Equivalent: Jurnal Ilmiah Sosial Teknik
Volume 8, Issue 3, 1222-1236
e_ISSN: 2775-0833
https://jurnalequivalent.id/index.php/jequi/index
DOI: doi.org/10.59261/jequi.v8i3.374

Digital Competency Assessment of Farmer Groups: A Training Needs Analysis for Agricultural Digital Transformation in West Java

Ikhsan Nendi[1]*
Politeknik Siber Cerdika Internasional,
Indonesia

Amelia[2]
Universitas Swadaya Gunung Jati,
Indonesia

***Corresponding author:**
Ikhsan Nendi, Politeknik Siber Cerdika Internasional, Indonesia.
✉ikhsan_nendi@polteksci.ac.id

Article Info:
Article history:
Received: June 12, 2026
Revised: July 27, 2026
Accepted: August 06, 2026

Keywords:
Agriculture 4.0; Digital Competency; Digital Transformation; Farmer Groups; Training Needs Assessment.

Abstract

Background: Agriculture 4.0 is reshaping farming worldwide, yet Indonesian farmer groups remain constrained by uneven digital competency. National census data show that 53.16 percent of the 28.19 million farmers in Indonesia still work without modern machinery or digital technology.
Objective: This study measures the digital competency level of farmer group members, ranks their priority training needs by domain, and tests the individual factors that shape those needs.
Methods: A cross sectional survey covered 210 members of 21 farmer groups in Indramayu, Subang, and Karawang, West Java, drawn by stratified random sampling. The instrument was adapted from DigComp 2.1 and validated by five experts. Analysis was run in SPSS 26 using descriptive statistics, gap analysis, the Training Priority Index, Importance-Performance Analysis, and multiple linear regression after classical assumption testing.
Results: Mean current competency reached 56.4 of 100 against a required standard of 80.0, a gap of 23.6 points. The widest gaps were digital agricultural applications (29.4), digital marketing (27.1), and precision farming technology (25.8). Education level (β = 0.412), digital infrastructure access (β = 0.376), and age (β = −0.318) significantly predicted competency and explained 42.8 percent of its variance.
Conclusion: Training for farmer groups should be differentiated rather than uniform, pairing foundational digital literacy for older and less educated members with advanced application and marketing modules for younger members who can act as digital champions. Extension agencies can use the Training Priority Index reported here to sequence modules and to schedule training alongside rural connectivity investment.

To cite this article: Nendi, I., & Amelia. (2026). Digital Competency Assessment of Farmer Groups: A Training Needs Analysis for Agricultural Digital Transformation in West Java. *Equivalent: Jurnal Ilmiah Sosial Teknik*, 8(3), 1222-1236. https://doi.org/10.59261/jequi.v8i3.374

INTRODUCTION

The global agricultural sector is undergoing an unprecedented transformation driven by digitalization, often referred to as Agriculture 4.0 or smart farming (Hein-Pensel, 2026; Patalon, 2026). Digital technologies such as Internet of Things (IoT) sensors, drone-based monitoring, precision fertilization systems, digital marketplace platforms, and data analytics are progressively being integrated into farming operations worldwide. These technologies hold enormous potential for improving productivity, reducing resource waste, and enhancing the livelihoods of farming communities, particularly in developing countries such as Indonesia. The benefits of this transition, however, are distributed unevenly. Mehrabi et al. (2021) reported that only 24% to 37% of farms smaller than one hectare were covered by 3G or 4G services, compared with 74%

to 80% of farms larger than 200 hectares, indicating that the smallholders who dominate Asian agriculture are structurally the last to benefit from digital connectivity (Al khatib & Alshaib, 2025). Klerkx et al. (2019) demonstrated that the social science literature on Agriculture 4.0 has expanded rapidly but remains concentrated on technology design rather than on the human capabilities required to operate these technologies (Kirmikil, 2026), while Barrett and Rose (2022) found that farmers and agricultural advisers anticipate skill displacement as one of the principal consequences of the fourth agricultural revolution.

Indonesia's agricultural sector employs more than 38 million people and contributes approximately 13.7% to the national GDP. However, the sector continues to face persistent challenges, including low productivity, inefficient supply chains, and limited access to modern technology. The Indonesian government has articulated a strategic vision for agricultural digitalization through various national programs. Despite these initiatives, the adoption of digital technologies among farmer groups (*kelompok tani*) remains markedly low, particularly in rural and semi-rural areas of West Java. National statistics further illustrate this gap. The 2023 Agricultural Census recorded 28.19 million farmers in Indonesia, of whom only 46.84% used modern agricultural machinery or digital technologies, leaving 53.16% operating without either ([BPS]., 2023). Farmers aged 19 to 39 years, the cohort considered most receptive to digital technologies, number 6.18 million, representing only 21.93% of the total farming population. Consequently, most of the workforce expected to adopt Agriculture 4.0 technologies is older than 39 years. West Java reflects this national pattern, with digital technology utilization concentrated among a relatively small number of better-connected farmer group members.

Farmer groups (*kelompok tani*) constitute the primary institutional unit for agricultural extension, knowledge dissemination, and collective action in Indonesia. A critical barrier to the effective utilization of digital agricultural technologies is the substantial competency gap among group members. Previous research suggests that without adequate digital literacy and competencies, even well-designed technological interventions fail to achieve their intended outcomes (Chávez Santos et al., 2026; Tengblad et al., 2026). The causal relationship implied by these findings is straightforward. Agricultural digital transformation increases the competency threshold required for productive farming, while the existing competency level of farmer group members remains substantially below that threshold. If this gap is left unmeasured, training budgets are likely to be allocated based on assumptions rather than empirical evidence. Consequently, Training Needs Assessment (TNA) is not merely an optional refinement but a strategic instrument for translating the broad agenda of agricultural digitalization into evidence-based, targeted, and fundable training programs (Rijswijk et al., 2021; Waseem et al., 2026).

Training Needs Assessment (TNA) provides a systematic framework for identifying gaps between existing and required competencies, thereby enabling the design of targeted and effective training programs (Borisoglebskaya et al., 2026). The application of TNA within the context of agricultural digital transformation is particularly relevant because it enables policymakers and agricultural extension officers to prioritize resources toward the most critical competency deficiencies.

