**INKUBIS: Jurnal Ekonomi dan Bisnis**
**Volume 8, Issue 1, 387-407**
**e_ISSN: 2775-3913**
https://inkubis.polteksci.ac.id/index.php/ink/indx
DOI: doi.org/10.59261/inkubis.v8i1.188

# Measuring Collaborative Maturity in Human–AI Work: Development and Validation of the CIQ Scale

**Andreas Raditya**[1*]
Universitas Ciputra, Indonesia

**Thomas Stefanus Kaihatu**[2]
Universitas Ciputra, Indonesia

**Timotius FCW Sutrisno**[3]
Universitas Ciputra, Indonesia

***Corresponding author:**
Andreas Raditya, Universitas Ciputra, Indonesia.
✉araditya03@student.ciputra.ac.id

**Article Info :**
**Article history:**
Received: March 18, 2026
Revised: April 23, 2026
Accepted: April 25, 2026

**Keywords:**
adaptive co-learning; collaborative intelligence quotient; cognitive synchronization; human–ai complementary intelligence; measurement validation.

**Abstract**

**Background:** Collaboration has emerged as an essential capability because it helps us achieve effective collective performance something we are now doing more often in digital and cross-functional organizations. Although the collaborative activities are becoming more intense, a variety of inconsistencies remain in terms of outcomes given the differences in shared cognition, interaction quality, and role integration between human beings and artificial intelligence (AI). This gap signifies the necessity of a holistic measurement tool that is able to quantify collaborative maturity in human–AI integrated workflows.
**Objectives:** This paper aims to develop and validate the collaborative intelligence quotient (CIQ) scale as a supporting diagnostic construct for measuring the collaborative maturity of human–AI integrated workflows in the diverse property development and integrated township sector in Indonesia.
**Methods:** A scale-development protocol was conducted using a purposive sample of 32 managerial practitioners in Indonesian property firms. Dimensionality, reliability, and convergent validity were examined sequentially using EFA followed by CFA.
**Results:** The EFA suggested a four-factor structure, and the CFAs conducted for further purification led to a relatively simple measurement model with three latent dimensions (Adaptive CoLearning; Cognitive Synchronization & Fluency Interaction; Human-AI Complementary Intelligence) and nine out of eleven indicators. The final model showed adequate internal consistency and convergent validity.
**Conclusion:** CIQ is a psychometrically reliable tool to systematically chart organizational collaborative maturity in utilizing AI for teamwork, and it could serve as an end-to-end foundation on which subsequent structural testing and capability scaling may be operationalized.

**To cite this article:** Author Name;. (2026). Measuring Collaborative Maturity in Human–AI Work: Development and Validation of the CIQ Scale. *INKUBIS: Jurnal Ekonomi dan Bisnis*, 8 (1), 387-407. https://doi.org/10.59261/inkubis.v8i1.188

## INTRODUCTION

Collaboration has become a central competence across organizations of different degrees of digital enablement and cross-functionality that combines distributed expertise into synchronized decisions (e.g., achieving coordination) (Englmaier et al., 2025; Larson & DeChurch, 2020). However, despite high levels of visible coordination, uneven collective outcomes exist because shared understanding and coordination quality differ across teams and conditions or within teams over time, with some behaviors being more easily and precisely orchestrated than others (Kordova & Hirschprung, 2023; Marlow et al., 2017; Niler et al., 2021). These vulnerabilities are exacerbated in high-throughput, parallel work where small bits of information can be lost along handoffs and everyday transitions, causing desynchronized action and quantifiable error, demonstrating how seemingly trivial communication gaps manifest as system-level performance threats (Paquette et al., 2023). Simultaneously, the presentation of AI as an active team member (as well as a tool) brings into everyday collaboration human–AI teaming, which reorients trust dynamics in new collaborative arrangements, changing communication and shared cognition (Berretta et al., 2023; Jarrahi, 2018; Schmutz et al., 2024). This shift essentially transforms collaboration into a sociotechnical orchestration problem, requiring organizations to integrate human decision-making, collective knowledge processes, and AI-assisted contributions into a unified workflow capable of maintaining trustworthy collective performance capabilities (Ali et al., 2025). Therefore, the observation of systematic differences in collective performance across groups and persistent findings indicating that teams under-realize their potential as coordination and common ground decline further underscore the need for more fine-grained measurement of collaborative maturity in environments where collaboration is frequent but its success remains uncertain (Leblanc et al., 2024; Riedl et al., 2021).

In this view, Collective Intelligence Theory frames collective performance less as an outcome and more as an emergent capability that unfolds over time via a team interaction process. These interaction processes, in contemporary organizations, act as an interacting system in which common understanding and aligned information synchrony determine whether top-down or targeted decisions and cross-functional execution remain congruent (Vuchkovski et al., 2023). As this system is more prone to drift and inefficiency consistent with recent quantitative syntheses indicating that group-level intelligence factors correlate with group performance but remain sensitive to team-level coordination and regulation of member-level cognition when that connective tissue weakens, collective potency diminishes (Rowe et al., 2021). These dynamics are compounded by digital transformation, where more work is taking place at a distance and in a technology-mediated fashion, such that sustaining cohesion and coordination becomes an issue of capability rather than routine communication (Janssens et al., 2022). More recently, the accelerating diffusion of AI into knowledge work expands interaction even further away from human–human exchange and toward human–AI teaming, which requires coordinating complementary strengths to achieve common objectives (Raisch & Krakowski, 2021; Seeber et al., 2020). Here, research on human–AI teams shows that common ground and shared mental models remain salient but more difficult to achieve and maintain when AI agents are included as teammates in sociotechnical workflows. Strikingly, present reviews on AI teaming note that coordination, communication, trust, and shared cognition become more susceptible to decay when AI teammates are introduced (Schmutz et al., 2024), underscoring the rationale for an operational assessment perspective capable of evaluating collaborative maturity in human–AI-integrated environments.

Established tools measure the individual dimensions of collaboration in silos and cannot address the paradox that organizations with high visible coordination still experience variability in their outcomes (Niler et al., 2021). Collective Intelligence Theory is grounded in solid theory, but organizational practice needs a psychometrically testable construct with greater operational utility for use in the field. To address this, the current research proposes an applied construct the Collaborative Intelligence Quotient (CIQ) as a quantitative lens through which to measure organizational collaborative maturity in terms of how effectively and seamlessly shared understanding, interaction fluency, complementary role integration, adaptive collaborative learning cycles, and intelligent-technology-supported augmentation are integrated into routine work. CIQ is therefore framed as an evidence-based, operationalized construct of the collective intelligence framework that goes beyond narrative and serves as a diagnostic tool, akin to recent work that translates collaboration readiness and team process assessment into validated measures. By introducing CIQ, the conversation about collective intelligence moves from prescriptive theorizing toward psychometrically grounded measurement that can serve purposes of organizational mapping and empirical evaluation indeed, as recent evidence demonstrates, there is opportunity for measurement based on quantifying common features of collective intelligence, and an increasing number of measurement matters in practice. In short, CIQ functions as an instrument through which collaborative maturity can be systematically assessed within sociotechnical workflows consisting of the intertwined human expertise and AI-enabled contributions that are presented in current human–AI teaming research as central challenges for reliable performance related to coordination, trust, and shared cognition.

The life cycle of the diversified property and integrated township development sector lends itself to intense orchestration even when using advanced technology, spanning planning, design, construction, commercialization, and area operations phases where stakeholder constellations and coordination demands shift radically, making it the selected context for this study (Hamdan et al., 2021; Rönndahl et al., 2025). For example, decisions made in master planning are interdependent with architectural and engineering design decisions, being highly sensitive to misinterpretation of small details, delays in information flow, and communication breakdowns (Alrasheed et al., 2026). Because such projects usually involve several public and private stakeholders conducting parallel workstreams, the quality of collaboration is a key variable for whether changes can be absorbed at greater speed without running the risk of breaking execution consistency (Hamdan et al., 2021; Kroh & Schultz, 2023). Simultaneously, digital platforms and data-rich models alongside AI-enabled tools increasingly contribute to reporting, coordination, and design decision-making, meaning that synergizing human judgment with technology-supported cognition is becoming even more important in daily workflows (Morin & Romero-Torres, 2024). The combination of interdependence, stakeholder multiplicity, and digitalization gives an empirical grounding for testing an organizational maturity measure that seeks to observe collaborative intelligence as an interconnected system instead of isolated collaboration indicators (Adebayo et al., 2025).

