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CULTIVATING PARTICIPATORY LEARNING ECOLOGIES: SOCIAL NETWORK ANALYSIS OF PEER-DRIVEN LEARNING NETWORK

Arief Budiman	Universitas Prasetiya Mulya, Tangerang, Indonesia	arief.budiman@prasetiyamulya.ac.id
Nur Aini Rakhmawati*	Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia	nur.aini@its.ac.id
Diana Purwitasari	Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia	diana@its.ac.id

* Corresponding author

ABSTRACT

Aim/Purpose	This study examines the role of peer networks in promoting social learning to address Veo3 (a web-based artificial intelligence (AI) video generation tool) rather than common top-down formal learning interventions.
Background	In a top-down formal learning intervention where the instructor is only present in a workshop, the teaching methods only outline how to write prompts. The instructor has little idea about the product or culture. This limitation hinders micro-entrepreneurs' ability to create contextually appropriate advertising content while experimenting with or implementing Veo3 prompts.
Methodology	A mixed-methods approach was utilized, integrating post-workshop retrospective interviews with SNA facilitated by Neo4j. The research included halal food craftsmen, participants from Kuningan, Indonesia, who participated in the Veo3 advertising workshop. Coding reliability was delivered through inter-coder agreement of $\alpha = 0.928$. We used SNA metrics, such as betweenness centrality, eigenvector centrality, and Louvain community detection, to create a quantitative map of the network structure before and after the formal top-down workshop.
Contribution	The primary contribution of this study lies in social learning theory, which provides empirical evidence that individuals acquire influence and knowledge

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	through participation and collaboration in a peer-driven, participatory learning ecology rather than through a top-down pre-workshop learning ecology.
Findings	The post-workshop peer-driven learning ecology encountered significant transformation in comparison to the pre-workshop learning ecology. The results support the following main hypothesis: (1) influence shifted from hierarchical figures (high betweenness) to active collaborators (high eigenvector centrality); (2) a core participatory sub-community emerged, while non-active participants were peripheral; and (3) this restructured network directly enabled sophisticated, iterative, and culturally grounded AI creation workflows among artisans.
Recommendations for Practitioners	Learning designers must prioritize making "community share abilities" participatory design that requires peer interaction before central instruction. Practitioners should design collaborative tasks that generate practice-based network edges, connect learners directly to institutional resources, and monitor network health using centrality metrics to identify structural vulnerabilities.
Recommendations for Researchers	Researchers need to examine the long-term impacts of these network structures on the resilience and cultural preservation of individual learners, as well as how this peer-driven learning ecology may enhance the workflows of advanced culturally grounded AI creation.
Impact on Society	When micro-entrepreneurs use Veo3 as an AI tool to preserve their culture and promote products relevant to their audience, this approach encourages individuals' computational empowerment.
Future Research	In the future, researchers should (1) use longitudinal SNA to determine out how long peer-driven learning ecologies last and how they affect business results and cultural preservation by examining how incremental individuals' computational empowerment affects them, (2) create more detailed SNA edge definitions to tell the difference between types of interaction (such as "help-seeking" and "co-creation"), and (3) set up standard procedures for turning qualitative data into network parameters so that studies can be compared.
Keywords	computational empowerment, learning ecology, social network analysis, participatory design, micro-small entrepreneurs, Neo4j

INTRODUCTION

Indonesian artisanal micro-small entrepreneurs (MSEs) face a dilemma when adopting AI marketing tools (Boussioux et al., 2024). Top-down workshops create three failures. First, instructors lack cultural knowledge to contextualize training (Kim et al., 2020; Seifert, 2016). Second, isolated learning prevents peer observation and modeling (Sasson Lazovsky et al., 2025). Third, artisans cannot translate generic templates into culturally authentic content (Edgell & Lee, 2023; Pan et al., 2025; Zhou et al., 2023). The result was technical skills without practical application. This disparity between classroom instruction and hands-on practice reveals a fundamental problem that instructional designers need frameworks that treat learning as dynamic and interconnected rather than hierarchical and discrete. The learning ecology framework (LEF) provides this perspective by positioning learning within multifaceted ecologies, where formal workshops, peer networks, and digital platforms interact to shape individual pathways (Barron, 2006; McCallen et al., 2019; Tidball & Krasny, 2011). The LEF identifies what constitutes a learning ecology.

Human-centered AI (HCAI) principles determine how interventions are designed within these ecologies (Knight et al., 2023; Schou et al., 2022; Susanty, 2024; Wasim et al., 2024) to preserve cultural authenticity while enabling technological adoption. The HCAI principles put learners at the center of ecology, not technology, by involving all participants and facilitating dialogues among various communities with varying interests (Memon & Memon, 2024). In this ecology, peer networks are important for sharing best practices, speeding up learning, and increasing motivation and self-efficacy in using prompt engineering (Anugerah et al., 2022; Mzwri & Turcsányi-Szabo, 2025; Wasim et al., 2024). Therefore, the main challenge is not only providing training but also actively developing and studying this learning ecology.

Social creativity emerges when individuals generate novel ideas through collaborative interactions within their community (Barrett et al., 2021). This process depends on shared knowledge, collective task completion, and cultural exchange among the network members (Tan et al., 2022). These structures are provided by social networks by facilitating information exchange, computational empowerment, and collaborative cultural preservation (KC et al., 2019; Wasim et al., 2024). However, empirical evidence is scarce (Cooper et al., 2023; Gilfoyle et al., 2022; Maya-Jariego, 2025; Shahreza et al., 2024; Ulug et al., 2025; van den Berk Clark et al., 2024). We lack quantitative proof that participatory interventions restructure social networks. Do participatory workshops actually restructure peer networks? Does network restructuring enable culturally-grounded AI adoption? Previous studies have conceptually described learning ecologies but rarely quantitatively measured network transformation (Topali et al., 2025). Addressing this gap requires both a theoretical framework that explains how learning occurs in networks and a methodological approach for designing interventions.

The learning, design, and technology (LDT) paradigm functions as both a framework and a methodology for learning ecology construction, highlighting human-centered and peer-driven learning ecologies as participatory design (Wu & Wang, 2024). Participatory design (PD) represents a fundamental methodological approach within LDT, particularly for creating human-centered learning ecologies (Gautam, 2024; Stone et al., 2018).

This study addresses this gap. We investigate how Indonesian artisans transform social learning networks through participatory design workshops. Using social network analysis (SNA), we measure whether the designed interventions shift influence from hierarchical figures to collaborative peers, enabling authentic AI adoption. This study's research question is how PD influences the social network structure for individuals' computational empowerment while maintaining cultural authenticity for promotional content creation.

THEORETICAL FRAMEWORK

This study employs a multi-theoretical framework to implement HCAI through social learning theory (SLT), the learning ecology framework (LEF), and participatory design (PD) principles. This combination provides researchers with a complete framework to answer the research question regarding how to preserve cultural heritage while also encouraging computational empowerment as a skill.

THE GUIDING PRINCIPLE OF HUMAN-CENTERED AI

HCAI places human-centered AI learning ecosystems at the top of its priorities. These ecosystems should augment human capabilities, align with human values, facilitate agency and governance, and maintain transparency and integrity (Shneiderman, 2020). HCAI establishes an ethical foundation that ensures AI tools augment human capabilities, align with human values, facilitate agency and governance, and maintain transparency (Hu et al., 2025; Putjorn et al., 2024; Wu & Wang, 2024). Incorporating technology poses risks for Indonesian artisanal MSEs, including cultural erasure and disempowerment. The intervention design emphasized human agency via participatory workshops, concentrated on augmentation rather than substitution, and ensured human oversight through iterative workflows. Therefore, HCAI functions as an ethical necessity to ensure that AI tools enhance capabilities transparently while preserving cultural authenticity (Giannakos, Horn, et al., 2025; Ozmen Garibay et al., 2023; Shneiderman, 2020).

THEORETICAL PILLARS WORKING TOGETHER

Social learning theory

Through observational learning and self-efficacy development, SLT elucidates the fundamental psychological mechanisms underpinning knowledge acquisition in entrepreneurial communities (Deguchi, 1984; Schunk & Hanson, 1985, 1989). Therefore, peer networks function as natural channels for SLT-driven processes and are strongly influenced by robust social connections and homophily (Becker et al., 2023; Ma et al., 2015). This idea makes peer learning more effective for observational learning (McIntyre-Mills et al., 2024). Although SLT explains the mechanism of social-based learning, it is not specific to how to design interventions that activate this mechanism in existing communities. Participatory design provides this methodological bridge.

Participatory design

The post-workshop intervention design demonstrates PD by moving beyond standard frameworks and placing artisans at the center of AI tool adoption through interactive sessions. These workshops exemplify co-design principles that prioritize user needs in developing AI-prompt engineering skills (Corazza et al., 2025). The sessions establish collaborative learning environments where participants explore AI applications while maintaining cultural preservation and integrating traditional patterns into AI-generated designs (He & Gao, 2025; Hu et al., 2025; Putjorn et al., 2024). PD represents a significant shift in how AI integrates with traditional artisanal practices by engaging all stakeholders in collective knowledge development (Gautam, 2024; Smith et al., 2020; Stone et al., 2018). This approach aligns with the principles of HCAI, which emphasizes the active role of humans (Shneiderman, 2020) by transforming artisans from passive recipients into active participants. However, PD interventions require a structural perspective to understand their systemic impact. The learning ecology framework provides an analytical perspective by mapping the distributed resources and relationships that restructure PD interventions.

Learning ecology framework

The LEF posits that learning is a complex, decentralized system comprising individuals, digital tools, and tangible environments (Barron, 2006). The LEF places learning within a complex structure where formal training events, informal peer networks, and digital platforms work together. This ecology includes face-to-face sessions, informal inter-peer knowledge exchanges, and digital access for artisanal MSME actors. These ecologies dynamically evolve through participant choice and interaction (Nofal, 2023; Putjorn et al., 2024).

We employed SNA to operationalize the LEF principles (Appendix A and B). Betweenness centrality measures information flow, identifies brokers, and reveals ecosystem fragility. Eigenvector centrality shows the power distribution, indicating whether the value derives from a hierarchical rank or collaborative activity. The Louvain community detection method identifies sub-communities or participatory niches, illustrating learner integration and isolation (Joksimović et al., 2016; Tabassum et al., 2018). This approach allows the study to move from a metaphorical understanding of a "learning ecology" to a quantitative analysis of its restructuring, directly testing the hypothesis that a participatory intervention changes the network topology.

