THINKING WITH MANY MINDS:
USING LARGE LANGUAGE MODELS
FOR MULTI-PERSPECTIVE PROBLEM-SOLVING

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ABSTRACT

Complex problem-solving requires cognitive flexibility—the capacity to entertain multiple perspectives while preserving their distinctiveness. This flexibility replicates the "wisdom of crowds" within a single individual, allowing them to "think with many minds." While mental simulation enables imagined deliberation, cognitive constraints limit its effectiveness. We propose synthetic deliberation, a Large Language Model (LLM)-based method that simulates discourse between agents embodying diverse perspectives, as a solution. Using a custom GPT-based model, we showcase its benefits: concurrent processing of multiple viewpoints without cognitive degradation, parallel exploration of perspectives, and precise control over viewpoint synthesis. By externalizing the deliberative process and distributing cognitive labor between parallel search and integration, synthetic deliberation transcends mental simulation's limitations. This approach shows promise for strategic planning, policymaking, and conflict resolution.

Keywords: Decision-Making, Artificial Intelligence and Machine Learning, Problem Solving, Cognitive Science, Computational Modeling

1. INTRODUCTION

Some of the most important and challenging problems society, policymakers, and organizations face are characterized by intricate interdependencies and competing criteria (Rittel & Webber, 1973). Solving such problems demands the capacity for *cognitive flexibility*—the ability to transition seamlessly between diverse concepts or viewpoints (Diamond, 2013) as one imagines possible futures. Cognitive flexibility effectively enables problem-solvers to benefit from imagining multiple possibilities, such as toggling between abstract versus concrete, structural versus functional perspectives, or employing approaches like goal-driven or data-driven methods (Krems, 2014). Its benefits also extend to multi-agent settings, where cognitive flexibility allows individuals to adopt and integrate multiple stakeholders' viewpoints, fostering the anticipation and resolution of objections to potential solutions. Cognitive flexibility can emulate some of the advantages of parallelism and diversity of perspectives that underpin the "wisdom of crowds" (Page, 2000) within a single individual, allowing that person to effectively "think with many minds."

However, cognitive flexibility is both difficult to achieve and hard to maintain. As F. Scott Fitzgerald (1936) famously noted, "The test of a first-rate intelligence is the ability to hold two opposed ideas in mind at the same time and still retain the ability to function." In this paper, we advance two key arguments about cognitive flexibility and its improvement. First, we posit that achieving cognitive flexibility requires balancing two complementary cognitive processes: *compartmentalization* and *integration*. Compartmentalization enables individuals to mentally separate conflicting perspectives, facilitating unbiased exploration and preventing premature fixation (Rafaeli & Hiller, 2010). Integration, on the other hand, synthesizes these perspectives into cohesive solutions through mutual adaptation, fostering adaptive synthesis (Holyoak &

Thagard, 1997). Compartmentalization segments conflicting perspectives into distinct cognitive "frames" (Jonassen, 2000; Newell & Simon, 1972), while integration reconciles these perspectives through dynamic reasoning and problem synthesis (Holyoak & Thagard, 1997; Guilford, 1967; Johnson-Laird, 2010). Humans often struggle to effectively compartmentalize and integrate different approaches to problem-solving, though this ability varies among individuals and can be cultivated through practice (Showers, 1992).

Second, we explore ***synthetic deliberation*** as a promising approach to overcoming these challenges in achieving in cognitive flexibility. We define synthetic deliberation *as a technology-supported process (specifically using Large Language Model) that simulates discourse between synthetic agents representing diverse perspectives on a problem*. While it shares methodological roots with simulation, digital-twinning, and agent-based modeling, synthetic deliberation is distinct in its structure and purpose. Rather than predicting outcomes (as in simulation) or establishing a direct correspondence between virtual and real-world systems (as in digital twinning), synthetic deliberation aims to simulate deliberative dialogue to enhance human cognitive flexibility. It also differs from agent-based modeling, where the objective is to explain the emergence of complexity from the aggregation of agents following relatively simple rules. Instead, synthetic deliberation provides a holistic framework for maintaining and integrating divergent perspectives, addressing the twin challenges of compartmentalization and integration.

We believe that synthetic deliberation offers substantial potential for enhancing decision-making in practice. For example, in strategic planning, businesses can use it to simulate market dynamics, competitive behavior, and customer responses, thereby refining their understanding of strategic options and their possible outcomes. Policymakers can leverage synthetic deliberation to assess the impacts of various policies on different stakeholder groups, enabling more informed and equitable decision-making. In conflict resolution, synthetic deliberation facilitates mutual understanding by simulating negotiations and compromises, ultimately fostering the discovery of mutually beneficial solutions.

In the sections that follow, we delve deeper into the theoretical underpinnings of synthetic deliberation, explore its practical applications, and evaluate its implications for enhancing cognitive flexibility in complex problem-solving contexts.

2. THEORETICAL FRAMEWORK

2.1. Cognitive Flexibility in Solving Complex Problems: Challenges

Problem solving fundamentally relies on the capacity to mentally simulate different courses of action to assess their likelihood of success (Szpunar, Spreng, & Schacter, 2014). By constructing a mental representation of a situation and virtually experiencing it through sensory, emotional, and cognitive dimensions, mental simulations allow individuals to anticipate outcomes, strategize, and prepare for various possibilities (Galinsky, Ku, & Wang, 2005; Parker, Atkins, & Axtell, 2008). This process can be likened to actors constructing a fitness landscape in their minds, navigating it to identify promising points in fitness terms (Thagard, 2005).

The process of mental simulation faces unique challenges when applied to complex problems. These problems can be visualized as rugged fitness landscapes, characterized by intricate interdependencies among components that generate numerous local peaks. Navigating these landscapes makes identifying globally optimal solutions particularly difficult, as the complexity often traps decision-makers in suboptimal outcomes (Rittel & Webber, 1973; Kauffman, 1993; Levinthal, 1997). In multi-actor scenarios, exploring such landscapes may become even more intricate, not only because the control of interdependent actions is distributed across different actors but also because the structure of interdependencies may produce uncorrelated (or even misaligned) fitness landscapes (Rivkin & Siggelkow, 2003; Koçak, Levinthal, & Puranam, 2023). Navigating such complexity necessitates a cognitive mechanism that enables problem-solvers to break free from entrapment on local peaks and explore distant alternatives in parallel as they are mentally simulating possible courses of actions and their likelihood of producing a solution.

