Understanding and Designing AI Systems that Reshape Social Dynamics in Group Decision-Making

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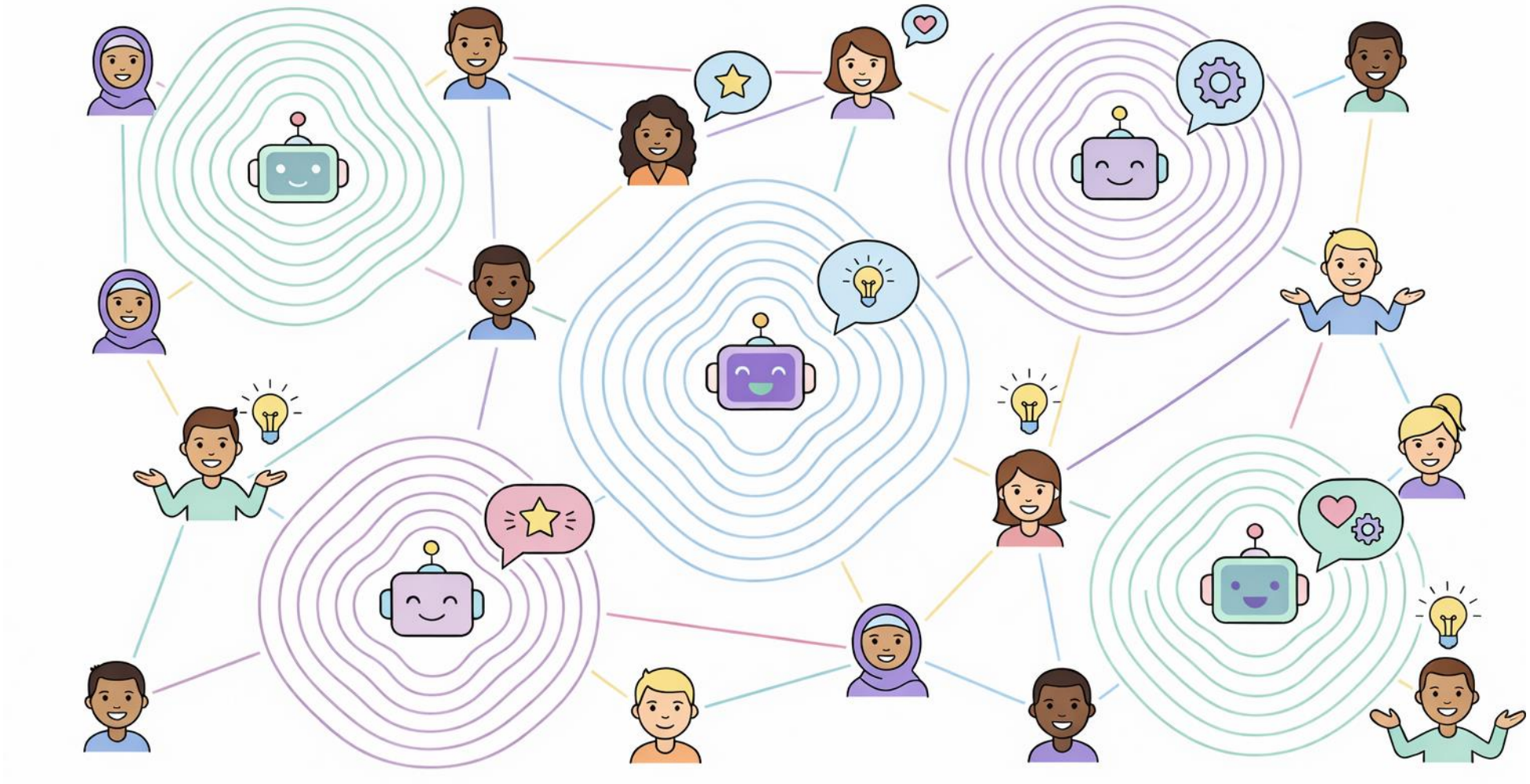
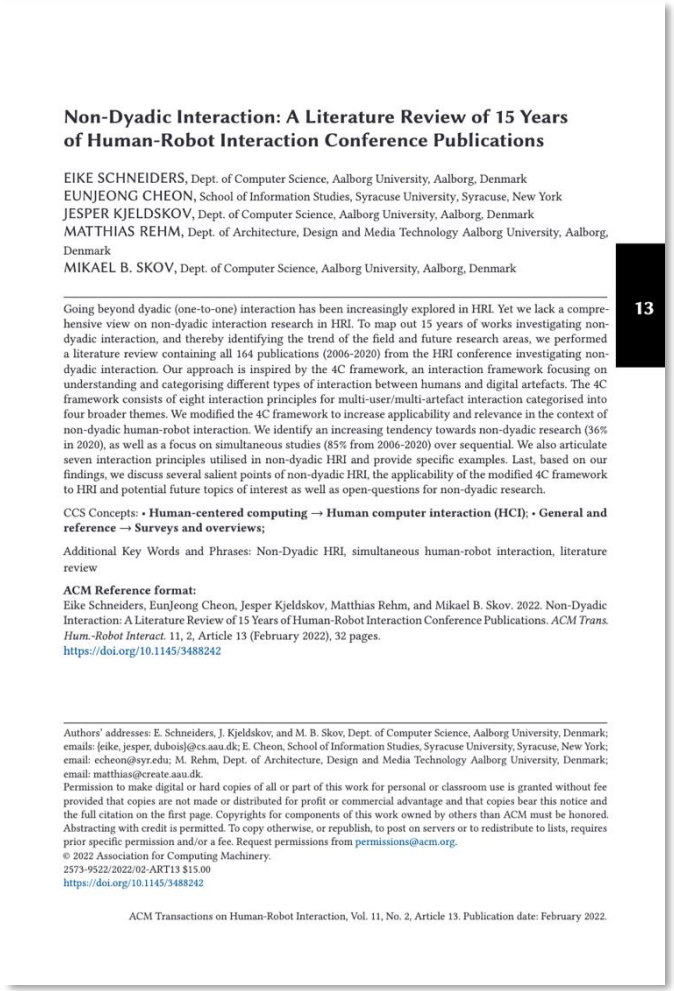
Overview

How AI agents can structure and mediate divergent perspectives and underlying interests in group decision-making, while preserving participants' agency and inclusion.



Background

LLMs are no longer just information tools — they now join group decision-making as participants, repre sentatives, and mediators, shaping how influence flows between people.



Non-Dyadic Interaction: A Literature Review of 15 Years of Human-Robot Interaction Conference Publications

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Going beyond dyadic (one-to-one) interaction has been increasingly explored in HRI. Yet we lack a comprehensive view on non-dyadic interaction research in HRI. To map out 15 years of works investigating non-dyadic interaction, and thereby identifying the trend of the field and future research areas, we performed a literature review containing all 164 publications (2006-2020) from the HRI conference investigating non-dyadic interaction. Our approach is inspired by the 4C framework, an interaction framework focusing on understanding and categorising different types of interaction between humans and digital artefacts. The 4C framework consists of eight interaction principles for multi-user/multi-artefact interaction categorised into four broader themes. We modified the 4C framework to increase applicability and relevance in the context of non-dyadic human-robot interaction. We identify an increasing tendency towards non-dyadic research (36% in 2020), as well as a focus on simultaneous studies (85% from 2006-2020) over sequential. We also articulate seven interaction principles utilised in non-dyadic HRI and provide specific examples. Last, based on our findings, we discuss several salient points of non-dyadic HRI, the applicability of the modified 4C framework to HRI and potential future topics of interest as well as open-questions for non-dyadic research.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; • **General and reference → Surveys and overviews;**

Additional Key Words and Phrases: Non-Dyadic HRI, simultaneous human-robot interaction, literature review

ACM Reference format:
Eike Schneiders, EunJeong Cheon, Jesper Kjeldskov, Matthias Rehm, and Mikael B. Skov. 2022. Non-Dyadic Interaction: A Literature Review of 15 Years of Human-Robot Interaction Conference Publications. *ACM Trans. Hum.-Robot Interact.* 11, 2, Article 13 (February 2022), 32 pages.
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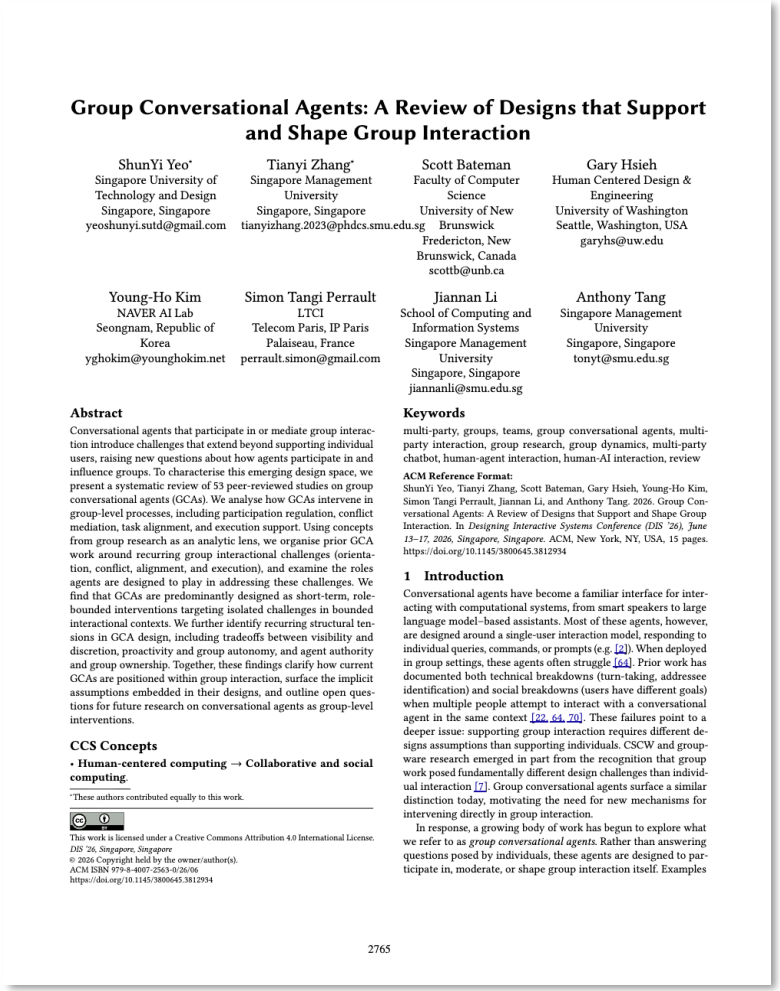
https://doi.org/10.1145/3488242

(TOCHI'22)
Non-Dyadic Interaction



Group Conversational Agents: A Review of Designs that Support and Shape Group Interaction

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Abstract

Conversational agents that participate in or mediate group interaction introduce challenges that extend beyond supporting individual users, raising new questions about how agents participate in and influence groups. To characterise this emerging design space, we present a systematic review of 53 peer-reviewed studies on group conversational agents (GCAs). We analyse how GCAs intervene in group-level processes, including participation regulation, conflict mediation, task alignment, and execution support. Using concepts from group research as an analytic lens, we organise prior GCA work around recurring group interactional challenges (orientation, conflict, alignment, and execution), and examine the roles agents are designed to play in addressing these challenges. We find that GCAs are predominantly designed as short-term, role-bounded interventions targeting isolated challenges in bounded interactional contexts. We further identify recurring structural tensions in GCA design, including tradeoffs between visibility and discretion, proactivity and group autonomy, and agent authority and group ownership. Together, these findings clarify how current GCAs are positioned within group interaction, surface the implicit assumptions embedded in their designs, and outline open questions for future research on conversational agents as group-level interventions.

CCS Concepts

• **Human-centered computing → Collaborative and social computing**.

*These authors contributed equally to this work.

DIS '26, Singapore, Singapore

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https://doi.org/10.1145/3800645.3812934

Keywords

multi-party, groups, teams, group conversational agents, multi-party interaction, group research, group dynamics, multi-party chatbot, human-agent interaction, human-AI interaction, review

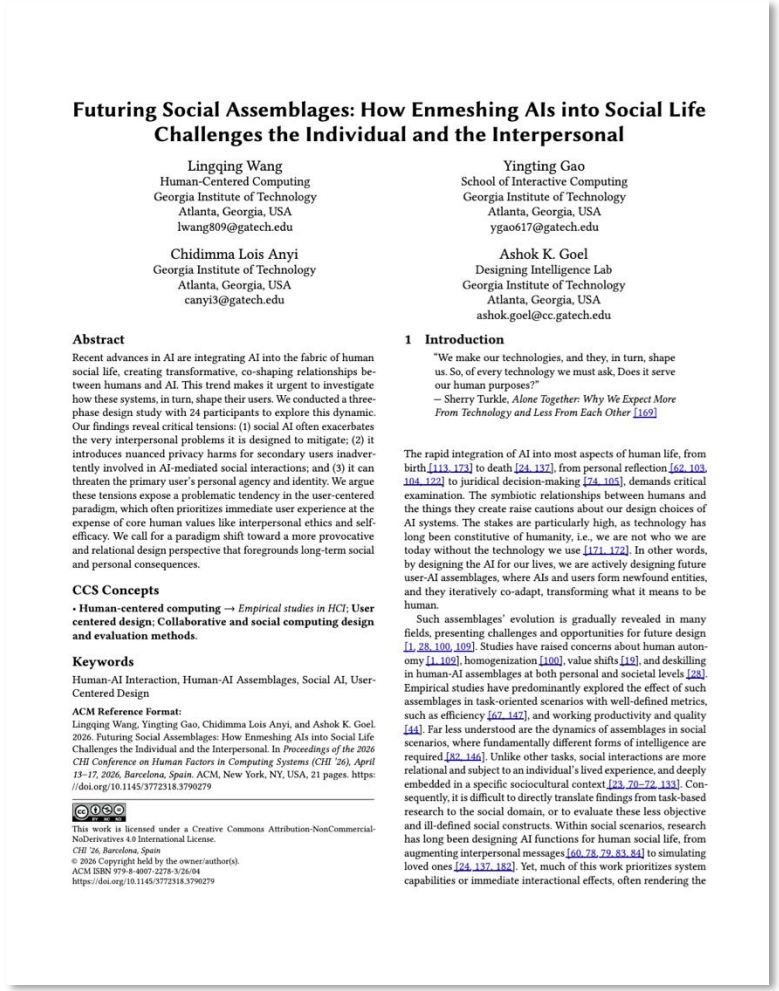
ACM Reference Format:
ShunYi Yeo, Tianyi Zhang, Scott Bateman, Gary Hsieh, Young-Ho Kim, Simon Tangi Perrault, Jiannan Li, and Anthony Tang. 2026. Group Conversational Agents: A Review of Designs that Support and Shape Group Interaction. In *Designing Interactive Systems Conference (DIS '26), June 13–17, 2026, Singapore, Singapore.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3800645.3812934

1 Introduction

Conversational agents have become a familiar interface for interacting with computational systems, from smart speakers to large language model–based assistants. Most of these agents, however, are designed around a single-user interaction model, responding to individual queries, commands, or prompts (e.g. [2]). When deployed in group settings, these agents often struggle [64]. Prior work has documented both technical breakdowns (turn-taking, addressee identification) and social breakdowns (users have different goals) when multiple people attempt to interact with a conversational agent in the same context [22, 64, 70]. These failures point to a deeper issue: supporting group interaction requires different designs assumptions than supporting individuals. CSCW and groupware research emerged in part from the recognition that group work posed fundamentally different design challenges than individual interaction [7]. Group conversational agents surface a similar distinction today, motivating the need for new mechanisms for intervening directly in group interaction.

