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MORALITY BEFORE KNOWLEDGE

Human resource development through ESG-oriented agricultural training: Knowledge outcomes in IoT-assisted and conventional irrigation settings

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ABSTRACT

Background: The social pillar of environmental, social, and governance (ESG) emphasizes human resource development, yet evidence on ESG-oriented agricultural training in non-farming urban communities remains limited. This study assesses changes in knowledge following an ESG-oriented agricultural training program and examines whether IoT-assisted infrastructure is associated with differential knowledge gains. **Methods:** A quasi-experimental pre-test/post-test design without a control group was employed among 20 female community beneficiaries across two sites in Batam, Indonesia, Barelang (IoT-assisted drip irrigation) and Nongsa (conventional irrigation). A purpose-built 25-item binary (yes/no) self-assessment instrument was administered before and after training, covering four domains; land preparation, plant maintenance, IoT and smart farming, and digital marketing. Participant baseline characteristics were collected separately. **Findings:** Mean scores increased significantly from 10.70 (SD = 4.71) to 22.20 (SD = 2.33) out of 25 (W = 210.0, p-value < 0.001). Plant maintenance and digital marketing showed substantial gains increasing from 11.7% to 93.3% and from 35.0% to 94.0% suggesting that applied training was accessible across educational backgrounds. However, the IoT domain diverged sharply: Barelang gained +3.35 items of 5 reaching near-perfect comprehension, while Nongsa declined by −0.33 items, which may indicate a possible response-shift phenomenon whereby theoretical instruction without hands-on technology exposure heightened awareness of knowledge limitations rather than consolidating applied competency. The small sample (n = 20) limits generalisability. **Conclusion:** Participants reported significantly higher self-assessed knowledge after ESG agricultural training regardless of educational diversity, while IoT-related outcomes appeared to differ by infrastructure access. **Novelty/Originality of this article:** This study contributes to the ESG literature by examining whether IoT infrastructure access is associated with human resource.

KEYWORDS: chili cultivation non-farming communities; community training; ESG; IoT drip irrigation; knowledge gain.

1. Introduction

Community-based agricultural programmes are widely used to support inclusive development, yet their human resource aspects often receive less attention than their technical and economic goals (Prayitno et al., 2025). Across developing economies, the integration of environmental, social, and governance (ESG) principles into corporate

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strategy has transformed such programs from philanthropic gestures into structured interventions designed to generate measurable social value, training workforces, expanding livelihoods, and bridging structural inequalities that markets alone have failed to address (Long, 2025). ESG-aligned agricultural interventions have proliferated across sectors, carrying significant promise for rural and peri-urban communities (Leite de Almeida et al., 2025). Yet when these programs are deployed, attention tends to concentrate on crop yields, technology adoption rates, and infrastructure investment, while the learning trajectories of beneficiaries, the dynamics of educational heterogeneity within training groups, and the organizational challenges of building agricultural knowledge among non-farming communities remain largely underexamined how much beneficiaries learn, and whether this differs by educational background or access to technology, remains largely underexamined among non-farming communities (Almeida et al., 2025). This gap matters because the durability of any community program depends largely not on the technology it deploys, but on the human capital it builds. Among the three ESG pillars, the social dimension has received the least rigorous scholarly attention (Barbosa et al., 2023). This study addresses this gap by evaluating self-reported knowledge gains from an ESG-oriented agricultural training programme. Specifically, this research examines the role of human capital development in ESG-driven agricultural programs, specifically it examines knowledge gains among non-farming women trained in chili cultivation, comparing Barelang (IoT drip irrigation) and Nongsa (conventional irrigation).

Batam exemplifies the challenges of developing agricultural human capital in a region with limited agricultural tradition. An industrial island whose workforce has been defined by maritime and manufacturing economies (Royle, 1997). Batam, which was designated as an industrial, trade, tourism, and maritime center owing to its strategic proximity to Singapore, has developed a predominantly manufacturing-based economy with negligible agricultural sector; consequently, the island remains heavily reliant on imports for most of its consumption needs, despite possessing a maritime area of 715 square kilometers within its total area of 1,575 square kilometers (Wibisono, 2018). Gustin & Roziqin (2019) further illustrate this marginality, their remote sensing analysis of land use change on Batam Island between 2010 and 2016 showed that non-agricultural land expanded with industrial growth, while agricultural land remained marginal despite a rise in agricultural companies non-agricultural land expansion correlates with industrial growth, whereas agricultural land use, despite a rise in agriculture companies, remains marginal in the island's industrial development trajectory. These findings indicate that the island presents substantial structural constraints for agricultural development. Nevertheless, review article from Arista & Susanto (2026) suggests that community-based agri-social interventions can enhance agricultural participation and capacity among non-farming urban communities. When an ESG program (Miracle seed of Wonder Ladies and Women Farmers of Indonesian Farmers' Harmony Association/*Himpunan Kerukunan Tani Indonesia* (HKTI)) introduced chili cultivation to non-farming communities across two of its districts, it confronted not only the agronomic complexity of the crop but a deeper set of human resource challenges: how to build agricultural knowledge among participants with no prior farming experience, how to manage educational heterogeneity within the same training ecosystem, and how to leverage differential access to Internet of Things (IoT) drip irrigation technology across implementation sites. Such conditions underscore the critical role of human capital development in building the adaptive capacity required for sustainable, particularly when human capital must be developed from diverse educational foundations (Prayitno et al., 2025). Chili was selected due to its promising local market demand, potential to strengthen regional food security, and suitability for agricultural development as a strategic commodity in Batam City (Arista & Susanto, 2026)

