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IMPROVING COMPETITIVENESS IN INTERNATIONAL MARKETS THROUGH THE APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN FRUIT AND VEGETABLE EXPORTS

Abstract. The intensification of competition on international horticultural markets has turned the modernization of fruit and vegetable export chains into a strategic priority for agro-exporting economies. This study examines how artificial intelligence (AI) technologies can be deployed across the export value chain to strengthen the international competitiveness of fruit and vegetable producers and exporters. Drawing on the case of Uzbekistan — one of the world's leading exporters of dried apricots, plums, raisins and fresh stone fruit — the paper combines secondary foreign-trade statistics with primary survey data collected from 142 fruit and vegetable exporting enterprises. A conceptual framework is developed that links five families of AI technologies (computer vision, machine-learning forecasting, IoT-enabled cold-chain analytics, natural-language market intelligence, and AI-based traceability and buyer-matching) to five stages of the export value chain and to four competitiveness outcomes. Revealed comparative advantage analysis confirms a strong but quality-constrained export position. Multiple regression analysis demonstrates that the firm-level AI Adoption Index is the strongest predictor of the Export Competitiveness Index ($\beta = 0.474$; $p < 0.001$) and that the full model explains 62.4% of its variance. Enterprises in the highest AI-adoption quartile achieved, on average, a 23% higher unit export price, a 41% lower consignment rejection rate and almost twice the market diversification of low-adoption firms. The paper concludes with a staged policy and managerial roadmap for AI-driven competitiveness upgrading.

Keywords: *artificial intelligence; export competitiveness; fruit and vegetable exports; agricultural value chain; post-harvest losses; machine learning; revealed comparative advantage; Uzbekistan.*

Annotatsiya. Xalqaro bog'dorchilik bozorlari raqobatining kuchayishi meva-sabzavot eksport zanjirlarini modernizatsiya qilishni agroeksportga yo'naltirilgan iqtisodiyotlar uchun strategik ustuvor vazifaga aylantirdi. Mazkur tadqiqot sun'iy intellekt (SI) texnologiyalarini eksport qiymat zanjiri bosqichlarida qo'llash orqali meva-sabzavot ishlab chiqaruvchilari va eksportyorlarining xalqaro raqobatbardoshligini qanday mustahkamlash mumkinligini tahlil qiladi. Tadqiqot dunyodagi yetakchi quritilgan o'rik, olxo'ri, mayiz va yangi danakli mevalar eksportchilaridan biri hisoblangan O'zbekiston misolida olib borilgan bo'lib, unda tashqi savdo bo'yicha ikkilamchi statistik ma'lumotlar hamda 142 ta meva-sabzavot eksport qiluvchi korxonalar o'rtasida o'tkazilgan so'rovnoma natijalari uyg'unlashtirilgan. Tadqiqotda sun'iy intellektning besh turdagi texnologiyalari (kompyuter ko'rishi, mashinaviy o'qitishga asoslangan prognozlash, IoT asosidagi sovuq zanjir tahlili, tabiiy tilga asoslangan bozor intellekti hamda SI asosidagi kuzatuv va xaridorlarni moslashtirish tizimlari) eksport qiymat zanjirining besh bosqichi va raqobatbardoshlikning to'rtta natijasi bilan bog'lovchi konseptual model ishlab chiqilgan. Aniqlangan qiyosiy ustunlik (RCA) tahlili O'zbekistonning eksport salohiyati yuqori ekanligini, biroq sifat bilan bog'liq cheklovlar mavjudligini ko'rsatdi. Ko'p omilli regressiya tahlili korxona darajasidagi SIni qo'llash indeksi Eksport raqobatbardoshligi indeksining eng kuchli bashorat qiluvchi omili ekanligini aniqladi ($\beta = 0.474$; $p < 0.001$) hamda model umumiy dispersiyaning 62,4 foizini izohlashini ko'rsatdi. Sun'iy intellektni qo'llash darajasi yuqori bo'lgan korxonalar past darajadagi korxonalarga nisbatan o'rtacha 23 foiz yuqori eksport birligi narxiga, 41 foiz kamroq yuk partiyalarining rad etilish holatlariga va deyarli ikki barobar kengroq bozor diversifikatsiyasiga erishgan. Tadqiqot yakunida sun'iy intellekt asosida raqobatbardoshlikni oshirishga qaratilgan bosqichma-bosqich davlat siyosati va boshqaruv yo'l xaritasi taklif etilgan.

Kalit so‘zlar: sun’iy intellekt; eksport raqobatbardoshligi; meva-sabzavot eksporti; qishloq xo‘jaligi qiymat zanjiri; hosildan keyingi yo‘qotishlar; mashinaviy o‘qitish; aniqlangan qiyosiy ustunlik; O‘zbekiston.

INTRODUCTION

International trade in fresh and processed fruit and vegetables has expanded faster than trade in most other agro-food categories over the past two decades, driven by rising incomes, year-round consumer demand, the diffusion of cold-chain infrastructure and the liberalization of agricultural markets. For middle-income and developing economies with favourable agro-climatic endowments, horticultural exports represent one of the few avenues for diversifying away from raw commodities towards higher value-added, employment-intensive activity. Yet the same products are biologically perishable, highly heterogeneous in quality, and subject to increasingly demanding sanitary, phytosanitary and private-standard requirements in destination markets. Competitiveness in this segment is therefore determined not by price alone but by a firm’s ability to deliver consistent quality, verifiable safety, reliable volumes and timely delivery — a combination that is difficult to achieve with traditional, experience-based management practices.

Competitiveness, following the classical formulation of Porter, is understood here as the sustained ability of firms and industries to design, produce and market products that compare favourably with those of rivals on both price and non-price attributes. In horticultural exports, non-price attributes — grade uniformity, residue compliance, traceability, shelf life and the speed and dependability of logistics — have become the principal battleground. A persistent obstacle for emerging exporters is the high level of post-harvest loss: empirical reviews place losses for fruit and vegetables in developing countries in the range of 20–40% of harvested volume, with cold-chain deficiencies alone capable of destroying more than 30% of perishable produce before it reaches the consumer. Each unit of avoidable loss simultaneously raises unit cost, depresses the average grade of exportable output and erodes the reliability on which long-term buyer relationships depend.

