Artificial Social Intelligence

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Artificial intelligence (AI) has been growing at an unprecedented pace. Many of us have experienced a "ChatGPT moment" — a realization that AI will profoundly transform our lives. While numerous challenges and calls for improvement remain, there is little doubt that AI agents will play a central role in shaping our future. We argue, however, that the prevailing perspective on AI agent design is insufficient for achieving desirable social welfare, not merely due to computational or regulatory constraints. A key shortcoming lies in overlooking the fact that AI agents operate within an AI ecosystem composed of multiple interacting agents. When such agents act jointly, misaligned incentives or incompatible technological designs may lead to poor social outcomes. Importantly, this perspective is orthogonal to the ongoing efforts to compare artificial and human behavior. Our argument is not merely conceptual but constitutes a concrete call to action: to establish a systematic research agenda on Artificial Social Intelligence. We illustrate this vision through four complementary research directions: (i) understanding multi-agent alignment in search ecosystems, (ii) analyzing model selection in language-based economics as a strategic choice, (iii) rethinking fairness and regulation through the lens of multi-agent ethics, and (iv) designing hybrid social laws for human–AI coexistence. We conclude by outlining a bold vision: the development of a unified theoretical and empirical framework that supports the investigation of the use cases discussed above, and potentially many more yet to be explored.

CCS Concepts: • **General and reference** → **Surveys and overviews**; *Evaluation*; **Empirical studies**; • **Theory of computation** → Algorithmic game theory; • **Applied computing** → **Economics**.

Additional Key Words and Phrases: Collective Intelligence, AI Economics, AI Alignment, Algorithmic Game Theory, Responsible AI, Human–AI Interaction

1 Introduction

Artificial intelligence (AI) has entered a transformative era. Recent breakthroughs in generative AI (GenAI), particularly large language models (LLMs), have led to the rapid emergence of AI agents capable of acting, interacting, and reasoning across domains traditionally dominated by humans. From information retrieval and content generation to negotiation, recommendation, and transportation, these agents increasingly populate the digital and physical spaces we inhabit. As AI systems begin to interact not only with humans but also with one another, a new question arises: *how do societies of AI agents behave?* Understanding this question is crucial for ensuring that the growing web of interacting artificial entities evolves in ways that serve collective welfare rather than undermining it.

Multi-agent systems (MAS) provide a natural theoretical foundation for this inquiry [22, 28, 46, 54, 56, 65]. Since its inception, MAS research has focused on coordination, cooperation, and competition among autonomous agents, developing tools to analyze fairness and efficiency [23, 26, 44], as well as equilibria and stability [3, 5, 11] in distributed settings. Game theory, mechanism design, and online learning have all contributed to a rigorous understanding of how rational or boundedly rational agents interact [9, 16, 17, 19, 64], particularly in dynamic, multi-agent settings [8, 12, 38, 39]. However, the modern AI landscape presents challenges that classical MAS theory could not have foreseen. Agents are now powered by heterogeneous technologies–ranging from symbolic reasoning systems [33, 34] to deep reinforcement learners [4, 15] and LLM-based decision makers [31, 57] , each endowed with distinct representations, inductive biases, and capabilities. Consequently, the traditional assumption of homogeneous rational agents gives way

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to a far more intricate reality: an ecosystem of *technologically diverse, incentive-driven, and strategically adaptive* AI agents.

Applications of such ecosystems are already visible. In search and recommendation systems, AI agents act on behalf of both producers and consumers, while AI-based rankers arbitrate their interactions and effectively define the incentive landscape [42, 45]. In digital marketplaces, automated buyers, sellers, and mediators negotiate through natural language [1, 21]. In high-stakes decision domains such as credit scoring, hiring, and insurance pricing, competing machine learning (ML) models are deployed by independent institutions, interacting indirectly to shape individuals' economic and social opportunities [2, 10, 32] . In transportation, autonomous vehicles share the road with drivers under hybrid rules [27, 36].

Across these domains, a shared principle emerges: system-level outcomes depend not only on the design of individual agents but on the *alignment between their objectives, information structures, and technological representations*. When these alignments fail, efficiency, fairness, and trust can all deteriorate—sometimes dramatically—despite each agent operating optimally in isolation.

