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RESEARCH PAPER

Financial Impact Modelling of AI-Driven Crop Disease Mitigation

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ABSTRACT

Adoption of the use of artificial intelligence (AI) in agricultural disease control has proven to be efficient in terms of technical improvement but economic justification has proved to be a foundation pillar in implementation strategies. This is a review article, which summarizes the existing approaches to measuring the financial changes brought about by AI-based crop disease detection and mitigation systems. The authors focus on the schemes of yield losses estimation, methods to value economic types of returns, and modelling, methods of return on investment (ROI) evaluation in varying agricultural application situations. By systematically reviewing the current body of such literature and case studies, this review confirms in part that AI- based early disease detection can yield losses of 15-40% of the end yield dependent on type of crop and time of intervention with the same investment returning on investment in the range of 150, 400% on a 3-year deployment period. But even there, there are major discrepancies in methodology in the area of impact assessment, especially in setting up of baseline, modelling attribution and long-term measures of sustainability. The current paper suggests the system of integrating the disease incidence modelling with the market-responsive economic valuation with the incorporation of AI model performance measures and the measures of the regional variability. Important results suggest that the financial feasibility is highly sensitive to other factors such as size of the fields, diseases and predominance, prices of crops in the market and the availability of infrastructure. The review reveals severe gaps in the research on applicability of smallholder applications, climate adaptation Case scenarios, and policy mechanisms used to enhance faster economic implementation of AI in crop protection. The suggested framework not only provides a methodology that a researcher and practitioner can reproduce to assess AI interventions, but it also emphasizes the one that requires standard measures of economic impacts in agricultural AI studies.

Keywords: Artificial intelligence, crop disease detection, economic impact assessment, yield loss modeling, return on investment, precision agriculture, disease mitigation, agricultural economics, AI adoption, financial sustainability

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Context of AI in Crop Disease Detection

The phenomenon of food security has never been more pose to global challenges since crop related diseases lead to estimated losses of more than 220 billion USD each year across the world with a loss rate of about 20-40 percent to the potential and actual crop yields (Savary *et al.* 2019). The use of traditional disease management methods which are mainly based on the periodic surveillance of the fields and the treatment of diseases on detection usually finds the infection after significant damages have already taken effect. The development of AI-based technologies the methods of computer vision, deep learning, and IoT-based sensing systems in particular changed the traditional capabilities of the early detection of the disease and allowed to perform the intervention at pre-symptomatic or early-symptomatic stages to achieve the maximum effect of treatment (Ferantinos, 2018; Saleem *et al.* 2019).

More recent developments such as convolutional neural networks and transformer-based systems and networks have been able to reach according to 95 per cent efficacies in differentiating the diseases in a variety of crop species like wheat, rice, maize, and potato (Barbedo, 2019; Chen *et al.* 2020). Mobile diagnostic devices and imaging devices on drone have made precision diagnostics more democratic, especially when resources are scarce (Kamilaris and Prenafeta-Boldu, 2018). Although the use of these technological advancements has increased, the adoption rate is still under 15 percent and there is more disparity between the developed and the developing agricultural economies worldwide (Javaid *et al.* 2023).

The difference between the technological capability and field level adoption mostly lie to do with lack of sufficient economic validation structures. Agronomic efficacy, either pinpointed by incident accuracy, time ineffective false positive, or time among others, is widely recorded; nevertheless, conversion of these technical metrics to tolerable economic achievements is not effectively portrayed (Shahhosseini *et al.* 2020). The agricultural cooperatives, policymakers, and farmers need maniputable cost benefit analysis that takes into consideration the cost of implementation, cost operating, gain offers of protecting the yields, and the unpredictability of the market forces.

The Need for Economic Validation

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Economic validation can fulfil several vital purposes: it allows informed decisions on investment per unit, as well as to classify intervention strategies and mechanisms of public support, and locate situations of maximum use of deployment options that are based on crop economics and disease pressure profiles (Liakos *et al.* 2018). Moreover, doubtful issues of technology lock-in, dependence on vendors, and extended sustainability that often hinder the adoption of agricultural technologies are rigorously tackled through the use of financial modelling.

The importance of having unified methodologies in the quantification of financial effect of AI-driven disease mitigation is urgent and the focus of the review. The authors are able to synthesize the existing approaches, identify breakdown in the methodology and put forward an integrated paradigm that has both analytical rigor and application in a wide range of agricultural systems. This analysis also concentrates on ex-post economic evaluation techniques as opposed to predictive modelling but includes reproducible measures to aid the evidence-based decision-making model.

Background and Related Work

1. Evolution of Yield Loss Assessment Methodologies

The techniques of yield loss estimation have gone through three different generations of procedures. Among the first-generation methods were those that used surveys of the experts and historical records of losses; they gave rough regional estimates of the loss less precise with time scales (Oerke, 2006). The high uncertainty of these techniques as well as the low specificity of attribution in the case of losses were found in the fact that losses accrued on a combination of multiple stress untying factors: diseases, pests and abiotic stressors.

The second-generation approaches brought forth field experience where there was an inoculation study that encompassed control (Savary *et al.* 2012). These methods measured grow-disease interactions in a given stipulated circumstances but were limited in terms of stocky regarding publicity to a tinkalite circumstance. The intensive resource investment was necessary in the past, as statistical crop loss assessment networks (including those of CIMMYT, wheat pathology programs) were producing useful data sets.

The third generation, which comes since 2015, with the help of remote sensing, IoT sensors, and machine learning, provides a possibility to monitor yields continuously in a spatially explicit mode (Mahlein, 2016; Ngugi *et al.* 2021). Regional loss attribution of vegetation indices (NDVI, EVI) using satellites with ground notions of assessment of disease assessments in sub-field are practical regional attributions. Nevertheless, such advanced approaches are not fully applied in the studies of the economic impact, which makes a gap between technical monitoring systems and financial assessment models.