Three research questions guide the inquiry, (1) how do beneficiaries with varying background respond to structured agricultural training and daily operational information in an esg-sponsored chili cultivation program?; (2) to what extent does the presence or absence of iot drip irrigation technology moderate participant engagement and perceived program outcomes across the two sites?; (3) what organizational and human resource

strategies most effectively support knowledge transfer among non-farming communities transitioning to structured agricultural activity? These questions sit at the intersection of several active streams of scholarship. On the side of technology and agricultural training, Maq (2024) documented an IoT-assisted drip irrigation program, finding that awareness-building and skills transfer must precede technology deployment if smallholder communities are to benefit fully from precision agriculture tools. A study on Indonesian young farmers shows that while educational attainment correlates positively with technology readiness, sustained and socially embedded training programs can bridge significant gaps even among participants with only basic schooling (Sumardjo et al., 2026). In Malaysia a digital literacy initiative for farmers showed that localized, visual, and language-sensitive materials are critical for rural communities with low digital literacy who encounter agricultural technology for the first time (Naseri & Idris, 2025).

Regarding the technology dimension, Kajanja et al. (2025) reported that IoT-enabled drip irrigation systems can improve crop performance, while highlighting key adoption barriers, including high initial investment costs, limited digital literacy, and inadequate institutional support. The study emphasized that these constraints should be addressed through appropriate policies and training interventions prior to technology deployment. Similarly, Manzoor et al. (2025) noted that equitable access to digital agricultural technologies remains a significant challenge for smallholders in developing regions and cannot be resolved solely through technological innovation.

This study draws on two complementary strands of theory. First, from human capital and human resource development theory, structured training is treated as an investment that converts latent capacity (participants' existing educational and experiential diversity) into applied competency, consistent with the ESG social pillar's emphasis on workforce and community capability-building. Second, from experiential theory, knowledge consolidation is expected to depend not only on instructional content but on the availability of a concrete, hands-on context in which that content can be applied; this predicts that IoT infrastructure access should moderate training outcomes not because the technology itself teaches, but because it supplies the situated practice environment that theoretical instruction alone cannot. Together, these two lenses motivate the study's central comparison between Barelang (training plus situated IoT practice) and Nongsa (training alone) as an exploratory comparison of whether access to infrastructure is associated with differences in self-reported knowledge gains.

A central debate in this literature concerns whether technology deployment or human capacity building should be the primary investment in community agricultural programs. Precision agriculture advocates hold that IoT tools generate productivity gains sufficiently large to justify prioritizing infrastructure investment (Herdiansyah et al., 2023). Agricultural extension theorists counter that technology without adequate human resource preparation produces adoption failures, particularly where participants lack prior agricultural experience and face high cognitive entry barriers (Loor & Roka, 2025; Naseri & Idris, 2025). Few studies have examined how educational heterogeneity within a single ESG program interacts with differential technology access to compound these effects, particularly among participants whose community identity, as in Batam's fishing communities and industrial sectors, may itself present cultural barriers to transitioning into structured farming roles.

This research is closest in design to Lamasigi et al. (2024), who evaluated an IoT-assisted chili cultivation programme in Indonesia through a university-community partnership model. Building on this work, the present study extends the existing approach in three significant ways, through a comparative site design contrasting IoT-enabled and conventional irrigation; through an examination of how knowledge gains vary across participants' backgrounds; and through the positioning of the intervention within a formal ESG framework. This integrated perspective is consistent with Bertacchini et al. (2025), who emphasized the importance of combining technical deployment with human capital development in advancing the social sustainability of agricultural interventions. This study is important for several reasons, primarily as it offers actionable insights for integrating

socio-technical interventions in non-agrarian coastal regions where urban farming is being introduced as an alternative livelihood. Furthermore, this paper presents a detailed case study of the Batam initiative, illustrating the practical challenges of training community members from fishing and informal-sector backgrounds in agricultural production. By comparing self-reported knowledge gains across participants with different educational backgrounds, this research offers initial insight into how training can serve diverse learners (Yuniarsih et al., 2024). By systematically evaluating these dynamics, the study provides initial empirical evidence for designing inclusive ESG-aligned agricultural programs that prioritize human-centric capacity building (Sher et al., 2025; Song et al., 2026). It also offers practical lessons for ESG programme designers on pairing training with access to technology, which may be relevant to similar initiatives in communities with limited farming experience.

2. Methods

2.1 Research design

This study employs a quasi-experimental pre-test/post-test design without a control group, a methodology designed to assess short-term self-reported knowledge gains following structured agricultural training interventions.from structured training interventions. The design is appropriate for this context because randomization was neither ethically feasible nor practically possible given the community-embedded nature of the ESG program and the fixed composition of beneficiary groups at each site. The pre-test/post-test approach without a control group allows baseline performance to serve as an internal reference point against which post-intervention change is described (Campbell & Stanley, 1963).