Current efforts to align AI, however, are almost exclusively focused on the relationship between a single AI model and its human overseers, ensuring that one system's outputs reflect human preferences, values, or intentions. While this form of alignment is essential, it overlooks the broader phenomenon that arises once multiple AIs interact. Our perspective is therefore complementary to, rather than competing with, studies that compare [37, 41, 52] or align [25, 30, 48] AI behavior with human behavior. Where those studies aim to make individual models human-compatible, we aim to make *ecosystems* of AI agents socially compatible. This calls for a new field of inquiry, *Artificial Social Intelligence*, that integrates insights from multi-agent theory, economics, and AI ethics to study how artificial agents interact, coordinate, and coexist.

This paper outlines a vision for Artificial Social Intelligence as a foundational step toward robust, fair, and trustworthy AI societies. We begin by highlighting four complementary existing lines of work that fall under our agenda, exemplifying different aspects of artificial social intelligence and multi-agent alignment (or lack thereof). We then outline a unified research agenda aimed at establishing both the theoretical foundations and empirical methodologies needed for investigating and advancing artificial social intelligence. Finally, we conclude with a concrete call to action, emphasizing the need for a multidisciplinary research effort that unites social sciences, economics, multi-agent systems and machine learning toward the development of socially aligned AI ecosystems.

2 Existing Work on Artificial Social Intelligence

2.1 The Search Ecosystem

The search ecosystem consists of three fundamental components: a corpus of documents, information needs expressed by users through queries or questions, and rankers that determine the relevance of content for a given query. In recent years, rankers have evolved from traditional lexical models (e.g., Okapi BM25 [50]) to neural approaches (e.g., E5 [62] and Contriever [24]), and more recently to a variety of LLM-based ranking architectures [35, 49]. At the same time, new AI technologies have emerged to serve other actors in the ecosystem: publishers now deploy *document agents* designed to promote their content [6], while users employ *query agents* that transform their information needs into effective queries [58]. Each of these agents may itself be lexical, neural, or LLM-based.

This multiplicity of interacting AI agents introduces a profound *multi-agent alignment problem*. The interplay among document, user, and ranker agents forms a complex strategic ecosystem whose efficiency and fairness depend on their

technological and incentive alignment. Understanding this interplay is essential for determining when this emerging economy of data producers and data consumers yields socially desirable outcomes. Importantly, this challenge is *orthogonal to traditional LLM alignment*, which focuses on aligning a *single* model with human expectations [63]. Here, the core question is how to achieve *alignment across multiple interacting AI agents*—a necessary step toward sustaining welfare in digital ecosystems [45].

To illustrate this, consider an experiment designed not to optimize a particular document agent's performance, but to study how document agents and ranker agents interact. Both types of agents can be implemented as lexical, semantic, or LLM-based. The results reveal a clear pattern: when the document agent and the ranker agent are *mismatched* in type, the document agent's ability to promote its content in rankings drops significantly. Conversely, *alignment* between their underlying technologies substantially improves ranking promotion. Table 1, taken from Nachimovsky et al. [45], illustrates this phenomenon: for example, the dense E5 ranker is most effectively influenced by a semantic (embedding-based) document agent, while LLM rankers respond best to LLM document agents, and lexical rankers to lexical document agents. Importantly, *multi-agent alignment should not be conflated with homogeneity of design*; as shown in Section 2.2, optimal outcomes may emerge precisely from interactions among technologically diverse agents.

Real-world ecosystems involve countless query, document, and ranking agents, each possibly using distinct representations and learning paradigms. Their alignment, or lack thereof, can impact both user experience and publisher welfare. Without a systematic study of such *multi-agent alignment*, AI technologies in search environments may yield unpredictable and suboptimal social outcomes.

Type	**Model**	**Lexical**		**Semantic**		**LLM**	
		BM25	**TF.IDF**	**Contriever**	**E5**	**Gemma**	**Llama**
Human	-	0.071	0.074	0.179	0.183	0.117	0.078
Lexical	-	**0.430**	**0.433**	0.253	0.236	0.158	0.049
Semantic	Contriever	0.269	0.267	**0.363**	0.289	0.226	0.094
Semantic	E5	0.229	0.233	0.308	**0.329**	0.183	0.092
LLM	Gemma	0.217	0.216	0.273	0.264	**0.497**	0.280
LLM	Llama	0.084	0.089	0.268	0.240	0.354	**0.640**

Table 1. From single agent alignment to multi-agent alignment in the search ecosystem, from Nachimovsky et al. [45].

