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# Human-AI Collaborative Leadership: How Academic Leaders Co-Create Decision Making with Generative AI in Indonesian Higher Education

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**Abstract.** The rapid proliferation of generative artificial intelligence (GenAI) has fundamentally transformed academic leadership landscapes across Indonesian higher education. This paper develops a Human-AI Collaborative Leadership conceptual framework and outlines the mixed methods research design through which the framework is to be empirically examined. Moving beyond conventional tool-use paradigms that treat AI as a passive instrument, the framework theorizes academic leaders' engagement with GenAI systems as a process of genuine co-creation in institutional decision-making. Drawing on Distributed Leadership Theory, Actor-Network Theory (ANT), and Sensemaking Theory within a critical realism paradigm, the framework identifies four interacting levels contextual factors, the collaborative process, decision outcomes, and multi dimensional consequences and derives a set of theoretically grounded, empirically testable propositions concerning collaboration modes, power dynamics, and leadership identity trajectories. The proposed embedded concurrent mixed-methods design (qual + quan) combines ethnographic observation, in-depth interviews, and document analysis of 12–15 academic leaders at AI-mature universities with a subsequent survey of 250–300 academic leaders across 20–30 institutions, intended to test and refine the propositions and to validate a newly developed Human-AI Collaboration Mode Scale. This paper's contribution is therefore twofold: a theoretically grounded conceptual framework with explicit propositions, and a transparent, replicable research protocol including participant recruitment procedures, institutional AI-maturity classification criteria, scale development steps, and a mixed-methods integration strategy intended to guide the subsequent empirical phase of this research program and to inform ethical AI governance in Indonesian higher education leadership.

**Keywords: Human AI Collaborative Leadership, Generative Artificial Intelligence, Academic Decision Making, Indonesian Higher Education, Distributed Leadership**
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## INTRODUCTION

The generative artificial intelligence (GenAI) revolution, initiated by the launch of ChatGPT in November 2022, has profoundly reshaped academic leadership across the globe [1]. In Indonesia home to 4,593 higher education institutions serving 9.2 million students and 298,900 faculty [2], [3] this transformation is particularly consequential. A striking paradox has emerged: while 87% of academic staff report awareness of AI tools, only 12% consistently integrate them into professional practice. This 75 percentage-point gap signals not merely a technology-adoption challenge, but a deeper paradigmatic question about how academic leadership is conceptualized and practiced in the digital age.

Existing literature on technology adoption in higher education, including the Technology Acceptance Model (TAM) [4] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [5], predominantly conceptualizes AI as a passive instrument in a unidirectional human to tool relationship. However, when a university rector engages in iterative dialogue with ChatGPT receiving counter questions,

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alternative perspectives, and challenges to existing assumptions AI arguably transcends the role of a mere tool and becomes a collaborative interlocutor. This relational dynamic is not well captured by conventional adoption frameworks, motivating the conceptual work undertaken here.

Leadership in Indonesian higher education occupies a uniquely demanding position. Rectors, Vice Rectors, Deans, and Program Chairs must simultaneously navigate global competitiveness pressures and structural constraints, including resource disparities, digital literacy gaps, and infrastructural limitations. These leaders are increasingly turning to GenAI not only for informational support but potentially as a decision-making collaborator a phenomenon that, if borne out empirically, would demand new theoretical framing.

While some studies have examined AI in organizational settings and others have addressed digital leadership transformation, few have theorized how academic leaders might co-create decisions with AI systems, and none have yet examined this phenomenon empirically within the Indonesian higher education context. Existing research has primarily focused on AI adoption rates and user attitudes, leaving a gap in theorizing the collaborative dynamics, power negotiations, and identity implications of human AI decision making partnerships. This paper addresses that gap at the conceptual and design stage: it aims to (1) develop a theoretically integrated Human-AI Collaborative Leadership framework; (2) derive testable propositions regarding collaboration modes, power dynamics, and leadership identity trajectories; and (3) specify a transparent, replicable mixed-methods protocol through which these propositions can subsequently be examined among academic leaders in Indonesian higher education.

It should be stated explicitly that this paper reports a *conceptual framework and research design*, not completed empirical findings. Data collection under the protocol described in the Methods section has not yet been undertaken. Accordingly, the *Theoretical Framework* section below develops the framework and its propositions from prior literature; the *Methods* section specifies the protocol through which those propositions are to be tested; and the *Proposed Conceptual Model, Theoretical Propositions, and Anticipated Contributions* section discusses the framework's expected theoretical and practical contributions, framed throughout in propositional rather than results language.

