

ARTIFICIAL INTELLIGENCE IN THE DEVELOPMENT OF PROFESSIONAL SKILLS IN RURAL AREAS: A CONCEPTUAL MODEL FOR THE DIGITALIZATION OF AGRICULTURAL TRAINING

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Abstract

The digital transformation of agriculture depends not only on the adoption of modern technologies, but also on the capacity of human resources in rural areas to use digital tools effectively in professional and entrepreneurial activities. This study aims to develop a conceptual model for using artificial intelligence to enhance the professional skills of farmers, farm managers, cooperative members, and rural entrepreneurs. The research is exploratory and applied in nature and is based on a documentary analysis of a digital vocational training platform that integrates adaptive artificial intelligence, behavioural assessment, personalized educational content, virtual simulations, and progress-monitoring tools. Based on the identified functionalities, the main training needs in agriculture were correlated with possible digital learning pathways focused on farm management, data use, negotiation, cooperation, communication, decision-making, and risk management. The analysis indicates that the platform contains functionalities that could support the personalization of the educational process, provide learner-adapted feedback, and document skill development. The proposed model may help reduce geographical barriers to training, increase the relevance of educational programs, and strengthen rural human capital. However, validating its effectiveness requires empirical research conducted in farms, cooperatives, and rural enterprises.

Keywords: artificial intelligence; professional skills; vocational training; digital agriculture; rural development; human capital; personalized learning.

JEL classification: I25; O33; Q16

1. Introduction

The digital transformation of agriculture involves integrating technological solutions capable of supporting production, monitoring, organization, and decision-making processes. The use of farm management platforms, data-analysis tools, automated systems, and artificial intelligence applications can improve resource use, anticipate risks, optimize agricultural activities, and strengthen relationships

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among producers, suppliers, and markets. Nevertheless, the introduction of technology does not automatically guarantee better economic and organizational outcomes.

The effectiveness of digitalization depends on users' ability to understand, interpret, and apply the information provided by digital systems. In this context, human-capital development becomes an essential component of the modernization of agriculture and the rural economy. The required skills are not limited to the technical use of equipment or applications, but also include information analysis, critical thinking, decision-making, communication, negotiation, cooperation, change management, and risk assessment. Vocational training needs in rural areas are highly diverse. Farmers, farm managers, employees, cooperative members, and rural entrepreneurs have different levels of professional experience, digital competence, education, and access to infrastructure. Farm size, field of activity, and organizational position also influence the type and complexity of the skills required. Under these conditions, standardized training programs may insufficiently address learners' specific characteristics and may limit the transfer of knowledge into practical work.

The need for differentiated training is reinforced by the uneven progress of digitalization across Romanian rural areas. Although internet access and the use of digital public services have expanded, significant disparities between rural and urban communities continue to affect the capacity of individuals and enterprises to benefit from technological change. These differences indicate that the introduction of digital training platforms should be accompanied by measures addressing accessibility, basic digital literacy, and the specific socioeconomic conditions of rural users (Epure et al., 2024).

Artificial intelligence makes it possible to build educational processes adapted to each user's profile. The analysis of responses, choices, and progress can support adjustments to the level of difficulty, learning pace, and type of content delivered. At the same time, natural-language interaction can facilitate access to information and support individualized feedback. By integrating digital simulations and professional scenarios, training can go beyond the theoretical transmission of information and include the practice of behaviors and decisions relevant to professional activity.

The model analyzed in this article was developed within the project "Next-Gen Learning: Growing People Through Digital Innovation." It was conceived as a digital ecosystem for adult vocational training and integrates adaptive artificial intelligence, natural-language processing, virtual simulation, behavioral assessment, and progress monitoring. The platform includes modules for managing online, in-person, blended, and e-learning courses, managing users and roles, course and examination registration, certificate administration, examination-session organization, and report generation.

The existing functional structure confirms the presence of distinct components for managing courses, users, registrations, roles, certificates, examination files, competencies, and assessment sessions. The platform also supports report preview and export, learner-activity tracking, and a dedicated module for generating reports with artificial intelligence assistance. These functionalities provide the technical basis for configuring differentiated learning pathways and systematically documenting the training process. Applying the model to agriculture may target both technical and digital skills and the development of transversal skills. A farmer may follow a pathway adapted to interpreting farm indicators, using data to plan operations, or evaluating an investment. A manager may be trained in resource organization, team coordination, and risk-situation management. Cooperative members may practice negotiation, communication, and conflict resolution, while rural entrepreneurs may benefit from simulations involving customer relations, product presentation, commercial-strategy selection, and crisis management. The research problem is the need to adapt the functionalities of an existing digital platform to the requirements of vocational training in agriculture and rural areas. The platform was developed for adult vocational training, but its architecture allows the configuration of content, scenarios, and learning pathways specific to agricultural and entrepreneurial activities. It is therefore

necessary to establish a correspondence between the available technological modules and the categories of skills relevant to economic actors in rural areas.

The general objective of the article is to develop a conceptual model for using artificial intelligence to develop professional skills in rural areas, based on the structure and functionalities of the platform created through the project. To achieve this objective, the study identifies components relevant to agricultural training, correlates them with the main categories of professional skills, defines learning pathways and scenarios applicable to agriculture, and highlights the benefits and limitations of implementing the model. Starting from the platform's functional architecture and its potential adaptation to the specific features of agriculture, the research formulates the general hypothesis that integrating artificial intelligence into vocational training processes can contribute to the more effective development of skills required by actors in rural areas. The study assumes that content personalization, progress monitoring, outcome assessment, and feedback-generation functionalities can support differentiated learning pathways according to learners' profiles, experience, and needs. It also assumes that the model can be configured to develop complementary digital, managerial, entrepreneurial, and relational skills relevant to farmers, farm managers, cooperative members, and rural entrepreneurs. Another hypothesis is that the integrated use of course-administration, assessment, certification, and reporting modules can improve the coherence of the training process and facilitate documentation of professional progress. At the same time, the effectiveness of applying the model in rural areas is assumed to depend on adapting content to agricultural activities, users' initial digital skills, access to infrastructure, and the degree of technology acceptance.

