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Merancang Adaptivitas Relasional Dalam Ekosistem Pembelajaran Nonformal Yang Didukung AI: Studi Penelitian Berbasis Desain Dua Siklus Di Komunitas Perkotaan

Designing Relational Adaptivity In An AI-Supported Non-Formal Learning Ecosystem: A Two-Cycle Design-Based Research Study In Urban Communities

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Abstract

Artificial intelligence can personalize educational support, yet technological responsiveness alone does not explain how a learning ecosystem adapts when intended relationships among technology, facilitators, learners, and community contexts are not enacted as expected. This study examined how an AI-supported, human-mediated non-formal learning ecosystem was configured and iteratively redesigned through two cycles of design-based research in urban and peri-urban communities in Jabodetabek, Indonesia. Contextual grounding involved 269 learner profiles across 24 community settings, complemented by program documentation, facilitator reflections, community mapping, and Cycle 2 implementation records. Cycle 1 revealed relational tensions involving didactic facilitation, facilitator expertise and learner agency, uneven participation, limited temporal continuity, and an under-specified connection between capacity development and situated enactment. Cycle 2 responded through team-based facilitation, shared reflection, peer-supported continuity, an extended learning rhythm, and more explicit opportunities for situated action while AI remained functionally bounded. Cross-cycle analysis showed that adaptation occurred primarily through redistribution and recoordination of educational functions rather than increased technological autonomy. The study conceptualizes this evidence-responsive ecosystem capacity as relational adaptivity.

Keywords*: Artificial Intelligence In Education; Relational Adaptivity; Non-Formal Education; Design-Based Research; Learning Ecosystem.*

Abstrak

Kecerdasan buatan (AI) dapat mempersonalisasi dukungan pendidikan, namun responsivitas teknologi semata tidak cukup untuk menjelaskan bagaimana ekosistem pembelajaran beradaptasi ketika hubungan yang direncanakan antara teknologi, fasilitator, peserta didik, dan konteks komunitas tidak terwujud sebagaimana mestinya. Studi ini mengkaji bagaimana ekosistem pembelajaran nonformal yang didukung oleh AI dan dimediasi oleh manusia dikonfigurasi serta dirancang ulang secara iteratif melalui dua siklus penelitian berbasis desain (design-based research) di komunitas perkotaan dan peri-urban di wilayah Jabodetabek, Indonesia. Landasan kontekstual studi ini mencakup 269 profil peserta didik di 24 lingkungan komunitas, yang dilengkapi dengan dokumentasi program, refleksi fasilitator, pemetaan komunitas, serta catatan pelaksanaan pada Siklus 2. Siklus 1 mengungkap adanya ketegangan relasional yang melibatkan fasilitasi didaktis, keahlian fasilitator dan agensi peserta didik, partisipasi yang tidak merata, kontinuitas waktu yang terbatas, serta hubungan yang kurang terdefinisi dengan jelas antara pengembangan kapasitas dan penerapan dalam konteks nyata. Siklus 2 merespons tantangan tersebut melalui fasilitasi berbasis tim, refleksi bersama, kontinuitas yang didukung oleh

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rekan sebaya, ritme pembelajaran yang lebih panjang, serta peluang yang lebih eksplisit untuk melakukan tindakan dalam konteks nyata, sementara peran AI tetap dibatasi secara fungsional. Analisis lintas siklus menunjukkan bahwa adaptasi terjadi terutama melalui redistribusi dan koordinasi ulang fungsi-fungsi pendidikan, bukan melalui peningkatan otonomi teknologi. Studi ini mengonseptualisasikan kapasitas ekosistem yang responsif terhadap bukti empiris ini sebagai "adaptivitas relasional" (relational adaptivity).
Kata kunci: Kecerdasan Buatan dalam Pendidikan; Adaptivitas Relasional; Pendidikan Nonformal; Penelitian Berbasis Desain; Ekosistem Pembelajaran.

1. Introduction

Artificial intelligence (AI) is entering education at a pace that is increasingly difficult for educational institutions and governance systems to match. Following the rapid diffusion of generative AI, a UNESCO global survey involving more than 450 schools and universities found that fewer than 10% had established institutional policies or formal guidance for its use, while approximately 13% of universities and only 7% of schools reported having any form of guidance; about 20% of respondents were unsure whether such guidance existed in their institutions (UNESCO, 2023b). This institutional lag is significant because digital technologies are already embedded across multiple educational functions, including content delivery, assessment, personalized tutoring, planning, and system management, while recent advances in AI have intensified debates about whether technology should supplement or replace forms of human educational interaction (UNESCO, 2023a). UNESCO's *Global Education Monitoring Report* consequently cautions that technological expansion should be evaluated in relation to relevance, equity, scalability, sustainability, and learners' interests rather than treated as educational progress by default (UNESCO, 2023a). The contemporary challenge is therefore no longer whether AI will enter education, but how educational systems can incorporate increasingly powerful technological assistance without allowing technological responsiveness to displace human judgment, learner participation, or contextual meaning-making.

Indonesia reflects this transition at considerable scale. In 2025, 96.5% of Indonesians aged 15–24 were reported to possess information and communication technology skills, while 94.18% of people in the same age group owned or controlled a mobile (Badan Pusat Statistik, 2026b, 2026a). The digital conditions are particularly pronounced in the metropolitan provinces relevant to the present study: ICT-skill rates among those aged 15–24 reached 98.89% in DKI Jakarta, 97.98% in West Java, and 98.27% in Banten in 2025 (Badan Pusat Statistik, 2026b). At the policy level, Indonesia has simultaneously moved from general digitalization toward explicit AI education: Permendikdasmen No. 13 of 2025 introduced Coding and Artificial Intelligence as an elective subject, with phased implementation beginning in the 2025/2026 academic year, while the national academic framework frames coding and AI learning as part of building an educational ecosystem capable of responding to technological change (Kementerian Pendidikan Dasar dan Menengah, 2025a, 2025b). These developments indicate that access to digital technologies and institutional recognition of AI are expanding rapidly; however, high digital penetration and formal inclusion of AI do not by themselves establish how technological assistance should be related to human mediation, learner agency, or situated learning in diverse educational settings.