THEORETICAL INTEGRATION AND RESEARCH GAPS

This research framework integrates HCAI and SLT with LEF and PD components to elucidate the learning mechanisms and facilitate the design, implementation, and evaluation of participatory learning ecology (Giannakos, Azevedo, et al., 2025). In this study, these four frameworks constitute a single conceptual framework, as shown in Table 1 and Figure 1. HCAI serves as the ethical basis for ensuring that interventions reinforce human agents rather than replacing them (Giannakos, Horn, et al., 2025; Ozmen Garibay et al., 2023). Furthermore, SLT explains the psychological processes involved in mastering learning through observation, imitation, and increased self-confidence. SLT answers the question of how individuals learn within networks (Bandura & Watts, 1996; Sabililhaq et al., 2024).

Table 1. A theoretical framework that guides the entire study

Theoretical framework	Primary role	Key concepts	Application to this study
Human-Centered AI (HCAI)	Philosophical guiding ethos	Human agency, supervision, ethical conduct, and enhancement of human skills.	The main goal is to create and develop AI prompt engineering skills that keep cultural authenticity and give artists more authority, making sure that technology meets human requirements.
Social Learning Theory (SLT)	Mechanism of learning	Learning by observing, modeling, vicarious reinforcement, and self-efficacy.	Describes how craftsmen develop AI prompt engineering skills by watching and working with other people and influential people in their network.
Learning Ecology Framework (LEF)	A structural model for analysis	Learning is distributed across actors (people), tools (technology), and environments (contexts).	Learning is spread among individuals (actors), tools (technology), and settings (contexts).
Participatory Design (PD)	Methodological approach	Working together, giving stakeholders authority, and being involved in the design process.	Frames the workshop intervention itself, putting craftsmen in the role of active co-designers who make and change AI prompt engineering to fit their own needs.

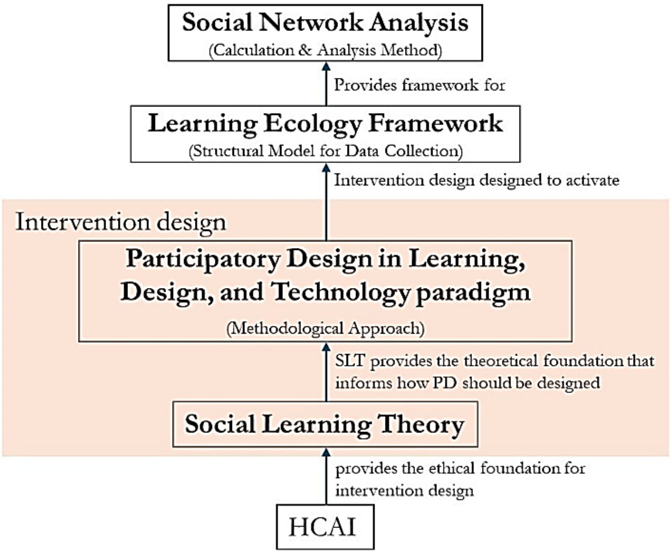


Figure 1. Integrated conceptual framework

The LEF provides a structural model for analyzing where these mechanisms operate. LEF maps the distributed actors, tools, and environments. The LEF answers the question of what constitutes a learning system. However, a significant research gap exists in the effective mapping and analysis of these complex, interconnected systems using SNA (Filvà et al., 2014). We employ SNA to operationalize the LEF by quantifying the network topology through centrality metrics and community detection (Filvà et al., 2014; Jan et al., 2019). SNA transforms the conceptual ecology of LEF into measurable network structures.

PD creates conditions that activate SLT processes within the LEF structure (Li, 2025; Olivares et al., 2024). PD designs collaborative tasks that deliberately generate network edges and reshape the ecology. PD guides the design of interventions that restructure networks. The integration operates cyclically, starting with PD interventions (method) that reshape the learning ecology (structure) and activate social learning mechanisms (process), all governed by human-centered principles (ethics). SNA is a diagnostic tool that reveals whether the designed interventions achieve the intended structural changes.

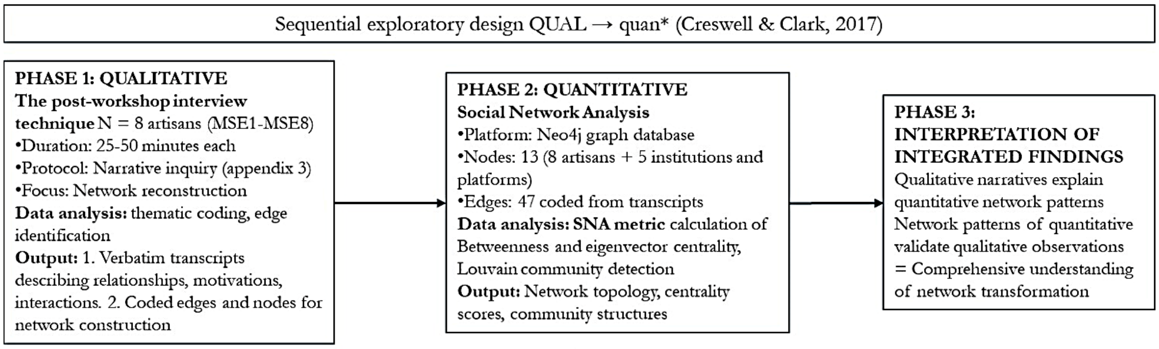
Research gap

However, three interconnected research gaps persist. First, a mechanistic gap exists regarding whether participatory interventions can shift the influence from hierarchical figures to collaborative peers (Hmelo-Silver & DeSimone, 2013). Second, a structural gap remains in quantitatively demonstrating how such interventions reconfigure the network topology in resource-constrained cultural communities (Franzato & Regina Diehl, 2025; Thamrin et al., 2019; Z. Zhao et al., 2020). Third, the outcome gap in linking network restructuring from PD intervention to tangible, culturally grounded creative outputs is underexplored (Bonazzi et al., 2024; Furtado & Payne, 2023; Nikolakopoulou & Koutsabasis, 2025; Thamrin et al., 2019; J. Wang, 2025). This study addresses these gaps by investigating whether PD workshop interventions can measurably restructure social networks via SNA, thereby facilitating the adoption of culturally authentic AI through activated peer learning within an artisan learning ecology.

The three hypotheses were tested. First, the balance of power will alter from centralized, hierarchical figures to active collaborators. Changes in betweenness and eigenvector centrality show this. Second, a core participating sub-community forms, defined by collaborative, task-based connections, while algorithms push those who do not participate to the edges. Third, this restructured network directly facilitates creative adaptation and computational empowerment grounded in culture. The subsequent methodology empirically tests this hypothesis and its constituent predictions.

METHODOLOGY

To test the hypothesis that a PD workshop reconfigures social learning networks, we employed a sequential exploratory research design (Figure 2) (Creswell & Clark, 2017). This method purposefully combined qualitative retrospective interviews with quantitative SNA to provide a comprehensive analysis of the learning ecology.



*Starts with qualitative to explore phenomenon, then uses qualitative insights to build quantitative instrument

Figure 2. Sequential exploratory research design

In the predecessor phase 1, the qualitative interviews using narrative protocols provided the researcher with the data to code into the SNA edges. In phase 2, quantitative SNA was generated to show that the structure of the learning network was altered and to investigate the ideas about community building and centrality directly. This integration of methods enabled the study to transcend the mere identification of network changes and to comprehend the underlying social processes.

Moreover, this study provides a comprehensive and nuanced understanding of how participatory interventions transform learning ecologies to promote computational empowerment, despite technological limitations.

RESEARCH PARTICIPANTS

This study was conducted between August and September 2025 in Kuningan Regency, West Java Province, Indonesia. The research setting was a five-day intensive workshop on Veo3 (Google's AI video generation tool) prompt engineering for promotional content creation, organized by Bank Indonesia (Indonesia's central bank) and the BelajarLagi community (a Jakarta-based educational organization) in Cirebon. We employed a two-stage sampling (Court et al., 2021). In stage one, cluster sampling was used to identify workshop participants from workshops organized across Indonesian regencies. We selected the Kuningan workshop cluster based on the following criteria: (1) homogeneous participant background (halal food artisans), (2) stable business operations (minimum of 3 years), and (3) active social media presence indicating digital readiness. In stage two, purposive sampling (Hutasuhut et al., 2023) was used to select the interview participants from the workshop cluster. The following were the selection criteria: (1) complete workshop attendance (5 days), (2) homework submission indicating engagement, (3) willingness to discuss peer interactions in detail (Maksum et al., 2020), and (4) active micro-enterprise operations at the time of study. The demographic characteristics of the eight participants are presented in Table 2.

Table 2. Participant characteristics (N=8)

Variable	n	%	M	SD	Range
Demographics					
Age (years)			36.5	9.2	24-52
Gender					
Female	5	62.5			
Male	3	37.5			
Business Profile					
Experience (years)			6.8	3.1	3-12
Product: Halal traditional foods	8	100			
Education					
High school	5	62.5			
Vocational diploma	1	12.5			
Bachelor's degree	2	25			
Technology Experience					
Prior experience with generative AI tools	0	0			
Use of social media tools	8	100			

M = mean, SD = standard deviation. All participants are artisanal micro-entrepreneurs in the halal food sector, Kuningan Regency, Indonesia.

The sample comprised artisanal micro-entrepreneurs operating traditional halal food businesses with products such as mie lidi, chili-based condiments, and keripik kangkung. None of the participants had prior experience with generative AI tools, although all of them used basic social media platforms for business promotion purposes. The workshop intervention was conducted as a five-day, on-site program in Cirebon. The workshop structure consisted of introductory training on Veo 3 basics and prompt writing during the first two days, followed by two days focused on integrating cultural content into AI-generated materials, and concluded with peer presentations and structured feedback on the fifth day. Following the in-person workshop, the participants received one month of additional support through weekly online mentoring sessions conducted via Zoom.

