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Taxonomy of key variables influencing Agricultural profitability for AI driven Influence

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ABSTRACT

Agricultural profitability is a key indicator of sustainable agricultural development. Its complete understanding is essential for developing intelligent decision support systems that enable evidence based agricultural planning. This paper suggests the possible taxonomical analysis for AI-based approaches in defining agricultural profitability. Attempt has been made to systematically classify such determinants are into major categories. Particular attention is given to machine learning, feature-selection, dimensionality-reduction, and explainable AI techniques for identifying influential variables over complex agricultural datasets. The research findings provide a conceptual foundation for future research on AI-enabled agricultural decision-support systems, particularly in data-intensive and climate-vulnerable agricultural regions.

KEYWORDS: Agricultural Profitability, Machine Learning, Feature Selection, Explainable Artificial Intelligence, Decision Support Systems.

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1. INTRODUCTION

Agriculture remains one of the most significant sectors of the global economy, supporting food security, rural livelihoods, employment generation, and sustainable economic development [1,3]. Despite remarkable advancements in agricultural technologies and crop productivity over the past several decades, improving farmers' income continues to be a major challenge across both developed and developing countries. Traditionally, agricultural success has been evaluated primarily in terms of crop yield and production volume. However, increasing evidence suggests that higher productivity alone does not necessarily result in improved economic returns [4,6]. Rising cultivation costs, climate variability, fluctuating market prices, inefficient resource utilization, labour shortages, and supply-chain uncertainties have significantly affected farm income, making agricultural profitability a more meaningful indicator of agricultural sustainability than production alone [2,4].Agricultural profitability is a multidimensional concept influenced by the interaction of environmental, agronomic, economic, technological, institutional, and socio-economic factors [6]. Unlike crop productivity, which primarily reflects biological performance, profitability depends on the efficient utilization of available resources under varying climatic, market, and policy conditions [7,8]. Environmental conditions, crop management practices, production costs, market dynamics, and technological interventions collectively determine the economic viability of farming enterprises [6,11]. Since these variables are highly interconnected, agricultural profitability cannot be adequately explained through isolated factor analysis, thereby necessitating integrated analytical approaches capable of capturing their combined influence [12,13]. The major categories of variables influencing agricultural profitability are discussed in detail in Section 3.

The rapid advancement of digital agriculture has fundamentally transformed agricultural management by enabling data-driven monitoring, analysis, and decision-making through emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), Geographic Information Systems (GIS), Remote Sensing, Internet of Things (IoT), cloud computing, and big-data analytics [14,15]. These technologies facilitate the integration of heterogeneous agricultural data collected from weather stations, satellite imagery, soil sensors, unmanned aerial vehicles, farm machinery, and market information systems, thereby supporting intelligent decision-support systems for precision farming and sustainable agricultural management [12,16]. Among these technologies, Artificial Intelligence has emerged as one of the most promising approaches for analysing complex agricultural datasets because of its ability to model nonlinear relationships, identify hidden patterns, and process high-dimensional data more effectively than conventional statistical techniques [14,15]. Consequently, AI-driven analytical models are increasingly being explored for agricultural decision-making and related farm-management applications, creating opportunities for profitability assessment [14,15].

Despite significant advances in agricultural analytics, identifying the key variables influencing agricultural profitability remains a major research challenge. Existing studies have predominantly focused on individual aspects of agricultural systems, such as crop yield prediction, irrigation management, soil fertility assessment, or market price forecasting, while comparatively fewer investigations have examined the combined influence of environmental, agronomic, economic, technological, institutional, and socio-economic variables within a unified analytical framework [13-14]. Traditional statistical models, particularly those based on linear assumptions, may face difficulties when relationships among agricultural variables are nonlinear or highly multidimensional [20,21]. Recent advances in Artificial Intelligence, particularly machine learning, feature selection techniques, and Explainable Artificial Intelligence (XAI), have demonstrated considerable potential for identifying influential variables while simultaneously improving prediction accuracy and model interpretability [17,18]. Nevertheless, comprehensive reviews integrating conventional analytical methods with emerging AI-driven approaches for agricultural profitability assessment remain limited, thereby restricting the development of transparent, reliable, and region-specific decision-support systems for sustainable agriculture [15,17].