2.2 Language-Based Economics

The search ecosystem already illustrates our claim that achieving social welfare through artificial social intelligence requires studying the *alignment* among interacting AI agents. However, similar challenges are expected to arise in other emerging markets populated by strategic AI agents. Persuasion, negotiation, and bargaining tasks are rapidly becoming automated, as large LLMs enable natural language interactions between autonomous agents. These central economic interactions are inherently multi-agent: whereas in the search ecosystem we encounter content producers, consumers, and rankers, here we face sellers, buyers, and market makers – each driven by distinct incentives and powered by potentially incompatible AI technologies. Understanding how the alignment between these agent types affects economic outcomes (such as efficiency and fairness) is essential. Without it, the AI economy risks systemic failures once autonomous agents begin interacting at scale.

To explore these dynamics, Shapira et al. [53] introduced `GLEE`, a unified framework for *Games in Language-Based Economic Environments*, focusing initially on two-player interactions. GLEE provides a principled methodology for

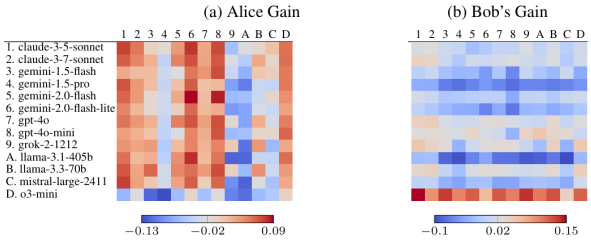

Fig. 1. The LLM selection meta-game of Shapira et al. [53].

evaluating the behavior of both LLM agents and human participants across a wide class of language-based economic scenarios. At its core lies a clear parameterization of the space of bargaining, negotiation, and persuasion games, defining consistent degrees of freedom and evaluation metrics across domains. The framework's richness stems from its flexible parameters, including the game horizon (number of rounds), information structure (knowledge of opponents' preferences), and communication form (free-form dialogue vs. structured messages). GLEE is implemented as an open-source platform that enables researchers to instantiate a wide range of economic games and systematically evaluate LLM behavior within them. While specific models may evolve, the framework and its evaluation metrics remain general.

An empirical analysis by Shapira et al. [53] reveals several behavioral and economic regularities. First, economic outcomes such as efficiency, fairness, and self-gain are strongly affected by structural market parameters such as information structure, communication form, and interaction horizon. Second, there is no universally dominant LLM: performance depends critically on the opponent's identity and behavior. Finally, human participants exhibit more extreme behavior: they either outperform all LLMs or perform significantly worse, depending on the context and role assigned. These findings demonstrate that GLEE serves not only as a research infrastructure but also as a tool for uncovering new insights into economic reasoning and strategic behavior in language-based interactions.

Figure 1 illustrates one such result. The figure shows how different combinations of buyer and seller LLMs affect efficiency (trades occur if and only if the buyer's value exceeds the seller's) and fairness (distance from the midpoint between buyer and seller values when trade occurs). This view highlights that the choice of LLM itself can be viewed as a *strategic decision* made by the agents' deployers. Before any negotiation occurs, each participant selects which LLM to deploy—thus defining a *meta-game* played over model choices. Notably, equilibrium and welfare-optimal outcomes do not always emerge when both agents use the same model type, showing that *alignment* is a richer notion than simple homogeneity.

The outcome of this meta-game determines the subsequent dynamics and efficiency of the underlying economic interaction. Understanding such higher-order strategic behavior—where AI deployers strategically select technologies that later interact—is crucial for anticipating systemic effects in markets populated by autonomous agents. This emphasizes that the design of Artificial Social Intelligence must extend beyond individual models to encompass the ecosystems in which they are selected and deployed.

2.3 Multi-Agent Ethics

In the previous sections, artificial agents participated in all parts of the ecosystem, including the *mediators* that govern these systems (e.g., the ranker in the search ecosystem or the market platform in language-based economic interactions).

However, this vision extends to ecosystems in which the mediator acts as a *regulator*, enforcing ethical constraints, fairness criteria, or social norms.