The program was implemented across two distinct geographical locations within Batam, Barelang and Nongsa, which constitute the two comparative units of analysis in this study. While both sites followed an identical training curriculum and program structure, Barelang was equipped with IoT-based drip irrigation infrastructure, whereas Nongsa operated under conventional, manually managed irrigation. This site-level variation was not experimentally assigned but arose from the program's phased infrastructure development, creating a natural comparison that allows an exploratory look at whether technology access is associated with differences in training outcomes between the two beneficiary groups.

2.2 Program structure and implementation context

The ESG program was structured in two sequential phases. The first phase involved community mobilization and participant recruitment, during which potential beneficiaries were gathered, briefed on the program's objectives, and formally enrolled. This stage was critical given the non-agricultural occupational background of most participants in Batam, a city whose workforce has historically been oriented toward maritime industries, particularly fishing, and manufacturing. Introducing chili cultivation as a structured economic activity to this community therefore required significant groundwork in terms of building conceptual familiarity with agricultural practice before technical training could meaningfully begin.

The second phase consisted of an ongoing, structured training and daily task management cycle. Participants received regular group-based training sessions covering five thematic domains: land preparation, plant maintenance, IoT and smart farming technology, digital marketing of agricultural produce,. Between formal training sessions, daily operational information was disseminated within the group to guide (the field manager communicated operational instructions through a WhatsApp group and reinforced them through in-person field demonstrations at the Barelang and Nongsa sites). task execution on the cultivation plots. This dual-mode delivery, combining episodic formal

training with continuous day-to-day guidance, reflects a peer-embedded extension model (Lox et al., 2025) designed to support participants whose prior knowledge baseline ranged from minimal to moderate, depending on their educational attainment and incidental exposure to agricultural activity.

2.3 Participants

A total of 20 women participated in the ESG program across the two sites: eight at Barelang (IoT-assisted) and twelve at Nongsa (conventional). The programme deliberately targeted women in the local agricultural workforce to address their limited access to digital technologies and technology-assisted agricultural practices, particularly in the use of modern agricultural equipment and IoT-based irrigation systems. Participants were recruited from the local community on a voluntary basis (sampling of programme beneficiaries at the two sites (programme participants were purposively selected based on their prior gardening experience and demonstrated willingness to engage in agricultural activities); site allocation followed the pre-existing programme rollout rather than randomisation) Participants also varied in age and prior occupational experience, with a predominant livelihood background in fishing and informal sector employment rather than agriculture. None of the participants had formal agricultural training prior to enrolment, and prior chili cultivation experience, assessed through the pre-test instrument, varied considerably across the group. The participants represented a range of backgrounds and capabilities across the two programme sites.

2.4 Data collection instrument

Data were collected using a purpose-built questionnaire instrument developed specifically for this program. The instrument was designed in Bahasa Indonesia to ensure linguistic accessibility across all educational levels represented in the participant group. The pre-test and post-test questionnaires are provided in *Bahasa Indonesia* with English translation as supplementary material.

The pre-test consisted of 25 items structured across five sections: (A) land preparation practices, (B) chili plant maintenance, (C) IoT and smart farming technology, (D) digital marketing of agricultural produce, and (E) participant baseline characteristics (prior cultivation experience, land access, and program commitment), collected separately and not treated as a knowledge domain; the pre-test therefore has no programme-understanding section. All items were presented in a binary Yes/No response format (indicated by a checkmark), reflecting participants' self-assessed practices and prior knowledge before the training program commenced. The pre-test was thus designed as a behavioral and experiential baseline, capturing what participants had previously done or knew, rather than a test of abstract competency.

The post-test consisted of 25 items structured across five parallel sections: (A) general program understanding, (B) land preparation knowledge, (C) chili plant maintenance understanding, (D) IoT and smart farming technology comprehension, and (E) digital marketing readiness. Importantly, the post-test shifted from behavioral self-reporting (what participants had done) to comprehension and readiness assessment (what participants now understood and were prepared to do), reflecting the pedagogical transition from baseline experience to trained knowledge. The pre-test and post-test assessments were used to examine changes in participants' self-reported knowledge following the training intervention. However, the use of different items across the two assessments represents a methodological limitation.

2.5 Data analysis

Quantitative data from the pre-test and post-test instruments were tabulated and analysed at both the individual and group levels. Given the binary (Yes/No) nature of all

response items, scores were computed as the total number of affirmative responses per section and per instrument, producing domain-specific knowledge profiles for each participant at both time points. Aggregate pre- and post-test scores across the five thematic domains were then compared to assess learning gains at the group level. Domain-level changes were descriptive only (no statistical test). Domain percentages were calculated as the mean number of affirmative items in a domain divided by the number of items in that domain, multiplied by 100.

To assess whether observed differences between pre- and post-test scores were statistically meaningful, a Wilcoxon Signed-Rank Test was applied as the appropriate non-parametric alternative to the paired-samples t-test, given the small sample size (n = 20) and the ordinal nature of summed binary scores. Site-level comparisons between Barelang (n = 8) and Nongsa (n = 12) were conducted descriptively, with effect sizes reported where applicable to enable substantive interpretation of observed differences in the presence of limited statistical power.