Cognitive flexibility, particularly the ability to balance compartmentalization and integration, provides such a mechanism. Compartmentalization allows individuals to mentally isolate conflicting perspectives or logics, minimizing interference and enabling the parallel exploration of new possibilities. In essence, compartmentalization permits the running of different mental simulations without one set of assumptions contaminating another. Achieving this requires not only motivation but also the capacity to navigate inconsistencies between current beliefs and the actions necessary to explore alternative solutions and viewpoints. Existing knowledge can constrain exploration by causing decision-makers (DMs) misleadingly apply it to distant alternatives. Mental compartmentalization mitigates this constraint by detaching new explorations from prior understandings, serving as a mechanism to break strong forms of path dependence.

This logic underscores the longstanding advice to incorporate a “devil’s advocate” perspective when addressing complex problems. Exposing individuals to opposing viewpoints has well-documented benefits: it prompts DMs to seek additional information (Nemeth & Rogers, 1996), consider a broader range of strategies (Nemeth & Kwan, 1987), and generate more original ideas (Nemeth, 1995). Further evidence supports the efficacy of considering the opposite or employing the devil’s advocacy as a corrective to various biases. For example, Lord, Lepper, and Preston (1984) found that both explicit instructions and indirect strategies to consider alternative perspectives significantly reduced biased inference and assimilation.

In professional settings, the legal domain provides clear examples of how engaging with dissenting opinions can improve decision-making. Burke (2006) emphasized the central role of counterarguments in legal practice, particularly the skill of acting as one's own devil's advocate. Similarly, Lidén, Gräns, and Juslin (2019) found that prosecutors routinely adopt this approach in pre-trial assessments to enhance the rigor of their evaluations. These examples highlight how systematically considering opposing viewpoints fosters better reasoning and decision-making outcomes in complex professional contexts.

In contrast to compartmentalization, integration facilitates the eventual synthesis of divergent perspectives into a more comprehensive understanding. It entails building a new meta-simulation that combines two or more compartmentalized simulations. This capacity for integration is closely linked to the concept of knowledge recombination, which has been studied extensively in the literature (e.g., Kogut & Zander 1993; Ahuja & Katila, 2004; Kaplan & Vakili, 2015; Fleming & Sorenson, 2004; Karim & Kaul, 2015; Rosenkopf & Nerkar, 2001; Yayavaram & Ahuja, 2008). This literature shows that successful integration through knowledge recombination requires both the ability to identity valuable combinations and the capacity to effectively synthesize them into new understandings.

In sum, compartmentalization minimizes interference between competing views, reducing the socio-cognitive burden of inconsistency. This separation allows DMs to engage in parallel explorations of different peaks in the fitness landscape. Integration, by contrast, leverages these divergent explorations by synthesizing them into novel solutions that surpass the value of any single perspective alone. This process is effective only when the diversity of perspectives is preserved and not prematurely discarded. Page (2007) highlights the crucial role of maintaining diverse perspectives in fostering integrative problem-solving, often yielding outcomes superior to those achieved by individuals with objectively higher abilities. Together, these processes enable DMs to perform “long jumps” across the fitness landscape, overcoming entrenched local peaks, but only when such jumps lead to genuine improvements over what is achievable within the local neighborhoods (Siggelkow & Levinthal, 2003).

Despite its potential, maintaining cognitive flexibility—balancing compartmentalization and integration—remains a significant challenge. On the one hand, both compartmentalization and integration of different perspectives are subject to socio-cognitive constraints inherent in individual decision-making. For instance, individuals are naturally inclined to seek confirmatory evidence that reinforces their existing beliefs about judgments, predictions, or decisions (Nickerson, 1998). Even when these beliefs are spurious or highly malleable, they persist because they offer a comforting sense of causal understanding about the world. Anderson and Sechsler (1986) showed that merely explaining a potential link between variables increases individuals’ confidence in their beliefs. This tendency, often rooted in cognitive biases like confirmation bias, can inhibit the exploration and integration of alternative perspectives. On the other hand, while mental compartmentalization and integration functionally complement each other, they may interfere with each other in their operations. For instance, the integration of diverse viewpoints may result in premature convergence in parallel exploration (e.g., Park & Puranam, 2023). At the same time, the compartmentalization of different perspectives may hamper the effective integration of them.

Taken together, understanding the interplay between problem complexity and cognitive flexibility highlights the critical role of compartmentalization and integration and its challenges.

While cognitive flexibility offers a powerful tool for navigating complex problems, its successful implementation requires the deliberate cultivation of strategies such as devil's advocacy and considering the opposite, as well as techniques for re-integrating diverse perspectives.

2.2. Cognitive Flexibility in Solving Complex Problems: Current Solutions

There is evidence that training can improve cognitive flexibility for problem-solving (Buitenweg, Van de Ven, Prinssen, Murre, & Ridderinkhof, 2017). Experimental evidence suggests that instructing individuals to engage in "counter-explanations" effectively reduces the cognitive bias in exploring and integrating different perspectives (Van Brussel, Timmermans, Verkoeijen, & Paas, 2020). Similar de-biasing effects have been observed in addressing anchoring (Mussweiler, Strack, & Pfeiffer, 2000), overconfidence (Griffin, Dunning, & Ross, 1990), and hindsight bias (Arkes, Faust, Guilmette, & Hart, 1988). These strategies not only counteract cognitive biases but also enhance information-seeking, strategy diversity, and originality in problem-solving (Nemeth, 1995; Nemeth & Rogers, 1996).

