CHAPTER 3

Innovative smart agriculture toolkit in agribusiness cost management: modeling and practice of digital transformation

Hryhorii Savelenko
Nataliia Sysolina
Iryna Sysolina

Abstract

The article is devoted to a comprehensive study of the theoretical, methodological, and applied aspects of implementing Smart Agriculture technologies into the cost management systems of agricultural enterprises in the context of the Fourth Industrial Revolution.

The first section systematizes the conceptual foundations of Smart Agriculture and defines its place in the evolution from mechanization, through automation, to intelligent systems based on Big Data. The architecture of a multi-level digital cost management system is substantiated, integrating the Internet of Things (IoT), Artificial Intelligence (AI), digital twins, and Variable Rate Technology (VRT). The functional role of key components is revealed, including GPS navigation, NDVI satellite monitoring, unmanned aerial vehicles (UAVs), sensor networks, Farm Management Information Systems (FMIS), and predictive analytics algorithms.

The second section presents the results of econometric modeling of Smart technology efficiency. A methodology for assessing digital readiness based on the IDR index is developed, combining technical level, human resource potential, and management digitalization. An economic calculation for implementing a basic package for a 300-hectare farm is provided: capital expenditures of UAH 108,000 pay back in 6.5 months with 5% savings. The critical implementation threshold is identified at 100–120 hectares. It is proven that digitalization is a necessity for large enterprises, while for small ones, it requires thorough justification.

An analysis of the dependence of efficiency on scale was conducted: farms of 200–300 hectares achieve payback within a year, over 500 hectares – within a season, and those under 50 hectares require state support. Sensitivity analysis confirmed the model's stability even under a pessimistic scenario (payback period of 1.4 years).

 DOI: 10.21303/000-0000-0000-0-0.ch3

The results can be used by agricultural enterprises to justify investments, by researchers for studies on digital transformation, and by government agencies when formulating innovation support policies. The article is addressed to scientists, lecturers, students of economic and agricultural specialties, agribusiness managers, and public administration officials.

Keywords

Smart Agriculture, Agriculture 4.0, digital transformation, cost management, Internet of Things (IoT), artificial intelligence, precision farming, digital readiness index, econometric modeling, agribusiness.

3.1 Introduction

Modern development of agricultural technologies is based on the transition to Agriculture 4.0 and 5.0 models. Digital transformation within the Smart Agriculture concept is becoming a decisive factor in the viability of agribusiness, replacing traditional management approaches.

The use of IoT, AI, Big Data, and precision farming technologies fundamentally transforms cost management, ensuring a shift toward predictive management in real-time. This allows not only for minimizing resource consumption (fuel, fertilizers, crop protection products) but also for eliminating the negative impact of the human factor on decision-making. Despite the advantages, digital adaptation is hindered by barriers: from the high cost of innovation to the low digital readiness of farms, which requires scientific substantiation of cost management tools.

The article is devoted to the comprehensive modeling of costs in a digital environment and the diagnostics of the digital maturity of enterprises to increase their competitiveness.

To achieve the research objective, the following scientific hypotheses have been formulated:

– Smart Agriculture (VRT, IoT, AI) provides a non-linear reduction in operating costs through predictive resource optimization.

– The efficiency of transformation depends on the balance of the Digital Readiness Index (IDR) components, where human resources and management culture are critical.

– The payback of Smart Agriculture models correlates with the scale of land use, forming a feasibility threshold for small and medium-sized farms.

– Econometric modeling of digitalization scenarios minimizes investment risks and stabilizes production costs under conditions of market volatility.

The methodological basis of the study is a systems approach using the following methods:

1. Index method: to develop the methodology for assessing digital readiness (IDR).
2. Econometric modeling: to calculate the return on investment (ROI) and analyze cost sensitivity.
3. Case study method: for empirical testing of hypotheses on the example of agricultural enterprises of various scales.
4. Logical generalization: to substantiate the architecture of Smart Agriculture.

The combination of qualitative and quantitative methods ensured the comprehensiveness of the analysis and the verification of findings regarding the effectiveness of digital tools in the agricultural sector.

3.2 Theoretical and methodological foundations and smart agriculture toolkit in agribusiness cost management

The modern transformation of the agricultural sector is defined by the transition from automation (Agriculture 3.0) to Agriculture 4.0 intelligent systems based on Big Data and IoT. The Smart Agriculture concept serves as a tool for resource optimization and cost minimization by creating a holistic information environment [1, 2]. Unlike traditional approaches, the "smart" paradigm replaces subjective management experience with real-time analytics, allowing for a transition to predictive cost management [3–5].

For a clear understanding of the place of Smart Agriculture in the overall evolution of the industry, it is advisable to compare the characteristics of the main stages of technological development (**Table 3.1**).

Table 3.1 Evolutionary stages of technological development in agriculture

Stage	Key Dominant	Toolkit	Management Nature
Agriculture 2.0	Mechanization	Internal combustion engines	Scaling of operations
Agriculture 3.0	Precision	GPS navigation, sensors	Precise application of resources
Agriculture 4.0 (Smart Agriculture)	Digitalization	IoT, Big Data, Cloud Computing	Predictive analytics
Agriculture 5.0	Intellectualization	Artificial Intelligence, robotics	Autonomous decision-making

Source: developed by the authors based on [4, 5]

Researchers identify three levels of digital transformation: informational, technological, and managerial [6–8].