2.6 Methodological limitations

First, the research instrument was purpose-built for this programme and has not undergone formal psychometric validation (no Cronbach's alpha or other internal-consistency reliability estimate is reported, and no pilot validity testing was conducted); all knowledge measures are therefore self-assessed rather than independently verified. Second, the pre-test and post-test contain different items. The pre-test asked about prior practice and experience, while the post-test asked about understanding and readiness, so the observed change cannot be read as a direct measure of learning. Third, the study uses a quasi-experimental design without a control group or random assignment to site, site allocation followed the pre-existing programme rollout, so the Barelang–Nongsa comparison should be read as an observational association between IoT access and outcomes rather than a randomised causal test, and unmeasured confounders (facilitator effects, group size, or community-specific factors) cannot be ruled out. Fourth, the sample (N = 20, unevenly split across two sites) is small, which limits statistical power and the generalisability of the findings beyond this specific programme and context. These limitations do not negate the study's descriptive findings but should be kept in mind when interpreting the strength and generalisability of the reported effects.

3. Results and Discussion

Human resource development serves as a fundamental catalyst for organizational modernization, transforming individual competencies into institutional assets that drive economic growth (Huda, 2020). By fostering a culture of continual learning and adaptability, such development programs enable organizations to bridge the gap between existing workforce capabilities and the evolving demands of technological integration (Mustafa & Lleshi, 2024). Specifically, within agricultural sectors, the integration of ESG principles necessitates that human resource development goes beyond basic technical training to encompass the cultivation of ethical responsibility and long-term environmental stewardship

3.1 Overall pre-training knowledge gains

A total of 20 participants completed both the pre-test and post-test instruments across the two programme sitesFurthermore, the heterogeneous educational attainment among participants necessitates approach that balances standardized agricultural instruction with individualized mentoring. The implementation of IoT-assisted drip irrigation in Barelang provides a unique testbed for analyzing how technological complexity influences skill acquisition among non-specialist farmers. The implementation of these high-tech systems necessitates an iterative training framework, as the pedagogical requirements for managing

automated water monitoring differ substantially from traditional manual techniques (Hayatuddin et al., 2025).

Baseline scores across all 20 participants in Table 1, yielding a mean pre-test score of 10.70 (SD = 4.71). This moderate spread indicates substantial heterogeneity in prior knowledge and experience within the cohort, an expected finding given the diversity in educational background and the varying degrees of incidental exposure to agricultural activity among participants. This distribution confirms that the programme confronted a genuinely heterogeneous human resource baseline and that standardised training was delivered across a wide spectrum of prior competency. Consequently, the integration of IoT-assisted irrigation in Barelang introduces an additional layer of complexity, requiring participants whose prior livelihoods had been oriented toward fishing, informal trade, and household management, rather than agriculture, to translate abstract technological interface data into practical agronomic decisions, even as they simultaneously absorb an entirely new farming domain for which they possess no prior experiential foundation. In this context, the adoption of IoT technology acts as both a barrier and a facilitator, as the shift toward data-driven decision-making requires participants to move beyond traditional manual farming practices (Herdiana et al., 2025).

Table 1. Individual pre-test and post-test scores by site

Group	N	Pre-test Mean ± SD	Post-test Mean ± SD	Mean Gain
Overall	20	10.70 ± 4.71	22.20 ± 2.33	11.5
Barelang	8	11.38 ± 6.55	24.25 ± 1.49	12.88
Nongsa	12	10.25 ± 3.25	20.83 ± 1.70	10.58

3.2 Overall post-training knowledge gains

Following completion of the full training programme (Table 1), the mean post-test score across all 20 participants increased to 22.20 (SD = 2.33), representing a mean gain of 11.5 points. A Wilcoxon Signed-Rank Test (Table 2) confirmed that this improvement was statistically significant (W = 210.0, p-value < 0.001), indicating a statistically significant improvement in participants' scores following the training programme. The effect was consistent across the participant pool, with every individual recording a higher post-test score than their pre-test baseline, and although at the domain level the Nongsa group recorded a modest mean decline in the IoT/Smart Farming domain specifically.

Table 2. Wilcoxon signed-rank test results

Group	W	p-value	Effect Size (r)	Interpretation
Overall	210	< 0.001	0.91	Large
Barelang	36	0.008	0.953	Large
Nongsa	78	< 0.001	0.934	Large

Note: Pre-test maximum = 25 items; Post-test maximum = 25 items. Wilcoxon signed-rank tests were conducted using a one-sided alternative hypothesis (POST > PRE)

Beyond its statistical significance, the consistency of these learning gains across all participants has important implications for ESG programme design. The universality of gain across all participants, regardless of initial score, educational background, or site location, is a finding of considerable significance for ESG programme design (Figure 1). It suggests that the combination of structured group-based training and continuous daily task guidance created sufficient scaffolding for participants at all knowledge levels to achieve meaningful comprehension gains within the programme period. This aligns with the findings of Raji et al. (2024), who demonstrated that sustained, community-embedded extension delivery can bridge significant knowledge gaps even among participants with limited formal education, provided training is both practically grounded and socially supported. In light of these results, the higher post-test scores in Barelang may be related to access to IoT infrastructure, although other differences between the sites cannot be ruled out. While this technological integration necessitates higher initial training efforts, it appears to foster a

deeper, more systematic engagement with agricultural variables that manual methods often lack.