Our analysis examines the structure of the learning ecosystem with n=8 participants and uses qualitative narrative evidence to explain why these patterns were formed. This method is in line with exploratory SNA, which is most suitable for small and limited networks where the main objective is to document all the details of network restructuring rather than make generalizations about the population (Borgatti et al., 2024)

RATIONALE FOR TOOL SELECTION

The Neo4j graph database was selected over alternative SNA tools for four key methodological reasons (Anuyah et al., 2024; Chicho & Mohammed, 2023; Do et al., 2022; Ferencz et al., 2025). First, the original Neo4j graph architecture stores relationships as edges with specific properties. This enables algorithms, such as betweenness centrality, to be used on directed networks. Second, the Cypher query language has a clear syntax that makes it easy to build networks that are accurate and can be repeated after being transposed from qualitative code. Third, making nodes one after the other makes sure that calculations can be repeated. Fourth, the Neo4j Bloom app makes it possible to see graphs interactively, which helps with qualitative checks of network structures.

PROTOCOL FOR POST-WORKSHOP RETROSPECTIVE INTERVIEW

The post-workshop interview technique (shown in Appendix C) was reconstructed using the sample ego network technique (Tabassum et al., 2018). An ego network maps connections from one individual's perspective (ego) to all others with whom they interact (alters), creating a participant-centered view of the learning ecology. The questions produced data that could be classified according to SNA parameters, consistent with the theoretical framework (Appendix B). Employing narrative interview methodologies (Altissimo, 2016; Gola, 2009), participants were regarded as storytellers, authentically disclosing motivations, relationships, and processes.

THE SNA CODING PROTOCOL

The protocol transformed unprocessed qualitative data into structured quantitative data (Figure 3) for network mapping and metric analysis (Escobedo et al., 2024; Hamilton, 2020) (Appendix D). People became nodes, relationships became edges, and the interaction frequency was measured as the edge weight (Ando et al., 2021). Appendix E shows how verbatim transcripts were used to code the edges. Directed graphs with grouped nodes and coded edges were generated using Neo4j Bloom for viewing them and the Neo4j browser to perform the calculations.

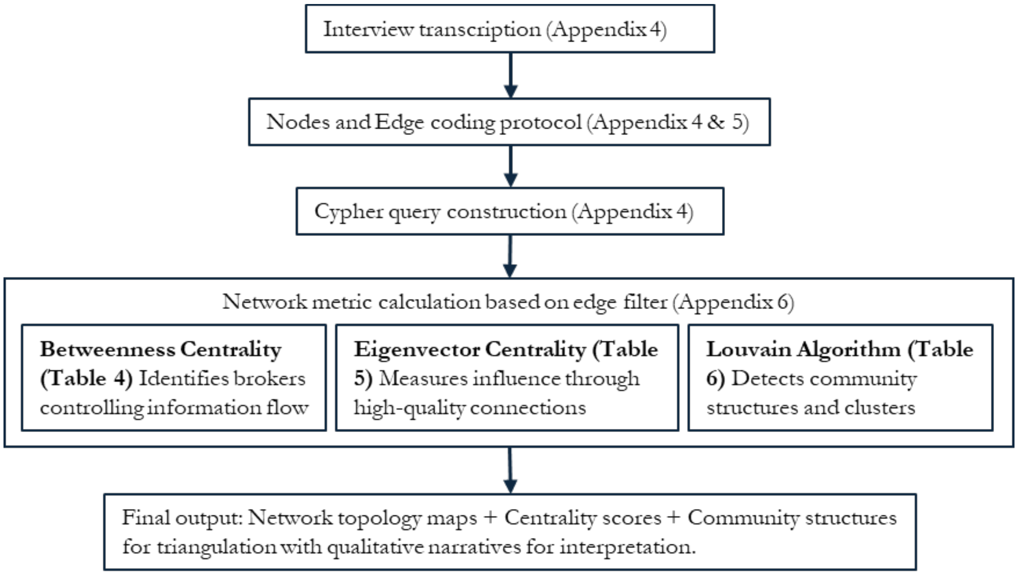


Figure 3. Data transformation pipeline, from narratives to network metrics

RESEARCH RIGOR AND TRUSTWORTHINESS

To ensure the validity, reliability, and dependability of the mixed-methods approach, particularly in converting qualitative narratives into quantitative edge data, we applied the strategies listed in Table 3.

Table 3. Strategies for ensuring research rigor and trustworthiness

Aspect of rigor	Procedure applied	Outcome/ evidence	Purpose
Intercoder reliability and analytic transparency	Dual independent coding of 25% of narrative segments; Krippendorff's alpha calculation (Appendix G). Clear decision tree methodologically documented (Appendix H).	Krippendorff's α >= 0.80	To establish coding consistency and minimize researcher bias.
Triangulation	Convergence of interview data and SNA calculation of eigenvector value (community formation).	Consistent patterns across two data sources.	To enhance validity through multiple evidence sources.
Member checking	Look at the qualitative findings from four participants for verification (community formation).	Context reassurance.	To ensure accurate representation of participants' experiences.
Audit trail	Full documentation of edge mapping rules and Neo4j Cypher syntax.	Complete reproducibility package available.	To enable study replication and verification.

Intercoder reliability, analytic transparency, and reproducibility

We employed Krippendorff's alpha (α) for content analysis for this research (Marzi et al., 2024). Two researchers independently coded a randomly chosen subset of 25% (van Enschot et al., 2024) of the narrative segments (n = 15 segments from eight interviews) using the edge-type protocol (Appendix G) for the intercoder reliability assessment. Initial α = 0.788 is below the 0.80 threshold (Krippendorff, 2022), indicating moderate agreement, constituted by three disagreements out of 15 segments (20% disagreement rate). The confused category pairs contributed from Segment 7 were code 5 vs 6 ("uncover_hint vs. practice_w"), Segment 8, code 1 vs 2 ("friend_with vs. connect_with"), and Segment 14, code 5 vs 7 ("uncover_hint vs search_into").

According to the decision tree, analytic transparency and reproducibility (Appendix H) to enable study replication and verification (Miñarro-Giménez et al., 2018), we need to proceed to Step 2: analyze disagreements since α < 0.80 (Baden et al., 2023; van Enschot et al., 2024; Zade et al., 2018). During Step 2, we return to the disagreement context, which is different and cannot simply be merged (Step 3) (van Enschot et al., 2024); therefore, if-then logic (Step 4) of onsite and online distinguishes the platform.

The Step 4 boundary case (Mai et al., 2013; X. Zhao et al., 2012, 2022) for resolution (Siegert et al., 2014) involved if-then decision logic for two ambiguous segments. For Segment 7 ("*discussion about writing prompts*"), we distinguished between task-focused practice ("practice_w") and general knowledge acquisition ("uncover_hint") by asking whether the activity was primarily task completion or knowledge acquisition (Appendix I). The contextual cue "*trial and error exercise*" (Appendix G) indicated a task completion, resulting in a new code as "practice_w" (Appendix K). For Segment 14 ("*find inspiration online*"), we differentiated targeted learning ("uncover_hint") from media affordance ("search_into") using the If-Then question: Is the search for a specific problem or general exploration? (Appendix I). The context "*looking for creation of other user of media TikTok or IG that might trigger ideas*" (Appendix G) signified a targeted learning goal, resulting in a new code as uncover_hint (Appendix K).

Step 4 boundary case (Mai et al., 2013; X. Zhao et al., 2012, 2022) for retained disagreement (Terence et al., 2024) persisted in Segment 8 ("Mutual follow on Instagram") between "friend_with" and "connect_with", reflecting a theoretical boundary case in which platform-mediated interactions ("connect_with") extend pre-existing physical relationships ("friend_with"). This disagreement was retained (Beckler et al., 2018; Eisele et al., 2019; Terence et al., 2024) as a recognized ambiguity in on-site-to-online relationship contexts. Subsequently, implementing the decision logic and retraining coders (Appendix J), the recalculation $\alpha = 0.928$, which exceeds α of 0.80 for intercoder reliability acceptance (Beckler et al., 2018; Eisele et al., 2019; Krippendorff, 2022; Terence et al., 2024).

Triangulation and member checking

We used methodological triangulation (Table 3, Figure 2, Phase 3) in triangulation (Meydan & Akkaş, 2024) and member checking (Rahal, 2024) by bringing together evidence from three sources: (1) retrospective interviews, (2) SNA calculation of eigenvector value, and (3) community detection patterns. Four participants (MSE4, MSE1, MSE5, and MSE2) verified qualitative findings from community formation analysis. Their contextual reassurance confirmed an accurate representation of collaborative experiences and network evolution patterns. This convergence aims to identify consistent patterns in the evolution of peer interactions, thereby augmenting the credibility of our interpretations, as reported in the Results section.

Audit trail

Complete documentation on edge mapping rules (Appendices 7 to 11) and code writing in Neo4j Cypher syntax is available in the GitHub repository (Budiman, 2025b, 2025a) to enable reproducibility.

DATA ANALYSIS

Network analysis employed common centrality metrics and community-level assessments (Mester et al., 2021) based on an edge filter in Appendix F. Betweenness centrality identifies prospective brokers who manage information flow, revealing network structural vulnerabilities (Mukhtar et al., 2023; Xiang et al., 2023). Eigenvector centrality assesses influence through associations with significant nodes (Tudisco et al., 2018). Eigenvectors above the mean indicate dominant network features, such as influential nodes or clusters. Those near or below the mean suggest a more evenly distributed influence. This interpretation helps identify key structures affecting network dynamics, revealing how influence concentrates or disperses within a social network.

High eigenvectors relative to the mean signal, central actors, or tight clusters are crucial to communication, cohesion, or information spread. This insight helps researchers identify critical network components whose removal significantly impacts the overall structure or function. The approach reveals hierarchies or core-periphery structures within the network (Davidsen & Ortiz-Arroyo, 2012). The Louvain algorithm for community detection identifies groups of nodes that help us better understand the structure (Eriksson et al., 2021; Rahiminejad et al., 2019; Vizcarra et al., 2021) and dynamics of complex networks (X. Wang et al., 2017).