Against this background, AI has expanded the capacity of educational systems to provide individualized feedback, recommendations, assessment, and learning

pathways based on learner characteristics and performance. Reviews of artificial intelligence in education (AIED) show that these applications now extend across teaching, learning, assessment, and educational decision support rather than being confined to intelligent tutoring systems (Chiu et al., 2023; Crompton & Burke, 2023). At the same time, AIED has progressively moved from AI-directed configurations toward AI-supported and AI-empowered arrangements in which learners can assume greater control over learning processes (Ouyang & Jiao, 2021). Yet technological responsiveness and educational adaptivity are not equivalent: a system may personalize resources or feedback without changing how educational responsibilities, participation, or decision-making are organized (Bernacki et al., 2021; Darvishi et al., 2024). The rapid diffusion of AI therefore creates a problem that is simultaneously technological and educational: whether the wider learning arrangement can itself adapt when the relationships through which AI is used do not operate as intended.

The distinction becomes particularly important when personalization is considered alongside learner agency. Personalized assistance can respond accurately to individual characteristics while still leaving learners with limited influence over goals, interpretations, choices, or subsequent action (Darvishi et al., 2024). Experimental evidence indicates that AI assistance may improve immediate task performance while also encouraging reliance on technological support when learners do not remain actively engaged in monitoring and regulating their own learning (Fan et al., 2025). Students likewise value the accessibility and individualized support offered by generative AI but express concerns about over-reliance, reliability, and the effects of AI use on independent judgment (Chan & Hu, 2023). Learner agency therefore cannot be inferred from personalization alone; it emerges through learners' opportunities to interpret, decide, contribute, and act within educational relationships (Mairitsch et al., 2023). If learner agency cannot be secured through personalization alone, the design question necessarily shifts toward how educational authority and responsibility are distributed between human and artificial actors.

Human-centered AIED addresses this problem by emphasizing meaningful human control, stakeholder participation, and complementarity between human and artificial intelligence (Alfredo et al., 2024; Fu & Weng, 2024). Research on teachers' engagement with AI shows that educators continue to perform functions that require contextual interpretation, pedagogical judgment, and evaluation of technological outputs even when AI supports instructional planning, assessment, or feedback (Celik et al., 2022). AI can nevertheless alter learner–instructor relationships, expectations, and responsibilities, demonstrating that retaining humans within an educational system does not leave pedagogical relationships unchanged (Seo et al., 2021). Consequently, locating formal authority in human actors is necessary but does not guarantee dialogic or learner-responsive enactment; human judgment itself must be exercised in ways that preserve meaningful learner participation (Mouta et al., 2025). Because neither technological personalization nor formal human control fully explains how learning relationships operate in practice, the analytical unit must extend beyond individual human–AI interactions.

An educational ecosystem perspective provides this wider analytical unit. AI-enabled educational ecosystems involve interconnected users, digital resources, services, pedagogical processes, and environments rather than isolated relationships between a learner and a technological application (Rojas & Chiappe, 2024). At this level, different actors may perform differentiated but interdependent educational

functions: AI may assist information processing and feedback, educators may retain contextual interpretation and pedagogical judgment, learners may contribute experience and regulate their learning, and peers may participate in collaborative regulation (Edwards et al., 2025; Ng et al., 2023). What matters, therefore, is not only which actors are present but how their responsibilities are distributed and how their contributions are coordinated. An ecosystem perspective consequently shifts the question from what should AI personalize? toward how should technological, pedagogical, learner, peer, and contextual functions work together?

Non-formal community education provides a particularly revealing context for this problem because learning is distributed across heterogeneous learners, facilitators, digital resources, everyday practices, and community conditions. Research on non-formal learning shows that practitioners regularly negotiate diverse participant needs, organizational conditions, facilitation capacities, and contextual constraints rather than operating within standardized instructional environments (Christidou et al., 2022). Studies of informal and non-formal learning similarly demonstrate considerable variation in settings, participation structures, and forms of interaction, making contextual responsiveness integral to educational design (Tisza et al., 2020). In the present study, contextual grounding across 269 learner profiles and 24 urban and peri-urban community settings revealed heterogeneous life-skill priorities, learning preferences, digital conditions, and community circumstances. These differences made it inappropriate to assume either that individualized learner priorities would automatically correspond with community conditions or that community concerns should simply override what learners themselves considered meaningful. The resulting design problem was relational: how could personally relevant learning, technological support, human mediation, and situated community conditions be connected without reducing one to another?

Such a problem requires a methodological approach capable of examining educational relationships while they are enacted and subsequently revised. Design-based research (DBR) connects theoretically informed design with implementation, systematic inquiry, and iterative refinement, making it possible to examine how design assumptions operate under authentic conditions (Obczovsky et al., 2025). Conjecture mapping strengthens this logic by specifying relationships among theoretical conjectures, design embodiments, mediating processes, and anticipated outcomes, allowing researchers to examine where an intended mechanism may be placed at risk during enactment (Tawfik et al., 2020). Multi-iteration research further demonstrates that conjectures and design structures can be reconsidered when evidence reveals discrepancies between anticipated and observed processes (Rehmat et al., 2024). If the central problem concerns how relationships among educational functions change when implementation reveals misalignment, then the methodological approach must be capable of tracing those relationships across successive configurations. DBR provides precisely this capacity.

Existing scholarship has therefore established several important components of the problem. Research explains how AI can personalize educational support, how learner agency may be strengthened or constrained, how humans can retain authority within AIED, and how educational ecosystems consist of interconnected technological and social components (Alfredo et al., 2024; Darvishi et al., 2024; Rojas & Chiappe, 2024). Human–AI collaboration research has also begun to investigate how artificial agents can participate in collective regulation rather than operate merely as

information-delivery tools (Edwards et al., 2025). What remains insufficiently explained is how the distribution and coordination of these educational functions can themselves be reconfigured when enactment evidence reveals relational misalignment. The unresolved issue is therefore not simply whether humans should remain *in the loop* or whether AI should become more personalized, but whether the relationships among technological assistance, pedagogical authority, learner participation, continuity, peer support, and situated action can become responsive to evidence generated through authentic learning.