The magnitude of these gains warrants careful reading. Expressed relative to the 25-item maximum, the cohort moved from a mean of approximately 42.8% (10.70/25) to approximately 89% (22.20/25). Notably, the Wilcoxon W statistic reached its theoretical maximum at every level of analysis, which occurs only when all paired differences are positive. The large effect sizes therefore reflect the consistent direction of change across participants rather than the size of the change itself, because the signed-rank procedure is sensitive to the rank order of differences and not to their absolute magnitude. Accordingly, these estimates should be read as evidence of uniform improvement and not as precise indicators of the training's impact. This caution is reinforced by the proximity of post-test scores to the instrument ceiling, which compresses variance and may conceal differences among higher-performing participants. The findings are directionally consistent with Piñeiro et al. (2020), who reported that capacity-building initiatives generate more sustainable agricultural outcomes than incentive-based mechanisms alone. However, because the present study captured only short-term self-reported knowledge, the durability of these gains remains an open empirical question.

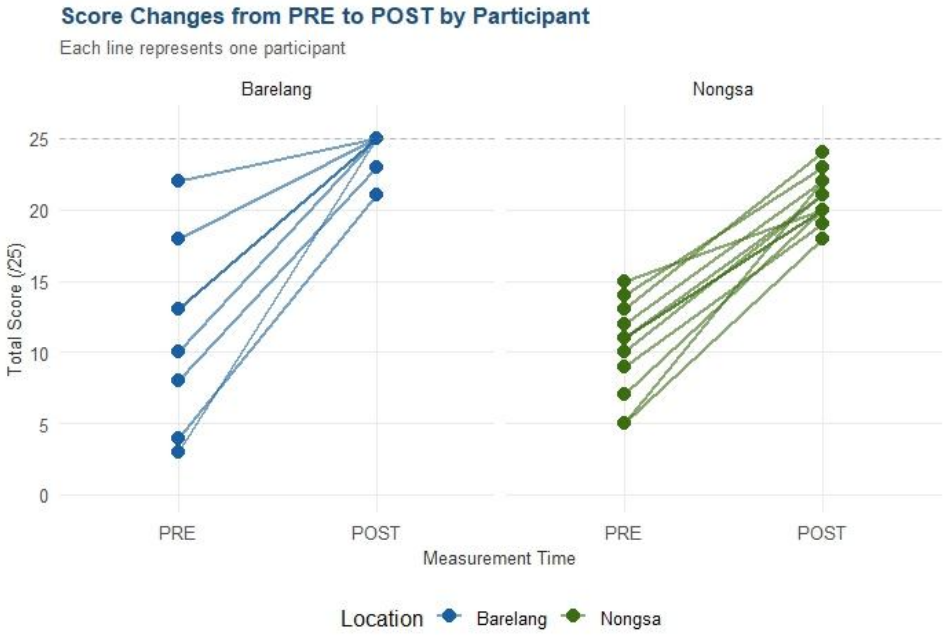


Fig. 1. Score changes from PRE to POST

3.3 Site-level comparison: Barelang (IoT-assisted) vs. Nongsa (conventional)

The comparison between pre-test and post-test results demonstrated substantial improvements across all learning domains, suggesting improvement after the training for enhancing participants' knowledge and competencies. Understanding of the program increased from 54.2% to 96.7%, while knowledge of land preparation improved from 44.2% to 91.7% (Table 3). The most pronounced improvement was observed in plant maintenance, which rose markedly from 11.7% to 93.3%, reflecting a significant enhancement in participants' technical understanding. Similarly, knowledge of digital marketing increased from 35.0% to 94.0%, suggesting that participants gained considerable capacity in marketing-related skills. Although the IoT/Smart Farming domain also showed improvement, increasing from 50.0% to 72.0%, its post-test score remained lower than those of the other domains, indicating that more intensive training or practical exposure may be required to strengthen participants' understanding of digital agriculture technologies. Overall, the results suggest that the program successfully improved participants' knowledge across both agricultural and business-related aspects.

Table 3. Domain-level mean scores (pre-test vs. post-test)

Domain	Pre (%)	Post (%)
Program Understanding	54.2	96.7
Land Preparation	44.2	91.7
Plant Maintenance	11.7	93.3
IoT/Smart Farming	50	72
Digital Marketing	35	94

These domain-level results reveal several important patterns (Figure 2). First, plant maintenance recorded the most dramatic gains at both sites, rising from near-zero baseline. This indicates that prior to the programme, almost no participant had practical experience in structured chili plant care, an entirely expected finding given the community's non-agricultural background, but that training delivery in this domain was highly effective and uniformly absorbed across both sites. The clarity and practicality of the training curriculum in this area appears to have transcended educational heterogeneity, confirming that applied, hands-on content is accessible to participants regardless of prior schooling level. Conversely, the divergent performance in the IoT domain highlights how infrastructure-embedded learning can either accelerate or constrain skill acquisition depending on the tools available (Nofiyanto et al., 2025). This suggests that the tangible feedback provided by sensor-driven irrigation may act as a scaffold for complex agricultural knowledge, possibly narrowing the competency gap for participants who otherwise lack formal scientific training. Furthermore, the data suggest that digital literacy among participants is not a static barrier but a malleable attribute that improves alongside technical exposure, as direct interaction with IoT interfaces provides a granular, immediate feedback loop that traditional agricultural pedagogy lacks

Second, Land Preparation showed stronger absolute gains at Nongsa than at Barelang, largely because Nongsa participants began with notably lower baseline scores in this domain. Nonetheless, both groups approached ceiling performance at post-test, indicating that training effectively closed the initial gap. Ultimately, the success observed in both locations demonstrates that structured, experiential learning is a robust mechanism for professional capacity building among non-specialist populations (Rohaeti & Nurhayati, 2023).