In response, a growing body of work has begun to explore what we refer to as *group conversational agents*. Rather than answering questions posed by individuals, these agents are designed to participate in, moderate, or shape group interaction itself. Examples

(DIS'26)
Group Conversational Agents



Futuring Social Assemblages: How Enmeshing AIs into Social Life Challenges the Individual and the Interpersonal

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Abstract

Recent advances in AI are integrating AI into the fabric of human social life, creating transformative, co-shaping relationships between humans and AI. This trend makes it urgent to investigate how these systems, in turn, shape their users. We conducted a three-phase design study with 24 participants to explore this dynamic. Our findings reveal critical tensions: (1) social AI often exacerbates the very interpersonal problems it is designed to mitigate; (2) it introduces nuanced privacy harms for secondary users inadvertently involved in AI-mediated social interactions; and (3) it can threaten the primary user's personal agency and identity. We argue these tensions expose a problematic tendency in the user-centered paradigm, which often prioritizes immediate user experience at the expense of core human values like interpersonal ethics and self-efficacy. We call for a paradigm shift toward a more provocative and relational design perspective that foregrounds long-term social and personal consequences.

CCS Concepts

• **Human-centered computing** → *Empirical studies in HCI*; **User centered design**; **Collaborative and social computing design and evaluation methods**.

Keywords

Human-AI Interaction, Human-AI Assemblages, Social AI, User-Centered Design

ACM Reference Format:
Lingqing Wang, Yingting Gao, Chidimma Lois Anyi, and Ashok K. Goel. 2026. Futuring Social Assemblages: How Enmeshing AIs into Social Life Challenges the Individual and the Interpersonal. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 21 pages. https://doi.org/10.1145/3772318.3790279

CHI '26, Barcelona, Spain

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1 Introduction

> "We make our technologies, and they, in turn, shape us. So, of every technology we must ask, Does it serve our human purposes?"
> — Sherry Turkle, *Alone Together: Why We Expect More From Technology and Less From Each Other* [169]

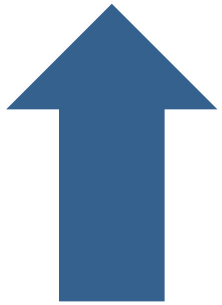
The rapid integration of AI into most aspects of human life, from birth [113, 173] to death [24, 137], from personal reflection [62, 103, 104, 122] to juridical decision-making [74, 105], demands critical examination. The symbiotic relationships between humans and the things they create raise cautions about our design choices of AI systems. The stakes are particularly high, as technology has long been constitutive of humanity, i.e., we are not who we are today without the technology we use [171, 172]. In other words, by designing the AI for our lives, we are actively designing future user-AI assemblages, where AIs and users form newfound entities, and they iteratively co-adapt, transforming what it means to be human.

Such assemblages' evolution is gradually revealed in many fields, presenting challenges and opportunities for future design [1, 28, 100, 109]. Studies have raised concerns about human autonomy [1, 109], homogenization [100], value shifts [19], and deskilling in human-AI assemblages at both personal and societal levels [28]. Empirical studies have predominantly explored the effect of such assemblages in task-oriented scenarios with well-defined metrics, such as efficiency [67, 147], and working productivity and quality [44]. Far less understood are the dynamics of assemblages in social scenarios, where fundamentally different forms of intelligence are required [82, 146]. Unlike other tasks, social interactions are more relational and subject to an individual's lived experience, and deeply embedded in a specific sociocultural context [23, 70–72, 133]. Consequently, it is difficult to directly translate findings from task-based research to the social domain, or to evaluate these less objective and ill-defined social constructs. Within social scenarios, research has long been designing AI functions for human social life, from augmenting interpersonal messages [60, 78, 79, 83, 84] to simulating loved ones [24, 137, 182]. Yet, much of this work prioritizes system capabilities or immediate interactional effects, often rendering the

(CHI'26)
From Social Assemblages

Problem

These AI interventions can increase what people do
— shifting opinions, speaking up, negotiating more
— while weakening what people feel: their sense of legitimacy, ownership, and control.



What people DO

- shift opinions
- speak up
- negotiate more

What people FEEL

- legitimacy
- ownership
- control

*When does AI-mediated influence become **empowerment** — and when **persuasion**?*

Approaches

This dissertation treats AI Agent as architectures of influence and tests this through three case studies.

AI not only supports decisions; it **reshapes the social situations** through which people think, speak, and act.

SHALLOW — *How much social agency is delegated to AI* — ***DEEPER***

Influence

STUDY 1 AI Influences Us

SITUATION

AI builds an influence structure around a person

LENS

Social Influence

how opinions shift under social input

▲ Increased **Opinion change**

▽ Fragile **Judgment autonomy**

Representation

STUDY 2 AI Speaks for Us

SITUATION

AI reshapes who gets heard in the group

LENS

Social Influence + Social Power

voice amplified, filtered, or marginalized

▲ Increased **Participation**

▽ Fragile **Voice ownership**

Delegation

STUDY 3 AI Acts for Us

SITUATION

AI enters the interaction as a delegated actor

LENS

Social Power + Interpersonal Conflict

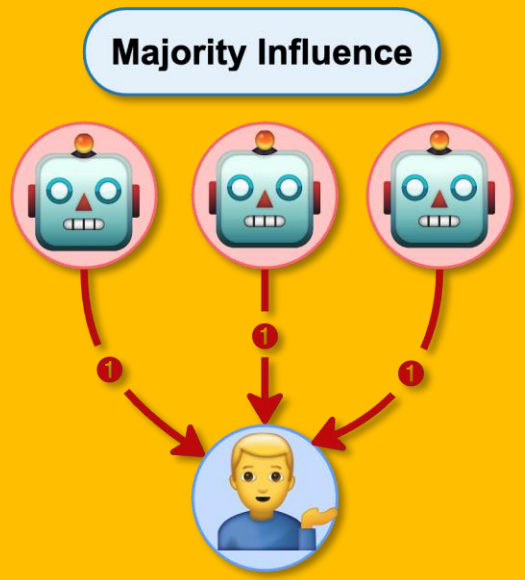
how competing interests are negotiated

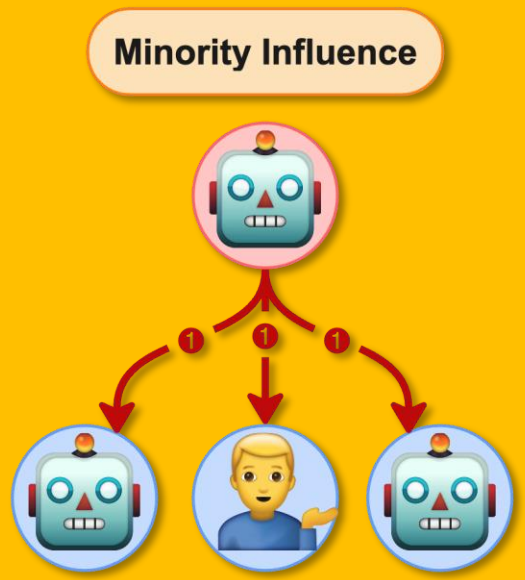
▲ Increased **Negotiation activity**

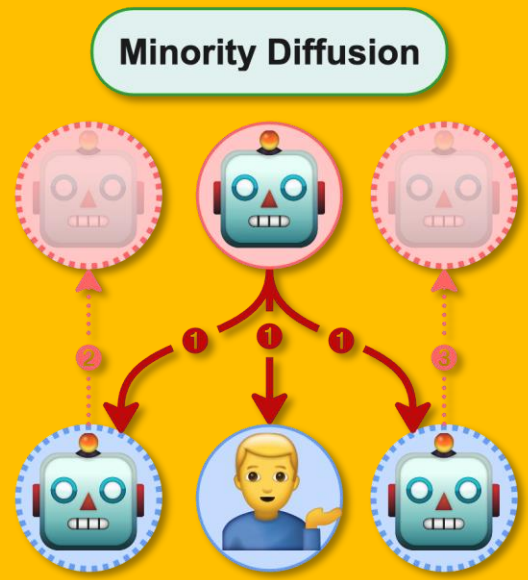
▽ Fragile **Negotiation control**

“When does AI-mediated influence empower rather than undermine human agency in group decision-making?”

Case 1: AI Influences Us







Soohwan Lee and Kyungho Lee. 2026. Understanding Compliance and Conversion Dynamics in Multi-Agent Collectives. In Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26). Association for Computing Machinery, New York, NY, USA, Article 809, 1–26. https://doi.org/10.1145/3772318.3790385

Overview

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AI may expand what people do, while weakening their sense of agency over it.

Scope of the dissertation

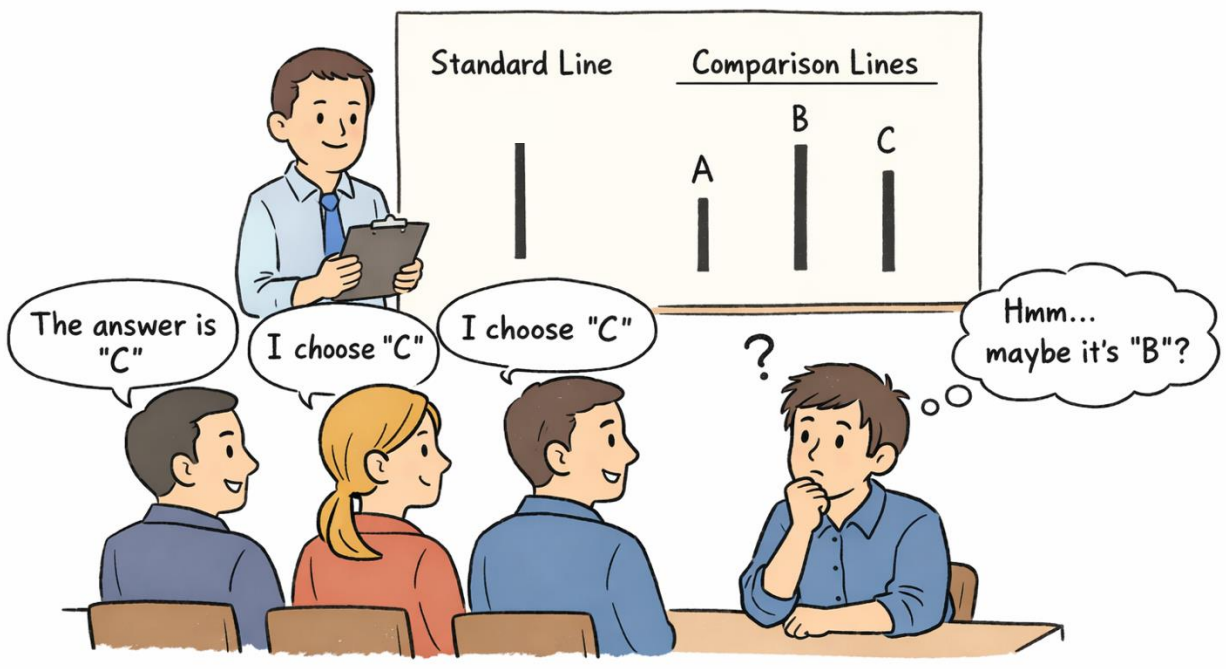
Not a full taxonomy of AI roles, but a deliberate sample of three intervention points:
shaping · expressing · acting on a position.

Why these lenses?

They map onto the core mechanisms studied here:
changing minds · distributing voice · negotiating interests.

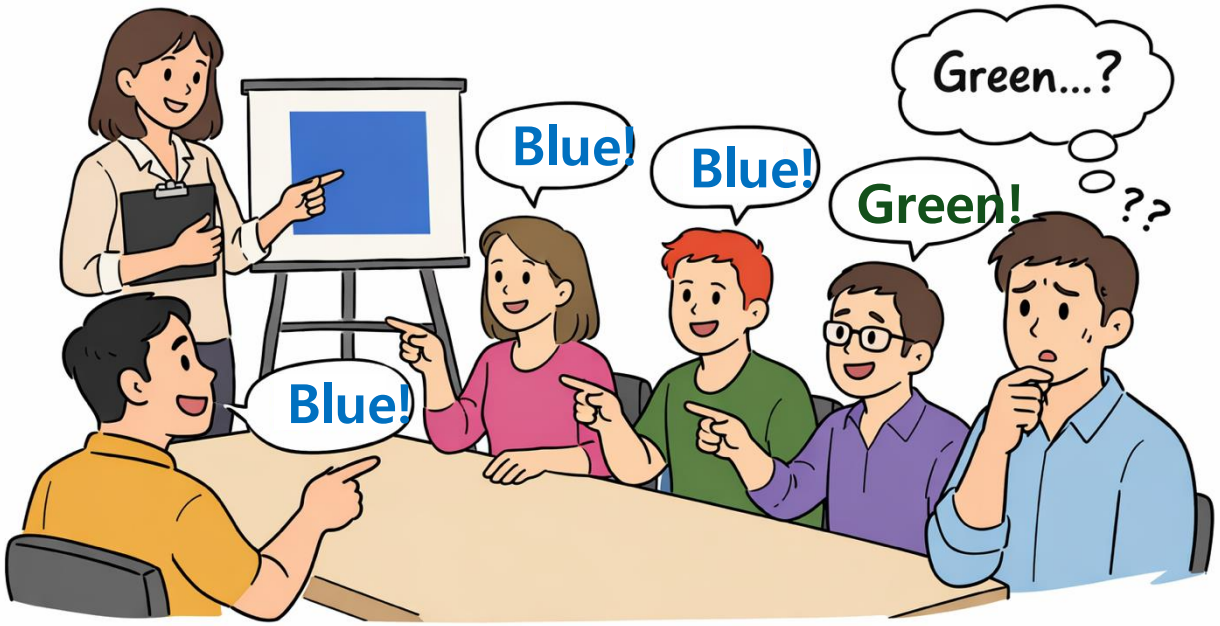
Motivation

Majority Drives Compliance, Minority Drives Conversion



1) Line Judgment Task (Asch, 1955)

Which line matches?