This study addresses that gap through a two-cycle DBR investigation of an AI-supported, human-mediated learning ecosystem in urban non-formal education. The initial configuration combined bounded AI assistance, human eco-facilitation, experiential transferable life-skills development, and situated enactment rather than positioning AI as the primary pedagogical agent. Cycle 1 was used to examine how those intended relationships operated under authentic conditions, while Cycle 2 represented an evidence-informed structural reconfiguration rather than an experimental treatment intended to establish comparative effectiveness. Cross-cycle analysis consequently focused on whether implementation evidence altered the distribution and coordination of educational functions. The study develops relational adaptivity from this empirical progression to describe the capacity of a learning ecosystem to reconfigure educational relationships in response to evidence about how intended learning processes are actually enacted.

The study was guided by the following central research question (RQ):
How can AI support, human eco-facilitation, transferable life-skills development, and community-based enactment be configured and iteratively redesigned as an integrated learning ecosystem for urban non-formal education?

Two subsidiary questions guided the empirical progression:
RQ1. What contextual requirements and relational tensions emerged when bounded AI support, human eco-facilitation, transferable life-skills development, and situated enactment were configured and implemented during the first DBR cycle?
RQ2. How did evidence from these implementation tensions inform the redistribution and recoordination of educational functions in the second DBR cycle?

2. Method

Research Design

This study employed a two-cycle design-based research (DBR) approach to develop and examine an AI-supported, human-mediated learning ecosystem in urban non-formal education. DBR integrates theory-informed design, authentic implementation, systematic inquiry, and iterative redesign (Hoadley & Campos, 2022; Jacobsen & McKenney, 2024; Obczovsky et al., 2025). Cycle 1 examined the initial design, while Cycle 2 introduced evidence-informed modifications rather than serving as an experimental comparison (Tawfik et al., 2020; Tinoca et al., 2022; Rehmat et al., 2024).

Research Context and Participants

The study involved 24 eco-facilitators across 24 community settings in five urban and peri-urban areas of Jabodetabek, Indonesia. They developed 269 profiles of youth aged approximately 16–30 to identify life-skill priorities, learning preferences, digital conditions, and community needs. Individual profiles and community mapping

were analyzed separately because they represented different analytical levels (Jacobsen & McKenney, 2024; Obczovsky et al., 2025). All facilitators continued into Cycle 2, reorganized into 10 teams. Differences in document counts reflected joint or individual submissions, not participant attrition.

Initial Design Conjecture

The initial design integrated five functions: contextual grounding, bounded AI support, human eco-facilitation, experiential life-skills development, and situated enactment. AI supported selected cognitive tasks, while facilitators retained responsibility for interpretation and participation. These functions were not assumed to produce automatic causal effects, consistent with human-centered AIED principles emphasizing human judgment and contextual conditions (Obczovsky et al., 2025; Tawfik et al., 2020; Alfredo et al., 2024; Fu & Weng, 2024).

AI Role and Functional Boundaries

AI supported drafting, information organization, activity ideation, categorization, tabulation, preliminary synthesis, and field documentation. Human responsibilities included contextual interpretation, pedagogical judgment, relational mediation, and learning decisions (Alfredo et al., 2024; Fu & Weng, 2024; Holmes et al., 2022). An audit of AI prompts covered 10 of 24 facilitator worksheets and was treated as illustrative rather than exhaustive evidence of implementation (Alfredo et al., 2024).

Data Analysis

Analysis involved five stages: (1) descriptive analysis of learner and community contexts; (2) qualitative examination of implementation tensions; (3) comparison of individual and community evidence while maintaining distinct analytical levels; (4) comparison of actual implementation with the initial design conjecture; and (5) tracing how Cycle 1 evidence informed Cycle 2 redesign. Qualitative interpretation acknowledged the researcher's role in identifying patterns (Braun & Clarke, 2021), while conjecture mapping clarified relationships between design features and expected learning processes (Tawfik et al., 2020). Evidence-to-redesign tracing ensured transparency between empirical findings and subsequent design decisions (Obczovsky et al., 2025).

3. Result and Discussion

Contextual Requirements for Ecosystem Design

Contextual grounding across 269 individual profiles and 24 community settings revealed substantial heterogeneity in participants' self-recognized developmental priorities. Assertive communication was the most frequently identified transferable life-skill priority (43.5%), followed by financial literacy (33.5%), future or career planning (29.7%), emotional and stress management (27.5%), digital literacy (27.1%), confidence and public speaking (26.4%), and problem solving (25.7%). By contrast, ecological or social-environmental concern appeared as a personally stated priority in only 0.4% of individual profiles. These findings indicated that participants entered the learning ecosystem primarily through immediately perceived personal-development needs rather than through explicitly environmental concerns.

Community-level evidence, however, revealed a different pattern. Mapping conducted independently across the 24 facilitator settings identified waste accumulation, flooding, and poor drainage as prominent local problems in 17 communities, or 71% of the mapped settings. The contrast between the 0.4% individual expression of ecological concern and the 71% community-level presence of environmental problems indicated that personally recognized learning priorities and locally visible collective conditions did not automatically converge. The two evidence levels therefore represented different forms of contextual relevance and were retained as analytically distinct rather than combined into a single indicator.

Learning preferences introduced a second design requirement. Direct practice was preferred by 41.6% of participants, followed by mentoring (20.4%) and two-way discussion (20.4%), whereas short videos (12.6%) and educational games (6.3%) were selected less frequently. Smartphone ownership was near universal, but internet stability and device capability varied, and digital activity was predominantly consumption-oriented rather than production-oriented. These patterns favored an experiential and dialogic learning design while also indicating that technological support needed to remain lightweight, flexible, and compatible with familiar digital practices.

Taken together, the grounding evidence generated four initial design requirements. First, heterogeneous life-skill priorities required multiple learner-responsive entry points rather than a standardized competency pathway. Second, preferences for practice, mentoring, and two-way discussion supported experiential and dialogic learning. Third, uneven digital conditions required flexible technological support rather than a design dependent on sophisticated infrastructure. Fourth, the divergence between individual priorities and community conditions required a deliberate bridge between personal relevance and situated community enactment.