There is a significant measurement gap: no assessment tool has yet been validated that evaluates the collaborative maturity of an organization as a single construct with human–AI role dimensions integrated. Prior work examining collective intelligence, team cognition, and collaboration effectiveness offers explanatory frameworks for team performance mechanisms but lacks organizational-level psychometric diagnostic utility (Castañer & Oliveira, 2020). CIQ is unique because it: (1) operationalizes human–AI collaborative maturity as a latent construct separate from individual team performance metrics; (2) combines five interrelated capability dimensions into a single scale; and (3) is designed primarily to be deployed across a collection of teams in an organization, rather than simply predicting outcomes for a single team. This distinguishes CIQ from collective intelligence (outcome-focused), team cognition (human-only, mental models), and collaboration effectiveness frameworks (missing AI-integrated components). Thus, this study has three objectives: (1) developing and validating CIQ indicators; (2) exploring validity and reliability through EFA and CFA; and (3) generating a validated CIQ model specifically suitable for the diversified property and integrated township industry.

**Table 1.** Foundational Components of CIQ

| Code | Indicator | Key Finding | References |
|---|---|---|---|
| CS1 | Goal Alignment between Team and AI | Goal alignment between human teams and AI systems significantly enhances collaborative effectiveness by fostering shared understanding, reducing coordination ambiguity, strengthening interdependent task execution, and improving overall team performance in human-AI teaming contexts. | (Attig et al., 2026; Endsley, 2023; McGrath et al., 2025) |
| CS2 | Cognitive Coordination between Humans and AI | Effective coordination of ideas and cognitive processes between humans and AI enhances collaborative problem-solving quality, improves shared reasoning, reduces misunderstandings, and strengthens joint decision-making performance in human-AI teams. | (Cabrera et al., 2023; Dang et al., 2025; Fang et al., 2025; Gomez et al., 2025; W. Li et al., 2025; Lopes et al., 2023; McGrath et al., 2025; Puerta-Beldarrain et al., 2025; Sidra & Mason, 2025) |

| Code | Indicator | Key Finding | References |
|---|---|---|---|
| CS3 | Decision Boundary Clarity between AI Recommendations and Human Authority | Clear delineation of decision authority between AI recommendations and human judgment enhances accountability, reduces role ambiguity, strengthens trust calibration, and improves decision quality within human-AI collaborative systems. | (Baird & Maruping, 2021; Bullock, 2019; Covilla, 2025; Mahajan, 2025; Raisch & Krakowski, 2021) |
| CS4 | Goal Misalignment between Humans and AI | Misalignment between human team objectives and AI system outputs increases coordination breakdowns, reduces trust calibration, creates performance inefficiencies, and weakens overall human-AI team effectiveness. | (Callaghan, 2025; Dung, 2023; Fox, 2024; Kasirzadeh, 2026; Kierans et al., 2025; X. Li et al., 2026; Shen et al., 2025; Vamplew et al., 2018) |
| IF1 | Instructional Ease in Human-AI Interaction | The ease of providing instructions to AI systems enhances task efficiency, reduces cognitive load, improves usability perception, and strengthens effective human-AI collaboration across work contexts. | (Aaron et al., 2025; Chou et al., 2022; Klar, 2025; Z. Peng & Wan, 2024) |
| IF2 | Bidirectional Feedback Fluency between Humans and AI | Smooth bidirectional feedback between humans and AI systems enhances adaptive learning, improves decision accuracy, strengthens mutual understanding, and increases collaborative performance in human-AI teams. | (Escalante et al., 2023; Kaliisa et al., 2026; Park & Goel, 2025; L. Peng et al., 2024; Zhan & Yan, 2025) |
| IF3 | Output Interpretability across Diverse Team Backgrounds | High interpretability of AI outputs across users with diverse expertise enhances shared understanding, reduces cognitive ambiguity, strengthens trust calibration, and improves collaborative decision-making in human-AI teams. | (W. Du et al., 2024; Gilpin et al., 2018; Kaur et al., 2020; Stevens & De Smedt, 2024; Y. Zhang et al., 2021) |
| IF4 | Output Interpretation Difficulty in Human-AI Teams | Difficulty in interpreting AI outputs increases cognitive strain, reduces trust alignment, creates coordination inefficiencies, and weakens overall human-AI collaborative performance. | (Abbasian Ardakani et al., 2024; Cabitza et al., 2019; Dobson, 2023; Elton, 2020; N. Kumar & Kumar, 2025) |
| CE1 | Human-AI Capability Integration for Team Performance | The integration of human expertise and AI capabilities enhances team performance by leveraging complementary strengths, improving task accuracy, increasing efficiency, and enabling superior collective outcomes compared to human-only or AI-only systems. | (Bansal et al., 2019; Carter & Wynne, 2024; Patel et al., 2025; Simón et al., 2024; Subramanian et al., 2024) |
| CE2 | Human-AI Complementarity in Task Execution | Complementarity between human judgment and AI analytical capabilities improves task effectiveness, enhances collaborative quality, strengthens adaptive | (Gonzalez & Heidari, 2025; Hemmer et al., 2025; Q. Zhang et al., 2022; X. Zhang & Chen, 2026) |

| Code | Indicator | Key Finding | References |
|---|---|---|---|
| | | problem-solving, and supports higher-value performance outcomes in human-AI teams. | |
| CE3 | Human-AI Collaborative Ideation Effectiveness | Effective human-AI collaboration enhances idea quality by combining human creativity and contextual reasoning with AI's generative and analytical capabilities, leading to more innovative, diverse, and higher-value outcomes in team settings. | (Baltà-Salvador et al., 2025; Chen & Zhao, 2025; Guo et al., 2024; Joosten et al., 2024; Kim & Maher, 2023; Komura & Yamada, 2026; Shin et al., 2023) |
| CE4 | Perceived Human Redundancy in AI-Supported Work | Perceptions that human contribution is unnecessary when AI is deployed reduce collaborative engagement, weaken augmentation benefits, and undermine hybrid intelligence outcomes by shifting from complementarity toward automation dominance. | (Komura & Yamada, 2026; Rožman et al., 2023; Wang & Zhou, 2025; Yang et al., 2026) |
| ACL1 | Rapid Iterative Adjustment in Human-AI Work Processes | The ability to conduct rapid iterative cycles in human-AI collaboration enhances adaptability, accelerates performance improvement, supports continuous learning, and strengthens dynamic task alignment in evolving work environments. | (Geroimenko, 2026; Oliveira et al., 2025; Sankaran et al., 2022; Zhao et al., 2025; Zhou et al., 2025) |
| ACL2 | Team-Based Correction for AI Output Improvement | Active team corrections and feedback loops enhance AI output quality, strengthen collaborative learning, improve system calibration, and foster continuous performance refinement in human-AI teaming contexts. | (Dawarka et al., 2026; Duan et al., 2024; S. Kumar et al., 2024; Tummala et al., 2025) |
| ACL3 | Adaptive Efficiency in Human-AI Collaboration under Changing Task Demands | Efficient human-AI collaboration under changing work demands enhances dynamic capability, improves task responsiveness, strengthens coordination resilience, and sustains performance in uncertain and evolving environments. | (Alix et al., 2021; T. Du et al., 2025; Holter & El-Assady, 2024; Rahmati, 2025) |
| ACL4 | Reflective and Continuous Improvement in Human-AI Collaboration | Reflective practices and continuous improvement in human-AI collaboration strengthen learning loops, enhance system calibration, improve coordination quality, and foster sustainable performance development in hybrid teams. | (Alam & Khan, 2024; H. Li et al., 2025; Matsumoto et al., 2024; Mseer & Ali Samhan, 2025) |
| ACL5 | Rigidity in Human-AI Collaborative Processes under Changing Task Demands | Rigidity in human-AI collaborative processes limits adaptive capability, reduces responsiveness to evolving task requirements, weakens dynamic coordination, and undermines sustainable performance in hybrid intelligence systems. | (Hermanns & Teubner, 2025; Kunz et al., 2025; Malik & Bilberg, 2019; Xu et al., 2025; Zhu et al., 2023) |

## METHOD

We chose the Indonesian diversified property and integrated township sector as the empirical context because it is currently an emerging market with high cross-functional coordination requirements, targeted for further AI-tool adoption in design, reporting, and decision-making processes, which provides a relevant high-stakes setting to validate a human–AI collaborative maturity instrument. Consistent with established organizational behavior research, we used a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) for all measurement items (Hair et al., 2019).

The construct was built by extracting and synthesizing potential CIQ indicators that reflect collaborative maturity as an integrated capability not isolated behaviors through a review of the literature up to date as of October 2023. Expert judgment then bolstered this synthesis by evaluating the indicators for conceptual relevance, clarity, and contextual fit with property-sector workflows. After seeking expert feedback, each indicator was given a preliminary code and placed into tentative clusters corresponding to putative CIQ dimensions, providing an overarching structure for instrument development. All indicators were then operationalized in the form of specific, concrete survey statements that would ideally increase interpretability for practitioners responding from real project contexts.