By formulating this model, the digitalization of agriculture is approached not only from the perspective of introducing equipment and applications, but also from the perspective of preparing human resources to use them effectively. Vocational training is thus positioned at the intersection of technological innovation, skills development, and modernization of the rural economy.

2. Literature Review and Theoretical Framework

The digitalization of agriculture must be analyzed as a socio-technical process in which technological performance is influenced by the relationship among infrastructure, skills, organizational practices, and the institutional context. The synthesis by Klerkx, Jakku, and Labarthe shows that the literature on digital agriculture has focused on technology adoption and use, the transformation of agricultural work, data governance, power relations, and responsibility associated with innovation. The authors emphasize that introducing digital tools is not a linear process, because technologies are reinterpreted and adapted according to farm structure, user experience, and existing knowledge networks. From this perspective, skills development cannot be reduced to technical instruction in the use of an application; it must also include the ability to interpret data, assess automated recommendations, and integrate digital information into economic and production decisions.

This approach supports the proposed model as a socio-technical training system in which artificial intelligence, educational content, and the rural user are interdependent components. However, the way intelligent educational platforms can intervene directly in developing the skills needed for farm digitalization remains insufficiently researched (Klerkx et al., 2019).

The adoption of smart agricultural technologies is influenced both by the characteristics of the solutions and by perceptions and operating conditions at farm level. Giua, Materia, and Camanzi distinguish between intention to use and actual adoption, showing that performance expectations, perceived complexity, and social influence shape farmers' willingness to use smart technologies. The transition from intention to use is also conditioned by farm characteristics, with more structured farms being advantaged in the digitalization process. The findings suggest that the mere availability of technology does not eliminate adoption difficulties and that training should reduce perceived complexity,

demonstrate practical usefulness, and allow gradual experimentation. Consequently, the theoretical framework of this study incorporates elements specific to technology-acceptance models but extends them by introducing personalized training as a mediating mechanism between platform characteristics and the user's capacity to integrate digital solutions into professional activity. The unresolved issue concerns how acceptance of a training platform subsequently translates into actual use of agricultural technologies (Giua et al., 2022).

At European Union level, digital skills are a distinct condition of agricultural transformation, while internet access alone is insufficient to reduce usage gaps. Radlińska's analysis, based on European indicators of digital skills and internet access in rural areas, highlights the relationship among infrastructure, human capital, and the agricultural sector's capacity to capitalize on available technologies. The importance of the study lies in separating physical access to technology from the ability to use it: connectivity creates the possibility of participating in the digital economy, but outcomes depend on users' skills. This distinction is relevant to the proposed conceptual model because the training platform is treated not only as educational infrastructure, but as a tool for transforming digital access into professional capacity. However, aggregate European-level analysis does not sufficiently capture differences among farmer categories, farm sizes, and specific learning needs. Therefore, an approach that differentiates learning pathways according to learner profile and professional context is required (Radlińska, 2026).

In the Romanian context, the structure of skills required by contemporary agriculture goes beyond the traditional separation between technical knowledge and general abilities. Grama and Bătrîna analyzed the skills associated with agricultural occupations by correlating the European skills taxonomy with job-ad requirements and the perceptions of students and farmers. Their results indicate the importance of information management, data analysis, communication, resource allocation, problem-solving, decision-making, and team coordination. At the same time, differences between the skills requested by employers and those considered important by practitioners show that training programs built exclusively around formal requirements may overlook relevant professional needs. This finding justifies including initial diagnostic and content-adaptation mechanisms in the proposed model so that training reflects both occupational requirements and users' concrete difficulties. The study's limitation lies in the small sample of farmers, which requires caution when generalizing the hierarchy of skills, but does not diminish the relevance of the multidimensional nature of the agricultural professional profile (Grama & Bătrîna, 2024).

Professional development in agriculture also requires mechanisms through which skills acquired in formal, nonformal, or practical contexts can be evaluated and recognized. Research concerning agricultural employees in Buzău County emphasizes the growing importance of qualification and certification, particularly in relation to employers' requirements and access to development opportunities. An artificial-intelligence-supported platform could complement existing certification structures by documenting learning activities, assessment results, and individual progress, without replacing the authorized institutions responsible for formally recognizing professional qualifications (Manolache et al., 2022).

Artificial intelligence expands the possibilities of digital training by moving from uniform content distribution to the configuration of adaptive educational experiences. The systematic review by Merino-Campos highlights the use of artificial intelligence for content recommendation, difficulty adjustment, individualized feedback, progress analysis, and identification of learning needs. The contribution of these systems lies in their ability to respond to learner heterogeneity, which is particularly relevant in rural areas where levels of education, professional experience, and digital literacy may differ considerably. Nevertheless, algorithmic personalization should not automatically be equated with pedagogical effectiveness.

The quality of outcomes depends on the validity of the data used, the transparency of recommendation criteria, the protection of personal information, and the maintenance of human control over the educational process. The literature also notes a lack of longitudinal assessments demonstrating the transfer of skills from the digital environment to professional activity. In the proposed model, artificial intelligence is therefore positioned as a tool supporting learning and assessment, not as a substitute for trainer expertise or practical experience (Merino-Campos, 2025).