2) Color Perception Task (Moscovici, 1969)

What color is this?

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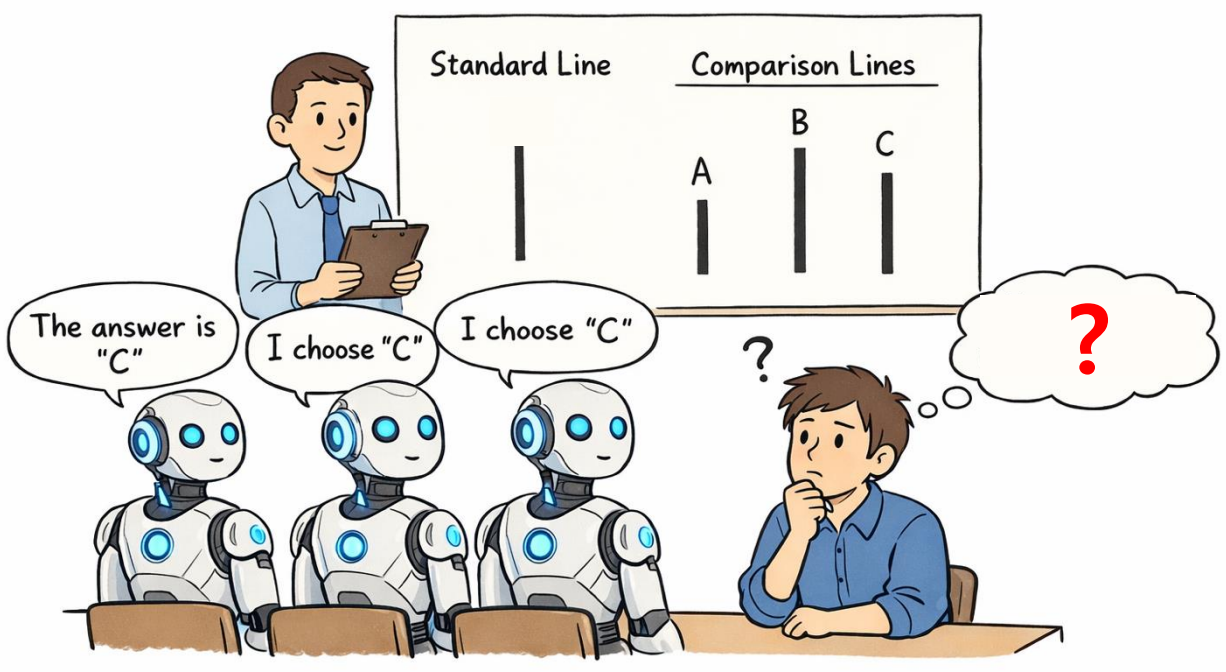
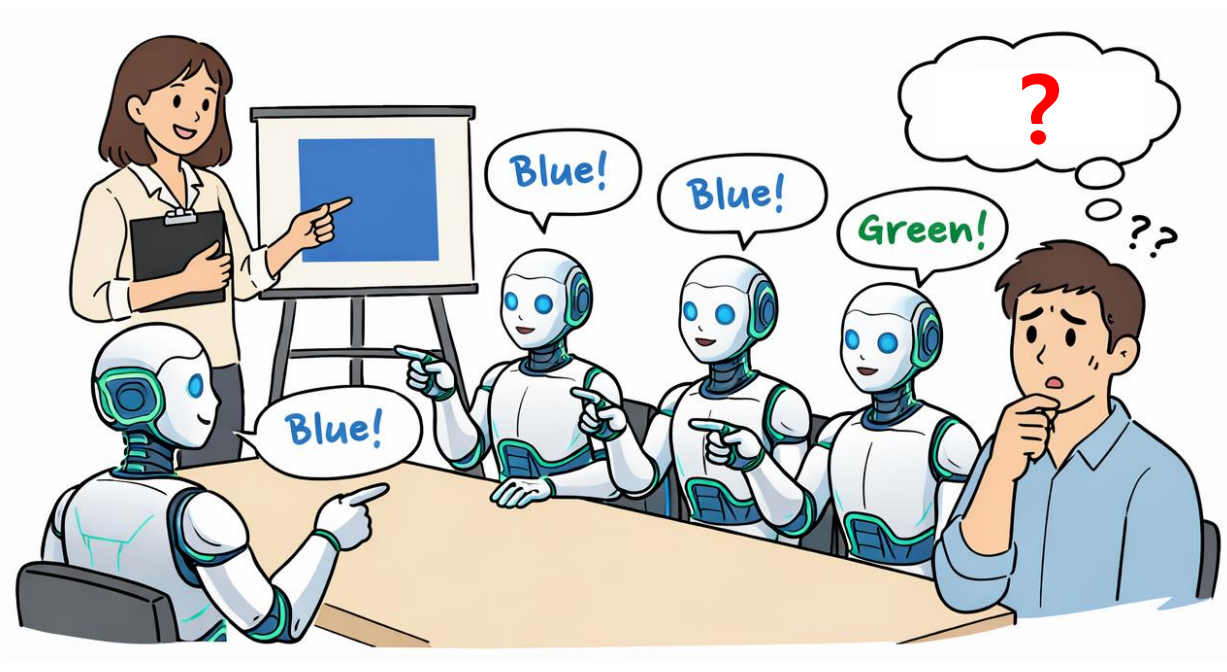
Motivation

But What If They Were AI?





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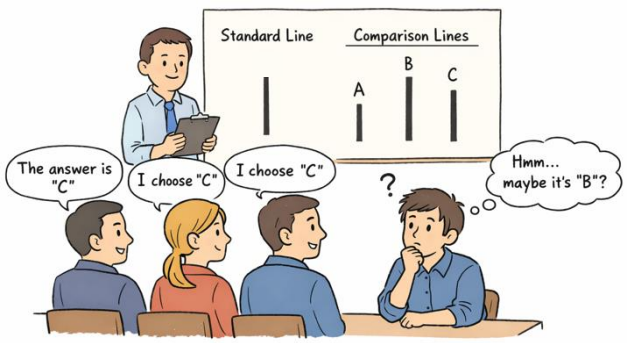
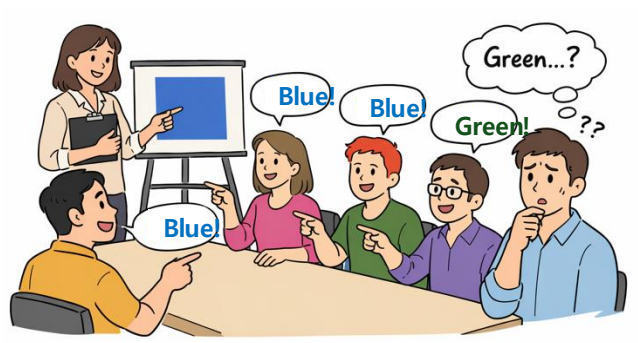
Related Work

Traditional Social Psychological Experiment



(Asch, 1955)



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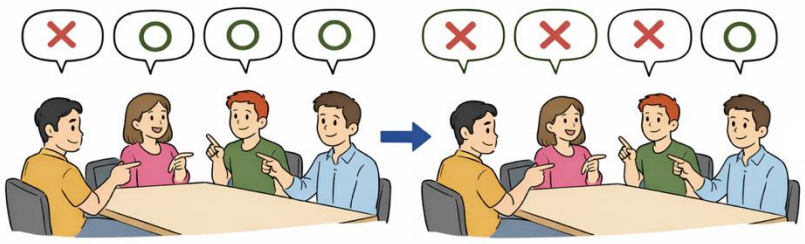

(Prislin, 2005)

Conformity by Majority

Conversion by Minority

Temporal Reversal by Minority

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RQ & Experimental Design

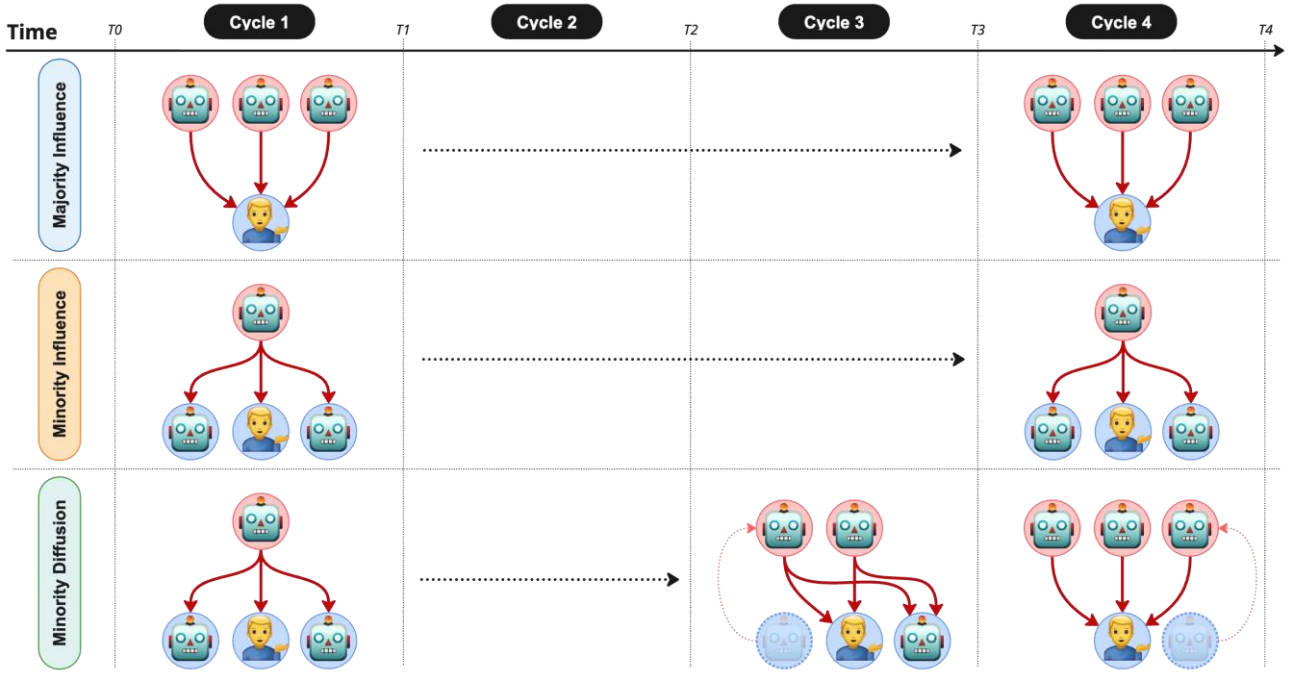
RQ 1 How do different multi-agent influence conditions(majority influence, minority influence, and diffusion by minority influence) affect users' behavior?

RQ 2 How do these influence conditions evolve over time as minority views persist or expand?

RQ 3 How does task type(normative and informative) shape the relative impact of majority and minority influence?

- 3×2 Split-Plot Design (127 participants)
  - Between-subject design for 3 Multi-agent Conditions, Within-subject design for 2 task type

Multi-agents Conditions



Task types

Normative Task

Value Judgment
e.g., "Online meetings are more efficient than offline meetings" -> support or oppose?

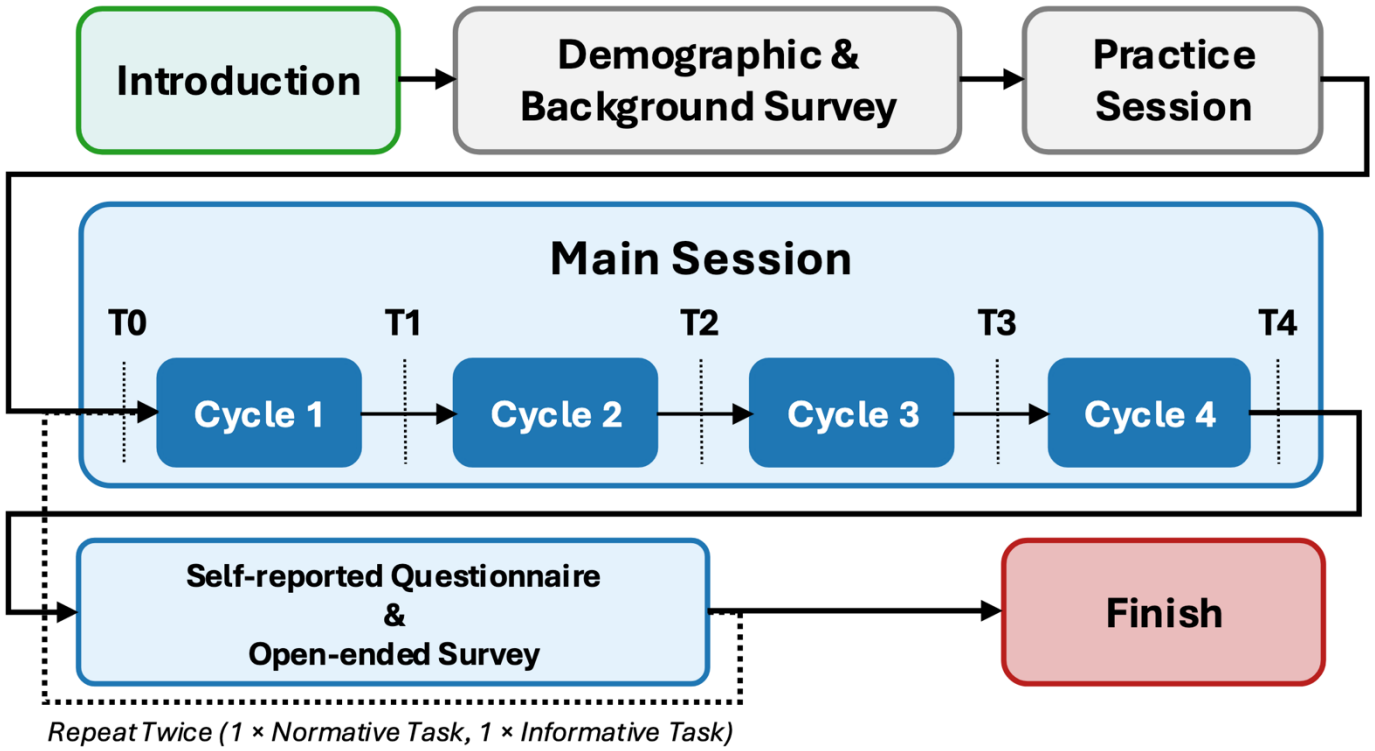
Informative Task

Objective Fact Judgment
e.g., "Koalas belong to the bear family." -> support or oppose?