Table 1. Contextual Evidence and Initial Ecosystem Design Requirements

Contextual dimension	Empirical evidence	Initial design requirement
Transferable life-skill priorities	Communication 43.5%; financial literacy 33.5%; career planning 29.7%; emotional/stress management 27.5%; digital literacy 27.1%; problem solving 25.7%	Multiple learner-responsive entry points
Learning preferences	Direct practice 41.6%; mentoring 20.4%; two-way discussion 20.4%	Experiential and dialogic learning
Digital conditions	Near-universal smartphone access with variable connectivity and device capability	Flexible and technologically lightweight support
Community conditions	Environmental problems identified in 17 of 24 settings	Context-sensitive opportunities for situated enactment
Individual–community relationship	Ecological concern identified by only 0.4% of individual profiles despite environmental problems in 71% of communities	Deliberate connection between personal relevance and community conditions

Note. Individual percentages use the 269 profiles as denominator; community observations use 24 settings. These evidence levels were not aggregated because they represented different analytical units.

The contextual evidence therefore did more than describe participants. It established the design conditions under which an AI-supported learning ecosystem would need to operate. In particular, it revealed a central relational problem: personally meaningful learning, technological support, and community relevance could not be assumed to align automatically.

Initial Bounded-AI, Human-Mediated Architecture

The contextual requirements were translated into an initial ecosystem architecture that distributed educational functions across technological, human, experiential, and community components. Rather than positioning AI as the principal instructional agent, the design assigned AI a bounded supporting role. AI assisted with information organization, activity ideation, categorization, tabulation, and preliminary synthesis, while contextual interpretation, pedagogical judgment, relational mediation, and decisions about learning activities remained human responsibilities.

Human eco-facilitation formed the principal mediating function between technological assistance and participants' learning experiences. Facilitators used grounding information to identify relevant learning entry points, organize dialogue, accompany experiential activities, observe participation, and support reflection. Transferable life-skills development provided the experiential capacity-building component, with activities organized around recognizable everyday needs rather than standardized content sequences. Situated enactment was positioned as the potential extension of learning into personal and community situations.

The architecture therefore connected five differentiated functions: contextual grounding → bounded AI support → human eco-facilitation → experiential transferable life-skills development → situated enactment. These functions were connected conceptually but were not treated as a deterministic causal chain. The design did not assume that AI assistance would independently improve learning, that facilitator involvement would automatically preserve learner agency, or that transferable capacities would inevitably result in community action.



Figure 1. Initial Architecture of the AI-Supported, Human-Mediated Learning Ecosystem

Note. The initial architecture integrates contextual grounding, bounded cognitive AI support, human eco-facilitation, experiential transferable life-skills development, and situated enactment. Arrows represent intended functional relationships and design progression rather than empirically established causal pathways.

Authentic implementation was therefore necessary to determne whether these intended relationships were sufficiently specified. This became particularly important because none of the 22 documented Cycle 1 programs explicitly adopted an environmental theme despite environmental problems being visible across 17 of the 24 mapped communities. The initial architecture successfully differentiated educational functions, but enactment was required to determine whether those functions were adequately connected in practice.

Relational Tensions During Authentic Enactment

Cycle 1 revealed a persistent tension between the intended dialogic role of eco-facilitation and the interaction patterns reported during implementation. At least 20 of the 23 post-implementation reflection records identified a risk of facilitation reverting toward *pendekatan menggurui*, or didactic instruction. The 23 reflection records represented the 24-facilitator cohort because one shared hub submitted a joint retrospective worksheet rather than separate documents. Although these reflections were not direct behavioral observations, the recurrence of the pattern across records indicated that formally assigning human pedagogical authority did not itself ensure learner-responsive enactment.

A second tension concerned the relationship between facilitator expertise and learner agency. Reflection records indicated that when facilitators possessed considerably greater technical knowledge than participants, interaction could shift toward explanation and information delivery. By contrast, situations grounded in experiences participants had personally encountered created stronger opportunities for learners to contribute interpretations and practical knowledge. The problem was therefore not expertise itself but the way expertise was positioned relative to learner contribution.

A third tension concerned dialogic participation. Open discussion created opportunities for interaction but could also advantage participants who were already confident in speaking. Less assertive participants did not necessarily obtain equivalent opportunities simply because a discussion format was available. The finding suggested that dialogic design required more than an invitation to participate; participation itself needed active facilitative support.

A fourth tension involved temporal continuity. Reflection records repeatedly indicated that the duration of engagement was perceived as insufficient and that follow-up support was needed after formal activities. The issue was not simply whether a learning session was completed, but whether participants had sufficient opportunities to revisit, practice, and sustain emerging capacities beyond the immediate facilitated encounter.

The fifth tension concerned the relationship between capacity development and situated enactment. Environmental problems were present in 17 of 24 mapped communities, yet ecological concern appeared in only 0.4% of individual learning priorities, and none of the 22 Cycle 1 programs explicitly centered an environmental theme. These patterns did not indicate that participants lacked environmental concern or that transferable life-skills development had failed. Rather, they demonstrated that

the relationship between personally meaningful capacity development and community-level application remained insufficiently specified within the initial architecture.

Table 2. Relational Tensions and Intended Mechanisms at Risk During Cycle 1

Relational tension	Empirical indication	Intended mechanism at risk	Inferential boundary
Instructional residue	≥20/23 reflection records identified didactic tendencies	Learner-responsive mediation	Reflective accounts, not direct behavioral observation
Expertise–agency tension	Explanatory dominance when facilitators held greater technical expertise	Co-construction and learner contribution	Does not establish a causal effect of expertise
Uneven dialogic participation	More confident participants could dominate discussion	Equitable participatory agency	Illustrative rather than prevalence estimate
Limited temporal continuity	Reflection records called for extended or follow-up support	Continuity and transfer	Longer duration cannot be assumed to improve outcomes
Capacity–enactment gap	Environmental problems in 17/24 communities; ecological priority 0.4%; environmental themes 0/22 Cycle 1 programs	Situated enactment	Does not demonstrate absence of environmental concern or failure of life-skills development

The analytical significance of these findings was not that Cycle 1 had failed. Rather, authentic enactment made the relationships anticipated by the initial design conjecture empirically inspectable. Instructional residue placed learner-responsive mediation at risk; expertise dominance challenged co-construction; uneven discussion exposed participation inequities; limited follow-up revealed a continuity problem; and the capacity–enactment gap showed that community application required more explicit architectural support.

Evidence-Informed Structural Reconfiguration

Cycle 1 tensions were interpreted as evidence about relationships within the ecosystem rather than as isolated implementation deficiencies. Cycle 2 therefore did not focus solely on changing activities, materials, or technological features. Instead, redesign altered several structural dimensions simultaneously, including facilitation, observation, reflection, temporal continuity, peer involvement, and opportunities for situated enactment.