2. AI-Based Interventions in Crop Health Management

Many technological modalities are applied in the implementation of AI in crop disease management. Depending on smartphones or stationary cameras, image diagnostic systems are based on the analysis of the symptoms on the leaf to determine the presence of a disease (Mohanty *et al.* 2016; Too *et al.* 2019). Such systems will use transfer learning based on a trained CNN, where 85-98% accuracy will be achieved in major disease categories. The amount of deployment can be cloud-based analysis that is under internet connection or edge-computing features that allow offlines.

Multi-spectral, Hyperspectral imaging systems detecting the onset of physiological changes long before the onset of the visual problems extend the intervention window by 3-14 days based on the rate of disease progression (Martinelli *et al.* 2015). These systems, which are frequently mounted on a drone or tractor, are field-scale mapping and the data of disease, with higher capital requirements (5,000 -50,000) than smartphone-based (0-500 per farm) solutions (Sishodia *et al.* 2020).

The Integrated pest and disease management (IPDM) systems are based on the combination of diagnostic AI with data indicators of weather conditions, soil sensors, and pest tracking to provide a recommended and efficient intervention strategy (Patricio and Rieder, 2018). Such decision support systems have proven yield protection strengths that are even better than independent diagnostic aids, and losses are reported to decrease faster by 18-35% than usual practice (van Klompenburg *et al.* 2020). Complexity and data needs might however be a limitation to adoption on small holders contexts.

3. Gaps in Financial Impact Literature

Although there is an increasing literature on technical aspects, the assessment of economic impact is still in a fragmented and methodologically uncertain state. In a systematic review of 127 studies in the field of agriculture AI published between 2018-2023, merely a quarter of these studies also contained a certain economic analysis, with only methodologies diversified significantly among them (Sharma *et al.* 2022). Common limitations include:

Attribution ambiguity support: In numerous studies that indicate improvements in the use of AI-assisted management, contamination of which is not invariably sought, both in fertilization or irrigation The individual efficacy of disease detection (Eli-Chukwu, 2019). There is incomplete cost-accounting: Deployment-costs have many missing components, including farmer training, system maintenance, internet connectivity, or even data-collection labour opportunity cost (Wolfert *et al.* 2017).

Short periods of evaluation: The majority of economic models are evaluated over a single growing period, and these models are not multi-year in nature, as they cannot capture dynamics such as learning curve effects, pest resistance, and technology depreciation (Klerkx *et al.* 2019).

Simplification of market prices: Financial models often use unchanging crop prices, seasonality, or assuming quality or disease-free premiums on agricultural crops, or local market inefficiency which causes substantial divergence of actual earned farmer incomes (Barrett *et al.* 2022).

Geographic bias: Economic studies about the food systems are biased towards highly income agricultural systems (North America, Western Europe) with little validation in the tropical and subtropical areas that have the greatest prevalence of diseases (Bacco *et al.* 2019).

The sum of these gaps in both evidence-based adoption of technologies and policy formulation is a limitation to the achievement that drives the creation of more integrated and streamlined economic evaluation systems.

Framework for Yield Loss Estimation

1. Disease Incidence and Severity Modelling

To measure quantitative loss in yield, the condition of a disease should be captured strongly in terms of characterization of the disease incidence (the proportion of affected plants) and severity (the degree of damage per affected plant). Classical assessment is an ordinal scale (e.g. 0-5 rating), with predetermined yield-loss functions of path systems of major magnitude (Bock *et al.* 2010). As in case of the potato late blight, empirical models have shown that a 1-percentage point increase in disease severity is associated with 0.8-1.2 percentage point decrease in the yield though this varies in response to the time of infection and environmental conditions (Haverkort *et al.* 2016).

AI based disease quantification allows objective steady evaluation of the disease that replaces manual scoring that might be subjective. The algorithms used to do pixel-level segmentation classify diseased tissue proportions as accurately as expert pathologists (DeChant *et al.* 2017). Neither Kronenfeld nor Time warp, sequential image expression, temporal disease progression models are predictive of epidemiological trajectories that enable when to anticipate intervention, or when to not intervene (Khanna *et al.* 2022).

The correlation between the measure of diseases and the yield loss is a crop-specific relation. In case of foliar diseases causing impairment of photosynthetic capacity the temperature corrected loss of precious foliar area (HAD) measure combines temporal development of the disease, and integrity loss of photosynthetic capacity (yield loss (YL)) is modelled as:

$$YL = \beta_0 + \beta_1(\text{HAD\_baseline} - \text{HAD\_infected}) \quad \ldots(1)$$

where β coefficients are crop and disease specific constants that are obtained as controlled experiments (Waggoner and Berger, 1987). Other forms of functional forms with plant physiological models would be required in the case of vascular diseases or root pathogens.

2. Incorporating AI Model Performance Metrics

The accuracy of AI models directly affects the economic value of disease detection systems because of its effects on the efficiency of interventions. A 95% sensitive and 70% specific model produces too many false positive and results in unnecessary treatment therefore increasing costs and even decreasing profitability despite detecting many diseases (Boulent *et al.* 2019).

The formulation of the economies of model performance can be formalized interpret in a decision theoretical model:

$$\begin{aligned}\text{Net Benefit} &= \text{TP} \times (\text{Treatment value} - \text{Treatment cost}) \\ &- \text{FP} \times \text{Treatment cost} - \text{FN} \times \text{Yield loss} \quad \ldots(2)\end{aligned}$$

TP, FP and FN are the true positives, false positives and false negatives respectively. The presented formulation links the measures of classification to the financial performance, which allows to optimize classifying metrics on economic goals instead of focusing exclusively on technical accuracy (Mahlein *et al.* 2018).

The timing of the intervention multiplicatively influences the efficacy of the treatments. In a pre-symptomatic through early-symptomatic (timely) detection, the treatment is normally effective (70-90%), whereas the efficacy of action at late stages becomes significantly lower (20-50) (Fenu & Malloci, 2021). The AI systems with the ability of 5-10 days early warfront in the detection stage over a visual scouting can thus multiply the ROI by an astronomic magnitude even with the slight improvement in accuracy.