The primary data were collected from a relatively limited sample of 32 managerial practitioners selected through purposive sampling in Indonesian property firms. Exploratory factor analysis (EFA) was used to identify latent structure; confirmatory factor analysis (CFA) was applied as an exploratory–confirmatory hybrid for model pruning, but not for full confirmatory inference. This is acknowledged as a key limitation given that N = 32 is below the conventional CFA minimum of 100 (Hair et al., 2020). Future studies should be designed with N ≥ 100 or use PLS-SEM, which is robust for small datasets (Hair et al., 2019). Cronbach's α and Composite Reliability (CR) were employed to evaluate reliability, while Average Variance Extracted (AVE) was used to assess convergent validity. All results are clearly stated to be initial evidence requiring replication. Because of the small sample size, confirmatory results should be considered preliminary evidence, sufficient only to inform model refinement, item reduction, and subsequent validation with a larger sample. The main result of this process is a CIQ measurement model that stands as a workable prototype whose measurement properties can be further refined and assessed in implementation studies conducted on larger, more representative samples.

## RESULTS AND DISCUSSION

### Results

*Demographic profile of the respondents*

Demographic and professional characteristics of participants (N = 32) from property companies in Indonesia are shown in Table 2. The age distribution skews toward more senior, experience-based cohorts, with most respondents aged 36–45 (43.75%) and above 45 years (37.50%); only 18.75% of respondents were in the 25–35 age group. Regarding gender, the sample is relatively male-dominated (56.25%) compared with females (43.75%). Academic qualifications are particularly high mostly Master's/Doctoral degrees (62.50%), followed by Bachelor's degrees (28.13%) and diplomas (9.38%). While 15.63% report a tenure of 1–3 years, work history further indicates organizational embeddedness, with a vast majority (84.38%) having spent more than five years in their respective organizations. In terms of organizational roles, more than half are Managers (50.00%) and a smaller percentage are General Managers (37.50%), with Coordinators amounting to 12.50%. Construct validity of the CIQ items is strengthened by the dominance of Master's/Doctoral degree holders (62.50%) and employees with more than five years of tenure (84.38%). Given that the majority comprises Managers and General Managers (87.50%), responses appear purposeful and strategic in nature, reflecting experience with cross-functional coordination key dimensions for Adaptive Co-Learning and Cognitive Synchronization. However, underrepresentation of operational staff (12.50% Coordinators) limits generalizability to non-managerial contexts, warranting multi-level sampling in future studies.

**Table 2.** Characteristics of participants

| Demographic Characteristics | Categories | Number of Respondents | Percentage (%) |
|---|---|---|---|
| Age | 25-35 years | 6 | 18.75 |
| | 36-45 years | 14 | 43.75 |
| | >45 years | 12 | 37.50 |
| Gender | Male | 18 | 56.25 |
| | Female | 14 | 43.75 |
| Education Level | Diploma | 3 | 9.38 |
| | Bachelor’s Degree | 9 | 28.13 |
| | Master’s/Doctoral Degree | 20 | 62.50 |
| Tenure (Years in Company) | 1-3 years | 5 | 15.63 |
| | >5 years | 27 | 84.38 |
| Position | Coordinator | 4 | 12.50 |
| | Manager | 16 | 50.00 |
| | General Manager | 12 | 37.50 |

### *Exploratory Factor Analysis (EFA)*

### A. Data Adequacy Assessment

Prior to conducting the EFA, the suitability of the dataset was evaluated using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. The results indicate a KMO value of 0.776, exceeding the minimum recommended threshold of 0.50, thereby confirming that the sample is adequate for factor analysis. Bartlett's Test of Sphericity was also statistically significant ($\chi^2 = 401.874$, $p < 0.001$), as presented in Table 3, indicating that the correlation matrix is not an identity matrix and that sufficient inter-item correlations exist to justify proceeding with factor extraction (Hair et al., 2020). Collectively, these findings confirm that the data satisfy the necessary assumptions for conducting EFA.

**Table 3.** Kaiser-Meyer-Olkin (KMO) dan Bartlett’s Test of Sphericity

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .776 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 401.874 |
| | Df | 136 |
| | Sig. | .000 |

### B. Total Variance Explained

Based on Table 4, factor retention was determined using the eigenvalue-greater-than-one criterion. This gave four components with initial eigenvalues of 8.063, 2.223, 1.637, and 1.145. The four factors in the first solution explained 76.865% of the total variance, suggesting excellent explanatory coverage of the manifest variables. As a result of data extraction via Principal Component Analysis (PCA), four factors were retained, cumulatively accounting for 69.172% of the total variance; first factor: 29.277%; second factor: 22.450%; third factor: 12.018%; fourth factor: 5.427%. After Varimax rotation, the variance distribution was also more even between components. The cumulative variance was 69.172%, with the first rotated factor explaining 20.724%, the second 18.166%, the third 17.800%, and the fourth 12.482%. By redistributing the variance, we improve interpretability, and we can say that the dimensions contribute approximately proportionally to the overall structure. These extraction and rotation results, taken together, provide empirical support for a stable four-factor structure of the construct CIQ (Hair et al., 2020).

**Table 4.** Eigenvalues and total variance explained

| Factor | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** |
| 1 | 8.063 | 47.427 | 47.427 | 4.977 | 29.277 | 29.277 | 3.523 | 20.724 | 20.724 |
| 2 | 2.223 | 13.078 | 60.505 | 3.817 | 22.450 | 51.727 | 3.088 | 18.166 | 38.891 |
| 3 | 1.637 | 9.627 | 70.132 | 2.043 | 12.018 | 63.745 | 3.026 | 17.800 | 56.691 |
| 4 | 1.145 | 6.732 | 76.865 | 0.923 | 5.427 | 69.172 | 2.122 | 12.482 | 69.172 |
| 5 | .714 | 4.202 | 81.067 | | | | | | |
| 6 | .651 | 3.826 | 84.893 | | | | | | |
| 7 | .528 | 3.105 | 87.998 | | | | | | |
| 8 | .454 | 2.672 | 90.671 | | | | | | |
| 9 | .378 | 2.222 | 92.893 | | | | | | |
| 10 | .317 | 1.867 | 94.760 | | | | | | |
| 11 | .234 | 1.374 | 96.134 | | | | | | |
| 12 | .191 | 1.126 | 97.260 | | | | | | |
| 13 | .161 | 0.945 | 98.204 | | | | | | |
| 14 | .131 | 0.770 | 98.974 | | | | | | |
| 15 | .078 | 0.459 | 99.433 | | | | | | |
| 16 | .054 | 0.318 | 99.751 | | | | | | |
| 17 | .042 | 0.249 | 100.000 | | | | | | |

*Communalities*

Communalities analysis in Table 5 assesses the proportion of variance for each indicator that is explained by the extracted factors. Items with extraction communalities values of 0.50 or greater suggest that the items contribute significantly to measuring the underlying latent construct (Hair et al., 2019). The results indicate that most indicators have communalities above the general threshold of 0.20, meaning they are sufficiently explained by the factor structure. Some items have a comparatively low communality, such as IF1 (0.401), ACL4 (0.381), and ACL5 (0.468). Even though these values are lower, they were kept in the first analysis phase because of their theoretical relevance and would be re-examined during the factor rotation stage.

**Tabel 5.** Communalities

| **Code** | **Initial** | **Extraction** |
|---|---|---|
| CS1 | .821 | .750 |
| CS2 | .822 | .594 |
| CS3 | .675 | .548 |
| CS4 | .570 | .526 |
| IF1 | .545 | .401 |
| IF2 | .825 | .853 |
| IF3 | .819 | .744 |
| IF4 | .907 | .999 |
| CE1 | .891 | .817 |
| CE2 | .680 | .646 |
| CE3 | .868 | .922 |
| CE4 | .813 | .803 |
| ACL1 | .715 | .606 |
| ACL2 | .850 | .856 |
| ACL3 | .879 | .845 |
| ACL4 | .763 | .381 |
| ACL5 | .779 | .468 |

A. Scree Plot

The scree plot (Figure 1) shows a large drop in eigenvalues from the first factor to the second and then a gradual decrease across the remaining factors. The first factor explains the majority of variance, as demonstrated by its much higher eigenvalue than the rest of the factors. An observable inflection point (elbow) appears around the fourth factor, where the slope of the curve begins to level off. After this point, eigenvalues decrease consistently and remain low, indicating that each additional factor explains a progressively smaller amount of variance.