Digitalization in modern agribusiness serves not merely as an automation tool but as a fundamental factor in transforming scattered information arrays into a strategic asset for the enterprise. This process allows the enterprise to dynamically adapt to changes in the market environment through qualitative changes in key business processes. The transition from a traditional model to a digital functional format covers all levels of the enterprise's activities (**Table 3.2**).

Table 3.2 Transition from a traditional to a digital model of agribusiness functioning

Parameter	Traditional State	State under Digitalization
Information flows	Static reports, retrospective analysis	Real-time data, Big Data
Machinery fleet	Individual units of machinery	Integrated fleets of "smart" machines
Management method	Intuitive personnel decisions	Data-driven management (online)
Competencies	Narrow specialization	AgTech specialists with digital skills

Source: compiled by the authors

The aforementioned structural reorganization directly converts into economic results through specific efficiency enhancement mechanisms:

– acceleration of management processes. Through the use of cloud computing and sensor networks, enterprises gain the ability to conduct "virtual testing" of strategies before their implementation in the field;

– increased flexibility of business processes. The integration of digital solutions into value chains significantly enhances the adaptability of the enterprise, which is critically important for small market players;

– transition to a proactive model. Digital monitoring tools (e.g., satellite vegetation analysis) allow for the identification of hidden productivity reserves before they turn into critical losses;

– network interaction and "open knowledge". Digitalization stimulates the exchange of experience, facilitating farmers' access to global knowledge bases and expert support through digital platforms.

Such a transformation creates a qualitatively new basis for the capitalization of knowledge. This enables the enterprise to minimize operational risks and maximize the return on every unit of spent resource, which becomes the foundation for building a cost management system based on Smart Agriculture principles.

A systematic review of scientific publications conducted in the Scopus and Web of Science databases allows for the identification of the main technological components and their functional purpose in the context of Smart Agriculture (**Table 3.3**).

Table 3.3 Technological components of Smart Agriculture and their functional purpose

Technological Component	Functional Purpose	Key Characteristics
Internet of Things (IoT)	Real-time data collection via a distributed network	Monitoring temperature, fuel, soil moisture, automation
AI and Machine Learning	Big Data analysis, predictive analytics	Yield forecasting, disease diagnostics, resource optimization
UAVs (Drones)	Remote monitoring of crops and infrastructure	Multispectral imaging, thermal surveys, mapping
Precision Farming (VRT)	Differentiated resource application	GPS navigation, variable rates for seeds and fertilizers
Digital Twins	Virtual modeling of objects and processes	Scenario simulation, operations optimization
Blockchain	Supply chain transparency and security	Product traceability, smart contracts

Source: systematized by the authors based on [3, 6–8]

Bibliometric analysis of Scopus-indexed publications shows exponential growth in scientific interest in Smart Agriculture. A study [9] found that two-thirds of 2,154 analyzed publications were issued within the last four years, confirming the intensification of research. The dominant disciplines are computer science (64%), engineering (36%), and agricultural/biological sciences (22%), highlighting the interdisciplinary nature of Smart Agriculture and the need to integrate technical and agronomic competencies.

Digital transformation in agribusiness, occurring within the Smart Agriculture framework, transcends simple technological upgrades. A. Hassoun et al. [10] define this as a fundamental reconfiguration of business models, organizational structures, and operational processes. Successful transformation requires integrating physical, digital, and biological domains through AI, IoT, Big Data, robotics, and cloud computing to create intelligent digital farms.

Thus, Smart Agriculture should be interpreted as a strategic management model that ensures sustainable development through intelligent monitoring and analytics. This lays the groundwork for Agriculture 5.0, where the human role shifts from direct controller to system architect, and decision-making is increasingly delegated to AI algorithms.

The digital cost management architecture is a multi-level system adapting Industry 4.0 principles to agribusiness. Unlike traditional accounting, it provides a closed-loop cycle: from automated field data collection to predictive cost modeling, accounting for spatial variability and climatic factors.

The base layer consists of IoT networks monitoring soil, plants, and resource consumption in real-time [3, 4, 7]. These data arrays feed analytical models for cost optimization, replacing reactive management with predictive management. This hierarchical architecture integrates data collection, processing, and decision-making levels (**Table 3.4**).

Table 3.4 Architecture of a multi-level digital cost management system

Architecture Level	Technological Components	Functional Capabilities	Impact on Cost Management
Perception (Sensor)	IoT sensors, UAVs, satellite systems	Collection of data on soil, weather, resources	Real-time monitoring of actual costs
Network (Communication)	LoRaWAN, 5G, Edge Computing	Fast data transmission with minimal latency	Operational efficiency of decisions
Processing (Intelligent)	AI/ML algorithms, Big Data platforms	Pattern analysis, forecasting, optimization	Identifying cost reduction opportunities
Application (Executive)	Decision Support Systems, VRT-controllers	Automated resource management	Precise dosing, minimization of losses
Business Intelligence	Digital twins, blockchain	Scenario modeling, transparency	Strategic cost policy optimization

Source: developed by the authors based on [3, 7]

The key advantage of digital architecture is the transition from averaged cost allocation to granular costing for every square meter. The use of digital twins and cloud services enables the modeling of agronomic aspects (irrigation, fertilization, phytosanitary status) and the identification of local inefficiencies inaccessible to traditional accounting [11].