Uzbekistan offers an instructive setting in which to study these dynamics. The country is among the world’s most specialized horticultural exporters: in January–November 2025 it shipped slightly more than 2.0 million tonnes of fruit and vegetables worth about 1.94 billion US dollars, a 36.8% increase in value over the comparable period of the previous year, with melons and tree-nut segments growing especially rapidly. National statistics rank the country third in the world for exports of dried apricots and plums, seventh for raisins and peaches, eighth for sweet cherries and thirteenth for grapes. This pronounced revealed specialization coexists, however, with well-documented structural weaknesses — fragmented smallholder supply, uneven grading, limited certified cold storage, a narrow set of destination markets and recurrent consignment rejections — that cap the unit values Uzbek exporters can capture. The policy ambition of lifting food exports beyond 3 billion US dollars consequently depends less on expanding volumes than on upgrading the quality, compliance and market intelligence of the export chain.

Artificial intelligence has emerged as a general-purpose technology capable of addressing precisely these constraints. Computer-vision and deep-learning systems perform non-destructive grading and defect detection at speeds and consistency unattainable by manual inspection; machine-learning models forecast demand, prices and optimal harvest timing; IoT sensors coupled with predictive analytics monitor temperature, humidity and ethylene along the cold chain and estimate remaining shelf life; natural-language processing converts fragmented regulatory texts and market signals into actionable intelligence; and AI-enabled traceability and buyer-matching platforms reduce information asymmetry between exporters and international purchasers. A growing body of evidence reports tangible gains — computer-vision sorting cutting post-harvest losses by up to 30%, AI-optimized cold storage reducing spoilage of perishables by as much as 60%, and machine-learning demand forecasting lowering inventory costs by 15–25%.

These applications are best understood as components of a broader transition often labelled Agriculture 4.0, in which sensing, connectivity, data and machine intelligence are progressively embedded throughout the agro-food chain. For agro-exporting economies the transition carries a double-edged significance. On one hand, AI offers a means of partially leapfrogging structural disadvantages, allowing firms with limited capital but favourable agro-climatic conditions to compete on quality and reliability rather than on price alone. On the other hand, because adoption is concentrated among well-resourced firms in advanced economies, the diffusion of AI also threatens to widen the productivity and quality gap between leading and lagging exporters — a digital divide that could erode the comparative advantage of countries that fail to act in time. Understanding the conditions under which AI adoption actually delivers competitiveness gains, and how those conditions can be created through deliberate policy, is therefore not merely a managerial question but a development one.

Despite this evidence, the scholarly literature remains fragmented in a way that limits its usefulness for export-oriented policy. Most studies analyse AI at the level of on-farm production or examine a single function — grading, yield prediction or traceability — in isolation. Comparatively few works treat export competitiveness as the explicit, multidimensional outcome variable, or trace systematically how distinct families of AI technology act on the successive stages of the export value chain of an emerging horticultural economy. The empirical question of how far firm-level AI adoption actually translates into measurable competitiveness gains, and which barriers slow that translation, is still largely open.

This paper addresses that gap. Its aim is to develop and empirically test an integrated framework linking AI technologies to the international competitiveness of fruit and vegetable exporters. Three objectives follow: (i) to construct a conceptual model mapping AI technology families to value-chain stages and competitiveness outcomes; (ii) to measure the current level of AI adoption among exporting enterprises and to estimate its statistical effect on export competitiveness; and (iii) to identify the principal barriers to adoption and to derive a staged policy and managerial roadmap. The study is guided by three research questions — RQ1: How are AI technologies distributed across the fruit and vegetable export value chain, and at what level are they currently adopted? RQ2: To what extent does firm-level AI adoption explain variation in export competitiveness once firm characteristics are controlled for? RQ3: What barriers constrain adoption, and how can they be sequenced for policy action? Two hypotheses are tested: H1 — firm-level AI adoption is positively and significantly associated with export competitiveness; H2 — the association remains significant after controlling for firm size, export experience, cold-chain capacity and certification status.

RESULTS AND DISCUSSION

The study adopts an explanatory sequential mixed-methods design. A quantitative core — secondary trade-statistics analysis and a structured firm survey — is complemented by qualitative expert interviews used to interpret the statistical findings and to refine the conceptual framework. This design is appropriate because the research seeks both to quantify an association (AI adoption and competitiveness) and to explain the mechanisms and barriers that lie behind it. The empirical work was conducted between March and October 2025.

The conceptual framework, presented in Figure 1, organizes the analysis into three layers. The technology layer comprises five families of AI applications relevant to horticultural exports: computer vision and deep learning; machine-learning forecasting and predictive analytics; IoT-enabled cold-chain and shelf-life monitoring; natural-language processing for market and regulatory intelligence; and AI-based traceability, blockchain and buyer-matching. The value-chain layer comprises five sequential stages: pre-harvest and harvest planning; post-harvest handling, sorting and grading; storage and cold-chain logistics; compliance, certification and traceability; and marketing, buyer access and trade logistics. The outcome layer specifies four competitiveness levers through which AI is expected to act: higher and more consistent product quality; lower post-harvest losses and unit cost; faster and more reliable standards compliance; and wider, better-diversified market access. The framework's central proposition is that AI technologies do not improve competitiveness directly but by reconfiguring specific value-chain activities, and that their combined effect is observable as an improvement in revealed comparative advantage and in firm-level competitiveness indicators.

