An Agentic Framework to Achieve Systematic Facilitation in Group Consensus Building

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***Abstract*—Consensus building is a core challenge in human-centered systems, particularly in group decision-making contexts. However, effective consensus formation remains difficult due to social dynamics, cognitive biases, communication barriers, and asymmetries in information and power. Existing approaches offer partial solutions but suffer from key limitations such as over-simplification of features, limited adaptability to dynamics, and lack of systematic overall organization. To address these issues, we propose an agentic consensus building framework (ACBF) in which AI agents act as facilitators or collaborators to support human participants throughout the online decision-making process. This framework integrates participant modeling, consensus process management, and intelligent facilitation. Agents define simple tasks, decompose complex consensus challenges into tractable subtasks, and orchestrate their execution to ensure coherent and goal-aligned outcomes. This work contributes to the design of next-generation human-centered group decision-making systems that integrate agentic AI to systematically support online collaborative consensus building at scale.**

***Index Terms*—agentic AI, consensus building, group decision support system**

I. Introduction

Building consensus is a central challenge in human-centered systems, especially in online contexts that require collaborative decision-making among diverse participants. Whether in participatory planning, policy design, collaborative innovation, or community governance, effective consensus building is critical for producing inclusive, legitimate, and sustainable outcomes [1]. However, real-world group consensus building is often difficult to achieve due to a range of deeply interwoven challenges that span individual, procedural, and organizational dimensions. Individuals in group settings bring a wide range of goals, values, cognitive styles, and knowledge levels. This diversity can be a strength [2], but it also creates significant friction. Cognitive biases, such as confirmation bias, anchoring, or overconfidence, can impair objective reasoning and openness to compromise [3]. Social dynamics, including dominance effects, conformity pressure, or uneven participation, may distort group interactions and reduce the representativeness of decisions [4]. In addition, from the process perspective, many group decision-making efforts suffer from poorly organized or ad hoc discussion structures. Without a clear process design, group dialogue often becomes unfocused, repetitive, or misaligned with the decision goals [5]. Participants may struggle to track the evolution of the conversation, synthesize arguments, or identify emerging consensus. Coordination of the process also becomes increasingly difficult as group size, issue complexity, and stakeholder diversity increase. Furthermore, from the facilitation perspective, skilled facilitators can help navigate these challenges by structuring dialogue, balancing contributions, resolving conflicts, and guiding the group towards convergence [6]. However, effective facilitation is difficult to be achieved because it requires real-time, unbiased management of complex group dynamics [7]. Human facilitators are not always available, and even when present, they may introduce unconscious biases or fail to adapt dynamically to evolving group needs, especially in a large scale online environment. The result is a lack of scalable, consistent, and context-sensitive support for effective consensus building.

To support online consensus building, early systems emphasized structured deliberation, guiding participants through stages of dialogue to frame issues and present arguments [5]. Argumentation tools, such as argument mapping and structured debate interfaces, have been utilized to visualize disagreements and track the evolution of proposals [8]. Recent advancements in natural language processing techniques such as automated summarization [9] and sentiment analysis [10] show the new perspectives of enhancing online deliberation. Large language model based agents are also proposed to achieve automated consensus building support [11]. Despite these advancements in individual subtasks, existing online consensus-building systems still face limitations in providing systematic support in the consensus building process and orchestrating the different facilitation tasks. To overcome these limitations, we propose shifting from static, individual task-centered approaches toward a dynamic framework that systematically treats consensus building as a continuously evolving process that requires real-time monitoring, adaptive