The field of AI ethics has grown rapidly [47], with fairness occupying a central role [40, 67]. Fairness principles have been embedded into ML models and are increasingly promoted by regulators and policy makers [51, 61]. Yet, a critical gap remains: in multi-agent environments, enforcing fairness at the *individual level* may not ensure fairness at the *system level*. When multiple firms or agents each employ "fair" classifiers, the aggregate outcome of their interactions can still be socially undesirable, sometimes even *less fair* than in the absence of fairness constraints. This systemic failure, documented in the literature [7, 13, 18], exemplifies the need for an explicitly multi-agent approach to AI ethics, accounting for interactions, competition, and incentive effects. We cannot expect isolated regulatory measures or unilateral commitments by individual firms to resolve these issues without addressing the broader ecosystem.

To gain intuition, consider a market with multiple lenders offering loans to a shared pool of borrowers. Gradwohl et al. [18] adopted a welfare-driven framework to formalize *fairness under competition*. Intuitively, an ecosystem satisfies fairness under competition if the welfare of different borrower groups is equalized once lenders deploy their classifiers. Building on the standard Equal Opportunity (EO) fairness criterion [20], Gradwohl et al. [18] defined a new concept: *Equal Opportunity under Competition (EOC)*. The EOC level measures how far the ecosystem is from satisfying fairness under competition (lower values indicating higher fairness).

Gradwohl et al. [18] show that even when each lender's classifier satisfies EO, the resulting ecosystem may deviate substantially from EOC. They provide quantitative bounds on this deviation, grounded in model primitives, and identify two primary mechanisms driving this discrepancy. The first arises when the correlation between classifiers differs across protected groups; the second when lenders' borrower pools overlap but are not identical. Both forces demonstrate how local fairness may no aggregate into global fairness.

This phenomenon has been further illustrated through experiments conducted on real and synthetic loan datasets of varying sizes. In each experiment, each classifier was trained using standard ML techniques constrained to satisfy EO, yet the results show significant violations of EOC across settings. These findings underscore a key insight: constraining individual agents or firms to obey fairness criteria fails to achieve genuine ethical outcomes at the system level. Addressing such multi-agent ethical failures is therefore a cornerstone of Artificial Social Intelligence.

2.4 Hybrid Social Laws

AI is rapidly transforming environments traditionally governed by human decision-making into fully autonomous multi-agent systems. A canonical example is the vision of autonomous transportation. Yet, an important and underexplored challenge lies in the design of *hybrid environments*: systems in which both human-controlled and AI-controlled agents coexist under potentially distinct social norms and regulations. Understanding how to govern such mixed populations effectively is an essential first step toward developing *hybrid social laws*: regulatory and behavioral frameworks that enable welfare-maximizing coexistence between humans and autonomous systems. Such laws are crucial for the gradual and safe transition toward fully automated ecosystems, and they call for joint attention from regulators, policy makers, and AI designers [29].

Current traffic laws and regulations are fundamentally designed for *human-driven vehicles* (HDVs). They rely on assumptions about human perception, cognition, and reaction times, embedding safety margins to account for human error and behavioral variability. For instance, speed limits are typically determined by worst-case considerations such as limited visibility, road curvature, and human reaction delays. These limits are calibrated to the capabilities of an average driver, not to the potential precision and coordination of autonomous vehicles. In contrast, *Communicating Autonomous*

Vehicles (CAVs), or self-driving cars, possess different capabilities: they can obey rules precisely, exchange information in real time, and process data far more rapidly than humans. Although these capabilities are still developing, even near-term CAVs can be expected to perform at least as safely and efficiently as competent human drivers. Moreover, the adoption of CAVs is likely to be gradual, leading to a transitional period characterized by mixed traffic composed of both human and autonomous vehicles.

Addressing this transition calls for a multi-agent perspective on transportation, treating each vehicle as an autonomous agent and traffic regulations as a form of *social law* [14, 55, 59, 60]. This view highlights the need for new, differentiated rules that acknowledge the heterogeneous capabilities of human and artificial drivers. In a recent work, Kraicer et al. [29] proposed *hybrid traffic laws*: a class of regulations tailored to mixed traffic environments that assign distinct behavioral requirements to CAVs and HDVs. Unlike approaches that rely solely on the superior driving skills of CAVs, hybrid traffic laws leverage their capacity to follow dynamically changing and context-sensitive rules. By exploiting these strengths, such laws can improve traffic flow and enhance safety.