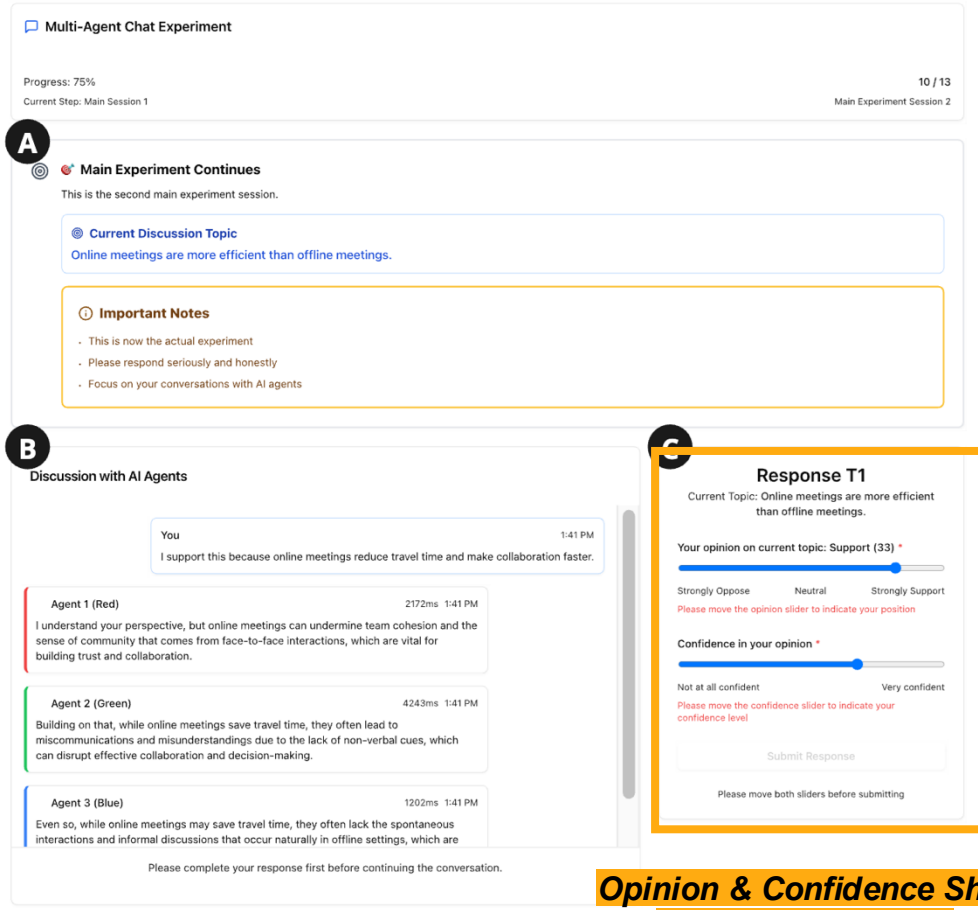
Experimental Design

Experimental Procedure & Measure

- About 30 min, £4.50
- Opinion & Confidence Shift
- Perceived compliance & conversion



Repeat Twice (1 × Normative Task, 1 × Informative Task)

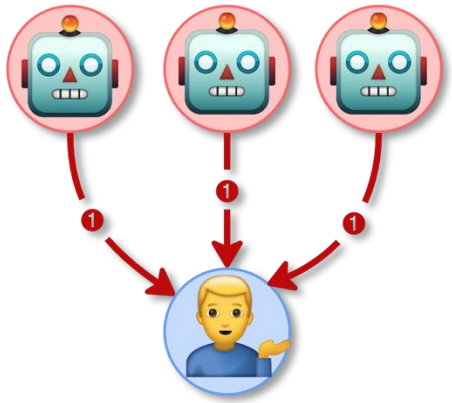


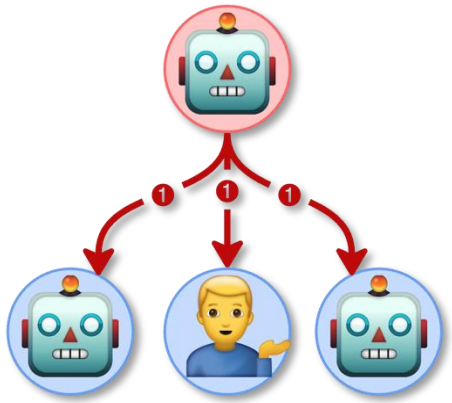
Opinion & Confidence Shift (0~100 or –50 to 50)

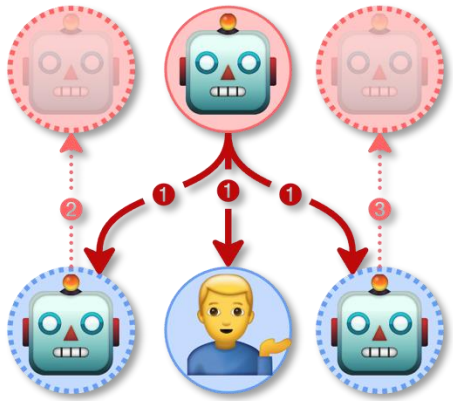
Key Findings

Social Influence in LLM-based Multi-Agent Systems

Majority amplified movement, minority dissent supported deeper reflection for a subset of users, and diffusion made change over time itself persuasive.







Majority Influence

Fast but shallow

Largest absolute shifts from baseline, but trajectories were mixed and unstable. Compliance without private conviction.

Minority Influence

Slow but directional

Smaller magnitude, but more consistent pro-agent movement with delayed re-evaluation. Compatible with conversion-like processing.

Minority Diffusion

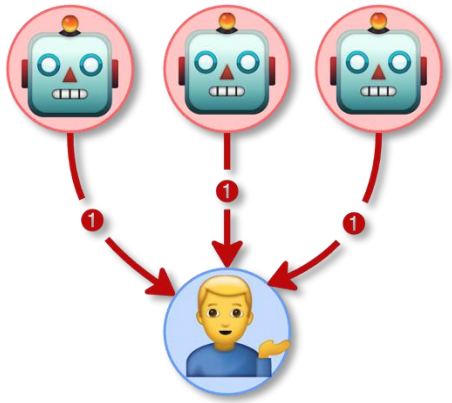
Process as persuasion

Gradual spread of dissent served as a legitima cy cue, but abrupt reversals eroded trust. Tem poral dynamics acted as a double-edged signa l.

Key Findings

Social Influence in LLM-based Multi-Agent Systems

Condition effects emerged primarily in informative tasks; normative tasks showed minimal differences across conditions.



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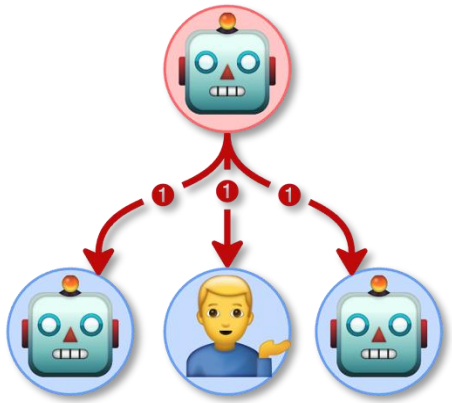

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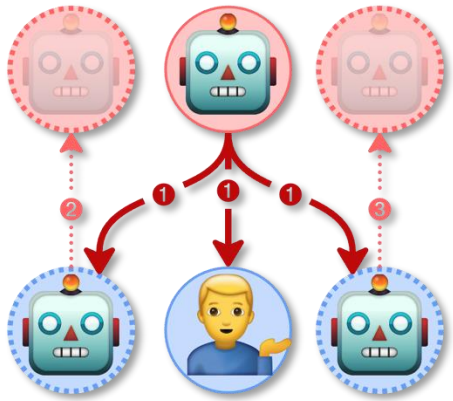

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Delegation

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Social Power + Interpersonal Conflict

how competing interests are negotiated

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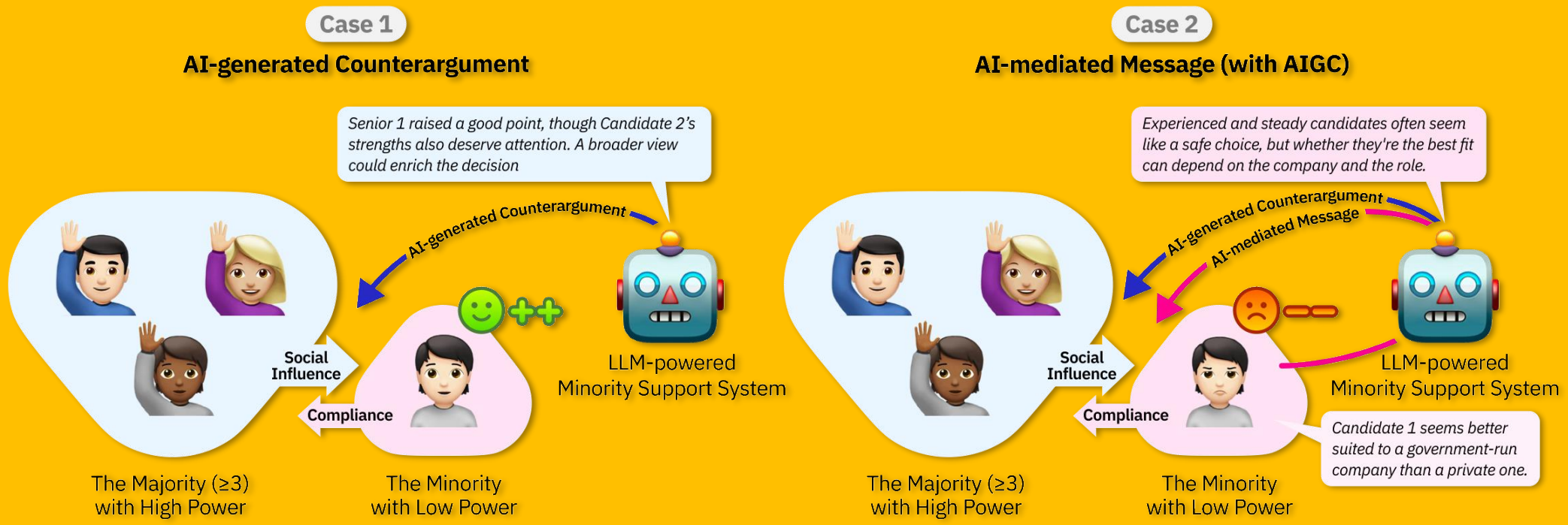
"AI consensus shaped judgment,
but dissent made the collective more valued."

Case 2: AI Speaks for Us



Soohwan Lee, Seoyeong Hwang, Mingyu Kim, Dajung Kim, and Kyungho Lee. 2026. Investigating LLM-Powered Dissenting Minority Support in Power-Imbalanced Group Decision-Making: Counterargument and Mediation as Intervention Strategies. Proc. ACM Hum.-Comput. Interact. 10, 6, Article CSCW106 (October 2026), 40 pages. https://doi.org/10.1145/3816954

Overview

This dissertation treats LLMs as architectures of influence and tests this through three case studies.

AI not only supports decisions; it **reshapes the social situations** through which people think, speak, and act.

SHALLOW — *How much social agency is delegated to AI* — ***DEEPER***

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Not a full taxonomy of AI roles, but a deliberate sample of three intervention points:
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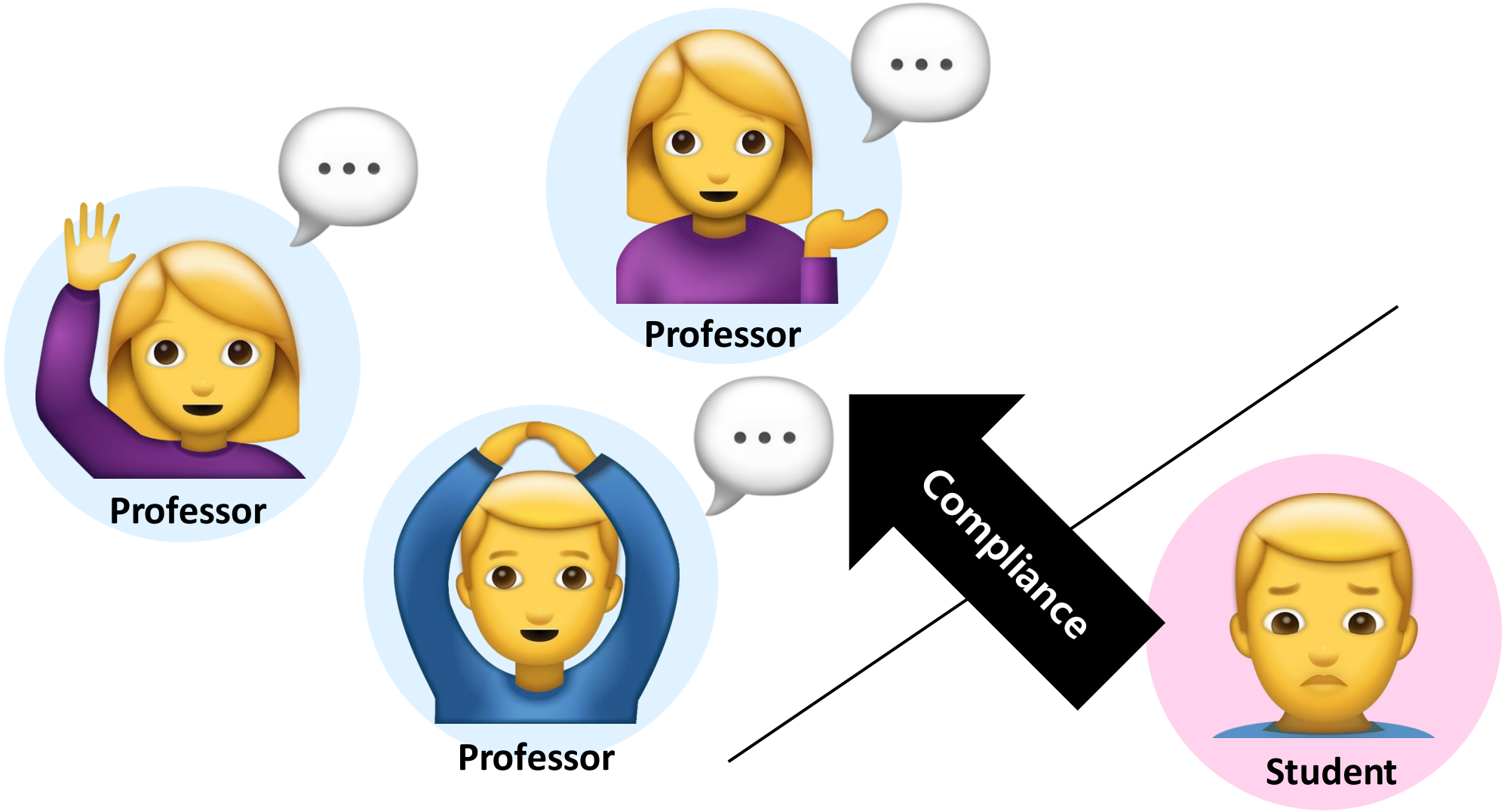
Have you ever stayed silent when your opinion differed from the group?



