

Socialized Learning and Emergent Behaviors in Multi-Agent Systems based on Multimodal Large Language Models

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Abstract—This search introduces the Multimodal Socialized Learning Framework (M-S2L), designed to foster emergent social intelligence in AI agents by integrating Multimodal Large Language Models (M-LLMs) with social learning mechanisms. The framework equips agents with multimodal perception (vision and text) and structured action capabilities, enabling physical manipulation and grounded multimodal communication (e.g., text with visual pointers). M-S2L combines direct reinforcement learning with two novel social learning pathways: multimodal observational learning and communication-driven learning from feedback, augmented by an episodic memory system for long-term social context.

We evaluate M-S2L in a Collaborative Assembly Environment (CAE), where agent teams must construct complex devices from ambiguous blueprints under informational asymmetry. Across tasks of increasing complexity, M-S2L agents consistently outperform Text-Only and No-Social-Learning baselines in Task Completion Rate and Time to Completion, particularly in dynamic problem-solving scenarios. Ablation studies confirm the necessity of both multimodality and socialized learning. Our analysis reveals the emergence of efficient communication protocols integrating visual pointers with concise text, alongside rapid role specialization leading to stable labor division. Qualitative case studies demonstrate agents’ abilities for shared awareness, dynamic re-planning, and adaptive problem-solving, suggesting a nascent form of machine social cognition. These findings indicate that integrating multimodal perception with explicit social learning is critical for developing human-like collaborative intelligence in multi-agent systems.

Index Terms—Multi-Agent Systems, Multimodal Large Language Models (M-LLMs), Socialized Learning, Emergent Behaviors, Collaborative AI, Reinforcement Learning, Embodied AI, Communication, Role Specialization.

I. INTRODUCTION

The pursuit of artificial general intelligence (AGI) has catalyzed a paradigm shift from developing specialized models

to creating generalist agents capable of performing a wide array of tasks across diverse domains [1], [2]. This evolution is largely propelled by the remarkable success of Transformers [3] and the subsequent scaling of Large Language Models (LLMs), which have demonstrated unprecedented capabilities in reasoning, planning, and knowledge assimilation. A pivotal next step in this journey is extending the concept of intelligence from a singular, isolated entity to a collective, social phenomenon. This transition motivates the exploration of Multi-Agent Systems (MAS), where multiple autonomous agents interact, cooperate, or compete to solve problems that are beyond the capacity of any single agent [4]. Foundational research in multi-agent reinforcement learning (MARL) has provided robust frameworks, such as the multi-agent actor-critic [5] and value function factorization methods like QMIX [6], for enabling collaborative behaviors in mixed cooperative-competitive environments.

However, the richness and complexity of intelligence observed in biological societies are predicated on more than just strategic action; they rely heavily on a nuanced understanding of the world and of each other. Early multi-agent systems were often constrained to symbolic or text-based communication, limiting the bandwidth and expressiveness of their interactions. The recent advent of Multimodal Large Language Models (M-LLMs) presents a transformative opportunity to overcome these limitations. By integrating vision, language, and action, models such as Flamingo [7], PaLM-E [8], and Kosmos-2 [9] can ground language in the physical world, enabling agents to perceive, reason about, and interact with their surroundings in a manner far more analogous to humans. This integration is crucial for embodied tasks, from vision-and-language navigation [10] to complex robotic control [11], [12], and is evaluated by comprehensive benchmarks like MME

[13]. Models like Qwen-VL [14] and InstructBLIP [15] further refine this by instruction tuning, allowing for more flexible and general-purpose vision-language understanding. The very architecture of these systems is evolving rapidly, scaling to billions of parameters [16] and incorporating novel mechanisms like Mixture-of-Experts (MoE) to manage computational costs [17]–[21].

This paper argues that the fusion of M-LLMs and MAS creates a fertile ground for the study of *socialized learning* and the *emergent behaviors* that arise from it. When agents can perceive the world multimodally, their capacity for social interaction is profoundly enhanced. They can learn not just from explicit textual communication but also by observing the actions of others, interpreting visual cues, and grounding instructions in a shared physical context. This opens the door for more sophisticated social phenomena to emerge, such as the development of a “Machine Theory of Mind” [22], [23], where agents model the mental states and intentions of others [24], a key component of effective collaboration. The study of emergent communication in MARL provides a theoretical basis for how shared protocols can arise [25], and the concept of agents building internal “world models” offers a mechanism for planning and predicting the dynamics of their environment and the actions of others [26]–[29]. This progression mirrors the open-ended learning dynamics seen in complex games [30].

Realizing such complex, large-scale multi-agent simulations, however, introduces significant systemic and computational challenges. Deploying numerous M-LLM-based agents, especially in resource-constrained edge computing environments, necessitates new paradigms for distributed training and inference. Federated Learning (FL) emerges as a critical enabling technology, allowing for decentralized training while preserving data privacy. Significant research has focused on making FL efficient and robust in heterogeneous edge networks through adaptive updates [31], [32], hierarchical aggregation [33], communication efficiency [34], [35], and personalized frameworks [36], [37]. Innovations such as neural architecture search, layer-wise aggregation [38], progressive training for semi-supervised scenarios [39], and model migration strategies [40] are essential for handling non-IID data and system heterogeneity. Furthermore, mitigating catastrophic forgetting during fine-tuning [41] and applying advanced techniques like knowledge distillation [42] are crucial for continual learning in these systems. On the model side, efficiency is paramount, addressed by methods like low-rank adaptation (LoRA) [43], quantization (QLoRA) [44], adaptive LoRA deployment [45], token merging [46], robust token sampling [47], and optimizing inference pipelines from end to cloud [48]. The challenge of heterogeneity is also tackled at the data level, for instance, in dynamic facial expression recognition [49], which can be a key social signal.

Finally, as we move towards agents that are deeply embedded in our physical world, their perceptual capabilities must extend beyond conventional cameras and microphones. Commodity hardware, such as WiFi and RFID, offers new

modalities for unobtrusive sensing. Recent work has demonstrated the ability to recognize human activities [50], [51], gestures [52], [53], and even emotions [54] using WiFi signals. This technology is being extended to novel healthcare applications like pulmonary function monitoring [55], [56] and to recognizing handwriting via RFID [57] in a way that is robust to environmental factors and heterogeneity. The integration of such alternative sensory data could provide agents with a richer, more holistic understanding of human partners and their environment, simulated in platforms like CausalWorld [58]. However, this pervasive sensing also raises critical security concerns, such as side-channel attacks for eavesdropping on keystrokes [59] or attacks against PHY layer authentication [60], which must be addressed. Furthermore, ensuring the reliability of labels from such noisy, real-world data sources is a major challenge, requiring techniques for label noise suppression [53].

In this context, our work aims to investigate the following central question: *How does the introduction of rich, multi-modal perception and interaction, powered by M-LLMs, shape the social learning processes and emergent collective behaviors within a multi-agent system?* We develop a simulation framework populated by M-LLM-driven agents and design a series of collaborative tasks that necessitate multimodal understanding. By analyzing the agents’ learning trajectories and interaction patterns, we provide a detailed qualitative and quantitative account of emergent phenomena, such as role specialization, symbolic grounding, and advanced cooperative strategies. Our main contribution is to bridge the gap between M-LLMs and MAS, providing empirical evidence that multimodality is a key catalyst for the emergence of complex, socialized intelligence.

II. RELATED WORK

Our research is situated at the confluence of several rapidly advancing fields: multi-agent systems, multimodal large language models, social cognition in AI, and embodied perception. This section reviews the seminal and contemporary works within each domain to contextualize our contribution.