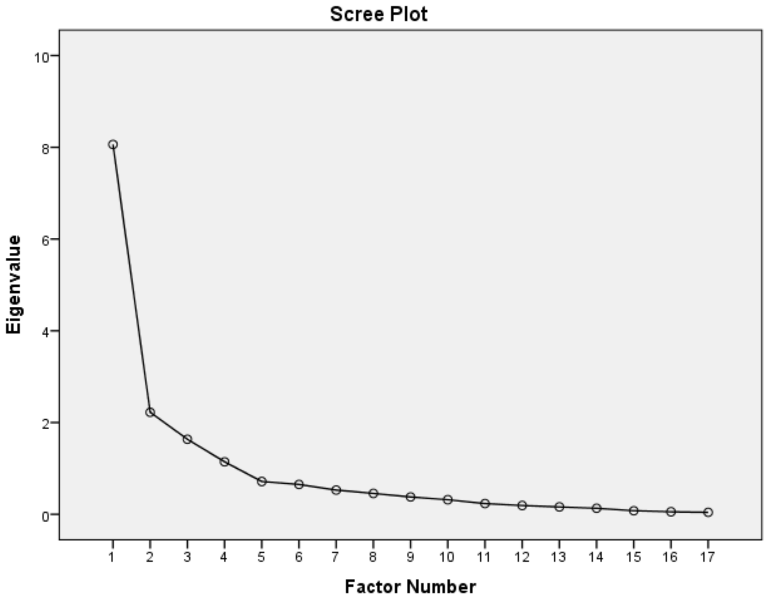

**Figure 1.** Scree Plot

B. Rotated Factor Matrix

The rotated factor matrix in Table 6 illustrates that the measurement items load consistently on four unique components, suggesting sufficient structural cohesion and discrimination between dimensions. The four factors were interpreted in relation to the rotated factor matrix and theoretical considerations as follows. Adaptive Co-Learning anchors the first dimension, which represents how agile teams and AI systems can adapt and develop new work processes in response to changes in task demands, iterate quickly in that collaborative process, and continuously improve it. ACL3 (0.903) and ACL2 (0.882) are the most defining variables of this factor, followed by ACL1, ACL5, and CE4, respectively. Cognitive Synchronization and Interaction Fluency, the second dimension, captures how aligned goals are, whether this alignment is clear in terms of decision boundaries, as well as how smooth human–AI interaction is. This dimension is primarily defined by items IF2, CS1, IF1, and CS4, with the largest contribution from item IF2 (0.846). This indicates that effective collaboration largely depends on bidirectional feedback and a common understanding among team members while acting collectively.

Complementary Expertise, the third dimension, symbolizes an overarching synergistic dynamic between human expertise and AI to augment the quality of both ideas and overall team performance. IF3, CE3, CE2, and ACL4 define this dimension, with IF3 (0.766) and CE3 contributing the highest loadings. The fourth dimension, AI Interpretability and Role Boundary, concerns the transparency of AI outputs and the limits of human decision-making authority in relation to perceived AI recommendations. This factor is primarily defined by IF4, CE1, and CS2, with IF4 (0.877) as the dominant indicator with the highest loading. The rotated structure as a whole exhibits a coherent four-dimensional configuration that undergirds the CIQ.

**Table 6.** Rotated Component Matrix

| Code | Item Statement | F1 | F2 | F3 | F4 |
|---|---|---|---|---|---|
| CS1 | In my company, teams and AI share a common understanding of task objectives. |  | 0.703 | 0.426 | 0.267 |
| CS2 | In my company, ideas and perspectives are coordinated between teams and AI during task execution. |  | 0.468 | 0.258 | 0.522 |
| CS3 | In my company, the boundary between AI recommendations and human decision-making is clearly defined. | 0.372 | 0.555 |  | 0.319 |
| CS4 | In my company, misalignment between team goals and AI outputs sometimes occurs during task execution. |  | 0.613 | 0.291 | 0.254 |
| IF1 | In my company, employees can easily provide instructions to AI for various task requirements. |  | 0.621 |  |  |
| IF2 | In my company, bidirectional feedback between teams and AI operates smoothly. |  | 0.846 | 0.310 |  |
| IF3 | In my company, AI outputs are easily understood by team members with diverse backgrounds. |  | 0.343 | 0.766 |  |
| IF4 | In my company, AI outputs are often difficult for teams to interpret. |  |  | 0.431 | 0.877 |
| CE1 | In my company, human and AI capabilities are integrated to improve overall team performance. | 0.259 | 0.452 | 0.424 | 0.605 |
| CE2 | In my company, human and AI capabilities complement each other to improve task effectiveness. | 0.333 |  | 0.623 | 0.369 |
| CE3 | In my company, collaboration with AI enhances the quality of ideas generated within teams. | 0.514 |  | 0.734 | 0.334 |
| CE4 | In my company, AI outputs are sufficiently adequate for work tasks even without human contribution. | 0.709 | 0.420 | 0.278 | 0.217 |
| ACL1 | In my company, teams engage in rapid iteration when working with AI. | 0.685 |  | 0.258 | 0.203 |

| Code | Item Statement | F1 | F2 | F3 | F4 |
|---|---|---|---|---|---|
| ACL2 | In my company, regular team corrections improve the quality of AI-generated outputs. | 0.882 | | | 0.247 |
| ACL3 | In my company, human-AI workflows remain efficient even when task requirements change. | 0.903 | | | |
| ACL4 | In my company, teams reflect and refine how they collaborate with AI after task completion. | | | 0.570 | |
| ACL5 | In my company, human-AI workflows rarely change despite shifts in task requirements. | 0.480 | | 0.467 | |

*Evaluation and Refinement of EFA Indicators*

While identifying a four-factor structure was effective in doing so, the exploratory factor analysis (EFA) results demonstrated multiple indicators showing cross-loadings and near-zero factor loadings, suggesting that further refinement is required before progressing to confirmatory factor analysis (CFA). To further improve the construct's clarity, parsimony, and structural integrity, items falling outside of acceptable statistical and conceptual criteria were discarded.

**Table 7.** Construct Refinement

| Identification | Latent Construct | Indicators |
|---|---|---|
| Factor 1 | Adaptive Co-Learning (ACL) | ACL3, ACL2, ACL1 |
| Factor 2 | Cognitive Synchronization & Interaction Fluency (CSIF) | IF2, CS1, IF 1 |
| Factor 3 | Complementary Expertise (CE) | IF3, CE3, CE2 |
| Factor 4 | AI Interpretability & Reflective Governance (AIRG) | IF4, ACL 4 |

*Confirmatory Factor Analysis*

A. CFA Results and Reliability Assessment

Table 8 and Figure 2 show the properties of the new measurement model for CIQ (secondary table in online supplementary file) including adequate reliability when measured on indices after CFA-based purification, along with convergent validity. To achieve a more parsimonious, structurally stable model without changing the theoretical conceptualization of the workflow construct, specific CFA refinement reduced the dimensionality from four to three latent dimensions and trimmed the total indicator set from 11 items to nine items. The Cronbach's alpha coefficients ranged from 0.774 to 0.869, all above the acceptable level of >0.70, suggesting good internal consistency. The CR values also range between 0.797 and 0.873, all greater than the recommended threshold of ≥0.70, confirming that all constructs are reliable. With regard to convergent validity, values of AVE fell between 0.635 and 0.668 all above the specified threshold (above 0.50) indicating that each construct explains a large proportion of variance in its indicators. Consistent with Hair et al. (2019), AVE values greater than 0.50 along with CR greater than 0.70 provide solid support for convergent validity. Together, these results demonstrate that the final three-dimensional, nine-indicator CIQ measurement model satisfies established reliability and validity thresholds and should be evaluated further at the structural level.

**Table 8.** CFA Results and Reliability Assessment

| Dimensions | Indicators | Estimate (Unstd) | SE | CR (t) | p-value | Cronbach's alpha | Composite reliability | AVE |
|---|---|---|---|---|---|---|---|---|
| Factor 1: Adaptive Co-Learning | ACL1 | 1.000 | - | - | - | 0.841 | 0.852 | 0.662 |
| | ACL2 | 1.412 | 0.375 | 3.762 | <0.001 | | | |

| Dimensions | Indicators | Estimate (Unstd) | SE | CR (t) | p-value | Cronbach's alpha | Composite reliability | AVE |
|---|---|---|---|---|---|---|---|---|
| | ACL3 | 1.583 | 0.421 | 3.763 | <0.001 | | | |
| Factor 2: Cognitive Synchronization & Interaction Fluency | CS1 | 1.000 | - | - | - | 0.774 | 0.797 | 0.668 |
| | IF2 | 1.056 | 0.283 | 3.739 | <0.001 | | | |
| Factor 3: Complementary Expertise | IF4 | 1.000 | - | - | - | 0.869 | 0.873 | 0.635 |
| | CE2 | 0.598 | 0.153 | 3.914 | <0.001 | | | |
| | CE3 | 0.797 | 0.144 | 5.534 | <0.001 | | | |
| | IF3 | 0.863 | 0.148 | 5.842 | <0.001 | | | |