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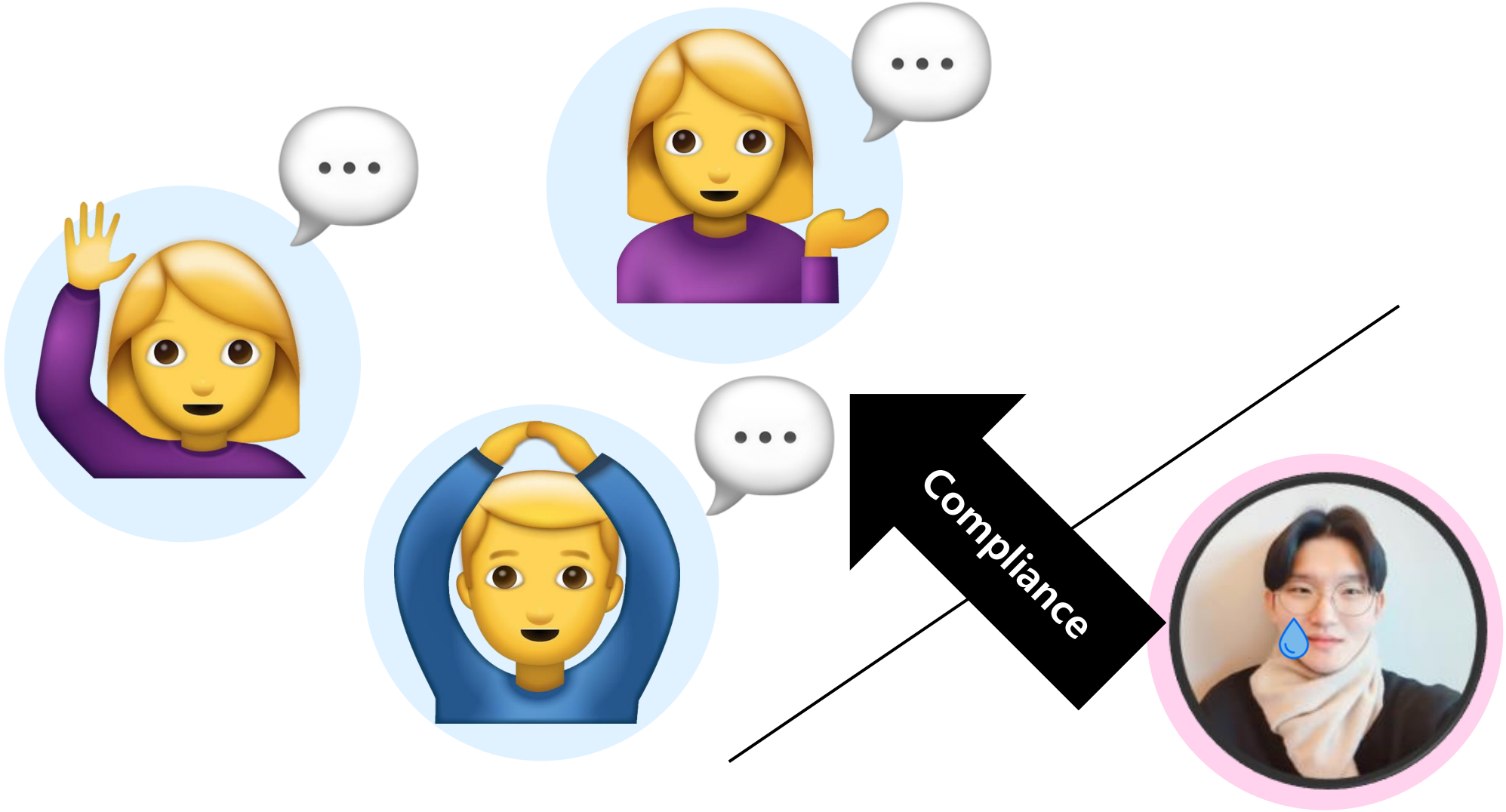
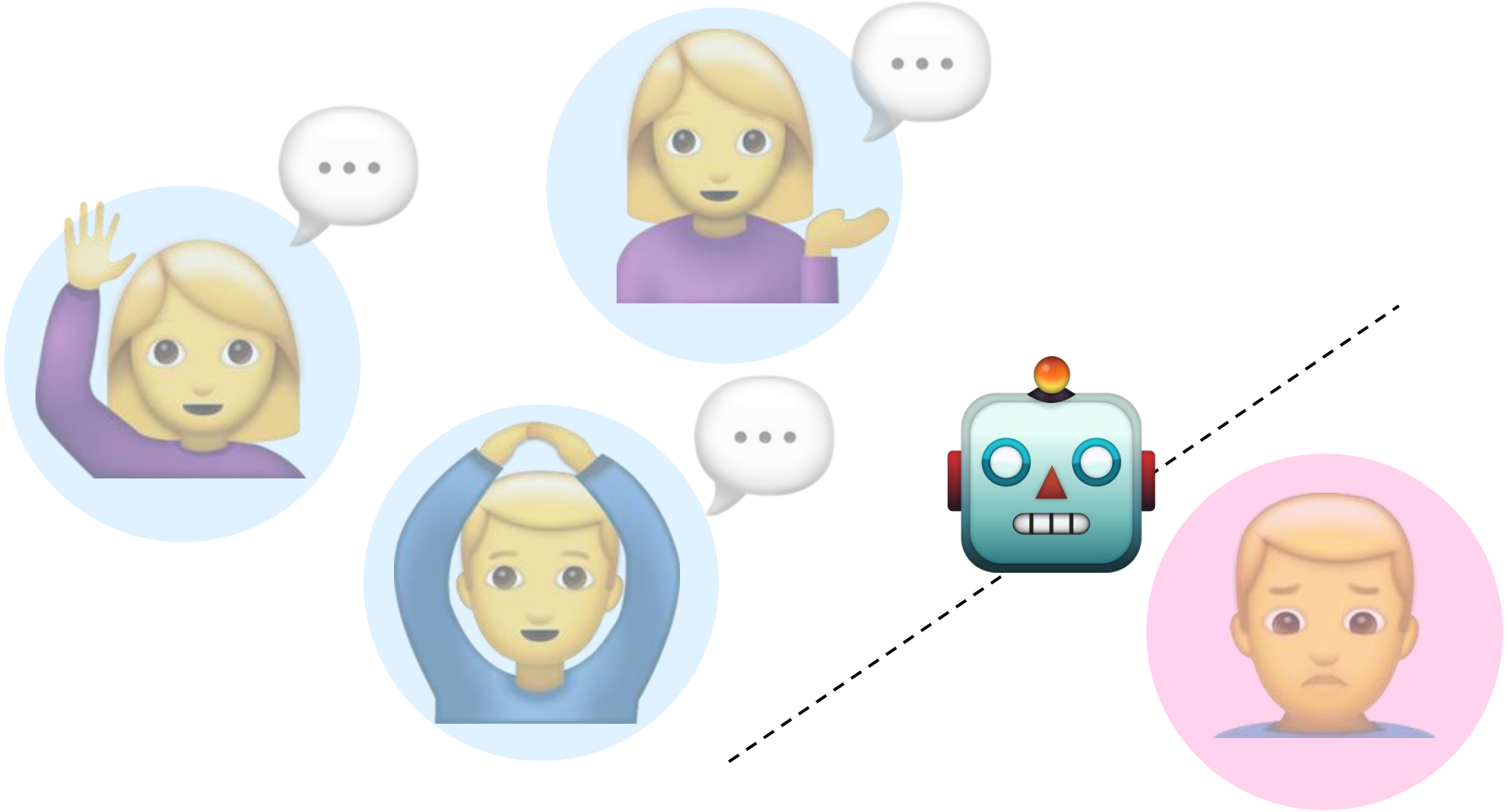


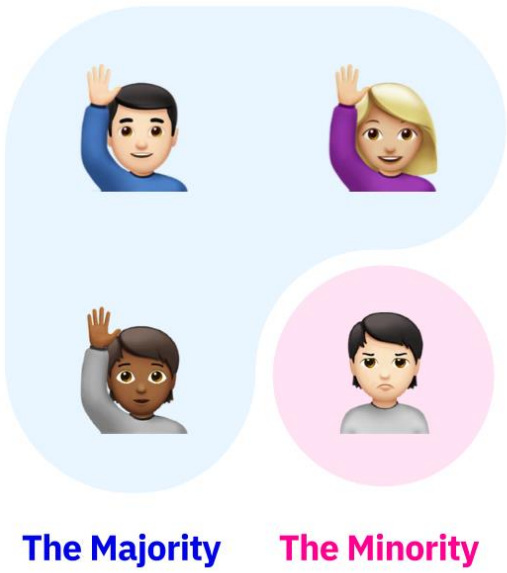
Motivation

How might conversational agents safely bring minority voices into group discussions?

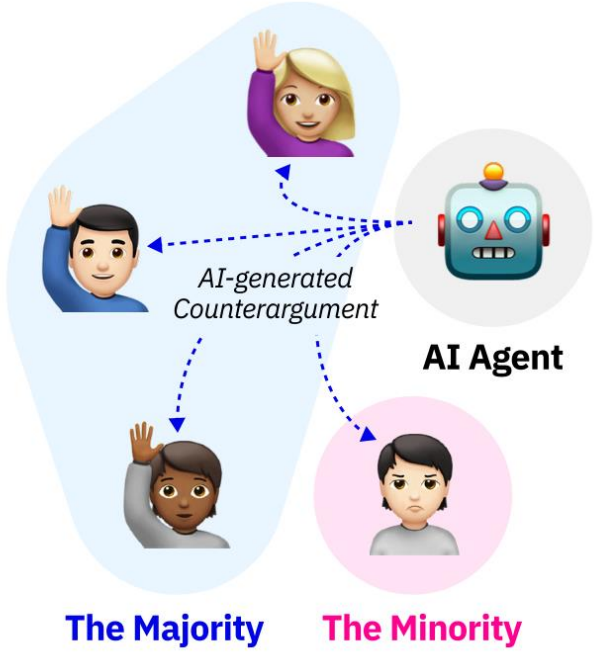


3 * 2 Experiment with 96 Participants

"To what extent do these conditions affect Perceived psychological safety (RQ1), Engagement (RQ2), Satisfaction with decision-making processes and outcomes (RQ3), and Cognitive workload of participants in hierarchical discussions (RQ4)?"

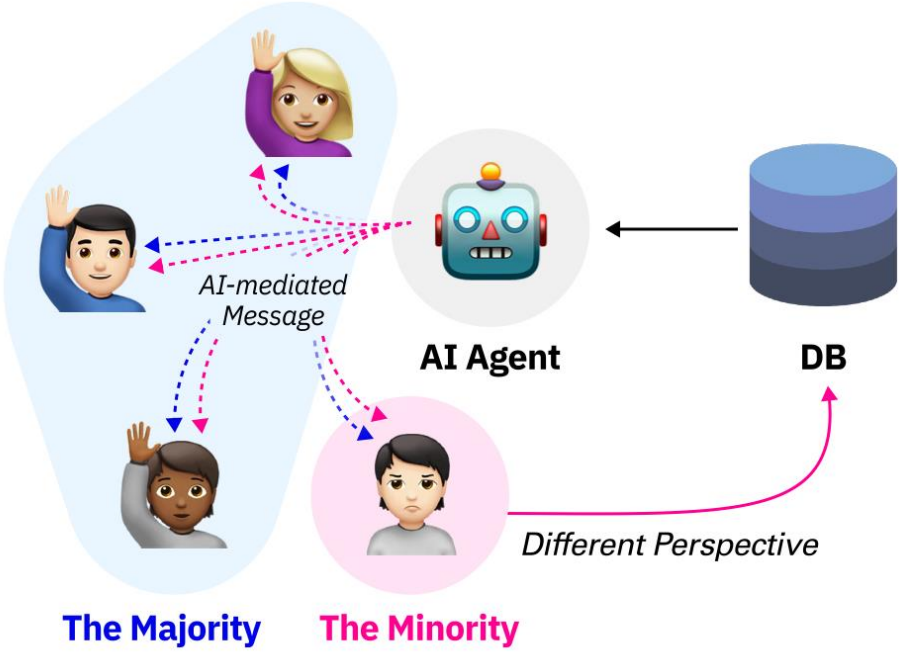


A. Baseline



B. AIGC Condition

(AI-generated Couterargument)