Some additional variance comes in the form of environmental and operational factors. Exceptional case of model performance Model performance frequently suffers in the field versus when winter-tested in the lab because of the changing lighting, variability around image quality, variability around disease expression, and novel disease strains (Barbedo, 2018). This performance gap should be reflected in the economic models, which should either assume accuracy changes that are conservative (those that downscale the published data, by 5-15 percent or foundational opportunity limits in the projections of benefits) or risk quantification (benefit limits).

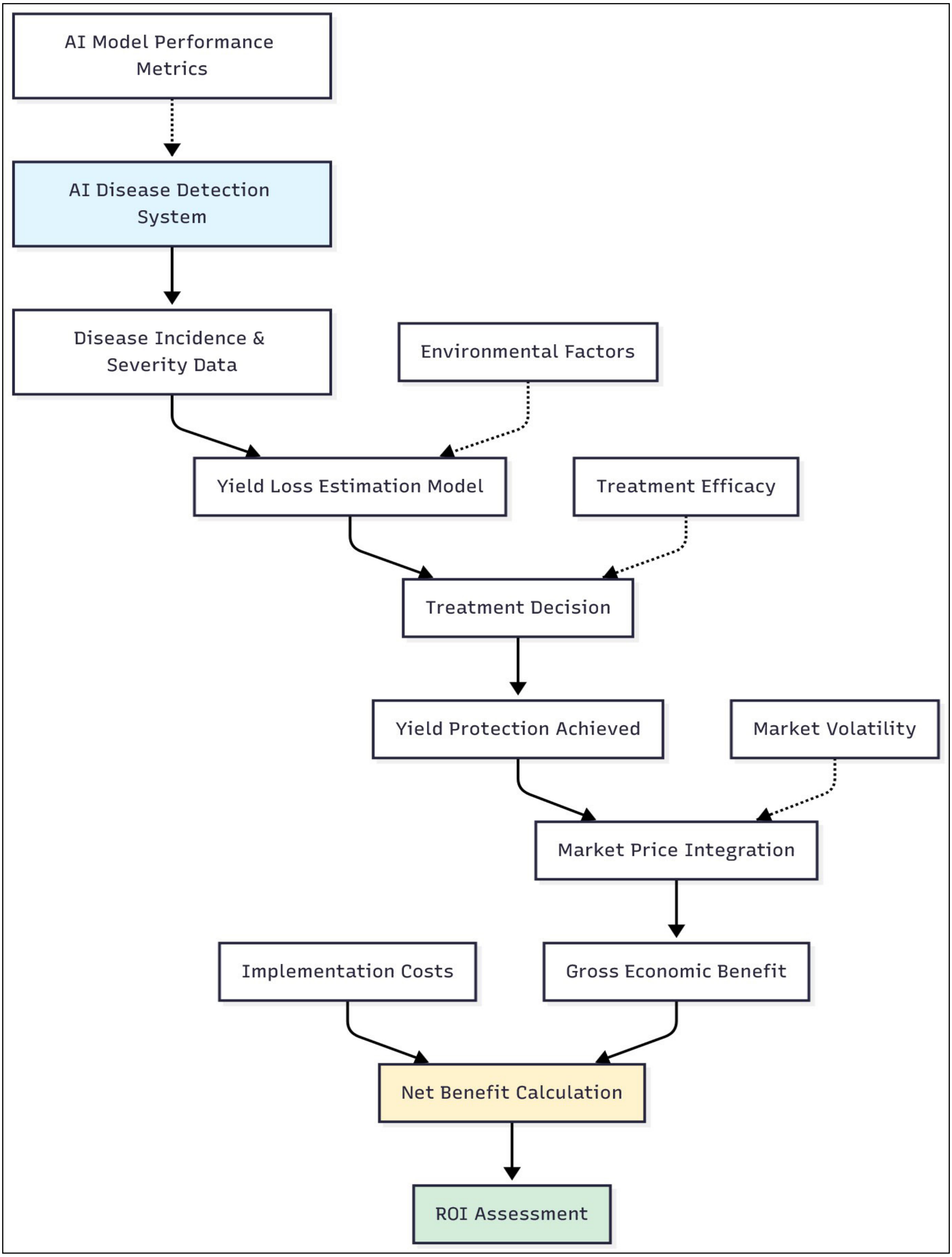

Fig. 1: Integrated Framework for Economic Impact Assessment

Economic Valuation Methodology

1. Mapping Yield Loss to Market Value

There are several markets factors integrated to convert the physical yield loss into financial calculations. The baseline calculation:

$$\text{Financial Loss Averted} = \text{Yield}_{\text{saved}} \times \text{Price} \times \text{Quality}_{\text{premium}} - \text{Treatment}_{\text{cost}} \quad \ldots(3)$$

with $Yield_{saved}$ denoting the additional yield protection credited to AI-based early intervention versus the conventional technique. Nevertheless, this simplistic expression would need a few modifications in order to be applicable in the real world (Janssen, van Ittersum, 2007).

Price volatility: There is a high level of temporal and spatial movements of agricultural products. For instance, prices of wheat fluctuated between 40–120% in 2022–2023, depending on the month and market (FAO, 2023). Conservative ROI analysis with multi-year average price should be included in economic models and stochastic price distribution to provide a definitive ROI estimation should be treated to stochastic price distributions. Effective price risk mitigation can be achieved with forward contracts and crop insurance schemes which change the effective value of yield insurance.

Quality premiums: Presence of the disease has an impact on the quantity of yield, grades and prices in the market. Even with a modest loss in yield, visible damage caused by disease can be deterred by 50-80 percent in products market value such as grapes or tomatoes (Carisse et al., 2020). Certified disease-free status on the other hand can attract huge premiums within seed popster, nursery markets, augmenting the worth of competent disease control than direct production immunity.

Access to the market: In most cases, remote areas with smallholder farmers cause 30-60% references market prices because of the cost of transportation and other margins applied by intermediaries and lack of bargaining (Barrett *et al.* 2022). Farm-gate price realized that are determined by the economic calculations should be incorporated in the economic calculations instead of the urban wholesale price or the international price so as to give an accurate representation of the incentives of farmers.