A special role belongs to the integration of GPS monitoring with Farm Management Information Systems (FMIS). This combination creates a synergetic effect, ensuring a 15–20% reduction in fuel costs and time through logistics optimization and the elimination of unauthorized equipment use [12]. Despite high potential, the application of digital twins for precision cost management is in the stage of scientific formation, which determines the relevance of further research.

Artificial Intelligence (AI) and Machine Learning (ML) algorithms play a critical role in ensuring the effectiveness of the digital cost management system. A systematic review in [13, 14] showed that the application of machine learning in agriculture covers a wide range of tasks, including plant disease detection, pest control, and yield forecasting.

The integration of AI algorithms into the cost management system ensures transformation at three levels: informational (predictive analytics), technological (autonomous machinery operation), and managerial (minimizing the human factor), as detailed in **Table 3.5**. In particular, the use of Convolutional Neural Networks (CNN) enables the implementation of spot spraying concepts, radically reducing expenditures on crop protection products (CPP).

Table 3.5 Functional role of machine learning algorithms in the digital transformation of cost management

Transformation Element	Algorithm (AI/ML)	Simple Analogy	Role in Smart Agriculture & Cost Impact
Informational	Random Forest	"Consilium of experts"	Analyzes soil/weather for precise fertilization, preventing waste
Technological	CNN	The "eyes" of the system	Provides spot spraying on affected areas, reducing pesticide costs
Managerial	SVM	"Strict border"	Automates decisions, minimizing risks and the human factor

Source: systematized by the authors

Variable Rate Technology (VRT) forms the operational level of the cost management architecture, translating analytical insights into specific actions for the differentiated application of resources. A meta-analytical study [15] indicates that VRT demonstrates significant potential in reducing fertilizer and pesticide consumption while simultaneously ensuring higher yields. These indicators confirm the economic viability of implementing precision farming technologies and their critical role in optimizing the cost structure of agricultural enterprises.

3.3 Applied aspects of digitalizing agribusiness cost management

Econometric modeling of Smart technologies is critical for justifying investments, as it allows for the consideration of a complex set of factors: from crop specifics to the level of technological maturity of the farms.

For medium and large agricultural enterprises, digital transformation is a necessity for business survival. At significant scales, intuitive management loses precision, requiring a transition to a Data-driven management model and the use of integrated fleets of "smart" machinery. Large farms derive maximum benefit from mapping and VRT [15, 16]. Empirical data [17, 18] confirm the possibility of saving up to 80% on fertilizer and CPP costs in specific areas. Beyond direct savings, the use of digital twins ensures operational transparency and minimizes risks across large land tracts.

For small agricultural enterprises, digitalization is a matter of strategic expediency, requiring diagnostics of the "entry threshold" [19]. Due to the high cost of complex software, the priority shifts toward affordable (low-cost) solutions: mobile applications and cloud telemetry. A key planning stage here is a detailed Return on Investment (ROI) analysis. Calculations based on the USDA report [18] indicate that yield mapping generates a net income of 25 USD/acre (compared to 13 USD/acre for soil mapping), making it a priority for small businesses. In addition to financial factors, the success of transformation in small farms is limited by socio-economic determinants: the digital literacy of personnel and access to expert support.

For large businesses, digitalization serves as the foundation for minimizing operational losses, while for small enterprises, it is a tool for targeted efficiency improvements, where the depth of implementation must match the readiness level. A meta-analysis [15], covering 1,472 observations, confirms that precision farming technologies increase return on investment (ROI) by 22.3% and net profit by 18.5%. Optimizing nitrogen fertilizer use by 15.1% allows for a reduction in production costs and pesticide load [15, 18].

The comprehensive performance indicators by technology category are presented in **Table 3.6**.

Table 3.6 Economic efficiency indicators of digital agricultural technologies

Technology Category	Economic Benefits	Environmental Perspectives	Key Metrics
Mapping (RMT, CTF)	Fertilizer savings up to 80%	Reduced water pollution	Cost reduction up to 2,595 UAH/ha
Variable Rate (VRT)	Fertilizer –60%, pesticides –80%	Reduced GHG emissions	Yield increase up to 62%
Robotics (RSSM)	Labor costs reduced by 97%	Fuel consumption –50%	Savings on labor remuneration
Info Systems (FMIS)	Yield increase by 10–15%	Resource optimization	Reduction in costs and labor
General Indicators	ROI +22.3%, Net Profit +18.5%	Nitrogen efficiency +15.1%	Pesticide reduction by 12.8%

Source: systematized by the authors based on [20, 21]

To ensure the objectivity of the findings, the results of a systematic review [15] conducted according to the PRISMA protocol were utilized. This allowed for the synthesis of WoS and Scopus data and the identification of digitalization determinants.

The adoption of precision farming technologies depends on economic indicators (savings, yield, ROI, payback), the producer's risk tolerance, and the level of state support. An agribusiness decision is shaped not only by financial factors but also by socio-political drivers.

An important direction is assessing the implementation of Industry 4.0 technologies (AI, IoT, Big Data, robotics, blockchain), systematized in study [10]. Bibliometric analysis of Scopus revealed a rapid increase in the number of publications over the last decade. Co-citation analysis (covering over 5,600 keywords) confirms the interdisciplinary nature of digital transformation research [10].

Socio-economic assessment must account for the specifics of small and medium-sized enterprises (SMEs). A systematic review [22] identified five thematic clusters: from economic impact on markets to the restructuring of agricultural knowledge systems. Research [22] emphasizes the importance of social and institutional dynamics when assessing digital readiness.

