

Socially Aware Multi-Character Simulation

A Framework for Emergent Narrative Intelligence¹

Bruce D'Ambrosio²

1. Abstract

We present a multi-character simulation framework that produces emergent narrative by using Large Language Models (LLMs) as the subsymbolic engines of cognition. Prompt-mediated information flows link perception, memory, drives, theory-of-mind, goal selection, and task planning, allowing each character to turn raw observations into coherent goals, plans, and acts without hand-authored scripts. Case studies show the hybrid symbolic/subsymbolic system generating internally consistent, character-driven stories in both sandbox and lightly guided runs. The framework doubles as a test-bed for cognitive-architecture research and as a practical platform for entertainment, education, and training scenarios demanding believable social dynamics.

2. Introduction

Simulating human-like social intelligence and emergent narrative understanding remain significant challenge in artificial intelligence research. Traditional approaches often rely on heavily scripted interactions or rule-based systems that struggle to capture the nuance, complexity, and spontaneity of human social behavior [Schank & Abelson, 1977]³. While recent advancements show promise [Dias et al, 2014; Park, 2023; Guo et al, 2025], achieving believable characters who engage in complex social reasoning and generate coherent, emergent narratives requires new architectural approaches.

Our research addresses this challenge by introducing a new multi-character⁴ simulation framework centered around use of Large Language Models (LLMs) as primary sub-symbolic functional elements embedded within a larger information-flow architecture. Instead of building distinct procedural computational modules for complex cognitive processes (e.g. memory, planning, reasoning, negotiation, etc), our approach leverages cognitive-science understanding to structure a set of sub-symbolic integrative computations and the information flows among them, resulting in a more fluid and believable dynamic. Our central hypothesis, then, is that cognitive architecture can best be modeled as this structuring of information flows among sub-symbolic, generative computational components. As a temporary practical matter we use ‘natural language’ as the form of these information flows, since it is the current lingua-franca of LLM I/O.

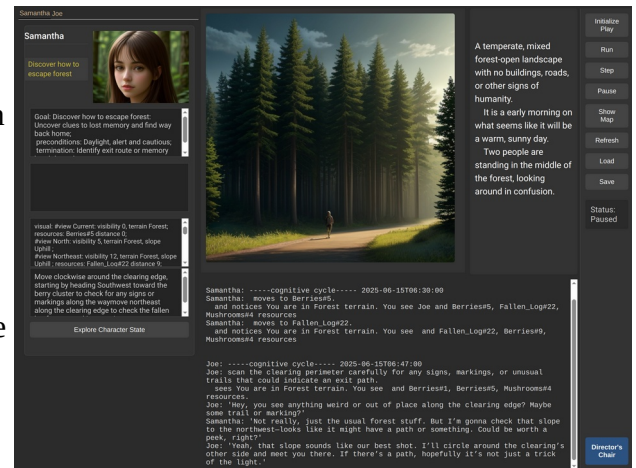


Figure 1: Figure 1 - UI - Lost scenario

- 1 <https://github.com/bdambrosio/AllTheWorldAPlay.git>
- 2 Tuuyi.com - Also Oregon State University, retired. bruce.dambrosio@gmail.com
- 3 This paper is intended as a technical report. I've attempted to provide a few key references newcomers can ‘follow forward’.
- 4 ‘Agent’ is so overloaded these days it has no meaning. I will use ‘character’ wherever possible instead, despite its extra syllables..

The key architectural elements of our framework include:

1. An *perceptual filter* that interprets raw observations based on the character's *drives, goals, surroundings*, and attention, creating situated *percepts* and *signals*.
2. A *dynamic social modeling system* where characters maintain unstructured textual Theory of Mind (ToM) models of self and other characters' traits, inferred states, and goals.
3. A *memory system* combining retrieved concrete experiences with abstractions based on semantic and temporal proximity.
4. A *cognitive_cycle* that includes *goal, task_plan*, and *act* generation and execution.

By orchestrating the interaction between these structured representations and the generative capabilities, our framework enables characters to exhibit complex, context-aware social behavior. They maintain distinct personalities, pursue goals, and adapt their understanding of others and themselves through interaction. Consequently, the system can generate *emergent narratives* that arise organically from the interplay between these characters, moving beyond predetermined scripts towards more dynamic and believable social simulations.

This paper outlines our framework's architecture (Section 3) and specific implementation (Section 4). We then present case studies demonstrating its capabilities in generating both guided and free-running narratives (Section 5), followed by a discussion of evaluation approaches (Section 6) and potential applications (Section 7). We conclude by outlining current limitations and directions for future work (Section 8).