Collectively, previous studies converge on three findings while differing on one important issue. They consistently demonstrate that digital competency constrains technology adoption more strongly than hardware availability, that education and age are robust predictors of digital competency, and that farmer groups represent an effective institutional channel for capability development. However, they differ regarding the relative importance of digital infrastructure. Mehrabi et al. (2021) identified connectivity as the principal constraint, whereas Chávez Santos et al. (2026) and Alkan (2025) argued that digital competency remains a significant determinant of technology adoption even where connectivity is already adequate. A common methodological limitation also emerges. Most existing studies describe adoption levels or user perceptions, whereas only a limited number directly quantify the gap between farmers' existing competencies and the competencies required for digital agriculture. Moreover, where competency measurement has been undertaken, the assessment frameworks have generally been adapted from enterprise, healthcare, or educational settings rather than agricultural extension. As a result, agriculture-specific competencies, such as operating precision agriculture technologies and navigating digital agricultural marketplaces, are not adequately represented in the assessment instruments (Kirmikil, 2026; Klerkx et al., 2019).

Three research gaps emerge from this review. First, no published study has measured the digital competency gap of Indonesian farmer groups against an explicitly defined competency standard, resulting in training priorities that are largely based on assumptions rather than empirical evidence. Second, existing Indonesian studies primarily report technology adoption rates without decomposing digital competency into measurable domains that can be directly translated into training modules, thereby limiting the ability of agricultural extension officers to prioritize and sequence training interventions. Third, the determinants of digital competency among farmer groups have not been examined simultaneously within a single analytical model, leaving it unclear whether the effects of age remain significant after controlling for education level and digital infrastructure access.

This study is the first to apply a comprehensive three-level Training Needs Assessment to Indonesian farmer groups using a DigComp 2.1 framework adapted specifically for agricultural contexts. It is also the first to develop and report a Training Priority Index for agricultural digital competency domains. The study's primary novelty lies in integrating three complementary analytical approaches within a single dataset: domain-level competency gap analysis, Importance–Performance Analysis (IPA), and multiple regression analysis. Together, these approaches identify not only which competencies are deficient, but also which competencies require immediate investment, and which characteristics of farmer groups significantly influence those competency deficiencies.

Figure 1 illustrates the conceptual framework tested in this study. Individual characteristics (including education level, age, digital infrastructure access, and previous training frequency) together with the institutional context of farmer groups (*kelompok tani*), influence the level of digital competency possessed by members. The discrepancy between existing competency and the competency standard required by Agriculture 4.0 represents the training need, which is quantified using the competency gap score, the Training Priority Index, and the Importance–Performance Analysis quadrant classification. Appropriately identified and effectively addressed training needs are expected to enhance farmers' readiness for agricultural digital transformation. Furthermore, successful technology adoption subsequently contributes to improving digital competency, thereby creating a continuous feedback loop that strengthens future adoption capacity.

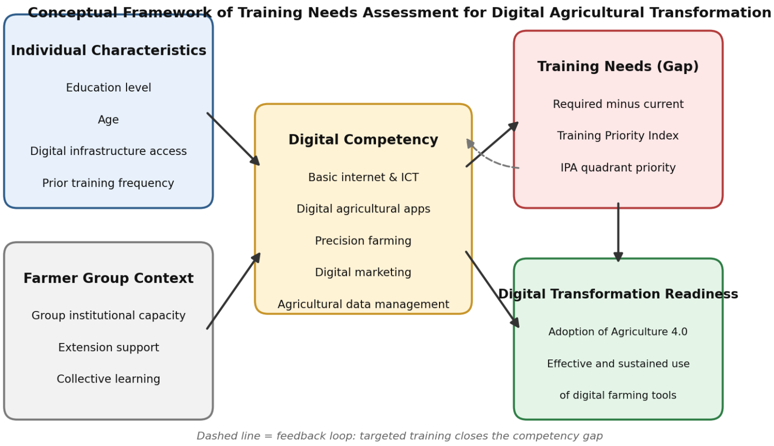

Figure 1. Conceptual framework linking individual characteristics, digital competency, training needs, and readiness for agricultural digital transformation.
Source: Developed by the authors (2026).

Despite the proliferation of digital agriculture programs in Indonesia, there is a paucity of empirical research systematically assessing the digital training needs of farmer groups. The specific digital competency gaps among smallholder farmer groups in the context of agricultural digital transformation remain underexplored. Without a rigorous Training Needs Assessment (TNA), training interventions are likely to be misaligned with actual needs, resulting in the inefficient use of public resources and limited improvements in farmer welfare. These gaps define the problem addressed in this study. Without domain-level measurement of competency gaps, training programs for farmer groups cannot be effectively sequenced, budgeted, or evaluated, and digitalization budgets are more likely to be allocated to the easiest training modules to deliver rather than those that address the most critical competency deficiencies.

Following directly from the three gaps identified above, this study pursues four interrelated objectives. First, it measures the current digital competency level of farmer group members against the competency standard required for agricultural digital transformation, thereby addressing the absence of gap-based measurement. Second, it decomposes the identified competency gap by domain and ranks the domains using a Training Priority Index (TPI), thereby addressing the lack of module-level evidence. Third, it identifies priority training needs based on that ranking. Finally, it examines whether education level, age, access to digital infrastructure, and prior training frequency jointly predict digital competency, thereby addressing the absence of an integrated explanatory model.

This study offers both theoretical and practical contributions. Theoretically, it extends Training Needs Assessment beyond its conventional corporate and clinical applications into the field of agricultural extension and operationalizes DigComp 2.1 for a smallholder farming population by incorporating an agricultural competency layer not included in the original framework (Abubakari et al., 2026; Carretero et al., 2017). It also provides an empirical examination of Human Resource Development (HRD) assumptions within a population characterized by relatively low levels of formal education. Practically, the study provides agricultural extension agencies with a prioritized sequence of training modules, equips farmer group leaders with a diagnostic instrument for periodic competency reassessment, and offers district governments an evidence-based foundation for aligning training investments with improvements in rural digital connectivity. The findings directly support Indonesia's agricultural modernization agenda and contribute to the achievement of Sustainable Development Goals (SDGs) 2 and 8.

Training Needs Assessment is a systematic process for identifying the gap between current performance and the desired performance standard, thereby establishing the basis for targeted training interventions (Borisoglebskaya et al., 2026). The most widely cited TNA framework is the three-level model proposed by McGhee and Thayer (1961), comprising organizational analysis, task analysis, and individual analysis. Contemporary TNA research increasingly employs quantitative approaches, including Importance–Performance Analysis (IPA), gap analysis, and regression modeling (Ahmadizadeh et al., 2026; Qawqzeh et al., 2025; Vogt et al., 2026).