Particularly relevant to our arguments, research on dialogue-based learning provides further evidence for the power of alternative perspectives in enhancing cognitive flexibility through structured compartmentalization and integration. Chi, Kang, and Yaghmourian (2017) found that dialogue formats were significantly more effective than monologues in facilitating the learning of complex concepts, primarily because dialogues naturally foster distinct mental simulations of competing viewpoints. The dialogue format effectively compartmentalizes different perspectives, enabling learners to run parallel mental simulations without one perspective interfering with the other—a critical mechanism for cognitive flexibility. This is further supported by research on vicarious learning through dialogue, where observers achieved learning outcomes comparable to direct participants (Craig, Discoll, & Gholson, 2004; Driscoll, Craig, Gholson, Hu, & Grasessner, 2003).

Moreover, dialogue observers demonstrated superior integration abilities, apparently successfully merging multiple compartmentalized simulations (i.e. imagine futures) into broader, cohesive meta-simulations. This effectiveness arises from dialogue's ability to promote both compartmentalization (by clearly delineating perspectives) and integration (by synthesizing conflicts and resolving viewpoints). Supporting this, prior research suggests that observing conflict episodes can enhance learning (Schunk, Hanson, & Cox, 1987) by offering refutation information (Muller, Bewes, Sharma, & Reimann, 2008) and fostering greater intrinsic motivation (Chi et al., 2017). Interestingly, while Chi et al. (2017) demonstrated that dialogue observers achieved comparable learning outcomes to direct participants, they also found that observers engaged differently with conflicting perspectives—often more effectively than the original dialogue participants themselves. This suggests that the externalization of the mental processes associated with observing dialogue might not simply augment our natural cognitive processes but fundamentally transform them. When perspectives are externalized through other agents, the observer may occupy a privileged position that enables more sophisticated compartmentalization and integration than either unaided thinking or direct participation in dialogue would allow.

This insight challenges traditional assumptions about the relationship between direct experience and vicarious learning. The observer's detachment from the immediate dialogue may enhance rather than impede cognitive flexibility. Drawing parallels with research on the duck-rabbit illusion (Gopnik & Rosati, 2001), where conscious awareness of perceptual switching often impedes the natural oscillation between perspectives, observation of dialogue might work precisely because it offloads the mechanical aspects of perspective-switching to other agents.

This may allow the observer to focus cognitive resources on higher-order integration processes while the dialogue participants maintain the distinctiveness of compartmentalized viewpoints. Such a division of cognitive labor suggests that observing deliberation is not merely a tool for enhancing existing mental simulation capabilities, but potentially a new form of hybrid cognition that transcends the limitations of an individual intelligence working in isolation.

However, the practical application of such approaches often encounters significant challenges. The most obvious is simply the cost of arranging for others to engage in a dialogue for the benefit of an observer. An alternative may be to mentally simulate such a deliberative process: just as one takes on a devil's advocate role, one might imagine mentally simulating multiple personalities, each arguing from a different perspective. However, this too faces inherent cognitive limitations, such as the finite capacity of working memory (Cowan, 2001). Under conditions of time and resource constraints, the likelihood of employing such corrective strategies diminishes further. For instance, shifting from their own viewpoints to the other's involves significant cognitive resources, especially when dealing with complex or unfamiliar problems. Simulating multiple actors places a greater demand on working memory and thus results in less immediate and robust simulations (Baddeley & Hitch, 1974), limiting its applicability to dynamic problems.

Even when individuals do engage in mental simulation of a dialogue between multiple perspectives, the underlying cognitive process is still susceptible to biases and information availability. In particular, the inherent tendency toward internal consistency (e.g., Nickerson, 1998) may prevent individuals from exploring conflicting viewpoints independently. These barriers limit the viability of mentally simulating deliberation between diverse perspectives as a means to enhance cognitive flexibility. In the next section, we argue that synthetic deliberation—which leverages Large Language Models (LLMs) to create a discussion among artificial agents that each represent a perspective on a problem - provides a powerful tool to improve cognitive flexibility for solving complex problems.

2.3. Synthetic Deliberation as a Means to Enhance Cognitive Flexibility

Synthetic deliberation builds on and extends the principles of mentally simulating dialogue between different perspectives, addressing its limitations by leveraging LLMs to simulate dynamic interactions and decision-making processes among multiple agents. Unlike mental simulation, which is confined to an individual's mind, synthetic deliberation externalizes the process, creating vivid and interactive representations of diverse viewpoints. This transformation turns a solitary, introspective exercise into a multi-agent discourse, allowing DMs to engage with a broader array of perspectives and explore their interactions in ways that would otherwise be cognitively prohibitive. Such constraints could stem from limited cognitive capacity (Cowan, 2001) or the risk of generating biased or skewed samples of viewpoints (Einhorn & Hogarth, 1978; Fiedler, 2000).

Synthetic deliberation represents a distinct approach to enhancing cognitive flexibility. By simulating deliberation and dialogue among agents with diverse perspective, it provides a structured framework for maintaining and integrating divergent viewpoints. This enables DMs to overcome the challenges of cognitive limitations and biases, fostering a more comprehensive exploration of complex problems. To illustrate how synthetic deliberation operates in practice, we provide a demonstration using a vignette adapted from Koçak, Puranam, & Yegin (2023) about corporate decision-making regarding green technology investment (see Appendix A). The vignette features three executives with conflicting perspectives on the investment: one prioritizing shareholder value, another emphasizing moral obligations to the environment, and the third questioning the technology's effectiveness. Using a customized chatbot built on GPT-based technology (https://chatgpt.com/share/6776864e-db20-8008-b555-d2ca8a1009bc), we simulate deliberation among these perspectives under varying levels of integration (α). This demonstration highlights how synthetic deliberation can enhance cognitive flexibility while maintaining the distinctness of diverse viewpoints. To fully appreciate the unique contributions of synthetic deliberation, it is important to contrast and differentiate it from related frameworks, such as digital twins, ABMs, and AI-based devil's advocates.