## METHODS

This study employs a critical realism paradigm [6], which acknowledges that reality exists independently of observation while recognizing that our understanding of it is always mediated by social contexts and interpretations. This paradigm is well suited to studying complex phenomena at the intersection of human agency and technological structure. The research design is an Embedded Concurrent Mixed Methods approach (qual + quan) [7], wherein qualitative inquiry serves as the primary method to answer 'how' and 'why' questions, and quantitative methods serve as a secondary tool for generalizability and descriptive pattern identification.

### *Qualitative Phase (Primary)*

**Ethnographic Observation.** A purposive sample of 12–15 academic leaders (Deans and Vice Rectors) from three Indonesian universities classified as high in AI maturity will be observed. Shadowing will be conducted over three half-days per leader (approximately 40–45 days in total), combined with screen-recorded AI interaction sessions, think-aloud protocols, and detailed field notes. This approach is intended to capture real-time collaboration processes, interaction patterns, decision contexts, and power dynamics as they unfold naturally.

**In-Depth Interviews. Semi-structured interviews of 90–120 minutes each will be conducted with the same 12–15 leaders plus 10–12 faculty followers nominated by each leader as frequent collaborators on AI-assisted decisions. Interview themes include: (1) AI collaboration practices and processes; (2) perceptions of relational power with AI; (3) leadership identity and authenticity concerns [8]; and (4) ethical considerations and future orientations.**

**Document Analysis.** Anonymized AI chat logs, decision artifacts (emails, institutional memos, draft policies), and formal AI governance documents will be analyzed using discourse analysis techniques to examine framing, authority claims, and accountability constructions.

### *Sampling, Recruitment, and Institutional AI-Maturity Classification*

Universities will first be screened against a composite AI-maturity rubric comprising four indicators: (1) existence of a formal institutional AI-use policy; (2) integration of AI tools into the institution's learning management or administrative systems; (3) availability of structured AI training programs for staff and faculty; and (4) self-reported faculty AI-adoption rate obtained from institutional records or a brief informant survey with institutional leadership. Each indicator will be scored 0–2, yielding a composite score

used to classify institutions as high, medium, or low AI maturity; only high maturity institutions will be eligible for the qualitative phase. Within eligible institutions, academic leaders will be recruited purposively through institutional AI-governance or rectorate offices, followed by snowball referral to faculty followers. Participation will require informed consent covering the recording of AI interaction sessions and the anonymization procedures applied to chat-log data prior to analysis.

***Qualitative Data Analysis and Coding Procedures***

Data will be coded using NVivo 14 across three rounds: (1) descriptive coding for interaction patterns, decision types, and emotional registers [9]; (2) thematic analysis following Braun and Clarke [10] to identify patterns responsive to the propositions in Table 1; and (3) process coding [11] to map temporal sequences and identify critical decision junctures. A codebook will be developed iteratively from the first three transcripts and then applied to the full corpus; approximately 20% of transcripts will be double-coded by a second trained coder blind to the first coder's codes. Inter-coder reliability will be calculated using Cohen's κ after the double-coded subsample, with a minimum threshold of 0.70; disagreements will be resolved through discussion and, where needed, arbitration by a third coder, with all decisions logged in a coding audit trail. A reflexivity journal will be maintained throughout to document analytic decisions and researcher positionality.

***Quantitative Phase (Secondary)***

**Survey Instrument.** A stratified sample of 250–300 academic leaders across 20–30 universities will be surveyed using a 30–40-item instrument. Stratification criteria include leadership role (Dean vs. Vice Rector), institutional AI-maturity level (using the classification rubric above), and institution type (public/PTN vs. private/PTS). The instrument incorporates the newly developed Human-AI Collaboration Mode Scale and Leadership Identity Change Scale, together with validated measures of decision-outcome quality.

***Scale Development and Validation***

The Human AI Collaboration Mode Scale and Leadership Identity Change Scale will be developed following standard scale-development procedures. An initial item pool will be generated from the qualitative phase findings and the theoretical propositions in Table 1, then reviewed by a panel of at least five subject-matter experts for content validity, with items retained at a content validity index (CVI) threshold of 0.78 or higher. The refined item pool will be pilot tested with approximately 40–60 academic leaders not included in the main sample, followed by exploratory factor analysis (EFA) to establish initial factor structure. In the main survey sample, confirmatory factor analysis (CFA) will be used to validate the resulting structure, with internal consistency assessed via Cronbach's alpha and composite reliability (both targeted at $\geq 0.70$).