3. Related Work

Our framework integrates concepts from artificial intelligence (AI), cognitive science, narrative theory, and multi-agent systems (MAS) to simulate socially-aware characters capable of emergent narrative. It follows the lineage of research into believable characters, including early work emphasized the role of emotion [Bates, 1994] and later architectures for interactive drama [Mateas, 1999; Mateas & Stern, 2005; Riedl et al, 2013]. We are inspired by the holistic goals of comprehensive cognitive architectures like Soar [Laird, 2012] and ACT-R [Anderson, 2007] that integrate perception, memory, and decision-making. However, our implementation adopts a fundamentally different, sub-symbolic centric approach to core cognitive functions. This is inspired by our hypothesis that integrative sub-symbolic processes underlay most of our cognitive function.

The core components of our characters are realized primarily through interactions with an LLM, prompted with curated contextual information:

- **Perception:** Characters perceive their environment primarily through simulated sensory events, notably the actions and dialogue of other characters within their vicinity. Unlike traditional systems that might directly translate observed events into symbolic representations, our framework utilizes an LLM-based perceptual filter. Raw observations (e.g., "Elijah says X," "Chrys moves Y") are processed by the LLM, conditioned by the perceiving character's current goals, emotional stance, and focus of attention. This filtering step generates a set of salient 'percepts' – interpretations of the raw events deemed relevant to the character's immediate context and objectives. This mechanism draws

inspiration from cognitive science concepts of selective attention [e.g., Broadbent, 1958; Treisman, 1964] and top-down perceptual processing, where internal state biases how environmental information is interpreted [e.g., Gregory, 1970; Gilbert & Li, 2013]. The generated percepts serve as the input for subsequent cognitive processes, including Theory of Mind updates and memory encoding, ensuring that characters react to a world interpreted through their own situated perspective [Brooks, 1991; Traum, 1994]

- **Memory:** Our system stores concrete experiences, drawing inspiration from psychological distinctions between episodic and semantic memory [Tulving, 1972; Conway, 2009]. Memory abstraction is achieved by computationally grouping concrete memories based on proximity in semantic embedding space and time, forming clusters of related experiences. This differs from symbolic abstraction mechanisms in traditional cognitive architectures and also from the explicit reflection-based summarization used in some recent LLM character systems [e.g., Park et al., 2023]. Relevant memory items (both concrete and potentially references to abstract clusters) are selected and included in future LLM prompts to ground reasoning and behavior.
- **Emotion, Drives, and Motivation:** While we are aware of appraisal-based computational emotion models like FAtiMA [Dias et al., 2014; Ortony, Clore, & Collins, 1988], our framework represents the character's internal state using explicit drives (with activation levels based on alerts from Perception) and an "Emotional Stance" characterized by descriptive tags across three dimensions (e.g., 'Anticipatory', 'Curious', 'Connecting'). These elements do not drive behavior through complex internal calculations but rather serve as key inputs within future prompts to condition the model's output, influencing the tone, style, and choice of generated actions and dialogue.
- **Social Modeling and Theory of Mind (ToM):** Simulating social awareness is achieved via a distinct LLM-mediated multi-step process. Raw observations of others are first processed to identify relevant 'percepts'. These percepts then inform another component that updates an unstructured textual model maintained for each known character, capturing inferred states, goals, and traits. This contrasts sharply with symbolic or decision-theoretic ToM approaches like PsychSim [Pynadath & Marsella, 2005]. The resulting textual models of others form part of the context provided to the sub-symbolic elements for subsequent goal, task, and action generation, deeply embedding social reasoning within the core behavioral loop. Simple chatbots can evidence TOM [Kosinski, 2023], but we believe longer-term and deeper TOM-based response requires more.
- **Dialogue, Planning, and Action Selection:** Foundational concepts in dialogue management [e.g., Traum, 1994; Allen & Perrault, 1980] are implicitly handled by separate subtasks for internal monologue and external dialogue. As demonstrated by the transcript in the appendix, the generation of goals, tasks, and specific actions (including dialogue 'Say' acts) is delegated to the LLM, which receives a comprehensive snapshot of the character's internal state (character profile, drives, goals, tasks), situation, relationships (textual ToM models), recent history, and emotional stance.

In terms of narrative generation [Aylett, 1999], our goal is for stories that arise from character interactions rather than explicitly predefined scripts [Schank & Abelson, 1977]. However, the emergence in our system is premised on the belief the core sub-symbolic elements will contain and apply a wide variety of stereotypical interactions, adapting them in situationally appropriate ways.