2.3.1. Synthetic deliberation vs digital twins. While both synthetic deliberation and digital twins utilize digital technology to enhance decision-making, their focus and mechanisms differ significantly. Digital twins aim to create a dynamic, two-way representations of real-world entities—such as products, processes, or organizations (Lyytinen, Weber, Becker, & Pentland, 2023). Their primary value lies in mirroring and predicting the behavior of these real-world counterparts, facilitating real-time monitoring, analysis, and intervention. Synthetic deliberation, by contrast, focuses on simulating deliberative discourse among agents representing diverse viewpoints on a problem. Leveraging LLMs, it creates a "synthetic" environment for exploring arguments, counterarguments, and potential outcomes of different decision options. Unlike digital twins, which strive for a faithful representation of reality, synthetic deliberation adopts a more abstract and hypothetical approach, prioritizing the exploration of alternative perspectives and the mitigation of cognitive biases.

Synthetic deliberation amplifies the benefits of mental simulation by facilitating engagement with diverse perspectives. Through interactions with LLM-powered agents, individual DMs can observe where different viewpoints diverge and how they interact, reason, and respond to challenges. This process, potentially combined with incentives (Epley, Keysar, Van Boven, & Gilovich, 2004), accountability (Tetlock, Skitka, & Boettger, 1989), and cognitive complexity (Suedfeld, Tetlock, & Streufert, 1992), enables a richer, more vivid understanding of diverse perspectives than mental simulation alone. In multi-actor problem-solving, such appreciation of the complexity of problems enhances empathy toward other stakeholders (Galinsky & Moskowitz, 2000), promotes psychological closeness (Cialdini, Brown, Lewis, Luce, & Neuberg, 1997), and encourages seeking disconfirming evidence (Todd, Galinsky, & Bodenhausen, 2012). Together, these effects facilitate a more holistic and unbiased approach to information processing, ultimately improving decision quality.

2.3.2. Synthetic deliberation vs agent-based models. Agent-based models (ABMs) employ Monte Carlo methods to generate probability distributions of potential outcomes by simulating interactions based on simple rules. The primary focus of ABMs is to explain complex outcomes through the interactions and dynamics arising from these rules (Knudsen, Levinthal, & Puranam, 2019). They are often used to model and predict the behavior of systems with many interacting agents, such as financial markets or ecosystems.

In contrast, synthetic deliberation leverages LLMs models to create environments that simulate deliberation, discourse, and dialogue among agents with different perspectives and interests. Rather than predicting specific outcomes or replicating real-world scenarios, synthetic deliberation aims to enhance human cognitive flexibility by simulating deliberative dialogue. It offers a structured framework for maintaining and integrating divergent perspectives, enabling richer explorations of alternative viewpoints.

In essence, ABMs act as mirrors that reflect and, in the case of digital twins, potentially control reality, while synthetic deliberation serves as a platform for constructing and challenging potential realities through simulated discourse.

2.3.3. Synthetic deliberation vs AI based devil's advocate. Recent research demonstrates that groups assisted by LLM-based "devil's advocates" achieve higher accuracy in decision-making tasks, particularly when interactive AI tools are employed (Chiang, Lu, Li, & Yin, 2024). Both synthetic deliberation and the AI-powered devil's advocate utilize AI to enhance decision-making by introducing diverse perspectives, but they differ in scope and implementation. The AI-powered devil's advocate specifically focuses on improving group decision-making in contexts where AI already provides recommendations. Its primary goal is to prevent over-reliance on AI by prompting human group members to critically evaluate the AI's suggestions. This approach is grounded in a specific decision context and aims to optimize the interaction between human groups and AI systems.

In contrast, synthetic deliberation adopts a broader perspective. It seeks to enhance individual cognitive flexibility in addressing complex problems by simulating multi-agent deliberation that goes beyond evaluating AI recommendations. This simulation exposes DMs to diverse viewpoints, arguments, and counterarguments, fostering a more comprehensive understanding of the problem. Unlike the AI devil's advocate, which centers on group dynamics, synthetic deliberation aims to augment human mental simulation, which is often constrained by cognitive biases and limited working memory. By externalizing this internal process, synthetic deliberation provides a more robust, AI-assisted framework for exploring complex problems.

In sum, synthetic deliberation is distinct from the existing computational modeling approaches, such as simulation in operation management and ABMs in social science, in both its purpose and promised benefits. In the following section, we formalize the process of synthetic deliberation to articulate how it helps individual DMs achieve cognitive flexibility in solving complex problems.

3. A FORMAL MODEL OF SYNTHETIC DELIBERATION

To systematically theorize how synthetic deliberation enhances cognitive flexibility by improving upon unaided mental simulation, we formalize the process of compartmentalization and integration in solving complex problems. Specifically, we build upon the formal framework introduced by Hong and Page (2004), in which agents with different perspectives (and/or search heuristics) collectively navigate the solution space of complex problems. Here, we adapt this framework to describe individual decision makers attempting to integrate multiple viewpoints into their decisions. Using this framework, we formalize and compare unaided mental simulation and synthetic deliberation by explicitly representing both the multiplicity of perspectives and their integration over time. The model consists of three components: the problem space, agents with diverse perspectives, and aggregation mechanisms.

3.1. Problem Space and Fitness

We assume the existence of $k \in \mathbb{N}$ agents, indexed by $i \in \{1, \dots, k\}$, each representing a distinct perspective on the problem. The problem space is represented as a landscape $\boldsymbol{\mathcal{L}}$ with an objective payoff function $\Pi(\mathbf{x})$ for any position $\mathbf{x} \in \boldsymbol{\mathcal{L}}$, which can be a multi-dimensional vector. Here, $\Pi(\mathbf{x})$ indicates the aggregate-level fitness (or welfare), serving as the DM's payoff, with peaks representing points of locally optimal welfare. Following prior work (e.g., Kauffman, 1993; Levinthal, 1997), we assume that payoffs for proximate solutions are not necessarily correlated. Consequently, the fitness landscape may feature multiple peaks (instead of a single peak) due to interdependencies and tradeoffs between attributes.

