

Article type:
Original Research

Article history:
Received 08 July 2026
Revised 26 August 2026
Accepted 15 October 2026
Initial Publish 24 October 2026
Published online 01 September 2027

Parvaneh. Rajabi¹, Seyyed Yaghoub.
Zeraatkish^{2*}, Amir. Mohamadinejad¹
², Reza. Moghaddasi²

1 Ph.D Student, Department of Agricultural
Economics, SR.C., Islamic Azad University, Tehran,
Iran

2 Department of Agricultural Economics, SR.C.,
Islamic Azad University, Tehran, Iran

Corresponding author email address:
y.zeratkish@iau.ac.ir

How to cite this article:
Rajabi, P., Zeraatkish, S. Y., Mohamadinejad, A., &
Moghaddasi, R. (2027). Design and Validation of a
Technical Knowledge Valuation Model for
Agricultural Knowledge-Based Companies Using
Structural Equation Modeling. *Future of Work and
Digital Management Journal*, 5(5), 1-24.
<https://doi.org/10.61838/fwdmj.389>



© 2027 the authors. This is an open access article
under the terms of the Creative Commons
Attribution-NonCommercial 4.0 International (CC
BY-NC 4.0) License.

Design and Validation of a Technical Knowledge Valuation Model for Agricultural Knowledge-Based Companies Using Structural Equation Modeling

ABSTRACT

This study aimed to design and validate a structural equation model for the valuation of technical knowledge in agricultural knowledge-based companies by examining the relationships among causal conditions, contextual conditions, intervening factors, the central phenomenon, strategies, and outcomes. This applied, quantitative, cross-sectional study was conducted on 150 university academics, managers, and specialists affiliated with agricultural knowledge-based companies, science and technology parks, and relevant research institutions. Participants were selected through simple random sampling from the eligible population. Data were collected using a researcher-developed questionnaire scored on a five-point Likert scale. The measurement model was evaluated using Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity criteria. Partial least squares structural equation modeling was performed using SmartPLS to assess the measurement and structural models, including standardized path coefficients, bootstrapped t statistics, R², Q², SRMR, and NFI. All principal structural relationships were statistically significant. Causal Conditions had a positive effect on the Central Phenomenon ($\beta = .681$, $t = 20.40$, $p < .001$). Contextual Conditions significantly predicted Strategies ($\beta = .350$, $t = 4.95$, $p < .001$), as did Intervening Factors ($\beta = .429$, $t = 6.73$, $p < .001$). The Central Phenomenon also had a positive but weaker effect on Strategies ($\beta = .134$, $t = 2.35$, $p = .019$). Strategies exerted the strongest direct effect on Outcomes ($\beta = .827$, $t = 44.30$, $p < .001$). The model explained 72.7% of the variance in Strategies and 68.4% of the variance in Outcomes. All Q² values were positive, and overall model fit was acceptable (SRMR = .069; NFI = .850). The validated model demonstrated that technical knowledge valuation in agricultural knowledge-based companies is a multidimensional process shaped by economic feasibility, scalability, contextual support, internal capabilities, and strategic mechanisms. Strategic actions played the most prominent role in translating technical knowledge into economic, organizational, environmental, developmental, and market-oriented outcomes.

Keywords: Technical Knowledge Valuation; Agricultural Knowledge-Based Companies; Agritech; Knowledge-Based Economy; Technology Valuation

Introduction

The accelerating transformation of agriculture through digitalization, biotechnology, artificial intelligence, smart sensing, platform-based services, and data-intensive decision-making has changed the economic meaning of technical knowledge within agricultural enterprises. Agricultural knowledge-based companies increasingly compete not only through ownership of physical assets but through their ability to generate, integrate, protect, commercialize, and scale specialized knowledge. In this environment, technical knowledge encompasses more than codified technological information; it also includes operational know-how, scientific expertise, process knowledge, technological routines, data capabilities, organizational

learning, and the capacity to convert research outputs into economically viable products and services. The rise of agritech has intensified this shift because many agricultural innovations now derive their value from combinations of software, sensors, artificial intelligence, biological knowledge, analytics, supply-chain intelligence, and specialized human expertise rather than from tangible assets alone. Recent research has documented the rapid expansion of technology-driven agricultural systems and the growing strategic importance of agritech in restructuring production, service delivery, and agribusiness competitiveness [1-3]. At the same time, the integration of artificial intelligence and Internet of Things technologies into agriculture has expanded the volume and complexity of knowledge embedded in agricultural technologies, making the assessment of their economic and strategic value increasingly difficult [4]. Consequently, the capacity to value technical knowledge has become a central managerial requirement for agricultural knowledge-based companies seeking investment, technology transfer, commercialization, strategic alliances, or sustainable growth.

The valuation of technical knowledge is especially challenging because knowledge-based assets differ fundamentally from conventional tangible assets. Unlike land, machinery, or inventory, technical knowledge may have uncertain boundaries, may be difficult to separate from the human and organizational context in which it is used, and may generate value only when complementary resources are available. The same body of technical knowledge can therefore produce very different economic outcomes depending on market demand, managerial capabilities, financing conditions, scalability, institutional support, and the technological maturity of the enterprise. Agricultural contexts add further complexity because value creation is influenced by biological cycles, natural-resource constraints, environmental conditions, spatial variation, and market volatility. Even the valuation of conventional agricultural assets requires attention to sector-specific factors such as soil fertility, productivity potential, and economic use [5], while research on biological assets has shown that recognition and measurement choices can vary substantially depending on accounting assumptions and the nature of agricultural production [6]. In knowledge-intensive agricultural firms, valuation is more difficult still because the principal source of competitive advantage may reside in invisible technological capabilities rather than readily observable physical assets. This creates a need for multidimensional valuation frameworks capable of incorporating economic feasibility, knowledge characteristics, operational functionality, development potential, organizational conditions, and external market and institutional influences within a unified analytical structure.

The growing financialization of agricultural assets and the expansion of investment in agritech further increase the practical importance of credible valuation mechanisms. Agricultural technologies and startups increasingly attract investors whose decisions depend on expectations concerning technological maturity, future market size, scalability, commercialization risk, and strategic flexibility. Wilson et al. demonstrated the relevance of real-options reasoning for agricultural technology startup valuation, highlighting the need to incorporate uncertainty and managerial flexibility into investment assessments [7]. Similarly, investment in innovative startups involves simultaneous consideration of expected returns and technological or commercial risks, requiring decision frameworks that move beyond static financial indicators [8]. Investor perspectives in emerging agricultural technologies also indicate that technological novelty alone is insufficient to determine commercial attractiveness; market structures, regulatory conditions, consumer acceptance, and scaling opportunities can substantially influence perceived value [9]. More broadly, the transformation of farmland and agricultural resources into financial assets illustrates how value in agriculture is increasingly shaped by institutional, investment, and sustainability considerations rather than simple productive output [10]. These developments suggest that valuation of technical knowledge should not be treated

as a narrowly financial exercise. Instead, it should capture how knowledge interacts with technological readiness, organizational capability, market opportunity, financing access, environmental sustainability, and institutional conditions to create future economic benefits.

Agricultural knowledge-based enterprises also operate within innovation ecosystems in which universities, incubators, accelerators, extension systems, public agencies, financial institutions, and producer organizations contribute to the development and commercialization of technology. The role of incubators and accelerators in the fourth agricultural revolution demonstrates the importance of ecosystem-level support in moving agricultural innovations from invention toward market application [11]. University knowledge exchange can likewise reshape the business models of agritech startups by connecting scientific capabilities to entrepreneurial and commercial processes [12]. Agricultural engineering education contributes to this ecosystem by building the technical competencies required for the development and implementation of agricultural technologies [13], while the changing role of extension professionals indicates that digital transformation requires new mechanisms for translating technological knowledge into practical agricultural use [14]. These relationships imply that the value of technical knowledge is partly relational: knowledge becomes more valuable when firms can access external expertise, complementary infrastructures, appropriate training, technological networks, and commercialization channels. Therefore, institutional context, human capital, knowledge maturity, and entrepreneurial support should be regarded as integral components of technical knowledge valuation rather than peripheral variables.

Market adoption represents another major determinant of the realized value of technical knowledge. A technology may be scientifically sophisticated and technically functional yet possess limited economic value if potential users lack the resources, incentives, capabilities, or willingness to adopt it. Research on agricultural technology adoption has repeatedly demonstrated that farmers' decisions are shaped by financial constraints, perceived usefulness, institutional conditions, infrastructure, and access to relevant information. Evidence from commercial farm managers shows that agritech adoption is affected by a combination of organizational and contextual factors [15], while studies of small-scale irrigation technologies demonstrate that demand and adoption can be constrained even when technologies have clear productive potential [16]. At the household level, heterogeneity in preferences can also influence demand for labor-saving agricultural technologies, indicating that technological value cannot be inferred solely from technical efficiency [17]. The wider diffusion of innovations in the agritech sector similarly depends on whether new technologies align with sustainability priorities, operational requirements, and user expectations [18]. Accordingly, the valuation of technical knowledge should consider not only what a technology can do but also whether it can be adopted, implemented, adapted, and sustained within real agricultural systems.

The economic value of technical knowledge is also closely linked to entrepreneurship and the capacity of firms to transform knowledge into scalable business opportunities. Agripreneurship has become an important mechanism for translating technological innovations into market-oriented agricultural enterprises, yet entrepreneurial outcomes are conditioned by organizational structures, financing systems, social norms, and policy environments. Farmer-producer companies can facilitate agripreneurship by connecting producers with markets, collective resources, and business capabilities [19]. At the same time, youth entrepreneurial intentions in agriculture are affected by perceived social norms and the broader social environment surrounding agricultural enterprise development [20]. Programs designed to promote agricultural youth entrepreneurship may generate social as well as economic returns, suggesting that the consequences of agricultural

knowledge-based activity extend beyond conventional firm-level profitability [21]. For women agripreneurs, financial inclusion remains particularly important because access to credit, financial services, and investment networks directly affects the ability to convert entrepreneurial knowledge into viable and expanding enterprises [22]. These findings reinforce the argument that technical knowledge valuation should incorporate both direct economic consequences and broader developmental, organizational, and social outcomes.