Motivated by the above research gaps, this paper presents a comprehensive review of conventional and AI-driven approaches for identifying the key variables influencing agricultural profitability. Unlike existing reviews that primarily focus on crop production, precision agriculture, or individual AI applications, this study provides an integrated perspective by systematically synthesizing the multidimensional factors affecting agricultural profitability and critically examining contemporary variable identification techniques [17,20]. Furthermore, the review proposes a structured classification of profitability variables, discusses the role of statistical and AI-based feature selection methods, and highlights current research challenges and emerging opportunities for intelligent agricultural decision-support systems. By consolidating fragmented knowledge into a unified conceptual framework, this review aims to support researchers, policymakers, and agricultural practitioners in developing transparent, data-driven, and region-specific solutions for improving agricultural profitability and promoting sustainable agricultural development [1,17]. The remainder of this paper is organized as follows. Section 2 reviews contemporary research on agricultural profitability. Section 3 presents a structured classification of variables influencing agricultural profitability. Section 4 discusses AI-driven approaches for variable identification. Section 5 highlights current research gaps and future research directions, and Section 6 concludes the paper.

2. CONTEMPORARY RESEARCH ON AGRICULTURAL PROFITABILITY

Agricultural profitability has increasingly become a central research topic because it provides a more comprehensive measure of farming performance than crop productivity alone. While earlier agricultural research primarily focused on maximizing production through improved crop varieties, irrigation, mechanization, and fertilizer management, contemporary studies recognize that higher production does not necessarily ensure higher economic returns. Climatic uncertainty, rising input costs, fluctuating market prices, and changing policy environments have gradually shifted agricultural research from production-oriented approaches toward profitability-oriented decision-making, making agricultural profitability a key indicator of sustainable agricultural development and long-term farm viability [3,6].

Early research on agricultural profitability was largely based on agricultural economics and farm management principles, where profitability was evaluated using indicators such as Net Farm Income, Gross Margin, Benefit-Cost Ratio, Return on Investment, and Cost of Cultivation. Statistical techniques including correlation analysis, regression models, factor analysis, and principal component analysis were widely adopted to investigate the relationships between production factors and economic performance. Although these approaches significantly improved the understanding of individual profitability determinants, they generally assumed linear relationships and often analysed environmental, agronomic, and economic variables independently. As agricultural systems became increasingly complex and data-intensive, conventional analytical methods encountered limitations in representing the multidimensional interactions influencing farm profitability. [6,20].

The rapid development of digital agriculture has transformed agricultural research through the integration of Geographic Information Systems (GIS), Global Positioning Systems (GPS), Remote Sensing, Internet of Things (IoT), cloud computing, and big-data analytics. These technologies enable continuous monitoring of environmental conditions, crop growth, resource utilization, and market information, generating large volumes of heterogeneous agricultural data. Consequently, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful analytical tools capable of modelling nonlinear relationships, processing high-dimensional datasets, and supporting intelligent agricultural decision-making. Their successful application in crop yield prediction, disease detection, irrigation scheduling, fertilizer recommendation, and precision farming has further expanded research toward profitability assessment and sustainable farm management [12,15].

Recent studies have increasingly emphasized that identifying influential variables is as important as improving predictive accuracy. Consequently, feature selection and Explainable Artificial Intelligence (XAI) have become important components of modern agricultural analytics. Techniques such as SHAP and LIME improve model interpretability, while Recursive Feature Elimination (RFE), permutation-based importance, and embedded feature-selection methods support variable selection and prioritization [17,18].

