that even a partial, heuristic calibration improves over conventional approaches. Thus, while not strictly intersectional, our framework offers a practical, actionable bridge between diagnostic analysis and forecasting—one that can be refined as more data become available.

4.6.3 | Future Research Directions

Longitudinal validation and periodic rolling window updates of these forecasts against observed adoption data are urgently needed, as are experimental studies that test the policy levers identified by our sensitivity analysis (such as comparing extension messages focused on loss-avoidance versus gain-framed narratives). To overcome the pragmatic compromises of heuristic calibration, future work should develop hierarchical Bayesian models that borrow statistical strength across intersectional strata, enabling fully stratified ADOPT parameterization even with sparse data. Additionally, extending the framework to other sectors—such as off-grid solar adoption in South Asia, telemedicine uptake in Latin America, or mobile money diffusion in East Africa—would test its portability and reveal context-specific variations in the asymmetry of risk perception and the role of skills as an accelerator. Finally, integrating real-time monitoring data into a rolling-window ADOPT would transform the tool from a static forecast into an adaptive governance instrument, allowing policy to respond dynamically as structural barriers shift over time.

5 | Conclusion

This study set out to move from diagnostic precision to equitable diffusion, offering a portable framework for forecasting inclusivity in technology adoption. By integrating empirical Bayesian-Ising diagnostics into CSIRO's ADOPT tool, we have demonstrated that innovation equity is not an add-on but a calibration input—a design parameter that must be embedded ex ante, not evaluated ex post. Our analysis of Climate-Smart Agriculture (CSA) diffusion among 569 smallholders in Western Kenya reveals a central paradox: while synergistic practice bundles hold substantial potential (84% adoption ceiling), their diffusion is slow (19-year timeline) and deeply uneven—masked by aggregate forecasts. Three critical, actionable insights emerge from this work.

First, profit perception sets the ceiling, but asymmetry defines the risk. The perceived economic benefit of an innovation is the strongest lever for adoption scale. Yet we find a profound asymmetry: a one-step negative shift in perceived income benefit reduces peak adoption by 19.9 percentage points—more than double the 8.9-point gain from an equivalent positive shift. This

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aligns with prospect theory and signals a fundamental reorientation for policy: de-risking adoption is more strategic than promoting benefits. A single failed story of low returns can collapse an entire scaling effort. Extension must therefore prioritize robust, localized, and demonstrable proof of economic gain, framed within loss-avoidance narratives.

Second, skills dictate the pace. The speed of diffusion is most sensitive to existing skills and knowledge. Reducing the proportion of farmers needing substantial new skills accelerates time-to-peak by 1.4 years — a critical period for climate-vulnerable households. Trialability and complexity have similarly large effects on adoption speed, though they do not raise the ultimate ceiling. This finding repositions capacity building from a secondary support activity to a core infrastructure investment. Training, demonstration plots, and simplified user interfaces are not "soft extras"; they are the primary accelerators of technological diffusion.

Third, equity is a calibration input, not an afterthought. By calibrating ADOPT with stratified attrition rates and synergy coefficients from a Bayesian-Ising diagnostic, we transform the model from predicting "if and when" to forecasting "for whom and why not." The aggregate forecast of 84% masks severe disparities: female-headed households in marginal zones have cumulative adoption probabilities of only 3.9% for advanced practices, despite high uptake of entry-level practices. Making these gaps visible, quantifiable, and actionable within the forecasting process itself is a methodological shift that directly supports the 2030 Agenda for Sustainable Development — specifically SDG 2 (Zero Hunger), SDG 5 (Gender Equality), SDG 10 (Reduced Inequalities), and SDG 13 (Climate Action).