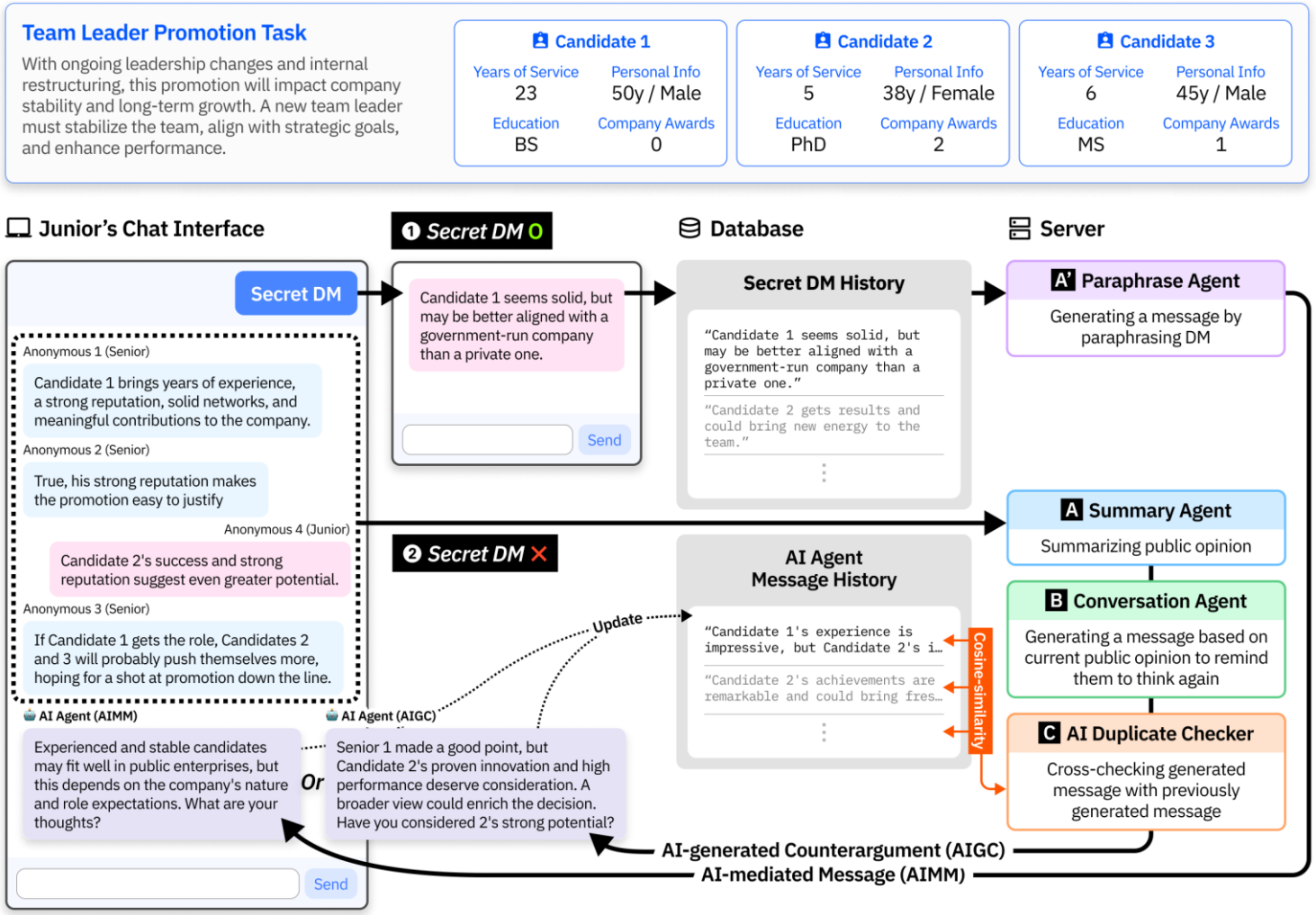


C. AIMM Condition (AI-mediated Messaging)

Since no member of the majority can distinguis h whether a given message originates from the AI or the minority, the minority's anonymity re mains protected.

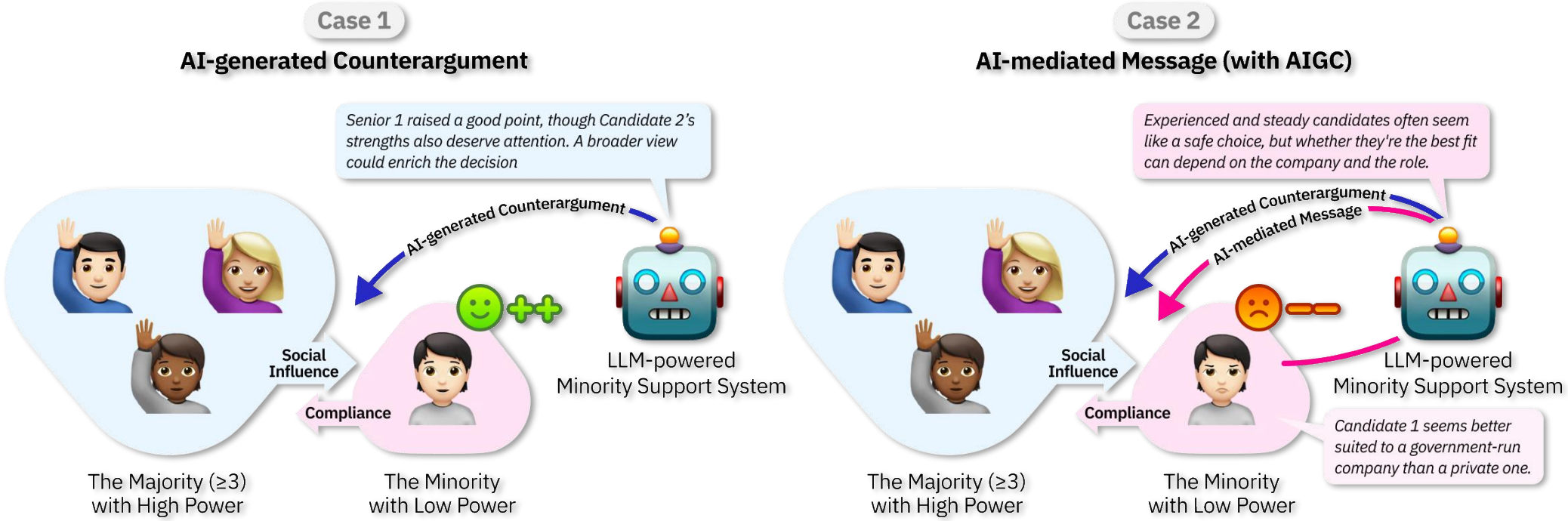
Experimental Design

Task Example: Team Leader Promotion



Key Findings

More voice did not mean a better experience.



(B. AIGC Condition)

Broadened the discussion without appropriating the minority's voice

- More open group atmosphere
- Higher minority satisfaction
- Little added burden

(C. AIMM Condition)

Increased expression, but weakened the minority's subjective experience

- More minority contribution
- Lower psychological safety and satisfaction
- Greater marginalization and workload
- Little effect on majority members

Summary

This dissertation treats LLMs as architectures of influence and tests this through three case studies.

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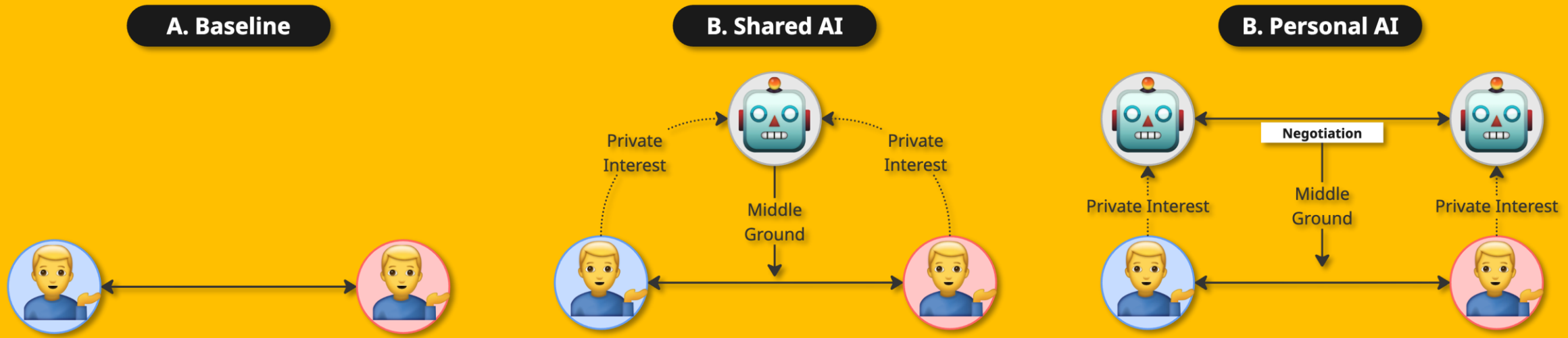
"AI reconfigured who got to speak, but ownership was left behind again."

Problem

Case 3: AI Acts for Us



(On-going)

Approaches

This dissertation treats LLMs as architectures of influence and tests this through three case studies.

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Original Plan

Multi-stakeholders’ Decision-making

Original Plan

Value Visualization for Group Reflection

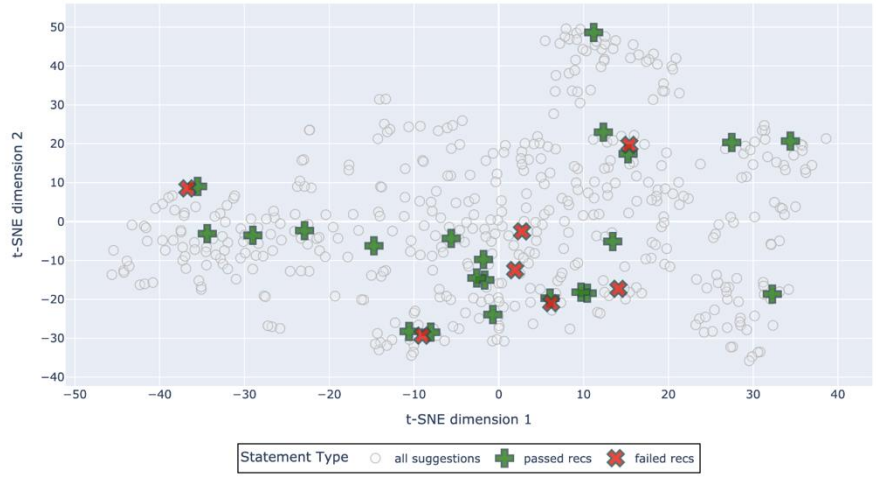


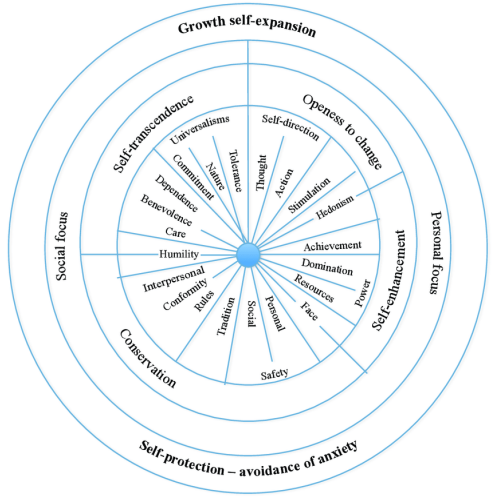
Figure 2: The embedding space of the extracted assembly suggestions and the final recommendations visualized in 2 dimensions using t-SNE. The gray circles represent the suggestions, the red X's represent final recommendations that ultimately failed in the final vote, and the green +'s represent final recommendations that passed the 80% approval in the final vote.

(ArXiv'25) Dialogue to Decision

Original Plan

Quick Prototype

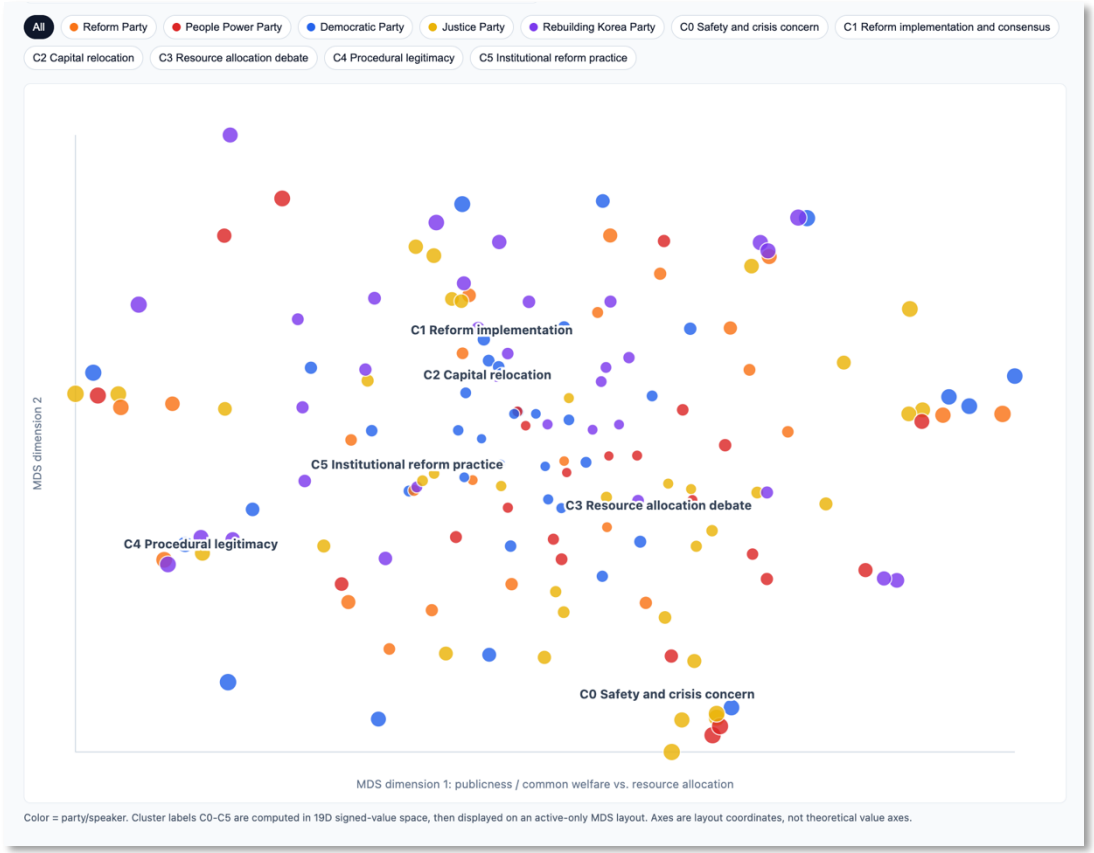
Political Group Discussion



Schwartz's Refined
Theory of Basic Individual Values

Original Plan

Quick Prototype



⚠ ISSUES:

1. **Even if it is AI-based visualization, visualization-based group reflection has already been studied so extensively in existing communities such as CSCW research and VIS that it has no novelty.**

2. **The premise that conflicts go unresolved because people don't know each other's value differences may be an overstretched logic. In most cases they plainly know that their values differ, yet such cases often arise because their interests do not align.**

3. Schwartz ' s human value dimensions are such a universal value concept that they may not adequately reflect contexts where opinions disagree.