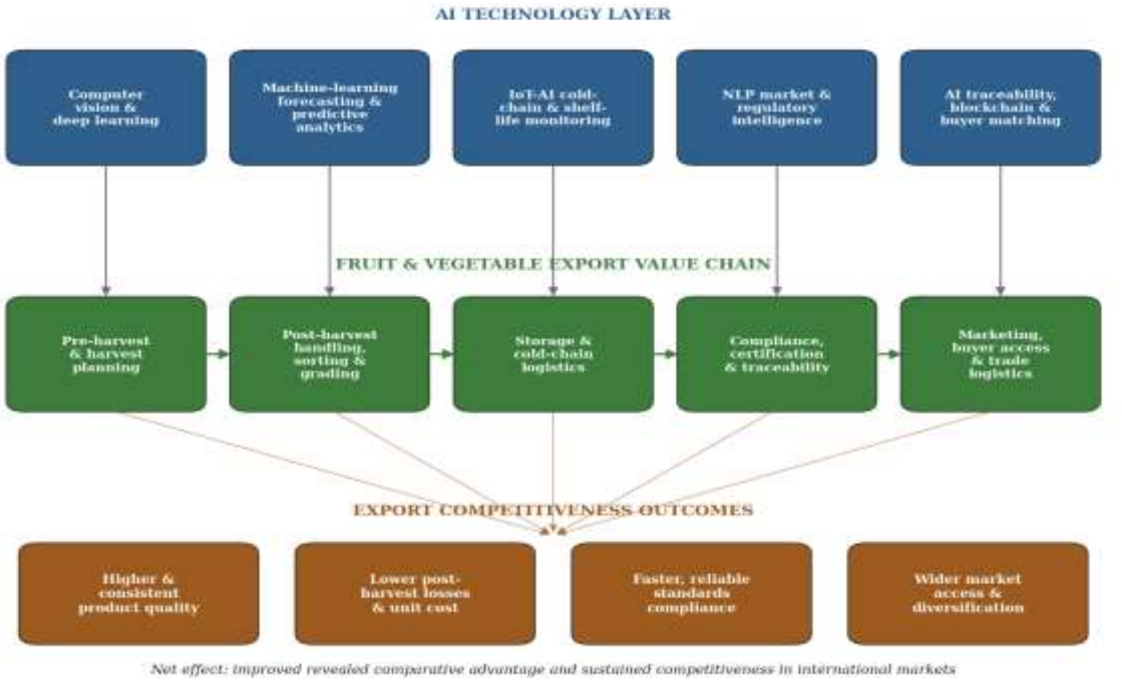

Figure 1. Conceptual framework: AI technologies, the fruit and vegetable export value chain, and competitiveness outcomes (developed by the author).

Two composite constructs were operationalized. The AI Adoption Index (AIAI) measures the breadth and depth of AI use at the firm level. For each of eight AI application categories, respondents indicated the depth of use on a five-point scale (0 = not used; 1 = aware/piloting; 2 = partial use; 3 = routine use; 4 = integrated and data-driven). Category scores were summed and rescaled to a 0–100 range. The Export Competitiveness Index (ECI) is a 0–100 composite of five equally weighted, standardized indicators: the unit value of exports relative to the sample median; the number of destination markets served; the consignment rejection or return rate (reverse-coded); the share of output sold to repeat buyers; and the breadth of valid quality and safety certifications. At the industry level, revealed comparative advantage was measured with the Balassa index, defined as the ratio of a product's share in national exports to its share in world exports; values above unity indicate revealed comparative advantage.

Secondary data on export values, volumes, destination structure and product composition were drawn from the official statistics of the national statistics authority and from international trade databases for the period 2019–2025. Primary data were obtained through a structured questionnaire administered to fruit and vegetable exporting enterprises. The sampling frame was compiled from registers of agro-exporters; a stratified sampling procedure was used to ensure representation across enterprise size and producing region. Of 175 enterprises approached, 142 returned usable questionnaires, a response rate of 81.1%. The questionnaire contained four blocks: firm profile; AI adoption across the eight application categories; export performance and competitiveness indicators; and perceived barriers to adoption. Barrier items were rated on a five-point importance scale. The instrument was pre-tested with twelve enterprises and refined for clarity; qualitative depth was added through fourteen semi-structured interviews with exporters, agronomists and trade officials.

Analysis proceeded in four steps. First, descriptive statistics and Balassa indices characterized the export structure and its competitive position. Second, the level and pattern of AI adoption were summarized across the eight application categories. Third, Pearson correlation analysis examined bivariate associations between AI adoption, control variables and the ECI. Fourth, ordinary-least-squares multiple regression estimated the effect of the AI Adoption Index on the Export Competitiveness Index while controlling for firm size (an ordinal measure based on employment), export experience (years of exporting), cold-chain capacity (a 0–100 index of owned or contracted refrigerated storage and transport) and certification status (a dummy equal to one for firms holding GlobalGAP or ISO food-safety certification). Regression diagnostics included variance-inflation factors to check multicollinearity, the Breusch–Pagan test for heteroscedasticity and the Durbin–Watson statistic for residual independence; robust standard errors were used as a precaution.

Content validity was established through expert review of the questionnaire by six specialists in agricultural economics and digital agriculture. Internal consistency was satisfactory: Cronbach's alpha was 0.88 for the AI Adoption Index and 0.81 for the Export Competitiveness Index, both above the 0.70 threshold. Three limitations should be acknowledged. The design is cross-sectional, so the regression identifies association rather than strict causation; AI adoption and competitiveness may be mutually reinforcing. Several variables rely on managerial self-report and may carry response bias. Finally, the evidence is drawn from a single national context, which aids internal consistency but limits direct generalization; the conceptual framework, however, is intended to be transferable to comparable horticultural exporters.

The central hypothesis was tested with the following linear specification, estimated by ordinary least squares:

$$ECIi = \beta 0 + \beta 1 \cdot AIAIi + \beta 2 \cdot CCCi + \beta 3 \cdot CERTi + \beta 4 \cdot SIZEi + \beta 5 \cdot EXPi + \varepsilon i$$

where ECI is the Export Competitiveness Index of firm i; AIAI is the AI Adoption Index; CCC is the cold-chain capacity index; CERT is the certification dummy; SIZE is the ordinal firm-size measure; EXP is years of export experience; and ε is the error term. Hypothesis H1 predicts $\beta_1 > 0$ in a bivariate model, and H2 predicts that β_1 remains positive and statistically significant in the full specification above. The coefficient of determination, the adjusted coefficient of determination and the F-statistic were used to assess overall model fit, and standardized coefficients were computed to permit comparison of the relative strength of predictors measured on different scales.

The Balassa analysis confirms a strongly specialized but quality-sensitive export profile. As Table 1 shows, dried apricots, dried plums, raisins, sweet cherries, melons and legumes all record revealed comparative advantage indices far above unity, indicating that the country exports these products in proportions well above the world average. The very high indices for dried fruit reflect both agro-climatic endowment and decades of accumulated processing experience. However, the indices for fresh produce — table grapes and especially fresh tomatoes — are markedly lower, and qualitative interviews attribute this gap chiefly to quality inconsistency, cold-chain limitations and difficulty in meeting destination-market standards rather than to any deficit of growing capacity. Revealed comparative advantage, in other words, is robust where post-harvest sophistication is highest and fragile where it is weakest.