Despite these advances, the existing literature remains fragmented, with many studies focusing on individual technologies or isolated categories of variables rather than providing an integrated understanding of agricultural profitability. Conventional agricultural economics, statistical modelling, machine learning, and explainable AI are often investigated independently, limiting the development of comprehensive decision-support systems capable of analysing the multidimensional determinants of farm profitability. This evolving research landscape highlights the need for a unified review that synthesizes conventional and AI-driven approaches while systematically classifying the variables influencing agricultural profitability. The following section addresses this need by presenting a structured taxonomy of the key variables reported in the contemporary literature [15,17].

Table 1: Evolution of Agricultural Profitability Research

Research Phase	Main Focus	Common Methods	Limitation
Conventional	Farm economics	Regression, B:C ratio	Linear assumptions
Precision Agriculture	Resource optimization	GIS, GPS, Remote Sensing	Limited economic integration
AI-driven Agriculture	Prediction	ML, DL	Black-box models
Explainable AI	Variable importance	SHAP, LIME, RFE	Emerging field

3. CLASSIFICATION OF VARIABLES INFLUENCING AGRICULTURAL PROFITABILITY

Agricultural profitability is influenced by numerous interrelated variables operating across the agricultural production system. Unlike crop productivity, profitability depends not only on biological performance but also on efficient resource utilization, economic viability, market conditions, technological adoption, institutional support, and farmer decision-making. Consequently, recent studies increasingly recognize that profitability should be analysed using an integrated framework rather than through isolated variables, as no single factor adequately explains farm performance under diverse agricultural conditions [6,12].Based on the synthesis of variables reported across the reviewed literature, this study organizes the determinants of agricultural profitability into seven major dimensions: Environmental, Agronomic, Economic, Market, Technological, Institutional, and Socio-economic &Behavioural variables. Environmental variables influence crop growth and production risk, agronomic variables determine production efficiency, while economic and market variables govern financial performance. Similarly, technological innovations, institutional support mechanisms, and farmer characteristics influence decision-making, resource utilization, and long-term sustainability. A structured taxonomy of these variables is presented in **Table 2**, providing a unified framework for understanding the multidimensional nature of agricultural profitability [6,15]. Although these categories are generally discussed independently, they operate as highly interconnected components within agricultural systems. Environmental conditions influence agronomic decisions, production practices determine production costs, market dynamics affect economic returns, while institutional policies and technological interventions modify farmers' management strategies. The interaction among these variables demonstrates that agricultural profitability should be regarded as a systems-level outcome requiring multidisciplinary analysis rather than isolated evaluation of individual determinants [12,15]. The proposed taxonomy provides a conceptual foundation for organizing existing research and identifying the variables most frequently associated with agricultural profitability. More importantly, it establishes the basis for AI-driven variable prioritization, where machine learning and explainable AI techniques can determine the relative importance of different variables under specific agricultural conditions. The following section therefore examines contemporary Artificial Intelligence approaches for identifying the key variables influencing agricultural profitability [14,17].

Table 2. Taxonomy of Key Variables Influencing Agricultural Profitability

Category	Representative Variables	Impact on Profitability
Environmental	Rainfall, Temperature, Soil Fertility, Soil Moisture, Humidity, Climate Variability, Water Availability	Crop growth, production risk, yield stability
Agronomic	Crop Variety, Irrigation, Fertilizer, Pest Management, Mechanization, Cropping Pattern	Production efficiency and resource utilization
Economic	Seed Cost, Labour Cost, Machinery Cost, Irrigation Cost, Credit, Farm Income	Financial viability and profitability
Market	Market Price, Demand, Transportation, Storage, Export Opportunity, Value Addition	Revenue generation and market competitiveness