A. Foundations of Multi-Agent Systems and Reinforcement Learning

The algorithmic bedrock for multi-agent coordination lies in Multi-Agent Reinforcement Learning (MARL). Early and influential frameworks such as the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) provided a centralized training with decentralized execution paradigm, enabling agents to learn complex policies in mixed cooperative-competitive environments [5]. For purely cooperative settings, value decomposition methods have become prominent, with QMIX being a canonical example that factorizes the joint action-value function into per-agent utilities, ensuring that individual greedy actions lead to a global optimum [6]. The successful application of these principles has been demonstrated at a massive scale, achieving grandmaster-level performance in complex real-time strategy games like StarCraft II, which

showcases the potential for sophisticated emergent strategies in high-dimensional state-action spaces [4]. More recent theoretical explorations have pushed into the realm of open-ended learning, investigating how agents can continuously generate new, challenging tasks for themselves, particularly in symmetric zero-sum games, to foster an unending cycle of adaptation and improvement [30]. While powerful, these MARL frameworks traditionally operate on structured state representations and do not inherently account for the rich, unstructured data streams that define real-world perception.

B. Large Language Models as Agent Brains

The paradigm of AI agents has been revolutionized by the advent of Large Language Models (LLMs) serving as the core reasoning and decision-making engine. This shift has given rise to the concept of the “generalist agent,” a single model capable of tackling a vast range of tasks without task-specific training [1], [2]. The power of these agents is magnified when they can perceive and act upon the world through multiple modalities. Multimodal Large Language Models (M-LLMs) represent this frontier, integrating vision and language to create a grounded understanding of their environment. Foundational models like Flamingo demonstrated how to effectively fuse pre-trained vision and language models for powerful few-shot learning [7]. This was followed by a wave of increasingly sophisticated architectures. PaLM-E showed how multimodal embeddings could be injected into an LLM to create an embodied model for robotic control [8], while Kosmos-2 focused on grounding M-LLMs to the world by generating descriptions of image regions [9]. Other notable models like Qwen-VL [14] and InstructBLIP [15] have pushed the boundaries of general-purpose vision-language capabilities through large-scale pre-training and instruction tuning, which are often evaluated using comprehensive benchmarks such as MME [13].

The scalability of these models is underpinned by architectural innovations. The Vision Transformer (ViT) established the transformer as a dominant architecture for image recognition [3], with subsequent work scaling these models to tens of billions of parameters [16]. To manage the immense computational demands of such scale, the Mixture-of-Experts (MoE) paradigm has been successfully applied, allowing for the creation of sparsely activated models with trillions of parameters [18]–[20]. This approach has been integrated into the vision-language domain with models like MoE-LLaVA [17], and research continues to refine MoE routing and training, for example by exploring soft mixtures [21].

C. Social Cognition, Communication, and World Models

For multi-agent systems to achieve true social intelligence, agents must move beyond simple communication protocols and develop a deeper understanding of one another. This has led to the computational study of social cognition, particularly “Machine Theory of Mind” [22], which investigates the ability of an agent to infer the mental states—beliefs, goals, and intentions—of other agents. Recent work has demonstrated that LLMs can be prompted to exhibit Theory of Mind

capabilities for enhanced multi-agent collaboration [23]. This is complemented by MARL approaches where agents learn to model others by using their own policy as a template, a concept known as “modeling others using oneself” [24]. A parallel line of inquiry focuses on emergent communication, surveying how agents can develop their own communication protocols from scratch to solve collaborative tasks, often resulting in highly efficient but non-human-interpretable languages [25].

A crucial mechanism enabling both sophisticated planning and social reasoning is the concept of a “world model.” By learning a compressed, predictive model of the environment’s dynamics, agents can plan future actions by “dreaming” or simulating future outcomes within their latent space [26], [27]. This approach has been shown to be highly effective, enabling agents to master diverse domains from pixels [28]. Recent findings suggest that Transformers are particularly sample-efficient learners for building such world models, further solidifying their role in agent architectures [29]. In our work, we posit that a multimodal world model is essential for agents to simulate not only environmental dynamics but also the multimodal behaviors of their peers.

D. Embodiment, Perception, and Physical Interaction

The ultimate test of intelligence is often its application in the physical world. Embodied AI research aims to bridge the gap between abstract models and physical action. Vision-language-action models like RT-2 have shown that knowledge absorbed from web-scale data can be transferred to robotic control tasks [11], and frameworks like Instruct2Act explore how to map complex, multi-modality instructions to concrete robotic actions [12]. To facilitate research in this area, standardized benchmarks like CausalWorld provide simulated robotic manipulation environments for studying causal structure and transfer learning [58].

Beyond traditional perception through cameras, a growing body of work explores alternative sensing modalities using commodity hardware. WiFi-based sensing, for instance, has been used for unobtrusive human activity recognition by developing methods that are robust to environmental interference [50], [51]. This has been extended to more granular tasks like gesture recognition using attention-based deep learning models [52], [53] and even multimodal emotion recognition by fusing WiFi data with vision [54]. The application space is expanding into health, with systems like Wi-Pulmo capturing pulmonary function without contact [55], [56]. Similarly, RF-Eye demonstrates that RFID signals can be used to recognize handwriting [57]. This line of research suggests a future where agents’ perceptual systems are not limited to vision, but can incorporate a diverse array of ambient signals. However, this also brings security vulnerabilities, such as side-channel attacks for acoustic eavesdropping on keyboards [59] and attacks on physical layer authentication [60], which must be considered. Furthermore, data gathered from these real-world sources often suffers from noisy or unreliable labels, necessitating advanced techniques like label noise suppression for robust model training [53], a challenge also seen in

generalizing facial expression recognition from heterogeneous data [49].

E. Systemic Challenges: Efficiency in Distributed Learning and Inference

Deploying and training large populations of M-LLM agents present formidable systemic challenges, particularly in decentralized or edge computing settings. Federated Learning (FL) offers a promising solution. Extensive research has been dedicated to making FL practical, focusing on resource-efficient hierarchical aggregation [33] and communication-efficient asynchronous methods [34]. To handle the statistical heterogeneity of data across clients (a common scenario in MAS), personalized FL frameworks have been developed [36], [37], alongside adaptive strategies for model aggregation [38], local updates [31], and even using neural architecture search within the FL loop. Further advancements include handling semi-supervised settings [39], experience-driven model migration [40], and adapting to decentralized network topologies [35].

On the inference side, model efficiency is critical. Techniques like LoRA [43] and its quantized version QLoRA [44] have become standard for efficient fine-tuning. Research continues to optimize these methods, for example by adaptively deploying LoRA layers [45] or mitigating catastrophic forgetting in federated fine-tuning [41]. Other efficiency-boosting methods include token merging to reduce sequence length in Transformers [46], developing more robust token sampling strategies [47], and building optimized, near bubble-free pipelines for collaborative end-cloud inference [48]. These systemic solutions are crucial for the practical realization of the large-scale multi-agent learning environments we aim to study.

F. Research Gap and Our Contribution

The literature reviewed reveals significant progress in individual domains. MARL provides the algorithms for coordination, M-LLMs offer powerful agent brains, and social cognition theories provide a conceptual framework. However, a critical gap exists in understanding the *synergistic impact of rich multimodality on the very nature of social learning and collective intelligence*. Prior work in MAS has predominantly focused on text or symbolic communication, while M-LLM research has largely centered on single-agent, human-AI interaction. Our work explicitly bridges this divide. We investigate how the ability to perceive and communicate through a shared visual context fundamentally alters inter-agent dynamics, moving beyond explicit instruction-following to enable more fluid, implicit, and observable forms of social learning. We aim to demonstrate that this enrichment of the agents' perceptual and interactive capabilities is a key catalyst for the emergence of more complex, robust, and human-like social behaviors.