Financing constraints and policy conditions are especially consequential for agricultural startups and knowledge-based companies because technological development often requires substantial upfront investment before commercial returns can be realized. Agritech startups may face long development cycles, uncertainty regarding regulatory approval, difficulties in proving market demand, and high costs associated with prototyping, testing, intellectual property protection, and scaling. Research on the Indian agristartup ecosystem has identified structural and policy constraints that can restrict the growth of new agricultural ventures despite substantial technological potential [23]. The expansion of data-driven agritech startups in India and Japan similarly demonstrates that data infrastructures, digital ecosystems, and institutional arrangements are crucial for the growth of technology-oriented agricultural firms [24]. Digital-economy planning can further transform agribusiness by integrating agricultural enterprises into broader smart infrastructures and market systems [25]. At the supply-chain level, next-generation agricultural technologies can improve traceability, coordination, forecasting, and operational efficiency, thereby creating new sources of economic value across agricultural value chains [26]. However, these benefits are contingent on the firm's ability to access financing, infrastructure, markets, and institutional support, which means that the economic potential of technical knowledge cannot be evaluated independently of the conditions under which it is commercialized.

The importance of information itself as an economic asset is particularly evident in modern agricultural value chains. High-quality information can influence market coordination, product differentiation, pricing, and decision quality, thereby generating measurable economic value [27]. As agricultural firms increasingly rely on data platforms, digital monitoring, predictive analytics, and artificial intelligence, technical knowledge and data capabilities become mutually reinforcing assets. The evolution of digital platforms toward financing and data-enabled business models illustrates how agricultural technology firms can move beyond their original service functions and create new forms of economic value through informational advantages [28]. Such transformations blur the traditional boundaries between technological capability, financial capability, and market capability. A technical knowledge valuation model must therefore account for the possibility that the value of knowledge is enhanced when firms can combine technological expertise with data, financing, market access, and platform-based coordination. This also highlights the significance of market-oriented and institutional strategies in converting knowledge resources into measurable outcomes.

Sustainability introduces another essential dimension into agricultural technology valuation. Technical knowledge in agriculture increasingly faces the dual expectation of generating commercial returns and contributing to environmental resilience. Agricultural technologies that improve resource efficiency, reduce environmental degradation, support climate adaptation, or strengthen the resilience of agricultural value chains may possess strategic value that conventional valuation approaches fail to recognize. Strategic risk management in horticultural value chains increasingly incorporates agritech and artificial intelligence as tools for resilience and adaptive capacity [29]. Likewise, sustainable open innovation in agritech shows that digital technologies can support shared value creation by simultaneously advancing business competitiveness and

sustainability objectives [30]. Research on agricultural benefit measurement has also questioned narrow yardsticks for assessing farm-sector value, emphasizing the need to recognize wider economic, social, and environmental benefits [31]. Territorial changes associated with agricultural energy and biodiesel development further illustrate that technological and economic transformations can generate spatial, environmental, and institutional consequences that extend beyond the firm itself [32]. Consequently, environmental compatibility and sustainability potential should be incorporated into the conceptual architecture of technical knowledge valuation rather than treated as external considerations.

Human resources and organizational knowledge are equally important because technical knowledge frequently remains inseparable from the people and routines through which it is applied. Agricultural innovations often require specialized combinations of scientific knowledge, engineering competence, managerial experience, and entrepreneurial judgment. The practical value of a technology may decline significantly if the firm lacks personnel capable of adapting it to different production contexts, integrating it with complementary systems, or communicating its benefits to users. In addition, creativity and entrepreneurship education can strengthen innovation capacities and entrepreneurial performance, reinforcing the role of knowledge development and human capital in technology-oriented environments [33]. The interaction between technological capabilities and organizational learning therefore affects not only whether knowledge can be generated but also whether it can be replicated, transferred, scaled, and commercially exploited. This is particularly relevant in agricultural knowledge-based companies, where technologies may need continual adjustment to biological, climatic, regional, and customer-specific conditions. A comprehensive valuation model must accordingly include human factors, knowledge maturity, cultural conditions, and organizational strategies as interconnected determinants of technical knowledge value.

Another important issue concerns the relationship between technological knowledge and the strategic configuration of the firm. Technical knowledge does not automatically produce superior outcomes; its value depends on strategic choices concerning financing, market orientation, institutional engagement, technological positioning, and organizational development. Companies may possess similar technological capabilities but achieve different results because they differ in their ability to secure investment, build market legitimacy, protect intellectual assets, develop partnerships, or scale their innovations. The emergence of new agritech business models demonstrates how technological transformation can alter the configuration of value creation itself, requiring firms to reconsider how scientific knowledge, customer relationships, digital platforms, and revenue models interact [12, 30]. Furthermore, technological innovation in agriculture increasingly requires firms to manage uncertainty across interconnected value chains, making strategic resilience a fundamental component of value creation [29]. From this perspective, valuation should capture not only the intrinsic attributes of technical knowledge but also the strategic mechanisms through which those attributes are converted into organizational and market outcomes.

Despite the growth of agritech scholarship, much of the existing literature remains fragmented across themes such as technology adoption, entrepreneurship, startup financing, digital transformation, sustainability, agricultural asset valuation, innovation ecosystems, and supply-chain modernization. Studies have provided valuable evidence regarding the expansion of agritech [1], investment risk [8], startup valuation [7], agricultural technology adoption [15], financial inclusion [22], knowledge exchange [12], and digital agricultural transformation [4, 24], yet these streams do not by themselves provide an integrated empirical framework for assessing how multiple dimensions jointly shape the valuation of technical knowledge in agricultural knowledge-based companies. A purely financial model may understate the importance of knowledge maturity, scalability, institutional infrastructure, or human capability, whereas a purely technological assessment may overlook market

attractiveness, financing conditions, organizational consequences, and sustainability. Similarly, single-factor analyses are insufficient when technical knowledge valuation emerges from simultaneous relationships among several latent variables and their observable indicators. This methodological limitation creates a strong rationale for using structural equation modeling, which can assess both the measurement quality of multidimensional constructs and the structural relationships among them within one coherent analytical framework.

PLS-based structural equation modeling is particularly appropriate for this purpose because the valuation of technical knowledge involves multiple interrelated latent constructs whose effects may occur simultaneously and indirectly. A model of agricultural technical knowledge valuation can incorporate causal conditions such as economic feasibility and development potential; contextual conditions including institutional, economic, infrastructural, market, human, entrepreneurial, and environmental environments; intervening factors such as knowledge maturity, human capabilities, cultural conditions, and adaptation and sustainability; strategic responses involving financing, market, cultural, and institutional strategies; and multidimensional consequences including economic, organizational, environmental, market-oriented, developmental, and operational outcomes. Such a framework recognizes that the value of technical knowledge is not generated by a single determinant but by the interaction of technological characteristics, organizational capacity, external conditions, and strategic action. This perspective is consistent with contemporary agritech research showing that technological innovation is embedded in complex systems of investment, adoption, information, sustainability, entrepreneurship, and institutional support [9, 18, 19]. It also offers a more realistic basis for managerial decision-making by identifying which latent dimensions make the strongest contribution to the overall valuation architecture.

Accordingly, developing and validating a multidimensional technical knowledge valuation model can provide both theoretical and practical contributions. Theoretically, such a model can integrate previously disconnected streams of agricultural innovation research and explain how technical, economic, institutional, human, market, strategic, and sustainability dimensions jointly contribute to value creation. Practically, a validated model can assist managers of agricultural knowledge-based companies in identifying the dimensions that strengthen the economic and strategic value of their technical knowledge, support investors in assessing knowledge-intensive agricultural ventures more systematically, and help policymakers design support mechanisms that address the factors most strongly associated with successful commercialization and sustainable growth. This need is especially important as agricultural technologies become more data-intensive, financially complex, and interconnected with broader innovation ecosystems, while expectations for resilience, environmental responsibility, and market scalability continue to increase [10, 25, 26]. Therefore, the aim of this study was to design and validate a structural equation model for the valuation of technical knowledge in agricultural knowledge-based companies by examining the measurement properties and structural relationships among its causal, contextual, intervening, strategic, central, and outcome dimensions.

Methodology

This study employed a quantitative, applied, cross-sectional survey design to validate a technical knowledge valuation model for agricultural knowledge-based companies using structural equation modeling. The methodological focus of the study was exclusively on evaluating the measurement properties of the proposed constructs and examining the structural relationships among the latent variables included in the conceptual model. Structural equation modeling was selected

because technical knowledge valuation in agricultural knowledge-based companies represents a multidimensional phenomenon composed of several interrelated latent constructs that cannot be adequately assessed through isolated bivariate relationships. The approach enabled the simultaneous assessment of relationships between observable indicators and their corresponding latent constructs, as well as the direct and indirect structural relationships among the major dimensions contributing to the valuation of technical knowledge. The study was therefore designed to determine whether the theoretically specified model was empirically supported by data obtained from individuals with appropriate scientific, managerial, and technological familiarity with agricultural knowledge-based activities.

The statistical population consisted of university academics with relevant expertise, managers and specialists of agricultural knowledge-based companies, professionals working in growth-stage companies located in science and technology parks, and relevant managers and specialists affiliated with the National Institute of Genetic Engineering and Biotechnology whose professional activities were related to agriculture, biotechnology, commercialization of technology, research and development, technological management, or knowledge-based enterprises. Participants were required to possess sufficient familiarity with the organizational, technological, economic, and managerial characteristics of technical knowledge in agricultural enterprises to provide informed evaluations of the indicators contained in the questionnaire. Individuals whose professional background was unrelated to agricultural technology, knowledge-based business development, research and development, technological commercialization, or management were not included in the study. The participants were selected using simple random sampling from the accessible population meeting the eligibility criteria.