RESULTS

RESTRUCTURING THE LEARNING ECOLOGY VIA PARTICIPATORY INTERVENTION

The PD workshop was an established strategy to change the learning ecology by adding new, task-oriented social practices. Social edges ("friend_with", "connect_with", "recruit_ws") that showed pre-existing, often passive social relationships were used to map the pre-workshop networks (Appendix F). The pre-workshop functions as a networking session before the workshop starts, whereas the post-workshop intervention design activities, including homework and presentations during the workshop, explained what happened during the workshop itself. The post-workshop intervention design analysis, utilizing edges produced by the PD activities ("join_ws", "uncover_hint", "practice_w", "connect_with"), indicates a significant transition from a socially-oriented network to a practice-oriented learning ecology (Appendix F).

Pre-workshop baseline

The pre-workshop ecology displayed a fragile, centralized structure that relied heavily on one node, "MSE4," resulting in a classic "hub-and-spoke" topology (Figure 4). Quantitative analysis (Table 4) substantiated this structural vulnerability, indicating that a predominant number of potential knowledge pathways were required to traverse this participant. Participant MSE3's statement, "*MSE4 encouraged me to actively participate in any available workshop*," shows how much they depended on MSE4 as a key gatekeeper for information and opportunities through recruit_ws ties. Pre-workshop network (Table 5) exhibited concentrated influence among nodes substantially above the mean (M = 0.24): MSE3, MSE4 (0.3844), MSE1 (0.3633), and RBUMN Cir (0.3385), indicating a hierarchical structure with dominant gatekeepers controlling information flow.

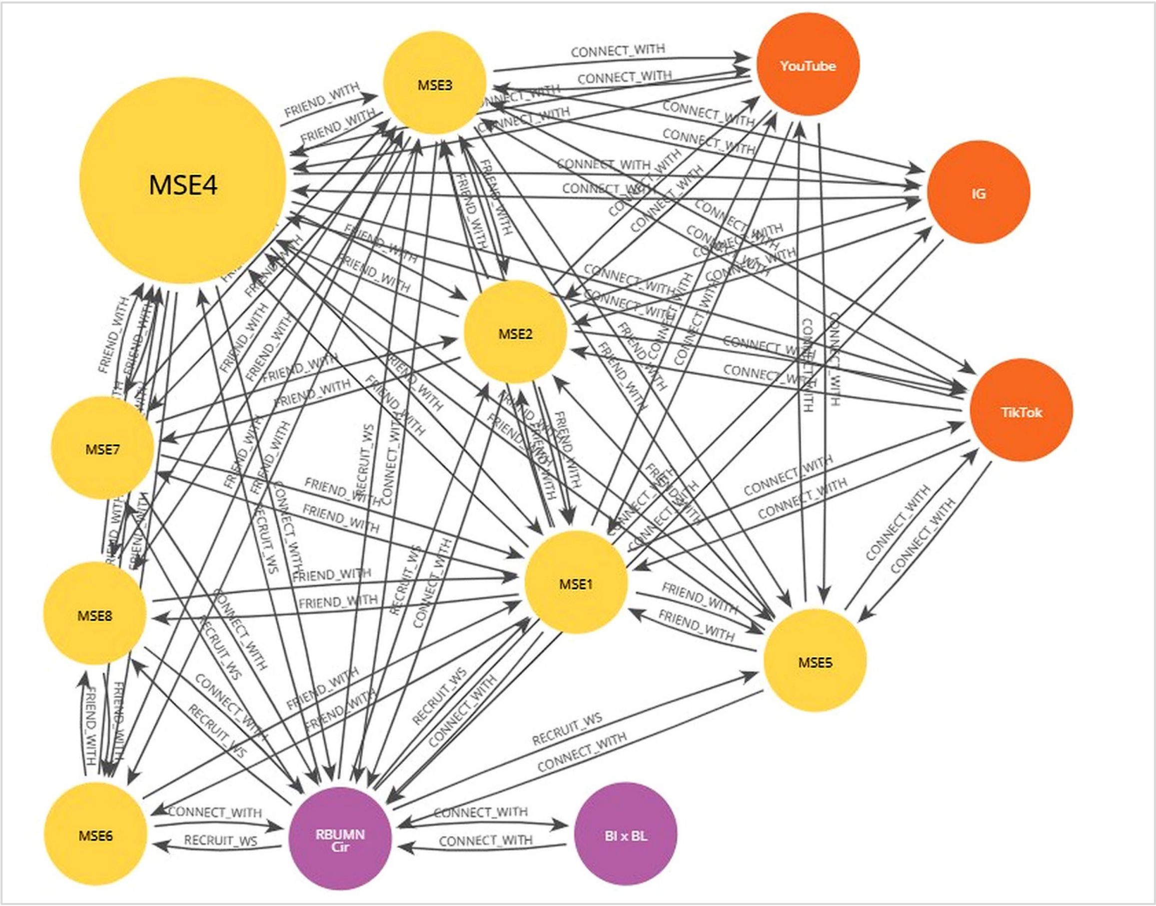


Figure 4. Learning ecology pre-workshop on betweenness centrality degree

From a participatory design standpoint, this structure posed a significant challenge: the vitality and educational capacity of the network relied on the actions of a single, central figure. This setup made it difficult for people to naturally exchange information with each other and created a single point of failure, which made the whole system weak and not ready for collaborative learning before the intervention.

Table 4. Betweenness centrality pre-workshop and post-workshop

Node	Node type	Pre-workshop	Post-workshop	Change	Interpretation
BI x BL	Institution	0	38	+38	Emerged as primary broker
RBUMN Cir	Institution	14.2	0	-14,2	Lost brokerage role
MSE3	Artisan	6.7	5.2	-1,5	Reduced brokerage
MSE4	Artisan	6.7	5.2	-1.5	Reduced brokerage
MSE2	Artisan	2.9	5.2	+2.3	Increased brokerage
MSE1	Artisan	4.6	2.2	-2.4	Reduced brokerage
MSE5	Artisan	1	2.2	+1.2	Increased brokerage
MSE6	Artisan	0	0	0	No brokerage role
MSE7	Artisan	0	0	0	No brokerage role
MSE8	Artisan	0	0	0	No brokerage role
YouTube	Platform	0	0	0	Direct access, not broker
TikTok	Platform	0	0	0	Direct access, not broker
IG	Platform	0	0	0	Direct access, not broker

Post-workshop transformation

The PD workshop purposefully added edges for behaviors that encourage active, collaborative learning. These new practices have directly changed the network structure.

1. The fall of the gatekeeper and the rise of the distributed brokerage: Individual hubs such as MSE4 and MSE5 have less betweenness centrality, which means that they are less important as gatekeepers (Figure 5). The PD workshop created new node types that made it easier for people to share knowledge directly and in parallel. The "join_ws" edge connected participants directly to the institutional organizers (Bank Indonesia x BelajarLagi), making it the second most important broker in terms of betweenness centrality. "Uncover_hint" is also connected to sites such as YouTube and TikTok, giving people direct, independent access to information and inspiration without the need for a human middleman. This shows that an instructional designer can create activities that connect learners directly to institutional resources and external tools ("join_ws", "uncover_hint"). This effectively decentralizes control and makes the learning environment more resilient to disruptions.
2. The redistribution of eigenvector centrality (Table 5, Figure 6) shows MSE2 and MSE5 ascending to above-mean status (0.3840, 0.3612) through moderate gains (+27%, +39% of the mean). They joined the collaborative core via "practice_w" edges, expanding the above-mean artisan group from four to six nodes.

   Artisans with "practice_w" ties (i.e., collaborative problem-solving, translation refinement, and outcome sharing) gain eigenvector centrality. Those without "practice_w" ties (MSE6, MSE7, MSE8) declined substantially below the mean (0.047), despite maintaining social connections from the pre-workshop network.

   From Table 5, the RBUMN Cir descended from above-mean dominance (0.3385) to far below the mean (0.0471), losing its structural centrality role (-121% of the mean). Simultaneously, BI x BL ascended from the marginal actor (0.0438) to above-mean prominence (0.3116) due to the workshop intervention. The large losses among non-participating artisans (MSE6, MSE7, MSE8: -71% to -77% of the mean) drove them substantially below the network mean (0.0471), creating a clear core-periphery structure. This explains why artisans who did not make "practice_w" ties (such as "MSE6," "MSE8", and "MSE7") were pushed to the edges of the algorithm, resulting in very low eigenvector scores, even though they had social connections before the workshop. This is an important lesson for instructional designers. When you design for specific, repeatable collaborative tasks ("practice_with"), you shift power from social leaders to active collaborators, making the ecology more fair and open.

Table 5. Eigenvector centrality pre-workshop and post-workshop

Node	Node type	Pre-workshop	Compare to mean	Post-workshop	Compare to mean
MSE3	Artisan	0.3844	Influential hub	0.3840	Central actor
MSE4	Artisan	0.3844	Influential hub	0.3840	Central actor
MSE2	Artisan	0.3190	Emerging influencer	0.3840	Central actor
MSE1	Artisan	0.3633	Influential hub	0.3612	Central actor
MSE5	Artisan	0.2684	Peripheral actor	0.3612	Central actor
BI x BL	Institution	0.0438	Marginal actor	0.3116	Institutional facilitator
YouTube	Platform	0.2225	Marginal actor	0.2832	Collaborative hub
TikTok	Platform	0.2225	Marginal actor	0.2832	Collaborative hub
IG	Platform	0.1845	Marginal actor	0.1740	Marginal actor
RBUMN Cir	Institution	0.3385	Institutional hub	0.0471	Marginal actor
MSE7	Artisan	0.2315	Peripheral actor	0.0471	Marginal actor
MSE6	Artisan	0.2185	Peripheral actor	0.0471	Marginal actor
MSE8	Artisan	0.2185	Peripheral actor	0.0471	Marginal actor
	Mean=	0.2615		0.2396	
	Combine mean=	0.24			

