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LEVERAGING ARTIFICIAL INTELLIGENCE FOR THE OPTIMIZATION OF TERROIR PRODUCT VALUE CHAINS: A PATH TOWARD SUSTAINABLE AGRICULTURE IN EMERGING ECONOMIES

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The olive oil sector constitutes a major pillar of the rural economy in the Marrakech region, characterized by the strong presence of small scale producers, cooperatives, and traditional oil mills. As a recognized *terroir* product, this activity plays a critical role in enhancing local resources, ensuring food security, and supporting the livelihoods of rural populations. Despite the efforts deployed through national initiatives such as the Green Morocco Plan (*Plan Maroc Vert*) and the Generation Green strategy (*Génération Green*), the sector continues to face numerous challenges. These include a disorganized value chain, weak traceability mechanisms, logistical inefficiencies, and limited access to structured markets.

A clear disconnect exists between the potential of artificial intelligence (AI) as a lever for sustainability and its effective integration into the olive oil sector within *terroir* territories. This raises a central research question:

How can artificial intelligence be contextually and sustainably leveraged to optimize the olive oil value chain in the Marrakech region?

- To identify the opportunities and barriers associated with the use of artificial intelligence across the various segments of the value chain.
- To assess the digital maturity of local stakeholders, including cooperatives, oil mills, and farmers.
- To propose a model for AI integration that is tailored to the technical, economic, and social specificities of the olive oil sector in this region.

The olive oil value chain in the Marrakech region fragmented and predominantly composed of small-scale producers could greatly benefit from targeted AI tools such as sensors for irrigation management, computer vision for quality control, and blockchain technologies to ensure traceability. The ultimate goal is to foster a more sustainable value chain economically, socially, and environmentally. As such, this conceptual framework provides a foundation for a context-specific digital support strategy for local agricultural sectors rooted in regional identity.

Table 1

Conceptual Framework – Integrating AI into the Olive Oil Value Chain

Level	Key elements	Role of A.I	Expected effects
1. Contextual Factors	National Strategies, Digitalization Challenges, and Traditional Systems Rural Areas with Limited Digitalization	Analytical Framework	«Influence on the Feasibility and Adoption of AI Solutions»:
2. The Olive Oil Value Chain	Production (Cultivation, Irrigation) Transformation (Crushing, Quality) Distribution (Logistics, Sales) Consumption (Certification, Traceability)	IoT Sensors, Computer Vision, Machine Learning Forecasting, Blockchain + AI	«Better Quality, Reduction of Losses, Better Market Adaptation»:
3. Artificial Intelligence Technologies	Machine Learning Computer Vision Blockchain IoT and Embedded Systems	«Optimization of Decisions and Flows Throughout the Chain»	Efficiency Gains, Responsiveness, Transparency»:
4. Sustainable Outcomes	Performance économique Inclusion sociale Préservation environnementale Valorisation des savoir-faire	Environmental Sustainability Economic Sustainability Social Sustainability	More Resilient, Fairer, and More Competitive Value Chain

Source: Self-produced

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The ultimate goal is to foster a more sustainable value chain economically, socially, and environmentally. As such, this conceptual framework provides a foundation for a context-specific digital support strategy for local agricultural sectors rooted in regional identity.

Machine learning is employed to analyze heterogeneous data streams from ground sensors, satellite imagery, and climate or agricultural databases to predict yields, detect diseases, and optimize agronomic decisions (Kamilaris & Prenafeta-Boldú, 2018). Algorithms such as random forests, support-vector machines (SVM), and neural networks are widely used for soil classification, crop management, and anomaly detection (Nemorin et al., 2022).

Deep learning, an advanced branch of ML, excels in image processing and automated vision tasks. Convolutional neural networks (CNNs) are extensively applied to plant-disease detection and fruit classification (Zhang et al., 2020). In agro food transformation, DL enables automated quality control via visual analysis (Koirala et al., 2019).

Computer vision is increasingly adopted on farms for visual crop monitoring, often via drones or fixed cameras. It facilitates ripeness detection, growth surveillance, and post-harvest analysis (Ferentinos, 2018). In processing units, it also aids in classifying product quality.