The required sample size was determined by considering both the statistical requirements of structural equation modeling and the expected number of observable indicators and latent constructs in the proposed model. An initial electronic administration of the questionnaire to 30 eligible members of the target population was used as a pilot assessment to examine response variability and the adequacy of the instrument prior to the principal data collection. Considering the estimated variability of the responses, the complexity of the structural model, the number of latent and observed variables, and the need to obtain adequate statistical power for estimating the structural paths, a final sample of **150 participants** was considered appropriate for the principal analysis. This sample size was also compatible with the use of partial least squares structural equation modeling, which is particularly suitable for relatively complex models involving multiple constructs and indicators and does not impose the same restrictive distributional assumptions and large-sample requirements associated with covariance-based structural equation modeling. Data were collected electronically, and respondents were informed about the purpose of the research, the voluntary nature of participation, confidentiality of responses, and the exclusive use of the collected information for scientific purposes. Questionnaires with substantial missing information or response patterns indicating inadequate engagement with the survey were excluded before statistical analysis, whereas complete and usable questionnaires were retained for model estimation.

Data were collected using a researcher-developed Technical Knowledge Valuation Questionnaire for Agricultural Knowledge-Based Companies. The questionnaire was specifically structured to operationalize the latent constructs and observable indicators incorporated into the proposed structural model of technical knowledge valuation. The instrument consisted of two major sections. The first section collected general demographic and professional information concerning the participants, such as educational level, professional position, area of expertise, and relevant occupational experience. These variables were used to describe the characteristics of the study sample and were not incorporated as principal constructs

within the structural model. The second and principal section contained the specialized items used to measure the dimensions of technical knowledge valuation in agricultural knowledge-based companies. Each item represented an observable indicator associated with one of the latent constructs specified in the conceptual framework. The questionnaire was designed so that the collective pattern of responses could be used to assess both the measurement model, which defined the relationships between latent constructs and their indicators, and the structural model, which represented the hypothesized relationships among the major dimensions of technical knowledge valuation.

All specialized items were scored on a five-point Likert scale ranging from 1 = very low to 5 = very high. Higher scores indicated a stronger perceived presence, importance, or contribution of the corresponding indicator to technical knowledge valuation. The use of a five-point response format provided a standardized metric for measuring respondents' evaluations across the different model dimensions and enabled the resulting item scores to be directly incorporated into partial least squares structural equation modeling. Prior to the main administration, the wording, clarity, relevance, comprehensibility, and correspondence of the questionnaire items with their intended constructs were reviewed by specialists familiar with agricultural technology, knowledge-based enterprises, management, and technical knowledge valuation. Necessary revisions were made to eliminate ambiguous wording, improve conceptual correspondence, and ensure that each item represented the intended domain of measurement.

The validity and reliability of the questionnaire were evaluated at both the preliminary instrument level and the structural equation modeling level. Face validity was assessed through expert examination of the apparent relevance, clarity, appropriateness, and interpretability of the questionnaire items. Content adequacy was similarly examined to ensure sufficient representation of the conceptual dimensions of technical knowledge valuation. Internal consistency reliability was initially assessed using Cronbach's alpha, with coefficients of 0.70 or greater considered indicative of satisfactory reliability. During assessment of the PLS-SEM measurement model, reliability was further evaluated using composite reliability, with values of at least 0.70 regarded as acceptable. Indicator reliability was examined through standardized outer loadings. Indicators with sufficiently high loadings on their intended constructs were retained, whereas indicators with weak loadings were evaluated with reference to their theoretical importance and their effect on construct reliability and validity before any decision concerning their retention was made.

Convergent validity was assessed using the average variance extracted (AVE). An AVE value of 0.50 or greater was interpreted as evidence that a latent construct explained at least half of the variance in its corresponding indicators and therefore demonstrated acceptable convergent validity. Discriminant validity was examined to determine whether conceptually distinct constructs demonstrated sufficient empirical differentiation. The Fornell-Larcker criterion was applied by comparing the square root of the AVE for each construct with its correlations with the other constructs. In addition, interconstruct relationships were examined to ensure that excessively high correlations did not indicate conceptual redundancy or insufficient distinction among the latent variables. These procedures enabled the evaluation of the questionnaire as a measurement system rather than relying solely on a single reliability coefficient, thereby providing evidence regarding indicator reliability, internal consistency, convergent validity, and discriminant validity before interpretation of the structural relationships.

Data analysis was conducted using descriptive statistics and partial least squares structural equation modeling (PLS-SEM) in SmartPLS software. Prior to estimation of the structural equation model, the dataset was screened for completeness,

coding accuracy, missing values, implausible response patterns, and potential data-entry errors. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were calculated to characterize the study participants and summarize the central tendency and dispersion of the questionnaire responses. The distributions of the observed variables were also inspected using skewness and kurtosis coefficients. Values falling approximately within the range of -2 to $+2$ were regarded as indicative of acceptable distributional behavior. Nevertheless, strict multivariate normality was not considered a prerequisite for the principal analysis because PLS-SEM is a variance-based, nonparametric-oriented structural modeling procedure that is relatively robust to departures from normality.

The structural equation analysis was implemented in two consecutive stages consisting of evaluation of the measurement model and evaluation of the structural model. Assessment of the measurement model was undertaken before testing the substantive relationships among the latent constructs to ensure that the indicators measured their intended theoretical concepts with adequate reliability and validity. Indicator reliability was examined using outer factor loadings. Loadings of approximately 0.70 or greater were regarded as desirable because they indicate substantial shared variance between an indicator and its underlying construct. Indicators with moderately lower loadings were not removed mechanically; instead, their theoretical importance, effect on composite reliability, and contribution to convergent validity were considered simultaneously. Internal consistency reliability was examined using Cronbach's alpha and composite reliability, with values of 0.70 or above regarded as acceptable. Convergent validity was evaluated using AVE, with values of at least 0.50 considered satisfactory. Discriminant validity was assessed using the Fornell-Larcker criterion and the pattern of correlations among constructs to establish that each latent variable represented an empirically distinguishable dimension of the technical knowledge valuation model.

After satisfactory establishment of the measurement model, the structural model was evaluated to determine the magnitude, direction, statistical significance, and explanatory capacity of the hypothesized relationships among the latent constructs. Before interpreting the structural paths, collinearity among predictor constructs was examined using the variance inflation factor (VIF). VIF values below conventional critical levels were considered indicative of the absence of problematic multicollinearity. Standardized path coefficients (β) were subsequently estimated to quantify the direction and strength of the relationships between constructs. Positive coefficients indicated relationships in the same direction, whereas negative coefficients indicated inverse relationships. Statistical significance of the path coefficients was assessed through the bootstrapping procedure implemented in SmartPLS. The resulting standard errors, t statistics, and probability values were used to determine whether the hypothesized structural relationships were statistically supported. At a two-tailed significance level of 0.05, absolute t values exceeding 1.96 were regarded as statistically significant. Where appropriate, direct and indirect effects were examined separately to provide a comprehensive assessment of the relationships represented within the structural model.

The explanatory power of the model was evaluated using the coefficient of determination (R^2) for endogenous constructs. R^2 represented the proportion of variance in each dependent latent construct explained collectively by its predictor constructs and was therefore used to assess the model's explanatory performance. Predictive relevance was evaluated using the Stone-Geisser Q^2 statistic, with Q^2 values greater than zero indicating that the model possessed predictive relevance for the corresponding endogenous construct. Effect sizes were also considered where necessary to determine the relative contribution of individual exogenous constructs to the explained variance of endogenous variables rather than relying

exclusively on statistical significance. Overall model adequacy was additionally considered through the goodness-of-fit information available for the estimated PLS model and the consistency of the measurement and structural results. The interpretation of model adequacy was therefore based on a combination of indicator reliability, internal consistency, convergent validity, discriminant validity, absence of problematic collinearity, significance and magnitude of structural path coefficients, explained variance, and predictive relevance rather than on any single statistical index.

The use of PLS-SEM was considered appropriate because the proposed technical knowledge valuation framework included multiple latent constructs, numerous observable indicators, and simultaneous interrelationships among organizational and technological dimensions. The method allowed estimation of the measurement and structural components within a unified analytical framework and was suitable for the sample size available in the present study. Accordingly, the analytical procedure provided an empirical basis for determining whether the proposed technical knowledge valuation model demonstrated satisfactory measurement quality, explanatory capacity, predictive relevance, and structural validity in the context of agricultural knowledge-based companies.

Findings and Results

The final sample consisted of 150 participants with professional or academic involvement in agricultural knowledge-based companies and related scientific and technological environments. Of the participants, 85 (56.7%) were men and 65 (43.3%) were women. Regarding educational attainment, 95 participants (63.3%) held a bachelor's degree, 25 (16.7%) held a master's degree, and 30 (20.0%) held a doctoral degree. In terms of professional experience, 17 participants (11.3%) had less than 7 years of experience, 35 (23.3%) had between 7 and 10 years, 55 (36.7%) had between 10 and 15 years, and 43 (28.7%) had more than 15 years of professional experience. The largest age group comprised participants aged 31–40 years ($n = 75$, 50.0%), followed by those aged 20–30 years ($n = 35$, 23.3%), 41–50 years ($n = 25$, 16.7%), 51–60 years ($n = 13$, 8.7%), and older than 60 years ($n = 2$, 1.3%). Overall, the demographic profile indicated that the respondents were predominantly experienced professionals, with 65.4% reporting at least 10 years of work experience, thereby providing an appropriate empirical basis for evaluating the proposed technical knowledge valuation model.