Table 1.

Revealed comparative advantage (Balassa index) for selected horticultural product groups

Product group	Balassa RCA index	World export rank	Competitive status
Dried apricots	41.3	3rd	Very strong advantage
Dried plums (prunes)	15.6	3rd	Very strong advantage
Raisins (dried grapes)	11.8	7th	Strong advantage
Sweet cherries (fresh)	8.4	8th	Strong advantage
Fresh apricots	7.1	–	Strong advantage
Melons and watermelons	6.7	–	Strong advantage
Kidney and mung beans	9.0	–	Strong advantage
Table grapes (fresh)	5.2	13th	Moderate advantage
Tomatoes (fresh)	2.3	–	Modest advantage

Source: author's estimates based on national and international trade statistics, 2024–2025. RCA > 1 indicates revealed comparative advantage.

The 142 responding enterprises are dominated by micro and small firms, which together account for almost three-quarters of the sample, with medium and large exporters forming the remainder (Table 2). Export experience is similarly skewed towards younger firms, although a substantial group has more than seven years of exporting activity. This structure mirrors the wider population of horticultural exporters and is important for interpreting the results, because firm scale and experience are themselves expected to influence both the capacity to adopt AI and competitive performance, and are therefore controlled for in the regression.

Table 2.

Profile of surveyed exporting enterprises (n = 142)

Characteristic	Category	Firms (n)	Share (%)
Enterprise size	Micro (1–10 employees)	45	31.7
	Small (11–50)	61	43.0
	Medium (51–250)	26	18.3
	Large (> 250)	10	7.0
Export experience	Under 3 years	32	22.5
	3–7 years	59	41.5
	8–15 years	38	26.8
	Over 15 years	13	9.2
Main export line	Dried fruit and nuts	52	36.6
	Fresh fruit and berries	51	35.9
	Fresh vegetables and melons	39	27.5

Source: author's enterprise survey, 2025.

AI adoption among horticultural exporters is at an early stage and uneven across functions. The mean AI Adoption Index for the sample is only 27.4 points out of 100 (standard deviation 19.6), and the distribution is right-skewed, indicating that a small group of advanced adopters coexists with a large majority of firms that use AI minimally or not at all. As Table 3 and Figure 2 show, adoption is highest in computer-vision quality grading and sorting (28.9% of firms), precision-agriculture yield prediction (26.1%) and digital buyer-matching platforms (23.9%), and lowest in the more knowledge-intensive functions of predictive cold-chain analytics (16.2%), AI-based logistics optimization (14.8%) and natural-language market and regulatory intelligence (12.0%). Mean use-intensity scores never exceed 1.4 on the 0–4 scale, confirming that even where AI is present it is rarely integrated into routine, data-driven decision-making.

Table 3.

AI adoption across application categories (n = 142)

AI application category	Adoption rate (%)	Mean use intensity (0–4)	Primary value-chain stage
Computer-vision quality grading and sorting	28.9	1.41	Post-harvest handling
Precision-agriculture yield prediction	26.1	1.18	Pre-harvest planning
Digital buyer-matching platforms	23.9	1.07	Marketing and access
Machine-learning demand and price forecasting	21.1	0.92	Marketing and access
AI traceability and compliance documentation	19.7	0.86	Compliance and certification
Predictive cold-chain / shelf-life analytics	16.2	0.71	Storage and logistics

AI logistics and route optimization	14.8	0.63	Storage and logistics
NLP market and regulatory intelligence	12.0	0.49	Marketing and compliance
Overall AI Adoption Index (0–100)	**27.4**	**SD = 19.6**	**All stages**

Source: author's enterprise survey, 2025.

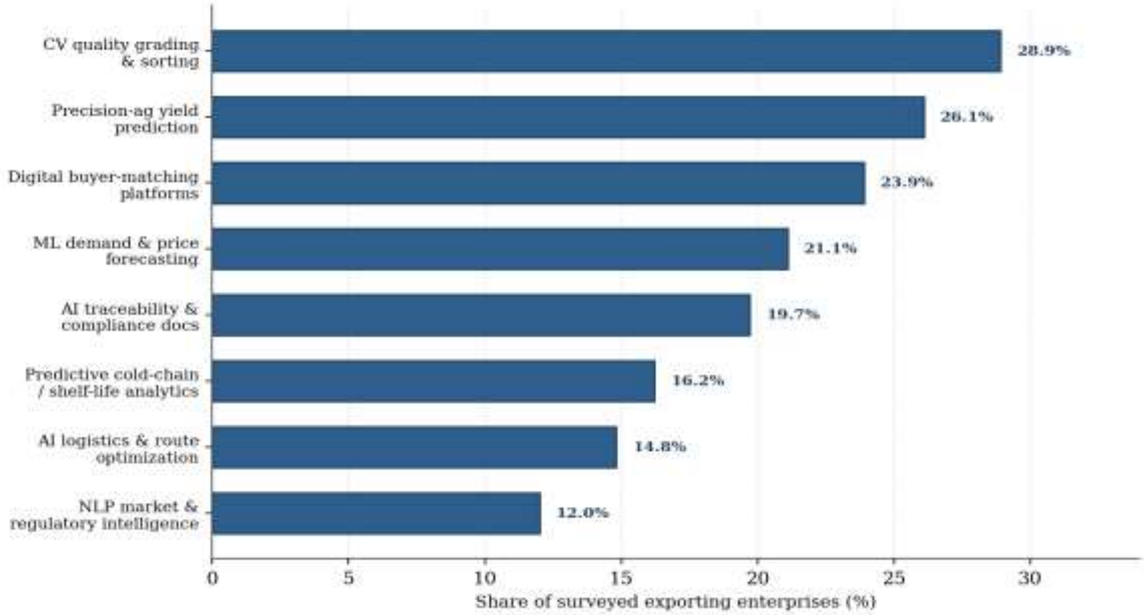

Figure 2. Adoption rate of AI applications among surveyed fruit and vegetable exporters (% of firms).

Table 4 consolidates the survey evidence and the interview material into an explicit mapping of AI technologies onto value-chain stages, the competitiveness lever each activates, and the magnitude of effect reported in the wider literature and corroborated by interviewees. The mapping makes clear that AI is not a single intervention but a portfolio whose components address different competitive weaknesses. For emerging horticultural exporters, the post-harvest grading and cold-chain stages are pivotal: they are simultaneously where losses are largest, where buyers form their quality judgements, and where AI applications are technically most mature.