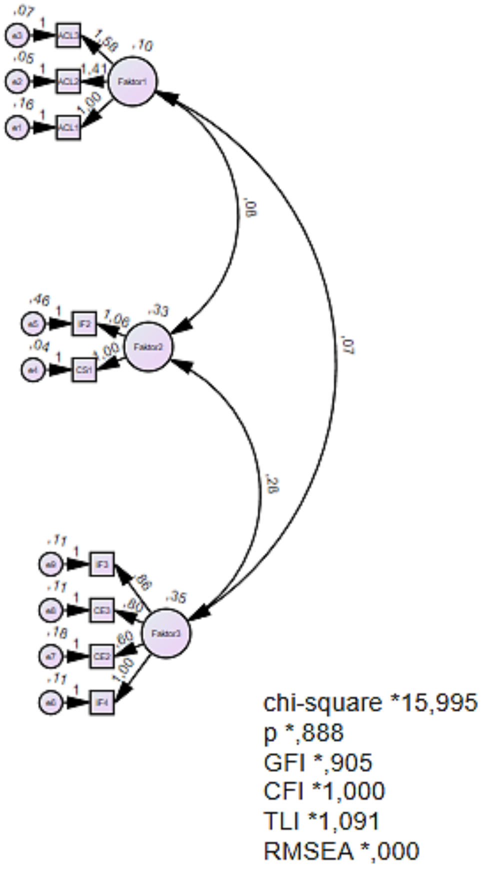

**Figure 2.** The measurement model of CIQ

B. Goodness of fit stats

The following model indices were within their recommended thresholds: CMIN/df = 0.666; NFI = 0.905; CFI = 1.000; GFI = 0.905; TLI = 1.091; and RMSEA based on the average fit function of an uninformative prior criterion was below .05 (see Table 9). Yet, because of the small sample size (N = 32) and model saturation indices that are close to perfect (RMSEA = 0.000; CFI = 1.000; TLI > 1.0), we view the apparent model fits as resulting from the mere dimensionality of the dataset rather than from true data-model adequacy. After adjusting for these caveats, the fit statistics should be regarded as preliminary findings only.

**Table 9.** Goodness of fit stats

| Fitness Index | CMIN/df | NFI | CFI | GFI | TLI | RMSEA |
|---|---|---|---|---|---|---|
| Criteria Source: (Awang, 2014; Greenspoon & Saklofske, 1998) | ≤ 3.0 | ≥ 0.90 | ≥ 0.90 | ≥ 0.80 | ≥ 0.90 | ≤ 0.08 |
| Initial Structural Model | 0.666 | 0.905 | 1.000 | 0.905 | 1.091 | 0.000 |

## Discussion

Learning, Cognitive Synchronization & Interaction Fluency; Human–AI Complementary Intelligence → Collective Intelligence Theory posits that group performance arises from the interaction processes and mutual cognition. A three-dimensional, nine-indicator CIQ model was generated using the EFA-CFA sequence. In contrast to team-level metrics such as the collective intelligence factor by Woolley et al. (2010), which predicts team performance based on task outcomes, CIQ is a direct organizational-level measure of the interaction processes that underlie these outcomes. CIQ also treats AI-enabled contributions as an explicit dimension something that contrasts with team cognition models that focus on shared mental models in human-only teams. For the purposes of our analyses, the CFA purification process (17 items down to 9 across three factors) demonstrated that collaborative maturity in human–AI workflows is best characterized through iterative learning cycles, cognitive synchronization, and capability integration. Notably, the identified dimensions Adaptive Co-Learning, Cognitive Synchronization & Interaction Fluency, and Human–AI Complementary Intelligence indicate theorizing more than confirmatory validation; this must be interpreted with caution (N = 32).

The prominence of Adaptive Co-Learning suggests that human–AI work will not mature through the simple introduction of new AI tools, but rather through ongoing evolution in how humans and AI interact as task demands change over time. Correction and iteration cycles are like a stabilizer in high-speed, parallel work. Even with AI, goal alignment and smooth reciprocal exchange still matter, as captured by the Cognitive Synchronization & Interaction Fluency dimension. Cognitive alignment may be tenuous, in which case teams act as a well-oiled machine while generating uneven outputs.

The development of Human–AI Complementary Intelligence as a retained dimension offers empirical support that complementarity (the combined use of human judgment and analytical intelligence via AI) is a unique, identifiable organizational capability. This directly builds upon the augmentation argument by Raisch & Krakowski (2021), who point out that value in AI-supported work relies not on the mere presence of AI but on the proper quality of integration. The CFA purification process, which removed cross-loading and unstable items, demonstrates that not all theoretically grounded indicators are empirically stable across settings, validating the need for rigorous scale refinement in new human–AI constructs. Together, the three retained dimensions represent CIQ as an integrated capability and depart from prior constructs by further identifying AI-specific dimensions as a key component of the definition.

From the applied lens, the validated CIQ model has immediate ramifications for collaboration governance in Indonesia's disparate property and integrated township domain, which requires tightly coupled handoffs across planning, design, construction, commercialization, and area operations to deliver large-scale projects. CIQ may be used as a diagnostic baseline to discern whether underlying collaboration vulnerabilities are predominantly attributable to underdeveloped learning-and-adjustment routines, interactional weak spots, misalignments across actors and workstreams, or insufficient integration of human expertise and AI contributions. It also allows for focused interventions that are more functionally specific, such as fortifying iteration and correction routines during design changes and site issue resolution; formalizing shared objectives and decision boundaries across functions and partners; and establishing interpretability practices when AI is used for reporting, planning, or coordination tasks. The CIQ can be integrated into the fabric of project governance and digitally upskilled performance reviews, and can allow managers to shift the collaboration ethos immediately from a nebulous ideal toward a tangible capability. This study has three main limitations: (1) small sample size (N = 32) this is the most significant limitation, as it hampers CFA robustness, generalizability, and the evaluation of discriminant validity. Future studies should target N ≥ 100 (Hair et al., 2020). (2) Focus on a single sector limits external generalizability; replications across industries in manufacturing, services, and public sector organizations are warranted. (3) Due to the cross-sectional nature of our study, causal inference cannot be drawn, and longitudinal designs will be required to determine whether CIQ improvements explain outcomes such as reduced rework, shorter coordination cycles, and greater performance stability under change.

## CONCLUSION

Constructs with good reliability (α = 0.774–0.869) and convergent validity (AVE = 0.635–0.668) comprising Adaptive Co-Learning, Cognitive Synchronization & Interaction Fluency, and Human–AI Complementary Intelligence (CIQ) a three-dimensional, nine-indicator diagnostic construct tested in Indonesia's diversified property and integrated township sector were developed with initial psychometric validation offered in response to the first research question (RQ1). We went for a parsimonious model, so we found support for the EFA–CFA sequence. CIQ not only expands Collective Intelligence Theory from explanatory theorizing to psychometric measurement at the organizational level, but it also helps advance human–AI teaming research by providing a systematic diagnostic tool that can simultaneously assess shared cognition, interaction fluency, adaptive learning, and complementary human–AI capability on a validated scale. CIQ allows organizations to identify key weaknesses of collaboration at the organizational level and then target improvements in individual dimensions that need strengthening for fully functional, AI-enabled cross-disciplinary teamwork.

CIQ provides a pragmatic diagnostic that can be integrated into project governance and digital-transformation assessments to surface and remediate precise collaboration weaknesses. Future validation steps should test the main shortcomings mentioned above using larger samples and cross-industry designs, followed up by longitudinal outcome assessment.

## ACKNOWLEDGEMENT

The authors would like to thank Universitas Ciputra for providing the material and support in conducting this research. We appreciate the input and support of all subjects and collaborators who contributed during the development and validation of the Collaborative Intelligence Quotient (CIQ).

## AUTHOR CONTRIBUTION STATEMENT

Conceptualization, methodology, and writing review and editing of the original draft manuscript were performed by Andreas Raditya. He was also involved in its review and editing. Thomas Stefanus Kaihatu was responsible for the data collection and analysis, writing of the original paper. Validation, investigation and data curation were performed by Timotius FCW Sutrisno, who also contributed to writing review and editing.

## REFERENCES

Aaron, C., Heap, T., Archibald, A., Keyes, L., Novosad, M., & Fein, A. (2025). Applications of human–AI interaction to optimize teaching workload and improve student writing. *Journal of Computing in Higher Education*, *37*(4), 1427–1459. https://doi.org/10.1007/s12528-025-09474-0

Abbasian Ardakani, A., Airom, O., Khorshidi, H., Bureau, N. J., Salvi, M., Molinari, F., & Acharya, U. R. (2024). Interpretation of Artificial Intelligence Models in Healthcare. *Journal of Ultrasound in Medicine*, *43*(10), 1789–1818. https://doi.org/10.1002/jum.16524

Adebayo, Y., Udoh, P., Kamudyariwa, X. B., & Osobajo, O. A. (2025). Artificial Intelligence in Construction Project Management: A Structured Literature Review of Its Evolution in Application and Future Trends. In *Digital* (Vol. 5, Number 3). https://doi.org/10.3390/digital5030026

Alam, S., & Khan, M. F. (2024). Enhancing AI-Human Collaborative Decision-Making in Industry 4.0 Management Practices. *IEEE Access*, *12*, 119433–119444. https://doi.org/10.1109/ACCESS.2024.3449415

Ali, I., Nguyen, K., Ali, A. M., & Cui, T. (2025). Human–AI collaboration in knowledge ecosystems: a multidisciplinary review, integrative framework and future directions. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-03-2025-0431