Digital transformation in agriculture encompasses the integration of digital technologies into farming practices, agricultural value chains, and farm management systems (Pham et al., 2026). The transition toward Agriculture 4.0 requires not only robust technological infrastructure but also substantial human capital development (Ceschel et al., 2026; Tengblad et al., 2026). Research conducted in developing-country contexts highlights that smallholder farmers face distinctive barriers to digital technology adoption, including limited educational attainment, inadequate internet connectivity, and insufficient agricultural extension support (Ihou & Mansingh, 2026; Stewart et al., 2026).

Digital competency refers to the knowledge, skills, and attitudes required to use digital technologies effectively in professional and social contexts. The European Commission's DigComp 2.1 framework identifies five core digital competency domains: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving (Chávez Santos et al., 2026; Commission., 2013). Within the agricultural context, these competencies are further extended to include precision farming tool operation, agricultural data management, digital market navigation, and remote sensing interpretation.

Human Resource Development (HRD) in agricultural settings encompasses planned and systematic learning activities designed to enhance the performance and capabilities of agricultural workers and farmers (Ceschel et al., 2026). Farmer groups serve as the primary organizational unit for HRD implementation within Indonesia's agricultural extension system. The concept of dynamic capabilities (Tengblad et al., 2026) provides a theoretical lens for understanding how farmer groups can identify emerging digital opportunities, seize those opportunities, and reconfigure existing practices to adapt to technological change.

A substantial body of literature identifies several key factors influencing digital competency in agricultural communities. Education level consistently emerges as a strong predictor of digital literacy (Alkan, 2025). Age is generally negatively associated with digital competency (Vogt et al., 2026). Access to digital infrastructure mediates the relationship between training participation and the effective use of digital technologies (Chávez Santos et al., 2026). In addition, social capital within farmer groups plays a significant role in facilitating digital competency development and technology adoption (Ihou & Mansingh, 2026; Stewart et al., 2026).

METHOD

This study employed a quantitative research design using a cross-sectional survey approach. The quantitative methodology was selected to enable the systematic measurement of digital competency gaps, statistical analysis of training needs priorities, and identification of factors influencing digital competency. This approach is consistent with contemporary training needs analysis (TNA) research practices (Ahmadizadeh et al., 2026; Vogt et al., 2026).

The study population comprised all registered farmer group members in three selected districts of West Java Province, Indonesia: Indramayu, Subang, and Karawang. Using the Slovin formula with a 5% margin of error, a minimum sample size of 196 respondents was determined. The study recruited 210 respondents using stratified random sampling across 21 farmer groups. Indramayu, Subang, and Karawang were selected purposively based on three criteria. First, they are the three largest rice-producing districts in West Java and therefore have the province's highest concentration of registered farmer groups. Second, each district has an active agricultural extension office through which digital agricultural programs are delivered, ensuring that any recommended training has an established implementation channel. Third, together they represent the province's range of digital connectivity, with Karawang being the most industrialized and best connected, Subang exhibiting intermediate conditions, and Indramayu being the most rural. This variation allows infrastructure access to differ meaningfully across the sample rather than remaining effectively constant. The sampled farmer groups were food crop farmer groups with at least 20 active members that had been formally registered with the district agricultural extension office for at least three years, thereby excluding newly established groups whose training history would be insufficient for assessment.

$$\mathbf{n = N / (1 + N \cdot e^2)} \quad \text{..........} \ (1)$$

Where: n = sample size; N = population size (2,450); e = margin of error (0.05)

Stratification was applied first by district and subsequently by farmer group. The 2,450 registered members were divided into three district strata. Within each stratum, seven farmer groups were randomly selected from the district agricultural extension register, and ten members were then chosen from each of the 21 groups using a random number sequence applied to the membership list. The resulting 210 respondents were allocated proportionally according to the population of each district, as presented in Table 1. Fieldwork achieved a 100% response rate because the questionnaires were administered during scheduled farmer group meetings, where attendance was officially recorded.

Table 1

Distribution of the Sample Across Districts and Farmer Groups

District	Registered Members	Farmer Groups Sampled	Respondents	Share of Sample (%)
Indramayu	1,010	7	87	41.4
Subang	830	7	71	33.8
Karawang	610	7	52	24.8
Total	**2,450**	**21**	**210**	**100.0**

Note: Respondents were allocated proportionally to the registered membership of each district stratum.

Source: District agricultural extension registers and primary data (2026)

A structured questionnaire was developed based on the DigComp 2.1 framework and adapted to the Indonesian agricultural context. The instrument comprised four sections: (1) respondent demographic profile (8 items), (2) current digital competency self-assessment (30 items, 5-point Likert scale), (3) required competency standard assessment (30 items), and (4) digital infrastructure access (5 items). Reliability was assessed using Cronbach's alpha ($\alpha = 0.891$ for current competency; $\alpha = 0.876$ for required competency), indicating high internal consistency (Shetty et al., 2026).

The adaptation of DigComp 2.1 (Abubakari et al., 2026; Carretero et al., 2017) proceeded in four stages. The five original competence areas were translated into Bahasa Indonesia and back-translated by an independent translator. Two agricultural extension specialists from the district extension offices, two lecturers specializing in agricultural human resource development, and one measurement specialist then reviewed each item for relevance and clarity. An agricultural competency layer covering precision agriculture tool operation, agricultural data management, digital market navigation, and remote sensing interpretation was added because DigComp 2.1 addresses generic rather than domain-specific competencies. Content validity was computed based on the ratings of the five experts, yielding an Aiken's V coefficient of 0.87 for the current competency scale and 0.84 for the required competency scale, both exceeding the recommended threshold of 0.80. The instrument was subsequently piloted with 30 farmer group members outside the sampled groups. Item validity was evaluated using corrected item–total correlations, and four items with coefficients below 0.30 were revised before the fieldwork. Table 2 presents the validity and reliability results.

Table 2

Validity and Reliability of the Adapted Instrument

Scale	Items	Aiken V	Item-Total Correlation	Cronbach's Alpha	Conclusion
Current digital competency	30	0.87	0.342 – 0.716	0.891	Valid, reliable
Required competency standard	30	0.84	0.318 – 0.689	0.876	Valid, reliable
Digital infrastructure access	5	0.85	0.401 – 0.663	0.812	Valid, reliable

Note: Aiken V computed from five expert raters; threshold 0.80. Item validity threshold 0.30.