The experiential component of the conceptual framework is supported by research on the use of virtual reality in skills development. Xie and colleagues show that virtual environments allow tasks to be repeated, difficulty levels to be controlled, dangerous or costly situations to be simulated, and user behavior to be recorded. These features are relevant to agricultural training because they can simulate decisions concerning resource use, risk situations, commercial interactions, work procedures, and organizational contexts that are difficult to reproduce in real conditions. However, the effectiveness of virtual reality does not result solely from immersion, but from coherence among pedagogical objectives, scenario structure, feedback, and assessment method.

The authors identify development costs, user discomfort, equipment requirements, and the difficulty of demonstrating transfer to real performance. Based on these findings, the proposed model combines artificial-intelligence personalization with experiential simulation but makes the use of virtual reality conditional on the practical relevance of scenarios and technological accessibility. The study's contribution lies in integrating agricultural skills, technology acceptance, adaptive learning, and professional simulation into a single framework, although these areas are often treated separately in the literature (Xie et al., 2021).

The integration of artificial intelligence into Romanian farms must be examined both in terms of operational benefits and the capacity of human resources to use new technologies. Artificial-intelligence applications can support activity monitoring, data analysis, risk anticipation, and decisions concerning resource use. However, exploiting these functionalities depends on appropriate digital and analytical skills, as well as users' ability to critically interpret recommendations generated by automated systems. In this context, vocational training becomes a necessary condition for the sustainable integration of artificial intelligence into farm management. The proposed conceptual model addresses this requirement by configuring differentiated learning pathways, monitoring progress, and using assessment and reporting mechanisms adapted to learner profiles. The platform can thus facilitate the transition from the mere availability of technology to its effective use in economic and decision-making processes in agriculture (Pleșa et al., 2024).

The implementation of digital training platforms should also be connected to broader mechanisms of technological transfer within the agro-food sector. In Romania, the practical adoption of innovation remains dependent on cooperation among farmers, research institutions, universities, public authorities, and private technology providers. Strengthening these relationships could facilitate the adaptation of artificial-intelligence-based training tools to real agricultural needs and improve the transfer of knowledge from research and development environments to farms and rural enterprises (Vlad & Stanciu, 2025).

Overall, the resulting theoretical framework articulates four complementary dimensions: digital agriculture as a socio-technical system, technology acceptance, human capital, and adaptive-experiential learning. The model assumes that digital infrastructure facilitates access to training, artificial intelligence adapts content and feedback, simulation enables knowledge application, and assessment and reporting modules document progress. The potential effects of the platform are nevertheless conditioned by initial skills, perceived usefulness, ease of use, content relevance, and the organizational characteristics of farms or rural enterprises. The contribution of this study is not to claim effectiveness that has already been empirically demonstrated, but to construct a conceptual link

between the functionalities of an existing platform and the training requirements generated by agricultural digitalization. The model therefore provides a basis for designing and subsequently evaluating pilot programs for farmers, farm managers, cooperative members, and rural entrepreneurs.

3. Materials and Methods

3.1. Study Design and Context

The research was designed as a conceptual and applied study with a qualitative approach, based on the analysis of a technological case represented by the vocational training platform developed within the project “NEXT-GEN LEARNING: GROWING PEOPLE THROUGH DIGITAL INNOVATION.” The project is implemented under Romania’s National Recovery and Resilience Plan, Component 9 – Support for the Private Sector, Research, Development and Innovation, Investment 3 – Aid schemes for the digitalization of small and medium-sized enterprises. The project beneficiary is CREȘTEM OAMENI S.R.L., and the conceptual documentation of innovative products and processes was carried out under activity A1, corresponding to contract 8.1.i3.c9.

The case was selected because of the integrated nature of the developed solution, which combines training-management functions with conversational artificial intelligence, adaptive learning pathways, virtual- and augmented-reality simulations, outcome assessment, and report generation. The platform is designed as a browser-accessible learning management system and includes components for managing courses, users, roles, registrations, examinations, and certificates. The solution uses its own secure infrastructure, with dedicated servers and artificial-intelligence-based processing components.

The analysis was conducted in the context of developing a model for using the platform in vocational training for agriculture and rural areas. The case was therefore not selected to assess the product’s commercial performance, but to examine the transferability of its functionalities to the training of farmers, farm managers, cooperative members, agricultural employees, and rural entrepreneurs. The primary unit of analysis was the platform’s functional and pedagogical architecture, while the secondary units were the technological modules, educational processes, and categories of data generated during use. The period analyzed corresponds to the design, development, and implementation stages documented through 2026. Project documentation provides for the completion of equipment delivery and configuration by 31 May 2026, and the implementation of software components, integrations, and initial courses by 31 July 2026. The study therefore reflects the conceptual and functional configuration available during the implementation stage and does not represent a post-implementation assessment conducted on a sample of agricultural users.

3.2. Data, Variables, and Material Selection

The research information base consisted of three categories of primary sources: the project business plan, the conceptual document on innovative products and processes, and the platform implementation documentation. These materials were supplemented by examining the functional interfaces shown in system screenshots. The sources were purposively selected to include documents containing information directly relevant to the study objective: platform architecture, pedagogical principles, available modules, user types, assessment processes, and reporting possibilities.

The analysis included sections describing user-centered design principles; artificial-intelligence personalization; natural-language processing; virtual-reality integration; course creation and administration; initial and final assessment; progress monitoring; certification; user and role administration; report generation; security; and data protection. The conceptual document states that the platform uses user-centered design, distinct learning pathways, calibrated virtual scenarios, and personalized feedback. The pedagogical model also integrates experiential learning, cognitive

processes, artificial-intelligence-based adaptability, and immersion through virtual scenarios, supported by continuous assessment.