The first reconfiguration concerned facilitation. The 24 facilitators were reorganized into 10 teams of two to three members, distributing responsibilities that had previously been concentrated more heavily within individual facilitators. At least five teams explicitly incorporated norms against didactic instruction and deficit framing into their working agreements. The change did not establish that team facilitation was inherently superior; rather, it made pedagogical enactment more available for collective observation, reflection, and adjustment.

The second reconfiguration addressed temporal continuity. Eight of the 10 teams incorporated a Week 4 reflection-and-regeneration structure in which one or two learners within each participating hub were designated as peer facilitators (*kader sebaya*). These peer roles were intended to provide light-touch continuity after formal facilitator involvement. Responsibility for continuity therefore became less

exclusively dependent on external facilitators and more distributed within the participant structure.

The third reconfiguration concerned the relationship between personally meaningful learning and community enactment. Cycle 2 retained transferable life skills as learner-responsive entry points but introduced shared-value framing and an explicit social-economic-ecological action component. Environmental concern was incorporated into the redesigned configuration, and subsequent hub-level social-contract documentation showed that environmental concern was selected as a shared value in 22 of 25 worksheets (88%). The redesign therefore made community relevance more explicit without replacing learner priorities with a predetermined environmental curriculum.

A fourth reconfiguration involved observation and reflection. Shared facilitation created opportunities for team members to observe how activities were enacted and to reflect collectively on participation, facilitation style, and emerging difficulties. This moved some aspects of pedagogical regulation from individual self-monitoring toward distributed observation and discussion.

Across these changes, the AI boundary remained comparatively stable. AI continued to function as bounded cognitive support rather than acquiring greater pedagogical authority. The principal change therefore occurred not in technological autonomy but in the distribution of facilitation, observation, continuity, peer participation, and situated action.

Table 3. Evidence-Informed Structural Reconfiguration From Cycle 1 to Cycle 2

Cycle 1 evidence	Relational diagnosis	Documented Cycle 2 response	Function reconfigured
Instructional residue	Human authority alone did not consistently sustain dialogic mediation	Team facilitation; anti-didactic/non-deficit norms in ≥5/10 teams	Facilitation and pedagogical reflection
Expertise–agency tension	Interpretive participation could become concentrated in facilitators	Shared facilitation and observation	Interpretation, observation, mediation
Limited continuity	Support remained heavily facilitator-dependent	Four-week rhythm and reflection/regeneration structure	Temporal support
Facilitator-dependent follow-up	Continuity lacked structural handover	Peer regeneration/*kader sebaya* in 8/10 teams	Continuity and coordination
Personal–community disconnect	Individual priorities and community conditions did not automatically converge	Shared-value framing and ecological concern within hub social contracts	Contextual connection
Under-specified enactment	Community application remained largely anticipated	Explicit social-economic-ecological action opportunity	Situated enactment
AI remained bounded	Observed tensions primarily concerned relational configuration	Continued bounded cognitive-support role	Technological authority remained bounded

Note. Cycle 2 modifications formed a coordinated redesign package. The table traces evidence-informed design reasoning and does not establish one-to-one causal effects between individual Cycle 1 findings and specific Cycle 2 modifications.

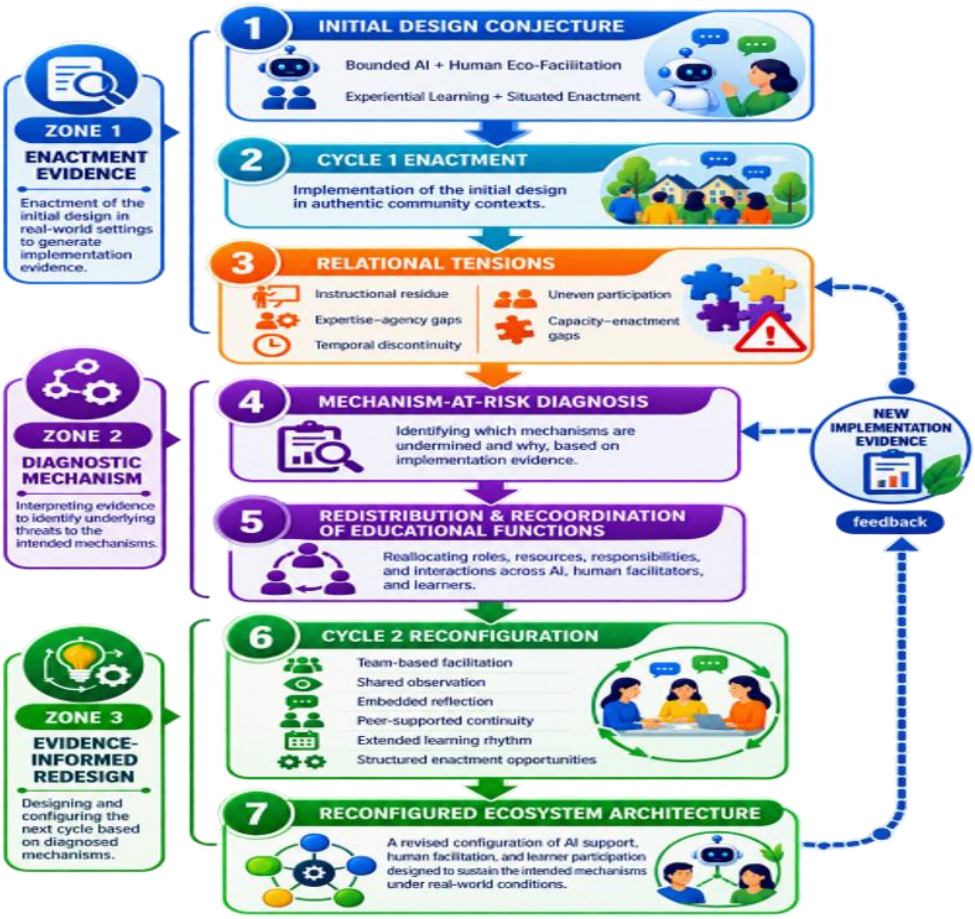

Figure 2. Eidence-Informed Reconfiguration Across the Two Design-Based Research Cycles

Note. Cycle 1 enactment generated evidence of relational tensions that was interpreted against intended learning mechanisms and subsequently informed redistribution and recoordination of educational functions in Cycle 2. The resulting configuration represents a reconfigured ecosystem architecture rather than evidence of improved learning outcomes. Arrows represent evidence-informed DBR reasoning and do not imply causal effects of individual modifications or comparative effectiveness between cycles.