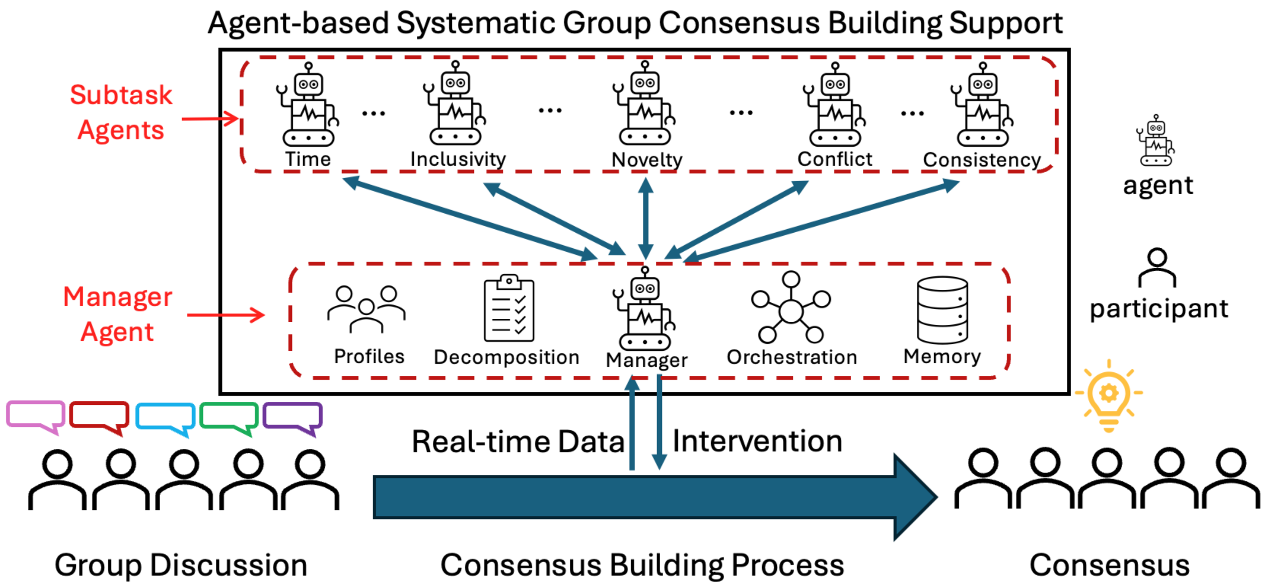

Fig. 1. Agentic Consensus Building Framework

task decomposition, and context-sensitive intervention. In this framework, we introduce the agentic AI concept [12] to address systematic facilitation that includes challenges such as time management, inclusivity, novelty, conflict resolution, coherence, and scalability that persist in online consensus building environments. This framework is designed to address the group consensus building support from two complementary perspectives, the organizational perspective and the operational perspective. It augments human facilitators (or substitutes where none are available) while preserving transparency, explainability, and human oversight.

II. Agentic Consensus Building Framework

We propose an agentic consensus building framework (ACBF) that contains two main modules, the Manager Agent module and the Subtask Agents module. As shown in Figure 1, a central Manager Agent monitors an ongoing online consensus building process in real time, decomposes emerging challenges into tractable subtasks, delegates those subtasks to specialized Subtask Agents, and orchestrates their outputs to determine and execute appropriate interventions.

A. Manager Agent

In ACBF, the Manager Agent plays an organizational role. It continuously ingests real-time data from the consensus building process (e.g., online discussion), constructs profiles for participants, evaluates the global state against objectives, decomposes high-level problems, assigns subtasks, orchestrates feedback, determines interventions to the discussion, and maintains a comprehensive memory of the entire process. Each of these functions requires the development of specific computational techniques to be effective in practice. For example, large language model (LLM)-based techniques can support semantic understanding of discussions, activity-based feature extraction can enrich participant modeling, and human facilitator based facilitation strategies can inform task decomposition and orchestration, ensuring that the system aligns with established facilitation practices.

B. Subtask Agents

The Subtask Agents module plays an operational role in the ACBF. Each Subtask Agent focuses on managing a specific subtask that has been decomposed and delegated by the Manager Agent. For instance, the phase agent monitors the real-time flow of discussion and determines whether a phase transition occurs, like from divergent phase to convergent phase. The inclusivity agent detects imbalances in participation and promotes participation from quieter or underrepresented voices. The conflict agent promotes constructive resolution of conflicts between different ideas, mitigating polarization and fostering mutual understanding. Each subtask agent operates in parallel, analyzing relevant aspects of the discussion and providing targeted recommendations or actions to support the overall consensus-building process. Designing and implementing Subtask Agents requires leveraging techniques from natural language processing, machine learning, and computational social science.

III. Conclusion

In this paper, we propose ACBF to achieve systematic facilitation in group consensus building. ACBF places a Manager Agent at the center of the process along with specialized Subtask Agents that handle individual tasks. Together, these components enable adaptive and human-centered facilitation, where interventions are informed. ACBF is elaborated through an online consensus building scenario. The core principles are applicable to a wide range of other domains. Future work will focus on the implementation and validation of ACBF.

ACKNOWLEDGMENT

This work was supported by JST CREST JPMJCR20D1, and JSPS KAKENHI Grant Number JP24K20900. Additional support for this work was provided by the UK Engineering and Physical Sciences Research Council (EPSRC) through a Turing AI Fellowship (EP/V022067/1) on Citizen-Centric AI Systems (https://ccais.ac.uk/) and through the FEVER Programme Grant (EP/W005883/1).

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