3.2. Agents with Diverse Perspectives

Initially, we assume that k agents are randomly assigned to positions (i.e., $\mathbf{x}_i$ for $i \in \{1, 2, \dots, k\}$)

on the landscape $\boldsymbol{\mathcal{L}}$, reflecting their diverse viewpoints on the complex problem. When searching for solutions, individual agents in our model have an imperfect understanding of the task environment and act based on their beliefs (i.e., perceived payoff functions). We represent an individual agent's perspective or belief as $\pi_i(\mathbf{x})$ for $i \in \{1, 2, \ldots, k\}$—which may deviate from both the true payoff $\Pi(\mathbf{x})$ and other agents' beliefs (i.e., $\pi_i(\mathbf{x}) \neq \pi_j(\mathbf{x})$ for $j \in \{1, 2, \ldots, k\} \backslash \{i\}$) due to their distinctive perspectives. The divergence in viewpoints arises from two key sources. First, agents value outcomes differently, leading to systematic variation in their perspectives. Second, agents differ in their understanding of how actions map onto outcomes. We formally capture these sources of divergence in the perceived payoff of agent i's as:

$$\pi_{it}(\mathbf{x}) = \Pi(\mathbf{x}) + \beta_i(\mathbf{x}) + \varepsilon_{it}. \tag{1}$$

In this formulation, $\beta_i(\mathbf{x})$ represents systematic divergence in perspectives, and ε_i captures evaluation noise. Without significant loss of generality, we suppress considerations of noise in the subsequent discussion.[1]

In a rugged landscape, the advantage of having multiple agents lies in their ability to utilize and maintain the diversity of their viewpoints. While adaptive agents with search scopes constrained to their local neighborhoods are prone to becoming trapped at local peaks (Kauffman, 1993; Levinthal, 1997), a system of multiple agents has a greater potential to discover the global peak, particularly when the agents are well-distributed across the solution space (i.e., possess diverse viewpoints) and when mechanism exist to aggregate their findings (Hong and Page, 2004).

To fully realize this potential, achieving a delicate balance between compartmentalization

[1] See Surowiecki (2005) and Hong and Page (2008) for relevant discussion for how groups in aggregate can cancel out noise in individual evaluations.

and integration is essential. Integration fosters the synthesis of diverse perspectives, enabling comparisons among agents' positions and to potentially discovering better peaks between their locations on the landscape. However, integration risks eroding diversity by causing agents to converge prematurely on a narrower solution space. Therefore, compartmentalization of individual agents' searches is also necessary to preserve their diverse initial viewpoints.

In the next section, we compare synthetic deliberation using LLMs with imagined deliberation via mental simulation as mechanisms to achieve this delicate balance for enhancing cognitive flexibility.

3.3. Deliberation, Imagined and Synthetic: A comparison

Here, we compare imagined deliberation, where a DM mentally simulates interactions among multiple imagined stakeholders, with synthetic deliberation, where such processes are externalized using LLMs. In particular, we focus on the structural properties that differentiate these mechanisms in aiding cognitive flexibility.

3.3.1. Imagined deliberation. We characterize "imagined deliberation" as a process in which an individual DM creates *k* imagined agents, each assigned a perspective. These agents then engage in a deliberation process. This corresponds to humans metaphorically stepping into a stakeholder's shoes (e.g., CEO, environmentalist, government) to generate suggestions and reasonings based on that stakeholder's viewpoint, followed by integrating ideas from the diverse perspectives.

We assume that the imagined agents engage in deliberation over *T* discrete rounds, indexed by $t \in \{1, \ldots, T\}$. Each round consists of two phases. First, one agent *i* is randomly selected to conduct a local search and propose a solution based on its perspective and position, π_i and $\mathbf{x}_{it}$. The agent's proposal is formally represented as:

$$\mathbf{x}_{i(t+1)} = \underset{\mathbf{x}}{\operatorname{argmax}}\{\pi_i(\mathbf{x})|\mathbf{x} \in \boldsymbol{\ell}(\mathbf{x}_{it})\}, \quad (2)$$

where $\boldsymbol{\ell}(\mathbf{x})$ denotes the set of positions accessible from $\mathbf{x}$, with $|\boldsymbol{\ell}(\mathbf{x})| < |\boldsymbol{\mathcal{L}}|$, implying that each agent engages in local search. This formulation captures how an agent's unique perspective shapes their initial proposed solutions to the problem.

In the second phase, the other agents engage in search while incorporating the proposal from the first agent into their consideration set along with positions proximate to their current one (i.e., $\boldsymbol{\ell}(\mathbf{x})$). This models how humans mentally simulate others' evaluations and reactions to the proposal—a process of perspective-taking. In the model, agents move toward the proposed solution at a rate of $\alpha_{i\to j}$, provided they believe it offers a better outcome than their current one. Formally, we represent their movements as:

$$\mathbf{x}_{j(t+1)} = (1 - \alpha_{i\to j})\mathbf{x}_{jt} + \alpha_{i\to j}\mathbf{x}_{i(t+1)} \text{ if } \pi_j\left(\mathbf{x}_{i(t+1)}\right) > \max\left\{\pi_j(\mathbf{x})\middle|\mathbf{x} \in \boldsymbol{\ell}\left(\mathbf{x}_{jt}\right)\right\}, \quad (3)$$

where $j \in \{1, \dots, k\}\backslash\{i\}$ and $\alpha \in [0, 1]$. Otherwise, if $\pi_j\left(\mathbf{x}_{i(t+1)}\right) \leq \max\left\{\pi_j(\mathbf{x})\middle|\mathbf{x} \in \boldsymbol{\ell}\left(\mathbf{x}_{jt}\right)\right\}$, the agent continues local search using Equation (2). This process models a multi-round deliberation in which one agent "speaks" during each round while others adjust their positions based on the proposal, simulating a dynamic exchange of ideas.