Alix, C., Lafond, D., Mattioli, J., Heer, J. De, Chattington, M., & Robic, P.-O. (2021). Empowering Adaptive Human Autonomy Collaboration with Artificial Intelligence. *2021 16th International Conference of System of Systems Engineering (SoSE)*, 126–131. https://doi.org/10.1109/SOSE52739.2021.9497497

Alrasheed, K., Hassaneiah, S., & Alselahi, N. S. (2026). Improving project outcomes through effective communication: A quantitative study of causes and solutions in Kuwait's construction industry. *Journal of Engineering Research (Kuwait)*. https://doi.org/10.1016/j.jer.2026.01.001

Attig, C., Winzer, L., Schrills, T., Zoubir, M., Mortaga, M., Wollstadt, P., Wiebel-Herboth, C., & Franke, T. (2026). Understanding successful human–AI teaming: The role of goal alignment and AI autonomy for social perception of LLM-based chatbots. *Computers in Human Behavior: Artificial Humans*, *7*, 100246. https://doi.org/10.1016/j.chbah.2025.100246

Awang, Z. (2014). Structural equation modeling using AMOS. Shah Alam. In *Malaysia: University Teknologi MARA Publication Center.*

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS Quarterly*, *45*(1), 315–341. https://doi.org/10.25300/MISQ/2021/15882

Baltà-Salvador, R., El-Madafri, I., Brasó-Vives, E., & Peña, M. (2025). Empowering Engineering Students Through Artificial Intelligence (AI): Blended Human–AI Creative Ideation Processes With ChatGPT. *Computer Applications in Engineering Education*, *33*(1). https://doi.org/10.1002/cae.22817

Bansal, G., Nushi, B., Kamar, E., Weld, D. S., Lasecki, W. S., & Horvitz, E. (2019). Updates in Human-AI Teams: Understanding and Addressing the Performance/Compatibility Tradeoff. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 2429–2437. https://doi.org/10.1609/aaai.v33i01.33012429

Berretta, S., Tausch, A., Ontrup, G., Gilles, B., Peifer, C., & Kluge, A. (2023). Defining human-AI teaming the human-centered way: a scoping review and network analysis. In *Frontiers in Artificial Intelligence* (Vol. 6). https://doi.org/10.3389/frai.2023.1250725

Bullock, J. B. (2019). Artificial Intelligence, Discretion, and Bureaucracy. *The American Review of Public Administration*, *49*(7), 751–761. https://doi.org/10.1177/0275074019856123

Cabitza, F., Campagner, A., & Ciucci, D. (2019). *New Frontiers in Explainable AI: Understanding the GI to Interpret the GO* (pp. 27–47). https://doi.org/10.1007/978-3-030-29726-8_3

Cabrera, Á. A., Perer, A., & Hong, J. I. (2023). Improving Human-AI Collaboration With Descriptions of AI Behavior. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1–21. https://doi.org/10.1145/3579612

Callaghan, C. (2025). Solving the Human–AI Goal Alignment Problem: Insights from Arrow–Debreu Alignment, Experiential Matrix Theory, and AI Safety Modelling. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5536962

Carter, W., & Wynne, K. T. (2024). Integrating artificial intelligence into team decision-making: Toward a theory of AI–human team effectiveness. *European Management Review*. https://doi.org/10.1111/emre.12685

Castañer, X., & Oliveira, N. (2020). Collaboration, Coordination, and Cooperation Among Organizations: Establishing the Distinctive Meanings of These Terms Through a Systematic Literature Review. *Journal of Management*, *46*(6). https://doi.org/10.1177/0149206320901565

Chen, S., & Zhao, Y. (2025). Why am I willing to collaborate with AI? Exploring the desire for collaboration in human-AI hybrid group brainstorming. *Kybernetes*. https://doi.org/10.1108/K-08-2024-2105

Chou, C.-M., Shen, T.-C., Shen, T.-C., & Shen, C.-H. (2022). Influencing factors on students' learning effectiveness of AI-based technology application: Mediation variable of the human-computer interaction experience. *Education and Information Technologies*, *27*(6), 8723–8750. https://doi.org/10.1007/s10639-021-10866-9

Covilla, J. C. (2025). Artificial Intelligence and Administrative Discretion: Exploring Adaptations and Boundaries. *European Journal of Risk Regulation*, *16*(1), 36–50. https://doi.org/10.1017/err.2024.76

Dang, B., Huynh, L., Gul, F., Rosé, C., Järvelä, S., & Nguyen, A. (2025). Human–AI collaborative learning in mixed reality: Examining the cognitive and socio-emotional interactions. *British Journal of Educational Technology*, *56*(5), 2078–2101. https://doi.org/10.1111/bjet.13607

Dawarka, V., Doargajudhur, M., & Dutot, V. (2026). AI in project teams: how trust calibration reconfigures team's collaboration and performance. *International Journal of Managing Projects in Business*, 1–22. https://doi.org/10.1108/IJMPB-07-2025-0285

Dobson, J. E. (2023). On reading and interpreting black box deep neural networks. *International Journal of Digital Humanities*, *5*(2–3), 431–449. https://doi.org/10.1007/s42803-023-00075-w

Du, T., Li, X., Jiang, N., Xu, Y., & Zhou, Y. (2025). Adaptive AI as Collaborator: Examining the Impact of an AI's Adaptability and Social Role on Individual Professional Efficacy and Credit Attribution in Human–AI Collaboration. *International Journal of Human–Computer Interaction*, *41*(19), 12422–12433. https://doi.org/10.1080/10447318.2025.2462120

Du, W., Liu, W., Guo, X., & Vogel, D. (2024). How Team Diversity Influences Online Medical Team Service Performance Through Shared Leadership: An Input-Process-Output Perspective. *Group Decision and Negotiation*, *33*(1), 27–54. https://doi.org/10.1007/s10726-023-09853-x

Duan, W., Zhou, S., Scalia, M. J., Yin, X., Weng, N., Zhang, R., Freeman, G., McNeese, N., Gorman, J., & Tolston, M. (2024). Understanding the Evolvement of Trust Over Time within Human-AI Teams. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1–31. https://doi.org/10.1145/3687060

Dung, L. (2023). Current cases of AI misalignment and their implications for future risks. *Synthese*, *202*(5), 138. https://doi.org/10.1007/s11229-023-04367-0

Elton, D. C. (2020). *Self-explaining AI as an Alternative to Interpretable AI* (pp. 95–106). https://doi.org/10.1007/978-3-030-52152-3_10

Endsley, M. R. (2023). Supporting Human-AI Teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior*, *140*, 107574. https://doi.org/10.1016/j.chb.2022.107574

Englmaier, F., Grimm, S., Grothe, D., Schindler, D., & Schudy, S. (2025). The value of leadership: Evidence from a large-scale field experiment. *Leadership Quarterly*, *36*(3). https://doi.org/10.1016/j.leaqua.2025.101869

Escalante, J., Pack, A., & Barrett, A. (2023). AI-generated feedback on writing: insights into efficacy and ENL student preference. *International Journal of Educational Technology in Higher Education*, *20*(1), 57. https://doi.org/10.1186/s41239-023-00425-2

Fang, C., Zhu, Y., Fang, L., Long, Y., Lin, H., Cong, Y., & Wang, S. J. (2025). Generative AI-enhanced human-AI collaborative conceptual design: A systematic literature review. *Design Studies*, *97*, 101300. https://doi.org/10.1016/j.destud.2025.101300

Fox, S. (2024). Adaptive AI Alignment: Established Resources for Aligning Machine Learning with Human Intentions and Values in Changing Environments. *Machine Learning and Knowledge Extraction*, *6*(4), 2570–2600. https://doi.org/10.3390/make6040124

Geroimenko, V. (2026). Feedback and Iterative Refinement: Improving AI Responses Through Interaction Cycles. In *Beyond and After Prompt Engineering: The Future of AI Communication* (pp. 203–230). Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-04569-0_11

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., & Kagal, L. (2018). Explaining Explanations: An Overview of Interpretability of Machine Learning. *2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)*, 80–89. https://doi.org/10.1109/DSAA.2018.00018

Gomez, C., Cho, S. M., Ke, S., Huang, C.-M., & Unberath, M. (2025). Human-AI collaboration is not very collaborative yet: a taxonomy of interaction patterns in AI-assisted decision making from a systematic review. *Frontiers in Computer Science*, *6*. https://doi.org/10.3389/fcomp.2024.1521066

Gonzalez, C., & Heidari, H. (2025). A cognitive approach to human–AI complementarity in dynamic decision-making. *Nature Reviews Psychology*, *4*(12), 808–822. https://doi.org/10.1038/s44159-025-00499-x

Greenspoon, P. J., & Saklofske, D. H. (1998). Confirmatory factor analysis of the multidimensional Students' Life Satisfaction Scale. *Personality and Individual Differences*, *25*(5), 965–971. https://doi.org/10.1016/S0191-8869(98)00115-9