3.1. Generative agents in socially demanding environments⁵

This reliance on LLMs for core cognitive and behavioral functions positions our work squarely within the recent paradigm of *LLM-powered generative agents* [Park et al., 2023; Wang et al., 2023; Guo, 2025]. Recent advances in large language models have given rise to a new class of **generative agents** that drive social simulations and emergent narratives. Park et al. (2023) introduced *Smallville*, a small town of 25 AI characters that wake up, plan their day, remember past interactions, and engage in open-ended social behaviors. Their architecture extends an LLM with long-term memory (a complete natural language log of experiences) and periodic *reflection* to synthesize those memories into higher-level recollections used to plan behavior. With this setup, believable **emergent social behaviors** occur: for instance, starting from a single user prompt that one agent wants to host a Valentine’s Day party, the agents autonomously spread invitations, form new acquaintances, ask each other on dates, and coordinate to attend the party together. An ablation study confirmed that each architectural component – observation, planning, and reflection – contributed to the **believability** of the agents’ behavior. Park et al.’s agents, however, did not maintain explicit models of others’ mental states (Theory of Mind), relying instead on the LLM’s general capacity to produce plausible interactions. In contrast, we place heavier emphasis on structured internal state (drives, goals, and textual Theory-of-Mind models of others) to guide social reasoning, which addresses some limitations observed in generative agents (e.g. gossip was limited to single facts or simple judgments in their dialogues).

Several contemporaneous projects build on the idea of LLM-driven multi-agent worlds, exploring different scales and architectural trade-offs. **Lyfe Agents** [Zhao et al., 2023] focus on enabling real-time, cost-efficient multi-agent interaction in a 3D virtual environment. To achieve this, they introduce an *option-action* decision framework that reduces expensive LLM calls for low-level actions, asynchronous self-monitoring to maintain consistency, and a “summarize-and-forget” mechanism that condenses memory on the fly. Despite using far fewer computational resources, a handful of Lyfe Agents exhibit **human-like autonomy** and social reasoning; for example, agents in their demo collaboratively solve a murder mystery by sharing information and coordinating investigation strategies. Impressively, these agents operated **10–100×** more efficiently in computation cost than prior LLM-based agents. Our framework shares Lyfe Agents’ aim of sustained, **self-motivated behavior**, but we prioritize detailed cognitive modeling (e.g. detailed memory and ToM) over real-time performance. On the other end of the spectrum, Piao et al. [Piao et al, 2025] scale up LLM-driven agents to *thousands* of characters with **AgentSociety**, a large-scale societal simulator. AgentSociety populates a realistic virtual society with over 10,000 agents and simulates **5 million** interactions, using LLMs to generate the agents’ dialogues and actions within a rich environment. This platform was used to study emergent social dynamics like polarization, the spread of rumors, the effects of universal basic income, and responses to crises. Remarkably, the macro-level outcomes are claimed to align well with known real-world trends and social science theories, demonstrating that even coarse-grained LLM agents can produce credible societal patterns at scale. Compared to our framework, which aims for **high-fidelity individual interactions** in a smaller group, AgentSociety sacrifices some individual complexity for scale, using the aggregate behavior of simple LLM agents to reproduce societal-level phenomena.

Another line of recent work incorporates **explicit planning, memory, and theory-of-mind mechanisms**, resulting in *hybrid architectures* that marry sub-symbolic LLM abilities with traditional AI modules. A prominent example is Meta’s *Cicero* agent [Meta AI (Bakhtin et al.), 2022], which achieved human-level

5 We revert to using ‘agents’ in this section to conform with most of the literature cited.

performance in the Diplomacy board game by combining an LLM-based dialogue module with a strategic planning engine. Cicero continually inferred other players’ beliefs and goals from conversation and mapped its plans into persuasive natural-language messages. This allowed it to negotiate alliances and coordinate actions with human players via free-form dialogue in a challenging multi-agent setting requiring both cooperation and deception. Cicero’s success underscores the value of explicit models of others and goal-directed planning alongside language generation. Our framework shares this philosophy: we maintain *textual models of other agents’ minds* and perform multi-step planning for goals, but in an open narrative context rather than a fixed game. Similarly, the recent CoALA architecture [Sumers et al., 2023] provides a general template for cognitive **language agents** with modular memory stores and structured decision processes inspired by cognitive science. This reflects a broader trend of integrating LLMs into cognitive architectures to achieve more **structured, interpretable control** over agent behavior. Our approach can be seen as a specific instance of this trend, where detailed memory (episodic and semantic clusters), drives, and ToM updates are used to ground an LLM’s responses in a persistent agent psyche.

