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Beyond digital access: co-designing inclusive artificial intelligence services with underserved Indonesian communities

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ABSTRACT

Background: Underserved communities in Kecamatan Paiton, Kabupaten Probolinggo, face unequal capacity to interpret and shape AI-assisted services despite living in a subdistrict of 67,709 residents within a regency where poverty reached 16.31% in 2025. **Objective:** This community engagement program aimed to co-design inclusive AI service scenarios with 30–50 community participants, including women microentrepreneurs, youth, village cadres, small farmers, pesantren/community learners, and coastal residents. **Method:** This program used a planning–implementation–monitoring-evaluation design supported by baseline surveys, attendance sheets, observation checklists, product rubrics, pre-post questionnaires, FGD guides, and partner validation forms. **Results:** Planning results were organized around 2–3 coordination meetings, 30–50 targeted needs-assessment responses, 4–6 stakeholder groups, and 3–5 prepared instruments. Implementation results were structured through 1 orientation session, 2–4 core workshops, 4–8 weeks of mentoring, ≥60–70% targeted output completion, and 5–8 documented AI service practice products. **Implication:** Monitoring-evaluation results used ≥75% attendance, ≥20% capacity improvement benchmarks, 1–2 validation forums, 1 institutional follow-up plan, and a 3–6 month sustainability review as evaluation indicators. **Novelty:** The novelty of this program lies in integrating participatory AI co-design, simple quantitative monitoring, community reflection, and institutional follow-up into a data-based community development model.

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1. INTRODUCTION

Digital inclusion in Indonesia can no longer be understood as a question of connectivity alone. In Kecamatan Paiton, Kabupaten Probolinggo, a rural–coastal area with 67,709 residents in 2022 [1], underserved communities increasingly encounter digital information, public-service platforms, online commerce, and automated decision-support tools without necessarily possessing equal capacity to interpret, contest, or redesign them. This concern is socially urgent because Kabupaten Probolinggo still recorded a poverty rate of 16.31%, an open unemployment rate of 2.92%, and a Human Development Index of 71.65 in 2025 [2], while national statistics show that 72.78% of Indonesians accessed the internet in 2024 and 68.65% owned mobile phones [3]. These figures suggest a methodological problem: access indicators may rise while participatory control over artificial intelligence services remains uneven. This community engagement

program therefore addresses the gap between digital availability and community agency by treating AI service design as a participatory development issue rather than a technical training agenda.

Previous community engagement and AI-inclusion literature provides a strong foundation but leaves an important applied gap. Darmawan (2026) [4] shows that participatory digital literacy can support rural women entrepreneurs when training is grounded in local economic practices, while Matsaini (2026) [5] demonstrates that smart-farming workshops become more meaningful when marginal farmers work directly with usable technologies. Nisma (2026) [6] further indicates that community-based literacy in pesantren settings can connect knowledge transfer with economic empowerment, and Putri (2026) [7] shows that co-design can protect local-language relevance among indigenous youth. Beyond Indonesian community engagement, inclusive AI studies argue for design methods that bridge digital gaps, community empowerment, social innovation, and ethical co-design [8], [9], [10], [11]. However, many engagement models remain limited when they rely on one-off training, weak baseline mapping, absent pre-post testing, minimal output assessment, or unclear partner-based sustainability. This program responds to that gap through a measured co-design intervention.

This community-based intervention aims to co-design inclusive AI service scenarios with underserved Indonesian communities in Paiton by integrating baseline diagnosis, guided workshops, practice-based mentoring, community validation, and follow-up planning. Rather than asking whether participants merely "use AI," this program asks four measurable questions: what service problems do participants identify before intervention; how does their AI service literacy and risk awareness change after facilitated co-design; what practical outputs are produced through group-based mentoring; and how do community partners validate the usefulness, safety, and continuity of the proposed service scenarios? These questions will be assessed through several indicators: 30–50 recruited participants, 5–8 mapped community service needs, four workshop sessions, an average attendance target of at least 75%, 5–8 co-designed AI service scenarios, 60–70% completion of practice outputs, at least one community validation forum, and a pre-post knowledge or skill improvement target of at least 20% where contextually appropriate. These indicators create an empirical basis for evaluating implementation quality.