Category	Representative Variables	Impact on Profitability
Technological	AI, Machine Learning, GIS, IoT, Remote Sensing, UAVs, Cloud Computing	Decision support and operational optimization
Institutional	MSP, Crop Insurance, Subsidies, Credit Facilities, Extension Services, Government Policies	Risk reduction and financial support
Socio-economic & Behavioural	Education, Farming Experience, Farm Size, Digital Literacy, Risk Perception, Technology Adoption	Management decisions and technology acceptance

4. AI-DRIVEN IDENTIFICATION OF KEY VARIABLES INFLUENCING AGRICULTURAL PROFITABILITY

The rapid growth of digital agriculture has fundamentally transformed agricultural profitability analysis from conventional statistical evaluation toward intelligent data-driven decision-making. Modern agricultural systems continuously generate large volumes of heterogeneous data from weather stations, satellite imagery, soil sensors, farm machinery, financial records, and market information systems. While these datasets provide unprecedented opportunities for understanding agricultural performance, they also introduce challenges associated with high dimensionality, nonlinear relationships, and redundant variables. Consequently, identifying influential variables has become a critical step in developing accurate profitability prediction models and intelligent agricultural decision-support systems [13, 20]. Conventional statistical techniques such as correlation analysis, regression models, analysis of variance, and principal component analysis have traditionally been employed to identify profitability determinants because of their simplicity and interpretability. However, recent research increasingly demonstrates that agricultural systems exhibit complex nonlinear interactions that cannot be adequately represented using traditional statistical assumptions. Artificial Intelligence (AI) and Machine Learning (ML) techniques, including Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting, XGBoost, Artificial Neural Networks, and Deep Learning, have therefore emerged as powerful alternatives for analysing multidimensional agricultural datasets and identifying influential profitability variables with improved predictive accuracy [14,15].Recent advances in Explainable Artificial Intelligence (XAI) have further strengthened AI-assisted agricultural analytics by improving model transparency and interpretability. Explainability techniques such as SHAP and LIME, together with feature-selection approaches such as RFE and permutation-based importance, can support variable interpretation and prioritization. Rather than focusing solely on predictive accuracy, contemporary agricultural research increasingly emphasizes interpretable and trustworthy AI models capable of supporting transparent decision-making for farmers, researchers, and policymakers [17,18]. Based on the literature synthesized in this review, an integrated AI-driven Agricultural Profitability Variable Identification Framework (APVIF) is proposed. The framework combines multi-source agricultural data acquisition, preprocessing, conventional statistical analysis, feature selection, machine learning, and explainable AI within a unified analytical workflow. By integrating domain knowledge with intelligent analytical techniques, APVIF enables systematic identification and prioritization of influential profitability variables while supporting transparent, region-specific, and data-driven agricultural decision-making. The proposed framework provides a conceptual foundation for future intelligent agricultural profitability assessment and naturally leads to the research challenges and future directions discussed in the following section [14,17].

Multi-source Agricultural Data

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Data Collection & Pre-processing

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Conventional Statistical Analysis

(Regression • PCA • Correlation • ANOVA)

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AI-Based Feature Selection

(RFE • SHAP • LIME • Permutation)

|

▼

Machine Learning Prediction Models

(RF • XGBoost • SVM • ANN • Deep Learning)

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Variable Importance Prioritization

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Agricultural Profitability Decision Support

Figure 2. Proposed Agricultural Profitability Variable Identification Framework (APVIF)

5. RESEARCH GAPS, CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The preceding discussion demonstrates that agricultural profitability has evolved from a conventional economic indicator into a multidimensional analytical problem involving environmental, agronomic, economic, technological, institutional, and socio-economic factors. Although significant progress has been achieved through statistical analysis, machine learning, and explainable artificial intelligence, the existing literature remains fragmented and several important challenges continue to limit the development of comprehensive profitability assessment frameworks. Most contemporary studies emphasize crop productivity, precision agriculture, or individual technological applications, whereas comparatively fewer investigations integrate the diverse factors influencing agricultural profitability within a unified analytical framework [12,15].