2. Data Sources and Regional Adaptation

State of the economic modelling involves combination of a wide variety of data streams:

Yield Data: The historical farm records, satellite-derived yield maps or the survey-based production statistics provide baselines and control comparisons. Commercial farming systems can be equipped with high-resolution plots containing yield monitors that can give accurate attribution to the plot size whereas smallholder systems may just have self-report attribution with an element of uncertainty (Lobell *et al.* 2020).

Disease surveillance information: The data generated by the AI system to monitor disease, in the form of records of the time of disease identification, category of disease severity, and spatial models build the baseline of the assignment of yield outcomes to disease pressure and treatment measures (Abdulridha *et al.* 2020).

Market price databases: Price time series are made available by the national agricultural statistics agencies, the commodity exchanges and the regional market information systems.

Standardized data to cross-regional analyses can be found on such platforms as AMIS (Agricultural Market Information System) and regional price bulletins (Tack *et al.* 2017).

Tracking of input costs: Main system costs (hardwares, program licenses, connectivity), operational cost of labour in running systems and other tasks and collection systems, cost of fungicides or treatment, and indirect costs such as cost of maintenance and training of farmers are required in comprehensive cost accounting (Tey and Brindal, 2012).

Economic model adaptation on an extended regional basis should take into consideration agricultural heterogeneity of system. Such factors need localization as prevalent disease complexes (fungicides pathogen differences in tropical and temperate regions differ significantly), input sources and prices (fungicides are frequently inaccessible), labour expenses, education level of farmworkers, and institutional backup systems (Wolfert *et al.* 2017).

ROI Modelling Using Regression Analysis

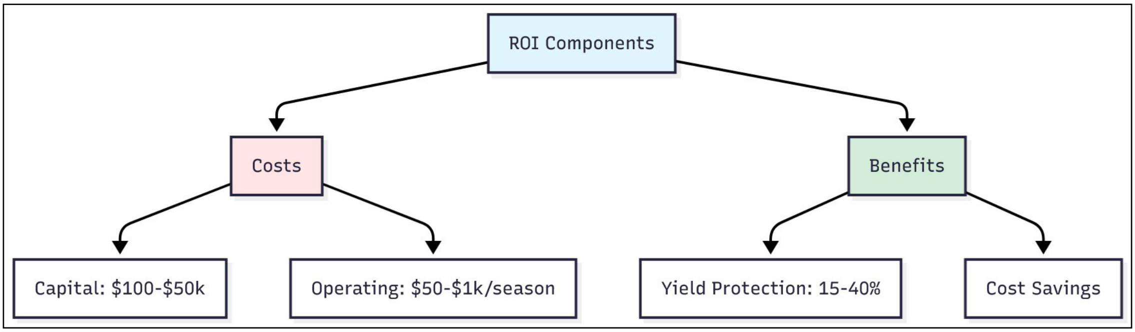

Fig. 2: Cost-Benefit Components Hierarchy

1. Variable Cost Estimation Framework

To enumerate exhaustive calculation ROI, cost categorization in terms of initial cost and ongoing operations should be put in an organized manner. A hierarchical cost model differentiates:

Capital costs (one-time)

- **Hardware:** smart phones, cameras, drones, edge computing devices ($100 - $50000, depending on sophistication of the system).
- **Software Licenses:** proprietary AI systems or open-source (Free-Free) versions ($0$5000) a year.
- **Infrastructure:** connectivity infrastructure, running edge server on farms, ($500$10000).
- **Training and Capacity Building:** first time farmer and extension agent training, (persons) $200 - $2000 per farm.

Operation expenses (daily per season)

- **Connectivity:** costs involved in transmission of data to a cloud system ($50-$500 per season).
- **Maintenance:** servicing of hardware, software updates ($100 - $1000 a year).
- **Labour:** time spent operating systems and taking pictures, implementing responses (10-50 hours per season at local wages).
- **Treatment inputs:** increased price of fungicides used on areas of the disease that are identified ($20-$500 / hectare depending on crop and disease).

Regression analytical model can be used to determine cost organizations and scale economies. A review of 45 cases of AI deployment found that expensive cost per hectare decreases logarithmically with the size of the farm:

$$\text{Cost per ha} = \alpha \times (\text{Farm\_size})^{-0.43} \qquad \text{...(4)}$$

means that scale benefits occur tremendously (Wolfert *et al.* 2017; Schrijver *et al.* 2021). This association presents difficulties to the economic viability of smallholders who lack exceptional expenses as cooperated organizations.

2. Output Benefit Modelling Across Crops

The variability in benefit quantification of different types of crops holds significant level of variance because of the varying economic value, susceptibility to disease, and responsiveness to treatment. The expected benefits have the form of a meta-regression model:

$$\text{Benefit} = \beta_0 + \beta_1(\text{Crop\_value}) + \beta_2(\text{Disease\_pressure}) + \beta_3(\text{Treatment\_efficacy}) + \beta_4(\text{Detection\_advancement}) \qquad \text{...(5)}$$

Estimation of coefficients based on published case studies and field trial data Coefficients may be estimated by empirical calibration:

High-value horticulture (vegetables, fruits): Crop values of 5,000 -30,000/ hectare with low disease pressure (potential loss 30-60 percent) represent high returns. The profits of tomato early blight control have been reported to be 250-420% ROI of AI-oriented systems and 150-200% ROI of conventional IPM rules (Atila *et al.* 2021; Mokhtar *et al.* 2021).

Staple cereals (wheat, rice, maize): Smaller values per-hectare values costing between $ 400 - $ 2000 demand larger scale of adoption in order to be profitable. Asia Rice management had ROI of 180-240 in large farms (> 10 hectares) but 60-120 in smallholdings (< 2 hectares) because it is expensive to manage the blight (Picon *et al.* 2019; Chen *et al.* 2020).

Industrial crops (cotton, sugarcane): Intermediate economic profiles that vary based on the ROI due to the disease pressure in the region. Pakistan demonstrated cotton leaf curl virus management with ROI of 150-300 based on the prevalence of infection break-even had to calm =15.0 disease incidence in the default-case situations (Abade *et al.* 2021).