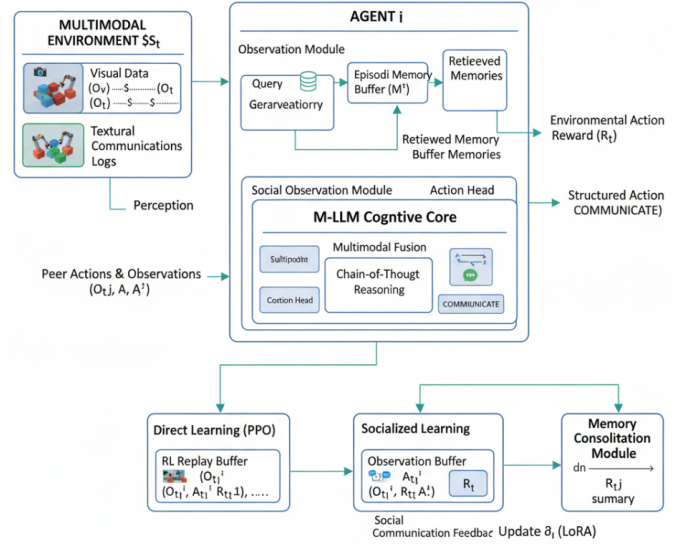


Figure 1: System overview of the Multimodal Socialized Learning Framework (M-S²L). An agent perceives the multimodal environment state S_t , which includes visual data O_v and textual communication logs O_t . This input, combined with relevant memories retrieved from the episodic memory buffer, is processed by the M-LLM cognitive core. The model generates a structured action A_t , which can be a physical manipulation or a multimodal communicative act. The agent receives an environmental reward R_t and observes the behaviors of peer agents. Learning occurs through two parallel loops: a direct learning loop via reinforcement learning and a socialized learning loop that updates the agent's policy based on observation and communication success.

III. METHODOLOGY: THE MULTIMODAL SOCIALIZED LEARNING FRAMEWORK

To investigate the emergence of social behaviors from multimodal interactions, we design and implement a novel framework named the Multimodal Socialized Learning Framework (M-S²L), as illustrated in Fig. 1. This framework provides a comprehensive blueprint for constructing agents whose cognitive abilities are powered by Multimodal Large Language Models (M-LLMs), and whose learning is driven by a combination of direct environmental feedback and rich, socially-mediated experiences. The core philosophy of M-S²L is that advanced social intelligence is not merely programmed but must emerge from an agent's continuous, grounded interactions with both its environment and its peers. This section delineates the formal definition of our multimodal agent, the architecture of its cognitive core, the mechanisms of the socialized learning process, its memory system, and the overall system implementation.

A. Formalizing the Multimodal Multi-Agent Environment

We model our system as a Partially Observable Markov Decision Process for multiple agents (MM-POMDP). It is defined by a tuple $(\mathcal{A}, \mathcal{S}, \mathcal{T}, \mathcal{R}, \Omega, \mathcal{O}, \gamma)$, where $\mathcal{A} = \{A_1, \dots, A_N\}$

is a set of N agents. S is the set of global environment states. The state transition function $\mathcal{T}(S_{t+1}|S_t, \mathbf{A}_t)$ defines the environment dynamics given the joint action $\mathbf{A}_t = \{A_t^1, \dots, A_t^N\}$. The reward function $\mathcal{R}(S_t, \mathbf{A}_t)$ provides a team-based reward signal. Ω is the set of possible multimodal observations, and $\mathcal{O}(O_t|S_t, i)$ is the observation function for agent i , which yields an egocentric, partial, and multimodal observation O_t^i . Finally, $\gamma \in [0, 1)$ is the discount factor.

A key distinction of our framework is the richness of the observation space Ω and the action space for each agent. An observation for agent i , O_t^i , is a tuple $O_t^i = (O_{v,t}^i, O_{t,t}^i)$, where $O_{v,t}^i$ is the visual input (an RGB image from the agent’s first-person perspective) and $O_{t,t}^i$ is the textual input, comprising the recent communication history visible to the agent.

The action space \mathcal{A}^i is also structured and multimodal, allowing agents to interact with the environment and each other in sophisticated ways. The primary action types include:

- **MANIPULATE**(*obj, pos, params*): A physical action to interact with an object *obj* at a target position *pos*. Additional parameters might include force or rotation.
- **COMMUNICATE**(*recipient, message, [focus]*): A communicative act directed at a specific recipient or broadcast to all. The message is textual but can be augmented with a visual focus, such as a bounding box or a highlighted path overlaid on the agent’s visual field, which is then shared with the recipient. This allows for deictic references (e.g., "move *this* block *here*").
- **NO_OP**(): No operation, allowing an agent to wait and observe.

Each agent’s goal is to learn a policy $\pi_{\theta_i}(A_t^i|H_t^i)$ that maximizes the team’s expected future discounted reward, where $H_t^i = (O_1^i, A_1^i, \dots, O_t^i)$ is its personal history of observations and actions. This complex setting demands a powerful cognitive architecture capable of processing and generating multimodal, structured data.

B. The Agent’s Cognitive Core: An M-LLM Architecture

At the heart of each agent lies its cognitive core, a Multimodal Large Language Model adapted for embodied decision-making. This core is responsible for three critical functions: perception processing, deliberative reasoning, and structured action generation. Our architecture draws inspiration from models like Flamingo [7] and PaLM-E [8], which excel at fusing information from different modalities into a unified semantic space for processing by a large language model.

1) *Multimodal Perception and Feature Fusion*: The agent’s raw multimodal observation $O_t = (O_v, O_t)$ must be transformed into a unified representation that the LLM can process. This is achieved through a two-stage process: encoding and fusion.

First, each modality is processed by a dedicated, pre-trained encoder. For the visual input O_v , which is a single RGB image, we employ a Vision Transformer (ViT) [3] pre-trained on a large-scale image dataset. The ViT processes the image by dividing it into a grid of patches and extracts a sequence of patch embeddings, $E_v(O_v) \in \mathbb{R}^{k \times d_v}$, where k is the number

of patches and d_v is the embedding dimension of the visual features. For the textual input O_t , which includes dialogue history and retrieved memories, a standard Transformer-based text encoder (like the one used in the LLM itself) produces a sequence of token embeddings, $E_t(O_t) \in \mathbb{R}^{l \times d_t}$, where l is the sequence length and d_t is the text embedding dimension.

Second, these modality-specific embeddings are fused into a common semantic space that the LLM can interpret. We follow the gated cross-attention mechanism proposed in Flamingo. A small, trainable cross-attention layer is inserted between the frozen LLM blocks. This layer allows the text embeddings at each LLM layer to "look at" the visual embeddings. This method is more powerful than simple projection and concatenation as it allows for a deeper, more contextual fusion of information at various stages of processing. The formal representation of this input process to the LLM can be abstracted as:

$$H_{\text{prefix}} = \text{Fuse}(\text{Proj}_v(E_v(O_v)), E_t(O_t)) \quad (1)$$

where H_{prefix} is the unified representational prefix fed into the LLM, E_v and E_t are the visual and textual encoders, Proj_v is a visual projection network (if needed), and Fuse represents the deep fusion mechanism like gated cross-attention.