Table 1

Descriptive Statistics for the Components of the Technical Knowledge Valuation Model

Higher-Order Construct	Component	n	Mean	SD	Minimum	Maximum
Causal Conditions	Economic Feasibility	150	3.15	1.35	1	5
Causal Conditions	Development and Scalability Potential	150	3.22	1.42	1	5
Intervening Factors	Human Factors	150	3.21	1.40	1	5
Intervening Factors	Knowledge Maturity	150	3.25	1.36	1	5
Intervening Factors	Cultural Conditions	150	3.24	1.37	1	5
Intervening Factors	Adaptation and Sustainability	150	3.22	1.36	1	5
Strategies	Institutional Strategies	150	3.23	1.43	1	5
Strategies	Financing Strategies	150	3.25	1.38	1	5
Strategies	Cultural Strategies	150	3.18	1.38	1	5
Strategies	Market-Oriented Strategies	150	3.24	1.37	1	5
Contextual Conditions	Institutional Context	150	3.31	1.35	1	5
Contextual Conditions	Economic and Financial Context	150	3.29	1.37	1	5
Contextual Conditions	Infrastructural Context	150	3.26	1.39	1	5
Contextual Conditions	Human and Cultural Context	150	3.28	1.35	1	5
Contextual Conditions	Market Context	150	3.23	1.38	1	5
Contextual Conditions	Environmental Context	150	3.17	1.36	1	5
Contextual Conditions	Entrepreneurial Context	150	3.22	1.35	1	5
Central Phenomenon	Operational Function	150	3.23	1.42	1	5

Central Phenomenon	Knowledge Characteristics	150	3.35	1.37	1	5
Outcomes	Economic and Financial Outcomes	150	3.24	1.35	1	5
Outcomes	Development and Scalability Outcomes	150	3.18	1.36	1	5
Outcomes	Technical and Performance Outcomes	150	3.26	1.33	1	5
Outcomes	Environmental Outcomes	150	3.26	1.34	1	5
Outcomes	Organizational Outcomes	150	3.18	1.36	1	5
Outcomes	Market-Oriented Outcomes	150	3.21	1.39	1	5

As presented in Table 1, the mean scores of the model components ranged from 3.15 to 3.35 on the five-point scale, indicating that respondents generally evaluated the components at levels slightly above the theoretical midpoint of 3.00. Knowledge Characteristics obtained the highest mean score ($M = 3.35$, $SD = 1.37$), followed by Institutional Context ($M = 3.31$, $SD = 1.35$), Economic and Financial Context ($M = 3.29$, $SD = 1.37$), and Human and Cultural Context ($M = 3.28$, $SD = 1.35$). Technical and Performance Outcomes, Environmental Outcomes, and Infrastructural Context each also received relatively high evaluations. Economic Feasibility showed the lowest mean ($M = 3.15$, $SD = 1.35$), followed by Environmental Context ($M = 3.17$, $SD = 1.36$), Cultural Strategies ($M = 3.18$, $SD = 1.38$), Development and Scalability Outcomes ($M = 3.18$, $SD = 1.36$), and Organizational Outcomes ($M = 3.18$, $SD = 1.36$). Nevertheless, all means exceeded 3.00, suggesting an overall positive assessment of the dimensions included in the technical knowledge valuation model. Standard deviations ranged from 1.33 to 1.43, indicating sufficient response dispersion to distinguish participants' evaluations across the measured dimensions.

Table 2

Internal Consistency Reliability of the Measurement Model

Construct	Cronbach's α	Composite Reliability (CR)	Reliability
Economic Feasibility	.801	.883	Supported
Adaptation and Sustainability	.789	.877	Supported
Economic Context	.771	.867	Supported
Market Context	.788	.876	Supported
Infrastructural Context	.769	.866	Supported
Institutional Context	.820	.893	Supported
Human Context	.788	.876	Supported
Environmental Context	.774	.869	Supported
Entrepreneurial Context	.800	.883	Supported
Knowledge Maturity	.825	.896	Supported
Financing Strategy	.783	.874	Supported
Market Strategy	.790	.877	Supported
Cultural Strategy	.778	.871	Supported
Institutional Strategy	.789	.877	Supported
Strategies	.884	.904	Supported
Cultural Conditions	.775	.870	Supported
Contextual Conditions	.930	.938	Supported
Causal Conditions	.836	.880	Supported
Intervening Factors	.890	.909	Supported
Human Factors	.808	.886	Supported
Knowledge Characteristics	.776	.870	Supported
Development and Scalability Potential	.815	.890	Supported
Central Phenomenon	.833	.878	Supported
Market-Oriented Outcomes	.768	.865	Supported
Development and Scalability Outcomes	.780	.872	Supported
Environmental Outcomes	.786	.875	Supported
Economic Outcomes	.795	.880	Supported
Organizational Outcomes	.783	.873	Supported
Performance Outcomes	.751	.858	Supported
Outcomes	.912	.923	Supported
Operational Function	.816	.891	Supported

Table 2 demonstrates satisfactory internal consistency reliability for all constructs incorporated into the measurement model. Cronbach's alpha coefficients ranged from .751 for Performance Outcomes to .930 for Contextual Conditions, and therefore every construct exceeded the minimum acceptable threshold of .70. Composite reliability coefficients ranged from .858 to .938 and similarly exceeded the recommended .70 criterion in all cases. Furthermore, composite reliability was higher than Cronbach's alpha for every construct, providing additional evidence of the internal consistency of the measurement model. Among the higher-order constructs, Contextual Conditions showed the strongest reliability ($\alpha = .930$, CR = .938), followed by Outcomes ($\alpha = .912$, CR = .923), Intervening Factors ($\alpha = .890$, CR = .909), and Strategies ($\alpha = .884$, CR = .904). The results therefore confirmed that the observable indicators consistently represented their corresponding latent constructs and that the measurement scales possessed sufficient reliability for subsequent evaluation of the structural model.

Table 3

Convergent Validity of the Measurement Model

Construct	AVE	Convergent Validity
Economic Feasibility	.716	Supported
Adaptation and Sustainability	.704	Supported
Economic Context	.686	Supported
Market Context	.702	Supported
Infrastructural Context	.683	Supported
Institutional Context	.736	Supported
Human Context	.703	Supported
Environmental Context	.689	Supported
Entrepreneurial Context	.715	Supported
Knowledge Maturity	.741	Supported
Financing Strategy	.697	Supported
Market Strategy	.704	Supported
Cultural Strategy	.693	Supported
Institutional Strategy	.703	Supported
Strategies	.541	Supported
Cultural Conditions	.691	Supported
Contextual Conditions	.519	Supported
Causal Conditions	.550	Supported
Intervening Factors	.556	Supported
Human Factors	.722	Supported
Knowledge Characteristics	.691	Supported
Development and Scalability Potential	.730	Supported
Central Phenomenon	.545	Supported
Market-Oriented Outcomes	.683	Supported
Development and Scalability Outcomes	.694	Supported
Environmental Outcomes	.701	Supported
Economic Outcomes	.710	Supported
Organizational Outcomes	.697	Supported
Performance Outcomes	.668	Supported
Outcomes	.502	Supported
Operational Function	.731	Supported

The AVE coefficients presented in Table 3 ranged from .502 to .741, and all values exceeded the recommended threshold of .50. Knowledge Maturity demonstrated the largest AVE (.741), followed by Institutional Context (.736), Operational Function (.731), Development and Scalability Potential (.730), and Human Factors (.722). Even the lowest AVE, which was observed for the higher-order Outcomes construct (.502), remained above the minimum required value. These findings established adequate convergent validity because each latent construct accounted for more than 50% of the variance in its indicators. Discriminant validity was separately evaluated using the heterotrait-monotrait ratio of correlations (HTMT). All

interconstruct HTMT coefficients were below .90, indicating that the latent variables demonstrated acceptable empirical distinction from one another. Accordingly, both convergent and discriminant validity of the measurement model were supported.

The global fit indices also indicated an acceptable correspondence between the proposed model and the observed data. The standardized root mean square residual was SRMR = .069, which was below the recommended upper limit of .08 and therefore indicated satisfactory approximate model fit. The normed fit index was NFI = .850, showing an acceptable degree of improvement relative to the null model, although it remained below values generally interpreted as indicating excellent fit. The model chi-square value was $\chi^2 = 53.76$. Taken together, and particularly considering the SRMR value, the results supported the overall adequacy of the proposed PLS-SEM model for explaining the structure of technical knowledge valuation in agricultural knowledge-based companies.

Table 4

Coefficients of Determination for the Endogenous Constructs

Endogenous Construct	R ²	Adjusted R ²	Explanatory Power
Economic Feasibility	.748	.747	Strong
Adaptation and Sustainability	.616	.615	Moderate
Economic Context	.470	.468	Moderate
Market Context	.712	.711	Strong
Infrastructural Context	.533	.532	Moderate
Institutional Context	.565	.532	Moderate
Human Context	.592	.564	Moderate
Environmental Context	.708	.707	Strong
Entrepreneurial Context	.601	.600	Moderate
Knowledge Maturity	.692	.691	Strong
Financing Strategy	.556	.555	Moderate
Market Strategy	.663	.662	Moderate
Cultural Strategy	.671	.670	Strong
Institutional Strategy	.631	.630	Moderate
Strategies	.727	.724	Strong
Cultural Conditions	.585	.584	Moderate
Human Factors	.658	.657	Moderate
Knowledge Characteristics	.745	.745	Strong
Development and Scalability Potential	.772	.772	Strong
Central Phenomenon	.464	.463	Moderate
Market-Oriented Outcomes	.622	.621	Moderate
Development and Scalability Outcomes	.563	.562	Moderate
Environmental Outcomes	.608	.607	Moderate
Economic Outcomes	.614	.612	Moderate
Organizational Outcomes	.590	.589	Moderate
Performance Outcomes	.495	.494	Moderate
Outcomes	.684	.683	Strong
Operational Function	.788	.787	Strong

As shown in Table 4, the model demonstrated moderate to strong explanatory power across all endogenous constructs. Based on the adopted reference values of .19, .33, and .67 for weak, moderate, and strong explanatory power, respectively, no endogenous construct demonstrated weak explanatory capacity. The highest coefficient of determination was observed for Operational Function ($R^2 = .788$), indicating that 78.8% of its variance was explained by its corresponding higher-order construct. This was followed by Development and Scalability Potential ($R^2 = .772$), Economic Feasibility ($R^2 = .748$), Knowledge Characteristics ($R^2 = .745$), Strategies ($R^2 = .727$), and Market Context ($R^2 = .712$). The higher-order Outcomes construct also demonstrated strong explanatory power ($R^2 = .684$). The Central Phenomenon had the lowest R^2 among the modeled

constructs ($R^2 = .464$), although this value still represented moderate explanatory capacity. Predictive relevance was additionally supported by the Stone-Geisser Q^2 coefficients. All Q^2 values were positive, ranging from .250 to .571. Most constructs exceeded .35 and therefore exhibited strong predictive relevance, while the Central Phenomenon ($Q^2 = .250$) and Outcomes ($Q^2 = .272$) demonstrated moderate predictive relevance. Operational Function showed the highest predictive relevance ($Q^2 = .571$), followed by Development and Scalability Potential ($Q^2 = .558$), Economic Feasibility ($Q^2 = .529$), Knowledge Characteristics ($Q^2 = .509$), and Knowledge Maturity ($Q^2 = .507$). Collectively, these findings indicated that the structural model possessed substantial explanatory and predictive capability.