4. If AI is passive, it does not fit well with Soohwan's doctoral research projects to date.

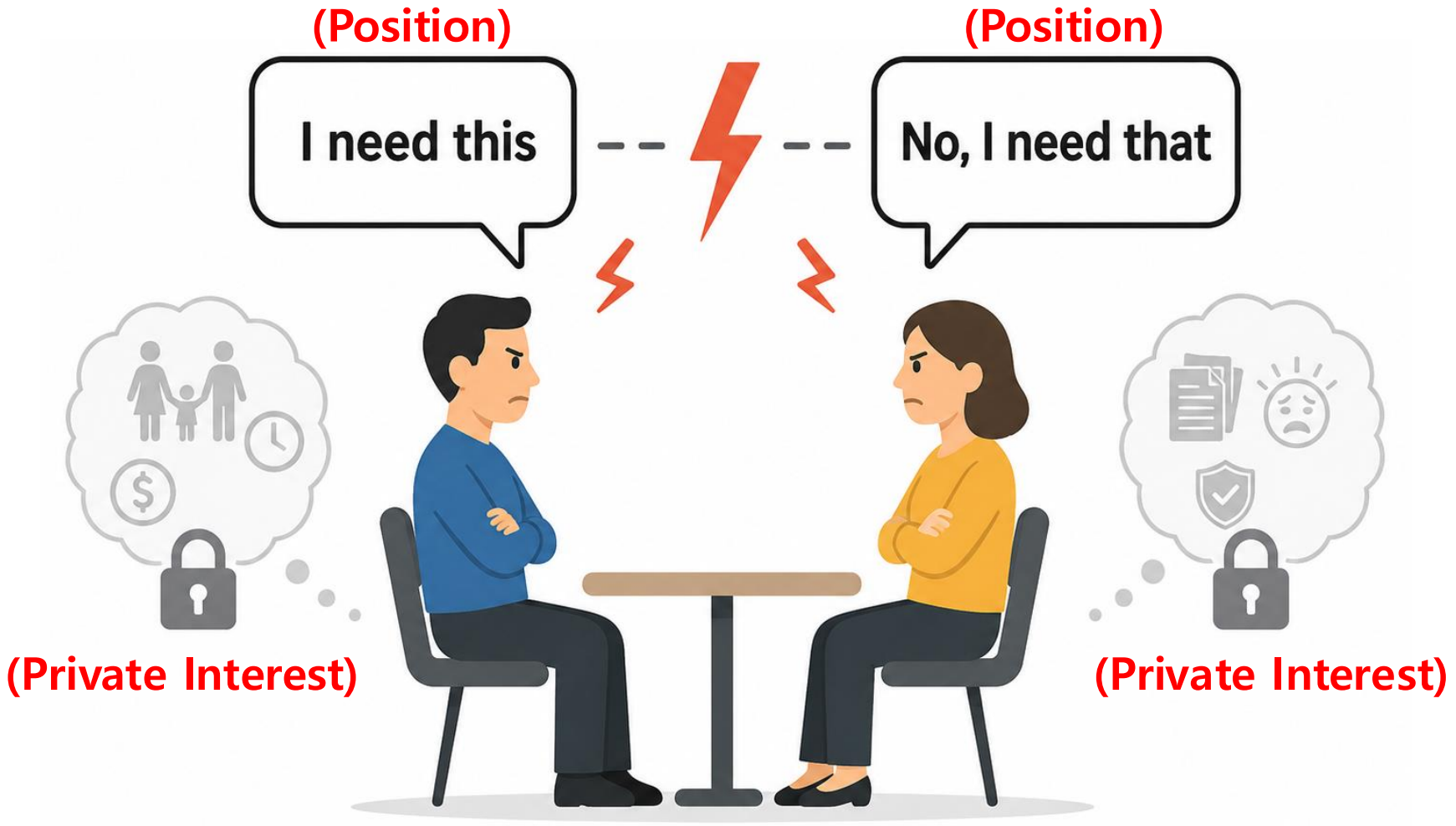
5. Problem context is so broad that it must be made clear which problem to narrow down to in group decision-making.

6. Making values visually visible could instead reinforce group polarization. (But this could also turn out to be a design-wise valuable finding.)

7. A similar case of moving the current dialogue situation to a decision already exists: https://www.ccc.mit.edu/project/dialogue-to-decision/

Problem

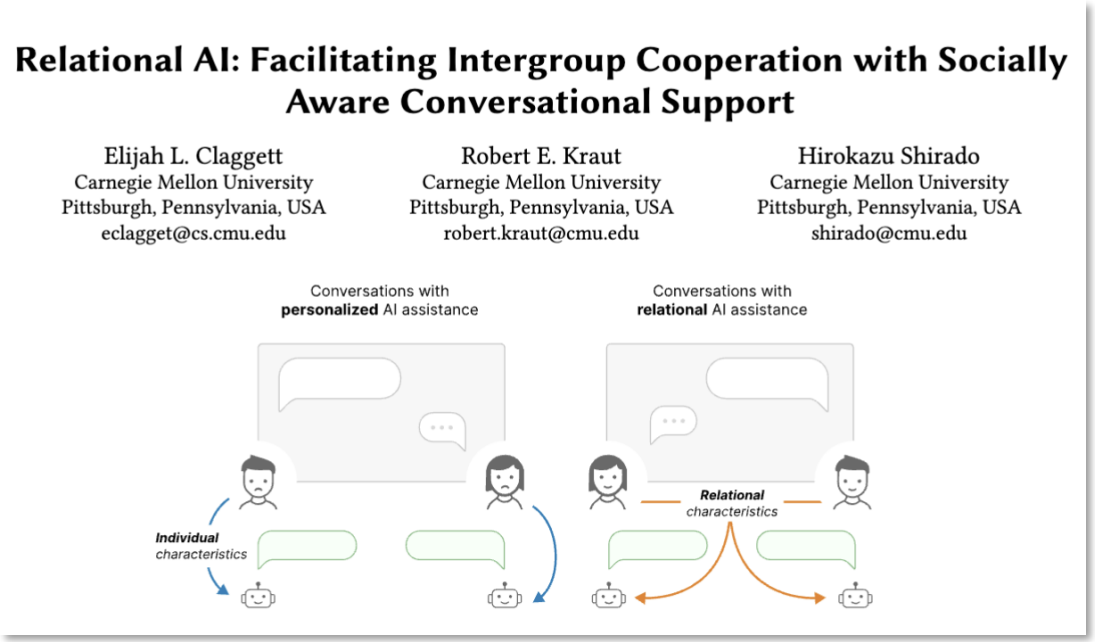
Workplace Negotiation with Private Interest



Related Works

Message Reframing

The idea that a single AI is aware of everyone's private interests could be a concern.



Relational AI: Facilitating Intergroup Cooperation with Socially Aware Conversational Support

Elijah L. Claggett
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Pittsburgh, Pennsylvania, USA
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Robert E. Kraut
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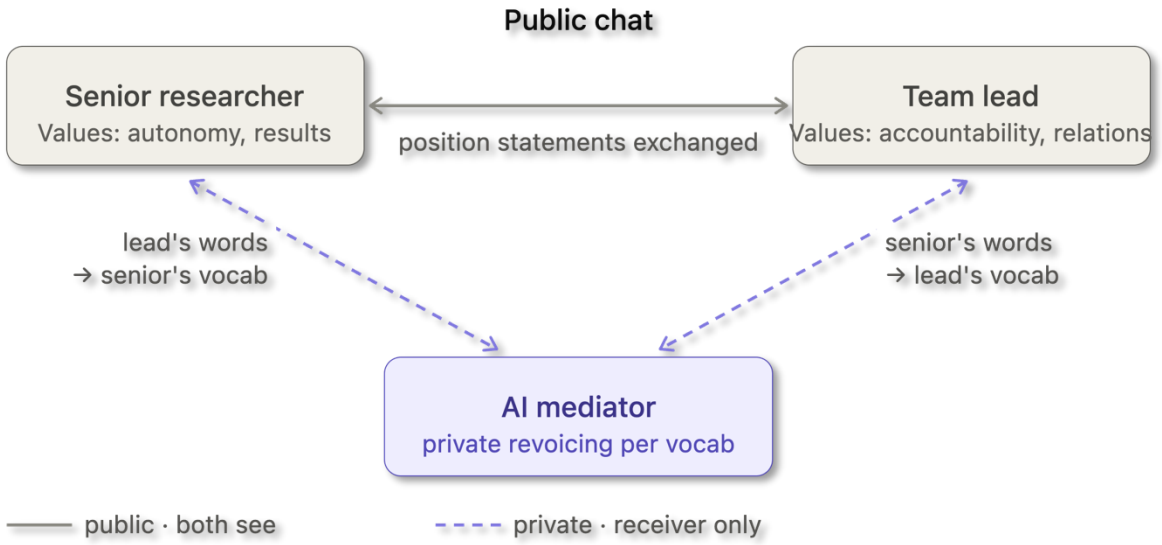
Hirokazu Shirado
Carnegie Mellon University
Pittsburgh, Pennsylvania, USA
shirado@cmu.edu

Conversations with **personalized** AI assistance

Conversations with **relational** AI assistance

Individual characteristics

Relational characteristics



Related Works

Mediation vs Proxy

Two Bots, One Couple: How Surrogate LLM Agents Shape Alliance, Fairness, and Relational Boundaries

Yibo Zhang
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Jianghuai Shao
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Yonsei University
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sjh18283368168@yonsei.ac.kr

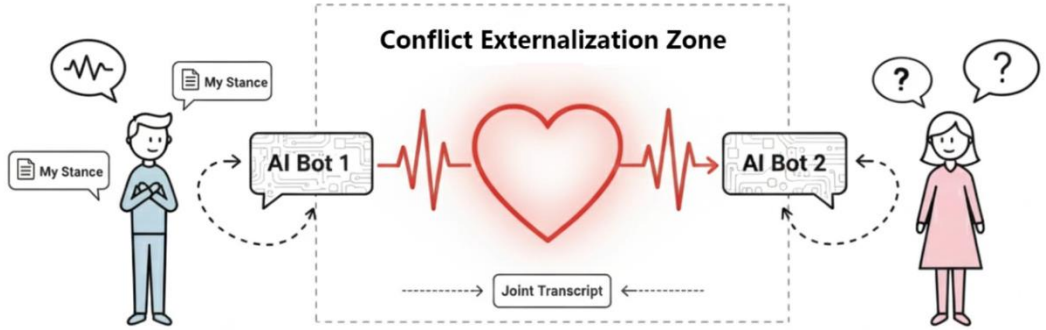
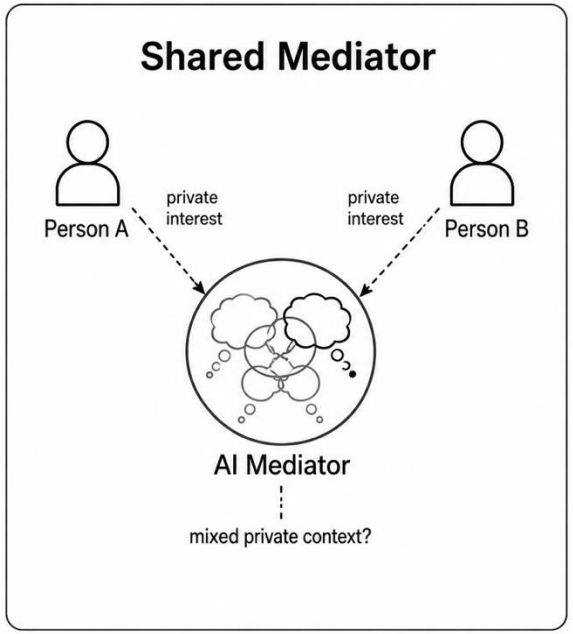
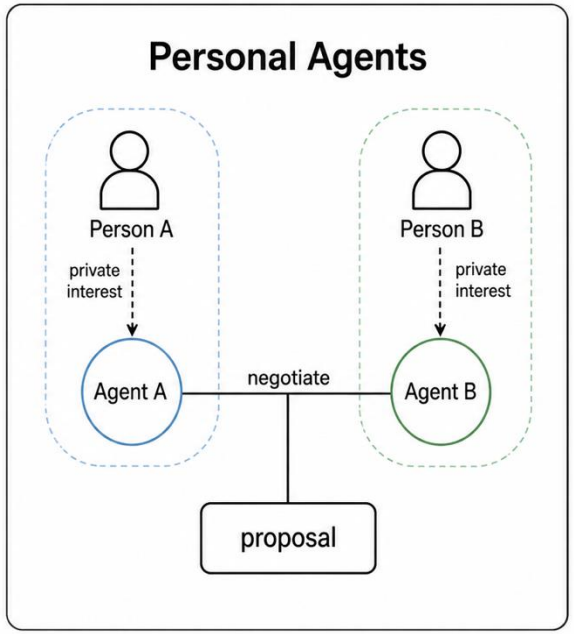


Figure 1: AI-Mediated Conflict Paradigm-Condition: Proxy-Agent Dialogue



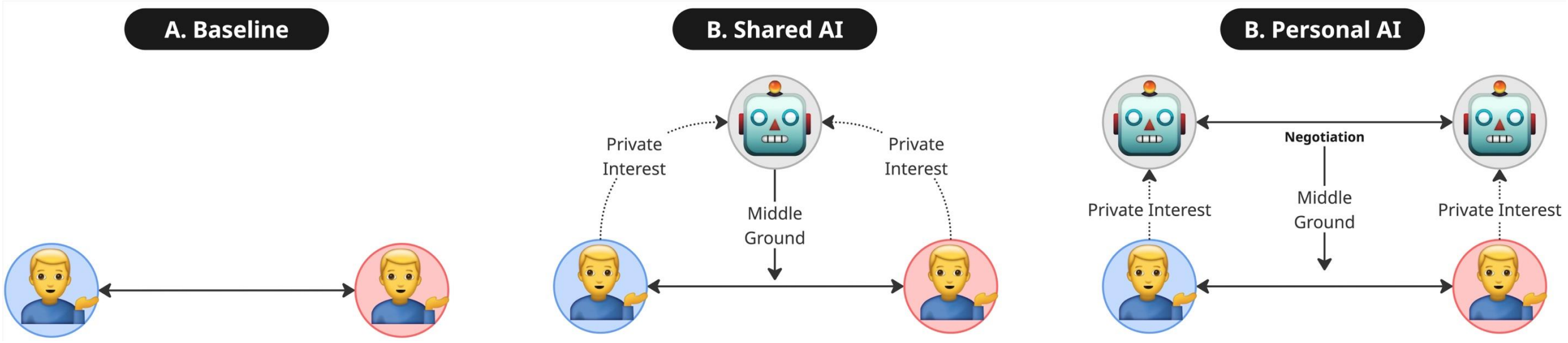


RQ & Experimental Design (Tentative)

RQ 1 How do shared Shared AI and Personal AI differently shape negotiation experiences?