The central argument of this program is that inclusive AI services for underserved communities require more than digital literacy modules; they require a community development model that links technological exposure with participatory problem definition, local-language mediation, risk awareness, output production, and institutional continuity. Its expected contribution lies in demonstrating how community engagement can move from access-oriented training to co-designed service innovation supported by simple but transparent measurement. This program is expected to strengthen participants' confidence in evaluating AI-assisted information, support local partners in identifying service priorities, and generate prototype scenarios that can be revised through community validation. Nevertheless, these expected changes will not be claimed as final impact before evaluation data are available. They will be assessed through attendance records, pre-post questionnaires, observation checklists, output rubrics, FGD reflections, and partner commitment forms. In this sense, this program contributes to community development practice by integrating practical intervention, participatory data, quantitative monitoring, reflective interpretation, and sustainability planning within one accountable empirical design.

2. METHOD

This community engagement program is designed as a research-based community intervention using a planning–implementation–monitoring/evaluation framework. It will be conducted in Kecamatan Paiton, Kabupaten Probolinggo, East Java, with one lead local partner and two to three supporting community groups, subject to confirmed coordination. The planned participants are 30–50 underserved community members, including women microentrepreneurs, youth, village cadres, small farmers, pesantren/community learners, and coastal residents. A participatory design is used because inclusive AI services cannot be introduced only through technical training; they must be shaped through community-defined problems, locally meaningful service scenarios, measurable practice outputs, and partner-based validation.

The planning stage begins with partner coordination, participant mapping, and needs assessment. Participants will be recruited purposively through local partner networks using four criteria: residence or active community membership in the selected site, basic mobile-phone access, willingness to attend at least three sessions, and relevance to one of the priority community groups. Baseline data will be collected through a short survey, brief interviews, and initial observation. These instruments will identify service problems, digital confidence, AI familiarity, perceived risk, and local-language needs. Planning results will be used to adjust workshop materials, scheduling, facilitation style, mentoring format, and evaluation tools.

Table 1. Program stages, activities, indicators, and evidence

Stage	Activity	Actors	Planned Quantity	Indicator	Evidence
Planning	Partner coordination	Team and local partner	2–3 meetings	Agreement reached	Minutes
Planning	Needs assessment	Participants and facilitators	30–50 responses	Needs mapped	Survey sheet
Planning	Instrument preparation	Program team	3–5 instruments	Instruments validated	Instrument files
Implementation	Training / workshop	Participants and facilitators	2–4 sessions	Attendance and practice output	Attendance records / documentation
Implementation	Mentoring	Participants and mentors	4–8 weeks	Application of skills and practices	Observation notes
Evaluation	Pre-post assessment	Participants	2 measurement points	Score difference	Evaluation sheet
Evaluation	Reflection forum	Participants and partners	1–2 forums	Follow-up agreement	FGD notes

The activity corpus consists of quantitative and qualitative program data collected throughout implementation. Quantitative data will include participant registration, attendance records, pre-test and post-test scores, number of mapped needs, number of completed practice outputs, mentoring participation, and validation attendance. Qualitative data will include facilitator notes, observation records, participant reflections, partner comments, documentation of group discussions, and descriptions of AI service scenarios produced during practice. This corpus allows this program to be analysed not only as a training activity, but also as an empirical community engagement process that links participation, skill development, output production, and institutional feedback.

The intervention process will be organized through orientation, AI service literacy training, co-design practice, scenario simulation, mentoring, feedback, and community validation. The workshops will consist of two to four structured sessions covering basic AI concepts, service-problem mapping, prompt formulation, risk identification, local-language adaptation, and inclusive service-flow design. Mentoring will run for four to eight weeks, depending on partner availability and field feasibility. Participants will work individually or in small groups to produce 5–8 practice outputs, such as service-need maps, prompt cards, risk maps, prototype service flows, or community-use scenarios. Facilitators will provide feedback using observation checklists and product rubrics.