Table 5

Structural Path Coefficients and Significance Tests

Structural Path	β	t	p	Result
Causal Conditions → Economic Feasibility	.865	53.70	<.001	Significant
Causal Conditions → Development and Scalability Potential	.879	72.10	<.001	Significant
Central Phenomenon → Knowledge Characteristics	.863	56.03	<.001	Significant
Central Phenomenon → Operational Function	.888	73.05	<.001	Significant
Strategies → Financing Strategy	.746	26.30	<.001	Significant
Strategies → Market Strategy	.814	37.80	<.001	Significant
Strategies → Cultural Strategy	.819	44.50	<.001	Significant
Strategies → Institutional Strategy	.794	35.80	<.001	Significant
Contextual Conditions → Economic Context	.686	21.80	<.001	Significant
Contextual Conditions → Market Context	.844	57.80	<.001	Significant
Contextual Conditions → Infrastructural Context	.730	27.40	<.001	Significant
Contextual Conditions → Institutional Context	.752	26.10	<.001	Significant
Contextual Conditions → Human Context	.770	33.10	<.001	Significant
Contextual Conditions → Environmental Context	.841	30.70	<.001	Significant
Contextual Conditions → Entrepreneurial Context	.775	32.20	<.001	Significant
Intervening Factors → Adaptation and Sustainability	.785	32.60	<.001	Significant
Intervening Factors → Knowledge Maturity	.832	47.90	<.001	Significant
Intervening Factors → Cultural Conditions	.765	28.10	<.001	Significant
Intervening Factors → Human Factors	.811	40.03	<.001	Significant
Outcomes → Market-Oriented Outcomes	.789	36.80	<.001	Significant
Outcomes → Development and Scalability Outcomes	.751	30.20	<.001	Significant
Outcomes → Environmental Outcomes	.780	33.40	<.001	Significant
Outcomes → Economic Outcomes	.783	34.90	<.001	Significant
Outcomes → Organizational Outcomes	.768	30.80	<.001	Significant
Outcomes → Performance Outcomes	.704	23.20	<.001	Significant
Causal Conditions → Central Phenomenon	.681	20.40	<.001	Significant
Contextual Conditions → Strategies	.350	4.95	<.001	Significant
Intervening Factors → Strategies	.429	6.73	<.001	Significant
Central Phenomenon → Strategies	.134	2.35	.019	Significant
Strategies → Outcomes	.827	44.30	<.001	Significant

Table 5 shows that all measurement and structural paths included in the model were positive and statistically significant. At the higher-order measurement level, the strongest relationship was observed between the Central Phenomenon and Operational Function ($\beta = .888$, $t = 73.05$, $p < .001$), followed by Causal Conditions and Development and Scalability Potential ($\beta = .879$, $t = 72.10$, $p < .001$), Causal Conditions and Economic Feasibility ($\beta = .865$, $t = 53.70$, $p < .001$), and the Central Phenomenon and Knowledge Characteristics ($\beta = .863$, $t = 56.03$, $p < .001$). Among the components of Contextual Conditions, Market Context ($\beta = .844$) and Environmental Context ($\beta = .841$) had the strongest associations with the higher-order construct. Knowledge Maturity showed the strongest relationship with Intervening Factors ($\beta = .832$), whereas Cultural Strategy had the highest loading among the strategy dimensions ($\beta = .819$). For Outcomes, Market-Oriented Outcomes demonstrated the strongest coefficient ($\beta = .789$), closely followed by Economic Outcomes ($\beta = .783$) and Environmental

Outcomes ($\beta = .780$). These findings confirmed that the first-order constructs were strongly represented by their corresponding higher-order dimensions.

The principal structural relationships among the major constructs were also statistically supported. Causal Conditions had a strong positive effect on the Central Phenomenon ($\beta = .681$, $t = 20.40$, $p < .001$). Contextual Conditions positively affected Strategies ($\beta = .350$, $t = 4.95$, $p < .001$), while Intervening Factors exerted a somewhat stronger positive effect on Strategies ($\beta = .429$, $t = 6.73$, $p < .001$). The Central Phenomenon also had a positive effect on Strategies, although this path was comparatively weaker ($\beta = .134$, $t = 2.35$, $p = .019$). The strongest principal structural relationship was the effect of Strategies on Outcomes ($\beta = .827$, $t = 44.30$, $p < .001$), indicating that improvements in the strategic mechanisms associated with technical knowledge valuation were strongly associated with improvements in its economic, market, organizational, developmental, environmental, and performance-related consequences. Thus, all hypothesized structural relationships were statistically significant; four of the five principal paths were significant at the .001 level, while the Central Phenomenon $\rightarrow$ Strategies relationship was significant at the .05 level.

Figure 1

PLS-SEM Model of Technical Knowledge Valuation in Agricultural Knowledge-Based Companies Showing Standardized Path Coefficients, Significance Levels, and R^2 Values

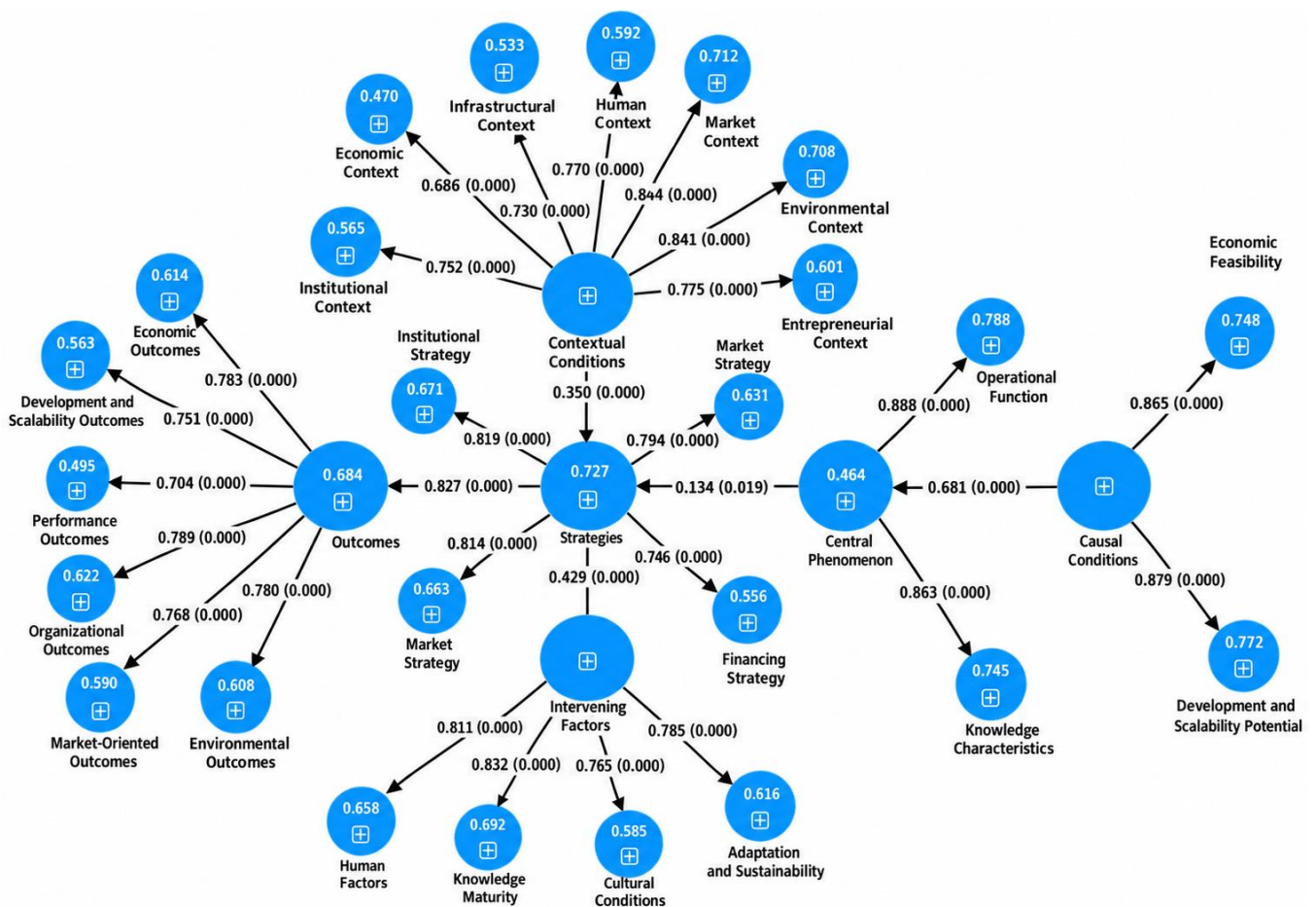


Figure 1 presents the standardized solution of the structural equation model and illustrates the direction and magnitude of the relationships among the major latent constructs. All principal path coefficients were positive, confirming that increases in the predictor constructs were associated with increases in their respective endogenous constructs. Causal Conditions

demonstrated a substantial positive relationship with the Central Phenomenon ($\beta = .681$), while Contextual Conditions ($\beta = .350$), Intervening Factors ($\beta = .429$), and the Central Phenomenon ($\beta = .134$) all contributed positively to Strategies. Among these antecedents, Intervening Factors exerted the strongest direct effect on Strategies. The strongest relationship in the principal structural model was observed from Strategies to Outcomes ($\beta = .827$), demonstrating the central role of strategic mechanisms in converting favorable valuation conditions into desirable consequences. The R^2 coefficients displayed within the endogenous constructs further indicated that the model explained substantial proportions of variance in the principal outcome variables, including 72.7% of the variance in Strategies and 68.4% of the variance in Outcomes.