Another major challenge is the increasing complexity of agricultural data and analytical modelling. Modern agricultural systems generate heterogeneous information from weather stations, satellite imagery, IoT devices, financial records, market databases, and farmer surveys, creating challenges related to data quality, interoperability, missing values, and regional variability. Although Artificial Intelligence has substantially improved predictive capabilities, many advanced machine learning models continue to operate as black-box systems with limited interpretability. Furthermore, profitability models developed for one geographical region often perform poorly under different climatic, economic, and socio-cultural conditions. These limitations highlight the need for standardized agricultural datasets, explainable AI techniques, and adaptive region-specific analytical frameworks capable of improving both prediction accuracy and stakeholder confidence [20,21].

Future agricultural profitability research should therefore move beyond isolated predictive models toward integrated intelligent ecosystems that combine agricultural economics, statistical analysis, Artificial Intelligence, feature selection, and Explainable Artificial Intelligence within a unified decision-support framework. Emerging technologies such as multimodal machine learning, digital twins, federated learning, Internet of Things, remote sensing, cloud computing, and edge intelligence provide promising opportunities for continuously monitoring environmental conditions, production practices, market behaviour, and resource utilization. At the same time, greater collaboration among agricultural scientists, economists, data scientists, environmental researchers, and policymakers will be essential for developing transparent, scalable, and region-specific profitability assessment systems capable of supporting sustainable agricultural development [15,16].

Overall, the literature demonstrates considerable progress in understanding agricultural profitability while simultaneously revealing substantial opportunities for methodological advancement. Integrating multidimensional agricultural data with explainable and intelligent analytical frameworks will improve variable identification, profitability prediction, and evidence-based agricultural decision-making. Such developments are expected to strengthen sustainable farm management, optimize resource utilization, enhance farmer income, and provide a robust foundation for future AI-enabled agricultural profitability assessment, leading naturally to the concluding remarks presented in the next section [17,18].

Table 3. Research Gaps and Future Research Opportunities

Research Gap	Current Limitation	Future Direction
Productivity-focused research	Limited profitability assessment	Integrated profitability modelling
Isolated variable analysis	Weak representation of interactions	Multidimensional AI frameworks
Heterogeneous agricultural data	Poor interoperability and data quality	Standardized agricultural datasets
Black-box AI models	Limited interpretability	Explainable AI (SHAP, LIME, XAI)
Region-specific variability	Poor model transferability	Adaptive regional AI models
Limited technology integration	Fragmented digital solutions	IoT, Digital Twins, Federated Learning, Multimodal AI

6. CONCLUSION AND FUTURE SCOPE

The proposed work has demonstrated taxonomical analysis of key variables affecting agricultural profitability. Attempts have been made to classify them into major categories, so as to provide a structured and unified perspective for understanding the determinants of agricultural profitability. Further agricultural profitability variable identification framework (APVIF) is proposed as a conceptual foundation. Overall, the taxonomy and APVIF offer a basis for future research on agricultural profitability modelling and AI-enabled decision-support systems, supporting more informed agricultural planning, efficient resource utilization, and sustainable improvements in farm profitability.

7. REFERENCES

1. Food and Agriculture Organization. The State of Food and Agriculture 2022: Leveraging Automation in Agriculture for Transforming Agrifood Systems. Rome, Italy: FAO, 2022.

2. Food and Agriculture Organization of the United Nations (FAO), International Fund for Agricultural Development (IFAD), United Nations Children's Fund (UNICEF), World Food Programme (WFP), and World Health Organization (WHO), The State of Food Security and Nutrition in the World 2023. Rome, Italy: FAO, 2023.

3. World Bank. World Development Report 2008: Agriculture for Development. Washington, DC: World Bank, 2008.

4. Intergovernmental Panel on Climate Change (IPCC), Climate Change 2023: Synthesis Report. Geneva, Switzerland: IPCC, 2023.