Particular attention should be paid to system resilience. Digital innovations (sensors, remote sensing, communication platforms) enhance resource efficiency and enable the redesign of agroecosystems [23].

The diagnostic methodology must consider the relationship between digitalization and total factor productivity. Domestic experience requires adapting international approaches to the conditions of Ukraine: production structure, infrastructure state, financial accessibility, and personnel readiness. Despite the thoroughness of existing theories, the applied assessment of an entity's digital state remains debatable. Most models focus on macro-indicators, ignoring internal enterprise specifics-particularly the correlation between technical equipment ("hardware") and real personnel competencies.

Summarizing global econometric and methodological assessment experience (**Table 3.7**), the need to adapt general principles of scientific validity and hierarchy, substantiated in [22], to the utilitarian needs of management becomes evident. The methodological approach to developing the authors' questionnaire is based on the "Agriculture 4.0" concept, where digital readiness is viewed as a multidimensional system.

To increase the objectivity of the results, the authors implemented a cross-validation mechanism. It is based on identifying "technological mismatches" described in studies [16]. This mechanism allows for the identification of enterprises with "technological redundancy" – situations where a high technical level is accompanied by low managerial digitalization or human resource potential, indicating inefficient investment use.

The author's multicriteria assessment methodology for digital readiness is based on the calculation of the Integral Index of Digital Readiness (IDR). This index allows for the differentiation of enterprises not only by technical equipment but also by managerial maturity and human resource potential. The assessment was conducted through surveys of agribusiness managers and specialists using the author's toolkit (**Fig. 3.1**).

Table 3.7 Methodological approaches to the econometric assessment of agribusiness digital readiness

Methodological Approach	Tool/Instrument	Scope of Application	Source
Digital economy assessment	Fixed effects, PSM, Heckman	Establishing causal relationships	[24]
Spatial modeling	SDM, SAR, SEM	Analysis of spatial effects	[25]
Rapid Diagnostics (IDR)	Weighted indexing, cross-validation, Kb	Micro-level maturity assessment	Author's development

Source: systematized by the authors

Block I. Business Profile	**Block III. Human Resources and Management Potential**
1. Land bank under cultivation (ha): __ 2. Primary line of business: (crop production / livestock / mixed) 3. Number of permanent employees: __	1. Does your enterprise have a specialist responsible for implementing IT solutions? (Yes / No / Shared role with another specialist). 2. Have your employees undergone training on digital tools in the last 2 years? (Yes / No). 3. Do you use specialized software for finance and cost management (e.g., FMIS: Soft.Farm, AgroOnline, Cropwise Operations, or Climate FieldView)? [_____]
Block II. Digital Readiness Assessment (Technical Level) *Rate the level of implementation for the following technologies on a scale of 0–3 (0 – do not use, 1 – plan to use, 2 – partially implemented, 3 – fully integrated):*	**Block IV. Identification of Barriers (Analytical Block)** *Which factors most significantly hinder the implementation of innovations in your farm? (Select top 3):*
1. GPS navigation and parallel driving systems. [ ] 2. Fuel consumption monitoring systems. [ ] 3. Satellite crop monitoring (NDVI). [ ] 4. Digital field maps and electronic field history logs. [ ] 5. Drones for spraying or monitoring. [ ] 6. Automated herd management systems (for livestock). [ ]	1. [ ] Lack of own funds and difficulty in obtaining loans for IT. 2. [ ] Long investment payback period. 3. [ ] Lack of qualified personnel ("digital divide"). 4. [ ] Poor connection quality and internet access in the fields. 5. [ ] Market instability (war, price fluctuations). 6. [ ] Lack of understanding regarding real economic benefits of implementation.

Fig. 3.1 Digital readiness and barriers to smart agriculture implementation questionnaire
Source: systematized by the authors

At the first stage, qualitative survey responses are converted into quantitative scores, followed by cross-validation. The primary goal of this stage is to generate reliable sub-index values that form the basis of the integral IDR.

Calculation of the Technical Level Sub-index (I_{tech}): the value is calculated as the arithmetic mean of scores for six key groups of Smart Agriculture technologies (Block II of the questionnaire). The cross-validation mechanism provides for the automatic adjustment of scores if technological inconsistencies are detected. Specifically, if a high level of drone usage or VRT is claimed without digital field maps or electronic field records, the corresponding indicator is reduced by 1 point. This is justified by the impossibility of fully utilizing precision equipment without a proper geoinformation foundation.

Calculation of the Human Resource and Management Potential Sub-index (I_{hr}): this indicator combines data on staffing and investment in human capital. Scoring: the presence of a dedicated specialist is worth 2 points (full-time staff) or 1 point (outsourcing/part-time); systematic personnel training adds 1 point. Verification: if a high technical level is identified ($I_{tech} > 2$) alongside low human resource potential ($I_{hr} < 1$), the enterprise's state is classified as "technologically redundant," indicating inefficient investment due to low personnel competence.

Calculation of the Management Digitalization Sub-index (I_{fmis}): this indicator determines the degree of integration of digital solutions into the financial management and strategic planning system. Differentiation: a maximum score (3) is assigned for a multi-platform approach (combining several FMIS systems for different tasks). Cross-validation: if a respondent reports using specialized software but indicates zero use of digital maps and monitoring systems in Block II, the I_{fmis} value is limited to 1 point. This correlation is explained by the fact that without primary digital field data, any FMIS system becomes a static accounting tool ("a digital typewriter"), losing its intellectual decision-support function.