Figure 2

PLS-SEM Model of Technical Knowledge Valuation in Agricultural Knowledge-Based Companies Showing Bootstrapped t Statistics and Average Variance Extracted Values

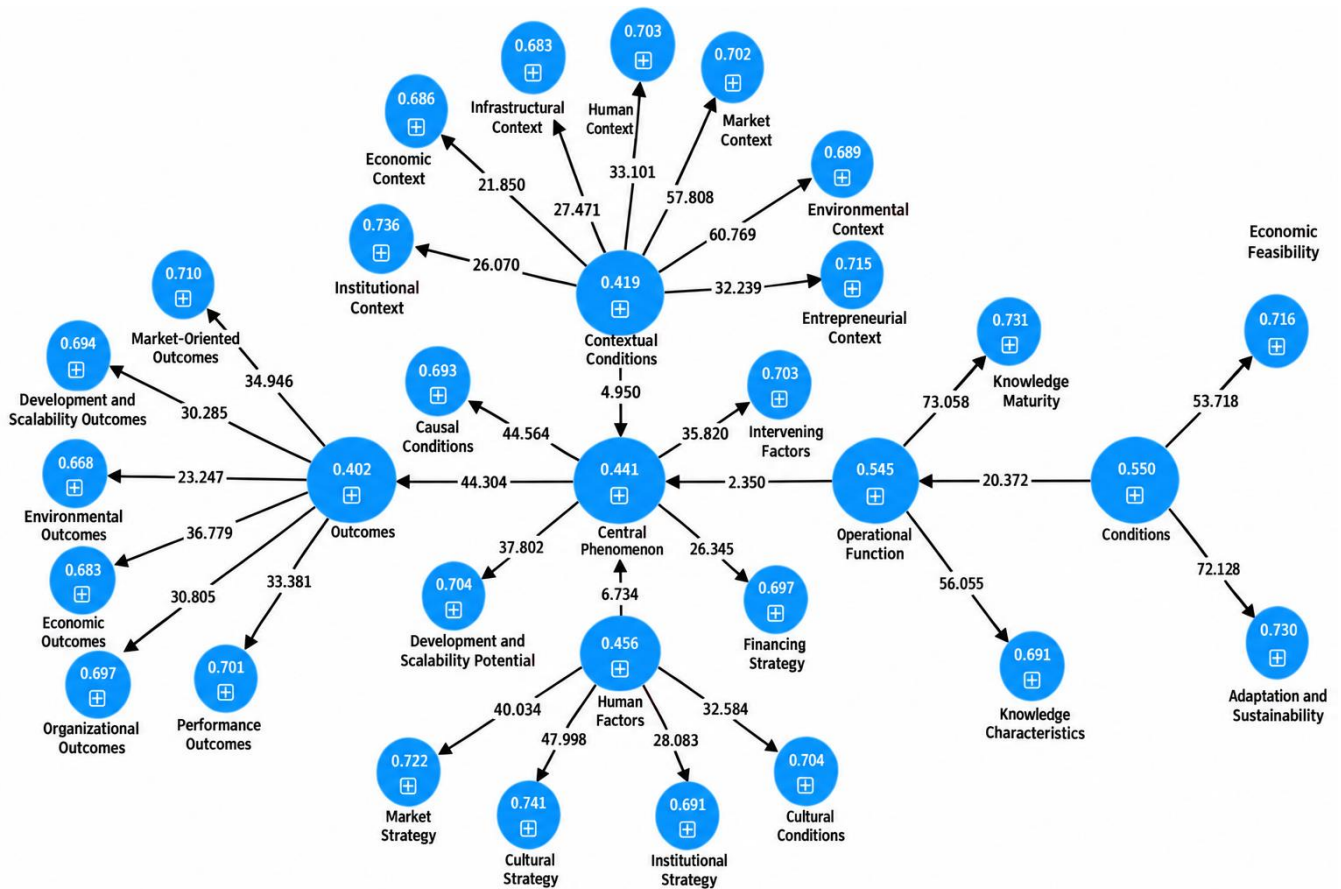


Figure 2 presents the bootstrapping results together with the AVE coefficients of the latent constructs. The t statistics confirmed the statistical significance of all specified relationships. For the principal structural model, the Causal Conditions → Central Phenomenon path produced $t = 20.40$, the Contextual Conditions → Strategies path produced $t = 4.95$, the Intervening Factors → Strategies path produced $t = 6.73$, the Central Phenomenon → Strategies path produced $t = 2.35$, and the Strategies → Outcomes path produced $t = 44.30$. Accordingly, all t statistics exceeded the critical value of 1.96 for a two-tailed test at the .05 significance level. The AVE coefficients simultaneously demonstrated satisfactory convergent validity, as every construct exceeded the .50 criterion. The combination of statistically significant structural paths, satisfactory AVE values, adequate internal consistency, acceptable discriminant validity, positive predictive relevance, and the satisfactory

SRMR value provided convergent evidence supporting the empirical validity of the proposed technical knowledge valuation model for agricultural knowledge-based companies.

Discussion and Conclusion

The present study was conducted to validate a structural equation model for the valuation of technical knowledge in agricultural knowledge-based companies and to determine how causal conditions, contextual conditions, intervening factors, the central phenomenon, strategies, and outcomes are structurally connected. Overall, the findings supported both the measurement model and the structural model. Reliability coefficients were satisfactory across all constructs, with Cronbach's alpha values ranging from .751 to .930 and composite reliability coefficients ranging from .858 to .938. Convergent validity was also confirmed because all average variance extracted values exceeded .50, while discriminant validity was supported by HTMT values below .90. The overall model demonstrated acceptable fit, particularly through an SRMR value of .069, which was below the conventional .08 threshold, while NFI was .850. Furthermore, the model showed moderate to strong explanatory power for all endogenous variables, and all Q^2 coefficients were positive, indicating meaningful predictive relevance. At the structural level, causal conditions exerted a strong positive effect on the central phenomenon ($\beta = .681$, $p < .001$), contextual conditions positively influenced strategies ($\beta = .350$, $p < .001$), intervening factors positively affected strategies ($\beta = .429$, $p < .001$), the central phenomenon had a smaller but significant effect on strategies ($\beta = .134$, $p = .019$), and strategies exerted the strongest direct effect on outcomes ($\beta = .827$, $p < .001$). These results collectively indicate that technical knowledge valuation in agricultural knowledge-based firms is a multidimensional process in which technological and economic characteristics acquire value through supportive contextual conditions and organizational strategies.

The strong effect of causal conditions on the central phenomenon indicates that economic feasibility and development and scalability potential constitute fundamental determinants of technical knowledge value. The respective relationships of causal conditions with economic feasibility ($\beta = .865$) and development and scalability potential ($\beta = .879$) were among the strongest coefficients observed in the model. This suggests that technical knowledge is valued not only according to its scientific novelty or technical sophistication but also according to whether it can be translated into commercially feasible and scalable applications. This finding is consistent with research emphasizing that valuation of agricultural technologies must incorporate uncertainty, future commercialization potential, and strategic flexibility rather than relying exclusively on current financial performance [7]. Similarly, investment decisions concerning innovative startups are shaped by both innovation potential and risk, making scalability and economic viability critical components of perceived enterprise value [8]. Gagnon et al. also showed that investors in emerging agricultural technologies evaluate market opportunity, commercialization trajectories, and the ability of innovations to reach viable scale [9]. The present findings therefore support the view that knowledge possesses greater economic value when it is capable of being transformed into repeatable, expandable, and financially sustainable applications.

The significance of economic feasibility is also consistent with broader agricultural valuation research. Agricultural assets and technologies frequently operate under uncertainty related to biological processes, market fluctuations, land quality, and regulatory conditions. Studies of economic valuation in agribusiness have demonstrated that productive potential and sector-specific economic characteristics must be incorporated into valuation processes [5], while accounting research on biological assets has highlighted the sensitivity of valuation to measurement assumptions and characteristics of agricultural production

[6]. Furthermore, the financialization of agriculture has increased the importance of understanding how future productive potential is converted into capital value [10]. In this context, the strong contribution of economic feasibility and scalability in the present model reflects the increasing need for knowledge-based agricultural companies to demonstrate not merely that their technologies function, but that these technologies can produce sustainable economic returns under realistic agricultural and market conditions.

The results also demonstrated that contextual conditions were strongly represented by institutional, economic, market, infrastructural, human, environmental, and entrepreneurial contexts, with particularly high coefficients for market context ($\beta = .844$), environmental context ($\beta = .841$), entrepreneurial context ($\beta = .775$), and human context ($\beta = .770$). These findings confirm that the valuation of technical knowledge is highly dependent on the ecosystem within which agricultural innovation is developed and commercialized. Knowledge-based agricultural firms do not operate in isolation; the value of their technologies depends partly on access to markets, infrastructure, skilled human resources, entrepreneurial support, regulatory legitimacy, and environmental compatibility. This interpretation aligns with research on agricultural innovation ecosystems showing that incubators and accelerators can significantly facilitate the commercialization of agricultural technologies by providing expertise, networks, infrastructure, and business support [11]. Similarly, knowledge exchange between universities and agritech startups can reshape business models and improve firms' capacity to transform scientific knowledge into marketable innovations [12]. Agricultural engineering education likewise contributes to the development of specialized capabilities necessary for technology-based agricultural systems [13].