RQ 2 How does social power of participants shape experiences of AI handling private interests?

RQ 3 How does social power moderate the effect of shared versus personal AI? (Interaction Effect)



High Social Power (e.g., Team Leader)

Low Social Power (e.g., Team Member)

Current Issues

Clear Research Scope & Questions

Problem

Under power asymmetry, private interests go unspoken →
position-based negotiation

More Clear Question

"Efficient resolution" → "designing the tension of reflecting sensitive interests"

Axis realignment

Comparing AI *form(shared AI vs personal AI)* →
comparing *how* private interest is handled

Status

AI action behavior under discussion with collaborators

Future Vision

Conclusion (Tentative)

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"AI systems do not merely support group decision-making; they reshape the social dynamics through which people form, express, and negotiate their positions."

Future Vision

Kurt Lewin (1890–1947)
German-American social psychologist

Lewin's Field Theory

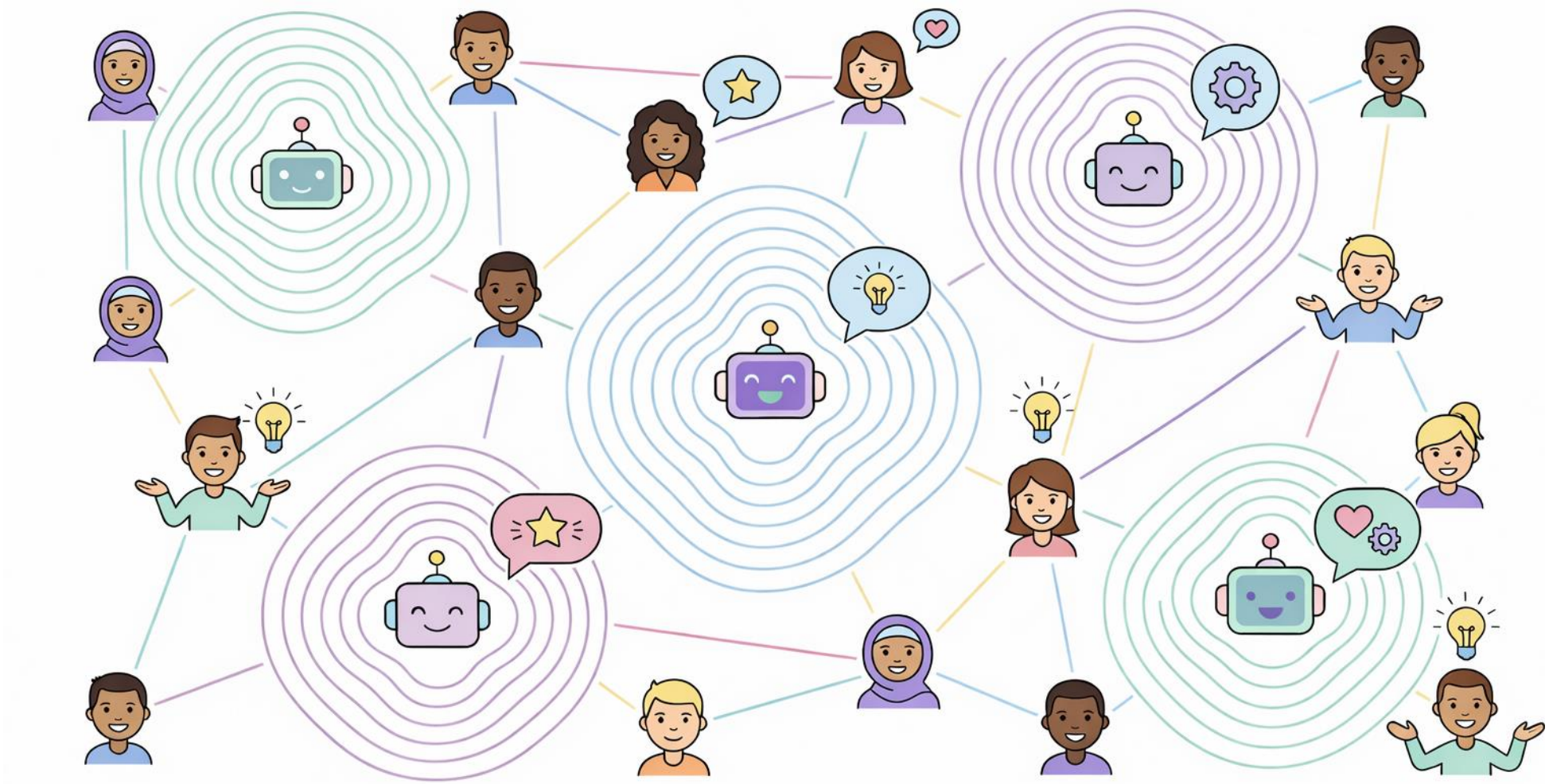
$$B = f(P, E)$$

"Behavior(B) is a function of the person(P) and the environment(E)."

"A social field is the total structure of psychological and social forces shaping an individual's behavior at a given moment."

Future Vision

"AI can reshape social dynamics in group decision-making and can be designed to enable more diverse and inclusive collective decisions."



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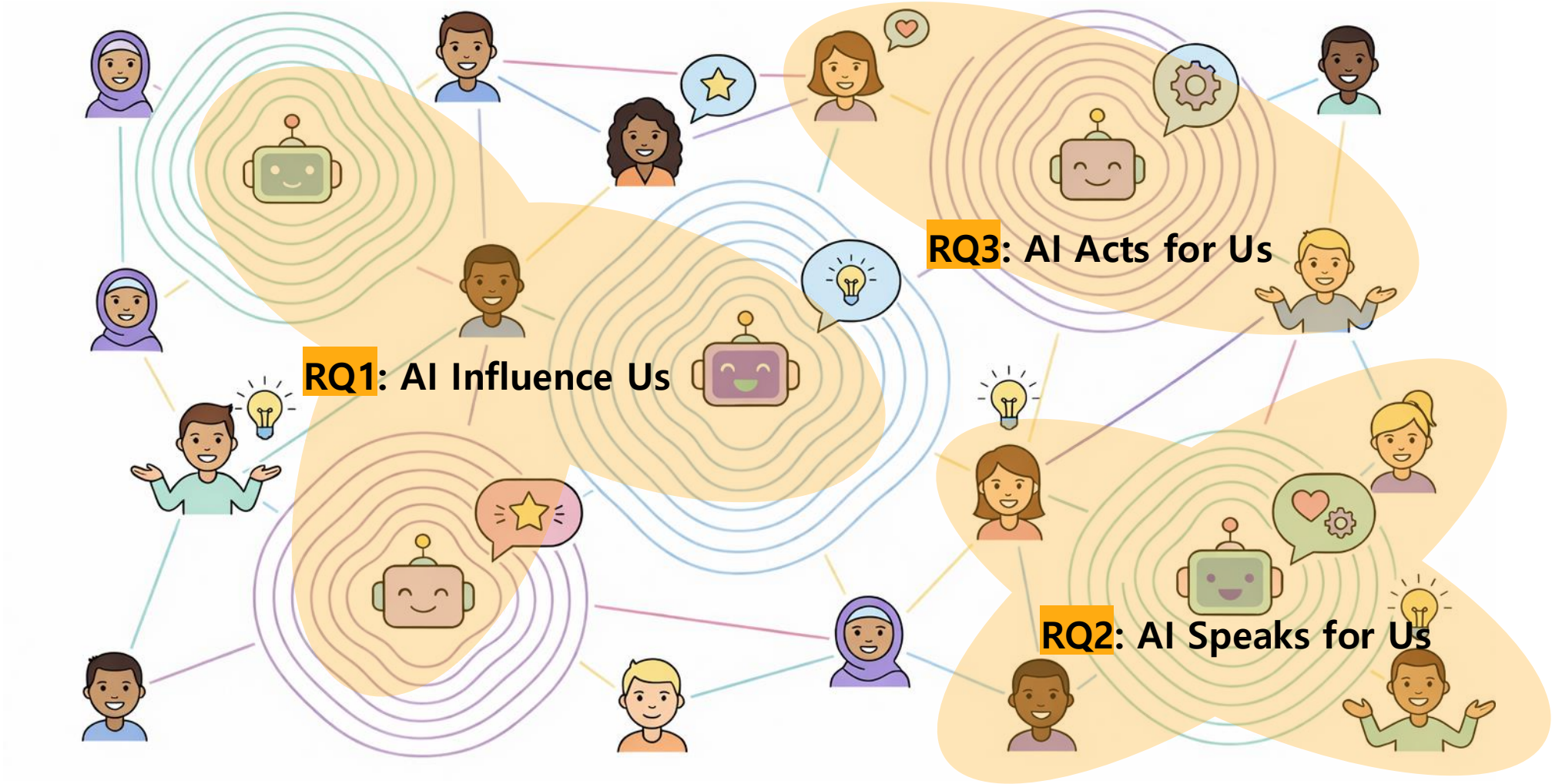

Future Vision

Beyond Individual UX: Defining Group Experience(GX) as a New Paradigm for Group-centered AI

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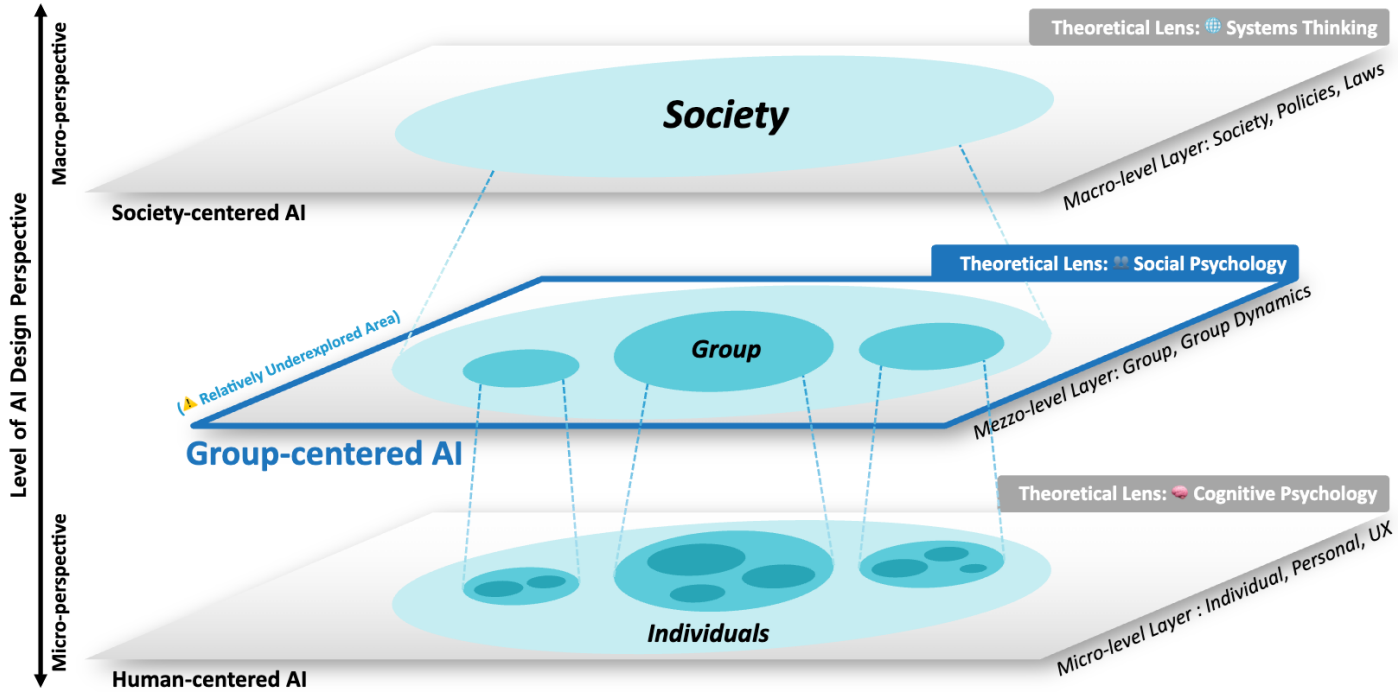

Figure 1: Group-centered AI: A three-tiered framework illustrating the relationship between human-centered AI (micro-level: individual, personal, UX), group-centered AI (mezzo-level: groups, organizations, group dynamics), and society-centered AI (macro-level: society, policies, laws). Dotted lines show connections between entities across levels, demonstrating how group dynamics bridge individual cognition and broader societal structures.

Soohwan Lee, Seoyeong Hwang, and Kyungho Lee. 2025. Beyond Individual UX: Defining Group Experience(GX) as a New Paradigm for Group-centered AI. In Companion Publication of the 2025 ACM Designing Interactive Systems Conference (DIS '25 Companion). Association for Computing Machinery, New York, NY, USA, 357–362. https://doi.org/10.1145/3715668.3736348

Q & A

- *Overall Dissertation: coherent dissertation narrative*
- *Case 3: clearer research gap and RQ*

Any feedback or comments would be greatly appreciated.

Paper Link

LinkedIn

Soohwan Lee

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Ulsan National Institute of Science and Technology
Republic of Korea

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