Guo, A., Pataranutaporn, P., & Maes, P. (2024). Exploring the Impact of AI Value Alignment in Collaborative Ideation: Effects on Perception, Ownership, and Output. *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, 1–11. https://doi.org/10.1145/3613905.3650892

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2020). *Multivariate Data Analysis* (8th ed.). Pearson.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Hamdan, H. A. M., Andersen, P. H., & de Boer, L. (2021). Stakeholder collaboration in sustainable neighborhood projects—A review and research agenda. In *Sustainable Cities and Society* (Vol. 68). https://doi.org/10.1016/j.scs.2021.102776

Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., & Satzger, G. (2025). Complementarity in human-AI collaboration: concept, sources, and evidence. *European Journal of Information Systems*, *34*(6), 979–1002. https://doi.org/10.1080/0960085X.2025.2475962

Hermanns, L., & Teubner, T. (2025). Under pressure: how time constraints, task complexity, and AI reliability shape human-AI interaction. *Behaviour & Information Technology*, 1–25. https://doi.org/10.1080/0144929X.2025.2587732

Holter, S., & El-Assady, M. (2024). Deconstructing Human-AI Collaboration: Agency, Interaction, and Adaptation. *Computer Graphics Forum*, *43*(3). https://doi.org/10.1111/cgf.15107

Janssens, M., Meslec, N., & Leenders, R. T. A. J. (2022). Collective intelligence in teams: Contextualizing collective intelligent behavior over time. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.989572

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4). https://doi.org/10.1016/j.bushor.2018.03.007

Joosten, J., Bilgram, V., Hahn, A., & Totzek, D. (2024). Comparing the Ideation Quality of Humans With Generative Artificial Intelligence. *IEEE Engineering Management Review*, *52*(2), 153–164. https://doi.org/10.1109/EMR.2024.3353338

Kaliisa, R., Misiejuk, K., López-Pernas, S., & Saqr, M. (2026). How does artificial intelligence compare to human feedback? A meta-analysis of performance, feedback perception, and learning dispositions. *Educational Psychology*, *46*(1), 80–111. https://doi.org/10.1080/01443410.2025.2553639

Kasirzadeh, A. (2026). The Many Faces of AI Alignment. In *Contemporary Debates in the Ethics of Artificial Intelligence* (pp. 263–281). Wiley. https://doi.org/10.1002/9781394258840.ch18

Kaur, H., Nori, H., Jenkins, S., Caruana, R., Wallach, H., & Wortman Vaughan, J. (2020). Interpreting Interpretability: Understanding Data Scientists' Use of Interpretability Tools for Machine Learning. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3313831.3376219

Kierans, A., Ghosh, A., Hazan, H., & Dori-Hacohen, S. (2025). Quantifying Misalignment Between Agents: Towards a Sociotechnical Understanding of Alignment. *Proceedings of the AAAI Conference on Artificial Intelligence*, *39*(26), 27365–27373. https://doi.org/10.1609/aaai.v39i26.34947

Kim, J., & Maher, M. Lou. (2023). The effect of AI-based inspiration on human design ideation. *International Journal of Design Creativity and Innovation*, *11*(2), 81–98. https://doi.org/10.1080/21650349.2023.2167124

Klar, M. (2025). Using ChatGPT is easy, using it effectively is tough? A mixed methods study on K-12 students' perceptions, interaction patterns, and support for learning with generative AI chatbots. *Smart Learning Environments*, *12*(1), 32. https://doi.org/10.1186/s40561-025-00385-2

Komura, K., & Yamada, S. (2026). Deepening ideas vs. exploring new ones: AI strategy effects in human-AI creative collaboration. *PLOS One*, *21*(1), e0340449. https://doi.org/10.1371/journal.pone.0340449

Kordova, S., & Hirschprung, R. S. (2023). Effectiveness of the forced usage of alternative digital platforms during the COVID-19 pandemic in project communication management. *Heliyon*, *9*(11). https://doi.org/10.1016/j.heliyon.2023.e21812

Kroh, J., & Schultz, C. (2023). In favor or against: The influence of skeptical stakeholders in urban innovation projects for green transformation. *International Journal of Project Management*, *41*(7). https://doi.org/10.1016/j.ijproman.2023.102515

Kumar, N., & Kumar, R. R. (2025). Human–AI collaboration in operations and supply chain management: a systematic literature review. *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00575-9

Kumar, S., Datta, S., Singh, V., Datta, D., Kumar Singh, S., & Sharma, R. (2024). Applications, Challenges, and Future Directions of Human-in-the-Loop Learning. *IEEE Access*, *12*, 75735–75760. https://doi.org/10.1109/ACCESS.2024.3401547

Kunz, W. H., Sajtos, L., & Flavián, C. (2025). Beyond replacement: human-machine collaboration in the age of AI. *Journal of Service Management*, *36*(4), 477–494. https://doi.org/10.1108/JOSM-04-2025-0194

Larson, L., & DeChurch, L. A. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *Leadership Quarterly*, *31*(1). https://doi.org/10.1016/j.leaqua.2019.101377

Leblanc, P. M., Harvey, J. F., & Rousseau, V. (2024). A meta-analysis of team reflexivity: Antecedents, outcomes, and boundary conditions. *Human Resource Management Review*, *34*(4). https://doi.org/10.1016/j.hrmr.2024.101042

Li, H., Wang, Y., & Qu, H. (2025). Reflection on Data Storytelling Tools in the Generative AI Era from the Human-AI Collaboration Perspective. *2025 IEEE Visualization and Visual Analytics (VIS)*, 21–25. https://doi.org/10.1109/VIS60296.2025.00009

Li, W., Liu, H., Huang, K., & Hussain, A. (2025). Reinforcement Learning for Human-AI Collaboration: Challenges, Mechanisms, and Methods. *Cognitive Computation*, *17*(5), 146. https://doi.org/10.1007/s12559-025-10500-7

Li, X., Jiang, Q., Jiang, L., Zhang, S., & Hu, S. (2026). The Landscape of AI Alignment: A Comprehensive Review of Theories and Methods. *International Journal of Pattern Recognition and Artificial Intelligence*, *40*(03). https://doi.org/10.1142/S021800142539001X

Lopes, S. L., Ferreira, A. I., Prada, R., & Schwarzer, R. (2023). Social robots as health promoting agents: An application of the health action process approach to human-robot interaction at the workplace. *International Journal of Human-Computer Studies*, *180*, 103124. https://doi.org/10.1016/j.ijhcs.2023.103124

Mahajan, S. (2025). The democratization dilemma: When everyone is an expert, who do we trust? *Humanities and Social Sciences Communications*, *12*(1), 455. https://doi.org/10.1057/s41599-025-04734-x

Malik, A. A., & Bilberg, A. (2019). Complexity-based task allocation in human-robot collaborative assembly. *Industrial Robot: The International Journal of Robotics Research and Application*, *46*(4), 471–480. https://doi.org/10.1108/IR-11-2018-0231

Marlow, S. L., Lacerenza, C. N., & Salas, E. (2017). Communication in virtual teams: a conceptual framework and research agenda. *Human Resource Management Review*, *27*(4). https://doi.org/10.1016/j.hrmr.2016.12.005

Matsumoto, T., Nishikawa, R., & Morimoto, C. (2024). Reflection through interaction with digital twin AI in the Human-AI-Collaboration SECI Model. *Procedia Computer Science*, *246*, 3743–3752. https://doi.org/10.1016/j.procs.2024.09.182

McGrath, M. J., Duenser, A., Lacey, J., & Paris, C. (2025). Collaborative human-AI trust (CHAI-T): A process framework for active management of trust in human-AI collaboration. *Computers in Human Behavior: Artificial Humans*, *6*, 100200. https://doi.org/10.1016/j.chbah.2025.100200

Morin, X., & Romero-Torres, A. (2024). How does building information modeling influence decision-making process in the project design? An input, process and output analysis. *Project Leadership and Society*, *5*. https://doi.org/10.1016/j.plas.2024.100160

Mseer, I., & Ali Samhan, A. A. (2025). *Collaboration Between Humans and AI* (pp. 1299–1308). https://doi.org/10.1007/978-3-031-87550-2_83

Niler, A. A., Mesmer-Magnus, J. R., Larson, L. E., Plummer, G., DeChurch, L. A., & Contractor, N. S. (2021). Conditioning team cognition: A meta-analysis. *Organizational Psychology Review*, *11*(2). https://doi.org/10.1177/2041386620972112

Oliveira, P., Carvalho, J. M. S., & Faria, S. (2025). AI Integration in Organisational Workflows: A Case Study on Job Reconfiguration, Efficiency, and Workforce Adaptation. *Information*, *16*(9), 764. https://doi.org/10.3390/info16090764