Finally, researchers have started critically evaluating the **scope of emergent behavior and social intelligence** in LLM-driven simulations. Zhou et al. [Zhou., 2024] introduce **SOTOPIA**, an evaluation framework with a suite of diverse multi-agent social scenarios to test how well LLM-based agents achieve social goals. In SOTOPIA, agents (or human participants playing agents) must negotiate, cooperate, and compete in role-play situations (e.g. bargaining, coordinating a group task, bluffing in a game). Results from this framework showed that even state-of-the-art models like GPT-4 struggle on the hardest social scenarios: for example, GPT-4 agents had significantly lower goal completion rates than humans and often failed at commonsense social reasoning or strategic communication. It motivates design features in our framework – such as explicit emotional state and Theory of Mind modeling – intended to push LLM agents closer to human-like social savvy.

Evaluation methodologies across recent works vary widely. Some, like Smallville, rely on qualitative case studies and human judge ratings of believability, while others use quantitative comparison to human performance (SOTOPIA’s success metrics) or to known social patterns (AgentSociety’s alignment with real-world data). Our own evaluation follows a multi-faceted approach: we use **case studies** to illustrate emergent narrative coherence, but also acknowledge the need for more systematic metrics.

In summary, the recent period has seen rapid progress in **LLM-driven agents for social simulation and narrative**. Across the board, these systems share our core vision of using LLMs to power believable agents that can remember, plan, and interact fluidly in open worlds. Key differences lie in architectural choices – how memory is handled (summarized reflections vs. semantic clustering), whether agents model each other’s minds or just themselves, how planning is implemented, and what constraints guide behavior. The scope of emergent behavior also varies: some frameworks aim for grounded *narrative coherence* in small-scale story scenarios (e.g. family drama in a sandbox town), while others seek *societal-level emergence* over thousands of agents. Likewise, levels of autonomy range from fully unscripted agent improvisation to systems that follow an author-specified storyline or role script (e.g. LLM-based storylets in *Drama Llama* combine open-ended generation with pre-authored plot pieces). Our hybrid approach positions our work as part of a new generation of **emergent narrative systems** that leverage LLMs while still retaining principled architectural elements to ensure consistency, theory-of-mind, and goal-directed story progression.

4. System Architecture

Our multi-character simulation framework consists of several interconnected components that together enable complex social behavior and narrative intelligence. The framework provides a simple ‘gridworld’ environment with varying terrain, visibility, and resource items. Unlike many such worlds, however, and in concert with our belief in the need to relax structural constraints on characters, both internally and externally, our environment allows characters to perform unstructured text acts in addition to the more typical ‘Think’, ‘Say’, and ‘Move’.

4.1. Cognitive Cycle

At the heart of each character is a cognitive cycle that integrates perception, memory processing, emotional appraisal, goal management, and action selection. The cycle follows these steps:

1. **Perception:** Observation of the environment, situation, and self through available sensory modalities (primarily visual and auditory, but including reflection over internal dialogs).
2. **Memory Consolidation:** Encoding of perceptions into structured memory and integration with existing knowledge. TOM models are updated based on self-actions and observations of others.
3. **Drive Assessment:** Processing of recent percepts against character drives (basic motivations) to generate *signals* and *signalClusters*, records of specific issues and opportunities.
4. **Goal Management:** Review existing goals and generate new goals as needed in response to *drive activation* and current *signalClusters*, followed by goal selection.
5. **Task Planning:** Decomposition of the selected goal into a specific situated short-term *task_plan*.
6. **Action Selection:** Generation and execution of action to effect a task step.

This cycle normally executes once for each character in each simulation step, although many step results are cached and only re-executed as needed. However, basic perception steps are executed for all relevant characters whenever any character generates sense data (i.e., by speech act, movement, or action in the world).

4.2. Perception

Our perception system transforms raw environmental and internal stimuli into percepts and signals that influence character behavior and cognition. Characters receive information from through various channels, including visual, auditory, and internal.

Visual Environmental (map) observations form the foundation of spatial awareness, with characters perceiving their surroundings in 2½D through a visibility system based on terrain slopes, heights, and distance. This system calculates what terrain, resources, and other characters are visible based on distance, line-of-sight calculations, and terrain occlusion patterns, creating a situated 360 field of view for each character. The perception system also processes observations of physical actions. When characters perform "Do" and "Move" actions, these generate environmental changes that others can observe. From simple movements through the environment to complex object manipulations and environment-altering behaviors

Auditory When characters say things using the ‘Say’ act, the text is sensed as an auditory sense item by all other characters within visible range. If the target chooses to respond, a ‘dialog’ is formed, and the dialog as an entity is also later processed by each of the conversation participants.