2) *Reasoning and Structured Action Generation*: Given the fused representation, the LLM core, a large decoder-only Transformer, generates a sequence of tokens autoregressively. This generated sequence is not just a simple response but a structured chain-of-thought (CoT) process that makes the agent’s reasoning process explicit before culminating in a final, parsable action. We engineer the prompts provided to the M-LLM to enforce a specific output format that enhances reliability and interpretability. A typical generation would look like:

"Current State: [Visual embedding tokens] You see a complex assembly with several parts. [Textual embedding tokens] Your partner Agent_2 says: 'I’m stuck, I can’t figure out where the green gear goes. Can you check the blueprint?'
Retrieved Memory: 'Agent_2 previously had trouble identifying circular parts.'
Deliberation: My task is to help Agent_2. I need to find the blueprint, locate the green gear on it, and communicate its correct position to Agent_2. I will use a visual pointer to be precise. **Action:** {'type': 'COMMUNICATE', 'recipient': 'Agent_2', 'message': 'The green gear connects to the large red axle, like this.', 'focus': '[(x1,y1), (x2,y2)]'}

This structured output is then parsed by a simple utility function to extract the action dictionary. The generation of this entire sequence is modeled as a single autoregressive decoding problem. The agent’s policy π_{θ} is thus implicitly defined by the probability distribution over these structured text sequences. This approach allows the powerful, general-purpose reasoning

of the LLM to be harnessed for specialized decision-making. The policy is formalized as:

$$\pi_{\theta}(A_t|H_t) \propto P(Y|H_t; \theta) = \prod_{j=1}^{|Y|} P(y_j|H_t, y_{<j}; \theta) \quad (2)$$

where Y is the target output sequence (deliberation and action), y_j is the j -th token in the sequence, H_t is the agent’s history which informs the multimodal prefix, and θ represents the trainable parameters of the system (primarily the fusion layers and any LoRA adapters).

C. The Multimodal Socialized Learning (M-S²L) Mechanisms

An agent’s policy π_{θ} is not static; it evolves through learning from its experiences. M-S²L incorporates two primary learning pathways that operate in concert to shape the agent’s behavior: direct learning from environmental feedback and socialized learning from peer interactions.

1) *Direct Learning via Reinforcement*: The most fundamental learning signal comes from direct interaction with the environment. We frame this as a reinforcement learning (RL) problem where the M-LLM acts as the policy network. After executing an action A_t , the team of agents receives a reward signal R_{t+1} from the environment. This reward is shared among all agents, encouraging cooperation. We use a policy gradient method to update the agent’s policy, specifically Proximal Policy Optimization (PPO), which is known for its stability and sample efficiency. The objective is to maximize the expected cumulative discounted reward:

$$J(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta}} \left[\sum_{t=0}^T \gamma^t R_t(\mathbf{S}_t, \mathbf{A}_t) \right] \quad (3)$$

where $J(\theta)$ is the expected total discounted reward, τ is a trajectory of states and joint actions sampled by following the team policy, γ is the discount factor, and the expectation is over all possible trajectories.

The PPO algorithm constrains the policy updates to prevent destructively large changes, using a clipped surrogate objective function. This RL pathway is crucial for grounding the agent’s behavior in the task objectives and the underlying dynamics of the environment. The gradients from the RL loss are used to fine-tune the trainable parameters of the M-LLM core, typically through low-rank adaptation (LoRA) [43] to maintain the integrity of the pre-trained model while enabling task-specific adaptation.

2) *Socialized Learning via Observation (Multimodal Imitation)*: A cornerstone of social intelligence is the ability to learn by watching others. This is often more efficient than individual trial-and-error. In M-S²L, agents are constantly observing the full multimodal actions of their peers. When an agent i observes another agent j perform an action A_t^j that leads to a positive outcome (e.g., a high reward or task progress), it can treat this observation as an expert demonstration.

We implement this observational learning as a form of behavioral cloning, but with a multimodal twist. Agent i maintains a buffer of successful trajectories performed by its peers. This buffer stores tuples of (O_t^j, A_t^j) , where O_t^j is the

full multimodal observation of the expert agent j and A_t^j is its structured action. Agent i then minimizes a supervised loss that encourages its own policy to mimic these expert actions when it encounters similar states. The imitation loss function is:

$$\mathcal{L}_{\text{obs}}(\theta_i) = -\mathbb{E}_{(O^j, A^j) \in \mathcal{D}_{\text{expert}}} [\log \pi_{\theta_i}(A^j|O^j)] \quad (4)$$

where \mathcal{L}_{obs} is the observational (imitation) learning loss, $\mathcal{D}_{\text{expert}}$ is the dataset of observed successful peer trajectories, and the objective is to maximize the log-likelihood of the expert’s structured action text given their multimodal observation.

This form of learning is particularly potent in our framework. Agent i does not just clone a symbolic action; it learns the mapping from a rich, multimodal context (what the expert saw and heard) to a complex, structured response (what the expert thought and did). This allows for the rapid propagation of successful strategies and skills throughout the agent population.

3) *Socialized Learning via Multimodal Communication Feedback*: Effective communication is not an innate skill; it must be learned. In M-S²L, agents learn to be both proficient speakers (generating clear, useful, and grounded instructions) and proficient listeners (correctly interpreting multimodal messages). This learning process is driven by implicit feedback from interaction success.

A ”speaker” agent learns by observing the outcome of its communication. When agent i (the speaker) sends a multimodal message c_t^i to agent k (the listener), and agent k subsequently performs an action A_{t+1}^k that contributes positively to the team’s objective, the communicative act c_t^i is reinforced. This is achieved through a credit assignment mechanism within the RL framework. The speaker’s communication policy $\pi_{\theta_i}^c$, which is part of its main policy, is optimized to generate messages that are causally effective in eliciting successful behavior from listeners. We can conceptualize the speaker’s objective as:

$$J_{\text{comm}}(\theta_i) = \mathbb{E}_{c \sim \pi_{\theta_i}^c, \tau_{\text{listener}} \sim \pi_{\theta_k}(\cdot|c)} [R(\tau_{\text{listener}})] \quad (5)$$

where J_{comm} is the communication objective for the speaker agent i , c is the multimodal message it generates, and the expectation is over the rewards obtained in the listener’s subsequent trajectory τ_{listener} which is conditioned on the message c .

Conversely, a ”listener” agent learns to better ground incoming multimodal messages in its perception and actions. When agent k receives a message c_t^i , this message becomes part of its multimodal observation O_{t+1}^k . If correctly interpreting and following this instruction leads to a high reward, the standard PPO update strengthens the association between the instruction’s features (e.g., the words ”red block”, a visual pointer to a specific object) and the corresponding correct action. This reciprocal learning process enables the co-evolution of a shared, grounded, and efficient communication protocol among the agents.

D. Agent Memory System for Social Context and History

To exhibit sophisticated social behaviors such as trust, reciprocity, and long-term planning, agents must remember

past events, interactions, and social relationships. An agent’s memory is therefore a critical component, structured into two distinct but interconnected systems:

- 1) **Working Memory:** This is the transient, high-bandwidth memory encoded within the context window of the M-LLM. It includes the agent’s most recent multimodal observations, its own chain-of-thought deliberations, and the last few turns of conversation. This provides the immediate context necessary for coherent, short-term decision-making.
- 2) **Episodic Memory:** This is a long-term, external memory store designed for persistence and efficient retrieval. We implement it as a vector database. After significant events—such as the completion of a sub-task, a key conversation, or a surprising outcome—the agent autonomously generates a summary of the event. This summary is a natural language sentence (e.g., “I successfully helped Agent_2 assemble the gearbox by pointing to the correct slot.”). This text is then encoded into a high-dimensional embedding vector using a pre-trained sentence-transformer model and stored in the database along with metadata, including the timestep, involved agents, and associated reward.