Source: Expert judgement and pilot test of 30 respondents 2026

Data were collected between 3 February and 28 March 2026. Questionnaires were administered face to face during scheduled farmer group meetings, with enumerators reading each item aloud for respondents with limited reading fluency, which reduced non response on the competency items to zero. Before administration every respondent received a written and verbal explanation of the study purpose, the voluntary nature of participation, and the anonymised treatment of responses, and then signed an informed consent form. Institutional permission was granted in advance by group leaders through the district extension office, and no personally identifying information was recorded. Three analytical methods were employed:

(a) Descriptive Statistics: Frequency distributions, means, and standard deviations for all variables.

(b) Gap Analysis: The Training Priority Index (TPI) was calculated for each competency domain:

$$\mathbf{TPI = (Required\ Score - Current\ Score) / Required\ Score \times 100} \quad \text{.......... (2)}$$

(c) Multiple Linear Regression to identify factors significantly influencing digital competency:

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon} \quad \text{.......... (3)}$$

Where: Y = digital competency score; X_1 = education level; X_2 = age; X_3 = digital infrastructure access; X_4 = training frequency; ε = error term

(d) Importance-Performance Analysis (IPA): A matrix plotting importance ratings against current performance scores for each competency domain to identify quadrant-based training priorities.
(e) Classical Assumption Testing: before the regression coefficients were interpreted, residual normality was examined with the Kolmogorov-Smirnov test and normal probability plots, multicollinearity with tolerance and variance inflation factor values, heteroscedasticity with the Glejser test and scatterplots of standardized residuals, linearity with the deviation from linearity test, and independence of residuals with the Durbin-Watson statistic. All analyses were conducted in IBM SPSS Statistics version 26, while the Importance-Performance matrix was plotted in Microsoft Excel 2021.

RESULTS AND DISCUSSION

Results

Respondent Demographic Profile

Table 3 presents the demographic characteristics of the 210 respondents. The sample was predominantly male (76.2%), reflecting the gender composition of formal farmer groups in the study area. The majority of respondents (48.6%) were in the 41–55 age group, while only 18.1% were under 35 years. Regarding education, 42.4% had completed junior high school (SMP), while only 11.9% held a diploma or higher qualification. Only 38.1% reported owning a smartphone with internet access.

Table 3
Demographic Characteristics of Respondents (n = 210)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	160	76.2
	Female	50	23.8
Age (years)	< 35	38	18.1
	35–40	42	20.0
	41–55	102	48.6
	> 55	28	13.3
Education	Elementary (SD)	45	21.4
	Junior High (SMP)	89	42.4
	Senior High (SMA)	51	24.3
	Diploma/Higher	25	11.9
Internet Access	Owns smartphone w/ internet	80	38.1
	No smartphone/limited access	130	61.9

Source: Primary data analysis (2026)

The practical meaning of this profile is that the training population is old, formally under educated, and only partly connected. Almost two thirds of members, 61.9 percent, do not own a smartphone with internet access, so any design that assumes a personal device in every participant's hand will exclude the majority; group owned devices or shared access points are a precondition rather than an enhancement. With 63.8 percent of members holding no more than junior high school education, instruction has to be built around demonstration and guided practice rather than written manuals. And because only 18.1 percent of members are under 35, the pool of potential peer trainers is small enough that identifying and equipping them should be treated as a distinct program component rather than as a by-product of general training.

Current Digital Competency Levels

Table 4 presents the mean scores for current and required digital competencies across five domains. The overall mean current competency score was 56.4 (SD = 11.3) out of 100, significantly below the required standard of 80.0. The largest gap was observed in digital agricultural applications (gap = 29.4), followed by digital marketing (gap = 27.1) and precision farming technology (gap = 25.8). Figure 2 visualizes these gaps, while Figure 3 illustrates the Training Priority Index ranking.

Table 4
Digital Competency Gap Analysis by Domain

Competency Domain	Current Score	Required Score	Gap	TPI (%)
Basic Internet & ICT Literacy	58.7	80.0	21.3	26.6
Digital Agricultural Apps	50.6	80.0	29.4	36.8
Precision Farming Technology	54.2	80.0	25.8	32.3
Digital Marketing	52.9	80.0	27.1	33.9
Agricultural Data Management	63.8	80.0	16.2	20.3
Overall Average	**56.4**	**80.0**	**23.6**	**29.5**

Note: TPI = Training Priority Index; Higher TPI = Higher Training Priority.
Source: Primary data (2026)

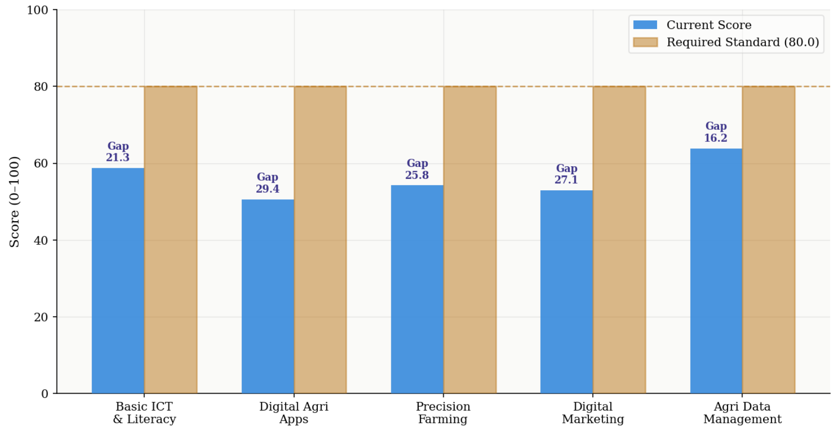

Figure 2. Digital Competency Gap Analysis by Domain (Current vs. Required Score, n = 210). Numbers above bars indicate gap score.
Source: Primary data (2026).