Perennial crops (coffee, cocoa, vineyards): Due to the duration of the production cycle, as well as elevated costs of establishing the production, the subject of disease prevention increases its value. Early coffee leaf rust solutions recorded ROI more than 300% within a lifetime of 5 years, and the returns could be increased after plant deemed to last (Esgario *et al.* 2020).

These are temporal dynamics of the ROI profiles. The first-year returns are usually not very good as the process of learning curves and non-perfect adoption take parts, whereas the Years 2-3 are the best as farmers learn how to make best use of the system. Adoption maturation functions have to be applied at the multi-year level to prevent false interpretation of pessimistic individual season outcomes using deceptively narrow tools (Klerkx *et al.* 2019).

Case Study Synthesis

1. Sample Crop Systems

1.1. Potato Late Blight (*Solanum tuberosum - Phytophthora infestans*)

Late blight is one of the damaging crop diseases in the world, and an annual deprivation of over 6 billion dollars is recorded by Haverkort *et al.* (2016) across the world. The economic value of the disease has encouraged a huge investment in initial detection technology. Franceschini *et al.* (2021) introduced a universal CNN-powered multispectral camera on a drone above 240 hectares of potted potatoes in the Netherlands to fully implement a dronebased system of early detection of any root occurring. Their system was also found to have a 92 percent detection system and it has actually succeeded in making a critical 6-day advance in the identification of the disease compared to the conventional methods of manual scouting.

The financial estimation done by Franceschini *et al.* (2021) indicated strong financial payoffs of the technology implementation. Over a 3-year period the cost of conducting the implementation exercise could be amortized to an average of 85 per hectare which was a fairly huge investment with regard to production of high-value crops. The system achieved an average yield protection that was 2.8 tonnes per hectare equivalent in 12 percent yield increase as compared to the traditional management methods. This yield protection had the gross benefits of EUR504 per hectare at a prevailing market value given by EUR180 per tonne. Moreover, the ability to target the areas exactly offered by the AI system allows a savings of EUR45 per hectare of costs associated with the treatment through displaying fungicides optimally. The net benefit thus of EUR464 per hectare had fifty-four six percent, ROI. According to Franceschini *et al.* (2021), these high returns are supported by a set of critical success factors such as great baseline disease pressure and losses up to 15-25 per cent, presence of the highly responsive munguxyl-based fungicides with 85 percent efficacy once applied at the initial 2-3 stages of an infection outbreak, and adequate scale of the farm to achieve effective cost amortization of the production site wins.

1.2. Rice Blast (*Oryza sativa - Magnaporthe oryzae*)

Rice blast is a thorn to the food security in the whole of Asia where Skamnioti and Gurr (2009) claim that the disease causes losses in the endemic areas reaching between 10-30%. Based on the specific susceptibility of smallholder farming systems, Kumar *et al.* (2022) implemented a smartphone-based system of diagnosis and combined with the risk models of diseases by weather forecasting on 450 smallholder farms, with an average agricultural area of only 1.2 hectares, in Tamil Nadu, India. Such deployment was very targeted to resource restrictions and scale limitation as in the case of the small holder agriculture in the region.

The results of economic indicators categories in Kumar *et al.* (2022) showed the potential and the difficulties with the adoption of AI in smallholder settings. The project expense amounted to 180 a year of deployment to a 3-year implementation of the system and yield gain per hectare was an average of 520 kg/hectare. These improvements in yield at the local market value of 320 per tonne were corresponding to the gross benefits of $166 per hectare. Nonetheless, Kumar *et al.* (2022) stated that the model of cooperative-based cost sharing became the key that will help to realize the economic feasibility as the individual financial cost was decreased to 60 dollars per farm because of sharing costs on hardware, bargaining capacity, and supporting coordination of all the farms towards the use of the latest agricultural inputs. The yield of net benefit of 138 per hectare had a ROI of 230% in the model of cooperation. Most importantly, Kumar *et al.* (2022) discovered that individual adoption stipulations devoid of collaborative support systems exhibited modestly profitable ROI with an ROI of 45-80 pointing at the essence of the application of organizational innovation in addition to the use of technology in smallholder conditions where fixed costs were disproportionately a barrier to reception.

1.3. Wheat Stripe Rust (*Triticum aestivum - Puccinia striiformis*)

Stripe rust of wheat has had a lot of economic repercussions in temperate wheat-producing world economies. The Abdulridha *et al.* (2020) was running a satellite monitoring system and select ground scouting experiments over 3200 hectares in Washington State, USA, which involved the application of satellite monitoring with remote sensing features of reviewing the expanses on a large scale through targeted scouts across the target area to conduct disease surveillance. Their solution was to use satellite images to detect the first signs and field scanning to confirm the presence of disease since it is a cost-effective mechanism.

According to Abdulridha *et al.* (2020), the economic performance indicated associated with the use of the facilities illustrated intermediate but positive returns typical of both commodity crops systems with less disease potential. This system was a cost of 35 per hectare per annum quite a measure of cheap investment due to economies of scale suggested by the satellite monitoring of extensive contiguous land. There was yield protection of 0.45 tonnes per hectare which was equivalent to 8 percent above conventional management. This amounted to at the market price of $200 per tonne to the gross benefits of 90 per hectare. Notably, the gains associated with potential cost reductions included an extra 42 per hectare cost / savings in the case of Abdulridha *et al.* (2020) who reported that the accuracy of targeting accumulated through the AI system resulted in the elimination of undue fungicide treatment in clean land areas. The net benefit of combining the two was found to be 97/hectare which got a ROI of 277. According to Abdulridha *et al.* (2020), this middle-range ROI indicates the reduced initiative of disease pressure in the area, and losses (are usually 8-12 percent) include the economics of production of wheat products where values of per-hectare are several times lower in relation to horticultural items. The end key to success in this area was landscape scale application, which would allow the cost-effective satellite tracking data infrastructure and accuracy treat dissimilarity apparatus, the capitals of which might be amortized over adequately sizable production zones.