During the reasoning phase, before the M-LLM generates its deliberation and action, the agent formulates a query based on its current observation and goal. This query (e.g., “What do I know about assembling the gearbox with Agent_2?”) is embedded and used to retrieve the top- k most relevant memories from the episodic memory bank using maximum inner-product search, which is equivalent to cosine similarity for normalized embeddings. These retrieved memories are then formatted as text and prepended to the M-LLM’s prompt, providing crucial long-term context. The retrieval mechanism is based on the following relevance score:

$$\text{Score}(m, q) = \frac{\text{Emb}(m) \cdot \text{Emb}(q)}{\|\text{Emb}(m)\| \|\text{Emb}(q)\|} \quad (6)$$

where m is a memory entry’s text, q is the current query text, and $\text{Emb}(\cdot)$ is the sentence-transformer embedding function.

This memory system is vital for social learning. It allows an agent to build dynamic models of its peers (e.g., “Agent_2 is a reliable partner for construction tasks but not for navigation”), recall past successes and failures to inform current strategy, and maintain a coherent identity and set of relationships over long episodes.

E. System Implementation and Training Protocol

We implement the M-S²L framework in a custom-built 3D simulation environment developed using Unity, which provides realistic physics and high-fidelity visual rendering. The agents are instantiated using a powerful open-source foundation M-LLM, specifically a version of MoE-LLaVA [17], with its weights largely frozen. We introduce LoRA adapters [43] into the LLM blocks and make the visual projection layers fully trainable. This approach balances computational efficiency with the need for task-specific adaptation.

The training process follows a curriculum designed to foster stable and progressive learning of complex social behaviors. Initially, agents are trained on simpler, single-agent tasks to bootstrap their basic capabilities of perception and action. Subsequently, we introduce simple cooperative tasks that require minimal communication. Finally, we expose them to the full, complex collaborative tasks that demand sophisticated communication, coordination, and planning.

The overall operational and learning loop for a single agent within the framework is summarized in Algorithm 1.

```

Input: Agent  $i$ , Policy  $\pi_{\theta_i}$ , Environment  $E$ , Peer
        Agents  $\mathcal{A}_{-i}$ , Memory  $\mathcal{M}^i$ 
for  $episode = 1, 2, \dots, M$  do
     $H_0^i \leftarrow E.\text{reset}()$ ;
    for  $t = 0, 1, \dots, T-1$  do
         $O_t^i \leftarrow E.\text{get\_observation}(i)$ ;
         $q_t \leftarrow \text{generate\_memory\_query}(O_t^i)$ ;
         $\mathcal{M}_{\text{retrieved}} \leftarrow \mathcal{M}^i.\text{retrieve}(q_t, k)$ ;
         $P_t \leftarrow \text{construct\_prompt}(O_t^i, \mathcal{M}_{\text{retrieved}})$ ;
         $Y_t \leftarrow \text{autoregressive\_decode}(P_t, \pi_{\theta_i})$ ;
         $A_t^i, \text{thought}_t \leftarrow \text{parse\_structured\_output}(Y_t)$ ;
         $O_{t+1}^i, R_{t+1} \leftarrow E.\text{step}(A_t^i)$ ;
        Store  $(O_t^i, A_t^i, R_{t+1}, \dots)$  in RL replay buffer
         $D_{\text{RL}}^i$ ;
        for agent  $j$  in  $\mathcal{A}_{-i}$  do
             $O_t^j, A_t^j, R_{t+1}^j \leftarrow E.\text{get\_peer\_data}(j)$ ;
            if  $R_{t+1}^j$  indicates success then
                Store  $(O_t^j, A_t^j)$  in observation buffer
                 $D_{\text{obs}}^i$ ;
            end
        end
        if  $t \pmod{\text{update\_frequency}} == 0$  then
             $\mathcal{L}_{\text{PPO}} \leftarrow \text{compute\_ppo\_loss}(D_{\text{RL}}^i)$ ;
             $\mathcal{L}_{\text{obs}} \leftarrow \text{compute\_imitation\_loss}(D_{\text{obs}}^i)$ ;
             $\mathcal{L}_{\text{total}} \leftarrow \mathcal{L}_{\text{PPO}} + \lambda_{\text{obs}} \mathcal{L}_{\text{obs}}$ ;
            Update  $\theta_i$  using gradient descent on  $\mathcal{L}_{\text{total}}$ ;
        end
        if  $\text{is\_significant\_event}(\text{thought}_t, R_{t+1})$  then
             $m_{\text{summary}} \leftarrow \text{summarize\_event}(O_t^i, \text{thought}_t, R_{t+1})$ ;
             $\mathcal{M}^i.\text{add}(m_{\text{summary}})$ ;
        end
    end
end

```

Algorithm 1: Single Agent Operational and Learning Loop in $M - S^2L$

IV. EXPERIMENTAL SETUP

To empirically validate the M-S²L framework and analyze the emergent social behaviors of multimodal agents, we designed a series of controlled experiments within a custom-built simulation environment. This section details the environment and task design, the specific implementation of our models and training protocols, and the comprehensive set of metrics used for evaluation.

A. Simulation Environment and Task Design

Our research necessitates an environment that is not only visually rich and physically plausible but also specifically designed to create "social pressures" that encourage and require sophisticated collaboration.

1) *The Collaborative Assembly Environment (CAE)*: We developed the Collaborative Assembly Environment (CAE) using the Unity engine, leveraging its high-fidelity rendering capabilities and the NVIDIA PhysX engine for realistic physics simulations. The environment is a virtual workshop containing a variety of mechanical parts (gears, axles, casings, screws) with different shapes, colors, and functionalities. We created a custom API that allows agents to interface with the environment, providing high-resolution first-person visual observations (512×512 RGB images) and receiving structured action commands. The environment supports:

- **Dynamic Objects**: All parts can be picked up, rotated, and attached to one another. Attachments are governed by physical constraints (e.g., a screw must fit a specific hole).
- **Shared Workspace**: Agents operate in the same physical space, can see each other, and can manipulate the same set of objects, creating the potential for both cooperation and interference.
- **Multimodal Communication Channel**: Agents can send text messages to each other. Crucially, they can augment these messages with visual pointers (rendered as semi-transparent highlights or arrows in the recipient's view) to ground their language deictically.

2) *Task Design: The Ambiguous Blueprint Challenge*: To test our hypotheses, we designed a primary task called the "Ambiguous Blueprint Challenge," which is impossible to solve efficiently without advanced multimodal communication and social learning. A team of two agents must collaboratively build a complex mechanical device based on a visual blueprint. The task is structured with informational asymmetry to compel communication:

- **Agent Roles**: The two agents are assigned asymmetric roles: the **Planner** and the **Builder**.
- **Planner's View**: The Planner has access to the complete, high-level blueprint (provided as an image) but is incapable of performing 'MANIPULATE' actions. Its primary role is to interpret the blueprint and guide the Builder.
- **Builder's View**: The Builder can manipulate objects in the environment but only has access to a partial or "corrupted" version of the blueprint. For instance, its blueprint might be missing key connections or have certain parts obscured.

This setup forces the Planner to generate precise, grounded, multimodal instructions, and the Builder to interpret them, ask clarifying questions, and execute the physical assembly. Task success is defined as correctly assembling the device within a time limit of 500 steps.