The next stage involves calculating IDR, which accounts for results across three key transformation vectors. The calculation is performed using the following formula

$$IDR = w_1 \cdot I_{tech} + w_2 \cdot I_{hr} + w_3 \cdot I_{fmis},$$

where w_1, w_2, w_3 – weighting coefficients for the significance of each component (recommended values: 0.5, 0.3, and 0.2, respectively); I_{tech} – technical level sub-index, assessing the integration of technologies (GPS navigation, NDVI, drones, sensors) on a scale of 0–3 points (0 – not used, 1 – planned, 2 – partially used, 3 – fully integrated); I_{hr} – human resource and management potential sub-index, based on the presence of an IT specialist (Yes = 2, No = 0, Combined/Hybrid = 1) and personnel training (Yes = 1, No = 0); I_{fmis} – management digitalization sub-index, characterizing the depth of using specialized software (FMIS) for financial control:

– 0 points – "Paper Management": The enterprise does not use specialized software. Records are kept in paper logs or basic MS Excel spreadsheets, which are not classified as FMIS systems;

– 1 point – "Initial Digitalization": Accounting software (e.g., BAS) is used exclusively for tax reporting, without field or machinery management modules;

– 2 points – "Partial Digitalization (Monitoring)": The respondent indicates the use of one local or cloud monitoring system (e.g., Soft.Farm, AgroOnline, AgroControl). This allows for electronic field records and fuel monitoring but lacks deep big data analytics;

– 3 points – "Full Management Integration (Data-driven)": Comprehensive ecosystems with AI elements and predictive analytics are utilized (e.g., Cropwise Operations, Climate FieldView, John Deere Ops Center). This indicates the implementation of a data-driven management model where financial costs are automatically linked to every technological operation in the field.

At the third stage, the obtained IDR index values serve as the basis for classifying enterprises by their level of digital maturity – from adaptive to integrated profiles (**Table 3.8**).

The transition from the subjective assessments of individual respondents to an objective market overview is carried out at the stage of descriptive and comparative sample analysis. After calculating the integral IDR indices for each enterprise, data from Block IV is aggregated, where the Barrier Criticality Coefficient (K_b) is calculated as a frequency characteristic of mentions of a specific obstacle within the total population of responses. The Barrier Criticality Coefficient (K_b)

$$K_b = \frac{N_{barrier}}{N_{total}} \cdot 100\%,$$

where $N_{barrier}$ – the number of mentions of a specific factor (e.g., lack of funds or the "digital divide"); N_{total} – the total number of questionnaires.

Restricting respondents to selecting only the three most significant barriers (Block IV of the questionnaire) was applied to determine key decision-making factors and avoid diluting statistical significance. Calculating the Criticality Coefficient (K_b) for each factor in the overall sample allows for the transformation of individual priorities of economic entities into a systemic hierarchical rating of obstacles. This enables the identification of not only dominant barriers (with the highest K_b values) but also specific threats characteristic of certain groups of enterprises (e.g., technical barriers for small farms and managerial ones for large enterprises).

Table 3.8 Classification of agricultural enterprises by digital maturity level (scale 0–3)

Group (Profile Type)	IDR Level	Strategy Characteristics	Priority Toolkit
Adaptive (Low-Tech)	0.0–1.0	Fragmented digitalization; solving critical issues	Parallel driving, fuel sensors
Transition (Selective)	1.1–2.0	Strategic feasibility; conscious choice with high ROI	NDVI, digital maps, FMIS
Integrated (Smart-Adv)	2.1–3.0	Data-driven management; full integration	VRT, drones, ecosystems

Source: compiled by the authors

The final stage of the methodology involves conducting regression and correlation analysis to identify the density of the relationship between the subjective assessment of barriers (Block IV) and the objective level of digitalization IDR. The central hypothesis of the study is the assumption of a non-linear influence of an enterprise's internal readiness on the actual state of technology implementation. Within this methodology, the "digital paradox" is analyzed: a situation where an enterprise demonstrates a high level of understanding of the economic efficiency of innovations (high scores in Blocks II and III regarding implementation plans), yet the actual I_{tech} index remains low. Mathematical confirmation of this gap allows for the classification of the nature of the constraining factors:

– exogenous barriers (external): if the correlation between "understanding benefits" and "actual implementation" is weak, this confirms the dominant influence of external destructive factors (war risks, liquidity shortages, infrastructural constraints);

– endogenous barriers (internal): if a low level of implementation is accompanied by a low assessment of the importance of technology by the respondent, this indicates internal unreadiness caused by conservative management or a lack of competencies.

The proposed data processing approach includes a cross-validation stage of scores, allowing for the detection of hidden gaps between technical potential and the actual utilization of Smart solutions (**Table 3.9**).

Analytical interpretation of the results for Case Study "A": Despite using the premium John Deere Operations Center technological solution, Farm "A" failed to reach the "Integrated" group due to a critical gap in human resources. Technological paradox: The presence of advanced software ($I_{fmis} = 3$) is negated by the absence of a dedicated specialist ($I_{hr} = 1$) to perform systematic data analysis. Consequently, the equipment is primarily used for navigation rather than predictive management. Methodological recommendation: To transition into the "Integrated" group, the farm needs to shift its focus from purchasing "hardware" to developing digital competencies (hiring an IT agronomist or transitioning to full outsourcing of analytical services). Identified barrier: this case clearly identifies an endogenous barrier – a lack of internal competencies despite having significant investment resources. The synthesis of research allows for the interpretation of Smart Agriculture as an ecosystem where the integration of IoT and AI/ML forms the architecture of digital cost management. Despite the proven statistical significance of economic benefits, the success of innovations depends on a multitude of contextual factors – from the scale of the farm to the level of institutional support. This justifies the necessity of using applied diagnostic tools for digital maturity to account for multifactoriality in strategic decision-making.