Strictly financial, legal, or commercial information that did not contribute to defining the educational model for agriculture was excluded. Statements concerning user impact that were not supported by empirical data were also excluded from the results analysis. Because the platform had not been tested on a sample of farmers at the time of the study, no individual data, questionnaire responses, learning scores, or statistical performance indicators were used.

Instead of statistical variables, analytical dimensions were defined to assess transferability to the agricultural context. The first dimension, technological functionality, included the presence of artificial-intelligence, virtual-reality, course-management, assessment, certification, and reporting modules. The second dimension, pedagogical function, examined the role of each component in diagnosing the initial level, personalizing content, practicing skills, providing feedback, and measuring progress. The third dimension, professional relevance to agriculture, indicated whether the function could be adapted to agricultural, managerial, commercial, or entrepreneurial activities. The fourth dimension, implementation conditions, included infrastructure, initial digital skills, accessibility, data security, and scalability.

The indicators used were nominal and ordinal. The presence of a functionality was coded using binary values, namely “present” or “absent.” Relevance to agricultural training was assessed on a three-level ordinal scale: low, medium, or high. Adaptability was evaluated against three criteria: the existence of an appropriate technical function, compatibility with an educational objective, and the possibility of constructing a rural professional scenario. The units of observation were platform modules and processes, not course participants.

The interface examined included modules for online, classroom-based, blended, and e-learning courses; user and role administration; course and examination registration; certificates; examination files; competencies; sessions; and export report. Screenshots were used to confirm the functional existence and organization of these components, without being treated as sources of data on pedagogical effectiveness.

3.3. Analytical Methods

The analysis was conducted in three successive stages. In the first stage, a qualitative content analysis of project documents was performed. Relevant fragments were coded according to their technological and educational roles.

The initial coding categories were defined deductively from the study objective: personalization, assessment, simulation, monitoring, certification, reporting, accessibility, and security. During the analysis, emergent categories were added, including conversational interaction, generation of branching pathways, result logging, and integration with external systems. In the second stage, a functional analysis of the platform was conducted. For each identified module, the relevant inputs, processes, and outputs were established. For example, the conversational component was analyzed in terms of the user’s voice or text input, speech-to-text conversion, contextualization, response generation, recommendation of the next step, and interaction logging. The documentation describes a flow involving speech-to-text conversion, the use of a language model to generate a response, text-to-speech conversion, and the recording of decisions and scores.

For the adaptive component, the types of data that the system can use were analyzed: decision speed, discourse, behavioral patterns, logical errors, reactions under pressure, and learning pace. These data are processed to adjust the level of difficulty, provide additional explanations, and generate a

personalized report. For virtual reality, the analysis examined how the device is associated with the session, how events are collected, and how results are transferred to reports.

In the third stage, a functional correspondence matrix was constructed by linking platform components with skill domains relevant to agriculture and the rural economy. Skills were grouped into four categories: digital and analytical skills, managerial and decision-making skills, commercial and entrepreneurial skills, and social and organizational skills.

Functionality was considered transferable when it simultaneously met the following conditions: it allowed agriculture-specific content to be configured, supported a measurable learning objective, and generated data usable for assessing progress. Internal validation of the model was performed through source triangulation, comparing information from the business plan, the conceptual document, implementation documentation, and visual interfaces. A functionality was included in the model only when it was described in the documentation or identified in the platform interface. Claims regarding potential impact were distinguished from observed results; in the absence of a pilot study, they were formulated as conceptual relationships requiring empirical testing.

The outcome of the methodological procedure is a conceptual model describing how the functionalities of an existing platform can be reorganized and contextualized for vocational training in agriculture. At this stage, the model does not demonstrate the platform's educational effectiveness or economic impact but provides a transparent basis for designing a subsequent pilot study in farms, cooperatives, and rural enterprises.

4. Results

The results present the platform's functional configuration and the correspondence between its components and the requirements of a training model for agriculture and rural areas. Given the conceptual and applied nature of the research and the absence of a learner sample, the results do not express statistically measured pedagogical effects. Therefore, no effect coefficients, confidence intervals, or significance levels were calculated. The analysis highlights existing functionalities, their educational role, and their adaptability to different categories of professional skills.

4.1. Functional Structure of the Platform

The analysis of the platform documentation and interface revealed a modular system in which educational-process administration is connected to artificial-intelligence, assessment, reporting, and certification functions.

The platform supports four modes of course delivery—online, classroom-based, blended, and e-learning—and includes distinct components for managing users, roles, registrations, examinations, certificates, and reports. The educational component is not limited to publishing content. The documentation provides for real-time adaptation of the learning pathway, branching virtual scenarios, contextualized feedback, and a final report that may include a skills map, score development, individualized recommendations, and a development plan.

The platform follows a user-centred approach that considers learning progress, information-processing style, and individual preferences.

For a concise presentation of the results, the identified components were grouped into four functional levels. As shown in Figure 1, the first level covers access and administration, the second focuses on educational activities, the third is dedicated to assessment and analysis, and the last ensures integration with other systems and data protection.