Internal Character’s have a ‘Think’ act, comparable to the ‘Say’ act but visible only to themselves. "Think" acts are processed as internal perceptual inputs⁶. Other significant internal events, such as recognition of task or goal completion, are also input to the perception system.

Finally, periodic world updates provide information about environmental shifts such as time-of-day transitions or weather events.

Perceptual Processing Pipeline

Raw inputs undergo transformation through several stages of processing. The first step involves sensory modality classification, where inputs are categorized according to their perceptual channel—visual, auditory, internal, movement, or unclassified. This classification is either specified as part of the input or performed using LLM-based analysis that examines the content and context of the input to determine its sensory character, enabling modality-specific processing and attention mechanisms.

Once classified, inputs pass through a relevance filtering stage that implements selective attention. This process evaluates incoming information against the character's current focus, goals, and tasks, rating its ‘significance’ and filtering out low-significance items. Next the filtered input is processed with the character's current state to generate a "percept"—a meaningful interpretation of the raw input that reflects the character's unique perspective. Visual input from a ‘Look’, in particular, is heavily processed to extract, for example, other characters never seen before.

These personalized percepts then undergo *signal detection* analysis, where they are evaluated to identify potential opportunities or threats related to a character drives. This process involves comparing percept content against drive definitions to identify issues or opportunities (*signals*) related to a drive and assigning urgency and importance values to detected *signals*. When a character observes a resource they need or notices a potentially threatening situation, this analysis generates appropriate signals that can motivate future action.

Generated signals are then grouped using a combination of semantic similarity and temporal proximity. This reduces the number of *signals* requiring attention to a small set of *signalClusters*. The clustering process⁷ assigns combined importance/urgency scores to these clusters, and uses LLM-mediated labeling to support downstream incorporation in prompts and to enable embedding for subsequent semantic retrieval. Example *signalClusters* at the end of Samantha’s first cognitive cycle:



Score: 98.2

Memory loss and unknown forest location with shelter options

Drives: solve the mystery of how they ended up in the forest with no memory. Find a way back home., immediate physiological needs: survival, shelter, water, food, rest.

Related signals:

⁶ Introduced primarily as a dramatic tool, these are quite effective at making concerns and issues explicit.

⁷ Clustering threshold is dynamically adjusted to maintain focus.

- Uncertain Location and Memory Loss: No memory and unknown forest location
 - Unclear Location and Memory Loss: No memory and unknown forest location complicate escape
 - Shelter Resources Available: Fallen logs can provide shelter or tools
 - Shelter and Rest Spots: Fallen logs offer potential shelter and rest
 - Shelter Construction Opportunity: Building lean-to with fallen logs nearby
- Last seen: 6/15/2025, 6:30:00 AM

Score: 85.6

Nearby spring water source provides fresh water access

Drives: immediate physiological needs: survival, shelter, water, food, rest.

Related signals:

- Presence of Water Source: Spring nearby offers water for survival
- Nearby Water Source: Spring#1 nearby offers fresh water
- Nearby Water Source: Spring located 5 units east offers water
- Water Source Nearby: Spring#1 provides fresh water access

Last seen: 6/15/2025, 6:30:00 AM

Additionally, an *emotionalStance* assessment determines the impact of each *signalCluster* on character emotional state, further influencing how the information will affect behavior. Character emotional states vary along three dimensions: Arousal, Tone, and Orientation. This emotional response to perception creates a feedback loop where current emotional state influences future perception, maintaining a coherent emotional thread in character behavior.

Integration with Memory

The perception system is integrated with memory processes. Significant percepts are encoded into concrete memory entries, complete with importance, confidence, and temporal markers as well as embeddings for semantic retrieval. These concrete memories preserve specific details of perceptual experiences for future reference and reasoning. More details in the next section, on Memory.

Through this perception architecture, characters develop an internal representation of their environment, external and internal, filtered through their unique perspective, drives, and goals. By transforming objective inputs into subjective percepts, the system creates the foundation for character-driven behavior that responds appropriately to environmental cues while maintaining consistency with established personality traits and motivations.

4.3. Memory

Our memory system implements a three-level architecture including episodic experience storage, semantic abstraction, and narrative summarization. This design draws inspiration from cognitive science models of human memory while adapting them to the practical needs of narrative characters. At the foundation of the memory system are concrete memories—individual experiential records (percepts) that capture specific character-situated events and observations.

Built upon this is a layer of abstract memories that represent higher-level patterns and concepts. These abstractions emerge through clustering processes that group related concrete memories based on semantic similarity and temporal proximity. When concrete memories frequently co-occur or share significant

thematic elements, they may be consolidated into an abstract representation that captures their essential meaning while discarding redundant details. This is somewhat analogous to the *signalCluster* process described earlier, but these are general purpose abstractions available to all downstream processes.