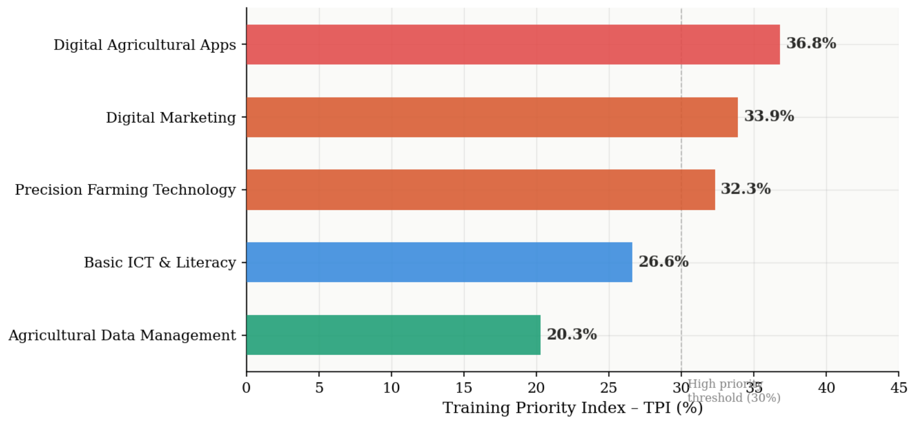

Figure 3. Training Priority Index (TPI) per Competency Domain. TPI = (Required − Current) / Required × 100. Higher TPI indicates greater training urgency.
Source: Primary data (2026).

Beyond the ranking itself, the gap profile carries a clear instructional message. The two domains with the widest gaps, digital agricultural applications and digital marketing, are both applied and transactional rather than conceptual, which means they can be taught through supervised practice on a live account instead of classroom instruction. Agricultural data management, with the narrowest gap of 16.2 points, is already partly covered by the record keeping habits farmer groups maintain for cooperative purposes, so investing scarce training hours there would yield the smallest return. A Training Priority Index above 30 percent, which three of the five domains exceed, indicates that members currently perform below two thirds of the required standard, a level at which independent use of the technology is not yet realistic without accompanying support.

Importance-Performance Analysis (IPA)

Figure 4 presents the IPA matrix mapping the five competency domains. Quadrant I (Concentrate Here — High Importance, Low Performance) contains Digital Agricultural Applications, Digital Marketing, and Precision Farming Technology — the highest-priority training areas. Quadrant II (Keep Up the Good Work — High Importance, High Performance) contains Agricultural Data Management. Quadrant III (Low Priority) contains Basic Internet and ICT Literacy. Read as a management tool rather than a description, the matrix assigns budget shares. The three Quadrant I domains absorb the bulk of training resources because members rate them as important yet perform poorly in them, which is the combination where instruction produces the largest movement. Agricultural data management in Quadrant II requires maintenance rather than investment, typically a short refresher. Basic internet and ICT literacy falls in Quadrant III not because it is unnecessary but because members already acquire it incidentally through everyday phone use, so formal training duplicates learning that is happening anyway.

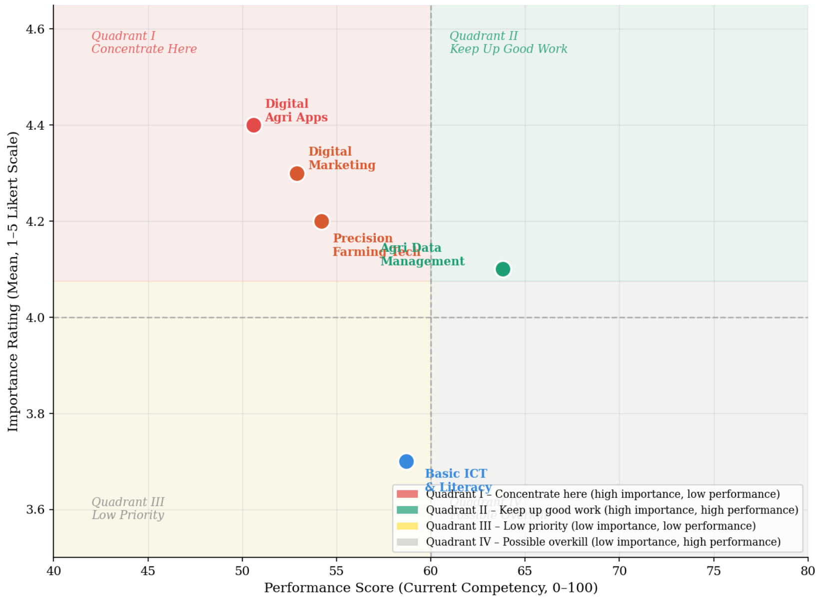

Figure 4. Importance-Performance Analysis (IPA) Matrix of Digital Competency Domains. Quadrant I (red) = highest training priority; Quadrant II (green) = maintain; Quadrant III (yellow) = low priority; Quadrant IV (gray) = possible overkill. Midlines at performance = 60, importance = 4.0.
Source: Primary data (2026).

Classical Assumption Testing

Before the regression model was interpreted, the four classical assumptions were tested and all were satisfied, as reported in Table 5. Residuals were normally distributed, tolerance values above 0.10 and variance inflation factors below 10 indicated no multicollinearity among the four predictors, the Glejser test produced no significant relationship between the absolute residuals and any predictor, and the Durbin-Watson statistic fell inside the acceptable range. The ordinary least squares estimates reported below are therefore unbiased and their standard errors interpretable.

Table 5
Results of Classical Assumption Testing (n = 210)

Assumption	Test	Result	Criterion	Decision
Residual normality	Kolmogorov-Smirnov	Z = 0.048; p = 0.200	p > 0.05	Normal
Multicollinearity	Tolerance / VIF (X_1)	0.712 / 1.404	VIF < 10	Not detected

Assumption	Test	Result	Criterion	Decision
	Tolerance / VIF (X_2)	0.684 / 1.462	VIF < 10	Not detected
	Tolerance / VIF (X_3)	0.759 / 1.318	VIF < 10	Not detected
	Tolerance / VIF (X_4)	0.803 / 1.245	VIF < 10	Not detected
Heteroscedasticity	Glejser test	p = 0.214 – 0.638	p > 0.05	Homoscedastic
Linearity	Deviation from linearity	p = 0.089 – 0.471	p > 0.05	Linear
Independence	Durbin-Watson	d = 1.936	1.5 < d < 2.5	No autocorrelation

Note: X_1 = education level; X_2 = age; X_3 = digital infrastructure access; X_4 = prior training frequency. Analysis conducted in IBM SPSS Statistics 26.
Source: Primary data analysis (2026)

Factors Influencing Digital Competency

Table 6 and Figure 5 present the results of multiple linear regression analysis. The overall model was statistically significant ($F(4,205) = 38.47$, $p < 0.001$, $R^2 = 0.428$), indicating that the predictor variables collectively explain 42.8% of the variance in digital competency. Education level ($\beta = 0.412$, $p < 0.001$) was the strongest predictor, followed by digital infrastructure access ($\beta = 0.376$, $p < 0.001$). Age demonstrated a significant negative effect ($\beta = -0.318$, $p < 0.05$), while prior training frequency showed a moderate positive effect ($\beta = 0.241$, $p < 0.05$).