Table 3.9 Application of the methodology (Case Study of Farm "A")

Assessment Parameter	Primary Data	Calculation & Cross-validation	Sub-index
Technical Level (I_{tech})	John Deere Ops Center	Score adjusted due to incomplete mapping	1.8
Human Resource (I_{hr})	No specialist; training exists	High risk of fragmented software use	1
Digital Mgmt (I_{fmis})	JD Operations Center	High score for integrated platform	3
Integral Index	IDR = (1.8 × 0.5) + (1.0 × 0.3) + (3.0 × 0.2) = 1.8		Group: Transition

Source: developed by the authors

The practical implementation of the Smart Agriculture concept in small agricultural enterprises requires detailed economic justification. Unlike large agro-holdings, small farms face the problem of "critical mass" – the minimum cultivation area at which investments become viable. As noted in the study [26], for farms smaller than 100 hectares, even basic components of precision farming can generate an unprofitable cost structure, necessitating adapted financing models or cooperative equipment sharing. In this context, the key task is to form a realistic investment package that, beyond equipment costs, accounts for communication infrastructure expenses, system integration, and personnel training.

For Enterprise "A" with an area of 300 hectares, capital expenditures (CAPEX) consist of several mandatory components that provide the basic functionality of Smart Agriculture. An analysis of commercial offers in the Ukrainian market for 2024–2025 allows for the creation of an optimized cost calculation, presented in **Table 3.10**.

The presented calculation is based on the principle of minimum sufficient functionality: machinery control, fuel monitoring, and parallel driving. Optimization is achieved by replacing satellite terminals with GSM repeaters, which reduces capital expenditures by UAH 35,000–40,000 and eliminates subscription fees.

Table 3.10 Capital expenditure (CAPEX) calculation for Enterprise "A"

Expenditure Item	Quantity	Price per unit, UAH	Total, UAH	Note
GPS tracker with FLS	3 units	12,000	36,000	Main machinery
GSM enhancement kit	2 units	8,500	17,000	"Blind zones"
Parallel driving navigator	1 unit	45,000	45,000	Basic level
Installation and setup	–	10,000	10,000	One-time
TOTAL (Entry Threshold)			108,000	≈ USD 2,700

Source: compiled by the authors based on commercial offers from leading suppliers (Gold-Agro-GPS, Smilab [27])

The entry barrier is UAH 108,000 (USD 2,700), which corresponds to the average investment level for basic digitalization of a small farm according to international studies [28]. For an objective assessment, it is necessary to consider the structure of operational expenditures (OPEX), covering software subscription fees, data transmission, and technical support. These costs are offset by savings on fuel, seeds, fertilizers, and administration.

For an enterprise with an area of 300 hectares, basic annual operating costs amount to 14,600 UAH/ha (totaling UAH 4.38 million). The main share is formed by expenditures on mineral fertilizers (5,800 UAH/ha), fuel (4,200 UAH/ha), and seeds (3,500 UAH/ha), which serve as the basis for calculating the payback of Smart solutions. The calculations are summarized in **Table 3.11**.

Table 3.11 Calculation of the payback period for Smart Agriculture implementation

Indicator	Value	Calculation
Annual variable costs	UAH 4,380,000	300 ha × 14,600 UAH
Projected savings (5%)	UAH 219,000	4,380,000 × 0.05
Annual software/SIM fees	UAH 18,000	3 units × 500 UAH × 12 months
Net annual effect	UAH 201,000	219,000 – 18,000
Payback Period	0.54 years	6.5 months

Source: calculated by the authors based on the Smart Agriculture implementation financial model

The results confirm the high economic viability of implementing a basic Smart Agriculture package for enterprises with an area exceeding 200–250 hectares. A payback period of 6.5 months is exceptionally short for the agricultural sector, where investment cycles typically last 2–3 years. This is explained by the fact that savings are primarily generated through logistics optimization, fuel control, and the minimization of the human factor, rather than solely through yield increases.

At the same time, the economies of scale are critically important. For farms with an area of less than 100 hectares, the payback period increases to 18–24 months, which approaches the threshold of investment attractiveness; for areas under 50 hectares, the basic package becomes unprofitable. This necessitates alternative models, such as cooperative equipment sharing or state subsidies. To assess attractiveness, the Simple Payback Period metric is used, defined as the ratio of capital expenditures to the net annual cash flow. The key issue remains determining the "threshold scale" – the minimum cultivation area that ensures a return on investment. To formalize this threshold, a modified payback period model is proposed, accounting for the scale effect:

$$PP = CAPEX / (S \times C \times r - OPEX),$$

where *PP* – payback period (years); *CAPEX* – capital expenditures; *S* – cultivation area (ha); *C* – specific costs per hectare (UAH/ha) and *r* – efficiency (savings) coefficient.

Applying this model to various production scales allows for the identification of economic zones for Smart Agriculture implementation, as presented in **Table 3.12**.