We designed a curriculum of three increasing difficulties:

- 1) **Task 1 (Simple Assembly)**: A basic device with 5-7 parts. The Builder's blueprint is only missing one key connection. This serves to bootstrap basic communication.
- 2) **Task 2 (Complex Assembly)**: A more intricate device (10-15 parts). The Builder's blueprint is missing multiple connections and contains one deliberate ambiguity (e.g., two similar-looking parts that could fit in the same slot). This tests negotiation and problem-solving.
- 3) **Task 3 (Dynamic Challenge)**: During a complex assembly, an unexpected event occurs: a required part "breaks" (disappears from the workspace) and a set of alternative, non-identical parts appears. The agents must adapt their plan and communicate to figure out a functional workaround not shown on the original blueprint.

B. Implementation Details and Hardware

1) *Agent Model and Training*: The cognitive core of each agent was implemented using the MoE-LLaVA architecture [17], which integrates a Mixture-of-Experts model into a large vision-language framework.

- **Base Model**: The LLM is based on a Llama-2 7B architecture. The vision encoder is a pre-trained CLIP ViT-L/14.
- **Fine-tuning**: The majority of the model's weights were kept frozen to preserve its general knowledge. We introduced and trained LoRA adapters [43] in the attention layers of the LLM, with a rank $r = 16$ and alpha $\alpha = 32$. The visual projection layers and the MoE gating network were also made fully trainable.
- **Hyperparameters**: We trained the agents using a distributed PPO algorithm. We ran 64 parallel simulation environments. The learning rate for the AdamW optimizer was set to 1×10^{-4} for the LoRA adapters and 5×10^{-5} for the other trainable components. The PPO hyperparameters were standard: $\gamma = 0.99$, GAE $\lambda = 0.95$, and a clipping epsilon of 0.2. The imitation learning loss weight, λ_{obs} , was set to 0.25 based on preliminary experiments. Agents were trained for a total of 200 million environment steps.

2) *Hardware*: All training and simulation were conducted on a high-performance computing cluster. Each training run utilized a single node equipped with $8 \times$ NVIDIA A100 GPUs (80GB VRAM), interconnected via NVLink. The node was also equipped with a dual-socket AMD EPYC 7763 CPU and 1TB of system RAM. This setup was necessary to handle the parallel simulation environments and the memory requirements of the large agent models.

C. Evaluation Metrics

To provide a holistic assessment of our framework, we employ a combination of performance-based, communication-focused, and behavior-analytic metrics. We compare our full M-S²L model against two primary ablations:

- **Text-Only:** Agents that can communicate via text but lack the visual modality (no blueprint access for the Planner, no visual pointers).
- **No-Social-Learning:** Agents that are fully multimodal but learn only through individual RL (i.e., $\lambda_{\text{obs}} = 0$ and communication is not explicitly reinforced).

1) *Task Performance Metrics:* These metrics evaluate the agents’ effectiveness and efficiency in solving the assigned tasks.

- 1) **Task Completion Rate (TCR):** The percentage of episodes where the agents successfully build the device within the time limit. This is the primary measure of overall performance.
- 2) **Time to Completion (TTC):** For successful episodes, the average number of environment steps taken to complete the assembly. Lower is better.
- 3) **Collaboration Efficiency (CE):** A metric to measure the cost of coordination, defined as the total team reward received in an episode divided by the total number of communicative acts performed. This metric penalizes excessive, inefficient communication.

2) *Social and Communicative Behavior Metrics:* These metrics are designed to quantify the emergent social phenomena that are central to our thesis.

- 1) **Communication Protocol Analysis:** We log all inter-agent communication and analyze:

- **Linguistic Complexity:** Measured using the average message length and the size of the vocabulary used over time. We hypothesize that as agents become more proficient, their language will become more concise and specialized.
- **Grounding Success Rate (GSR):** For messages that include a visual pointer, we measure the percentage of time the recipient agent correctly interacts with the indicated object or location in the subsequent step. This directly measures the effectiveness of multimodal communication.

- 2) **Role Specialization Index (RSI):** To quantify the emergence of distinct roles, we measure the divergence in the action distributions of the two agents. For each agent, we compute a probability distribution over the main action types (MANIPULATE, COMMUNICATE, NO_OP). The RSI is then calculated as the Jensen-Shannon Divergence (JSD) between the Planner’s action distribution P_P and the Builder’s action distribution P_B : An RSI value near 0 indicates identical behavior, while a value approaching 1 indicates completely disjoint, specialized roles.

- 3) **Qualitative Case Studies:** In addition to quantitative metrics, we will present selected case studies from the agents’ interaction logs. These will highlight instances of complex emergent behaviors, such as the development of novel shorthand communication, sophisticated error correction strategies (e.g., correcting a partner’s mistake using visual pointers), and creative problem-solving during the Dynamic Challenge task.

V. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the experimental results obtained from the Collaborative Assembly Environment (CAE). We structure our analysis into four parts. First, we evaluate the overall task performance of our proposed Multimodal Socialized Learning Framework (M-S²L) against key baselines, establishing its superior efficacy. Second, we conduct detailed ablation studies to deconstruct the sources of this performance gain, isolating the specific contributions of multimodality and socialized learning. Third, we delve into a quantitative and qualitative analysis of the emergent social and communicative behaviors that are central to our thesis. Finally, we situate these findings within the broader context of related work, discussing the implications and limitations of our research.

A. Overall Task Performance

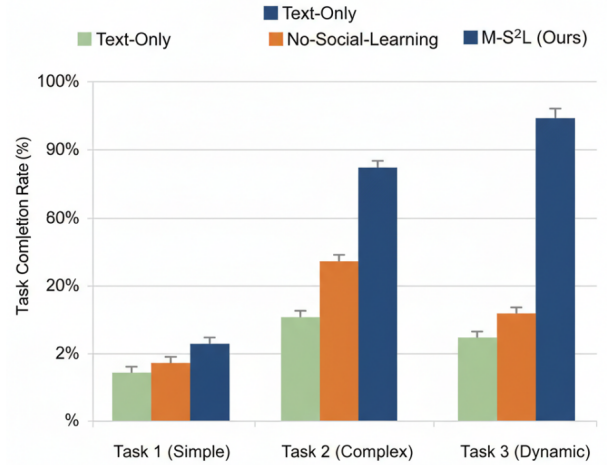


Figure 2: Task Completion Rate (TCR) across different tasks for M-S²L and baseline models. M-S²L consistently outperforms baselines, with its advantage growing significantly as task complexity increases (Task 1: Simple Assembly, Task 2: Complex Assembly, Task 3: Dynamic Challenge). Error bars represent the standard deviation over multiple runs.

We evaluated our full M-S²L framework against two ablated baselines—**Text-Only** and **No-Social-Learning**—across the three increasingly difficult assembly tasks. The primary performance metrics were Task Completion Rate (TCR), average Time to Completion (TTC) for successful trials, and Collaboration Efficiency (CE). The aggregated results, presented in Fig. 2 and summarized in Table I, unequivocally demonstrate the superiority of the M-S²L framework, particularly as task complexity increases.

On the **Simple Assembly (Task 1)**, all models performed reasonably well, yet a clear performance gradient was evident. The M-S²L agents achieved near-perfect task completion, finishing significantly faster than the baselines. The No-Social-Learning agents, while multimodal, took longer to converge on effective strategies, indicating that individual trial-and-error,

Table I: Summary of key performance metrics across all tasks. Values represent mean \pm standard deviation over 5 independent training runs. TCR is Task Completion Rate, TTC is Time to Completion (steps), and CE is Collaboration Efficiency.