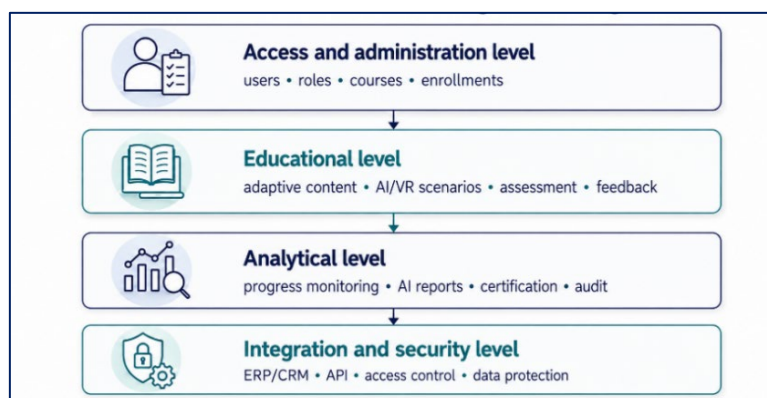


Figure 1. Functional architecture of the digital training model

Source: Authors' processing based on project documentation and the platform interface.

Note: AI = artificial intelligence; VR = virtual reality; ERP = enterprise resource planning system; CRM = customer relationship management system; API = application programming interface.

The results of the functional analysis are summarized in Table 1.

Table 1. Platform functionalities and their role in the vocational training model

Component analyzed	Main function	Output generated	Relevance to agricultural training
Course administration	Creation, classification, and publication of training programs	Online, classroom-based, blended, and e-learning courses	High
User administration	Creation and management of learner profiles	Participant records and training history	High
Role administration	Differentiation of access rights and responsibilities	Access configured for administrator, trainer, client, and learner	Medium
Course registration	Allocation of participants to educational activities	Learner lists and attendance records	High
Conversational artificial intelligence	Natural-language interaction and response adaptation	Clarifications, recommendations, and contextualized responses	High
AI/VR scenarios	Practice of decisions and behaviors in simulated contexts	Events, choices, scores, and branching pathways	High
Assessment and examination	Verification of knowledge and skills	Individual results and pass status	High
Certification	Documentation of program completion	Certificates and records of acquired skills	Medium
Reporting and analysis	Aggregation of activity and progress data	Reports on courses, registrations, sessions, and examinations	High
Integration and security	Controlled data exchange and information protection	Traceability, access control, and ERP/CRM integration	Medium

Source: Authors' processing based on project documentation and inspection of the platform interface.

Note: Relevance was assessed on a three-level ordinal scale: low, medium, and high. "High" indicates a direct relationship with the design, delivery, or assessment of training; "medium" indicates an organizational or administrative support function. AI = artificial intelligence; VR = virtual reality; ERP = enterprise resource planning system; CRM = customer relationship management system.

For each component, the dominant function, the type of output generated, and its relevance to adapting the model for vocational training in agriculture were identified. Of the ten components analyzed, seven were classified as highly relevant to agricultural training and three as moderately

relevant. No component was identified as having low relevance. This distribution indicates that the existing architecture covers both core pedagogical functions and the administrative processes required to implement programs for farms, cooperatives, and rural enterprises. The result does not express component effectiveness, but their functional compatibility with the requirements of a vocational training program.

4.2. Personalization and Monitoring of the Learning Pathway

The analysis identified a circular rather than strictly linear educational flow. The process begins by identifying the learner's profile and needs, continues with the configuration of activities, and concludes with assessment and the generation of a development plan. The results obtained can be fed back into the system to adjust content and difficulty levels.

The platform allows two users enrolled in the same course to undertake different activities depending on their responses, pace, and identified difficulties. The documentation describes exercises adapted to the user's level, scenarios calibrated to behavioral style, personalized explanations, and automatic adjustment of learning pace. The integration of AI and VR also allows the scenario to be modified according to behavior, immediate feedback to be provided, and indicators such as reaction time, discourse structure, decision patterns, and pressure management to be analyzed. The resulting flow is presented in Figure 2.

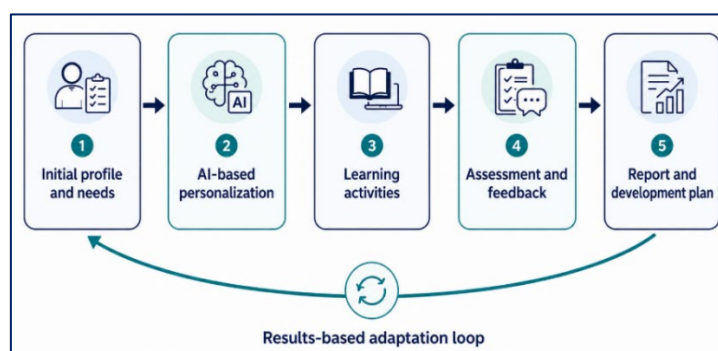


Figure 2. Adaptive flow of the artificial-intelligence-based training process

Source: Authors' processing based on the educational processes described in the project documentation.

Note: The lower arrow represents the feedback loop through which assessment results can lead to recalibration of content, difficulty, or recommended activities.

Regarding the hypothesis on educational-process personalization, the analysis supports the existence of the functional conditions necessary to construct differentiated pathways. The system can use the initial profile, responses, and intermediate results to adjust activities, while reporting modules make it possible to document progress. This conclusion is functional in nature and does not demonstrate that personalization produces superior educational outcomes, which requires validation through a pilot study.

4.3. Correspondence Between Functionalities and Skills Relevant to Rural Areas

The transfer of the model to agriculture was analysed by associating the platform functionalities with four main categories of professional skills: digital and analytical skills, managerial and decision-making skills, commercial and entrepreneurial skills, and social and organizational skills. This classification was used to determine whether the existing technological components could support different types of learning objectives relevant to farmers, farm managers, cooperative members, agricultural employees, and rural entrepreneurs.

The correspondence analysis focused on the practical role of each platform component in the training process. Adaptive content and conversational artificial intelligence were considered suitable for activities requiring information interpretation, clarification of technical concepts, and gradual adjustment of difficulty. Branching scenarios and virtual-reality functions were associated with situations involving decisions under pressure, resource allocation, conflict management, negotiation, and risk assessment. Reporting and assessment modules were linked to the documentation of learner responses, completion patterns, progress, and the recommendations generated during the training pathway.