Table 6
Multiple Linear Regression: Factors Influencing Digital Competency

Variable	B	Std. Error	Beta (β)	p-value
Constant	32.14	4.82	–	< 0.001
Education Level (X_1)	5.83	0.97	0.412**	< 0.001
Age (X_2)	-0.34	0.12	-0.318*	0.018
Digital Infrastructure Access (X_3)	8.41	1.54	0.376**	< 0.001
Prior Training Frequency (X_4)	3.12	1.09	0.241*	0.032
$R^2 = 0.428$; $F(4,205) = 38.47$; $p < 0.001$				

Note: ** p < 0.01, * p < 0.05. Dependent variable: Digital Competency Score (0–100).
Source: Primary data analysis (2026)

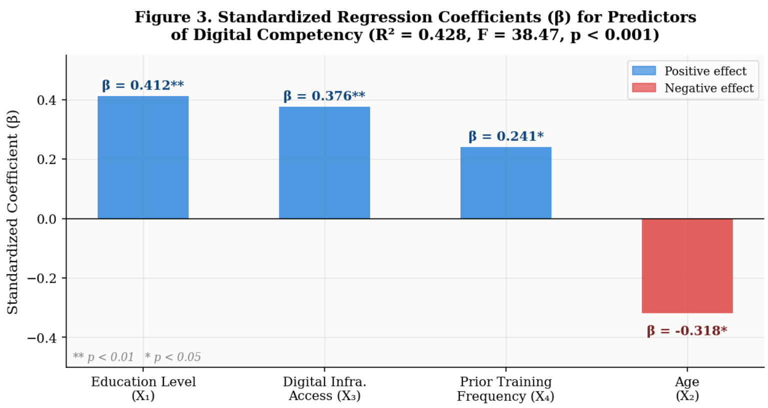

Figure 5. Standardized Regression Coefficients (β) for Predictors of Digital Competency. Model: $F(4,205) = 38.47$; $R^2 = 0.428$; $p < 0.001$. Positive β (blue) = enhances competency; Negative β (red) = reduces competency. ** p < 0.01, * p < 0.05.
Source: Primary data (2026).

Translated into program terms, the coefficients describe who needs what. Each additional level of schooling is associated with a rise of 5.83 points in competency, so the distance between an elementary and a senior high school graduate is roughly 11.7 points, close to half the measured gap; members with elementary schooling therefore need a foundational module that others can skip. The age coefficient of −0.34 means that a member aged 55 scores about 6.8 points below a member aged 35 with the same education and access, a difference small enough to be closed by training but large enough to justify slower pacing for older cohorts. The largest single effect belongs to infrastructure access, where owning a connected smartphone is worth 8.41 points, more than a full level of schooling; this is the one predictor training cannot move, which is why device provision or shared access has to be budgeted alongside instruction. Prior training frequency adds 3.12 points per additional training episode, confirming that repeated exposure rather than a single workshop is what accumulates competency.

Discussion

Overall Competency Gap and Training Priority

The overall digital competency gap of 23.6 points underscores the urgent need for systematic training interventions. This result is consistent with broader literature on digital skills gaps in agricultural communities (Chávez Santos et al., 2026; Tengblad et al., 2026). The IPA analysis provides strategic clarity: the concentration of digital agricultural applications, digital marketing, and precision farming technology in Quadrant I reflects critical alignment with Indonesia's agricultural digital transformation agenda (Ihou & Mansingh, 2026; Stewart et al., 2026).

These results can be read against two theoretical traditions. From a Human Resource Development perspective the pattern fits performance improvement logic, in which measured performance gaps rather than expressed preferences define the legitimate object of training, and it supports the human capital argument that prior education raises the return on subsequent training instead of substituting for it. From a technology adoption perspective, the significance of infrastructure access alongside competency corresponds to the facilitating conditions construct in the Unified Theory of Acceptance and Use of Technology, while the negative age coefficient maps onto the late majority and laggard categories in diffusion of innovations theory. Both traditions converge on the same practical conclusion: competency is a necessary but not a sufficient condition for adoption, and it has to be developed in parallel with the conditions that make use possible (Rijswijk et al., 2021; Waseem et al., 2026).

Not all published findings point the same way, and the divergence is informative. Barrett and Rose (2022) report that farmers with high self-assessed digital confidence still resisted adoption because they anticipated a loss of autonomy, which suggests that competency gains do not automatically translate into use where the technology is seen to shift control away from the farm. Studies of connectivity constrained settings reach the opposite emphasis to this study: Mehrabi et al. (2021) find infrastructure so limiting that competency variation becomes almost irrelevant, whereas in the present sample 38.1 percent of members already hold connected devices and competency therefore remains the active constraint (Al khatib & Alshaib, 2025). The reconciliation is one of sequence rather than contradiction. Below a connectivity threshold infrastructure dominates; above it competency becomes binding; and the three districts studied here sit just above that threshold.

The primacy of digital agricultural applications over the other four domains deserves explanation rather than assertion, and three factors account for it. First, the required standard for this domain is set by programs in which farmer groups are already formally enrolled, so the expectation is externally imposed and immediate rather than aspirational. Second, the domain has the shallowest existing base at 50.6 points, because unlike basic internet literacy it cannot be acquired incidentally through social media use; nothing in ordinary phone use teaches a farmer to log input applications or read an advisory dashboard. Third, it is the gateway domain, since precision farming and digital marketing both depend on the ability to operate an application interface, so a gap here propagates into the two domains ranked immediately below it. Agricultural data management shows the smallest gap for the mirror image reason, as record keeping has an established analogue tradition in farmer groups that transfers with relatively little instruction.

Influence of Education and Demographics

The strong positive effect of education level (β = 0.412) is aligned with findings from Alkan (2025) and Vogt et al. (2026), confirming that foundational academic preparation provides cognitive scaffolding for digital skill acquisition. The negative age effect (β = −0.318) corroborates studies by Nampijja et al. (2026), suggesting that older farmers face greater barriers to digital adoption. The significant positive effect of digital infrastructure access (β = 0.376) highlights a structural barrier that training programs alone cannot address, simultaneous investment in connectivity is essential (Ceschel et al., 2026; Pham et al., 2026).