Kraicer et al. [29] explored a range of hybrid policy designs across varying proportions of autonomous vehicles. Their analysis demonstrated that, by recognizing CAV-specific abilities, regulators can create policies that maintain efficiency and safety even during the transitional phase toward full automation. In particular, their experiments show that well-designed hybrid traffic laws–where certain constraints apply selectively to human drivers–can substantially improve aggregate efficiency and reduce congestion. These findings underscore the potential of hybrid social laws as a regulatory bridge between human and fully autonomous societies. Looking ahead, it is reasonable to expect similar challenges to arise not only in ecosystems where humans and AI coexist, but also in future societies composed entirely of diverse AI agents, each operating under its own objectives, capabilities, and social norms.

3 Research Agenda and a Broader Perspective

The case studies above reveal a common structural shift in modern AI: system outcomes are no longer determined by a single intelligent model, but by the interaction among multiple autonomous systems. These agents may differ in objectives, capabilities, representations, and the stakeholders that deploy them. As a result, desirable behavior cannot be specified at the level of an individual model alone. Instead, it emerges from the induced interaction dynamics, jointly shaped by incentives, communication protocols, and governing rules. We therefore propose to treat such environments as *AI ecosystems*: populations of heterogeneous AI agents whose collective behavior constitutes the primary object of study. Artificial Social Intelligence studies these ecosystems and the conditions under which their emergent behavior aligns with societal objectives such as welfare, fairness, and stability.

Much of contemporary AI research implicitly assumes that improving individual models improves overall system outcomes. This assumption is increasingly false. In many modern deployments, multiple AI agents interact strategically, adapt to one another, and reshape the data and incentives faced by others. As a result, optimizing a model in isolation may degrade collective performance: individually aligned systems can produce collectively misaligned behavior. The challenge is therefore not merely to build better models, but to understand and design the environments in which models coexist. Artificial Social Intelligence proposes a shift in the unit of analysis: from optimizing agents to governing ecosystems.

This shift calls not only for new applications but for new scientific infrastructure. Artificial Social Intelligence requires theoretical models and experimental frameworks that treat interacting AI agents, humans, and institutions within a unified setting. Such a framework should enable researchers to study multiple use cases within a shared language, compare outcomes across environments, and inform system design decisions. Central questions include how societal

objectives can be enforced with system-level guarantees rather than local constraints; how agents can be trained to be incentive-aware rather than merely task-optimal; and how deployers' choices of models induce a meta-game whose equilibria determine collective outcomes. More broadly, we seek principles for incentivizing cooperation, producing trustworthy collective behavior, and integrating AI agents with human decision makers. Ultimately, the goal is a joint theoretical and empirical methodology in which human–human, human–AI, and AI–AI interactions can be analyzed within the same conceptual framework.

Artificial Social Intelligence is not a replacement for existing alignment efforts, but an orthogonal form of alignment. Traditional AI alignment asks whether a single model behaves according to human intentions. Multi-agent systems study how multiple agents interact, given fixed behaviors. In contrast, modern AI deployments involve stakeholders strategically choosing models, models adapting to one another, and data distributions emerging endogenously from their interaction. The object of alignment therefore shifts: not aligning a model with a user, nor predicting the equilibrium of fixed agents, but aligning the emergent behavior of a socio-technical ecosystem with societal objectives. This perspective challenges a central assumption underlying current evaluation practice — that correctness, safety, or fairness can be assessed per model. Instead, these properties may only be well-defined at the ecosystem level.

We therefore propose the following shift in perspective: the primary subject of study in modern AI should be *the induced behavior of interacting learning systems under incentives.* In such environments, models are no longer fixed decision rules but adaptive participants whose training, deployment, and selection jointly determine the environment itself. Consequently, the relevant notion of alignment is ecosystem-level: a system is aligned not when each component behaves appropriately in isolation, but when their joint dynamics produce socially desirable outcomes. Artificial Social Intelligence seeks principles, guarantees, and evaluation methodologies for achieving this broader form of alignment. Crucially, aligning agents with their immediate incentives is insufficient; socially aligned AI ecosystems require aligning both agents' incentives and the incentives of the stakeholders who design and deploy them.