The results of this association are presented in Table 2. They indicate that the same technological infrastructure can support several categories of professional skills without requiring changes to the platform's basic architecture. The main differences would occur at the level of educational content, scenario design, knowledge bases, performance indicators, and assessment criteria. This suggests that the platform has a modular structure in which technological functions remain relatively stable, while the learning experience can be adapted to the professional context and the characteristics of the target group.

For example, the conversational component can be used to explain a technical concept, guide a learner through the interpretation of farm indicators, simulate a commercial negotiation, or reproduce an organizational conflict. Similarly, branching scenarios can be configured for decisions concerning resource allocation, climatic risks, operational disruptions, customer relations, or cooperation among members of an agricultural organization. The recorded indicators would therefore vary according to the objective of the activity, ranging from response accuracy and completion time to decision sequence, communication coherence, or the identification of relevant risks.

Table 2. Correspondence between skill domains, proposed activities, and platform indicators

Skill domain	Example of educational activity	Functionalities used	Indicators that can be recorded
Digital and analytical	Interpreting farm indicators and selecting an action	Adaptive content, conversational AI, assessment	Response accuracy, number of attempts, completion time
Managerial and decision-making	Prioritizing activities under limited resources	Branching scenario, VR, AI feedback	Selected option, reaction time, sequence of decisions
Commercial and entrepreneurial	Negotiating a delivery contract or presenting a product	Conversational simulation, response analysis, reporting	Argument structure, choices made, scenario completion
Social and organizational	Managing conflict among members or employees	Conversational scenario, VR, behavioural assessment	Response type, communication coherence, pathway followed
Risk management	Responding to a critical climatic, economic, or operational situation	Branching simulation, microlearning, assessment	Risks identified, decision adopted, response time
Learning and continuous development	Building an individual development plan	AI report, recommendations, certification	Progress between assessments, modules completed, recommendations generated

Source: Authors' processing based on the correspondence matrix between platform functionalities and professional activities in agriculture.

Note: The indicators represent data that can be recorded by the platform, not results measured in the present study. AI = artificial intelligence; VR = virtual reality.

Regarding the hypothesis on developing complementary categories of skills, the results support the possibility of a multidimensional approach. The model does not separate digital skills from managerial or relational skills but allows them to be integrated into a common pathway. This feature is relevant to

agricultural activity, where the use of technology is often associated with data interpretation, decision-making, and communication of that decision within the organization.

4.4. Assessment, Reporting, and Documentation of Progress

The interface analysis revealed separate sections for course registrations, examination registrations, sessions, files, certificates, and export report. The reporting module allows distinct categories of data to be selected, including courses, registrations, sessions, examinations, and activity audits. In the platform documentation, the final report is designed to combine comparative scores, learner progress, recommendations, and an individual development plan. This structure supports the hypothesis that integrating administration, assessment, and reporting functions can ensure informational continuity throughout the training process. Data generated while courses are undertaken can be associated with the user profile and used to document results. In an agricultural context, reports may be configured at individual, farm, cooperative, or training-program level, subject to access and data-protection rules.

However, the existence of reporting tools is not equivalent to the validity of pedagogical indicators. Before the platform is used in an empirical study, each skill must be operationally defined, scoring criteria must be established, and agreement between system results and assessments by human experts must be verified.

4.5. Identified Implementation Conditions

The analysis identified four main conditions for applying the model in rural areas. The first is adapting content to real agricultural activities and situations. The second concerns access to infrastructure and users' ability to operate the necessary devices. The third concerns data protection, especially when responses, results, and behavioral indicators are collected. The fourth relates to the involvement of trainers and agricultural specialists in validating the scenarios and recommendations provided by the system.

The documentation provides platform integration with ERP and CRM systems, differentiated role administration, result logging, and the use of standard mechanisms for authorization, traceability, and audit. For AR/VR experiences, the flow includes securely associating the device with the session, collecting events, and transmitting results to reports. These functions provide technical prerequisites for implementation, but their applicability in different rural areas depends on equipment accessibility and initial levels of digital competence.

Overall, the results conceptually support the general research hypothesis: the existing platform contains the functionalities needed to configure a vocational training model for agriculture and rural areas. Support for the hypothesis is limited to the functional and pedagogical compatibility identified through document and interface analysis. The model's effectiveness, its effect on skills, and its acceptance by users cannot be established without empirical testing. These dimensions should be assessed by applying standardized instruments before and after training and comparing the results with those of a group completing a conventional program.

5. Discussion

The findings indicate that the analysed platform has an architecture flexible enough to support the design of vocational training programs adapted to agriculture and rural areas. The relevance of the model does not derive solely from the existence of artificial-intelligence functions, but from their integration with course administration, skills assessment, progress monitoring, reporting, and certification. This combination allows a transition from a training model cantered on uniform content distribution to one in which the learning pathway can be adjusted according to the learner's initial level, learning pace, and encountered difficulties. In relation to the research objective, the central

contribution therefore consists in identifying functional compatibility between an existing digital platform and the requirements of vocational training in agriculture.

The interpretation of the results confirms the view that agricultural digitalization should be approached as a socio-technical process rather than as the simple introduction of equipment or applications. Klerkx, Jakku, and Labarthe emphasized that the effects of digital agriculture are influenced by user practices, organizational structure, and actors' capacity to integrate technology into current activities. The analysed model responds to this perspective by including functions aimed not only at transmitting information, but also at practicing decisions, assessing behaviours, and tracking progress. Training thus becomes a component of the farm's digital infrastructure, while learner skills are treated as a condition for effective technology use rather than a secondary result of digitalization.