Third, and most critically, the IoT domain exhibited the sharpest site-level divergence. Barelang participants recorded comprehensive comprehension of IoT sensor functions, data-driven irrigation decision-making, and digital agricultural tools. Nongsa participants, by contrast, recorded a slight decline. This negative shift does not indicate learning regression; rather, it may reflect the absence of physical IoT equipment at the Nongsa site, which precluded experiential engagement with the technology. Without hands-on exposure to soil sensors, automated irrigation dashboards, and real-time data interfaces, Nongsa participants may have been less able to translate abstract training content into concrete comprehension gains. This finding is consistent with reports that digital literacy barriers and inadequate infrastructure are important obstacles to IoT adoption among smallholder communities (Kajanja et al., 2025). By bridging the gap between theoretical instruction and practical deployment, such programs foster sustainable agricultural resilience while simultaneously elevating the digital competencies of diverse, non-specialist workforces.

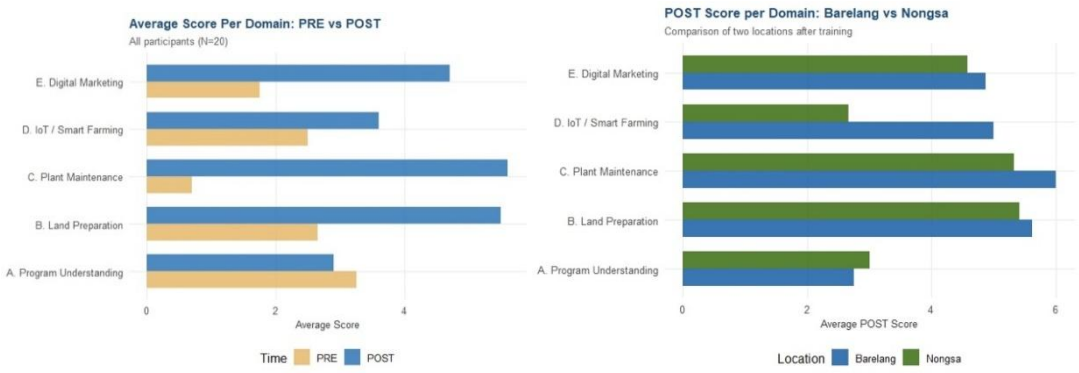
Table 4. Pre-test and post-test scores for the IoT/smart farming domain by site

Site	n	Mean		Mean Change	Maximum Score
		Pre-test	Post-test		
Barelang (IoT drip irrigation)	8	1.75	5	3.25	5
Nongsa (conventional irrigation)	12	3	2.67	−0.33	5

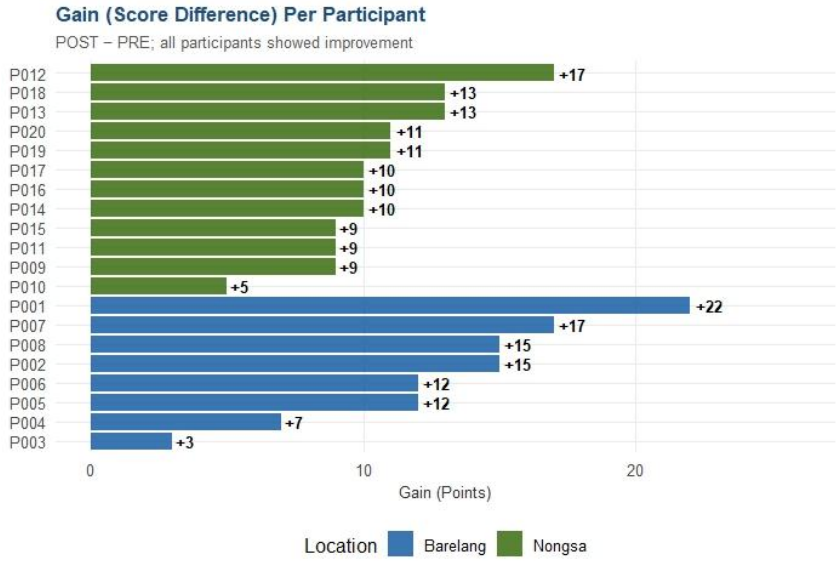
Note: Scores represent the number of affirmative items in the IoT/Smart Farming domain, with a maximum of 5 items. Mean change was calculated as post-test minus pre-test. Positive values indicate an increase in scores, whereas negative values indicate a decrease.

In the IoT/Smart Farming domain, Barelang participants (n = 8) showed an increase in mean scores from 1.75 at pre-test to 5.00 at post-test, representing a gain of 3.25 points on a five-point scale. In contrast, Nongsa participants (n = 12) showed a decrease from 3.00 to 2.67, corresponding to a mean change of −0.33 points. These contrasting patterns indicate that post-test performance differed between the two sites, with Barelang reaching the maximum domain score while Nongsa showed a modest decline relative to its pre-test score (Table 4).