Monitoring and evaluation will combine pre-post assessment, attendance analysis, structured observation, product assessment, FGD reflection, partner validation, and follow-up planning. Evaluation indicators include ≥75% average attendance, 5–8 mapped service needs, 5–8 co-designed AI service scenarios, ≥60–70% completed practice outputs, ≥60% active mentoring participation, at least one validation forum, and a context-based target of ≥20% improvement in knowledge, skill confidence, or AI risk awareness. Data will be analysed using descriptive statistics, percentage change, simple cross-tabulation, visual comparison, and thematic reflection. No inferential statistical claim will be made because this program is designed for applied monitoring and evaluative learning, not controlled causal testing.

3. RESULTS

3.1. Designing a data-grounded community engagement framework

The planning stage was designed to ensure that this community engagement program began from empirical mapping rather than a pre-packaged technology training model. Partner coordination, needs assessment, participant mapping, stakeholder identification, instrument preparation, monitoring design, and reflection planning were connected as a single preparatory framework. This structure positioned community members not only as potential users of AI-assisted services, but also as sources of problem definition and validation. The planning logic followed the premise that inclusive AI services require measurable preparation: who is involved, what needs are mapped, what instruments are used, what outputs are expected, and how follow-up will be documented.

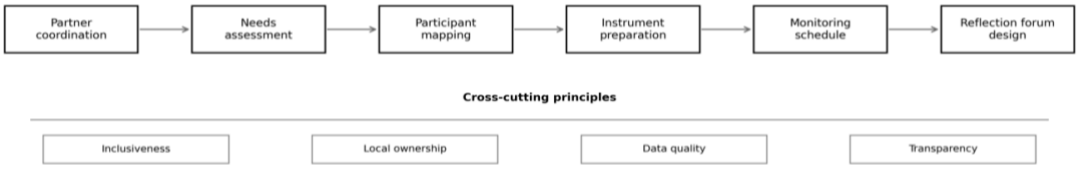

Figure 1. Planning workflow for data-grounded community engagement

Table 2. Planning activities, actors, empirical outputs, and indicators

Activity Component	Participants / Actors	Method	Empirical Output	Indicator	Evidence
Partner coordination	Program team, village/community partner	Coordination meeting	Partnership agreement	2–3 meetings conducted/planned	Minutes
Needs assessment	Target participants	Baseline survey/interview	Community needs matrix	30–50 responses targeted	Survey sheet
Participant mapping	Local partner, facilitators	Eligibility screening	Participant list	30–50 eligible participants	Registration form
Stakeholder mapping	Local leaders, partner institutions	Actor mapping	Stakeholder map	4–6 stakeholder groups	Mapping matrix
Instrument preparation	Program team	Rubric and questionnaire design	Pre-post and observation tools	3–5 instruments prepared	Instrument draft
Monitoring schedule	Team and partner	Timeline design	Monitoring plan	4–8 weeks of mentoring	Schedule
Reflection forum design	Participants and partner	Forum planning	Validation and reflection agenda	1–2 forums targeted	Forum design