The results are also consistent with conclusions concerning the acceptance of smart technologies in agriculture. Giua, Materia, and Camanzi showed that intention to use and actual adoption are influenced by perceived usefulness, solution complexity, and conditions at farm level. From this perspective, personalization of the learning pathway can reduce perceived difficulty and allow digital concepts or functions to be introduced gradually. The ability to adapt content to user experience is particularly important in rural areas, where differences among learners can be substantial. Nevertheless, the functional compatibility identified in this study does not demonstrate that the platform will be uniformly accepted by all user categories. Initial digital-skill levels, previous experience, and trust in artificial-intelligence systems may significantly influence implementation outcomes.

The model also supports the idea that training for digital agriculture must include a broad skills profile. The analysis conducted for the Romanian context identified the possibility of using the same infrastructure for digital and analytical, managerial, commercial, entrepreneurial, and organizational skills. This approach is consistent with the findings of Grama and Bătrîna, who emphasized the importance of information analysis, decision-making, communication, coordination, and resource management in contemporary agricultural occupations. The model contributes by bringing these domains together in an integrated learning pathway. In practice, the use of an agricultural application cannot be fully separated from data interpretation, risk assessment, or communication of a decision to employees, partners, or cooperative members.

The integration of artificial intelligence into the educational process nevertheless introduces several methodological and ethical conditions. Recommendation, adaptation, and feedback-generation functions can increase the relevance of training, but their quality depends on the content used, the assessment criteria, and the accuracy of the data entered the system. The findings are compatible with Merino-Campos's observations regarding the potential of personalized learning and the need to maintain pedagogical control and decision-process transparency. Artificial intelligence should not be treated as an autonomous authority in skills assessment, but as a support tool. In agricultural training, validation of content and recommendations by field experts is essential because incorrect information may have economic, technical, or safety consequences.

The simulation component is one of the functions with the highest applied potential. Situations such as negotiating a contract, resolving a conflict, responding to an operational risk, or prioritizing work under resource constraints can be practiced in a controlled environment. This interpretation is consistent with the analysis by Xie and colleagues, according to which virtual reality allows task repetition, difficulty adjustment, and observation of user behaviour. However, merely using an immersive environment does not guarantee learning. Scenarios must be linked to explicit educational objectives, and the indicators used for assessment must be validated. Otherwise, the virtual component may become primarily demonstrative, with no clear effects on professional skills.

An important finding is that the value of the model is not concentrated exclusively in advanced artificial-intelligence and virtual-reality modules. Administrative functions, such as managing users, roles, registrations, sessions, certificates, and reports, make a significant contribution to the coherence of the training process. These components allow activity traceability, comparison of results, and documentation of progress. In rural areas, where training programs may involve farms, cooperatives, advisory providers, and public institutions, a shared administrative infrastructure may be just as important as content personalization. This finding was not the study's main hypothesis, but it indicates that educational effectiveness also depends on the quality of information management.

The theoretical contribution of the research lies in articulating a framework that connects digital agriculture, human capital, technology acceptance, and adaptive-experiential learning. The proposed model assumes that platform access creates the technical condition for participation, artificial intelligence supports content differentiation, simulations facilitate knowledge application, and assessment and reporting document progress. However, the relationship among these components is not automatic. The effect on skills is mediated by content relevance, technological accessibility, user experience, and the quality of pedagogical intervention.

The contextual contribution concerns adapting a platform developed in Romania to the needs of agriculture and rural development. Instead of designing a system exclusively for a single category of farmers or a single technology, the study proposes a modular architecture capable of hosting different programs, from basic digital skills to management, negotiation, and risk management. This modular character may be relevant to the heterogeneous structure of Romanian agriculture, but requires differentiated pathways according to farm size, type of activity, and learners' initial level.

Empirically, the study provides a systematic analysis of the functionalities of an existing platform and constructs a correspondence matrix between these functionalities and professional skill domains. However, the empirical contribution is limited to documenting the architecture and transfer possibilities. No changes in skills, behaviour, or economic performance were measured. The results should therefore be interpreted as a basis for designing an intervention rather than as evidence of its effectiveness.

6. Conclusions

The study aimed to develop a conceptual model for using artificial intelligence to develop professional skills in rural areas, starting from the functionalities of a digital platform created through the project "Next-Gen Learning: Growing People Through Digital Innovation." The analysis showed that the platform includes relevant components for course administration, personalization of learning pathways, simulation of professional situations, outcome assessment, progress monitoring, certification, and reporting. The main finding is that the existing architecture can be adapted to train farmers, farm managers, cooperative members, agricultural employees, and rural entrepreneurs. This adaptation can target digital and analytical skills as well as managerial, commercial, entrepreneurial, and organizational skills. Differentiating the programs does not require changing the platform's general structure, but developing content, scenarios, and assessment criteria specific to agricultural activities.

The study contributes by formulating a conceptual and functional link between the digitalization of agriculture and the digitalization of vocational training. The proposed model treats human capital as a central element of technological transformation and shows that artificial intelligence can support personalization, feedback, and monitoring, provided that appropriate pedagogical and professional oversight is maintained. The broader relevance of the model derives from its possible use in different rural contexts, including individual farms, cooperatives, agri-food enterprises, and institutional training programs. However, the conclusions concern the platform's functional compatibility with the

requirements of agricultural training, not its demonstrated effectiveness for users. Confirming educational and organizational effects requires empirical testing.