This iterative process repeats until the agents reach a consensus (i.e., converge on a specific solution) or the terminal round, *T* is reached. Then, the final decision $\mathbf{X}_t$ is determined by aggregating the positions of all agents.

$$\mathbf{X}_t = f(\mathbf{x}_{1t,}\mathbf{x}_{2t} \dots \mathbf{x}_{Nt}) \quad \mathbf{(4)}$$

We leave this aggregation process unspecified for now. This generality is intentional, as it allows for multiple roles for the DM: They may act as pure observer aggregating the agents' positions, participate actively by incorporating their own beliefs into the aggregation, or employ any combination of these approaches.

This process allows imagined deliberation to foster holistic solutions by incorporating diverse perspectives, avoiding the inefficiencies that arise from relying on a single perspective. By mentally simulating different perspectives independently, individuals can effectively compartmentalize them, while simultaneously enabling better integration by envisioning how different stakeholders might reconcile their views.

However, realizing the full potential of imagined deliberation presents significant cognitive challenges to human DMs. The resources requires to simulate each perspective—and its associated local search process—increase at least linearly in k, the number of perspectives being considered. Additionally, maintaining strict compartmentalization between these perspectives within a single DM's mind is inherently difficult, further straining cognitive capacity.

The integration of perspectives hinges in part on the influence parameter α in Equation (3), which determines the extent to which the imagined agents adjust their perspectives in response to others' proposals (see Koçak, Levinthal, & Puranam, 2023). This parameter plays a crucial role in balancing the preservation of diverse perspectives with the need for eventual convergence. When $\alpha = 0$, there is no mutual influence, and agents essentially search independently, emphasizing compartmentalization alone. In this case, the DM mentally simulates diverse perspectives and compiles the resulting ideas to be aggregated later via (4). However, in rugged landscapes (Levinthal, 1997), aggregating proposals located in widely disparate regions can be problematic, as interpolation between these locations might yield worse fitness outcomes than those achieved at individual points.

By setting $\alpha = 0$, the DM underutilizes the natural convergence that might emerge from identifying shared beliefs between across perspectives. Such convergence could simplify the aggregation problem by reducing the distance between proposals under consideration—akin to reaching a consensus in a group that is allowed to converse versus one that is not. On the other hand, if $\alpha = 1$ (i.e., integration only), perspectives converge immediately, sacrificing exploration and eliminating diversity. This immediate alignment forecloses the potential to discover novel or varied solutions, ultimately undermining the effectiveness of the deliberation process.

While neither extreme ($\alpha = 0$ or 1) is desirable, identifying the optimal level of α poses significant cognitive demands. Each imagined agent must evaluate its relative expertise in comparison to others (i.e., "who knows better") to determine both the direction and magnitude of belief adjustment (e.g., Argote, Aven, & Kush, 2018; Bachrach et al., 2019; Klapper et al. 2021). This expertise recognition must hold for every dyadic relationship among agents, causing the cognitive resources required to scale quadratically with the number of perspectives being considered. Additionally, consistently applying a dyad-specific α across multiple imagined rounds of deliberation adds further complexity, challenging the DM's ability to sustain effective coordination.

3.3.2. Synthetic deliberation. This process offers a way to overcome these challenges by allowing the DM to act as an observer and delegate the articulation of perspectives to LLMs. This can be achieved either by assigning one LLM to each perspective or instructing a single LLM to simulate k distinct agents, while maintaining strict compartmentalization of information. In this setup, information exchange occurs explicitly through deliberation, preserving the integrity of individual perspectives. A key assumption underlying synthetic deliberation is:

Assumption: An LLM can simulate the arguments that an agent with a particular perspective is likely to make at least as well as a human can mentally simulate such an agent (***reasonable emulation***).

LLMs can be trained to emulate diverse perspectives through role-playing, but their accuracy, particularly in novel or "unseen" situations, is inherently uncertain. Despite this challenge, there is room for optimism as a growing body of research explores the potential of LLMs to act as "synthetic subjects," simulating human behavior in surveys and experiments (e.g. Horton, 2023; Mannekote et al, 2024; Tranchero et al, 2024). Another promising avenue investigates whether LLMs can function as "synthetic scientists"—capable not only of analyzing data but also of making accurate predictions about potential outcomes (e.g., Manning et al., 2024, Lippert et al., 2024; also see Luo et al 2024 for an application in neuroscience). However, LLMs are trained on historical data that may unevenly represent diverse viewpoints, embedding existing biases and inequalities into their simulations. Such biases risk producing skewed or unfair representations of perspectives, particularly for marginalized or underrepresented groups (Parikh, Teeple, Navathe, 2019). Nevertheless, as we will discuss, while the assumption of reasonably accurate emulation is sufficient for our results, it is not strictly necessary. Even if an LLM is somewhat less effective than humans at simulating a particular perspective, synthetic deliberation can still outperform alternative approaches.

Similar to imagined deliberation based on mental simulation, synthetic deliberation involves a process of parallel search and mutual influence among agents that unfolds over T discrete rounds. However, synthetic deliberation holds two distinct advantages over unaided mental simulation: (1) the externalization of the simulation process and (2) the division of cognitive labor between search and integration. We now proceed to formalize the conditions under which synthetic deliberation can outperform imagined deliberation through mental simulation.

4. PROPOSITIONS

The behavior and effectiveness of synthetic deliberation, compared to imagined deliberation, are shaped by the interplay of three key parameters: the number of perspectives k, the number of deliberation rounds T, and the integration parameter α. Together, these parameters influence both the scope of parallel exploration and the extent of perspective integration achieved during the deliberation processes. By examining the individual and combined effects of these parameters, we theorize how synthetic deliberation may outperform mental simulation in facilitating effective decision-making.

4.1. Simulating Multiple Perspectives: Capacity

Navigating solutions to complex problems presents significant challenges when relying on imagined deliberation through mental simulation. Cognitive constraints inherently limit an individual's ability to simultaneously maintain and process multiple distinct perspectives. While humans can attempt to consider various viewpoints, the difficulty of preserving their distinctiveness increases as the number of perspectives k grows. The cognitive capacity required to simulate interdependencies among these perspectives scales exponentially with k, making it increasingly challenging to manage. Furthermore, humans often struggle to compartmentalize cognitive processes effectively, which undermines the potential benefits of parallel experimentation—challenges that become even more pronounced as k increases.