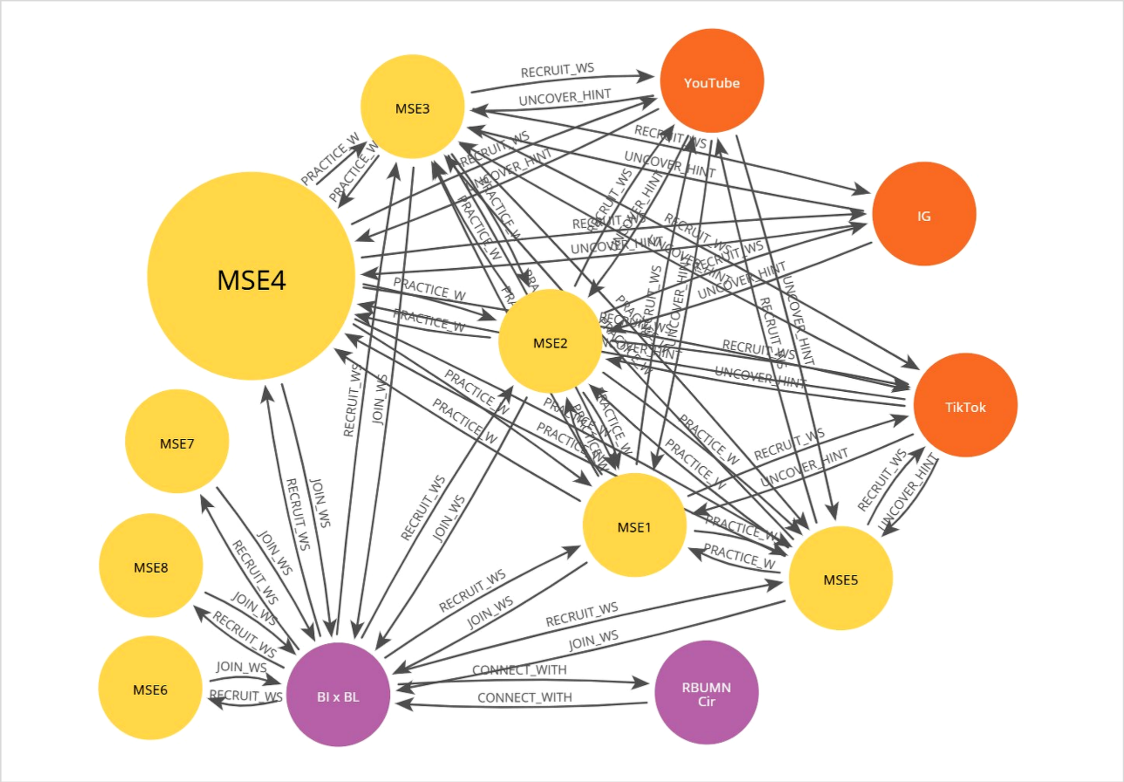


Figure 5. Learning ecology post-workshop workshop on betweenness centrality degree

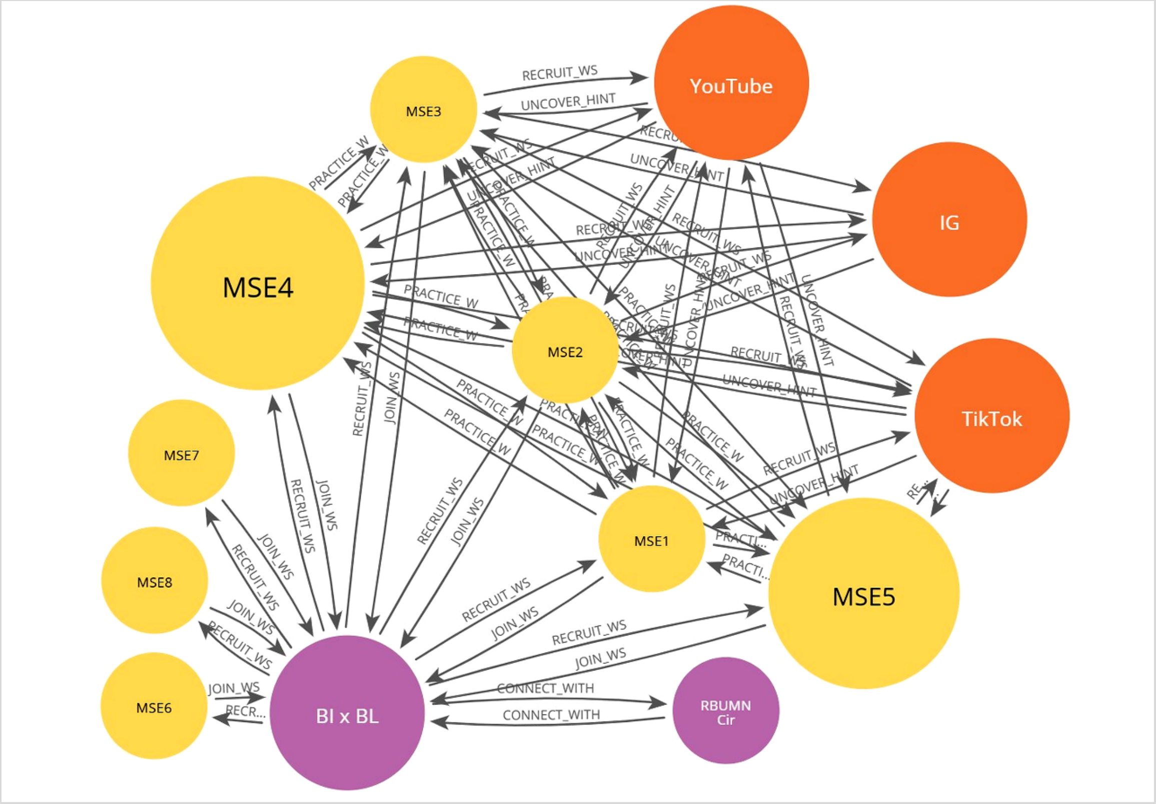


Figure 6. Learning ecology post-workshop workshop on eigenvector centrality degree

A high above-mean eigenvector value (Table 4) now signals collaborative engagement capacity rather than brokerage monopoly, fundamentally altering which nodes are critical to network function. Pre-workshop hierarchy concentrated influence among gatekeepers above the network mean, creating a fragile structure dependent on specific brokers. The collaborative structure of the post-workshop intervention design distributed influence across the expanded core (six above-mean nodes), creating a resilient ecology in which multiple redundant pathways support knowledge flow. This structural shift from concentrated to distributed dominance demonstrates that participatory design interventions can fundamentally alter which nodes constitute critical network features, transforming monopolistic brokerage into collaborative engagement capacity.

Community formation

The educational community bridge function is a good example of how MSEs might use a planned way for exchanging ideas. “Onboarding Bank Indonesia x BelajarLagi, as an educational community, runs a week’s worth of onsite materials and assignments in Cirebon, followed by a month of mentoring, with weekly Zoom sessions where assignments are given and mentoring is provided to ensure that the assignments are completed” (MSE1). The program, organized by Bank Indonesia and BelajarLagi, illustrated how formal and informal learning can collaborate within an ecosystem. This is shown by the Louvain community detection method. The community structure in Table 6 highlights how effectively the post-workshop intervention design created a participatory learning environment for MSEs.

The community structure in Table 6 illustrates the effectiveness of the post-workshop participatory design process. Community 7 emerged as the core participatory group (n=8), including five artisans and three platform nodes (YouTube, TikTok, IG), unified by “practice_w” edges. Community 3 contained peripheral non-participants (n=5), consisting of three artisans (MSE6, MSE7, and MSE8) and two institutional nodes, lacking "practice_w" connections despite pre-workshop social ties. Participation in collaborative AI experimentation proved essential for integration into the central knowledge flow, whereas nonparticipation resulted in algorithmic marginalization, irrespective of pre-workshop network position.

Table 6. Louvin community detection pre-workshop and post-workshop

Node	Node type	Community number		Community	
		Pre-workshop	Post-workshop	Status	Role
Core Participatory (Community 7)					
MSE1	Artisan	6	7	Change	Active collaborator
MSE2	Artisan	1	7	Change	Active collaborator
MSE3	Artisan	11	7	Change	Active collaborator
MSE4	Artisan	6	7	Change	Active collaborator
MSE5	Artisan	6	7	Change	Active collaborator
YouTube	Platform	6	7	Unchanged	Resource node
TikTok	Platform	6	7	Unchanged	Resource node
IG	Platform	1	7	Change	Resource node
Peripheral Group (Community 3)					
MSE6	Artisan	11	3	Change	Non-participant
MSE7	Artisan	1	3	Change	Non-participant
MSE8	Artisan	11	3	Change	Non-participant
BI x BL	Institution	1	3	Change	Institutional broker
RBUMN Cir	Institution	1	3	Change	Institutional broker

"Unchanged" indicates node remained in same community cluster number between pre- and post-workshop (though cluster composition may have changed). "Change" indicates node moved to different community number. Pre-workshop communities (1, 6, 11) were fragmented; post-workshop consolidated into two main communities: Community 7 (core, n=8) and Community 3 (periphery, n=5).

The structural changes described in Figure 7, particularly the redistribution of influence and the formation of collaborative informal hubs, create the conditions necessary for robust learning outcomes. This explains how the new learning ecosystem enables artisans to creatively adapt to AI technology. The eigenvector centrality transformation validates the LEF's proposition that learning ecologies can be deliberately restructured.