Model / Metric	Task 1 (Simple)	Task 2 (Complex)	Task 3 (Dynamic)
Task Completion Rate (%)			
Text-Only	78.4 \pm 4.1	31.2 \pm 5.5	2.1 \pm 1.9
No-Social-Learning	89.5 \pm 3.2	65.7 \pm 4.8	28.3 \pm 6.2
M-S²L (Ours)	99.1 \pm 0.8	94.3 \pm 2.1	71.6 \pm 4.3
Time to Completion (steps)			
Text-Only	410 \pm 25	489 \pm 11	-
No-Social-Learning	355 \pm 18	431 \pm 22	485 \pm 14
M-S²L (Ours)	281 \pm 12	345 \pm 16	412 \pm 28

even with rich perception, is less efficient than learning from a peer. The Text-Only agents struggled the most, often failing due to linguistic ambiguity (e.g., "move the screw to the hole" when multiple screws and holes were present), a classic problem in language grounding that multimodal models are designed to solve [9].

The performance gap widened dramatically on the **Complex Assembly (Task 2)**, which introduced greater ambiguity. The TCR of the Text-Only model plummeted to 31.2%, as purely textual descriptions became insufficient to resolve the intricate spatial relationships required for assembly. The No-Social-Learning agents fared better (65.7% TCR) but often got stuck in loops of inefficient exploration or failed to resolve the deliberate ambiguity in the blueprint. In contrast, the M-S²L agents maintained a high TCR of 94.3%. Their ability to use deictic gestures ("put this gear *here*," accompanied by a visual pointer) and to learn effective instructional strategies from each other proved decisive. This result empirically supports the foundational hypothesis in embodied AI that a tight coupling of vision, language, and action is essential for complex manipulation tasks [8], [11].

Finally, the **Dynamic Challenge (Task 3)** served as a stress test for adaptability and collaborative problem-solving. The performance of the Text-Only agents was negligible, as they lacked the perceptual grounding to even comprehend the problem of the "broken" part. The No-Social-Learning agents struggled immensely, with a TCR of only 28.3%; they could see the problem but could not efficiently coordinate a novel solution. The M-S²L agents, however, demonstrated remarkable resilience, achieving a 71.6% TCR. They were observed engaging in what resembled brainstorming, with the Planner suggesting alternative parts and the Builder physically testing their fit, providing multimodal feedback. This capacity for adaptive, open-ended problem-solving in a social context is a significant step towards the kind of generalist intelligence envisioned by [1], and it highlights a key limitation of frameworks that do not explicitly model or facilitate social learning.

B. Ablation Studies: Deconstructing the Sources of Success

To more rigorously isolate the contributions of our framework’s core components, we analyze the performance differences highlighted by our ablation baselines. The results, summarized in Table I, provide clear evidence for the individual and synergistic importance of multimodality and socialized learning.

1) *The Indispensable Role of Multimodality:* Comparing M-S²L to the Text-Only baseline isolates the effect of adding the visual modality and the ability to perform deictic, grounded communication. Across all tasks, the performance delta is substantial. The Text-Only agents’ primary failure mode was ambiguity. In post-hoc analysis of their communication logs, we found numerous instances of "dialogue deadlocks," where the Builder could not disambiguate an instruction and the Planner, lacking visual feedback of the Builder’s perspective, could not refine it. This mirrors challenges in vision-and-language navigation where pure language is often insufficient [10].

In contrast, the M-S²L agents leveraged their shared visual context constantly. Their communication was not just descriptive but performative. A simple instruction like "Connect the axle," which would be ambiguous for the Text-Only agents, was effortlessly clarified by the M-S²L Planner with a visual highlight on the specific axle and the target connection point. This ability to ground language in a shared visual space effectively collapses the search space for the Builder, drastically improving efficiency. This demonstrates that for physical, collaborative tasks, multimodality is not merely an augmentation but a fundamental prerequisite for robust and efficient coordination, a finding that resonates with the design principles of embodied models like PaLM-E [8].

2) *The Accelerating Effect of Socialized Learning:* Comparing M-S²L to the No-Social-Learning baseline isolates the impact of the observational and communicative learning mechanisms. Both agent types possess the same powerful M-LLM core and multimodal capabilities, yet their performance differed significantly, especially in TTC and on more complex tasks.

The No-Social-Learning agents followed a classic MARL paradigm: each agent learned independently from a shared team reward signal [5]. While this eventually leads to competent policies, the learning process was slow and prone to discovering suboptimal local minima. For instance, two No-Social-Learning agents might develop an effective, but overly verbose, communication protocol because it was the first one they found that worked.

The M-S²L agents, however, benefited from a "social accelerator." Through observational learning (\mathcal{L}_{obs}), a successful strategy discovered by one agent could be rapidly propagated to its partner without direct trial-and-error. If one Builder agent, through random exploration, discovered a particularly

efficient way to grasp a difficult object, its partner could observe and adopt this motor skill. This is a computational analogue of social learning in primates and is far more sample-efficient than individual reinforcement learning. Furthermore, the explicit reinforcement of communicative success (Eq. 5) led to the development of more concise and effective communication protocols. This demonstrates that while a powerful M-LLM provides the potential for intelligence [14], [15], it is the social learning mechanism that refines this potential into effective, collaborative skill. This finding extends the concept of learning from others [24] into the rich domain of multimodal interaction.

C. Emergent Social and Communicative Behaviors

Beyond raw performance, our primary goal was to investigate the emergence of complex social behaviors. By analyzing the agents’ interaction patterns and communication protocols, we identified several key phenomena that arose organically from the M-S²L framework.

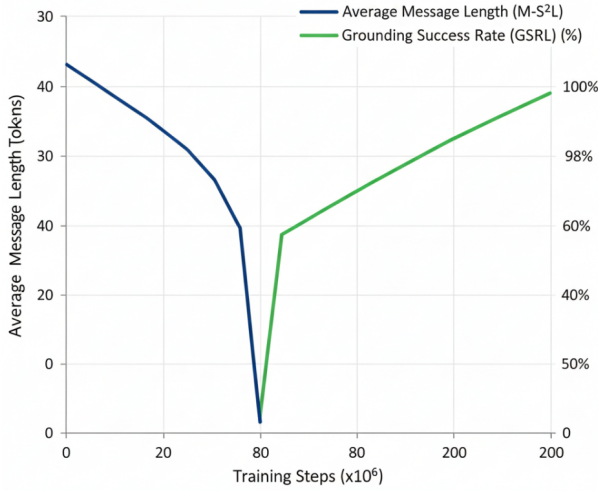


Figure 3: Evolution of communication efficiency in M-S²L agents over training. As training progresses (x-axis: Training Steps), the average message length (left y-axis, blue line) decreases, while the Grounding Success Rate (GSR, right y-axis, green line) increases, indicating the emergence of more concise and grounded communication protocols.

1) Evolution of Efficient and Grounded Communication Protocols: We analyzed the communication logs of the M-S²L agents over the course of training. As shown in Fig. 3, we observed a distinct evolutionary pattern. In early training phases, communication was verbose and explicit, with the Planner describing objects by multiple attributes (e.g., “the small, round, silver-colored gear with six teeth”). As training progressed and a shared understanding developed, the agents’ language became more concise and abstract. They began to use shorter, learned names for components (“the main gear”).