In contrast, synthetic deliberation leverages multiple agents trained to represent distinct perspectives, ensuring that these viewpoints remain well-defined without degradation, regardless of k. As the number of perspectives grows, this capability becomes increasingly advantageous, allowing us to derive:

Proposition 1 (P1): Relative to imagined deliberation, synthetic deliberation excels

in addressing problems requiring the integration of many diverse viewpoints.

Thus, synthetic deliberation enables the simulation of numerous perspectives without overwhelming the DM's cognitive capacity. By externalizing the parallel search and interaction processes of multiple agents, synthetic deliberation not only alleviates the cognitive burden associated with managing a large number of perspectives but also mitigates cognitive biases (e.g., anchoring) that often arise when switching between perspectives.

4.2. Characteristics of Problems and Deliberation Processes

First, beyond parallel exploration and integration, the characteristics of problems and deliberation processes significantly influence the relative utility of synthetic deliberation. First, in deliberation rounds T, which are inversely related to time constraints or dynamic environments, humans are prone to cognitive fatigue and memory limitations that may lead to perspective collapse—where distinct viewpoints blur together over time. Synthetic deliberation, by maintaining perspective distinctness for extended periods, enables more thorough exploration of the solution space.

Second, the benefits from synthetic deliberation are amplified with increasing problem complexity. When interdependencies among components and criteria are minimal, simpler methods such as straightforward integration or local hill climbing may suffice to achieve satisfactory outcomes. However, for problems requiring multiple iterative explorations across perspectives or those situated in rugged fitness landscapes, synthetic deliberation enables effective navigation and coordination of complex interdependencies, allowing us to derive:

Proposition 2 (P2): Compared to imagined deliberation, synthetic deliberation is particularly advantageous for addressing complex problems characterized by high interdependencies and rugged fitness landscapes, especially as required deliberation

time increases.

4.3. Integrating Multiple Perspectives: Tunability

In our model, the integration parameter α plays a crucial role in determining how effectively different perspectives are combined. If α is too high, the integration process results in premature convergence, failing to fully leverage the benefits of diversity. Conversely, if α is too low, diverse viewpoints remain segregated without achieving synergies. In mental simulation, humans tend to either under-integrate perspectives (keeping them separate without synthesis) or over-integrate them (losing their distinctive insights). For instance, they may be anchored to their own perspective, under-integrating inconsistent ones (e.g., Tversky & Kahneman, 1974; Nickerson, 1998), or over-generalize existing perspectives when understanding distinct viewpoints.

Synthetic deliberation, however, provides the ability to control the degree of integration through explicit parameterization, as in equation (3). By simulating multiple epochs of synthetic deliberation with different values of α, synthetic deliberation achieves a level of tunability that is harder to accomplish in mental simulation. A notable instance of tunability occurs when the DM sets $\alpha = 0$, allowing the LLMs to perform compartmentalized search while the DM focuses entirely on integration. This approach ensures that expertise recognition between DM and k synthetic stakeholders is sufficient, reducing computational resource demands to linear (rather than quadratic) growth with k. Additionally, the tunable integration parameter enables synthetic deliberation to adapt the degree of convergence dynamically based on the problem's characteristics, allowing us to derive:

Proposition 3 (P3): Relative to imagined deliberation, synthetic deliberation is particularly valuable for addressing problems that require integrating many distinct perspectives with uncertain relative accuracy.

In summary, we anticipate that synthetic deliberation will excel in addressing problems characterized by the presence of multiple genuinely distinct perspectives, each offering partially valid insights. These scenarios benefit from extended deliberation to arrive at robust solutions and require a carefully calibrated integration of perspectives. Conversely, for simpler problems requiring fewer perspectives or where rapid convergence is preferable, the advantages of synthetic deliberation may diminish or even become a drawback when considering its computational overhead.

5. GENERAL DISCUSSION

5. 1. Theoretical and Practical Implications

Our model of synthetic deliberation, based on the two cognitive processes of compartmentalization and integration, builds upon important prior work on cognitive flexibility, particularly Laureiro-Martínez and Brusoni's (2018) conceptualization of matching cognitive processing to problem types. Both frameworks recognize the importance of identifying diverse perspectives and connecting them to generate adaptive solutions. Our model extends this foundation by introducing a dynamic perspective that captures how compartmentalization and integration operate iteratively over time to balance exploration and synthesis. While existing models effectively describe cognitive flexibility at a point in time, our framework uniquely addresses the temporal dynamics of how perspectives evolve, separate, and reconcile, particularly in contexts characterized by tension or uncertainty. This attention to dynamics offers novel insights into cognitive flexibility when managing conflicting views and changing problem conditions.

Our model's emphasis on compartmentalization and integration also aligns with fundamental cognitive mechanisms identified in neuroscience research. For instance, Sigman and Dehaene (2008) demonstrated that the human brain employs both serial and parallel processing during complex tasks, with certain cognitive networks operating sequentially while others function simultaneously. This biological foundation supports our theoretical framework where compartmentalization (parallel processing of different perspectives) and integration (serial processing for synthesis) can coexist and complement each other. Furthermore, structured approaches like De Bono's (2017) six thinking hats method demonstrate how compartmentalization and integration can be systematically implemented in practice, allowing individuals to deliberately separate different modes of thinking before synthesizing insights into comprehensive solutions.

Our findings also contribute to the theoretical understanding of group decision-making and the role of AI-assisted processes. For example, Chiang et al. (2024) demonstrated through a randomized human-subject experiment that interactive LLM-powered devil's advocates are perceived as more collaborative and of higher quality. Similarly, Google's Notebook LM demonstrates the practical value of dialogue-based communication in AI systems, where multiple perspectives can be surfaced and debated through structured discourse. Notably, the interactive devil's advocate is particularly effective because it facilitates both the separation and synthesis of competing perspectives, aligning closely with our model of compartmentalization and integration. By dynamically engaging with group members and challenging AI recommendations, interactive advocates foster a structured deliberative process that supports unbiased exploration (compartmentalization) while enabling the reconciliation of diverse viewpoints (integration). Our model extends beyond these findings by providing a broader theoretical framework for cognitive flexibility, which balances divergent and convergent thinking across diverse decision-making contexts. This generalizability makes our model a valuable tool not only for enhancing AI-assisted group decision-making but also for informing structured deliberation and synthesis in other complex problem-solving domains, advancing both theory and practice.