Table 4.

AI technologies, value-chain stages and competitiveness effects

Value-chain stage	Representative AI technologies	Competitiveness lever	Reported / expected effect
Pre-harvest and harvest planning	ML yield prediction; satellite and weather analytics; optimal harvest-timing models	Volume reliability; quality at harvest	Better matching of supply to contracts; reduced over- and under-supply
Post-harvest handling, sorting and grading	Computer vision; deep-learning defect detection; hyperspectral imaging	Quality consistency; lower loss	Post-harvest losses cut by up to 30%; uniform export grades
Storage and cold-chain logistics	IoT sensors with predictive analytics; shelf-life and spoilage models	Lower loss; longer market reach	Spoilage of perishables reduced by up to 60% under AI-optimized storage
Compliance, certification and traceability	AI document processing; blockchain-	Faster, verifiable compliance	Lower rejection risk; faster certification;

	linked traceability; residue-risk models		reduced food-fraud exposure
Marketing, buyer access and trade logistics	NLP market intelligence; demand and price forecasting; buyer-matching platforms; route optimization	Market access and diversification	Inventory costs lower by 15–25%; new destination markets; better price capture

Source: compiled by the author from the enterprise survey, expert interviews and the reviewed literature.

Two features of this mapping deserve emphasis. First, the levers are sequential and cumulative: yield prediction improves the raw material that grading then sorts, grading determines what cold-chain analytics must preserve, and the integrity preserved through storage is what traceability finally certifies to the buyer. A weakness at any stage caps the value that downstream AI applications can add, which is why a portfolio approach generally outperforms isolated point solutions. Second, the stages differ in adoption readiness. Computer-vision grading and basic cold-chain monitoring rest on mature, commercially available technology and yield quickly visible returns, making them natural entry points. Forecasting, traceability and market-intelligence applications demand more data, more skill and more organizational change, and therefore tend to be adopted later. This readiness gradient, rather than the theoretical potential of each technology, largely explains the adoption pattern documented in Table 3 and Figure 2.

Table 5 reports descriptive statistics and the bivariate correlation of each variable with the Export Competitiveness Index. The mean ECI of 48.4 points indicates considerable scope for improvement. All predictors correlate with the ECI in the expected direction. The AI Adoption Index shows the strongest positive association ($r = 0.69$; $p < 0.001$), followed by export-market count and cold-chain capacity, while the consignment rejection rate is negatively associated with competitiveness. The scatter of the ECI against the AI Adoption Index, with its fitted line, is shown in Figure 3 and visually confirms a clear positive gradient.

Table 5.

Descriptive statistics and correlation with the Export Competitiveness Index

Variable	Mean	SD	r with ECI	p-value
Export Competitiveness Index (0–100)	48.4	18.4	1.00	–
AI Adoption Index (0–100)	27.4	19.6	0.69	< 0.001
Cold-chain capacity index (0–100)	41.2	23.5	0.52	< 0.001
Export-market count (number)	4.3	2.6	0.58	< 0.001
Firm size (ordinal, 1–4)	2.01	0.88	0.34	< 0.001
Export experience (years)	7.6	5.4	0.31	< 0.001
Certification (share certified)	0.37	0.48	0.40	< 0.001
Consignment rejection rate (%)	6.8	4.9	−0.47	< 0.001

Source: author's enterprise survey, 2025.

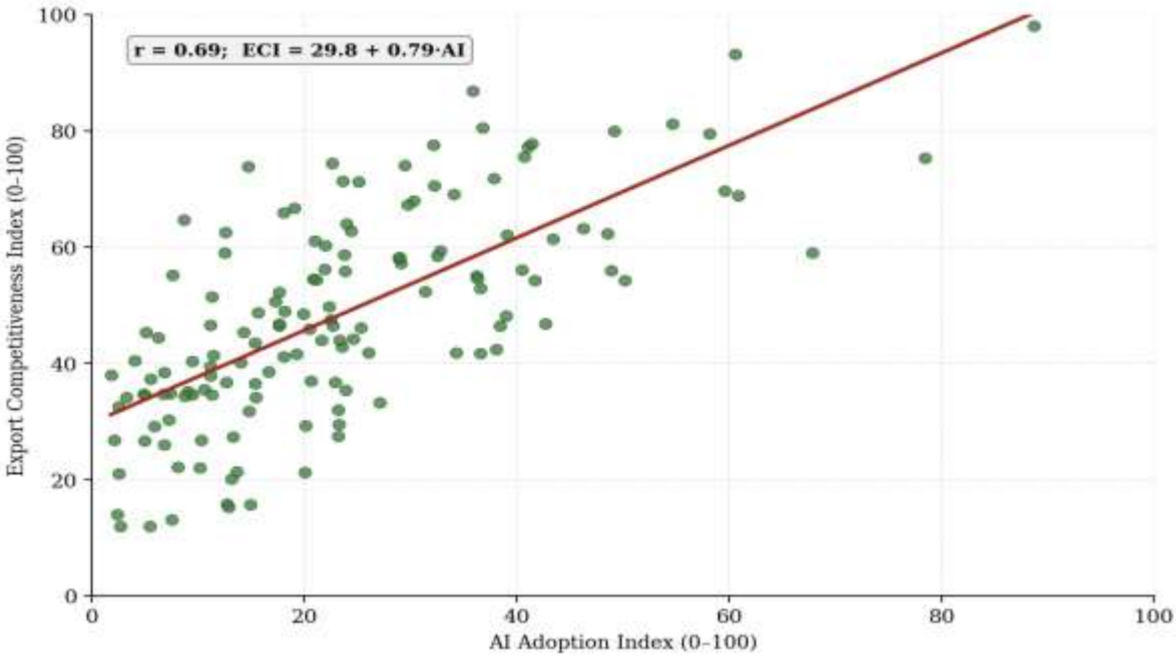

Figure 3. Relationship between the AI Adoption Index and the Export Competitiveness Index (n = 142).