6.1. Practical and Public-Policy Implications

In practical terms, implementation of the model should begin with a limited number of pilot programs focused on clearly defined needs. Suitable areas for testing include the use of data in farm management, adoption of digital tools, commercial negotiation, cooperation within producer organizations, and risk management. Selecting concrete topics would facilitate outcome assessment and reduce the risk of creating excessively general courses.

Training providers should organize mixed teams consisting of specialists in pedagogy, artificial intelligence, software development, and agriculture. Content and scenarios must be validated by agricultural experts, and performance indicators must be defined before the programs are launched. Automated feedback should be complemented by trainer intervention, especially for complex skills or decisions with economic and technical implications. For farms and cooperatives, the platform can be used as a diagnostic and continuous-development tool. Initial assessment can reveal differences among participants, while personalized pathways can reduce the time devoted to content already mastered. Reports can support the planning of development programs, but should not be used in isolation for hiring, promotion, or disciplinary decisions without human verification. At institutional level, agricultural organizations, chambers of commerce, educational institutions, and advisory services can use the platform to develop joint programs. Interoperability and reporting functions can facilitate the tracking of participation and outcomes, provided that clear rules are established regarding data ownership, access, and use.

From a public-policy perspective, agricultural digitalization should be accompanied by explicit skills-development measures. Programs financing equipment, applications, or automation could include mandatory training components adapted to beneficiaries' level. Public support may also target the creation of regional equipment-access and training centers, particularly for users who lack the necessary infrastructure. Standards should be developed regarding the transparency of artificial-intelligence-assisted assessment, the protection of learner data, and the validation of professional content. For groups with low levels of digital competence, programs should include introductory modules and technical assistance. Application of the model must avoid creating a new divide between farms with sufficient resources and those unable to access the technology.

6.2. Limitations and Directions for Future Research

The main limitation of the study is its conceptual and exploratory nature. The analysis was based on project documentation, the platform interface, and identified functionalities, without actual testing on a sample of farmers or rural entrepreneurs. Consequently, no conclusions can be drawn regarding pedagogical effectiveness, adoption rate, or impact on professional performance.

A second limitation is the use of a single technological case. The characteristics of the analyzed platform may differ from those of other learning management systems or other artificial-intelligence-based solutions. The results should therefore be generalized with caution.

A third limitation concerns the assessment of functional relevance through conceptual analysis. The classification of components and construction of the correspondence matrix were not validated by an independent expert panel. A subsequent study could use the Delphi method or a multicriteria assessment to verify the relevance of the proposed skills, scenarios, and indicators.

Future research should include a pilot study with participants from different categories, such as individual farmers, farm managers, cooperative members, and rural entrepreneurs. Assessment could

be performed before and after training using knowledge tests, practical tasks, platform-generated indicators, and technology-acceptance scales. Comparing a group using adaptive pathways with a group completing a conventional program would make it possible to estimate the effect of personalization. The transfer of skills from the platform to professional activity also needs to be investigated. Immediate assessments may show improved performance within a course, but do not demonstrate skill retention or changes in farm practices. Future studies should therefore include longitudinal measurements and observations conducted several months after program completion.

Other research directions concern rural users' acceptance of artificial intelligence, the cost-effectiveness of virtual scenarios, accessibility for people with low digital literacy, and the validity of behavioral indicators. Differences among rural regions, farm types, and age categories also need to be analyzed to avoid applying a uniform model in a highly diverse context.

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References

- Creștem Oameni S.R.L. (n.d.). Creștem Oameni: Digital vocational training platform [Online learning management platform]. Retrieved August 4, 2026, from <https://lms.crestem-oameni.ro>
- Epure, C., Pila, M., & Stanciu, S. (2024). Rural development and digitalization: Perspectives and economic impact in Romania. *Annals of "Dunarea de Jos" University of Galati, Fascicle I: Economics and Applied Informatics*, 30(2), 5–13. <https://doi.org/10.35219/eai15840409405>
- Giua, C., Materia, V. C., & Camanzi, L. (2022). Smart farming technologies adoption: Which factors play a role in the digital transition? *Technology in Society*, 68, 101869. <https://doi.org/10.1016/j.techsoc.2022.101869>
- Grama, A. V., & Bătrîna, Ș. L. (2024). Adaptation of the farmers' skills to the requirements of the future agriculture. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 24(2), 485–494.
- 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, 100315. <https://doi.org/10.1016/j.njas.2019.100315>
- Manolache, B.-S., Manolache, C., & Stanciu, S. (2022). The role of the qualification certification centers for agricultural employees in Buzau County, Romania. *Communications of International Proceedings*, 2022(9), Article 4042922.
- Merino-Campos, C. (2025). The impact of artificial intelligence on personalized learning in higher education: A systematic review. *Trends in Higher Education*, 4(2), Article 17. <https://doi.org/10.3390/higheredu4020017>
- Pleșa, M., Mărcuță, A., Mărcuță, L., & Gușan, O. (2024). The integration of artificial intelligence in the activity of agricultural farms: A need to ensure sustainability. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 24(3).
- Radlińska, K. (2026). The role of digital skills in the digital transformation of agriculture—Evidence from the European Union. *Sustainability*, 18(3), 1495. <https://doi.org/10.3390/su18031495>
- Vlad, C., & Stanciu, S. (2025). Technology transfer in Romania's agro-food sector: An overview. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, 25(3), 893–901.
- Xie, B., Liu, H., Alghofaili, R., Zhang, Y., Jiang, Y., Lobo, F. D., Li, C., Li, W., Huang, H., Akdere, M., Mousas, C., & Yu, L.-F. (2021). A review on virtual reality skill training applications. *Frontiers in Virtual Reality*, 2, 645153. <https://doi.org/10.3389/fvrr.2021.645153>