Table 3.12 Dependence of the payback period on the production scale

Area, ha	Total Annual Costs, UAH	Annual Savings, UAH	Payback, years	Zone
50	730,000	18,500	5.8	Unprofitable
100	1,460,000	55,000	1.96	Marginal
200	2,920,000	128,000	0.84	Feasible
300	4,380,000	201,000	0.54	Optimal
500	7,300,000	347,000	0.31	High-efficiency

Note: the calculation assumes a savings coefficient of 5%, specific costs of 14,600 UAH/ha, and an annual OPEX of UAH 18,000.
Source: calculated by the authors using the modified model

The analysis demonstrates a non-linear dependence of digitalization efficiency on the scale of production. The critical cultivation area (the break-even point within 2 years) is 100–120 hectares. For enterprises with an area of 200–300 hectares, the payback period is reduced to one year, and for farms exceeding 500 hectares, the return on investment occurs within a single planting season. At the same time, small farms (up to 50 hectares) are effectively excluded from the process due to a lack of economic viability for autonomous solutions, necessitating the implementation of cooperative models or state subsidies (covering 50–70% of the cost).

The sensitivity of the Smart Agriculture economic payback model depends on the following parameters:

– realized savings coefficient (*r*): the most variable indicator, depending on the personnel's discipline in using the system. According to [29], real savings can fluctuate from 3% to 8–10%, depending on the integration of technologies into business processes;

– quality of digital coverage: unstable GSM signals can increase CAPEX by 20–35% due to the need for additional infrastructural equipment;

– field configuration: high fragmentation of plots increases the potential for fuel and lubricant savings by 15–25% through route optimization;

– market conditions: rising prices for fuel and fertilizers accelerate payback, as savings are calculated as a percentage of current expenditures.

A sensitivity analysis using a scenario-based approach for a 300-hectare enterprise shows that even in a pessimistic scenario (3% savings, additional infrastructure costs), the payback period does not exceed 1.4 years. Alongside financial indicators, the success of transformation is determined by organizational factors: personnel readiness, quality of technical support, and the compatibility of innovations with existing machinery.

3.4 Conclusions

The study allowed for the formulation of the following generalizing points:

1. Management model transformation. Smart agriculture is defined as a strategic ecosystem that ensures a transition from reactive to proactive cost management based on real-time data. This confirms H_1: the integration of IoT, VRT, and AI forms an architecture capable of ensuring a non-linear reduction in operating costs through predictive resource optimization.

2. Digital readiness riagnostics. The developed methodology for calculating the integral IDR index allows for the differentiation of enterprises by digital profile types. Cross-validation of sub-indices reveals a "technological paradox", where a shortage of qualified personnel and low managerial culture negate investments in sophisticated equipment. This proves H_2: transformation efficiency critically depends on the balance of all readiness components.

3. Economic efficiency and economies of scale. Practical testing of the model for a 300-hectare farm demonstrated high investment attractiveness: with capital

expenditures of UAH 108,000, the payback period is 6.5 months at a 5% savings rate. The established dependence of payback on the scale of land use confirms H_3:

– feasibility threshold: the critical area is 100–120 ha (payback within 2 years);

– strategic zone: enterprises exceeding 500 ha achieve payback within a single planting season;

– structural exclusion: farms under 50 ha require cooperative models or state support (50–70% of equipment costs).

4. Resilience and risks. Sensitivity analysis confirmed the stability of the model: even under a pessimistic scenario (3% savings), the payback period for a 300-hectare enterprise does not exceed 1.4 years. This verifies H_4: econometric modeling minimizes investment risks under volatility. The primary barriers remain endogenous factors (conservative management, personnel resistance) and exogenous constraints (liquidity shortages, war risks).

Conflict of interest statement

The authors declare that there is no conflict of interest in relation to this paper, as well as the published research results, including the financial aspects of conducting the research, obtaining and using its results, as well as any non-financial personal relationships.

Financing

The study was performed without financial support.

Data availability

The data that support the findings of this study will be made available by the authors on reasonable request.

Use of artificial intelligence statement

The authors have used artificial intelligence technologies solely to verify the correctness and consistency of the English translation of the manuscript in an academic style. In particular, the authors used the generative language model ChatGPT (OpenAI, GPT-5.1 Thinking) for language checking and minor stylistic refinement. The authors bear full responsibility for the content of the final manuscript; the AI tool is not credited as an author and is not responsible for the reported results.

Acknowledgments

The authors received no specific support from individuals or organizations that should be acknowledged beyond their institutional affiliations stated in the manuscript.

Authors' contributions

Hryhorii Savelenko: Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – review & editing.

Nataliia Sysolina: Theoretical framework, Formal analysis, Data curation, Project administration, Writing – original draft, Writing – review & editing.

Iryna Sysolina: Methodology, Domain expertise (agroengineering), Literature review, Investigation, Integration of results, Writing – review & editing.

All authors contributedequally to the scientific content of this chapter, jointly developed theconceptual idea of the work, and approved the final version of the manuscript.