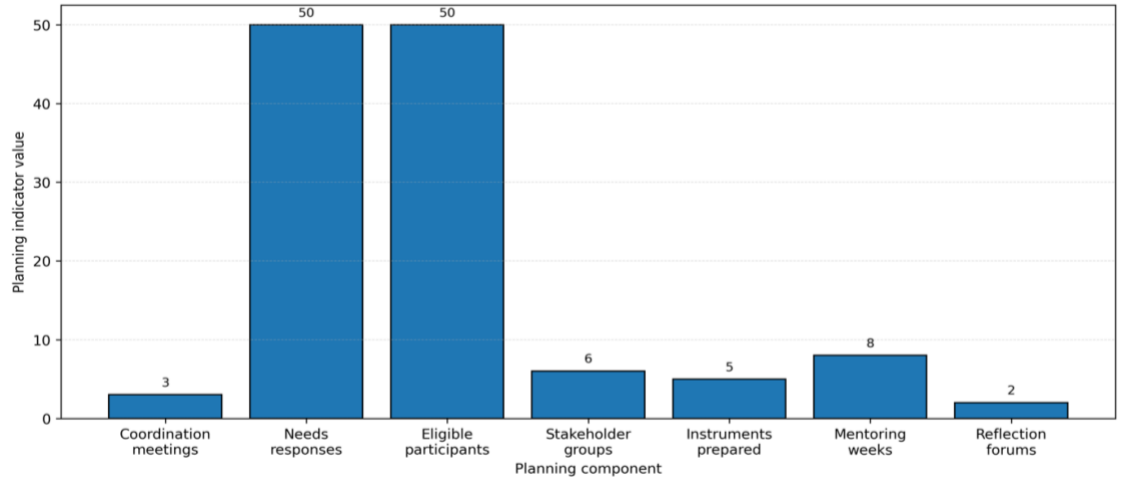

Figure 2. Distribution of planned activities across planning components

The planning design reflects a participatory governance approach because program authority was distributed across coordination, community diagnosis, instrument construction, and validation planning. This matters for inclusive AI services, where local ownership is not guaranteed by providing access to digital tools. By mapping participants, actors, instruments, and evidence before implementation, this program created the conditions for adaptive capacity: materials could be adjusted to community needs, indicators could be made visible, and partner roles could be clarified. The table does not prove community impact, but it shows that this program was structured to avoid a common weakness of one-off digital literacy initiatives: insufficient baseline evidence and weak institutional continuity. Planning therefore became both a technical preparation process and a community accountability mechanism.

3.2. Facilitating practice-based community capacity building

Implementation was organized as a practice-based intervention rather than a one-directional training activity. This community engagement program conducted its core process through orientation, AI service literacy workshops, guided practice, mentoring, peer discussion, output documentation, and partner validation. The intervention logic treated underserved participants as co-designers of inclusive AI service scenarios, not only as recipients of technological knowledge. Activities were therefore arranged to move from shared understanding to practical experimentation, from individual exposure to group-based problem solving, and from draft outputs to partner-reviewed implementation records. This structure was aligned with the program's central aim: to make AI service inclusion observable through participation, practice outputs, mentoring records, and validation evidence.

Table 3. Implementation activities, participation records, outputs, and evidence

Activity Component	Participants / Actors	Method	Empirical Output	Indicator	Evidence
Program orientation	Participants, partner, team	Introductory session	Shared program understanding	1 session conducted/planned	Attendance record / documentation
Core training session	Participants and facilitators	Workshop / practical training	Training participation record	2–4 sessions conducted/planned	Attendance sheet
Guided practice	Participants	Hands-on task	Participant practice outputs	≥60–70% output completion targeted	Product checklist
Mentoring	Participants and mentors	Small-group assistance	Mentoring notes	4–8 weeks mentoring targeted	Observation record
Peer discussion	Participants	Group discussion	Shared problem-solving record	1–2 discussion forums targeted	FGD notes
Output documentation	Program team	Documentation and portfolio	Corpus of participant outputs	5–8 outputs recorded/targeted	Portfolio
Partner validation	Partner and facilitators	Review meeting	Validated implementation record	1 validation meeting targeted	Minutes