Overall, the cross-cycle pattern showed that redesign involved redistribution and recoordination of educational functions rather than increased technological autonomy. Facilitation became more distributed, reflection became more embedded, continuity became partly peer-supported, and situated enactment became more explicitly structured. AI remained functionally bounded throughout this reconfiguration. The principal empirical shift therefore occurred in the relationships through which learning was organized, sustained, and connected to context, providing the foundation for the subsequent interpretation of relational adaptivity.

Discussion

Beyond Algorithmic Adaptivity

The findings indicate that adaptivity in AI-supported non-formal learning cannot be located exclusively in technological personalization. Contemporary AIED scholarship has moved beyond AI-directed learning toward configurations that

emphasize learner control, human–AI collaboration, and responsible limits on automation (Alfredo et al., 2024; Ouyang & Jiao, 2021). Yet the present study shows that the most consequential changes across the two DBR cycles occurred while the technological role of AI remained comparatively stable. AI continued to function as bounded cognitive support, whereas substantial redesign occurred in facilitation, observation, continuity, peer participation, and situated enactment. This pattern suggests that an educational ecosystem can become more adaptive without granting AI greater pedagogical autonomy.

This finding extends existing work on AI-enabled educational ecosystems. Rojas and Chiappe (2024) conceptualize AI as one component within interconnected educational digital ecosystems composed of users, services, resources, and environments. The present study adds a further proposition: not only can multiple components coexist within an ecosystem, but the relationships among their educational functions can themselves become objects of evidence-informed redesign. In Cycle 2, adaptation was expressed through the reorganization of facilitation, redistribution of responsibility for continuity, explicit structuring of peer roles, and stronger connections between personal learning and community enactment, rather than through increased algorithmic sophistication.

This distinction provides the basis for the construct of relational adaptivity. Relational adaptivity refers to the capacity of a learning ecosystem to reconfigure the distribution and coordination of technological assistance, human judgment, learner agency, and situated participation in response to evidence about how intended learning mechanisms are enacted. The construct does not replace algorithmic personalization, human-centered AI, or human–AI collaboration. Instead, it identifies an additional locus of adaptation at the level of educational relationships. The implication is that an AI-supported learning ecosystem should be evaluated not only by how accurately its technology responds to learners, but also by whether the ecosystem can revise its own relational arrangements when implementation reveals misalignment.

Scaffolded Human Authority

Cycle 1 sharpens an important distinction within human-centered AIED: retaining human authority is necessary but insufficient for learner-responsive enactment. The initial architecture deliberately reserved interpretation and pedagogical judgment for facilitators while bounding AI to cognitive-support functions. Nevertheless, at least 20 of 23 post-implementation reflection records identified tendencies toward didactic or *menggurui* facilitation. This pattern indicates that locating authority in human actors does not guarantee that pedagogical interaction will remain dialogic, participatory, or responsive to learner contribution.

This finding is consistent with research showing that AI-supported education can reshape learner–instructor relationships even when educators formally retain decision-making authority (Seo et al., 2021). It also aligns with recent work on teacher agency in AIED, which argues that educators themselves need opportunities to interpret, question, and shape AI-supported arrangements rather than simply occupy a nominally human-controlled position (Mouta et al., 2025). The present study extends this argument by showing that human authority must also remain open to scrutiny in relation to learner participation. The critical issue is therefore not only whether

humans retain control over AI, but whether the exercise of human authority enables learners to contribute meaningfully to educational interpretation and action.

The expertise–agency tension provides a more specific explanation. Reflection records suggested that when facilitators possessed considerably greater technical expertise, interaction could shift toward explanation-dominated patterns, whereas activities grounded in situations participants had personally experienced created stronger opportunities for learner contribution. Expertise itself was not problematic; the issue concerned how expertise was positioned relative to learners' experiential knowledge. In Cycle 2, team facilitation, shared observation, and explicit anti-didactic norms made pedagogical practice more visible to collective reflection.

These findings support the proposition of scaffolded human authority: human authority should be retained in AI-supported education, but it must also be observable, reflectable, and open to relational reconfiguration when its enactment constrains learner participation. This proposition qualifies a simplistic human-in-the-loop assumption. Human involvement is not automatically human-centered; it becomes human-centered when pedagogical authority is exercised in ways that remain accountable to learner agency and evidence from enactment.

Redistribution of Educational Functions

The transition from Cycle 1 to Cycle 2 indicates that relational adaptivity may operate through redistribution and recoordination of educational functions. Multiple actors were already present in the initial architecture, but their mere presence did not make the ecosystem relationally adaptive. Adaptation became visible when implementation evidence altered where responsibilities were located, how they were shared, and how different functions were connected.

This distinction separates distribution from redistribution. Distribution describes the existing allocation of functions; redistribution describes evidence-responsive changes in that allocation. In Cycle 2, facilitation shifted from primarily individual arrangements toward teams, continuity became partly supported by peer facilitators, reflection became more structurally embedded, and situated action became more explicit. At the same time, AI did not acquire additional pedagogical authority. The adaptive center of the ecosystem was therefore not the technology itself, but the reorganization of relationships through which educational work was carried out.

This interpretation is compatible with research on hybrid human–AI collaboration, which emphasizes that effective systems depend on the coordination of complementary capabilities rather than on maximizing automation (Edwards et al., 2025). It also resonates with human-centered AIED research that stresses the importance of distributing responsibility across technological and human actors in ways that preserve meaningful judgment and participation (Alfredo et al., 2024; Fu & Weng, 2024). The present study adds that such distributions should remain revisable when evidence indicates that intended educational processes are not being realized.

The resulting proposition is functional redistribution: a learning ecosystem becomes relationally adaptive when evidence from enactment can alter the distribution and coordination of educational functions across technological, human, learner, peer, temporal, and contextual structures. This proposition does not imply that team facilitation, peer cadres, or a four-week rhythm are universally superior

arrangements. Their significance lies in demonstrating that the ecosystem was able to reorganize functions in response to identified tensions.