The positive effect of contextual conditions on strategies ($\beta = .350$, $p < .001$) further indicates that firms formulate and implement their valuation-related strategies in response to their operating environment. When institutional, economic, infrastructural, market, and entrepreneurial environments are supportive, companies are better positioned to develop financing, market, cultural, and institutional strategies for extracting value from technical knowledge. This result is compatible with findings from studies of digital agriculture and agritech ecosystems. Suresh et al. showed that the development of data-driven agritech startups depends on the interaction between technological capabilities and national innovation environments [24]. Pambudi similarly emphasized the importance of digital infrastructure and coordinated planning for transforming agribusiness within a digital economy [25]. The modernization of agricultural supply chains through technology also requires enabling infrastructure and coordination across actors rather than isolated technological investment [26]. Thus, the present results reinforce the idea that technical knowledge becomes strategically valuable when firms operate within ecosystems capable of supporting commercialization, diffusion, financing, and technological adaptation.

Intervening factors had a somewhat stronger effect on strategies than contextual conditions ($\beta = .429$, $p < .001$). Within this construct, knowledge maturity had the strongest relationship ($\beta = .832$), followed by human factors ($\beta = .811$), adaptation and sustainability ($\beta = .785$), and cultural conditions ($\beta = .765$). This pattern highlights the internal organizational capacities required to convert technical knowledge into strategic value. Knowledge maturity is particularly important because immature technologies may still face unresolved technical uncertainties, limited documentation, insufficient standardization, or dependence on specific individuals. Mature knowledge, in contrast, is more likely to be transferable, replicable, scalable, and suitable for commercialization. The importance of human factors further indicates that technical knowledge cannot be detached from the capabilities of those who develop and apply it. Recent research on smart agriculture has similarly shown that the growing use of AI, sensing systems, and IoT technologies requires advanced technical competencies and integrated

knowledge capabilities [4]. The shifting role of agricultural extension personnel in digitalized agricultural systems also demonstrates that technological value depends on human capacity to interpret, transfer, and implement knowledge effectively [14].

The importance of adaptation and sustainability within the intervening factors is similarly consistent with contemporary agritech research. Agricultural innovations operate in environments characterized by climate variability, biological uncertainty, natural-resource constraints, and changing regulatory expectations. Consequently, technologies that cannot adapt to environmental and operational variability may have limited long-term value even if they are technically effective in controlled settings. Njavro et al. emphasized the role of agritech and artificial intelligence in strengthening resilience and strategic risk management in horticultural value chains [29]. Wahab et al. likewise argued that sustainable adoption of agritech innovations requires alignment between technological advancement and environmental and organizational conditions [18]. Rialti et al. further demonstrated that digital technologies can facilitate sustainable open innovation and shared value creation when technological development is integrated with sustainability-oriented business strategies [30]. The present findings therefore suggest that adaptation and sustainability should not be regarded merely as desirable external outcomes but as conditions that directly influence the strategic value of technical knowledge.

The central phenomenon was strongly reflected by operational function ($\beta = .888$) and knowledge characteristics ($\beta = .863$), demonstrating that the core of technical knowledge valuation is rooted in both what the knowledge is and what it can practically accomplish. Operational function represents the capacity of knowledge to improve processes, solve problems, increase efficiency, or contribute to agricultural production and management, whereas knowledge characteristics reflect properties such as specificity, distinctiveness, applicability, and technical content. This finding aligns with research demonstrating that the economic value of agricultural information depends on its usability and contribution to decision-making rather than on information availability alone [27]. Similarly, the expansion of platform-based agricultural systems illustrates how technical knowledge can gain value when it supports new financial, informational, or coordination functions [28]. The rise of smart agricultural technologies also confirms that the value of technical knowledge increasingly derives from integration among data, sensing, algorithms, and practical operational applications [3, 4].

Nevertheless, the direct effect of the central phenomenon on strategies was comparatively modest ($\beta = .134$, $p = .019$). Although statistically significant, this relationship was substantially weaker than the effects of contextual conditions and intervening factors on strategies. This is an important result because it indicates that possessing valuable technical knowledge alone is insufficient to generate strong strategic responses. Even when knowledge possesses desirable operational and technical characteristics, firms still require favorable contextual environments and internal organizational capacities to translate that knowledge into effective financing, market, institutional, and cultural strategies. This interpretation is consistent with research on agricultural technology adoption showing that technologically useful innovations may face limited diffusion when financing, infrastructure, organizational readiness, or user acceptance are insufficient [15, 16]. Similarly, heterogeneity in user preferences can reduce demand even for technologies with apparent productive benefits [17]. Thus, technical quality appears to be necessary but not sufficient for effective value realization.

The strongest principal structural relationship in the model was the effect of strategies on outcomes ($\beta = .827$, $p < .001$), with strategies explaining a substantial proportion of variance in the outcome construct. This result indicates that strategic implementation is the principal mechanism through which technical knowledge is translated into economic, developmental,

environmental, organizational, market, and performance outcomes. The finding is supported by the relatively strong relationships of the strategy construct with cultural strategy ($\beta = .819$), market strategy ($\beta = .814$), institutional strategy ($\beta = .794$), and financing strategy ($\beta = .746$). These results suggest that technical knowledge valuation is not simply an assessment process but also a strategic management process. Firms capable of aligning financing mechanisms, market development, institutional relationships, and organizational culture with their technological assets are more likely to convert those assets into valuable outcomes. This interpretation is consistent with evidence that agritech startups face policy, financing, and commercialization constraints that can prevent technically promising ventures from achieving their potential [23]. Financial inclusion has likewise been identified as a critical enabler of agripreneurial growth and commercialization [22].

The strong effect of strategies on outcomes also corresponds with research emphasizing entrepreneurship and organizational capacity in agriculture. Farmer-producer companies can foster agripreneurship by creating institutional and market mechanisms that support enterprise development [19], while social norms can shape entrepreneurial intentions and consequently influence the willingness of individuals to participate in agricultural enterprise creation [20]. Entrepreneurship programs can also generate broader social and economic returns beyond the immediate performance of individual firms [21]. The current model extends these observations by suggesting that the outcomes of technical knowledge valuation are multidimensional. Economic outcomes were important, but environmental, market-oriented, organizational, development-oriented, and performance consequences were also strongly associated with the overall outcome construct. This multidimensionality is consistent with arguments that agricultural benefits should be evaluated through broader metrics than conventional financial returns alone [31].

The predictive performance of the model further strengthens these interpretations. R^2 values were moderate to strong across the endogenous constructs, with especially high values for Operational Function ($R^2 = .788$), Development and Scalability Potential ($R^2 = .772$), Economic Feasibility ($R^2 = .748$), Knowledge Characteristics ($R^2 = .745$), Strategies ($R^2 = .727$), and Outcomes ($R^2 = .684$). Furthermore, all Stone-Geisser Q^2 values were positive, and most exceeded .35, indicating substantial predictive relevance. These findings suggest that the proposed model does more than reproduce correlations among constructs; it provides a meaningful framework for explaining and predicting important dimensions of technical knowledge valuation. In this respect, the model responds to the fragmented nature of previous agritech literature, which has often considered investment, adoption, sustainability, entrepreneurship, digital transformation, or valuation separately [1, 2]. By integrating these dimensions in a single structural framework, the present study demonstrates that technical knowledge value emerges through interconnected technological, contextual, organizational, and strategic mechanisms.

The study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design captures perceptions at a single point in time and therefore cannot determine how technical knowledge valuation changes as technologies mature, markets develop, or organizational capabilities evolve. Second, the sample size of 150, although adequate for the applied PLS-SEM procedure, limits the extent to which subgroup analyses can be performed across different agricultural industries, organizational sizes, technological domains, or stages of company development. Third, the data were based on questionnaire responses and therefore remain subject to perceptual bias, common-method effects, and differences in respondents' familiarity with specific forms of technical knowledge. Fourth, the model evaluates technical knowledge primarily through organizational and managerial perceptions rather than through direct monetary valuation, actual transaction prices, licensing revenues, patent values, or longitudinal firm performance. Finally, the model was validated

within the specific context of agricultural knowledge-based companies, and its applicability to other technology-intensive sectors should not be assumed without additional empirical examination.

Future studies should validate the proposed model using larger and more heterogeneous samples drawn from different agricultural subsectors, regions, and types of knowledge-based enterprises. Longitudinal research would be particularly valuable for examining whether the structural relationships change as firms move from early technology development to commercialization, market expansion, and technological maturity. Researchers could also integrate objective financial and technological indicators, such as research and development expenditure, patent portfolios, licensing income, technology readiness levels, commercialization revenues, investment rounds, export performance, and market growth, with perceptual measures of technical knowledge value. Comparative studies could test measurement invariance across different company sizes, technological fields, or national innovation systems. Future research may also examine mediating and moderating effects, including the roles of intellectual property protection, absorptive capacity, innovation capability, digital maturity, access to finance, and environmental uncertainty. Finally, the predictive accuracy of the proposed SEM model could be compared with machine-learning or hybrid valuation approaches to determine whether combining structural explanation with algorithmic prediction improves technical knowledge valuation.