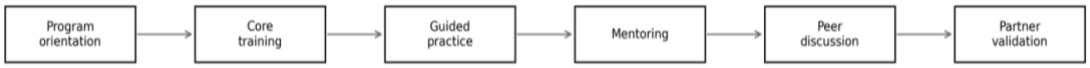

Figure 3. Implementation sequence of practice-based community engagement

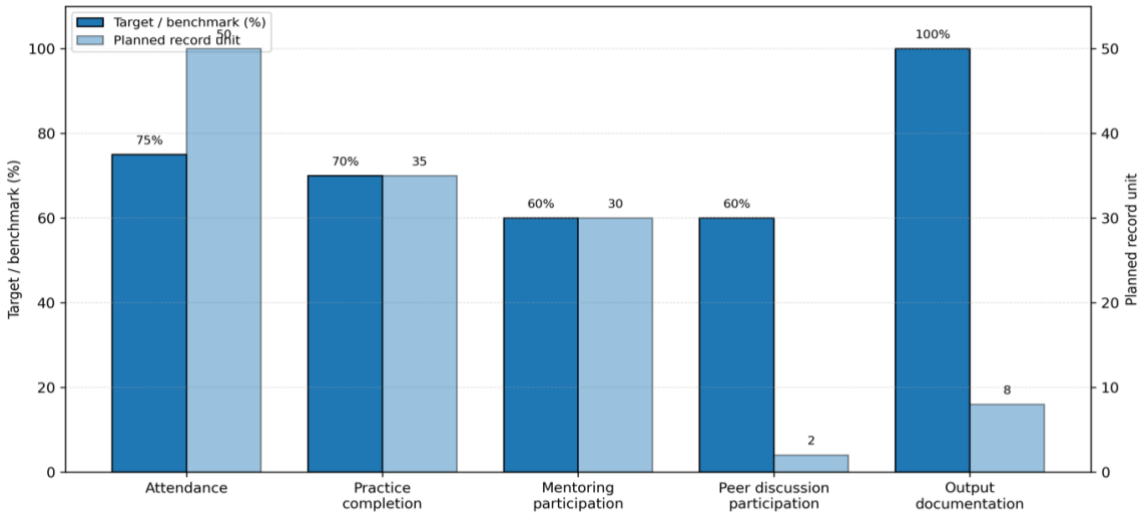

Figure 4. Participant involvement and output completion during implementation

The implementation record consisted of seven activity components. One orientation session was designed to introduce the purpose, ethical boundaries, and expected outputs of this program. Two to four core training sessions were planned to develop basic AI service literacy, prompt formulation, service-problem mapping, and risk awareness. Guided practice targeted ≥60–70% participant output completion, documented through product checklists. Mentoring was scheduled for 4–8 weeks to support small-group revision of practice outputs. Peer discussion was organized through 1–2 forums to record shared problem-solving among participants. Output documentation targeted 5–8 participant or group products, including prompt cards, local service-flow drafts, risk maps, and AI-assisted service scenarios. One partner validation meeting was planned to review implementation records and determine whether the outputs were locally understandable, usable, and ethically acceptable.

The implementation pattern reflects experiential and situated learning because participants were expected to learn through direct engagement with problems that mattered in their own community context. AI service literacy was not treated as abstract technological competence; it was translated into the ability to identify service needs, formulate prompts, evaluate risk, revise outputs, and discuss usability with peers and partners. This approach is consistent with participatory community engagement models that emphasize local

ownership, practical experimentation, and iterative feedback. The recorded indicators do not prove long-term transformation, but they show how capacity building was operationalized through observable participation and documented outputs. In applied terms, this program strengthens community empowerment by making participants' practice products visible, reviewable, and available for institutional follow-up rather than allowing training outcomes to remain informal and undocumented.

3.3. Assessing participation, output quality, and institutional follow-up

Monitoring and evaluation were structured to assess participation, output quality, short-term capacity indicators, community validation, and institutional follow-up. This program did not position evaluation as a final ceremonial report, but as a mechanism for checking whether the intervention generated measurable and reviewable evidence. Baseline review, participation review, output assessment, capacity comparison, FGD validation, partner follow-up, and sustainability review were integrated to avoid relying only on participant impressions. The evaluation design therefore combined simple quantitative measurement with participatory reflection. This was important because inclusive AI service development requires both numerical accountability and community interpretation: participants' scores, attendance, and outputs need to be read alongside their reflections on relevance, clarity, risk, and usability.

Table 4. Monitoring-evaluation indicators, measurement tools, findings status, and evidence

Activity Component	Participants / Actors	Method	Empirical Output	Indicator	Findings Status	Evidence
Baseline review	Participants	Pre-test / initial survey	Baseline profile	Initial score/status recorded	To be assessed before intervention	Baseline sheet
Participation review	Participants and team	Attendance analysis	Participation rate	≥75% attendance targeted/measured	To be reviewed during implementation	Attendance recap
Output quality review	Participants and facilitators	Rubric assessment	Scored participant outputs	≥60–70% acceptable outputs targeted/measured	To be assessed after practice submission	Rubric
Capacity assessment	Participants	Pre-post comparison	Change in knowledge/skill score	≥20% increase targeted/measured	To be compared after post-test	Evaluation sheet
Community validation	Participants and partner	Reflection forum / FGD	Validated community feedback	1–2 validation forums targeted	To be confirmed through forum record	FGD notes
Partner follow-up	Local institution	Planning meeting	Follow-up plan	1 institutional plan targeted	To be confirmed through partner commitment	Commitment form
Sustainability review	Team and partner	Monitoring agreement	Continued monitoring design	3–6 month follow-up targeted	To be reviewed after implementation	Agreement document