A call for theoretical foundations. A central component of this agenda is the development of theoretical models of AI ecosystems. Existing frameworks from game theory and multi-agent systems provide a natural starting point, yet they fall short of capturing several essential features of modern AI deployments. In classical models, agents' strategies are fixed decision rules and payoffs are explicitly defined. In AI ecosystems, however, stakeholders select learning systems rather than actions, and the resulting behavior (and payoffs) emerge from the interaction of adaptive models.

A simple abstraction, used for instance in language-based economic environments, treats this as a meta-game: each stakeholder chooses a model, and the utility of a strategy profile is the expected outcome of the agents' interaction, estimated via repeated simulations. This perspective is appealing because it allows the application of equilibrium analysis and mechanism design tools. Yet it remains insufficient. Real deployments involve agents that learn over time, adapt to one another, modify the data distribution they encounter, and can be configured along multiple dimensions beyond model choice, such as prompts, tools, and training procedures. Moreover, stakeholders themselves may act strategically across repeated interactions, anticipating future ecosystem responses.

We therefore call for a unified theoretical framework that treats learning systems, their configuration choices, and their induced data-generating processes as endogenous components of the environment. Such a framework should enable reasoning about stability, welfare, and incentives in settings where behavior is not specified directly but produced by interacting adaptive systems, ideally drawing on existing work on equilibrium learning [8, 38, 39]. Developing this abstraction poses a modeling challenge at the intersection of ML and economic theory, and requires close collaboration

with data science practitioners to ensure that theoretical constructs reflect real deployment mechanisms rather than stylized simplifications.

A call for empirical methodologies. Complementing the theoretical challenge is the need for a new empirical methodology. Current evaluation paradigms assess models in isolation on static datasets or predefined tasks. In AI ecosystems, however, the data itself is generated by interacting agents whose behavior depends on incentives and on one another. Consequently, evaluation must shift from measuring task performance to measuring system behavior.

We propose the development of ecosystem-level benchmarks in which multiple agents, artificial and human, interact under controlled but flexible protocols. Such benchmarks would allow researchers to vary model architectures, training procedures, prompts, and institutional rules, and observe the resulting collective outcomes. Rather than reporting accuracy or reward alone, evaluation would quantify properties such as welfare, fairness, stability, robustness to strategic behavior, and reliability of collective decisions. While previous work indeed made such progress in some specific domains, such as search and recommendation [43, 66], we call for the development of benchmarks that would enable comparison across domains, making it possible to study a wider range of environments within a shared experimental framework.

This perspective reframes evaluation as a data science problem: instead of mining patterns from a fixed dataset, we design environments that generate informative behavioral data. By systematically varying ecosystem components and measuring resulting outcomes, researchers can identify which design choices promote socially desirable behavior and which lead to failure modes. Such infrastructure would provide a common empirical foundation for Artificial Social Intelligence, analogous to how standardized benchmarks enabled progress in supervised learning and reinforcement learning.

4 Conclusion with a Call to Arms

Artificial Social Intelligence envisions a world where ecosystems of AI agents—each with distinct technologies, incentives, and objectives—interact, adapt, and co-evolve. Rather than focusing on isolated intelligence, this vision emphasizes the emergent properties of *societies* of intelligent agents. It challenges the prevailing paradigm of aligning a single model with human intent and instead asks: *How do we align a world of AIs with each other, and with us?*

The cases discussed in this paper—search ecosystems, language-based markets, multi-agent ethics, and hybrid social laws—are only early proof-of-concepts of this broader research direction. They illustrate that progress toward socially beneficial AI requires understanding incentives, communication, and coordination *between* artificial entities, not only between humans and machines. Without such a perspective, even powerful AI systems risk generating fragmented and inefficient ecosystems—an "intelligence without society." Our central claim is thus bold yet necessary: *without addressing Artificial Social Intelligence, the pursuit of socially-beneficial, cooperative AI will remain fundamentally incomplete.*

Realizing this vision requires an interdisciplinary agenda spanning data science, economics, multi-agent systems, and AI. We must study alignment, competition, and cooperation among artificial agents using societal criteria such as efficiency, fairness, and stability, while engaging regulators in shaping environments where diverse AIs can coexist productively. Artificial Social Intelligence is therefore not only a scientific direction but a rethinking of how AI is designed, deployed, and governed. Socially aligned AI will emerge not from a single model, but from understanding the ecosystems they create — an intellectual frontier at the intersection of technology, economics, and human values.

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