5. Pretty, J. "Agricultural Sustainability: Concepts, Principles and Evidence." Philosophical Transactions of

the Royal Society B: Biological Sciences, vol. 363, no. 1491, pp. 447–465, 2008.

6. Kay, R. D., Edwards, W. M., & Duffy, P. A. Farm Management, 8th ed. New York: McGraw-Hill Education, 2016.

7. D. B. Lobell, W. Schlenker, and J. Costa-Roberts, "Climate trends and global crop production since 1980," Science, vol. 333, no. 6042, pp. 616–620, 2011, doi: 10.1126/science.1204531.

8. C. Rosenzweig, J. Elliott, D. Deryng, A. C. Ruane, C. Müller, A. Arneth, K. J. Boote,C. Folberth, M. Glotter, N. Khabarov, K. Neumann, F. Piontek, T. A. M. Pugh, E. Schmid, E. Stehfest, H. Yang, and J. W. Jones, "Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison," Proceedings of the National Academy of Sciences, vol. 111, no. 9, pp. 3268–3273, 2014, doi: 10.1073/pnas.1222463110.

9. R. Gebbers and V. I. Adamchuk, "Precision agriculture and food security," Science, vol. 327, no. 5967, pp. 828–831, 2010, doi: 10.1126/science.1183899.

10. N. Zhang, M. Wang, and N. Wang, "Precision agriculture—A worldwide overview," Computers and Electronics in Agriculture, vol. 36, no. 2–3, pp. 113–132, 2002.J. L. Dillon and J. B. Hardaker, Farm Management Research for Small Farmer Development, 2nd ed. Rome, Italy: FAO, 1993.

11. S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big data in smart farming—Areview," Agricultural Systems, vol. 153, pp. 69–80, 2017, doi: 10.1016/j.agsy.2017.01.023.

12. T. van Klompenburg, A. Kassahun, and C. Catal, "Crop yield prediction using machine learning: A systematic literature review," Computers and Electronics in Agriculture, vol. 177, Art. no. 105709, 2020, doi: 10.1016/j.compag.2020.105709.

13. K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," Sensors, vol. 18, no. 8, Art. no. 2674, 2018, doi: 10.3390/s18082674.

14. T. Chen, L. Lv, D. Wang, J. Zhang, Y. Yang, Z. Zhao, C. Wang, X. Guo, H. Chen, Q. Wang, Y. Xu, Q. Zhang, B. Du, L. Zhang, and D. Tao, "Empowering agrifood system with artificial intelligence: A survey of the progress, challenges and opportunities," ACM Computing Surveys, vol. 57, no. 2, 2024, doi: 10.1145/3698589.

15. C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: A review," Precision Agriculture, vol. 13, no. 6, pp. 693–712, 2012.

16. D. G. Pai, M. Balachandra, and R. Kamath, "Explainable AI in agriculture: Review of applications, methodologies, and future directions," Engineering Research Express, vol. 7, no. 3, Art. no. 032202, 2025.

A. Rajbongshi, F. T. Johora, A. Hossain, M. S. Sarker, M. H. Rahman, M. W. Rahman, F. T. Alotaibi, and M. A. Moni, "Leveraging explainable artificial intelligence for sustainable agriculture: A comprehensive review of recent advances," Artificial Intelligence Review, vol. 59, no. 3, Art. no. 105, pp. 1–46, 2026, doi: 10.1007/s10462-025-11459-5.

17. Aashu, K. Rajwar, M. Pant, and K. Deep, "Application of machine learning inagriculture: Recent trends and future research avenues," arXiv:2405.17465, 2024, doi: 10.48550/arXiv.2405.17465.

18. G. James, D. Witten, T. Hastie, and R. Tibshirani, An Introduction to Statistical Learning, 2nd ed. New York, NY, USA: Springer, 2021.

19. D. C. Montgomery, E. A. Peck, and G. G. Vining, Introduction to Linear Regression Analysis, 5th ed. Hoboken, NJ, USA: Wiley, 2012