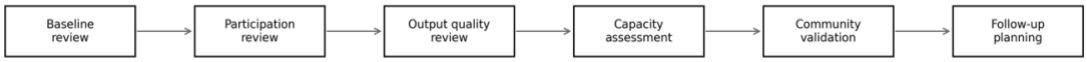

Figure 5. Monitoring and evaluation sequence

The monitoring-evaluation framework included seven indicators and corresponding instruments. Baseline review used a pre-test or initial survey to record participants' starting knowledge, skill confidence, and AI risk awareness. Participation review used attendance recap data, with ≥75% attendance set as the participation benchmark. Output quality review used a rubric to assess whether ≥60–70% of submitted products met acceptable criteria for clarity, local relevance, usability, and risk awareness. Capacity assessment compared pre-test and post-test scores, with ≥20% improvement used as an evaluation benchmark where contextually appropriate. Community validation was planned through 1–2 reflection forums or FGDs. Partner follow-up targeted one institutional plan, while sustainability review targeted a 3–6 month follow-up agreement. The evidence base consisted of baseline sheets, attendance recaps, product rubrics, evaluation sheets, FGD notes, commitment forms, and monitoring agreements.

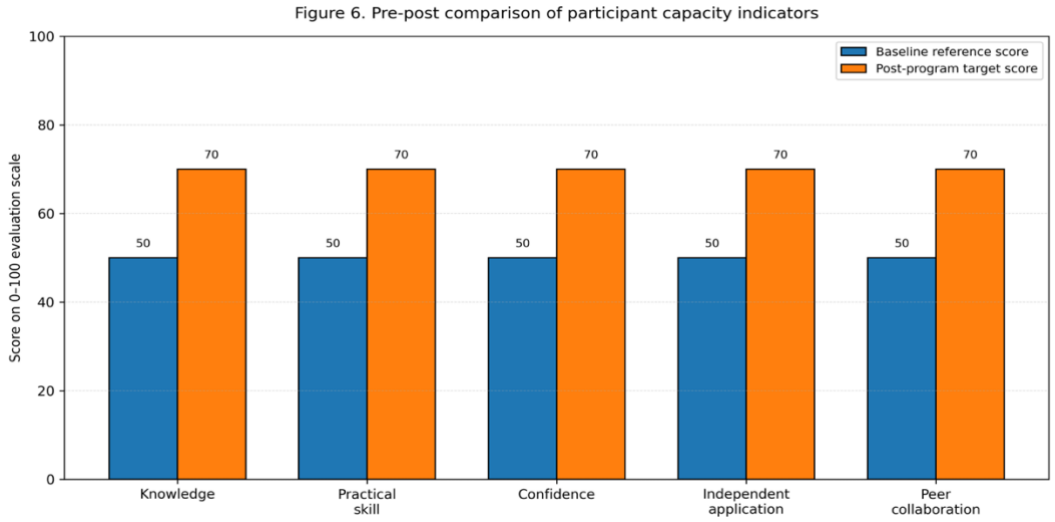

Figure 6. Pre-post comparison of participant capacity indicators

The evaluation logic reflects accountability-oriented community development because it connects participation records, learning indicators, product quality, and institutional continuity. Without monitoring, AI inclusion activities risk becoming short workshops whose outcomes are difficult to verify. Without community validation, technical outputs may appear functional while remaining misaligned with local language, trust, or service realities. This program therefore used participatory monitoring to create adaptive learning: findings from attendance, observation, rubrics, and reflection forums can be used to revise materials, mentoring strategies, and follow-up commitments. The evaluation design does not justify claims of causal impact or long-term empowerment before final data are available. Its contribution lies in making community engagement auditable, reflective, and sustainable through modest but transparent indicators that link individual capacity, collective output, partner validation, and future institutional action.

