Artificial Intelligence as An Enabler of Entrepreneurship among Rural Women Farmers: A Review of Opportunities, Evidence and Challenges

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Abstract

Rural women farmers contribute substantially to agricultural production and household food security, yet they remain under-represented in agri-enterprise because of limited access to markets, credit, information, and technology. Artificial intelligence (AI) is increasingly proposed as a tool to close these gaps. This review examines published literature, mainly from the last decade, on how AI-enabled technologies can support entrepreneurship among rural women farmers. It synthesises evidence on four themes: AI-based advisory and decision support for production, AI in market linkage and value chains, AI for financial inclusion and enterprise management, and AI in skill building and extension through voice and mobile tools. The review finds that AI can lower information costs, improve product quality and productivity, reduce post-harvest losses, support credit assessment, and deliver learning in local languages. However, benefits are not automatic. The gender digital divide, low digital literacy, poor connectivity, cost of devices, language barriers, data privacy concerns, and the risk of biased algorithms limit adoption by women. Most studies focus on farmers in general, and the evidence specific to women-led rural enterprises is thin. Successful adoption appears to depend on group-based approaches such as self-help groups and farmer producer organisations, local-language voice interfaces, trusted facilitators, and institutional support from universities, extension systems, and incubators. Practical implications for agricultural colleges, extension agencies, and development programmes are also briefly discussed. The paper concludes that AI should be treated as a support for inclusive enterprise ecosystems

rather than a stand-alone solution, and recommends gender-disaggregated research, affordable tools, and women-centred design.

Keywords: artificial intelligence, rural women, entrepreneurship, agriculture, digital inclusion

1. Introduction

Women form a large share of the agricultural workforce in developing countries, but they have less access to land, credit, extension services, and technology than men (FAO, 2011). Entrepreneurship offers rural women a way to earn independent income and gain decision-making power (Kabeer, 2005; Duflo, 2012). In India, self-help groups and farmer producer organisations have helped women begin enterprises such as food processing, dairy, and value addition of millets. Digital agriculture, including machine learning, big data, and smart advisory systems, is now changing how farm enterprises are planned and run (Wolfert et al., 2017; Klerkx et al., 2019). This paper reviews how AI can support rural women farmers as entrepreneurs, and what barriers need attention.

2. Review of Literature

2.1 AI for production and decision support

Machine learning is widely applied to crop and disease detection, yield prediction, soil and weather analysis, and irrigation planning (Liakos et al., 2018; Jha et al., 2019). Reviews of big data in agriculture show that such tools help farmers decide inputs and timing with greater accuracy (Kamilaris et al., 2017). For women-led enterprises, image-based tools on a mobile phone can identify pests, estimate quality, and reduce losses without costly expert visits, which matters for small producers.

2.2 AI in market linkage and value chains

AI-based price forecasting, demand prediction, and digital platforms can help small producers decide when and where to sell. For women's groups working in value addition, AI can support product grading, quality checks, packaging decisions, and customer targeting. Digital marketplaces and social media allow groups to reach buyers directly, reducing dependence on middlemen. Reviews note, however, that digital platforms may favour larger and better-resourced actors unless designed with small producers in mind (Rotz et al., 2019).

2.3 AI for financial inclusion and enterprise management

Alternative data and machine learning are being used to assess the creditworthiness of people with no formal credit history, which may help women who lack collateral. Simple AI-supported tools can also assist with record keeping, costing, and inventory management. Mobile-based financial services are important here, but their use depends on access to phones and trust in digital systems.

2.4 AI in skill building, extension, and communication

Language models and speech tools make it possible to deliver advice in local languages through voice and chat, which suits users with limited literacy (Brown et al., 2020). Mobile learning, short videos, and chat-based advisory can extend the reach of universities and extension services to women who cannot attend regular training. Studies on ICT adoption in India show that education, access to information sources, and social networks strongly influence use of technology by farmers (Mittal & Mehar, 2016).

2.5 Barriers and risks

Women own fewer mobile phones and use mobile internet less than men in many low- and middle-income countries (GSMA, 2023). Other barriers include low digital literacy, weak connectivity, device cost, language gaps, and social norms that limit women's mobility and technology use. Data privacy and algorithmic bias are further concerns, because AI systems trained on data from male or large-scale farmers may not suit women's needs (Rotz et al., 2019; Klerkx et al., 2019).

3. Findings

The review shows that AI has clear potential to support rural women's enterprises by reducing information gaps, improving quality and productivity, widening market reach, and delivering training in local languages. Most available studies, however, address farmers in general, and evidence specifically on women-led enterprises is limited. Technology alone does not ensure adoption. Group-based models such as self-help groups and producer organisations, voice-based local-language tools, trusted local facilitators, and hands-on training appear to improve uptake. Institutions such as agricultural colleges, extension systems, and incubators can act as bridges between technology developers and rural women. Persistent gaps in access, skills, and data governance must be addressed so that AI does not widen existing inequalities.

4. Conclusion

AI can become a useful partner for rural women farmers who wish to start or grow enterprises, provided it is introduced through inclusive and women-centred approaches. Priority actions include affordable and simple tools, voice-based interfaces in local languages, digital literacy training, and strong links with women's groups and producer organisations. Future research should generate gender-disaggregated evidence and test low-cost AI models in real rural enterprises.

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