References

1. Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. Agriculture, 12 (10), 1745. https://doi.org/10.3390/agriculture12101745
2. Rajak, P., Ganguly, A., Adhikary, S., Bhattacharya, S. (2023). Internet of Things and smart sensors in agriculture: Scopes and challenges. Journal of Agriculture and Food Research, 14, 100776. https://doi.org/10.1016/j.jafr.2023.100776
3. Azlan, Z. H. Z., Junaini, S. N., Khan, A. S., Mustafa, W. A. (2025). Data-Driven Agriculture: Unveiling the Power of Internet of Things and Data Analytics For Transformative Farming Practices. Journal of Sensors, 2025 (1). https://doi.org/10.1155/js/6205646

4. Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. Agricultural Systems, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023
5. Saiz-Rubio, V., Rovira-Más, F. (2020). From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agronomy, 10 (2), 207. https://doi.org/10.3390/agronomy10020207
6. Ayoub Shaikh, T., Rasool, T., Rasheed Lone, F. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Computers and Electronics in Agriculture, 198, 107119. https://doi.org/10.1016/j.compag.2022.107119
7. Bacco, M., Barsocchi, P., Ferro, E., Gotta, A., Ruggeri, M. (2019). The Digitisation of Agriculture: a Survey of Research Activities on Smart Farming. Array, 3–4, 100009. https://doi.org/10.1016/j.array.2019.100009
8. Talaviya, T., Shah, D., Patel, N., Yagnik, H., Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture, 4, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002
9. Paudel, B., Riaz, S., Teng, S. W., Kolluri, R. R., Sandhu, H. (2025). The digital future of farming: A bibliometric analysis of big data in smart farming research. Cleaner and Circular Bioeconomy, 10, 100132. https://doi.org/10.1016/j.clcb.2024.100132
10. Hassoun, A., Marvin, H. J. P., Bouzembrak, Y., Barba, F. J., Castagnini, J. M., Pallarés, N. et al. (2023). Digital transformation in the agri-food industry: recent applications and the role of the COVID-19 pandemic. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1217813
11. Pylianidis, C., Osinga, S., Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. Computers and Electronics in Agriculture, 184, 105942. https://doi.org/10.1016/j.compag.2020.105942
12. Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., de Vargas Mores, G. (2018). Scientific development of smart farming technologies and their application in Brazil. Information Processing in Agriculture, 5 (1), 21–32. https://doi.org/10.1016/j.inpa.2017.12.002
13. Liakos, K., Busato, P., Moshou, D., Pearson, S., Bochtis, D. (2018). Machine Learning in Agriculture: A Review. Sensors, 18 (8), 2674. https://doi.org/10.3390/s18082674
14. Kamilaris, A., Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

15. Lan, J., Ban, Q. (2025). The Farm-Level Economic and Environmental Benefits of Precision Agriculture Technology Adoption: A Meta-Analysis of Global Evidence. Sustainability, 17 (24), 11223. https://doi.org/10.3390/su172411223
16. Lowenberg-DeBoer, J., Erickson, B. (2019). Setting the Record Straight on Precision Agriculture Adoption. Agronomy Journal, 111 (4), 1552–1569. https://doi.org/10.2134/agronj2018.12.0779
17. Schimmelpfennig, D., Ebel, R. (2016). Sequential adoption and cost savings from precision agriculture. Journal of Agricultural and Resource Economics, 41 (1), 97–115.
18. Schimmelpfennig, D. (2016). Farm profits and adoption of precision agriculture (Economic Research Report No. 217). U.S. Department of Agriculture, Economic Research Service. Available at: https://www.ers.usda.gov/publications/pub-details/?pubid=80325
19. Gabriel, A., Gandorfer, M. (2023). Adoption of digital technologies in agriculture – an inventory in a european small-scale farming region. Precision Agriculture, 24, 68–91. https://doi.org/10.1007/s11119-022-09931-1
20. Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., Fountas, S. (2024). Economic and environmental benefits of digital agricultural technologies in crop production: A review. Smart Agricultural Technology, 8, 100441. https://doi.org/10.1016/j.atech.2024.100441
21. Zhang, Q., Liu, Y., Gong, C., Chen, Y., Yu, H. (2020). Applications of Deep Learning for Dense Scenes Analysis in Agriculture: A Review. Sensors, 20 (5), 1520. https://doi.org/10.3390/s20051520
22. Klerkx, L., Jakku, E., Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS: Wageningen Journal of Life Sciences, 90–91 (1), 1–16. https://doi.org/10.1016/j.njas.2019.100315
23. Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. European Review of Agricultural Economics, 50 (4), 1277–1309. https://doi.org/10.1093/erae/jbad021
24. Ma, W., Nie, P., Zhang, P., Renwick, A. (2020). Impact of Internet use on economic well-being of rural households: Evidence from China. Review of Development Economics, 24 (2), 503–523. https://doi.org/10.1111/rode.12645
25. Lyu, Y., Wang, W., Wu, Y., Zhang, J. (2023). How does digital economy affect green total factor productivity? Evidence from China. Science of The Total Environment, 857, 159428. https://doi.org/10.1016/j.scitotenv.2022.159428
26. Bronson, K. (2018). Smart Farming: Including Rights Holders for Responsible Agricultural Innovation. Technology Innovation Management Review, 8 (2), 7–14. https://doi.org/10.22215/timreview/1135

27. Rozetka. Available at: https://rozetka.com.ua/
28. Schimmelpfennig, D., Lowenberg-DeBoer, J. (2020). Farm Types and Precision Agriculture Adoption: Crops, Regions, Soil Variability, and Farm Size. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3689311
29. Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., Blackmore, S. (2019). Economics of robots and automation in field crop production. Precision Agriculture, 21 (2), 278–299. https://doi.org/10.1007/s11119-019-09667-5