A further pattern in Table 1 concerns the dispersion of scores rather than their central tendency. The pooled standard deviation fell from 4.71 at pre-test to 2.33 at post-test, and the contraction was sharper at Barelang (from 6.55 to 1.49) than at Nongsa (from 3.25 to 1.70). These changes indicate that post-test scores were less dispersed than baseline scores at both sites, although the descriptive statistics do not establish whether participants with lower baseline scores gained more (Figure 2c). From a human capital perspective, reduced score dispersion may indicate more consistent post-training performance across participants, although it does not by itself demonstrate that the programme reduced educational disparities. Two qualifications nevertheless apply. First, convergence toward a ceiling is partly a measurement artefact, because a bounded 25-item instrument cannot register further gains among high performers. Second, with only eight participants at Barelang, a small number of extreme scores can shift the site mean substantially, and the comparison with Nongsa should be interpreted accordingly.



(a) (b)



(c)

Fig. 2. Score from PRE to POST (a) average score per domain; (b) POST score per domain; (c) Gain per participant)

3.4 The role of iot infrastructure in human resource development outcomes

Baseline scores in the IoT domain were higher at Nongsa (mean = 3.00 out of 5) than at Barelang (mean = 1.75) (Table 4), giving Barelang greater scope for improvement and making the two sites' changes difficult to compare without accounting for their initial differences. Second, site-specific factors, including facilitation, group dynamics, and the intensity of field supervision, may also have contributed to the observed patterns, although these factors were not independently assessed. Third, the change in item framing discussed above may have influenced responses at both sites, potentially to different extents. These considerations do not rule out a situated-learning interpretation, but they limit the strength of the conclusions that can be drawn from the present comparison. Future research could administer equivalent items at both time points, introduce IoT infrastructure in a staggered or otherwise controlled design, and complement knowledge assessments with objective performance tasks to distinguish the contributions of technology access and other contextual factors. Accordingly, the present findings are best interpreted as a site-specific association between IoT-enabled drip irrigation and more favourable changes in IoT-domain scores, rather than as evidence of a causal effect. This interpretation is consistent with the broader argument attributed to Manzoor et al. (2025) that equitable access to digital agricultural technologies requires attention beyond technological innovation alone. In this context, equipment and training may operate as complementary inputs, although their interaction remains to be tested empirically.

The Nongsa IoT domain result demands deeper interpretive engagement, as it constitutes the study's most theoretically significant finding. The pre-test data reveal that Nongsa participants actually reported higher baseline IoT awareness than Barelang participants. The absence of a control group or randomization, reliance on self-assessed rather than observed competency, and a pre-/post-test instrument that shifted from behavioural self-report to comprehension assessment which mean the IoT-access findings are best characterised as a suggestive observational pattern rather than a firmly established causal mechanism. Despite this, their post-test performance in the IoT domain in Nongsa was lower than their own pre-test score, an outcome that can be explained by the shift in instrument framing; the post-test moved from behavioural self-reporting "I have used a soil sensor" to comprehension assessment "I understand the function of a soil sensor", a distinction that may have prompted more critical self-evaluation among participants who, having received theoretical training but no practical exposure, recognized the limits of their understanding. One possible explanation is a response-shift effect (Okumah et al., 2021), although this design cannot confirm it. The same shift in item framing (I have used to I understand) also applies to Barelang participants, so their gain may likewise be affected

This phenomenon carries important implications for ESG programme designers. The Barelang experience demonstrates that when IoT infrastructure is physically present and integrated into daily cultivation tasks, with participants interacting with drip irrigation sensors, monitoring soil moisture data, and making watering decisions based on digital readouts, comprehension gains in the technology domain are not only achievable but can reach ceiling levels even among participants with limited prior digital literacy. The physical presence of the technology, embedded within a routine of daily task guidance and group learning, created a situated learning environment (Lox et al., 2025) in which abstract knowledge was immediately contextualised and reinforced. Nongsa participants, receiving the same theoretical content without this experiential anchor, were unable to achieve equivalent consolidation. The findings suggest that access to IoT infrastructure may contribute to improved learning outcomes.

3.5 *Digital marketing outcomes and cross-site convergence*

Digital Marketing represents the one domain in which Nongsa participants approached Barelang-level post-test performance. This convergence is notable because digital marketing encompassing WhatsApp-based produce promotion, product photography,

online price monitoring, and digital sales strategy does not depend on physical agricultural infrastructure. Participants at both sites were already familiar with smartphones and messaging platforms in their daily lives, providing a technology foundation that allowed training content to build on existing capabilities rather than introducing entirely unfamiliar tools. This finding echoes the AGRIKIT study, which found that digital marketing training yields more equitable outcomes across educational levels when the technology involved (mobile phones, social media platforms) is already embedded in participants' social routines, as opposed to novel precision agriculture hardware (Naseri & Idris, 2025). Moreover, the ease of adoption observed in marketing modules underscores the necessity of matching pedagogical strategies with the existing digital literacy and social trust frameworks of rural communities.

As all participants at both sites were introduced to digital marketing concepts and practices, this shared exposure highlights a potential pathway for strengthening market engagement among women farmers, while IoT infrastructure roll-out may face logistical and financial constraints, digital marketing capacity can be meaningfully developed at low cost across both sites and constitutes an immediately actionable livelihood skill. Empowering these farmers with low-cost digital tools facilitates a more direct connection between production and market demand, thereby reducing the reliance on intermediaries and increasing overall income.