Learner Agency as a Constitutive Function

The findings also clarify the role of learner agency within adaptive educational design. Contextual grounding did not merely collect information about participants so that a system could personalize what they received. Participants' stated priorities shaped learning entry points, while their experiences supplied material for dialogue, practice, and interpretation. Learner information therefore functioned both as design evidence and as a basis for participation in educational meaning-making.

This distinction matters because personalization and agency are not equivalent. Research on AI-supported learning shows that individualized assistance can coexist with reduced self-regulatory effort or increased reliance on technological support (Darvishi et al., 2024; Fan et al., 2025). Conversely, relational accounts of learner agency emphasize that agency emerges through opportunities to contribute, choose, interpret, and act within socially structured environments (Mairitsch et al., 2023). The Cycle 1 expertise–agency tension illustrates this problem: learners could remain formally central to the program while their experiential knowledge became less consequential when facilitation shifted toward explanation.

Cycle 2 redistributed additional functions toward learners through peer regeneration and situated participation. Eight of ten teams introduced *kader sebaya* roles to support continuity, while the redesigned architecture created more explicit opportunities for learners to connect capacity development with social-economic-ecological action. These changes do not establish that learner agency increased quantitatively, because agency was not measured through equivalent standardized instruments across the two cycles. They do, however, show that the architecture positioned learners as contributors to continuity, interpretation, and enactment rather than solely as recipients of support.

This supports the proposition of participatory learner agency: relational adaptivity requires learners to function as contributors to meaning-making, choice, continuity, and situated action, rather than merely as sources of data for personalization. The implication is that learner agency should be treated as part of the operating architecture of an adaptive ecosystem, not simply as an outcome that the system seeks to improve.

Situated Participation

The divergence between individual learning priorities and community conditions demonstrates why the adaptive unit cannot be restricted to learner–technology interaction. Only 0.4% of individual profiles identified ecological or social-environmental concerns as personal priorities, whereas environmental problems were documented in 17 of 24 community settings. Designing solely around individually expressed priorities could therefore preserve immediate relevance while leaving broader community conditions disconnected from learning. Conversely, imposing community priorities regardless of learner interests could weaken personal meaning and agency.

Cycle 2 addressed this tension architecturally rather than by replacing learner-responsive life-skills development with a predetermined environmental curriculum. Shared-value framing and an explicit social-economic-ecological action component

created a structured interface between personal capacity development and community circumstances. Environmental concern appeared as a shared value in 22 of 25 hub-level social-contract worksheets. The importance of this finding lies not in proving sustained environmental behavior, which the study did not measure, but in showing that situated enactment moved from an implicit expectation toward an explicit design component.

This finding aligns with relational conceptions of learning and agency, in which action acquires meaning through interaction with social and contextual affordances rather than through individual capacity alone (Mairitsch et al., 2023). In non-formal education, such contextual embedding is particularly relevant because learning often crosses boundaries between facilitated activity and everyday community life (Christidou et al., 2022; Tisza et al., 2020). Context thus functions not only as the location where learning is applied but also as a source of evidence about whether existing support structures remain adequate.

The resulting proposition is situated adaptation: when educational purposes require capacities to operate beyond the facilitated learning encounter, relational adaptivity requires explicit opportunities for situated participation. Through such participation, learners encounter authentic social and community conditions, while those encounters generate new evidence that may inform further redesign. In this sense, context becomes both a site of enactment and a potential feedback source for adaptation.

DBR as Mechanism-Diagnostic Inquiry

The two-cycle process also demonstrates how DBR can function as a form of mechanism-diagnostic inquiry. The analytical value of Cycle 1 did not depend on whether the intervention could be judged globally successful or unsuccessful. Instead, authentic enactment made it possible to compare intended relationships with documented implementation and identify where mechanisms were placed at risk.

This use of DBR is consistent with contemporary design-research methodology, which emphasizes traceability between theoretical assumptions, design decisions, enactment, evidence, and redesign (Obczovsky et al., 2025). Conjecture mapping further supports this form of inquiry by making explicit how particular design embodiments are expected to activate mediating processes, allowing discrepancies between intention and enactment to become analytically visible (Tawfik et al., 2020). Multi-cycle research similarly shows how conjectures can be revised as evidence accumulates across iterations (Rehmat et al., 2024).

In the present study, this logic can be represented as:

design conjecture → enactment → relational tension → mechanism-at-risk diagnosis → redistribution/recoordination → reconfiguration

The sequence shifts attention from whether an educational intervention "worked" to how and where its intended relationships became vulnerable during enactment. Instructional residue indicated risk to learner-responsive mediation; expertise dominance indicated risk to co-construction; limited follow-up indicated risk to continuity; and the capacity–enactment gap indicated risk to situated participation. These diagnoses then informed structural changes in Cycle 2.

The methodological contribution is not to claim that mechanism diagnosis is a newly invented function of DBR. Rather, the contribution lies in making relational configuration itself the object of diagnosis. The study asks who interprets, facilitates,

observes, sustains participation, and creates opportunities for enactment, and whether those functions require redistribution. This reframing may be useful for other AI-supported educational settings in which the central problem concerns not a single technological feature but the coordination of multiple educational actors and functions.

Theoretical Contribution and Boundary Conditions

The principal theoretical contribution of the study is to relocate part of the adaptive function from technological personalization toward the relationships through which educational functions are coordinated. Existing AIED research explains how AI can personalize learning, how human-centered approaches can preserve human control, and how learner agency can be supported within AI-mediated environments (Alfredo et al., 2024; Darvishi et al., 2024; Fu & Weng, 2024). Educational ecosystem research further establishes that technological and human components should be understood as interconnected rather than isolated (Rojas & Chiappe, 2024). Relational adaptivity extends these perspectives by asking whether those relationships themselves can become responsive to implementation evidence.

The construct is analytically distinguishable from ordinary iterative improvement. Changing an interface, activity, prompt, or resource does not necessarily constitute relational adaptation. Three elements are required: evidence of enactment, diagnosis concerning relationships among educational functions, and subsequent redistribution or recoordination of those functions. This formulation preserves algorithmic adaptivity as one legitimate form of responsiveness while refusing to assume that AI must always constitute the primary locus of adaptation. Figure 3 synthesizes this construct as an ecosystem-level design model.