The framework we have developed is portable. While the specific empirical findings from Western Kenya are context-bound — reflecting local structural barriers of land tenure, labor constraints, and agroecological risk — the analytical workflow is designed for replication. The same three-step process — conduct a stratified diagnostic analysis, define synergistic innovation bundles, and calibrate ADOPT using explicit mapping rules — can be deployed in any setting where stratified adoption data are available. This portability extends beyond agriculture to renewable energy (forecasting solar home system uptake among gender-disadvantaged households), digital health (predicting telemedicine adoption stratified by literacy and connectivity), and financial inclusion (modelling mobile money diffusion across asset-based strata).

For policymakers, this means moving from generic scaling strategies to targeted, lever-based interventions that preempt negative perceptions, compress skill gaps, and prioritize synergistic bundles. For development agencies, it means that equity audits should be embedded into technology forecasting as a routine practice, not an occasional evaluation. For researchers, it offers a transparent, replicable blueprint for converting diagnostic data into equitable policy-ready forecasts or strategic projections.

Ultimately, this research reframes the challenge of technology diffusion. Achieving scale is not merely a technical or economic problem — it is a socio-technical design challenge that requires forecasting tools capable of seeing, quantifying, and responding to inequity. The future of Sustainable Development lies not only in what we innovate, but in how equitably and insightfully we forecast its reach. By bridging the gap between diagnostic precision and predictive modelling, we offer a pathway to more inclusive, responsible, and effective innovation scaling in the Global South and beyond. The Bayesian-Ising-ADOPT ensemble is offered in that spirit: not as a universal prescription, but as a reproducible diagnostic toolkit for identifying where climate adaptation systems are most likely to exclude, stall, or reinforce advantage — and for designing interventions that leave no one behind.

Author Contributions

Denis Momanyi: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, funding acquisition, visualization, resources, writing – original draft, writing – review and editing. **Jiqin Han:** conceptualization, methodology, investigation, validation, supervision, visualization, project administration, resources, writing – original draft, writing – review and editing. **Job K. Lagat:** conceptualization, methodology, investigation, validation, supervision, visualization, project administration, resources, writing – original draft, writing – review and editing. **Robert A. Marchant:** conceptualization, methodology, investigation, validation, supervision, visualization, project administration, resources, writing – original draft, writing – review and editing. **George M. Ogendi:** conceptualization, methodology, investigation, validation, supervision, visualization, project administration, resources, writing – original draft, writing – review and editing. **Hermann Lotze-Campen:** conceptualization, methodology, investigation, validation, supervision, funding acquisition, visualization, project administration, resources, writing – original draft, writing – review and editing. **Stefan Sieber:** conceptualization, methodology, software, data curation, investigation, validation, formal analysis, supervision, funding acquisition, visualization, project administration, resources, writing – original draft, writing – review and editing.

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Ethics Statement

This research received ethical clearance from the Kenya National Commission for Science, Technology and Innovation (NACOSTI), under License No. NACOSTI/P/23/28688. Internal ethical compliance was maintained in accordance with the research guidelines of the Leibniz Centre for Agricultural Landscape Research (ZALF) and

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Humboldt-Universität zu Berlin, following the standards set by the German Research Foundation (DFG).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

This study contributes to the first author's doctoral dissertation at Humboldt-Universität zu Berlin. Due to the inclusion of sensitive, georeferenced household data, the dataset is currently restricted under data-sharing agreements until the dissertation is formally submitted and published. Interested researchers may request access by contacting the corresponding author and providing a signed data use agreement. Upon dissertation publication, the full dataset and replication materials will be made available via an open-access repository (Zenodo).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Climate-Smart Agricultural (CSA) practice categories and descriptions. **Figure S1:** Key adoption metrics from the ADOPT model simulation for CSA bundles in Western Kenya. Outputs show a predicted peak adoption level of 84% and a time to near-peak adoption (99% of maximum) of 19 years. **Figure S2:** Additional adoption milestones: 16% of the target population is expected to adopt by year 5, 56% by year 10, and 50% of the peak adoption is reached after 8.2 years. **Table S2:** Bayesian-Ising cumulative pathway completion probabilities (Momanyi et al. 2026). **Data S1:** Supporting Information. **Data S2:** Supporting Information.

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