The contrast between the IoT and digital marketing domains also clarifies how technology-oriented content might be sequenced for novice learners. Digital marketing drew on tools that participants already used in daily life, namely smartphones and messaging applications, and post-test performance at Nongsa approached that of Barelang without any specialised hardware. IoT content, by contrast, required participants to interpret unfamiliar sensor data and convert it into agronomic decisions, a task that appears to depend on repeated practice with the equipment itself. This distinction supports Maq's (2024) position that awareness-building and skills transfer should precede technology deployment, while adding a qualification suggested by the present data: for technologies with no familiar analogue in participants' routines, instruction alone may be insufficient and should be coupled with access to the equipment. A sequenced model is therefore plausible, in which low-barrier digital skills such as marketing are introduced first to build confidence and early livelihood returns, followed by IoT instruction delivered alongside hands-on infrastructure. Such an approach also speaks to the adoption barriers identified by Kajanja et al. (2025), including limited digital literacy and inadequate institutional support, since early success in low-cost domains may help build the readiness on which later infrastructure investment depends.

3.6 *Implications for esg programme design in non-agricultural communities*

Taken together, the results of this study yield three overarching implications for the design and evaluation of ESG social programmes in Indonesia and comparable development contexts. First, pre-test/post-test evaluation instruments constitute valuable programme management tools not merely for academic reporting but for adaptive programme deliverySecond, the Barelang-Nongsa comparison suggests that providing IoT infrastructure alongside training may support learning in the technology domain, the human resource outcomes of technology-adjacent ESG programmes are substantively stronger when participants can learn by doing rather than learn by hearing. Third, the high post-test performance across all five domains, even in the absence of IoT equipment at Nongsa, suggests that community-based agricultural training is feasible and associated with higher self-reported knowledge in non-farming urban communities, provided it is delivered through sustained, group-based, and practically oriented pedagogical approaches. These findings demonstrate that human capital development in ESG initiatives is most effective when it transcends mere knowledge acquisition, integrating entrepreneurial competencies that enable participants to convert newly acquired agricultural skills into tangible economic value (Yao et al., 2023).

These findings contribute to the growing body of evidence that the social pillar of ESG is not adequately measured by participation rates or training hours alone. The quality of human resource development operationalised here through domain-specific knowledge gains, site-level differential analysis, and individual learning trajectories must become a standard metric in ESG programme evaluation if the social commitments embedded in sustainability frameworks are to be rendered accountable and credible. Ultimately, integrating such metrics into broader policy frameworks allows for the customization of community engagement strategies that address the specific socioeconomic needs of urban environments (Harsono, 2024). In this study, pre-test and post-test scores revealed variation in learning outcomes across domains and between sites, providing a more differentiated account of programme performance than participation metrics alone. Such information can inform the identification of domains requiring further support and help guide adjustments to programme implementation. More broadly, the findings illustrate the distinction between reporting programme outputs, such as attendance and training hours, and assessing proximal outcomes reflected in participants' test performance. However, these outcomes should not be equated with sustained changes in agricultural practice or broader social impact, which require further evaluation.

4. Conclusions

This study found that participants in an ESG-sponsored agricultural training programmes reported higher self-assessed knowledge after training, across a wide range of eduactional backgrounds. The structured, applied, and group-embedded training model deployed across both Barelang and Nongsa demonstrated that educational heterogeneity, ranging from primary school to university level, does not constitute an insurmountable barrier to human resource development in agri-social programmes, as domain-specific comprehension gains were broadly distributed across the educational spectrum in plant maintenance, land preparation, and digital marketing. The study's most original contribution, however, lies in its identification of IoT infrastructure access as an important contextual factor in training outcomes. Although this remains an observational association rather than a causal effect, Barelang participants, who trained with a working IoT drip irrigation system, reported near-perfect smart farming scores, while Nongsa participants showed a slight decline in self-assessed IoT knowledge.

These findings should be interpreted in light of the study's relatively small sample size of 20 participants, the use of different pre-test and post-test items, and the lack of a control group, which limits the generalizability of the results beyond the study context. The observed performance gap between Barelang and Nongsa may reflect differences in infrastructure access within the same programme, a distinction that challenges the prevailing practice of staging technology deployment after training delivery. ESG programmes operating in non-agricultural communities should consider synchronising infrastructure provision with training content if human resource outcomes are to be equitably achieved across all implementation sites. Future research should use the same items before and after training, include an objective knowledge test and a comparison group, and to longitudinal productivity and behavioural outcomes, and investigate whether gender, age, and livelihood background further moderate knowledge consolidation trajectories among ESG beneficiary communities in Indonesia's rapidly evolving sustainability landscape.

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Author Contribution

This work were solely conducted by N.I.D.A., & D.N.S., who were responsible for the conceptualization, methodology, data collection, analysis, and writing of the manuscript.

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Ethical Review Board Statement

Ethical review and approval were waived for this study because the research involved a voluntary and anonymous questionnaire survey, collected no personally identifiable information, posed minimal risk to participants, and did not involve any medical, clinical, or psychological intervention. All participants were informed about the purpose of the study and provided their consent before completing the questionnaire.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study prior to their participation in the questionnaire survey.

Data Availability Statement

Not available.

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of Generative AI Use

During the preparation of this work, the authors used Grammarly to assist in improving grammar, clarity, and academic tone of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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