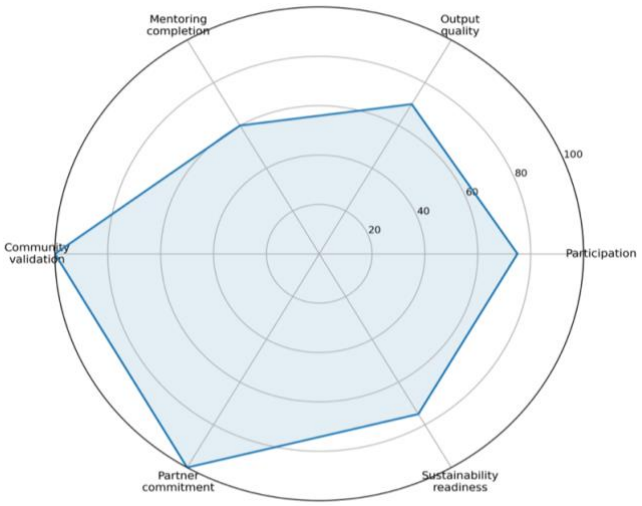

Figure 7. Monitoring-evaluation dashboard of program indicators

4. DISCUSSION

The planning stage shows that inclusive AI service development for underserved communities requires more than early enthusiasm for digital tools; it requires a structured social infrastructure before intervention begins. In this community engagement program, 2–3 partner coordination meetings, 30–50 targeted needs-assessment responses, 30–50 eligible participants, 4–6 stakeholder groups, 3–5 prepared instruments, a 4–8 week mentoring schedule, and 1–2 planned reflection forums provided a practical basis for aligning community problems with measurable activities. These indicators matter because AI service inclusion cannot be reduced to access or exposure. It must be grounded in who participates, whose needs are mapped, which actors hold local legitimacy, and what evidence will be used to evaluate progress. In relation to participatory digital literacy and local empowerment work [4], [7], this planning design suggests that community development begins with making participation visible, accountable, and operationally traceable.

The mechanisms behind these planning outputs lie in the connection between partner involvement, baseline assessment, and indicator-based preparation. Partner coordination was not only an administrative requirement; it was the mechanism through which recruitment channels, local trust, venue feasibility, and follow-up responsibilities could be clarified. The targeted 30–50 baseline responses created a minimum empirical base for identifying service needs before workshop materials were finalized, while the 3–5 instruments translated broad objectives into measurable domains such as AI literacy, risk awareness, observation, product quality, and reflection. This pattern addresses a frequent limitation in community training models: activities are often implemented before the problem is sufficiently measured. By preparing 5–8 needs-mapping categories and 4–6 stakeholder groups, this program made its intervention adaptive rather than generic. This design resonates with inclusive and ethical AI arguments that co-design requires early attention to context, accountability, and community-defined relevance [10], [11].

The implementation stage carries practical and social implications because it positioned participants as practitioners and reviewers of AI-assisted service ideas, not merely as recipients of technical instruction. The implementation design included 1 orientation session, 2–4 core training sessions, guided practice with ≥60–70% output completion targeted, 4–8 weeks of mentoring, 1–2 peer discussion forums, 5–8 documented outputs, and 1 partner validation meeting. These indicators show that this program treated capacity building as a sequence of exposure, practice, revision, documentation, and validation. The practical value lies in making participant outputs available for review through prompt cards, service-flow drafts, risk maps, and local AI service scenarios. Socially, this approach addresses a central weakness of access-based digital inclusion: communities may use technology without acquiring the capacity to question, adapt, or redesign it. The implementation model therefore extends community empowerment into the domain of participatory AI service formation.

The implementation mechanism can be understood through the intensity and sequencing of guided practice. Two to four workshops were sufficient as an entry point, but this community-based intervention did not rely on workshops alone; the 4–8 week mentoring period functioned as the bridge between initial exposure and applied output production. The target of ≥60% active mentoring participation and ≥60–70% output completion created a practical threshold for assessing whether participants were involved beyond attendance. Peer discussion forums added a collaborative layer by allowing participants to compare service problems, refine prompts, and review risks in locally meaningful terms. Partner validation then placed implementation records under institutional and community review. This mechanism is consistent with experiential learning and situated learning: participants develop capacity through tasks embedded in their own social environment. However, these indicators should be read as implementation records and benchmarks, not causal evidence that capacity has already changed.