Managers of agricultural knowledge-based companies should treat technical knowledge valuation as an integrated strategic process rather than as a purely accounting or financial calculation. Particular attention should be given to the economic feasibility and scalability of technologies, because knowledge that cannot be commercialized or expanded is unlikely to realize its full potential value. Firms should strengthen knowledge maturity through documentation, standardization, testing, codification, intellectual property management, and reduction of excessive dependence on individual experts. Because contextual and intervening factors were important predictors of strategic responses, managers should actively develop partnerships with universities, science and technology parks, investors, agricultural organizations, public institutions, and market intermediaries. Financing, market, institutional, and cultural strategies should be explicitly linked to technical knowledge assets, and valuation assessments should incorporate economic, organizational, environmental, developmental, market, and performance consequences. Investors and policymakers can also use the validated dimensions as a structured framework for evaluating agricultural knowledge-based companies and identifying which firms require financial support, infrastructure, commercialization assistance, or capability development before their technical knowledge can achieve its full economic and strategic value.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

References

- [1] K. Haritha, A. Sharma, P. Venkatesh, A. Devi, P. Anbukkani, and A. Kumar, "Rise of Agritech: A Landscape of Technology Driven Agricultural Sector in India," *Agricultural Economics Research Review*, vol. 36, no. 2, pp. 145-154, 2023, doi: 10.5958/0974-0279.2023.00028.9.
- [2] L. Judijanto, M. A. Pujiyanto, E. S. Azizi, and W. Widyastuti, "Exploring Recent Trends in Agricultural Economics With a Focus on Agritech and Agribusiness," *West Science Interdisciplinary Studies*, vol. 1, no. 10, pp. 1006-1018, 2023, doi: 10.58812/wsis.v1i10.275.
- [3] S. Sapienza, "Smart Solutions In AgriTech: Research Trajectories In the Digital Transition," pp. 150-162, 2022, doi: 10.1007/978-3-031-12673-4_11.
- [4] T. Miller, G. Mikiciuk, I. Durlik, M. Mikiciuk, A. Łobodzińska, and M. Śnieg, "The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies," *Sensors*, vol. 25, no. 12, p. 3583, 2025, doi: 10.3390/s25123583.
- [5] R. K. Dash, A. Kriviņš, and V. Kaže, "Economic Evaluation of Land in Agribusiness: Soil Fertility Factor," *Access Access to Science Business Innovation in Digital Economy*, vol. 6, no. 1, pp. 25-45, 2024, doi: 10.46656/access.2025.6.1(2).
- [6] D. d. L. Oliveira and S. H. Nakao, "Uniformidade E Consistência Das Escolhas No Reconhecimento E Mensuração De Ativos Biológicos," *Revista Contemporânea De Contabilidade*, vol. 20, no. 54, pp. 1-22, 2023, doi: 10.5007/2175-8069.2023.e83268.
- [7] W. W. Wilson, L. Vetsch, and D. W. Bullock, "Valuing an Agricultural Technology Startup Using Real Options," *Agribusiness*, vol. 38, no. 4, pp. 771-785, 2022, doi: 10.1002/agr.21744.
- [8] M. K. Srivastava, A. Dash, and I. Shaikh, "Funding Innovation and Risk: A Grey-Based Startup Investment Decision," *Evaluation Review*, vol. 49, no. 2, pp. 304-342, 2024, doi: 10.1177/0193841x241262887.
- [9] M. Gagnon, G. M. Broad, K. Grandison, and R. M. Chiles, "AgriTech Investor and Informant Perspectives About Cellular Agriculture," *International Food and Agribusiness Management Review*, vol. 26, no. 1, pp. 89-110, 2023, doi: 10.22434/ifamr2022.0017.
- [10] D. Silva and E. Arima, "When Land Becomes Capital: Farmland Financialization and Sustainability in Brazil," *Environmental Research Letters*, vol. 20, no. 11, p. 114030, 2025, doi: 10.1088/1748-9326/ae0faf.
- [11] R. Newell, L. Newman, and Z. Mendly-Zambo, "The Role of Incubators and Accelerators in the Fourth Agricultural Revolution: A Case Study of Canada," *Agriculture*, vol. 11, no. 11, p. 1066, 2021, doi: 10.3390/agriculture11111066.
- [12] N. T. T. Thùy, C. J. Brown, and N. T. H. Giang, "A Comparative Research on Communities of Practice, University Knowledge Exchange and Business Model Changes Between the United Kingdom and Vietnamese Agri-Tech Start-Ups," *Vnu Journal of Economics and Business*, vol. 2, no. 2, 2022, doi: 10.57110/jeb.v2i2.4723.
- [13] G. Civeira, A. Maz-Machado, F. A. Menéndez, and C. Pedrosa-Jesús, "The Objectives of Agricultural Engineering Training in Argentina," *Tem Journal*, pp. 104-110, 2023, doi: 10.18421/tem121-14.

- [14] C. Sugihono, H. A. Juniarti, and N. C. Nugroho, "Digital Transformation in the Agriculture Sector: Exploring the Shifting Role of Extension Workers," *Sti Policy and Management Journal*, vol. 7, no. 2, 2022, doi: 10.14203/stipm.2022.350.
- [15] S. Mamba and A. Beharry-Ramraj, "Factors Influencing Agricultural Technology (Agritech) Adoption Among KwaZulu-Natal Commercial Farm Managers," *E-Journal of Humanities Arts and Social Sciences*, pp. 15-28, 2024, doi: 10.38159/ehass.2024592.
- [16] M. Z. Tesfaye, B. Balana, and J. C. Bizimana, "Assessment of Smallholder Farmers' Demand for and Adoption Constraints to Small-Scale Irrigation Technologies: Evidence From Ethiopia," *Agricultural Water Management*, vol. 250, p. 106855, 2021, doi: 10.1016/j.agwat.2021.106855.
- [17] K. Gulati, P. S. Ward, T. J. Lybbert, and D. J. Spielman, "Intrahousehold Preference Heterogeneity and Demand for Labor-saving Agricultural Technology," *American Journal of Agricultural Economics*, vol. 106, no. 2, pp. 684-711, 2023, doi: 10.1111/ajae.12430.
- [18] S. A. Wahab, N. M. Nor, and A. A. Rashid, "Adopting Innovations in Agri-Tech Sector for a Sustainable Future," *Environment-Behaviour Proceedings Journal*, vol. 9, no. SI19, pp. 83-89, 2024, doi: 10.21834/e-bpj.v9isi19.5773.
- [19] S. Dahiya and M. B. Khandare, "The Role of Farmer-Producer Companies in Fostering Agripreneurship: A Case Study of Haryana," *Sedme (Small Enterprises Development Management & Extension Journal) a Worldwide Window on Msme Studies*, vol. 52, no. 2, pp. 154-163, 2025, doi: 10.1177/09708464251334893.
- [20] A. N. Ephrem, P. M. D. Nguetzet, M. Murimbika, Z. Bamba, and V. M. Manyong, "Perceived Social Norms and Agripreneurial Intention Among Youths in Eastern DRC," *Sustainability*, vol. 13, no. 6, p. 3442, 2021, doi: 10.3390/su13063442.
- [21] Nurlaili, A. Warnaen, U. Romadi, and S. B. Udrayana, "Measuring the Social Impact of the Agricultural Youth Entrepreneurship Program On <i>santri</i> Social Return on Investment (SROI) Analysis," *Iop Conference Series Earth and Environmental Science*, vol. 1625, no. 1, p. 012009, 2026, doi: 10.1088/1755-1315/1625/1/012009.
- [22] S. Mbangiswano, E. N. Ndlovu, and Z. S. Vuthela, "Empowering Rural Women Agripreneurs Through Financial Inclusion: Lessons From South Africa for the G20 Development Agenda," *Administrative Sciences*, vol. 15, no. 9, p. 340, 2025, doi: 10.3390/admsci15090340.
- [23] B. W. Pandey, R. Manohar, and M. Arya, "Navigating the Agristart-Up Revolution in India: Constraints and Policy Imperatives," *Indian Journal of Public Administration*, vol. 71, no. 3, pp. 586-600, 2025, doi: 10.1177/00195561251369068.
- [24] D. Suresh, A. Choudhury, Y. Zhang, Z. Zhao, and R. Shaw, "The Role of Data-Driven Agritech Startups—The Case of India and Japan," *Sustainability*, vol. 16, no. 11, p. 4504, 2024, doi: 10.3390/su16114504.
- [25] D. Pambudi, "Harvesting Opportunities: Transforming Indonesia's Agribusiness Through Smart City Planning in the Digital Economy Era," *Academic Society for Appropriate Technology*, vol. 10, no. 1, pp. 9-19, 2024, doi: 10.37675/jat.2023.00472.
- [26] J. S. Adesiyun and A. E. Raffington, "AgriTech Revolution: Next-Generation Supply Chain in America's Agriculture," *International Journal of Environment and Climate Change*, vol. 14, no. 2, pp. 254-272, 2024, doi: 10.9734/ijecc/2024/v14i23943.
- [27] Y. Zhang, N. Hoang, D. Baker, L. E. Morales, and G. R. Griffith, "Unlocking the Monetary Value: Investigating the Importance of Quality Information in Australian Red Meat Chains," *Animal Production Science*, vol. 64, no. 1, 2023, doi: 10.1071/an23180.
- [28] Y. Zhang, "From Platform Provider to Big-Data-Enabled Financier: Industrial Upgrading in China's Hog Sector," *Big Data & Society*, vol. 12, no. 3, 2025, doi: 10.1177/20539517251367445.
- [29] M. Njavro, T. Čop, and B. Duralija, "Strategic Risk Management in Horticultural Value Chains: A Structured Conceptual Review and Framework for Resilience Through Agritech and AI," *Horticulturae*, vol. 12, no. 9, p. 1071, 2026, doi: 10.3390/horticulturae12091071.
- [30] R. Rialti, A. Marrucci, L. Zollo, and C. Ciappei, "Digital Technologies, Sustainable Open Innovation and Shared Value Creation: Evidence From an Italian Agritech Business," *British Food Journal*, vol. 124, no. 6, pp. 1838-1856, 2022, doi: 10.1108/bfj-03-2021-0327.
- [31] P. Sharma, M. Verma, C. Tiwari, G. K. Kadekodi, K. N. Ninan, and A. Guha, "Transforming the Yardstick Used to Measure Benefits From the Farm Sector," *Wripub*, 2023, doi: 10.46830/wriwp.21.00028.
- [32] V. T. López, "Territorial Changes Around Biodiesel: A Case Study of North-Western Argentina," pp. 239-261, 2021, doi: 10.1007/978-3-030-68944-5_12.

- [33] Q. Jing, "Eco-Environmental Approach to Evaluating and Optimizing Creativity and Entrepreneurship Education With PSO," *International Journal of Agricultural and Environmental Information Systems*, vol. 16, no. 1, pp. 1-22, 2025, doi: 10.4018/ijaeis.393783.