Methodological Contributions

This study contributes methodologically by integrating gap analysis, IPA, and multiple regression. This triangulated quantitative approach provides a more nuanced understanding of training needs than single-method studies (Ahmadizadeh et al., 2026; Saffenreuther et al., 2026). The application of the Training Priority Index (TPI) provides a standardized, replicable metric for prioritizing training domains adaptable to other agricultural development contexts.

Theoretical Contribution

This study contributes to Training Needs Assessment theory in three ways. It extends the McGhee and Thayer (1961) three level model to a setting in which the organizational level is a voluntary association rather than a firm, showing that group institutional capacity operates as a moderating rather than a determining level (Qawqzeh et al., 2025). It introduces the Training Priority Index as a standardized ratio measure that makes gap magnitudes comparable across domains with different required standards, which addresses a long-standing weakness of raw gap scores. And it demonstrates that Human Resource Development constructs developed in formal employment settings retain explanatory power in informal agricultural organizations, provided that infrastructure access is modelled as a distinct predictor rather than folded into individual capability.

Implications for Agricultural HRD Policy

The findings carry significant implications for agricultural HRD policy. Existing extension programs, which predominantly focus on basic agricultural techniques, need substantial redesign to address advanced digital domains. Complementary policies addressing digital connectivity in rural areas are essential prerequisites for training program effectiveness (Hein-Pensel, 2026; Pham et al., 2026). Differentiated training strategies are needed: foundational digital literacy for older, less-educated farmers, and advanced precision agriculture training for younger members who can serve as digital champions within their groups (Tengblad et al., 2026). Responsibility for implementation is distributed across four actors. District governments hold the budget authority to fund both training and the connectivity investment that the results show to be inseparable from it, and they control the extension office through which delivery is scheduled. Agricultural extension workers form the delivery layer and would require prior upskilling of their own, since the domains with the widest gaps are also those least represented in current extension curricula. Farmer groups supply the organizational unit for scheduling, peer learning, and shared device custody, and their leaders are the natural custodians of the diagnostic instrument for periodic reassessment. Digital support institutions, including agricultural technology providers, telecommunications operators, and vocational training centers, supply content, connectivity, and certification, and their involvement is what converts a one-off training event into a maintained capability.

Limitations and Directions for Future Research

Three limitations bound these findings. The cross-sectional design establishes association rather than causation, self-assessed competency may diverge from demonstrated skill, and the three districts studied are among the better connected in Indonesia, so the gaps reported here are probably conservative relative to more remote regions. Future work should address these directly. A longitudinal design tracking the same members before and after a training intervention would establish whether closing the measured gap produces the adoption gains assumed here. A mixed methods extension combining the present instrument with observed task performance and with interviews on perceived autonomy would test whether competency gains translate into actual use. And a randomized training intervention comparing modules sequenced by the Training Priority Index against conventional uniform training would provide the strongest test of the practical claim this study makes.

CONCLUSION

This study systematically assessed the digital training needs of 210 farmer group members in West Java, Indonesia, using a quantitative TNA approach. The findings reveal a substantial overall digital competency gap of 23.6 points, with the most critical training priorities in digital agricultural applications, digital marketing, and precision farming technology. Education level, digital infrastructure access, and age were identified as significant predictors of digital competency. The IPA analysis identified three competency domains requiring immediate concentrated training investment. Beyond these measurements the study makes two contributions that extend past the sampled districts. For policy, it supplies a replicable diagnostic procedure through which district extension offices can derive their own training priorities instead of inheriting a national curriculum, and it establishes that training budgets allocated without a parallel connectivity commitment will underperform, since infrastructure access carried the largest single unstandardized effect in the model. For theory, it positions the Training Priority Index as a transferable instrument for comparing competency gaps across domains with different required standards, and it shows that Training Needs Assessment developed for formal organizations remains valid in voluntary agricultural associations once infrastructure is modelled separately from individual capability. Subsequent research should test whether training sequenced by this index outperforms uniform training under a longitudinal or experimental design.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to Politeknik Siber Cerdika Internasional and Universitas Swadaya Gunung Jati for providing academic support and a conducive environment for the completion of this research. Appreciation is also extended to the farmer groups and relevant stakeholders who contributed valuable information and insights regarding digital competencies and training needs for agricultural digital transformation in West Java. Their participation and support were essential to the completion of this study.

AUTHOR CONTRIBUTION STATEMENT

Ikhsan Nendi contributed to the conceptualization, research design, data collection, data analysis, interpretation of findings, and preparation of the original manuscript. Amelia contributed to methodology development, validation, critical review, and refinement of the manuscript. Both authors collaboratively contributed to the development of the research framework, discussion of the findings, manuscript revision, and final approval of the submitted version. Both authors take responsibility for the integrity, accuracy, and accountability of all aspects of the research.

REFERENCES

Abubakari, M. S., Zakaria, G. A. N., & Musa, J. (2026). Comparative assessment of digital competences among students in higher education using DigComp 2.1 framework. *Cogent Education*, *13*(1), 2620198.

Ahmadizadeh, M., Khodabakhshzadeh, H., Rostamian, M., & Hamid, A. (2026). The state of assessment training in EFL teachers' courses: aligning policies, standards, and language assessment course syllabi. *Language Testing in Asia*, *16*(1), 32. https://doi.org/10.1186/s40468-026-00448-2

Al khatib, A. M. G., & Alshaib, B. M. (2025). Data-Driven Farming: Harnessing Big Data for