Table 1: Comparative Economic Analysis of AI-Based Disease Detection Systems Across Three Crop Pathosystems

Parameter	**Potato Late Blight (Netherlands)**	**Rice Blast (Tamil Nadu, India)**	**Wheat Stripe Rust (Washington, USA)**
Pathosystem	*Solanum tuberosum Phytophthora infestans*	*Oryza sativa - Magnaporthe oryzae*	*Triticum aestivum - Puccinia striiformis*
Technology Type	Drone-mounted multispectral imaging	Smartphone-based diagnostics + weather models	Satellite monitoring + targeted scouting
Detection Accuracy	92%	Not specified	Not specified
Early Detection Advantage	6 days vs. manual scouting	Integrated risk modelling	Landscape-scale surveillance
Farm Scale	240 hectares	450 farms (avg. 1.2 ha each)	3,200 hectares
Implementation Cost	$85/ha (3-year amortized)	$180/farm ($60 with cooperative)	$35/ha annually
Baseline Disease Pressure	15-25% yield loss	10-30% yield loss	8-12% yield loss
Yield Protection	2.8 tonnes/ha (12% improvement)	520 kg/ha	0.45 tonnes/ha (8% improvement)
Market Value (per tonne)	€180	$320	$200
Gross Benefit	€504/ha	$166/ha	$90/ha
Additional Savings	€45/ha (precision targeting)	N/A	$42/ha (reduced fungicide)
Net Benefit	€464/ha	$138/ha	$97/ha
ROI	546%	230% (cooperative); 45-80% (individual)	277%
Critical Success Factors	High disease pressure, responsive treatments, farm scale	Cooperative cost sharing, collective bargaining	Landscape-scale deployment, satellite economies
Reference	Franceschini *et al.* (2021); Haverkort *et al.* (2016)	Kumar *et al.* (2022); Skamnioti & Gurr (2009)	Abdulridha *et al.* (2020)

2. Comparative Regional Analysis

There is a systematic cross-regional difference based on economics of AI-based disease management in various agricultural conditions.

The substantial user-friendliness of technology in North America and Europe due to the high level of mechanization, big farm size, and well-developed infrastructure provide a positive environment to employ new technologies, and the average ROI will vary between 200-350 per cent (Kamilaris & Prenafeta-Boldu, 2018). Nevertheless, Kamilaris and Prenafeta-Boldu (2018) add such burdens as early investment reluctance and inability to unify the AI systems with the pre-existing farm management systems. These returns, which are relatively high in such locations, are a replica of the ability to exploit economies of scale and technical intrastrain that aid in smooths deployment of technology.

The situation in South Asia is paradoxical as this category of farmers dominates and has a high disease burden against a backdrop of a lack of resources, which forms the steepest benefit and the highest adoption barriers (Javaid *et al.* 2023). It is proven that cooperation models tend to demonstrate better options due to 180 to 280 ROI once noticed (Javaid *et al.* 2023), which is lower in case of an individual adoption and will generate only 40-120 returns. Such a large disparity highlights the dire need to have collective action mechanisms that would overcome the fixed cost barriers that impact the smaller scaled farmers with huge disproportions. The pressure of the disease in the region is so theoretically favourable to the beneficial intervention of AI, but due to limited resources and even separation of landholdings, new forms of organization are mandatory to ensure the economic sustainability of the region.

Sub-Saharan Africa is very unequivocal in the availability and access to infrastructure, access to markets, and institutional reproduction, generating extremely contextual economic performances (Shahhosseini *et al.* 2020). According to Shahhosseini *et al.* (2020), mobile-based diagnostics installed in more connected areas has a ROI of 150-250 which proves the feasibility of the business model when the simplest forms of digital infrastructures are present. Conversely, offline of edge-computing applications that are deployed in physically remote locations with low connectivity promise remunerations modest returns 80-180 per cent of the incremental price of standalone systems and the complexity of sourcing markets with poor infrastructure and low input rates.

The intensive farming technologies of East Asia coupled with the significant level of government aid packages and yielding high-value crops are some of the factors that create a more advantageous environment to adopt AI (van Klompenburg *et al.* 2020). According to Van Klompenburg *et al.* (2020), the average slated ROI in the region is 220-380 percent, which exceeds most of the other parts of the world. Nevertheless, these authors also establish new challenges such as saturation of the market with particular technologies in developed economies and the aspects of demographics such as aging of farmers in some countries such as Japan which might become the limiting factor of the potential of their further expansion despite the generally positive data situation in these economies.

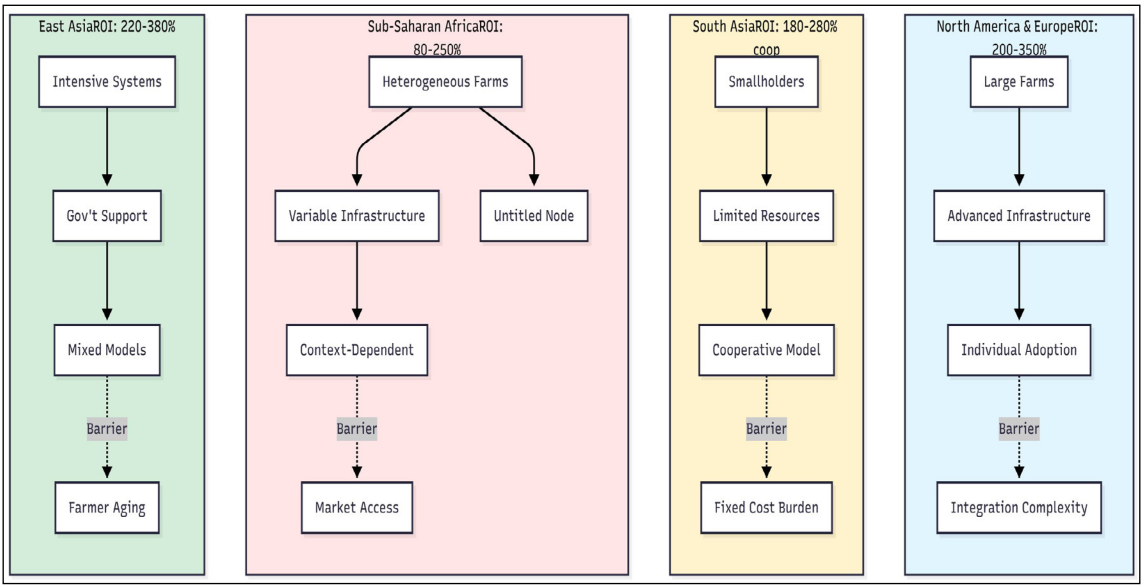

Fig. 3: Regional Adoption Pathways and Barriers

Table 2: Regional Comparison of AI-Based Crop Disease Management Economics and Adoption Contexts