***Quantitative Data Analysis***

Analyses will be conducted using SPSS 29, R, and Mplus, including: descriptive statistics for usage patterns and demographics; EFA → CFA to validate the Human AI Collaboration Mode Scale; cluster analysis to identify leader profiles (e.g., AI Skeptics, Enthusiasts, Balanced Collaborators); regression and path analysis to test the relationships proposed in P1–P6 between collaboration mode, decision quality, and identity change; and social network analysis to map human-AI interaction patterns and centrality metrics.

***Mixed-Methods Integration Strategy***

Qualitative and quantitative findings will be integrated through three mechanisms: (1) joint display tables juxtaposing QUAL and quan results against each proposition in Table 1 to identify convergence and divergence; (2) meta-inferences articulating what the two strands together reveal beyond what either could alone, to be checked against a subsample of participants through member checking; and (3) theoretical model refinement, whereby the conceptual framework and its propositions are iteratively revised based on the integrated empirical results.

## RESULT AND DISCUSSION

Building on the Collaborative Process level of the conceptual model, ethnographic observation is designed to examine whether human-AI collaboration unfolds across five iterative stages: (1) Problem Framing, in which the leader constructs the decision problem for AI a step that itself may constrain potential solutions; (2) Initial Prompting, in which the leader initiates dialogue; (3) AI Response and Reframing, in which AI output confirms, challenges, or reframes the leader's initial understanding; (4) Iterative Refinement, hypothesized to average 3–8 dialogue rounds; and (5) Decision Integration, in which the leader synthesizes AI input with contextual knowledge to reach a final decision.

Cluster analysis in the quantitative phase is intended to test whether leaders' practices sort into the four-mode typology summarized in Table 2, which is derived theoretically from the framework rather than from

prevalence data. Each mode's grounding in the three theoretical traditions is indicated in the table's third column.

**Table 2. Proposed Human-AI Collaboration Mode Typology**

| Mode | Theoretical Characteristics | Theoretical Basis / Grounding | Illustrative Decision Context |
|---|---|---|---|
| AI-Advisory | Low AI influence; leader consults AI for validation or information gathering while retaining independent judgment. | Consistent with ANT's notion of AI as a low-centrality actant [12]; aligns with risk-averse, accountability-sensitive decision framings. | Decisions requiring high stakeholder buy-in or political sensitivity. |
| Co-Creative | Balanced influence; iterative dialogue with mutual shaping of the decision outcome by leader and AI. | Central to the hybrid leadership assemblage construct (Distributed Leadership Theory) [13] and to collaborative sensemaking. | Unstructured, value-laden, or “wicked” problems. |
| AI-Guided | High AI influence; leader relies substantially on AI recommendations with comparatively limited critical evaluation. | Reflects ANT's translation process [14] where AI's framing dominates network associations. | Structured, analytical decisions with clear data inputs. |
| Hybrid-Situational | Flexible; mode adapted dynamically according to decision context and stakes. | Reflects contingency logic within Distributed Leadership Theory [15]; requires high AI literacy to shift modes appropriately. | Leaders with high AI literacy managing diverse decision portfolios. |

***Power Dynamics and Agency (P2, P5)***

Applying ANT-informed analysis, the framework predicts (P2) that power distribution will vary systematically with decision context: AI agency is expected to increase when decisions are framed in technical and analytical terms (e.g., budget optimization, resource allocation), while human agency is expected to predominate when decisions invoke institutional values, political considerations, or ethical dilemmas. This prediction extends prior organizational AI-power literature from generic workplace settings to the specific institutional logics of Indonesian higher education, where accountability structures differ markedly between public (PTN) and private (PTS) institutions.

A related, and more contested, prediction (P5) concerns the disclosure of AI involvement in decision-making. Institutional-accountability literature suggests that transparency effects on trust are not uniform across governance regimes; the framework accordingly proposes that disclosure of AI involvement will increase stakeholder trust more strongly in public universities, where external accountability expectations are higher, than in private universities, where such disclosure may instead be read as a signal of reduced leader ownership of the decision. This divergence, if empirically confirmed, would suggest that a single national disclosure policy may be insufficient and that institution-type-sensitive AI-governance guidance is warranted a question the survey phase is explicitly designed to test rather than assume.