Finally, *narrativeSummaries* are generated from the memory system to maintain a coherent internal story. The *narrativeSummary* component periodically processes recent memories and abstractions to create concise textual summaries of *recentEvents*, *ongoingActivities*, and important relationship developments. These summaries are intended to provide characters with an integrated understanding of their experiences that informs identity and decision-making.

Forgetting is handled through importance-based retention and abstraction consolidation. Less important concrete memories are more likely to be discarded during memory maintenance operations, while their essential information may still be preserved in abstract form. This prevents memory bloat while maintaining access to significant past learnings.

Integration with Cognition and Memory Retrieval

The memory system offers multiple retrieval pathways that serve different cognitive functions, creating a flexible and context-sensitive access to past experiences:

Recency-Based Retrieval: The most straightforward retrieval mechanism accesses memories based on their temporal recency. This function supports immediate continuity of thought and action by providing the character with a short-term context of their recent experiences. The method retrieves a specified number of recent memories in chronological order, enabling characters to maintain awareness of their immediate history.

Drive-Related Retrieval: Characters can access memories specifically relevant to one or all fundamental drives. This retrieval pathway identifies memories with high semantic similarity to drive definitions, allowing characters to recall experiences that speak to their core motivations. This mechanism is particularly valuable during goal formation, where drive-relevant memories are intended to help shape meaningful objectives.

Semantic Query Retrieval: Retrieval based on semantic similarity to arbitrary text queries allows characters to search their memory based on concepts, entities, or situations described in natural language. Characters use this during planning and decision-making to find experiences relevant to current challenges.

Abstract Pattern Access: These functions allow characters to reason about ongoing activities and recognize broader patterns across experiences. This abstraction-level access supports narrative coherence by helping characters understand their current situation within larger behavioral arcs.

During cognitive operations, these retrieval mechanisms are used in concert to provide contextually appropriate access to past experiences:

For goal formation, drive-related memories are retrieved to identify recurring issues and opportunities. These memories inform the selection and prioritization of goals that address the character's fundamental needs and motivations.

In task planning, semantic query retrieval helps characters find strategies that worked in similar situations previously. By querying their memory with descriptions of the current challenge, characters can locate and adapt past successful approaches.

When interpreting others' actions, characters retrieve memories related to those individuals using both semantic similarity and recency factors. This creates a temporally weighted access that balances recent interactions with established patterns in relationships.

During narrative reflection, abstract pattern access allows characters to develop a coherent understanding of their evolving story. By accessing higher-level abstractions, characters can reflect on their journey and develop a sense of continuity in their experiences.

Through this memory architecture and its varied retrieval pathways, characters maintain a balance between episodic specificity and semantic efficiency. We hope the system provides a foundation for subsequent work in learning from experience, and maintaining a coherent sense of personal history, grounding their behavior in a consistent narrative foundation.

4.4. Drive System and Cognitive Control Flow

Our drive system forms the motivational core of each character, translating fundamental needs and desires into coherent goal-directed behavior. At the foundation of character motivation are drives—fundamental needs and desires that orient behavior. Each drive is represented by a textual description along with an embedding representation that enables semantic matching against perceptual inputs. While play-specific, we typically include basic drives covering physiological needs, safety concerns, social belonging, and self-esteem, inspired by the Maslow [Maslow, 1943] hierarchy of needs. Drives at the moment are largely static, although there is the beginning of reflective update of drives on goal completion.

Cognitive Cycle Flow

The Cognitive Cycle is the central control loop that orchestrates character behavior. It begins with the perception of the environment and culminates in the execution of specific actions:

1. **Memory consolidation** allows the character to integrate new experiences into their understanding. The MemoryConsolidator compacts concrete memories into abstractions and updates narrative summaries and actor TOM and relationship models as needed.
2. **Goal management**, where existing goals are evaluated and potentially new ones are generated. If no current focus goal exists, the character generates and selects a new goal to pursue.
3. **Task planning**, where the character decomposes their goal into concrete tasks that can be executed. If no task_plan is available for the current goal, a new task plan is generated.
4. **Action generation and execution**, where the character generates specific actions to accomplish their current task and carries them out.

This cycle normally executes once for each character in each simulation step, though many results are cached for efficiency. The cycle can be interrupted by urgent percepts (e.g. conversations with others, or task commitments made in a conversation), allowing characters to respond to unexpected developments in their environment.