Region	**Agricultural Characteristics**	**Infrastructure & Support**	**Average ROI Range**	**Adoption Model**	**Primary Barriers**	**Primary opportunities**	**Reference**
North America & Europe	Large-scale mechanized farming; high technical - capacity	Advanced digital infrastructure; established farm management systems	200-350%	Individual farm adoption; commercial service providers	Initial investment hesitancy; system integration complexity	Economies of scale; existing technical expertise; stable markets	Kamilaris & Prenafeta Boldu (2018)
South Asia	Smallholder dominance (avg. ¡2 ha); high disease pressure	Limited infrastructure; variable connectivity; strong cooperative tradition	180-280% (cooperative); 40-120% (individual)	Cooperative/ collective models essential	Fixed cost barriers; fragmented landholdings; limited capital	High disease burden creates strong incentive; government support potential	Javaid *et al.* (2023)
Sub-Saharan Africa	Extreme heterogeneity; mixed smallholder & commercial farms	Highly variable; urban rural digital divide	150-250% (connected areas); 80180% (remote areas)	Context dependent; mobile-based in connected regions; edge computing in remote areas	Infrastructure gaps; market access limitations; institutional weakness	Mobile technology penetration; high disease losses; development program support	Shahhosseini *et al.* (2020)
East Asia	Intensive agriculture; high value crops; aging farmer population	Strong government support; advanced infrastructure; high digitalization	220-380%	Mix of individual and cooperative; government subsidized programs	Market saturation; demographic challenges (aging); high expectations	Government investment; intensive production systems; premium markets	van Klompenburg *et al.* (2020)

Insights, Limitations, and Policy Implications

1. Key Insights on Economic Viability

Comparative analysis in various settings shows that there are a number of generalizable principles:

Scale economies are dominated by profitability: The per-unit costs are decreasing sharply as the farm size or scale of collective adoption increase. Break-even will usually entail individual farms of over 5-10 hectares or cooperation ones with 50+ hectares that rely on crop economics (Wolfert *et al.* 2017).

The pressure on the disease makes returns: There is an overall optimum sensitivity of ROI to underlying disease incidence. Systems that are installed in low-pressure settings (losses to the baseline) seldom perform with an appealing payoff except where affordable products of very high value are dealt with. Risk assessment of the pre-deployment disease is necessary (Martinelli *et al.* 2015).

The responsiveness of the treatment approach: Unless there are economically viable and effective treatments available even the most effective detection of the disease offers minimal value. This especially concerns viral infections and microbes about which there are few promotion criteria (Ferentinos, 2018).

The values of integration are increased: When kept separate, diagnostic systems do not perform well unlike the system of integrated decisions support that encompasses disease diagnosis using weather prediction, input optimization, and intermingles markets. Nonetheless, integrated systems create challenges to complexity and training needs as well (Patricio & Rieder, 2018).