Table 6 reports the multiple regression of the Export Competitiveness Index on the AI Adoption Index and four control variables. The model is statistically significant and explanatory, with an adjusted coefficient of determination of 0.610, meaning that the five predictors jointly account for about 62.4% of the variance in export competitiveness ($F(5, 136) = 45.11$; $p < 0.001$). Regression diagnostics were satisfactory: variance-inflation factors ranged from 1.2 to 1.7, well below the threshold of concern, and the Durbin–Watson statistic of 1.94 indicated no serial correlation in the residuals.

The AI Adoption Index is the strongest predictor by a wide margin. Its standardized coefficient of 0.474 ($p < 0.001$) implies that a one-standard-deviation increase in firm-level AI adoption is associated with almost half a standard-deviation increase in export competitiveness, holding firm size, experience, cold-chain capacity and certification constant. Cold-chain capacity, certification, firm size and export experience all retain positive and statistically significant coefficients, confirming that AI complements rather than replaces conventional sources of competitiveness. These results support both hypotheses: H1 is confirmed by the strong bivariate association, and H2 by the persistence of a large, significant AI coefficient after the introduction of controls.

Table 6.

Multiple regression of the Export Competitiveness Index (n = 142)

Predictor	B (SE)	Std. β	t	p-value
Constant	14.83 (3.21)	–	4.62	< 0.001
AI Adoption Index	0.412 (0.061)	0.474	6.75	< 0.001
Cold-chain capacity index	0.151 (0.049)	0.221	3.08	0.002
Certification (GlobalGAP / ISO)	6.41 (2.34)	0.179	2.74	0.007
Firm size (ordinal)	3.07 (1.18)	0.158	2.60	0.010
Export experience (years)	0.43 (0.16)	0.171	2.69	0.008
$R^2 = 0.624$; Adjusted $R^2 = 0.610$; $F(5, 136) = 45.11$; $p < 0.001$; Durbin–Watson = 1.94				

Source: author's estimation. The final row spans all columns. Dependent variable: Export Competitiveness Index.

To translate the regression into managerially meaningful terms, enterprises were ranked by their AI Adoption Index and divided into quartiles. Firms in the top adoption quartile outperformed those in the bottom quartile across every component of competitiveness. Their mean unit export price was about 23% higher; their consignment rejection rate was 41% lower (5.7% against 9.7%); and they served on average 5.8 destination markets compared with 3.1 — almost twice the diversification. The composite ECI averaged 61.2 points for the top quartile and 35.8 points for the bottom quartile, a gap of more than 25 points. The pattern indicates that AI adoption is associated not with a single advantage but with a coherent upgrading of price capture, reliability and market reach simultaneously.

Although the performance evidence is favourable, adoption remains low, pointing to an adoption paradox that the barrier analysis helps to explain. Table 7 ranks the nine barriers by mean importance score. The most binding constraints are financial and human rather than purely technical: the high upfront cost of technology, a shortage of AI and digital skills in the workforce, and limited digital infrastructure top the list, followed by uncertainty about return on investment and the small, fragmented scale of operations. Regulatory and awareness gaps, while real, were rated less critical. The clustering of the leading barriers around cost, skills and infrastructure indicates that adoption is constrained less by the maturity of the technology than by the enabling environment surrounding the firm.

Table 7.

Barriers to AI adoption ranked by perceived importance (n = 142)

Rank	Barrier	Mean (1–5)	SD	Rated important / critical (%)
1	High upfront investment and technology cost	4.31	0.74	84.5
2	Shortage of AI and digital skills in the workforce	4.18	0.79	80.3
3	Limited digital infrastructure (connectivity, sensors)	3.94	0.88	73.2
4	Uncertainty about return on investment	3.77	0.91	67.6
5	Small and fragmented scale of operations	3.65	0.95	62.0
6	Limited access to finance and credit	3.58	0.97	59.2
7	Data scarcity and poor data quality	3.42	1.01	54.2
8	Weak awareness of available solutions	3.20	1.06	47.9
9	Regulatory and standardization gaps	2.96	1.08	40.1

Source: author's enterprise survey, 2025.

Several checks were carried out to assess the stability of the central finding. First, the regression was re-estimated with heteroscedasticity-robust standard errors; the significance and approximate magnitude of all coefficients were unchanged, and the Breusch–Pagan test did not indicate problematic heteroscedasticity. Second, the model was re-run separately for the three main export lines — dried fruit and nuts, fresh fruit, and vegetables and melons. The AI Adoption Index remained positive and statistically significant in every sub-sample, although its standardized coefficient was largest for fresh fruit, the segment in which perishability and quality variance are highest and where AI applications in grading and cold-chain monitoring therefore have the greatest scope to act. Third, an alternative competitiveness measure based solely on unit export value, excluding the diversification and rejection components, was regressed on the same predictors; the AI coefficient again retained its sign, significance and leading position. Finally, replacing the composite AI Adoption Index with a simple count of AI applications used at routine level or above produced consistent results. Taken together, these checks indicate that the association between AI adoption and export competitiveness is not an artefact of a particular variable definition, product segment or estimation choice.

The findings provide consistent, multi-method evidence that artificial intelligence is a significant lever of international competitiveness for fruit and vegetable exporters. The regression results, in which the AI Adoption Index emerges as the dominant predictor of the Export Competitiveness Index, and the quartile comparison, in which advanced adopters outperform laggards across price, reliability and diversification simultaneously, together indicate that AI acts not as a marginal efficiency tool but as a systemic upgrading mechanism. This section interprets that result through the four competitiveness levers of the conceptual framework, situates it in the existing literature, and draws out its theoretical and practical implications.

The first lever is quality consistency. Computer-vision grading replaces subjective, fatigue-prone manual inspection with objective, repeatable classification, narrowing the variance of exported grades. Because international buyers price uniformity heavily, the reduction in grade dispersion is a plausible mechanism behind the higher unit values observed among advanced adopters. The second lever is loss and cost reduction. Predictive cold-chain analytics and shelf-life models allow exporters to detect spoilage risk early and to prioritize consignments by remaining shelf life; the literature reports spoilage reductions of substantial magnitude under AI-optimized storage, and since avoidable loss inflates the unit cost of every successfully exported unit, even moderate loss reduction improves price competitiveness. The third lever is compliance speed and reliability. AI-assisted document processing and traceability shorten certification cycles and lower the probability of border rejection — directly visible in the markedly lower consignment rejection rate of high-adoption firms. The fourth lever is market access. Natural-language market intelligence and buyer-matching platforms reduce the information asymmetry that confines small exporters to a few familiar destinations; the near-doubling of destination markets among advanced adopters is consistent with this mechanism.