***Identity and Sensemaking (P3, P4)***

Drawing on identity-work literature [16], the framework proposes three candidate leadership identity trajectories to be examined narratively and thematically in the qualitative phase: Identity Threat, characterized by a sense of diminishment or obsolescence ('Am I still needed?') [17]; Identity Enhancement, in which AI is reframed as augmentation ('AI makes me a better leader'), potentially producing narratives such as the 'AI Steward' or 'Hybrid Thinker' consistent with emerging research on augmented professionalism and Identity Negotiation, reflecting ambivalence and ongoing identity work as leaders reconcile authenticity concerns with technological mediation. Whether these trajectories are mutually exclusive, sequential, or context-dependent is treated as an open empirical question rather than a settled distribution.

Consistent with Sensemaking Theory [18], [19] (P3), the framework further proposes that AI engagement helps leaders identify cognitive blind spots and consider perspectives they might otherwise overlook, while simultaneously raising concerns about over-reliance eroding independent human judgment a tension that mirrors broader societal anxieties about AI augmentation and deskilling. Both sides of this tension are

treated as competing hypotheses to be adjudicated by the interview and survey evidence, rather than as an established balance of benefit and risk.

***Anticipated Outcomes, Risks, and Boundary Conditions (P6)***

If the collaborative dynamics theorized above are empirically supported, several outcomes would be expected on the basis of adjacent literature: faster decision cycles for analytical decisions, greater perceived decision comprehensiveness, and consistent with prior findings on resource-constrained institutions gaining disproportionate benefit from shared digital infrastructure a possible democratization effect in which under-resourced institutions gain access to analytical capacity previously unavailable to them. Set against these anticipated benefits, the framework also flags risks documented in adjacent AI organizational literature that plausibly transfer to this context: uncritical AI reliance without adequate evaluation, analytical deskilling through repeated dependence, bias amplification wherein AI reinforces institutional biases embedded in training data [20], and accountability ambiguity when AI assisted decisions produce harmful outcomes.

Synthesizing the propositions above, the framework specifies (P6) that the realization of collaboration's benefits and the mitigation of its risks is contingent on five interacting boundary conditions: (1) AI literacy, a foundational understanding of how AI systems work, their limitations, and appropriate use cases; (2) critical thinking, the capacity to evaluate AI outputs rigorously rather than accepting them at face value; (3) prompting skill, the ability to formulate precise and contextually appropriate prompts; (4) organizational support, in the form of clear institutional policies, ethical guidelines, and structured training; and (5) cultural readiness, an organizational climate open to innovation and tolerant of experimentation with new decision-making architectures. These five conditions are operationalized as moderator variables in the quantitative phase (Section Methods).

Multigroup analysis is designed to examine whether institution type and institutional AI maturity moderate mode adoption and the boundary conditions above, and whether leader age and cultural dimensions such as collectivism consistent with Hofstede's [21] characterization of Indonesian organizational culture moderate mode preference. These are stated here as directions of inquiry for the empirical phase, not as findings.

## CONCLUSION

This paper has developed a Human-AI Collaborative Leadership conceptual framework and a corresponding research protocol for studying how academic leaders in Indonesian higher education engage with generative AI in institutional decision-making. By integrating Distributed Leadership Theory, Actor-Network Theory, and Sensemaking Theory within a critical realism paradigm, the framework repositions AI as a potential legitimate participant in leadership networks rather than a mere instrument, and reconceptualizes leadership decisions as potentially co-created outcomes of hybrid human-AI agency. The paper's contribution at this stage is conceptual and methodological rather than empirical: six theoretically grounded propositions (P1–P6), a four-mode collaboration typology derived from theory, and a transparent, replicable embedded concurrent mixed-methods protocol including explicit institutional AI-maturity classification criteria, scale-development procedures, and coding protocols intended to test these propositions among 12–15 academic leaders through ethnographic and interview data and among 250–300 academic leaders through survey data across 20–30 Indonesian universities. The empirical phase specified in the Methods section is the necessary next step of this research program and will determine which of the propositions in Table 1 are supported, which require revision, and what actual distribution of collaboration modes, power dynamics, and identity trajectories characterizes Indonesian academic leadership under GenAI collaboration. Once completed, that phase is expected to yield actionable competency frameworks, policy guidance emphasizing transparency and accountability, and training curriculum recommendations for leadership development and national AI governance in higher education. Future extensions of this program should examine longitudinal change in collaboration patterns as AI capabilities evolve, extend comparison to other Southeast Asian cultural contexts, and empirically test the boundary conditions under which AI collaboration enhances rather than erodes human leadership capacity.

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