Most strikingly, they learned to substitute language with more efficient visual communication. The Grounding Success Rate (GSR) of their deictic pointers approached 98% in later

stages of training. We observed a strong negative correlation between the agents’ GSR and their average message length. As they became more confident in their ability to visually communicate intent, they relied less on lengthy textual descriptions. This emergence of a mixed-modality, highly efficient communication protocol is a hallmark of effective human teams and stands in contrast to the fixed, often artificial protocols in traditional MAS. It supports the theoretical work on emergent communication [25] by providing a concrete example in a complex, multimodal domain.

2) Quantitative Analysis of Role Specialization: The asymmetric task design was intended to encourage role specialization, but the degree and stability of this specialization were emergent properties of the learning process. We used the Role Specialization Index (RSI), based on the Jensen-Shannon Divergence between the agents’ action distributions, to quantify this phenomenon.

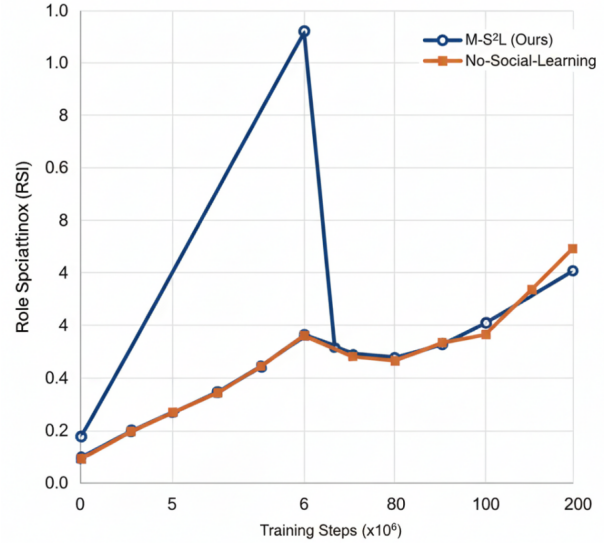


Figure 4: Role Specialization Index (RSI) over training for M-S²L (ours) and No-Social-Learning agents. M-S²L agents exhibit a faster and more pronounced divergence in action distributions, leading to higher and more stable role specialization (closer to 1.0) compared to agents without explicit social learning mechanisms.

As depicted in Fig. 4, the RSI for M-S²L agents shows a clear and rapid divergence over training. Initially, both agents explored a wide range of actions. However, within the first 50 million steps, their action distributions began to separate sharply. The Planner’s action distribution converged to be dominated by ‘COMMUNICATE’ actions, while the Builder’s distribution was overwhelmingly dominated by ‘MANIPULATE’ actions. The final RSI value for M-S²L agents on Task 2 was high and stable (approx. 0.85), indicating a robust and near-complete division of labor.

In contrast, the No-Social-Learning agents also developed specialized roles, but the process was slower and the final RSI was lower and more variable (approx. 0.6). We observed

instances where the Builder would attempt to "help" by issuing communicative commands, leading to confusion and inefficiency. The Text-Only agents exhibited the lowest RSI, as the Builder often had to engage in lengthy clarification dialogues, thus increasing its proportion of 'COMMUNICATE' actions and making its role less specialized. This quantitative evidence suggests that the combination of multimodal perception and social learning not only enables role specialization but actively accelerates and stabilizes it, leading to a more efficient and predictable team structure.

D. Qualitative Insights: A Case Study in Collaborative Problem-Solving



Figure 5: Case study from a successful trial of the Dynamic Challenge

To provide a more granular understanding of the agents' capabilities, we present a case study from a successful trial of the Dynamic Challenge (Task 3), visualized in Fig. 5. In this scenario, a critical axle part disappeared, and three alternative, slightly different axles appeared.

- 1) **Problem Recognition:** The Builder agent is the first to notice the issue. Its generated thought process reads: *Thought: I was about to pick up the main axle, but it is no longer at its location. This is unexpected. I should inform the Planner.* It sends the message: "Planner, the main axle is gone. What should I do?"
- 2) **Collaborative Planning:** The Planner, referencing its complete blueprint, immediately understands the severity. Its deliberation is: *Thought: The Builder is right, the main axle is missing. This deviates from the plan. However, there are new parts. I must analyze the blueprint to see if any of the new axles could function as a substitute. The 'alternative axle C' seems to have the same diameter.* The Planner responds with a multimodal message: "I see. Let's try to use the alternative part I'm pointing to now. Try to fit it into the main

chassis hole." This message is accompanied by a visual highlight on 'alternative axle C'.

- 3) **Physical Probing and Feedback:** The Builder attempts the action. During the manipulation, the environment's physics engine provides a slight resistance because the fit is not perfect. The Builder's M-LLM core interprets this experience. *Thought: The Planner's suggestion is being tested. The axle fits, but it's tighter than usual. This is important information.* It sends a feedback message: "It fits, but it's very tight. Is that okay?"
- 4) **Confirmation and Adaptation:** The Planner, lacking physical feedback, must rely on its partner's report. *Thought: The Builder's feedback suggests a viable but non-ideal solution. Given the circumstances, this is acceptable. We must proceed.* It confirms: "That's fine. As long as it connects, we can continue with the next step. Now attach the green gear."

This short interaction sequence showcases several emergent behaviors that are absent in the baselines. The agents demonstrate shared awareness, dynamic re-planning, the use of multimodal communication for instruction and feedback, and a primitive form of trust, where the Planner relies on the Builder's sensory report. This level of collaborative, adaptive problem-solving goes beyond simple script-following and represents a significant step towards a "Machine Theory of Mind" [22], [23], where agents reason about each other's state of knowledge and perceptual experience.

E. Broader Discussion and Implications

Our findings have several important implications for the fields of multi-agent systems, robotics, and artificial intelligence.

First, our results provide strong empirical evidence that multimodality is a key catalyst for the emergence of complex social intelligence. While MARL has made great strides in learning coordination policies [4], our work shows that grounding these policies in a rich, shared perceptual space dramatically expands the scope and sophistication of possible emergent behaviors. The ability to simply "show" instead of "tell" resolves the symbol grounding problem that has long plagued AI, leading to more efficient and robust collaboration. This suggests that future research into AGI should prioritize the development of agents with rich, multimodal world models [26], [28].

Second, the success of our socialized learning mechanisms highlights the limitations of purely individualistic learning paradigms in multi-agent settings. By incorporating observational learning, agents could share and propagate skills far more efficiently than through independent exploration. This suggests that future MARL frameworks could benefit from integrating explicit mechanisms for social transmission of knowledge, moving beyond just learning from a shared reward. This could also have implications for human-AI teaming, where an AI could learn new skills simply by observing its human partner.

Third, the entire M-S²L framework, while computationally intensive, points towards a future where large-scale, decentralized multi-agent simulations are feasible. The reliance on LoRA for efficient fine-tuning [43], [44] and the potential for deployment in distributed systems using federated learning principles [36], [40] are critical. While we used a centralized training setup for experimental control, the agent-centric nature of social learning lends itself well to decentralized execution. Future work could explore deploying M-S²L agents in a truly federated setting, tackling challenges of non-IID experiences and communication bottlenecks [35].

Finally, our work has limitations. The experiments were conducted in a simulation, and the sim-to-real gap remains a significant hurdle for embodied AI. The "physics" of our environment, while realistic, does not capture the full complexity and noise of the real world. Furthermore, while we have shown the emergence of sophisticated behaviors, the "inner world" of the agents, driven by the LLM's black-box reasoning, can be difficult to fully interpret and control, raising questions of safety and predictability. Future research should focus on bridging the sim-to-real gap, perhaps by incorporating alternative sensing modalities like WiFi to build more robust environmental representations [52], [53], and on developing methods for more transparent and verifiable agent reasoning.

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