Goal Generation and Selection

We are interested in characters immersed in their physical and social environment, and believe most behavior in such cases is ‘unplanned’, that is, is not the result of deliberate conscious logic-based ‘planning’. Rather, we are exploring simple multi-level reactive planning in which most steps are performed at the sub-symbolic level. When a character lacks a focus goal, the `generate_goal_alternatives` method creates potential objectives based on the character's situation and drives. This method receives several key inputs:

- The character's current drive signal clusters, ranked by importance and urgency
- A narrative summary of recent events and ongoing activities
- The character's definition (including drives) and traits
- Current surroundings and situational context
- Recent memories
- Models of relationships with other characters

Using these inputs, the LLM generates 2-3 candidate goals, each containing:

- A concise name for the goal
- A detailed description
- Names of other actors involved, if any
- Preconditions necessary before pursuing the goal
- Termination conditions that define goal completion
- Reference to the signalCluster that motivated the goal

For example, Samantha in the *Lost*⁸ play generated these three initial goals in a recent performance:

```
#goal Secure basic survival needs
#description Obtain water, food, and shelter to ensure immediate survival
#otherActorName
#signalCluster_id sc31
#preconditions daylight, access to spring and food sources
#termination Water, food, and shelter secured
##

#goal Uncover memory and location mystery
#description Investigate surroundings and clues to regain memory and find way home
#otherActorName
#signalCluster_id sc33
#preconditions calm state, daylight
#termination Partial memory recovery or clear escape plan formed
##

#goal Establish cautious trust with Joe
#description Build guarded cooperation to improve chances of survival and escape
#otherActorName Joe
#signalCluster_id sc33
#preconditions mutual willingness to communicate
```

8 Samantha and Joe awake in a forest with no memory, even of their own histories or each other.

```
#termination Trust level sufficient for effective teamwork
##
```

Once alternatives are generated, the character selects a focus goal through either autonomous selection (prioritizing goals derived from high-scoring signal clusters) or user choice in interactive scenarios. The selected goal becomes the character's focus, orienting subsequent cognition and behavior. Goals persist until their termination conditions are met or they are superseded by more urgent concerns. The system periodically checks whether current goals have been satisfied (ie, termination conditions are met), potentially triggering goal updates or new goal generation. The termination test is stochastic, ensuring eventual termination.

We have found a simple hack useful for generating believable narrative performances: If no goal is admissible (preconditions are met), subgoals are generated to satisfy preconditions for inadmissible goals. Subgoals have no preconditions, and so are admissible by definition. If at termination the termination criterion of a primary goal is still unmet (i.e., termination via stochastic timeout), a subgoal is generated with the termination condition as its description. This subgoal has no precondition or termination. This design allows one act to attempt to satisfy preconditions and one act to attempt to satisfy termination. In each case, the main goal precondition (termination condition) is removed following subgoal execution.

Task Planning

With a focus goal established, the `cognitive_cycle` creates a sequence of tasks to achieve that goal. This sequence is generated as a single object by a single LLM call. Inputs include:

- The character's focus goal with all its metadata
- Current environmental situation
- Character's capabilities and traits
- Recent history and ongoing activities
- Models of other characters involved in the goal

The task planner generates 3-6 sequential tasks, each specifying:

- A task name and description
- The specific reason this task advances the goal
- A list of actors involved in the task
- Expected start time and duration
- Termination conditions for task completion

These tasks are arranged in a logical sequence, typically moving from preparation to execution to verification. The first task becomes the character's initial focus, pushed onto the `focus_task` stack to be executed. For example, having selected the *Secure basic survival needs* goal, Samantha then generates the following `task_plan`⁹:

```
#task10
#name Construct makeshift shelter
#description Gather fallen logs and build a temporary shelter
```

⁹ Actually somewhat surprising. Usually one or the other will initiate conversation to 'scope out' the other character.

¹⁰ Our unusual *hash-formatted* LLM responses are designed to minimize formatting tokens, unlike JSON or XML. We make dozens of LLM calls per cognitive cycle. Output tokens are expensive both computationally and in elapsed time.

```
#reason Shelter essential for protection and rest
#actors Samantha, Joe
#start_time 06:40 AM
#duration 30 minutes
#termination Shelter structure stable and provides cover
##
```

```
#task
#name Purify spring water
#description Collect water from spring and purify it by boiling
#reason Safe drinking water prevents illness
#actors Samantha, Joe
#start_time 07:10 AM
#duration 15 minutes
#termination Water boiled and ready for drinking
##
```

```
#task
#name Harvest and prepare food
#description Pick apples and gather mushrooms, clean and prepare them
#reason Food needed to maintain energy and health
#actors Samantha, Joe
#start_time 07:25 AM
#duration 20 minutes
#termination Food gathered and ready to eat safely
##
```

```
#task
#name Establish secure camp perimeter
#description Clear area around shelter and set simple deterrents
#reason Safety from wildlife and environmental hazards
#actors Samantha, Joe
#start_time 07:45 AM
#duration 15 minutes
#termination Camp perimeter clear and deterrents in place
##
```

The task system implements a stack-based architecture that allows for task interruption and resumption. When new high-priority tasks arise (such as responding to a conversation), they can be pushed onto the stack, temporarily suspending the original task until the interruption is addressed.