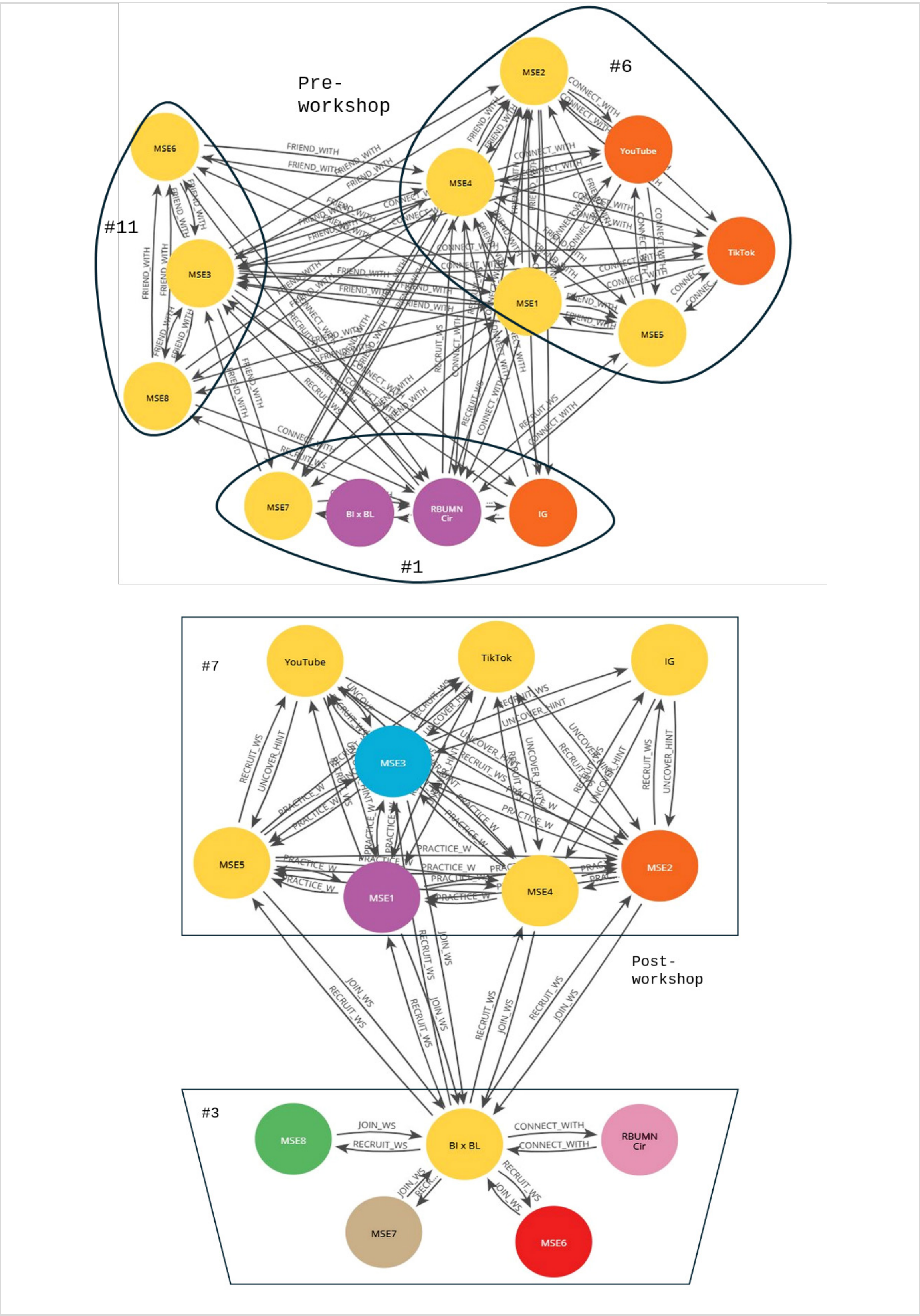


Figure 7. Louvain community detection community structures where the numerical labels (#1, #3, #6, #7, #11) correspond to the community numbers defined in Table 6

The preceding structural transformations provide empirical validation for the three research hypotheses. Hypothesis 1 (redistribution of influence) rationalizes the eigenvector centrality alterations (Table 5), which show that the balance of power changed from centralized, hierarchical figures to active collaborators. Before the workshop, MSE4, MSE3, and RBUMN Cir (0.3385 - 0.3844) had the most power. After the workshop, MSE2 and MSE5 gained +27% and +39%, respectively, through "practice_w" edges. This empirically substantiates the notion that participatory design interventions reallocate influence from ascribed social status to attained collaborative engagement.

Hypothesis 2 (the formation of a core community) was answered by a key sub-community that emerged, distinguished by collaborative, task-oriented connections, while algorithms marginalized non-participants. Louvain detection identified Community 7 (n=8) unified by "practice_w" edges, while Community 3 (n=5) lacked collaborative ties and was on the periphery. This confirms that collaborative task design establishes a quantifiable structural differentiation between engaged and marginalized members.

Hypothesis 3 (cultural adaptation made possible) is supported by the fact that the restructured network directly enabled culturally based creative adaptation and computational empowerment, as demonstrated in the Section Live In A New Learning Ecology. Through repeated "practice_w" interactions, artisans created advanced Indonesian-English translation protocols, multi-tool workflows (DeepL -> Gemini -> DeepL -> Veo3), and standards for cultural appropriateness, which were checked by their peers. This proves that changing the structure of a network makes it possible to use advanced AI that is aware of different cultures.

LIVE IN A NEW LEARNING ECOLOGY

The restructured learning ecology enables artisans to develop sophisticated adaptation strategies. Their collaborative troubleshooting efforts exemplify this capacity through iterative problem-solving, as exemplified by one artisan's experience: "On a par with the failure in prompt writing, Pak. The first two days were entirely unsuccessful, but by the third day, the prompt was correct, yet the result was inaccurate. For instance, the language spoken was English instead of Indonesian. It became apparent that the command needed to be in English, while the dialogue within quotation marks remained in Indonesian" (MSE4). This is a perceived change in the shared social learning experience that highlights the collective approach to addressing language barriers.

Furthermore, the artists' creative adaptation is shown by how they use AI tools and other resources in new ways. MSE4 said, "When I engage with ChatGPT or Gemini AI, I prioritize the content idea. Once it was generated, I issued another command to generate prompt VEO 3 on Gemini AI. However, the outcome often deviates from expectations, necessitating substantial modifications on our part, although it provides a foundational idea. Upon creating the Indonesian prompt, I subsequently instructed a translation into English utilizing DeepL, omitting the quotation marks." This multi-step process illustrates the authors' resourcefulness in addressing the constraints of individual AI tools. Additionally, the artisans sought inspiration from diverse sources as a response to perceived change in learning discovery by MSE3's statement: "We went to TikTok to look for references." The challenges of prompt engineering and daily usage limits as perceived change in experience-based discovery prompts were further elucidated by MSE2: "After AI generates content ideas, we refine prompts … Translate using DeepL, but keep the quotation marks in Indonesian". Even though it fails a lot, this imposes daily usage restrictions of three times a day. "Wait until tomorrow"(MSE2). These experiences show how the core participatory community works as a cultural authenticity engine, where the distributed network makes it easy to quickly share and improve localized solutions, transforming individual frustration into collective intelligence.

DISCUSSION

THEORETICAL CONTRIBUTIONS

This study advances the SLT by demonstrating that participatory structures fundamentally alter how social learning operates. Traditional SLT research emphasizes vicarious learning, where individuals observe models and imitate behaviors (van der Wal et al., 2014). We reveal a qualitative difference when learning occurs within the ecologies designed.

The eigenvector transformation (Section Post-Workshop transformation) provides empirical evidence. Before the workshop began, eigenvector centrality was mostly found in actors with high social positions, such as MSE4 and MSE3, indicating that the main influence came from the physical community. After the workshop, the high eigenvector centrality shifted to actors involved in collaborative practices, such as MSE2 and MSE5. This finding suggests that post-workshop influence is related to the social learning experience. This change in eigenvector centrality is supported by qualitative reports on collaborative task completion, such as translating Indonesian into English. The PD intervention was found to have an impact on the learning network. This shift indicates that PD can deliberately change previous social conditions to produce the effects of SLT on a network.

This study extends SLT theory in three specific ways. First, rather than occurring spontaneously, observational learning can be deliberately activated through network restructuring (Yaqian & Qinhua, 2024). Second, the influence shifts from passive observation of high-status models to active participation in collaborative task completion (Chang et al., 2017). Third, the learning mechanism changes from individual cognitive modeling to distributed collective sense-making (Hmelo-Silver & DeSimone, 2013). These findings suggest that PD serves as the enabling intervention for SLT mechanisms in peer learning networks.

METHODOLOGICAL ADVANCES: SNA AS LEF OPERATIONALIZATION

This study advances the LEF by demonstrating that ecological resilience depends on pathway diversification rather than hub elimination (González-Sanmamed et al., 2019; R. Wang & Zhang, 2025). Notably, participant MSE4 maintained a high degree of centrality post-workshop intervention design, yet the overall ecology became more robust through the emergence of alternative brokerage pathways via institutional and digital platform nodes. This finding challenges the conventional assumption that decentralization necessitates the dissolution of central figures, instead proposing that multiple, functionally distinct conduits for knowledge flow characterize resilient learning ecologies.

PRACTICAL IMPLICATIONS FOR LEARNING DESIGN PRACTICE

For the learning designers

For learning designers, this study demonstrates that social learning networks can be intentionally designed and diagnostically monitored. Three suggestions can be made based on the observed network transformation.

First, design practice-focused learning programs. This study shows that developing a learning ecosystem that considers previous social practices and empowers peer networks results in active participation in the learning process. Therefore, interventions must be strategically designed for collaborative tasks (such as the “practice_w” interaction in our study) that shift the influence from passive learning to active collaboration for a strong ecosystem.

Second, instructional architecture design must create direct access to various resources to decentralize the role of instructors as brokers. This means creating “join_ws” and “uncover_hint” edges on purpose that link students directly to institutional support and carefully chosen digital platforms. For example, in addition to expert-led demonstrations, designers should include activities that require participants to independently find, evaluate, and share learning. This creates a robust knowledge path that can spread the brokerage functions.

Third, designers must adopt a diagnostic approach by monitoring the network's health using SNA metrics. Effective ecological management requires continuous assessments. Lightweight network surveys (e.g., "Who did you collaborate with this week?") at strategic points should be measured using other analytical tools, such as Gephi. Designers should calculate betweenness centrality to identify structural fragility, track eigenvector centrality to confirm influence redistribution toward active collaborators, and apply community detection algorithms to identify isolated participants for timely interventions.

For educational institutions

Educational institutions supporting artisan communities and vocational training programs should fundamentally reorient their infrastructure from instructor-centric delivery models to enabling and sustaining peer-driven learning ecologies. This requires the implementation of dedicated digital platforms, such as moderated forums or messaging groups structured around task completion threads, to facilitate ongoing "practice_w" interactions beyond temporary workshops.

Structured mentorship has facilitators with different skill levels working with different groups. This rotation helps people learn from each other and makes them less dependent on the brokers. Resource libraries must function like social networks. It is necessary to add input from other people, keep track of how often people use it, and develop systems that propose things. These properties create real "uncover_hint" edges.

Educational institutions require new methods to keep track of things. Do not merely consider how many people finish. It is important to monitor how often peers talk to each other, how fast the network expands, and how many people are working together on key activities. Move money from creating content to helping the community. Invest in diagnostic SNA tools and training. These tools make participatory learning structures more robust.