What unites these four levers is that each addresses a form of uncertainty that has historically penalized emerging exporters. Buyers in high-value markets discount produce whose quality, safety, availability and arrival condition they cannot predict; that discount is the implicit price of uncertainty. AI applications, in essence, convert the dispersed and previously unused data of the export chain — images, sensor readings, transaction records, regulatory texts — into reliable predictions, and in doing so they shrink the uncertainty premium. Viewed this way, the competitiveness gain documented in this study is not the sum of several unrelated efficiency improvements but the coherent outcome of a single underlying capability: the capacity to make the export chain more predictable. This interpretation also explains why the benefits appear together rather than in isolation, and why a portfolio of complementary AI applications outperforms isolated point solutions.

The results both confirm and extend the existing literature. They corroborate technical studies reporting that computer-vision sorting reduces post-harvest losses by up to 30% and that AI-optimized cold storage and machine-learning logistics yield large reductions in spoilage and inventory cost. The present study’s contribution is to connect those function-level engineering gains to a firm-level, economically meaningful outcome — export competitiveness measured as a composite of price, reliability, diversification and compliance. Whereas much earlier work analyses AI either on the farm or within a single post-harvest function, the framework and evidence here treat the export value chain as an integrated system and show that the competitive payoff is greatest where AI is applied at the post-harvest and logistics stages that emerging exporters have historically managed least well. The barrier findings are also consistent with reviews of AI in agribusiness that emphasize cost, skills and infrastructure as the principal obstacles to adoption in developing economies.

At the same time, the study qualifies an optimism that sometimes accompanies the digital-agriculture literature. Much of the published evidence on AI gains derives from controlled trials or from large, well-capitalized firms, and may overstate what a typical small exporter can realistically achieve in the short term. The present results show that the average exporter in the sample uses AI only minimally, that adoption depth rarely exceeds an early stage, and that the firms capturing the largest benefits are disproportionately the larger and more experienced ones. This suggests that AI, if left to market forces alone, may reinforce rather than reduce the dualism of horticultural export sectors, in which a small modern segment coexists with a fragmented smallholder base. The policy implication is that the distributional design of AI promotion — who gains access, on what terms, and through which intermediaries — matters as much as the aggregate encouragement of adoption.

Theoretically, the study extends competitiveness analysis into the era of digital and data-driven production. Porter's diamond stresses the role of factor conditions, demand, related industries and firm strategy; the evidence here suggests that AI capability is becoming a distinct, cross-cutting determinant that operates on several of those facets at once. Read through the lens of the resource-based view and dynamic-capabilities theory, the firm-level AI Adoption Index can be interpreted as a proxy for a valuable, hard-to-imitate organizational capability — the capacity to sense market and quality signals, to seize opportunities and to reconfigure routines around data. The persistence of a large AI coefficient after controlling for size, experience, cold-chain capacity and certification implies that this capability is analytically separable from conventional tangible assets, and that competitiveness increasingly depends on the firm's position on a digital-capability continuum rather than on physical endowment alone.

The coexistence of clear performance benefits with low average adoption — the adoption paradox — is the study's central practical puzzle. Because the leading barriers are financial, human and infrastructural rather than technological, policy can realistically relax them. A staged roadmap is proposed. In the short term, the priority is to lower the cost and risk of entry: shared AI-enabled grading and packing hubs serving clusters of smallholders and small exporters, targeted co-financing or subsidized credit for sensor and cold-chain investment, and demonstration projects that make the return on investment visible. In the medium term, the binding constraint shifts to skills and data: vocational and university programmes in agro-digital competencies, extension services capable of supporting AI tools, and the development of shared, good-quality datasets and traceability standards that individual small firms cannot build alone. In the longer term, attention turns to integration and governance: interoperable national traceability infrastructure, alignment of AI-generated compliance documentation with destination-market requirements, and data-governance rules that protect firms while enabling the data-sharing on which accurate models depend. Sequencing matters because attempting integration before cost and skill barriers are addressed risks widening the gap between a few advanced exporters and the smallholder majority.

The roadmap also implies a clear allocation of institutional roles. Export-promotion agencies are well placed to operate or accredit shared AI-enabled grading and traceability facilities and to disseminate market intelligence as a public good; development banks and agricultural-finance institutions can design risk-sharing instruments — partial guarantees, leasing schemes or results-based grants — that lower the effective cost of the first AI investment; universities and vocational colleges are needed to supply agro-digital skills and to embed AI literacy in agronomy and agribusiness curricula; and producer cooperatives and exporter associations can aggregate the volumes and data of small firms to the scale at which AI tools become viable. Industry standards bodies, finally, must ensure that AI-generated quality and compliance records are recognized by certification schemes and by the customs authorities of destination markets, since technology that improves internal decision-making but is not trusted externally delivers only part of its potential competitive value. The effectiveness of AI promotion therefore depends less on any single instrument than on the coherence of this institutional ecosystem.

For exporting firms, the evidence suggests a pragmatic adoption sequence rather than wholesale digital transformation. Investment should begin where the technology is mature and the competitive return is clearest — computer-vision grading and basic cold-chain monitoring — and proceed towards forecasting, traceability and market-intelligence tools as data and skills accumulate. Smaller firms unable to invest individually can capture much of the benefit through cooperatives, service providers or shared facilities. Critically, AI should be treated as complementary to, not a substitute for, certification and cold-chain investment, since the regression shows each contributes independently to competitiveness.

The quartile comparison provides managers with a concrete benchmark for the stakes involved. Firms in the top adoption quartile commanded unit export prices roughly twenty-three per cent above those of the bottom quartile, reduced consignment rejection rates from 9.7 to 5.7 per cent, served almost twice as many destination markets, and recorded an Export Competitiveness Index of 61.2 against 35.8. These differences are large enough to alter a firm's strategic position rather than merely its operating margin, and they accumulate: higher realized prices and lower rejection losses generate the retained earnings that finance the next stage of digital investment, while a wider market portfolio diversifies the demand shocks that would otherwise interrupt that investment. Adoption should therefore be planned as a self-reinforcing cycle, in which early, low-risk applications fund and de-risk the more data-intensive tools that follow. Managers are also advised to pair each AI investment with deliberate capability-building — staff training, data-collection routines and supplier engagement — because the technology delivers its return only when embedded in revised decision processes; the firms that gain most are those that treat AI adoption as an organizational change programme rather than a procurement decision.