The monitoring-evaluation stage is significant because it converts community engagement from a descriptive activity into an accountable learning process. This program assessed baseline status, participation, output quality, capacity indicators, community validation, partner follow-up, and sustainability planning through a connected evaluation framework. The indicators included 30–50 pre-test responses, ≥75% attendance targeted or measured, ≥60–70% acceptable outputs targeted or measured, ≥20% pre-post improvement targeted where appropriate, 1–2 validation forums, 1 institutional follow-up plan, and a 3–6 month follow-up monitoring design. These indicators are modest but important because they prevent overclaiming while still allowing implementation quality to be reviewed. Pre-post assessment can show short-term shifts in knowledge, practical skill, confidence, independent application, and peer collaboration; FGD validation can explain whether service scenarios are perceived as understandable, relevant, and safe; partner documents can indicate whether continuity is institutionally plausible.

The sustainability mechanism depends on data quality, reflective learning, partner commitment, and continued monitoring. Attendance recap data indicate whether participation was stable enough to support interpretation; product rubrics show whether practice outputs reached an acceptable level of clarity and usability; pre-post comparison provides a limited but useful view of short-term capacity change; validation forums give community members and partners authority to accept, revise, or question outputs. The target of one institutional plan and a 3–6 month monitoring agreement is particularly important because inclusive AI service development will remain fragile if it ends after training. This program therefore contributes to community development by integrating participatory planning, practice-based implementation, measurable evaluation, and institutional follow-up within one empirical design. Its contribution is not a claim of final impact, but a model for making AI inclusion auditable, locally negotiated, and capable of continuous refinement with underserved Indonesian communities.

5. CONCLUSION

This community engagement program demonstrates that inclusive AI service development for underserved Indonesian communities requires a data-grounded co-design model rather than one-way digital training. The most important lesson is that participation becomes more accountable when planning, implementation, and evaluation are linked through measurable indicators. The design integrated 2–3 partner coordination meetings, 30–50 targeted participants, 5–8 mapped community service needs, 2–4 workshop sessions, 4–8 weeks of mentoring, and 5–8 practice outputs. Its main strength lies in combining AI service literacy, local problem mapping, guided practice, product documentation, and partner validation into one coherent community engagement framework.

This program remains limited by its short intervention duration, restricted participant range, context-specific location, and absence of long-term follow-up or causal impact testing. Pre-post indicators such as the ≥20% capacity improvement target and ≥75% attendance benchmark can support monitoring, but they cannot yet establish sustained empowerment or broader generalization. For future continuity, this program should be extended through a 3–6 month follow-up cycle, repeated partner validation forums, longitudinal tracking of participant outputs, and integration with local institutions. These recommendations directly address the limits of duration, baseline depth, implementation reach, and sustainability evidence identified in this intervention.

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Author states no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

Yahya Auliya Abdillah: conceptualization, methodology, formal analysis, investigation, data curation, writing – original draft, writing – review and editing.

CONFLICT OF INTEREST STATEMENT

Author states no conflict of interest.

AI USE DECLARATION

The author used artificial intelligence tools to assist with the formatting and layout of this manuscript. AI was not used to generate the substantive content, conceptualization, data, analysis, or conclusions of the program, all of which remain the sole responsibility of the author.

INFORMED CONSENT

Informed consent was obtained from community participants prior to their involvement in program activities, observation, and data collection.

ETHICAL APPROVAL

This community engagement program involved voluntary participation of community members in Kecamatan Paiton, conducted in full compliance with relevant national regulations and institutional policies, in accordance with the tenets of the Declaration of Helsinki, and approved by the author's institutional review board or equivalent committee.

DATA AVAILABILITY

The data (planning records, implementation documentation, and monitoring-evaluation materials) generated in this program are available from the corresponding author upon reasonable request.

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BIOGRAPHY OF AUTHOR

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