For policymakers

Policy Principle 1: Funding Peer-Learning Infrastructure, not isolated Training. Conventional cultural preservation policies often prioritize discrete and individual training. This study demonstrates that sustainable technological integration requires investment in the underlying peer-learning infrastructure. We recommend shifting policy metrics from counting trained individuals to measuring the sustained networks. Tracking post-program interaction rates and community-of-practice longevity. Funding should shift toward supporting long-term digital platforms for collaboration and backing peer-facilitator roles within communities, instead of only paying for outside expert-led workshops. For example, dedicating resources to an intensive, ongoing program for a core group with built-in network support can create a denser and more resilient learning environment than short, widespread training, leading to deeper and more lasting cultural and technological changes.

Policy Principle 2: Evaluate Programs using Network Health Metrics. To assess the health and sustainability of learning environments shaped by intervention programs, policy evaluation must include network-based indicators, moving beyond traditional individual outcome metrics. Key metrics include a pre-post program increase in network density (e.g., >50%), a community structure modularity score indicating sustained collaboration (e.g., >0.40 at follow-up), and an equity measure, such as a Gini coefficient for eigenvector centrality below 0.30, to ensure distributed influence. These indicators allow policymakers to distinguish between programs that merely transfer skills and those that successfully cultivate self-sustaining and collaborative communities capable of ongoing adaptation and cultural preservation.

Policy Principle 3: Mandatory Participatory Design to prevent Technology Colonialism. Funding from the government for modernizing technology must require a participatory design. This requirement prevents cultural homogenization and technological colonization. Steps to design activities with communities that will benefit from the allocation of funds, such as mechanisms to involve at least 30% of individuals from the community in assessing cultural adaptation using AI. Their representation and participation aim to evaluate the effectiveness of technologies implemented by communities that AI support cultural diversity rather than weakening it.

ADDRESSING THE RESEARCH QUESTION:

This study investigated the following central research question: How does participatory design influence social network structure to foster computational empowerment while maintaining cultural authenticity in promotional content creation? The findings provide a tripartite answer, revealing the measurable structural and functional transformations enacted by a participatory intervention (Brady et al., 2021; Hutasuhut et al., 2023; Rendell et al., 2011; Wasim et al., 2024).

The analysis first demonstrates that participatory design directly and measurably restructures the social learning networks. As documented in Section Pre-Workshop baseline, the pre-workshop ecology exhibited a hierarchical topology with concentrated betweenness centrality. The network transformed into a distributed topology with multiple brokerage pathways after the workshop intervention design. This structural change was driven by the intentional creation of specific edge types: “join_ws” edges linked learners directly to institutional resources, “uncover_hint” edges allowed independent access to digital platforms, and “practice_w” edges promoted strong peer collaboration, collectively redesigning the network’s connections.

The restructured network operates as the primary means of empowering individuals. Empowerment occurred through three network-enabled paths: direct resource access via “uncover_hint” edges cut down reliance on technical intermediaries, collaborative task completion along “practice_w” edges that built a collective ability greater than individual skills, and a shift in influence, shown by changes in eigenvector centrality, that turned multiple participants into resource nodes, establishing a resilient and redundant support system within the network.

The participatory process and resulting network structure play key roles in maintaining cultural authenticity. Authenticity was maintained through peer-validated adaptation within the emergent collaborative core (Community 7). This community developed shared implicit standards for cultural appropriateness, such as prioritizing Indonesian dialogue and traditional aesthetics through iterative “practice_w” interactions (Chen & Teng, 2017; Taylor et al., 2017). Thus, the network provides a mechanism for social accountability, ensuring that cultural alignment emerges organically from within the peer network rather than from the outside.

In particular, this study offers a practical framework for designing and evaluating learning ecosystems by combining HCAI, SLT, LEF, PD, and SNA. In summary, focused participatory tasks that create specific advantages can change the structure to support the desired results. This proves that social learning frameworks can be intentionally designed (Giannakos, Horn, et al., 2025; Ozmen Garibay et al., 2023; Shneiderman, 2020). This finding directly addresses the research question by showing that PD affects the network structure to create conditions that promote empowerment and authenticity.

CONCLUSION

This study examined the impact of participatory design workshops on social learning networks to facilitate culturally relevant AI adoption by Indonesian artisan micro-entrepreneurs. PD workshops that follow HCAI principles transform hierarchical social learning networks into decentralized, strong ecosystems. This study substantiates three hypotheses: influences transition from hierarchical figures to active collaborators, collaborative tasks constitute a fundamental aspect of the participatory community, and networks are restructured to promote culturally informed creative adaptation. Designers should prioritize participatory design by engaging with peers, leveraging digital platforms, and respecting cultural contexts.

Subsequent research should utilize longitudinal social network analysis to evaluate the resilience of reformed ecology over protracted durations, encompassing three-month intervals (Jiang, 2025; Wu & Wang, 2024). Important questions still need to be answered: How does incremental individual computational empowerment affect them? Future research should prioritize the development of more refined edge definitions in SNA (Sarma et al., 2025; Tsugawa & Ohsaki, 2015).

This study utilized fundamental interaction codes, including "practice_with." Future research may cover more specific categories, including "seeks help from," "co-creates with," and "inspires." This modification would enable researchers to progress beyond the mere identification of connections and investigate the qualitative aspects of collaborative learning, thus facilitating a more comprehensive understanding of innovation dissemination within networks. Future research should focus on formulating standardized protocols for the transformation of qualitative data into precise network parameters to facilitate substantial cross-study comparisons and further SNA in the context of collaborative learning ecology.

The model of using PD to transform learning ecologies requires broader testing in diverse contexts, application in varied forms, and comparative analysis against alternative models to identify effective components such as collaborative learning and adaptations for local cultural and social systems (Aynsley et al., 2025; Hu et al., 2025).

ETHICAL CONSIDERATIONS

This study received ethical approval from the Ethics Committee of the School of Interdisciplinary Management and Technology at Institut Teknologi Sepuluh Nopember in Surabaya, Indonesia. Following approval, verbal informed consent was obtained from all participants during community gatherings held on December 5, 2024, at the Kantor Desa Kalapa Gunung, Kuningan. To ensure confidentiality, participant identities were anonymized through systematic coding (MSE1–MSE8), and all real names, specific business locations, and identifying product details were removed from transcripts and publications. Furthermore, as part of a committed ethical engagement process, the study findings will be shared with the participating artisans in an accessible format and presented in Indonesian.

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APPENDIX

Appendix A. The alignment between SNA and LEF

Social network analysis methodology	Learning ecology framework concept	Application on methodology
Identifying Nodes. The points in the network represent entities.	Actors/Nodes. The different people, organizations, and platforms that facilitate learning.	Defining your nodes as: Micro-entrepreneurs, Formal Institutions (Bank Indonesia), Media Platforms (YouTube, TikTok). This isn't just a list; it's a map of the human and non-human actors in the ecology.
Defining Edges. The lines connecting nodes represent relationships.	Interactions/Relationships. The ways in which actors interact and exchange knowledge.	Defining edges based on interactions: "friend_with", "connect_with", "practice_with". These are the types of learning relationships that form the ecology's structure.
Centrality Measures. Metrics that quantify the role and position of each node.	Structure of the Ecology. Is the ecosystem collaborative, hierarchical, or fragile?	Betweenness centrality directly measured the ecology's resilience and dependency (e.g., over-reliance on "MSE1"). Eigenvector centrality measures influence and integration within the ecology.
Community Detection. Algorithms that detect clusters of densely connected nodes.	Sub-Communities. These smaller, often tighter-knit groups form within the larger ecosystem.	The Louvain algorithm didn't just find groups; it identified sub-ecologies or niches within the larger system (e.g., the core participatory group vs. the isolated outliers).

Appendix B. Network reconstruction interview protocol

Network reconstruction	SNA parameters	Purpose in SNA
Network mapping	Node & Edge Identification	To identify all relevant nodes (actors and tools) in the participant's post-workshop intervention design.
Nature of interactions	Edge Type Definition	To provide the narrative evidence required to code the specific type of edge between the participant and each node.
Reasoning and influence	Edge Weight & Direction Rationale	To uncover the motivations behind the connections, which helps explain the network structure and adds qualitative depth to the quantitative edges.
Perceived change	Pre/Post-Workshop Contrast	To gather subjective data on the intervention's impact, which can be triangulated with the objective SNA metrics to explain why the network changed.

Appendix C. Narrative interview instrument

Network reconstruction	Narrative interview instrument
Network mapping	1. Tell me with whom you connect post-workshop and pre-workshop, the AI-powered video creation workshop. 2. Tell me the tools or platforms you use to stay updated and enhance your understanding and skills.
Nature of interactions	3. Tell me the story of your relationship with [Person X/Platform Y].
Reasoning and influence	4. Does the motivation differ when it is post-workshop versus pre-workshop?
Perceived change in learning discovery	5. Tell me the story of how you discovered what makes AI respond well to you. 6. Describe what happened when you watched someone else's approach to asking AI questions.
Perceived change in social learning	7. Tell me the story of learning from others' mistakes or successes with AI prompts.
Perceived change in experience-based discovery prompts	8. Share the story of your journey from struggling to get good AI responses to that moment when you figured out how to frame your requests effectively.

Appendix D. The step-by-step conversion of verbatim into SNA data structures

Step	Action
1	Define the types of entities that will be considered nodes in your graph.
2	Define the edge between nodes as the nature of the relationship, name each edge entity unique assignment, with intercoder reliability assessment..
3	Assign the sequence based on the interview verbatim result in the participatory design in Cypher query language. Note: 1. The order of creation is important in Neo4j because it affects how the graph is stored and processed. 2. Neo4j assigns internal node IDs sequentially based on the order. These internal IDs are used by algorithms for calculation and affect the results.
4	Upload to neo4j platform.
5	Run network calculation betweenness, eigenvector, and Louvin in Neo4j browser and visualize in Neo4j Bloom.