Beyond commercial competitiveness, AI-driven upgrading of the export chain generates wider co-benefits that strengthen the case for public support. Post-harvest losses represent the embedded waste of land, water, fertilizer, labour and energy that were expended to produce food that is never consumed; in water-scarce horticultural regions this resource cost is especially severe. By reducing avoidable loss at the grading, storage and logistics stages, AI applications lower the environmental footprint per unit of successfully exported produce and improve the efficiency with which scarce inputs are used. Loss reduction also has a food-security dimension: produce diverted from waste either reaches export markets or becomes available domestically, raising effective food availability without additional cultivation. Furthermore, AI-enabled traceability supports food safety for domestic as well as international consumers, and more accurate demand forecasting reduces the price volatility that harms both growers and buyers. These co-benefits mean that the social return to AI adoption in horticultural exports is likely to exceed the private return captured by individual firms — a classic justification for the public co-financing, shared infrastructure and skills investment recommended above.

Three limitations qualify the conclusions. First, the cross-sectional design establishes a strong, theoretically grounded association but cannot fully exclude reverse causation, since more competitive firms may also have greater capacity to adopt AI; panel data or quasi-experimental evaluation of specific AI interventions would allow firmer causal identification. Second, the reliance on managerial self-report for some variables invites future use of objective customs and sensor data. Third, the single-country setting limits direct generalization. Future research could test the framework comparatively across several horticultural exporting economies, quantify the return on investment of individual AI applications, examine the distributional consequences of AI adoption for smallholders, and assess the environmental and food-security co-benefits of AI-driven loss reduction.

CONCLUSION

This study set out to determine whether, and how, artificial intelligence technologies can strengthen the competitiveness of fruit and vegetable exporters in international markets. Combining revealed comparative advantage analysis with a survey of 142 exporting enterprises, it developed and tested an integrated framework linking five families of AI technology to five export value-chain stages and four competitiveness outcomes. The evidence is clear and consistent. The export base is strongly specialized but quality-constrained, with revealed comparative advantage robust in processed products and fragile where post-harvest sophistication is weakest. Firm-level AI adoption is currently low and uneven, yet it is the single strongest predictor of export competitiveness, accounting — together with cold-chain capacity, certification and firm characteristics — for 62.4% of its variance; enterprises in the top adoption quartile achieved higher unit prices, far fewer consignment rejections and almost double the market diversification of low-adoption firms.

The principal contribution of the paper is to reframe AI not as an isolated farm-level or engineering improvement but as a systemic determinant of export competitiveness that acts simultaneously on quality, cost, compliance and market access. The central practical message is the adoption paradox: the benefits are demonstrable, but adoption is held back by cost, skills and infrastructure barriers that lie within the reach of policy. A staged roadmap — lowering entry cost and risk first, then building skills and data, then pursuing integration and governance — offers a realistic path by which agro-exporting economies can convert favourable natural endowments into durable, technology-enabled competitiveness. For policymakers and exporters alike, AI is best understood not as an optional modern accessory but as emerging core infrastructure for competing in the international fruit and vegetable trade.

Looking ahead, the competitive landscape of horticultural trade is likely to be shaped less by which countries possess the most favourable land and climate — endowments that change slowly — than by which can most rapidly build the data, skills and institutions required to exploit AI across the export chain. For economies with a strong but quality-constrained horticultural base, the strategic task is therefore to treat the present period as a window of opportunity: to move deliberately from isolated pilots towards system-wide adoption before the digital divide in agro-food trade hardens into a durable competitiveness gap. The framework and evidence offered in this paper are intended as a practical contribution to that task, and as a foundation for the comparative, longitudinal and intervention-based research that will be needed to refine it.

REFERENCES

1. Aghababaei, A., et al. (2025). Artificial intelligence in agro-food systems: From farm to fork. *Foods, 14*(3), 411.

2. FAO. (2021). *Digital agriculture in action: Artificial intelligence for agriculture*. Food and Agriculture Organization of the United Nations.

3. FAO. (2025). *Digital agriculture and AI innovation*. Food and Agriculture Organization of the United Nations.

4. ITU, & FAO. (2016). *E-agriculture strategy guide*. International Telecommunication Union and Food and Agriculture Organization.

5. McFadden, J., Casalini, F., Griffin, T., & Antón, J. (2022). *The digitalisation of agriculture: A literature review and emerging policy issues*. OECD Publishing.

6. McFadden, J., Casalini, F., Griffin, T., & Antón, J. (2022). *Policies to bolster trust in agricultural digitalisation*. OECD Publishing.

7. OECD. (2025). *Artificial intelligence*. Organisation for Economic Co-operation and Development.

8. Schroeder, K., Lampietti, J., & Elabed, G. (2021). *What's cooking: Digital transformation of the agrifood system*. World Bank.

9. Webber, C. M., & Labaste, P. (2010). *Building competitiveness in Africa's agriculture: A guide to value chain concepts and applications*. World Bank.

10. World Bank. (2025). *Digital agriculture roadmap playbook*. World Bank.

11. World Bank. (2025). *Harnessing artificial intelligence for agricultural transformation*. World Bank.

12. Porter, M. E. (1990). *The competitive advantage of nations*. Free Press.

13. Kotler, P., Kartajaya, H., & Setiawan, I. (2021). *Marketing 5.0: Technology for humanity*. Wiley.

14. Chaffey, D., & Ellis-Chadwick, F. (2022). *Digital marketing: Strategy, implementation and practice* (8th ed.). Pearson.

15. Davenport, T. H. (2018). *The AI advantage: How to put the artificial intelligence revolution to work*. MIT Press.

16. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

17. Kumar, V., Dixit, A., Javalgi, R. G., & Dass, M. (2016). Research framework, strategies, and applications of intelligent agent technologies in marketing. *Journal of the Academy of Marketing Science, 44*, 24–45.

18. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674.

19. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90.

20. Trienekens, J. H. (2011). Agricultural value chains in developing countries: A framework for analysis. *International Food and Agribusiness Management Review, 14*(2), 51–82.