Paquette, S., Kilcullen, M., Hoffman, O., Hernandez, J., Mehta, A., Salas, E., & Greilich, P. E. (2023). Handoffs and the challenges to implementing teamwork training in the perioperative environment. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1187262

Park, J., & Goel, A. K. (2025). Human-Centric Teaching at Scale in Online Education through Bidirectional Feedback in Human-AI Interaction. *Proceedings of the AAAI Symposium Series*, *5*(1), 93–94. https://doi.org/10.1609/aaaiss.v5i1.35566

Patel, V., Singh, A. K., Jain, A., Thaker, M., Menon, P., & Patrikar, A. (2025). The impact of Automation and AI: Exploring how automation and AI will reshape team dynamics and the skill set needed for the future high-performing team. *2025 Eighth International Conference on Image Information Processing (ICIIP)*, 490–495. https://doi.org/10.1109/ICIIP68302.2025.11346362

Peng, L., Li, D., Zhang, Z., Zhang, T., Huang, A., Yang, S., & Hu, Y. (2024). Human-AI collaboration: Unraveling the effects of user proficiency and AI agent capability in intelligent decision support systems. *International Journal of Industrial Ergonomics*, *103*, 103629. https://doi.org/10.1016/j.ergon.2024.103629

Peng, Z., & Wan, Y. (2024). Human vs. AI: Exploring students' preferences between human and AI TA and the effect of social anxiety and problem complexity. *Education and Information Technologies*, *29*(1), 1217–1246. https://doi.org/10.1007/s10639-023-12374-4

Puerta-Beldarrain, M., Gómez-Carmona, O., Sánchez-Corcuera, R., Casado-Mansilla, D., López-de-Ipiña, D., & Chen, L. (2025). A Multifaceted Vision of the Human-AI Collaboration: A Comprehensive Review. *IEEE Access*, *13*, 29375–29405. https://doi.org/10.1109/ACCESS.2025.3536095

Rahmati, M. (2025). Dynamic role-adaptive collaborative robots for sustainable smart manufacturing: an AI-driven approach. *Journal of Intelligent Manufacturing and Special Equipment*, *6*(2), 101–115. https://doi.org/10.1108/JIMSE-01-2025-0001

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1). https://doi.org/10.5465/AMR.2018.0072

Riedl, C., Kim, Y. J., Gupta, P., Malone, T. W., & Woolley, A. W. (2021). Quantifying collective intelligence in human groups. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(21). https://doi.org/10.1073/pnas.2005737118

Rönndahl, C., Bosch-Sijtsema, P., Rempling, R., & Karlsson, M. (2025). Making sense of collaboration in major infrastructure construction projects. *Project Leadership and Society*, *6*. https://doi.org/10.1016/j.plas.2025.100178

Rowe, L. I., Hattie, J., & Hester, R. (2021). g versus c: comparing individual and collective intelligence across two meta-analyses. In *Cognitive Research: Principles and Implications* (Vol. 6, Number 1). https://doi.org/10.1186/s41235-021-00285-2

Rožman, M., Oreški, D., & Tominc, P. (2023). Artificial-Intelligence-Supported Reduction of Employees' Workload to Increase the Company's Performance in Today's VUCA Environment. *Sustainability*, *15*(6), 5019. https://doi.org/10.3390/su15065019

Sankaran, G., Palomino, M., Knahl, M., & Siestrup, G. (2022). A Modeling Approach for Measuring the Performance of a Human-AI Collaborative Process. *Applied Sciences*, *12*(22), 11642. https://doi.org/10.3390/app122211642

Schmutz, J. B., Outland, N., Kerstan, S., Georganta, E., & Ulfert, A. S. (2024). AI-teaming: Redefining collaboration in the digital era. In *Current Opinion in Psychology* (Vol. 58). https://doi.org/10.1016/j.copsyc.2024.101837

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information and Management*, *57*(2). https://doi.org/10.1016/j.im.2019.103174

Shen, H., Knearem, T., Ghosh, R., Liu, M. X., Monroy-Hernández, A., Wu, T., Yang, D., Huang, Y., Mitra, T., Li, Y., & Hearst, M. (2025). Bidirectional Human-AI Alignment: Emerging Challenges and Opportunities. *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, 1–6. https://doi.org/10.1145/3706599.3716291

Shin, J. G., Koch, J., Lucero, A., Dalsgaard, P., & Mackay, W. E. (2023). Integrating AI in Human-Human Collaborative Ideation. *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–5. https://doi.org/10.1145/3544549.3573802

Sidra, S., & Mason, C. (2025). Generative AI in Human-AI Collaboration: Validation of the Collaborative AI Literacy and Collaborative AI Metacognition Scales for Effective Use. *International Journal of Human–Computer Interaction*, 1–25. https://doi.org/10.1080/10447318.2025.2543997

Simón, C., Revilla, E., & Jesús Sáenz, M. (2024). Integrating AI in organizations for value creation through Human-AI teaming: A dynamic-capabilities approach. *Journal of Business Research*, *182*, 114783. https://doi.org/10.1016/j.jbusres.2024.114783

Stevens, A., & De Smedt, J. (2024). Explainability in process outcome prediction: Guidelines to obtain interpretable and faithful models. *European Journal of Operational Research*, *317*(2), 317–329. https://doi.org/10.1016/j.ejor.2023.09.010

Subramanian, H. V., Canfield, C., & Shank, D. B. (2024). Designing explainable AI to improve human-AI team performance: A medical stakeholder-driven scoping review. *Artificial Intelligence in Medicine*, *149*, 102780. https://doi.org/10.1016/j.artmed.2024.102780

Tummala, V. S., Burris-Melville, T. S., & Eskridge, T. C. (2025). AI as a Team Member: Redefining Collaboration. *Journal of Leadership Studies*, *18*(4), 67–80. https://doi.org/10.1002/jls.70003

Vamplew, P., Dazeley, R., Foale, C., Firmin, S., & Mummery, J. (2018). Human-aligned artificial intelligence is a multiobjective problem. *Ethics and Information Technology*, *20*(1), 27–40. https://doi.org/10.1007/s10676-017-9440-6

Vuchkovski, D., Zalaznik, M., Mitręga, M., & Pfajfar, G. (2023). A look at the future of work: The digital transformation of teams from conventional to virtual. *Journal of Business Research*, *163*. https://doi.org/10.1016/j.jbusres.2023.113912

Wang, D., & Zhou, X. (2025). The Impact of AI Awareness on Employees' Job Burnout: A Chain Mediation of Perceived Organizational Support and Organizational Commitment. *Sage Open*, *15*(4). https://doi.org/10.1177/21582440251400532

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science*, *330*(6004). https://doi.org/10.1126/science.1193147

Xu, G., Murthy, S. V., & Jia, B. (2025). Enhancing Intuitive Decision-Making and Reliance Through Human–AI Collaboration: A Review. *Informatics*, *12*(4), 135. https://doi.org/10.3390/informatics12040135

Yang, M. M., Lu, Y., & Cooke, F. L. (2026). Demystifying AI for the Workforce: The Role of Explainable AI in Worker Acceptance and Management Relations. *Journal of Management Studies*, *63*(2), 438–472. https://doi.org/10.1111/joms.70039

Zhan, Y., & Yan, Z. (2025). Students' engagement with ChatGPT feedback: implications for student feedback literacy in the context of generative artificial intelligence. *Assessment & Evaluation in Higher Education*, 1–14. https://doi.org/10.1080/02602938.2025.2471821

Zhang, Q., Lee, M. L., & Carter, S. (2022). You Complete Me: Human-AI Teams and Complementary Expertise. *CHI Conference on Human Factors in Computing Systems*, 1–28. https://doi.org/10.1145/3491102.3517791

Zhang, X., & Chen, N. (2026). The Role of Shared Mental Models in Driving Knowledge Complementarity: Enhancing Human–AI Team Effectiveness. *International Journal of Human–Computer Interaction*, 1–21. https://doi.org/10.1080/10447318.2025.2598670

Zhang, Y., Tino, P., Leonardis, A., & Tang, K. (2021). A Survey on Neural Network Interpretability. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *5*(5), 726–742. https://doi.org/10.1109/TETCI.2021.3100641

Zhao, M., Simmons, R., & Admoni, H. (2025). The Role of Adaptation in Collective Human–AI Teaming. *Topics in Cognitive Science*, *17*(2), 291–323. https://doi.org/10.1111/tops.12633

Zhou, C., Zhang, X., & Yu, C. (2025). How does AI promote design iteration? The optimal time to integrate AI into the design process. *Journal of Engineering Design*, *36*(11), 1904–1931. https://doi.org/10.1080/09544828.2023.2290915

Zhu, Y., Wang, T., Wang, C., Quan, W., & Tang, M. (2023). Complexity-Driven Trust Dynamics in Human–Robot Interactions: Insights from AI-Enhanced Collaborative Engagements. *Applied Sciences*, *13*(24), 12989. https://doi.org/10.3390/app132412989