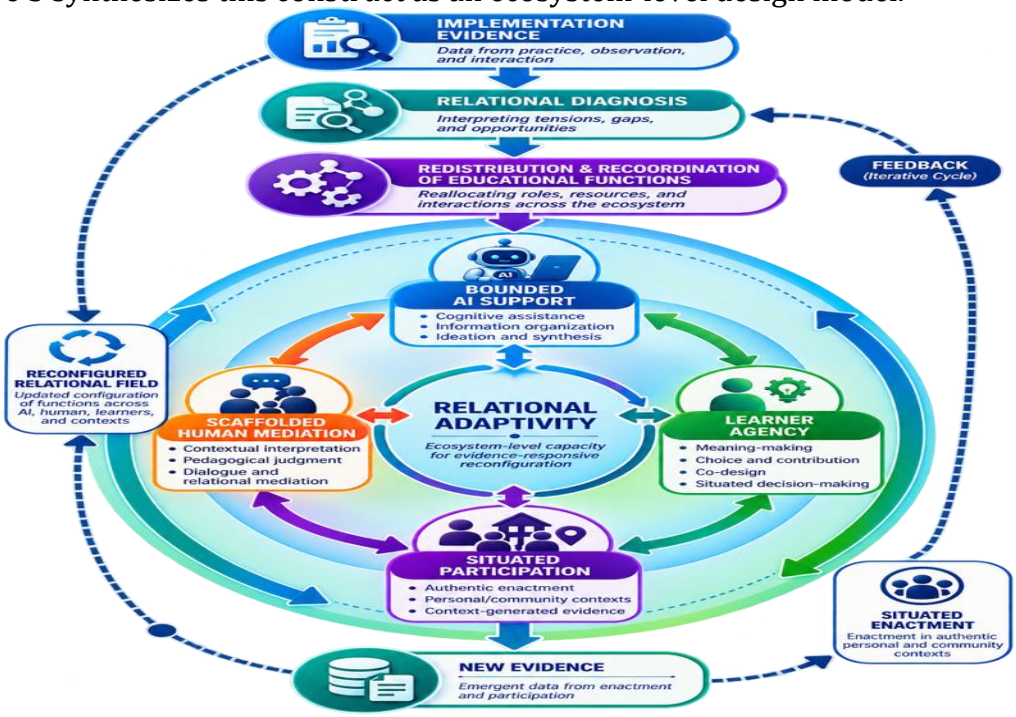

Figure 3. Relational Adaptivity as an Ecosystem-Level Design Construct

Note. Relational adaptivity represents the evidence-responsive capacity of a learning ecosystem to reconfigure the distribution and coordination of educational functions. In this study, the construct is organized around four substantive components—

bounded AI support, scaffolded human mediation, learner agency, and situated participation—and three process elements—implementation evidence, relational diagnosis, and redistribution or recoordination of functions. The arrows indicate iterative and evidence-informed reconfiguration across the ecosystem rather than deterministic causal effects or a fixed developmental sequence. The figure is a theoretical synthesis derived from the study's cross-cycle analysis and is intended to clarify the construct, not to claim universal validity or causal superiority of any specific arrangement.

The concept nevertheless remains provisional. It was derived from one urban non-formal education setting in which AI was deliberately bounded, human facilitation was central, and learning was intended to extend toward community contexts. Documentary units varied across stages; several tensions relied substantially on facilitator reflections rather than direct observational evidence; the close audit of actual AI prompting covered only a subset of available records; and multiple Cycle 2 modifications were introduced simultaneously. These conditions prevent causal attribution to individual redesign features and limit claims of statistical generalizability.

Accordingly, the study advances analytical and conditional generalization rather than a universal theory. Relational adaptivity should be examined in formal schooling, higher education, workplace learning, online environments, and settings in which AI is granted greater autonomy. Future research should also employ stronger observational, longitudinal, and comparative designs to examine whether particular forms of functional redistribution are associated with measurable changes in learner agency, continuity, participation, learning outcomes, or situated action.

The theoretical implication is therefore deliberately bounded. Relational adaptivity does not suggest that every educational function should be redistributed in every iteration, nor that team facilitation, peer cadres, or community action structures are universally superior. It proposes instead that an AI-supported learning ecosystem becomes relationally adaptive when evidence about enactment can inform diagnosis of how educational functions are coordinated and when that diagnosis can lead to their reconfiguration. This shifts the central design question from *How should AI adapt to the learner?* toward *What within the learning ecosystem needs to adapt when intended educational relationships are not being enacted as anticipated?*

4. Conclusion

This two-cycle design-based research (DBR) study examined how bounded AI support, human eco-facilitation, transferable life-skills development, and community-based enactment could be integrated into an urban non-formal learning ecosystem. Contextual grounding involving 269 learner profiles and 24 community settings highlighted diverse learning priorities, preferences, digital conditions, and community needs. Accordingly, AI was positioned as a cognitive-support resource, while interpretation, pedagogical judgment, and relational mediation remained human responsibilities.

Cycle 1 revealed challenges involving didactic instruction, facilitator dominance, uneven participation, limited continuity, and weak connections between capacity development and community enactment. Cycle 2 addressed these challenges through team-based facilitation, shared reflection, peer-supported continuity, extended

learning activities, and more explicit opportunities for situated enactment, while maintaining the existing AI functional boundaries.

These findings underpin relational adaptivity, defined as the capacity of a learning ecosystem to reorganize technological assistance, human judgment, learner agency, and contextual participation in response to implementation evidence. Four propositions inform this concept: (1) scaffolded human authority, ensuring pedagogical judgment remains responsive to learner participation; (2) functional redistribution, reallocating educational responsibilities based on evidence; (3) participatory learner agency, positioning learners as contributors to meaning-making and learning continuity; and (4) situated adaptation, deliberately designing opportunities to apply learning in authentic contexts.

The findings must be interpreted cautiously because the cycles were not equivalent experimental conditions, documentary units varied, some evidence relied on facilitator reflections rather than systematic observation, and multiple redesign changes occurred simultaneously. Therefore, the study does not establish Cycle 2's causal superiority or validate relational adaptivity as a general theory. Instead, it proposes an empirically grounded construct for further investigation across educational and workplace settings.

The principal implication is that adaptive education requires more than personalizing technology. It also requires learning ecosystems capable of identifying and reorganizing relationships among AI, facilitators, learners, peers, and community contexts to support meaningful participation, continuity, and practical application.

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