Appendix E. Example steps 2 and 3 naming the interactions

Transcript example	Edge coded as
I have known MSE1 since we were in the same community in Kuningan.	friend_with
I was invited to join a workshop from Rumah BUMN Cirebon.	recruit_ws
We also refer to YouTube for tutorials	uncover_hint
MSE3 and I worked together to test different prompts to do homework.	practice_with

Appendix F. Edge code pre-workshop and post-workshop the workshop

Participatory design	Edge code list
Pre-workshop	"friend_with", "connect_with", "recruit_ws"
Post-workshop	"join_ws", "uncover_hint", "practice_w", "connect_with"

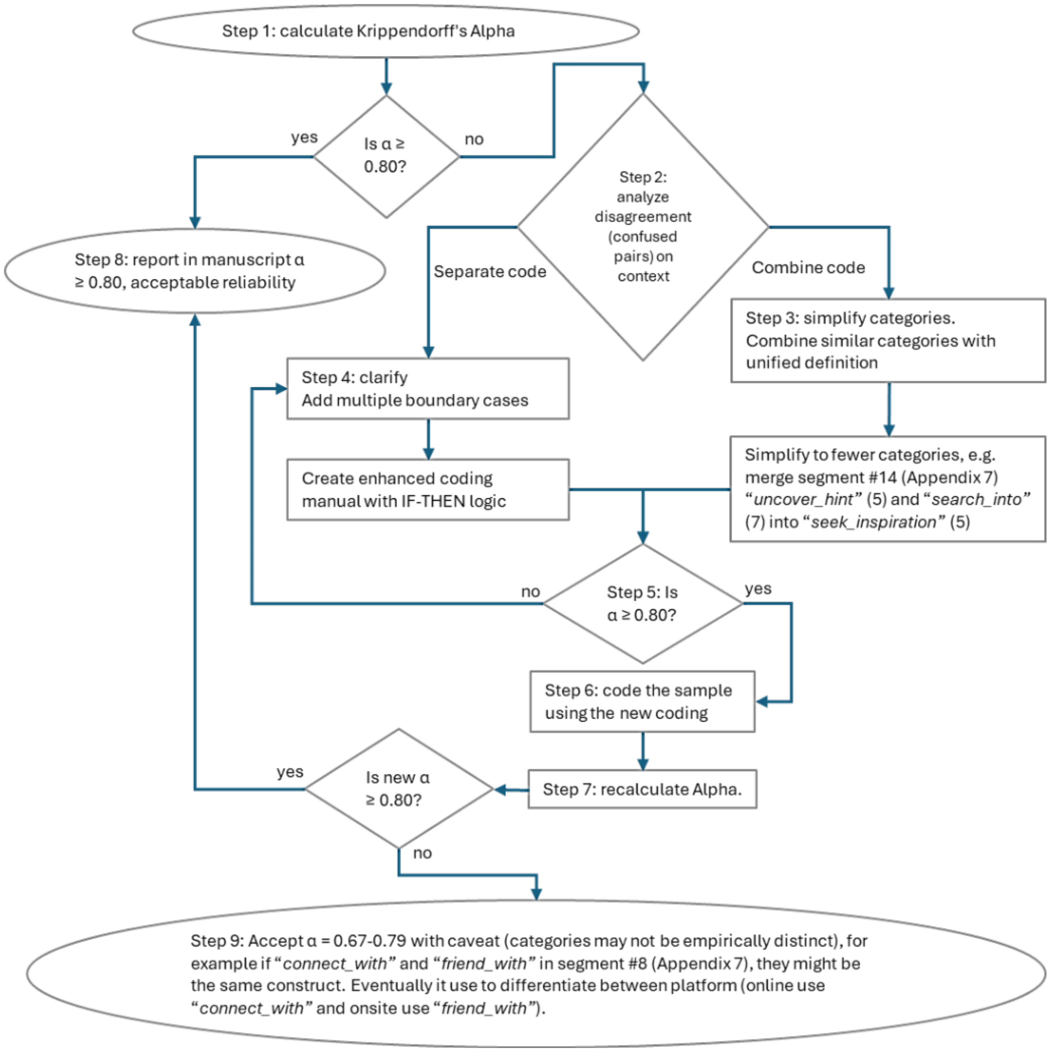
Appendix G. Sample on 15 segments from 8 interviews for intercoder reliability assessment

Segment	Narrative (Simplified)	Coder A	Coder B	Context markers by Coder A	Context markers by Coder B	Edge codes result	Observed disagreement
1	*We have been friends for a long time*	1	1	onsite friendship outside workshop	onsite friendship outside workshop	friend_with (1)	-
2	*Engages via WhatsApp group*	2	2	member of same community (online)	member of same community (online)	connect_with (2)	-
3	*Invited to a workshop by MSE4*	3	3	MSE4 ask to join the Veo3 training by RBUMN Cirebon	MSE4 ask to join the Veo3 training RBUMN Cirebon	recruit_ws (3)	-
4	*Join the Bank Indonesia workshop*	4	4	Participating in post-workshop	Participating in post-workshop	join_ws (4)	-
5	*We also refer to YouTube for tutorials*	5	5	looking for creation of other user of media Tiktok or IG	looking for creation of other user of media Tiktok or IG	uncover_hint (5)	-
6	*MSE3 and I worked together to test different prompts to do homework*	6	6	doing exercise/homework	doing exercise/homework	practice_w (6)	-
7	*Discussion about writing prompts*	5	6	when **discussing** what and how to write the prompt	doing **trial** and **error exercise**	uncover_hint (5) vs practice_w (6)	Disagreement
8	*Mutual follow-on Instagram*	1	2	mutual friend on **onsite** platform continues to online platform	connect/follow other on **online** platform	friend_with (1) vs connect_with (2)	Disagreement
9	*See some examples on TikTok*	5	5	looking for creation of other user of media Tiktok or IG	looking for creation of other user of media Tiktok or IG	uncover_hint (5)	-
10	*Translation from Indonesian to English revision collaboration*	6	6	doing exercise/homework	doing exercise/homework	practice_w (6)	-
11	*Join the Zoom mentoring session*	4	4	weekly online mentoring sessions	weekly online mentoring sessions	join_ws (4)	-
12	*I was invited to join workshop from Rumah BUMN Cirebon to join the Veo3 training*	3	3	RBUMN Cirebon inviting to join workshop	RBUMN Cirebon inviting to join workshop	recruit_ws (3)	-

Segment	**Narrative** (Simplified)	**Coder A**	**Coder B**	**Context markers by Coder A**	**Context markers by Coder B**	**Edge codes result**	**Observed disagreement**
13	*I have known MSE1 since we were in the same community in Kuningan*	1	1	member of same community	member of same community	friend_with (1)	-
14	*Find inspiration online through TikTok or IG*	5	7	looking for **content** other user that might trigger ideas	literally use the **media** affordance to search for ideas	uncover_hint (5) vs search_into (7)	Disagreement
15	*Testing prompt joint work*	6	6	doing exercise/homework	doing exercise/homework	practice_w (6)	-

Code mapping: 1 = friend_with, 2 = connect_with, 3 = recruit_ws, 4 = join_ws, 5 = uncover_hint, 6 = practice_w, 7= search_into

Appendix H. Analytic transparency and reproducibility decision tree (Krippendorff, 2022)



Appendix I. Step 4: Boundary case description, if-then logic for defining agreement

Segment	7	14
Narrative excerpt	"Discussion about writing prompts"	"Find inspiration online through TikTok or Instagram"
Confused pair	uncover_hint (5) vs practice_w (6)	uncover_hint (5) vs search_into (7)
Boundary case description	Learning discussion during structured work	Online information seeking for creative ideas
If-Then logic question	Is the primary activity focused on task completion? If Yes (task-focused with specific goals) Then code = practice_w. If No (exploratory browsing) Then code = uncover_hint.	Is there a specific learning objective? If Yes (targeted learning) Then code = uncover_hint. If No (due to media affordance) Then code = uncover_hint.
Final code	practice_w (6)	uncover_hint (5)
Defining agreement	Context indicates "*trial and error exercise*" interpret as task-focused	"*Find inspiration*" involves seeking specific examples that might trigger ideas interpret as targeted learning

Appendix J. Step 4: Platform boundary case description for defining separate code

Coding	Platform context	Definition	Boundary case description	Defining separate code
friend_with (1)	Onsite/Physical Community	Relationships established through in-person interactions within physical communities	Blended relationships that began onsite but continue online	Coder A interprets it as a relationship extension (onsite friendship extending online as friend_with)
connect_with (2)	Online/Digital Community	Relationships formed primarily through digital platforms without prior physical interaction	Online connections on a digital platform	Coder B interprets as a platform-mediated connection (just literally connect)

Appendix K. Step 6: Code the sample using new coding for intercoder reliability assessment

Segment	Narrative	Initial codes	If-then logic result	New coding	Status
7	Discussion about writing prompts	5 vs 6	Task-focused agreement = practice_w	Both: 6	agreement
8	Mutual follow-on Instagram	1 vs 2	Use platform boundary case (Appendix 10)	1 vs 2	Retained disagreement
14	Find inspiration online	5 vs 7	Targeted learning agreement = uncover_hint	Both: 5	agreement

AUTHORS

Arief Budiman is a doctoral candidate at the School of Interdisciplinary Technology Management, Institut Teknologi Sepuluh Nopember (ITS), Surabaya. His research examines technology education and innovation management for sustainability through a *network-based view* paradigm. By investigating social creativity and network dynamics in learning environments, his work bridges theory and practice to offer insights for researchers and learning designers.

Nur Aini Rakhmawati is a professor in the Information Systems Department and Deputy Head of the Halal Center at Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. She completed her PhD at the Insight Centre for Data Analytics, NUI Galway, Ireland; her MS at the National Taiwan University of Science and Technology; and her BS at ITS. Her research interests include knowledge graphs, big data, and computer ethics.

Diana Purwitasari (Senior Member, IEEE) received a PhD in computer science and engineering from the Multimedia Computing Laboratory, Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia, in 2020. She is currently a professor in the Informatics Department, Faculty of Intelligent Electrical and Informatics Technology (ELECTICS), ITS. Her research focuses on information retrieval, social network analysis, computational intelligence, and web mining. Since 2020, she has actively contributed to several national initiatives, including the Design Task Force for AI Toward Indonesia Vision 2045, the University Center of Excellence on Artificial Intelligence for Healthcare and Society (UCE AIHeS), the Industrial Electronics Society (IES) Chapter of the Indonesia Section, and the national AI Research Consortium under the Ministry of Research and Technology.