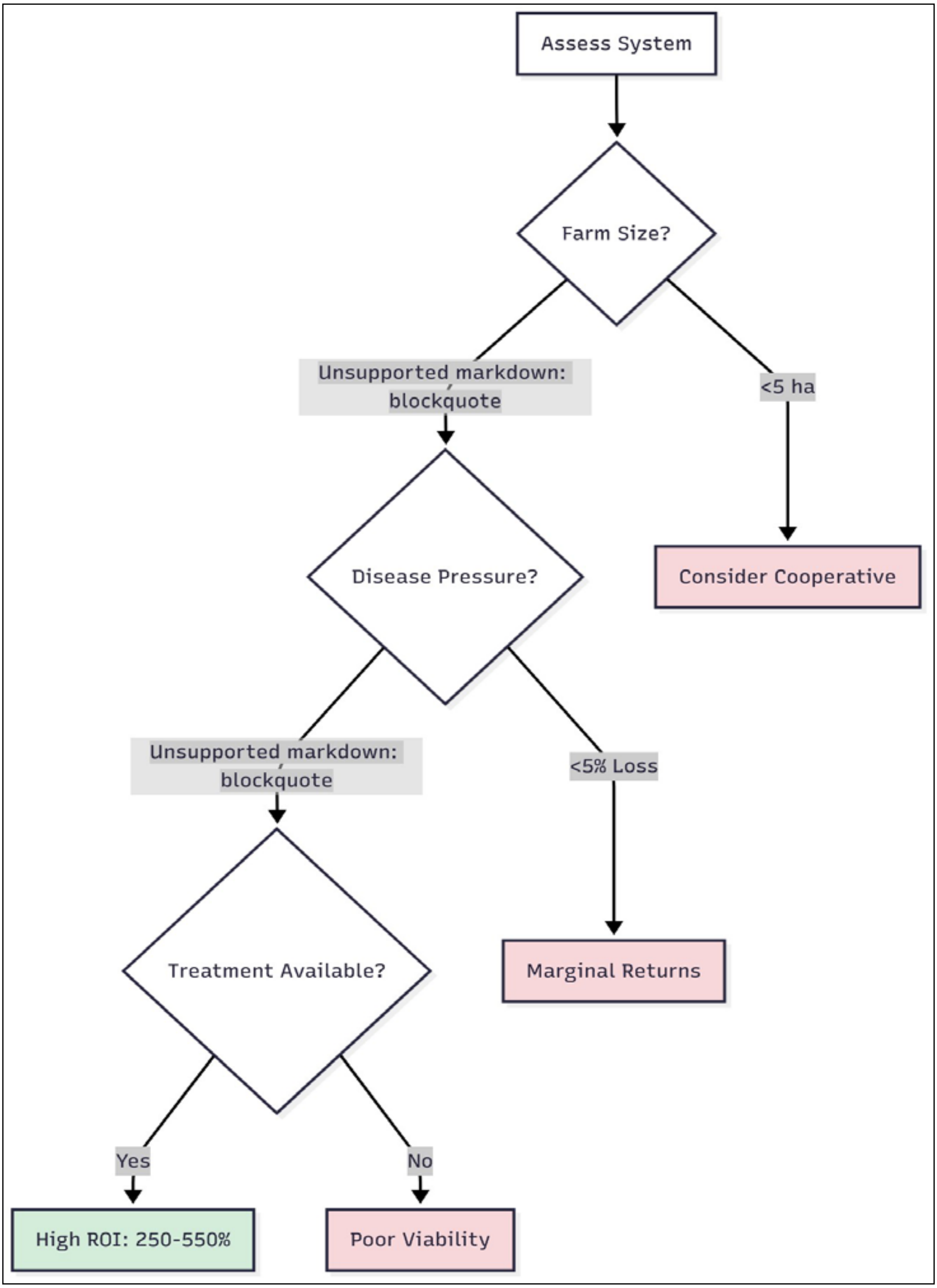

Fig. 4: Decision Tree for Technology Adoption Viability

2. Methodological Limitations

The existing methods of economic assessment are limited in a number of ways:

Attribution problems: From a methodological standpoint, it is hard to isolate disease discovery benefits within the presence of management benefits (precise fertilization, optimized irrigation) of simultaneous interest. There are resource-intensive experimental designs with the necessary controls, which are hardly ever used on large scale (Eli-Chukwu, 2019).

Exclusions of externality: The previously mentioned technologies usually only include benefits to the society at large (less environmental impact of pesticides, better rural jobs in form of technical services), and excludes spill overs of knowledge to non-users. These social costs can even vindicate ex ante government spending despite the existence of unshovel-head privately.

Dynamic complexity: Changes in long-term system dynamics (pest and pathogen adapting), effects of climate change on disease pressure, market structure development, and technology obsolescence are not well modelled with static models (Liakos *et al.* 2018).

Limitations in data quality: Yield and disease data of smallholder-managed systems often have substantial measurement errors, recall bias, non-random missing data points and these do not create reliable statistics at all (Barrett *et al.* 2022).

3. Policy Recommendations for Accelerated Adoption

Policy interventions that may help to ensure an economically viable use of AI would include:

Tiered subsidy plans: Social cost-saving determined by farm size and local economic suppositions. Proposed structure: 70-80 percent subsidy to the smallholders (below two hectares), 50-60 percent to medium farms (between two and ten hectares), 20-30 percent to large farms (more than ten hectares), non-renewable so as to promote dependency (Tey and Brindal, 2012).

Cooperative promotion: Power and money is institutional surrounding of farmer cooperatives and producer entities coalition investments in technology with the purpose of the scale epochs without declining the exposure of the smallholders (Javaid *et al.* 2023).

Public diagnostic services: Diagnostic facilities run by the government or on a PPP model offer AI-based identification of diseases as an additional service, and the access to technology and the need to own technology separately (Kamilaris and Prenafeta-Boldu, 2018).

Market linkage integration: Integrating disease management and quality certification and premium market access will find more value capture possibilities than yield protection. AI-certified low-disease-produced certification schemes can help increase returns (Carisse *et al.* 2020).

Research infrastructure: Continuous monitoring networks have been established as a long-term commitment to produce standardized data which will help validate the economy, accumulate evidence and have this refinement in the models across regions and crops (Savary *et al.* 2019).

Conclusion and Future Research Directions

1. Summary of Key Findings

In this review, it is determined that AI-based fruit disease detection systems have potential to yield high-economic returns given the right conditions, and ROI is likely to be 150400 percent over 3-years in varying cattle systems. The economic viability, however, is most affected by the specific circumstances of the environment, the major determinants in which are the size of the farm, the level of disease pressure, the value of crops in the market and institutional support structures. The suggested comprehensive framework that links disease incidence modelling, AI performance metrics and market-versatile valuation presents the means of market responsive valuation as a repeatable market responsive way of conducting economic impact assessment. Standardized metrics still have critical gaps, essential length-term validation, interventions with smallholder specifics (where needs are farther and adoption barriers most intense) still require a system adjustment. Targeted policy support and cooperative organizational models are promising as establishing this gap, but they are not well assessed by rigorous impact evaluation.

2. Priority Research Directions

Research work should focus on future should include:

Longitudinal impact studies: A series of follow-up studies over multiple divisions that are grounded in adoption patterns, learning experiences, and the benefits of extended postimplementation to correct one-year designs and establish realistic ROI expectations (Klerkx *et al.* 2019).

Climate adaptation modeling: Risk and economic impact modeling to incorporate climate change in the scenarios, as projections might imply the displacement of certain pathogens and the emergence of new areas suitable for crops within the next decades (Challinor *et al.* 2014).

Smallholder-specific innovations: Systems and organizational models aimed at simplifying and reducing costs of farms below their current economic cross-over point should be developed and tested, possibly in the form of shared equalling, mobile diagnostic care or integrated agricultural advisory services (Wolfert *et al.* 2017).

Impact attribution methods: Better attribution in observational designs where there is no feasibility of a randomized trial should rely on advanced techniques of attribution through causal inference (instrumental variables, synthetic controls, machine learning-based matching) (Lobell *et al.* 2020).

Quantification of externality: Quantitative measurements [environmental benefits (less pesticide application), health effects, knowledge spill overs, and food security provision to inform social cost-benefit analysis in the use of that estimative outcome to guide social investment (Barrett *et al.* 2022).

Top-of-technology: The new technologies, such as hyperspectral sensors, environmental DNA detection, and integrated pest and disease management AI, can be used to explore the new opportunities, and their economic viability is being examined (Martinelli *et al.* 2015).

The combination of the rising status of AI, the falling cost of sensors, and the ever-increasing awareness of the benefits of precision agriculture presents unprecedented opportunity of undergoing economically sustainable disease management change. The possibility of realizing this potential depends on further research which strengthens the existing evidence foundation, policy programs that minimize adoption barriers, and technology programs with a high priority on both accessibility and performance.

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