The IoT is pivotal in connected agriculture through intelligent sensors embedded in soil, plants, or the surrounding environment. These sensors track parameters such as soil moisture, temperature, and irrigation needs in real time (Wolfert et al., 2017). IoT data are frequently paired with AI algorithms to automatically adjust inputs fertilizers, water, or phytosanitary treatments.

Decision support systems serve as the interface between collected data and producer decision making. They integrate AI based predictive models to recommend optimal actions such as the best timing for sowing, irrigating, or harvesting (Liakos et al., 2018). DSS tools are especially relevant for smallholders in developing countries, where technical expertise may be limited (Benos et al., 2021).

Data specific to the Marrakech-Safi case study were collected over a full agricultural cycle (12 months) at the National Office for Food Safety 'ONSSA'.

– Participants: 50 smallholder members, 5 cooperative managers, and 3 technical staff from ARWA Solutions and DeepLeaf.

– Focus: Digital literacy, perceptions of AI tools (FILAHI, smart irrigation, foliar analysis), observed changes in cultivation and processing practices, and constraints to technology use.

– Format: Each interview lasted 45–60 minutes and followed an interview guide refined through pilot testing.

– Yield and Quality: Monthly measurement of yield per hectare and oil-quality parameters (free acidity, peroxide value, phenolic content) using standard laboratory protocols.

– Resource Use: Continuous logging of water volumes applied via ARWA smart-irrigation meters and energy consumption of milling operations.

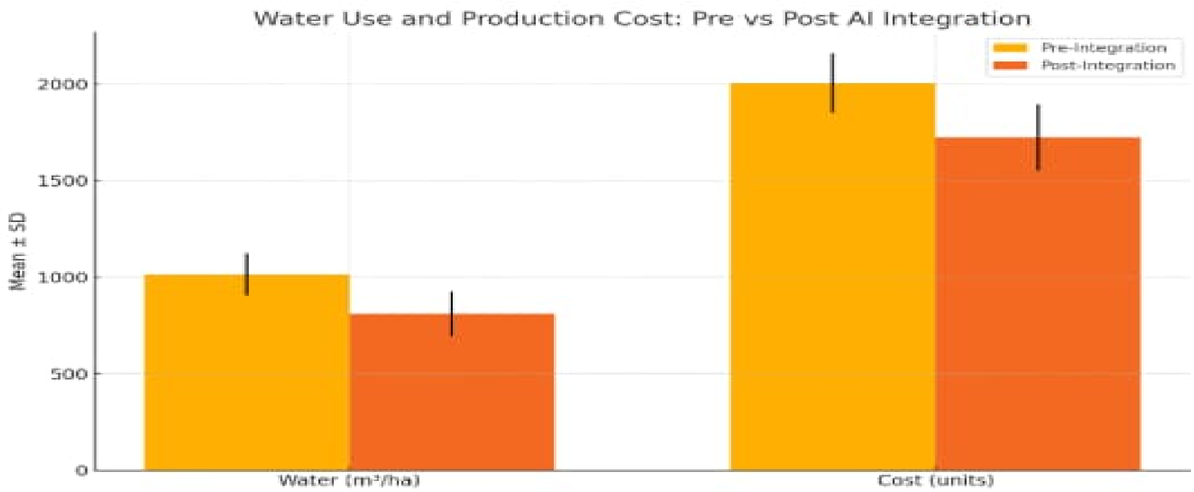
– Economic Data: Detailed recording of input costs (water, energy, labor) and output revenues.

FILAHI Satellite Data: Employed to monitor crop health, soil-moisture levels, and to predict optimal harvesting windows.

ARWA Solutions: Deployment of intelligent irrigation systems that adjust water supply in real time based on soil and weather data.

DeepLeaf Foliar Analysis: Use of AI-powered foliar-analysis tools to detect early signs of disease and nutrient deficiencies.