Beyond group decision-making, our analysis also contributes to organizational learning literature by providing a novel solution to knowledge recombination challenges. Prior work has emphasized how successful innovation depends on an organization's ability to recombine existing knowledge in new ways (Kogut & Zander, 1992; Fleming & Sorenson, 2004). However, such recombination proves challenging in practice because structural recombination efforts often disrupt existing knowledge resources during integration attempts, potentially destroying value while trying to create it (Karim & Kaul, 2015). Synthetic deliberation provides a solution by offering a low-cost simulation environment where organizations can experiment with different recombination approaches before actual implementation. Through compartmentalization, organizations can maintain the integrity of distinct knowledge domains in separate AI agents, while the tunable integration parameters allow systematic experimentation with different ways of combining these knowledge domains. This enables organizations to identify valuable recombination opportunities while avoiding the disruption costs typically associated with structural reorganization.

These theoretical insights translate into significant practical implications of our model across a range of domains, addressing key limitations in human decision-making such as difficulty holding multiple competing ideas, biased representations of stakeholder perspectives, reliance on biased sampling, and cognitive overload when scaling up deliberations. For instance, in strategic business planning, synthetic deliberation allows organizations to model market dynamics, competitor behavior, and customer responses, enabling more comprehensive and informed strategic responses. For policymakers, synthetic deliberation facilitates navigation of complex problems with competing stakeholder objectives, such as climate change, tax policy, or justice reform, by simulating the impacts of various policies and promoting equitable, evidence-based decisions. In conflict resolution, it alleviates cognitive and emotional barriers by simulating negotiations and exploring compromises, leading to balanced solutions that satisfy diverse interests. Synthetic deliberation thus provides a practical framework for addressing these human limitations and improving decision-making in critical, high-stakes contexts.

5.2. Limitations and Future Directions

While synthetic deliberation offers promising insights into decision-making processes, it is not without limitations and risks. First, the AI-driven agents in synthetic deliberation may reflect biases inherent in their training data, potentially skewing the representation of perspectives and underrepresenting minority viewpoints. Second, the arguments generated by AI agents might lack depth or authenticity, reducing the richness and credibility of the deliberative process. Third, the system could oversimplify complex perspectives, especially in cases requiring nuanced understanding of interdependencies, limiting its applicability to highly intricate problems. Furthermore, the quality of synthetic deliberation depends heavily on the capabilities of the underlying AI model; outdated or poorly designed models may fail to produce relevant or coherent outputs. Questions of privacy, autonomy, and potential manipulation also raise significant ethical concerns (Safdar, Banja, & Meltzer, 2020). For example, if simulations are used to predict or influence behavior without transparency, they could lead to unintended consequences, including the erosion of trust and accountability. Finally, synthetic deliberation may struggle to adapt to rapidly evolving problems where new information emerges in real-time, making it less effective in dynamic, high-stakes contexts such as crisis management. In such cases, human creativity and adaptability remain essential, and over-reliance on synthetic agents could constrain rather than enhance cognitive flexibility. Addressing these limitations through continuous model refinement, bias mitigation, transparency, and ethical safeguards will be critical for enhancing the system's reliability and applicability.

Beyond these technical limitations, the adoption of synthetic deliberation faces significant behavioral challenges in practice. A critical tension emerges in how users integrate the simulated perspectives. On one side, simulation models can appear deceptively credible and convincing, leading to over-reliance where users uncritically accept simulated perspectives without maintaining their own viewpoint (Zhai, Wibowo, & Li, 2024). On the other side, algorithmic aversion may cause users to under-integrate valuable insights, particularly when simulated perspectives conflict with their pre-existing views. In such cases, users might dismissively attribute these inconsistencies to algorithmic error rather than engaging with the substantive disagreement. While the tunability of the integration process theoretically allows for balancing these extremes, achieving this balance in practice requires careful attention to how users interact with and interpret synthetic deliberation outputs.

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Appendix A: Demonstration of Synthetic Deliberation

This appendix offers a practical demonstration using a customized bot built on GPT4o-based technology (https://chatgpt.com/share/6776864e-db20-8008-b555-d2ca8a1009bc). The user prompt is provided below (Appendix A1), and the sample output is available on the Open Science Framework (https://osf.io/sk45r/?view_only=8af3c825e5d3430eab9e2c9351e244d6).

A.1 User Prompt

You will simulate a deliberation between three executives discussing a green technology investment, based on their independently formed views as described below. Use this vignette as their starting positions:

[Vignette]
In thinking independently and privately about the proposed green technology investment, A, B, and C each had distinctive concerns and priorities. A acknowledged that the project would substantially reduce carbon emissions well below legal requirements but maintained that such reductions shouldn't come at the expense of shareholder value, noting that returns would be significantly lower compared to alternative investments. B, while agreeing about the emission reductions, argued passionately that the company had a moral obligation to minimize environmental impact regardless of legal minimums, viewing the investment as essential despite its lower financial returns. C, however, questioned the fundamental premise – while supporting environmental initiatives in principle, they had serious doubts about the technology's effectiveness, citing inconsistent test results and a lack of large-scale implementation data. Their technical analysis suggested the claimed emission reductions were likely overstated due to maintenance issues and operational constraints not accounted for in the initial projections.

Your task is to simulate a synthetic deliberation between these three executives, with their willingness to adjust positions, alpha (α), set as [input value between 0 and 1, inclusive].

A.2 Sample Output

The sample output of this prompt for alpha=0, 0.5, and 1 is available on the Open Science Framework: https://osf.io/sk45r/?view_only=8af3c825e5d3430eab9e2c9351e244d6