Agriculture. In *Transforming Agriculture through Artificial Intelligence for Sustainable Food Systems* (pp. 55–72). Springer.
Alkan, A. (2025). Analysis of factors affecting academic success with machine learning: Data-driven inferences in education. *Turkish Journal of Engineering*, *10*(1), 48–62. https://doi.org/10.31127/tuje.1779491
Barrett, H., & Rose, D. C. (2022). Perceptions of the fourth agricultural revolution: What's in, what's out, and what consequences are anticipated? *Sociologia Ruralis*, *62*(2), 162–189. https://doi.org/10.1111/soru.12324
Borisoglebskaya, L. N., Snimshchikova, I. A., Firsova, O. A., Revyakina, M. O., Maryin, G. G., & Medvedeva, E. A. (2026). The innovative approaches to medical education in the countries of the BRICS: Project training as a mode of professional competences formation. *Problemy Sotsial'noi Gigieny, Zdravookhraneniia i Istorii Meditsiny, 34(1), 113–118.* https://doi.org/10.32687/0869-866X-2026-34-1-113-118
BPS. (2023). *Hasil Pencacahan Lengkap Sensus Pertanian 2023 – Tahap I*. Badan Pusat Statistik Republik Indonesia. https://www.bps.go.id/id/pressrelease/2023/12/04/2050/hasil-pencacahan-lengkap-sensus-pertanian-2023---tahap-i.html
Carretero, S., Vuorikari, R., & Punie, Y. (2017). *DigComp 2.1: The Digital Competence Framework for Citizens with eight proficiency levels and examples of use (EUR 28558 EN)*. Publications Office of the European Union. https://doi.org/10.2760/38842
Ceschel, F., Marchegiani, L., Bartoli, C., Gerardi, M. L., & Boccardelli, P. (2026). Head in the clouds, feet on the ground: Navigating paradoxes in the twin transitions. *Management Decision*, *64*(13), 361–383. https://doi.org/10.1108/MD-01-2025-0157
Chávez Santos, R., Reina Marín, Y., Cruz Caro, O., Campos Trigoso, J. A., Maicelo Guevara, J. L., Alva Tuesta, J. N., & Sánchez Bardales, E. (2026). Analysis of the digital competencies of regional micro and small enterprises (MSEs). *Journal of Innovation and Entrepreneurship*, *15*(1), 20. https://doi.org/10.1186/s13731-026-00647-4
Commission., E. (2013). *DIGCOMP: A Framework for Developing and Understanding Digital Competence in Europe*. Publications Office of the European Union. https://scholar.google.com/scholar?q=DIGCOMP%3A A Framework for Developing and Understanding Digital Competence in Europe
Hein-Pensel, F. (2026). Organizational identity meets digital transformation: Understanding the interplay between transformation and identity in Industry 5.0. *Journal of Organizational Change Management*, *39*(8), 1–21. https://doi.org/10.1108/JOCM-04-2025-0352
Ihou, A. F. Y., & Mansingh, P. J. (2026). Unveiling government support in shaping farmers' entrepreneurial mindset and intention. *Humanities and Social Sciences Communications*, *13*(1), 659. https://doi.org/10.1057/s41599-026-06739-6
Kirmikil, M. (2026). Agriculture 4.0 Research (2018–2025): Bibliometric Insights into Trends, Gaps, and Global Inequalities. *Journal of Biological and Environmental Sciences*, *58*.
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
McGhee, W., & Thayer, P. W. (1961). *Training in Business and Industry*. Wiley. https://scholar.google.com/scholar?q=Training in Business and Industry
Mehrabi, Z., McDowell, M. J., Ricciardi, V., Levers, C., Martinez, J. D., Mehrabi, N., Wittman, H., Ramankutty, N., & Jarvis, A. (2021). The global divide in data-driven farming. *Nature Sustainability*, *4*(2), 154–160. https://doi.org/10.1038/s41893-020-00631-0
Nampijja, Z., Nakakaawa, C. J., Zziwa, E., Kugonza, D. R., Walusimbi, S. S., Kiggundu, M., Nabanoga, G. N., & Bamutaze, Y. (2026). Understanding climate variability through meteorological trends and chicken farmers' perceptions in Soroti district Uganda. *Discover Environment*, *4*(1), 118. https://doi.org/10.1007/s44274-026-00599-2
Patalon, M. (2026). Situated isomorphism: Institutional logics and the interpretive dynamics of municipal digital transformation. *Journal of Organizational Change Management*, *39*(8), 39–55. https://doi.org/10.1108/JOCM-06-2025-0521
Pham, T. P., Nguyen, D. N., & Tran, T. B. (2026). Relationship between search volume for digital

transformation and stock returns: An empirical study in Vietnam. *RAUSP Management Journal*, *61*, 6–23. https://doi.org/10.1108/RAUSP-10-2023-0214

Qawqzeh, Y., Shraah, A. Al, Rizwan, A., Sánchez-Chero, M., More, L. A. V., & Shabaz, M. (2025). Exploring the effectiveness of virtual reality-based training for sustainable health and occupational safety in industry 4.0. *Scientific Reports*, *15*(1), 28930.

Rijswijk, K., Klerkx, L., Bacco, M., Bartolini, F., Bulten, E., Debruyne, L., Dessein, J., Scotti, I., & Brunori, G. (2021). Digital transformation of agriculture and rural areas: A socio-cyber-physical system framework to support responsibilisation. *Journal of Rural Studies*, *85*, 79–90. https://doi.org/10.1016/j.jrurstud.2021.05.003

Saffenreuther, A.-K., Greimel, E., Primbs, R., Iglhaut, L., Kaubisch, S., Schulte-Körne, G., & Feldmann, L. (2026). Evaluation of an online training course for educational professionals on depression and mental health in childhood and adolescence. *Child and Adolescent Psychiatry and Mental Health*, *20*(1), 8. https://doi.org/10.1186/s13034-025-01007-y

Shetty, P. K., Dindalkoppa, M., Rao, S. S., Pilli, G. S., & Sudhakar, S. (2026). Perception of case-based collaborative learning in pathology through panel discussion using concept mapping. *BMC Medical Education*, *26*(1), 51. https://doi.org/10.1186/s12909-025-08334-w

Stewart, I. T., Baez Morales, A., Maurer, E. P., Li, Q., Díaz, R. S., Guingona, B., & Torres Torres Landa, A. (2026). Challenges and opportunities in building community-driven adaptive capacity under climate change for smallholder farmers in the Global South. *International Journal of Climate Change Strategies and Management*, *18*(1), 20–41. https://doi.org/10.1108/IJCCSM-08-2025-0258

Tengblad, O., Olsson, A. K., & Eriksson, K. M. (2026). Listening to the pulse – An exploration of manufacturing management and learning in the era of Industry 5.0. *Journal of Organizational Change Management*, *39*(8), 125–142. https://doi.org/10.1108/JOCM-05-2025-0464

Vogt, M., Geissler, M. E., Gerdes, S., Bereuter, J.-P., Schuchardt, N., Geissler, R. B., Glauche, I., Roeder, I., Deußen, A., & Günther, L. (2026). Scientific education in German medical schools: Nationwide cross-sectional study reveals student needs and gaps. *BMC Medical Education*, *26*(1), 729. https://doi.org/10.1186/s12909-026-09311-7

Waseem, M., Batool, H., Rehman, T. U., Majeed, Y., Ahmad, F., Syed, H. H., & Nadeem, T. (2026). *Transforming Agriculture with Cyber-Physical Systems: An Insight into Future Smart Farming*.