4.2 Impact of AI Integration



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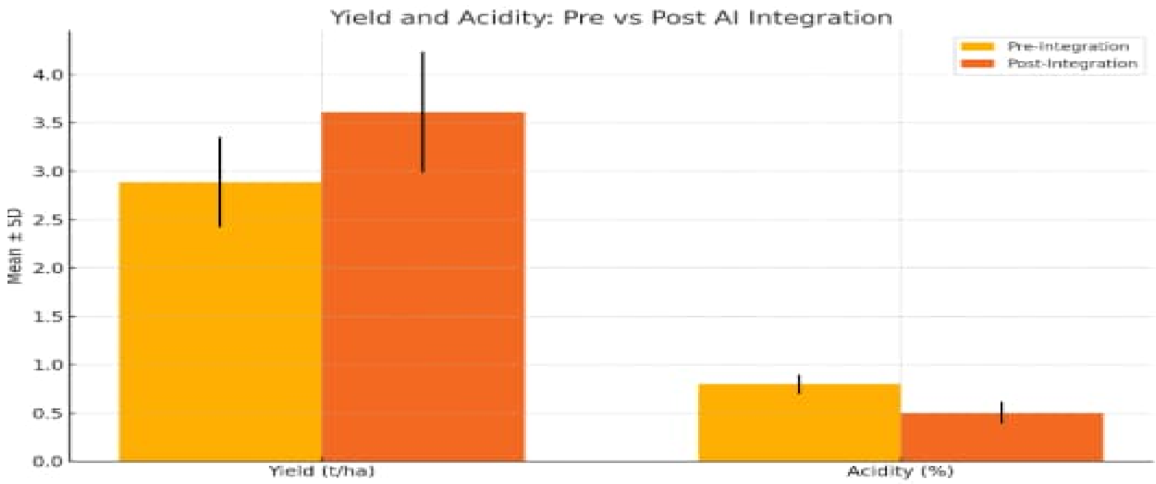

Source: Self produced

Yield (t/ha): increased from 3.02 ± 0.49 to 3.77 ± 0.46 (+25%).
Free acidity (%): decreased from 0.80 ± 0.10 to 0.49 ± 0.08 (–0.31 pp).
Water use (m^3/ha): decreased from 997 ± 96 to 799 ± 74 (–20%).
Production cost (units): decreased from 1 991 ± 210 to 1 694 ± 148 (–15%).
Yield: $t(49)=23.24$, $p<0.0001$
Acidity: $t(49)=–46.81$, $p<0.0001$
Water use: $t(49)=–27.83$, $p<0.0001$
Cost: $t(49)=–20.21$, $p<0.0001$

Conclusion

This study demonstrates that context-tailored AI tools satellite monitoring, smart irrigation, and AI-driven foliar analysis can markedly enhance olive-oil production. Over one year, AI integration delivered a 25 % yield increase, 0.3 pp reduction in acidity, 20 % water savings, and 15 % cost reduction, all statistically significant. Digital literacy among members ranged from low (30 %) to high (20 %), underscoring the need for targeted training. A SWOT analysis revealed efficiency, quality, and sustainability gains as strengths; high initial costs and skill gaps as weaknesses; new market access and product differentiation as opportunities; and resistance to change as a threat. Using an abductive, mixed methods design ensured robust, context sensitive insights. To scale impact, the study recommends modular capacity building, subsidized financing for AI hardware, interoperable IoT AI blockchain platforms, and participatory governance. This framework offers a blueprint for sustainable valorization of terroir products in emerging economy regions.

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THE IMPACT OF THE USE OF ARTIFICIAL INTELLIGENCE TOOLS IN SCIENTIFIC RESEARCH

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This study focuses on the transparent and thoughtful use of artificial intelligence (AI) tools within scientific research. While a full presentation of results will be shared in due course, the following sections detail the methodology adopted for this work.

Today’s large language models (LLMs) – including ChatGPT4, Gemini, and Perplexity – are profoundly changing how researchers write, gather information, and conduct analysis. In an academic environment where AI tools are increasingly pervasive, it is essential to document every