4.5. Action Generation and Execution

At the most concrete level, the `generate_acts` method produces specific actions to execute the current focus task. This method receives:

- The current focus task with all metadata

- The character's emotional stance
- Current environmental situation
- Recent history of actions and their results

It generates three alternative acts, each specifying:

- The action mode (Think, Say, Do, Look, or Move)
- The specific action content (thoughts, words, or physical actions)
- Target of the action (if applicable)
- Expected duration

These alternatives allow for varied approaches to the task, from which the character selects based on either autonomous preference or user choice. Action modes include:

- **Say:** Verbal communication with other characters
- **Think:** Internal reflection or reasoning
- **Do:** Physical actions in the environment
- **Look:** Directed observation of surroundings
- **Move:** Navigation to new locations

Samantha generates two alternative actions to implement the first task in her task plan:

```
#mode Say
#action Hey, Joe, let's grab those logs over by Fallen_Log#8 and Fallen_Log#9 and start stacking 'em
up. Think we can make a solid lean-to real quick?
#duration 1 minute
#target Joe
##

#mode Move
#action Fallen_Log#8
#duration 3 minutes
##'
```

Once an action is selected, the `act_on_action` method executes it, calling the appropriate specialized handler based on action mode. This typically involves the `acts` method, which processes the action, updates the world state, and captures results. The execution flow continues through `step_task`, which iteratively generates and executes actions until the current task is either completed or interrupted. The `step_tasks` method manages the task stack, popping completed tasks and pushing new ones as needed to maintain behavioral coherence.

4.6. Autonomy and User Interaction

The drive system supports varying levels of autonomy, allowing characters to operate fully autonomously or with user guidance at key decision points. The Autonomy class tracks which cognitive components (goal selection, task planning, action selection) operate autonomously and which await user input. This paper focuses on full autonomous operation. In interactive operation, the system presents users with decision points

for non-autonomous components, offering alternatives generated by the character's cognitive processes but deferring final selection to user choice, and also allowing the user to enter custom, user-specified, goals, tasks, or acts. This creates a spectrum from fully autonomous simulation to interactive narrative experiences where users have full control over decisions of one or more characters.

Through this integrated drive system and cognitive control flow, characters maintain coherent, goal-directed behavior while remaining responsive to environmental developments. The hierarchical structure of drives, goals, tasks, and acts creates a comprehensible progression from abstract motivation to concrete behavior, enabling characters to navigate complex social and physical environments with apparent purpose and intention.

4.7. Social Modeling

Our social modeling system provides characters with symbolic representations of themselves and others, forming the foundation for social interactions. At the heart of this system is the KnownActorManager, which creates and maintains unstructured textual models of characters that evolve through interaction and observation.

Actor Model Structure

Each KnownActor instance represents a character's internal model of another character in the simulation. Rather than using rigid symbolic representations with predefined attributes, these models take the form of textual descriptions to allow capture of the complexity and nuance of social understanding. A KnownActor maintains several key elements:

The core of each actor model is a relationship description—an unstructured text that captures the character's understanding of and feelings toward the modeled individual. A particular focus of the prompt that maintains this description is evaluation of trust: can I trust this other character? Are their goals aligned with mine? How emotionally stable are they right now? This description evolves over time as interactions accumulate, reflecting the dynamic nature of social relationships.

Each model also tracks conversation history through a Dialog object that maintains a transcript of interactions. This history provides context for future interactions and serves as material for updating relationship models. The system tracks whether a dialog is active, manages turn-taking, and records dialog fatigue—a mechanism that naturally brings conversations to closure after extended exchanges.

Actor models include additional metadata such as visibility status (whether the modeled character is currently observable), inferred goals, and physical distance. This information helps characters reason about others' accessibility and intentions when planning social interactions. As an example, Samantha's internal model of Joe after their initial interaction:

Samantha sees Joe as a steady, practical partner who's growing more open and cooperative. She feels cautious optimism and a budding sense of teamwork, appreciating their shared goals for survival and escape. Trust is functional and guarded—she relies on him but remains watchful. Their recent progress in communication and joint efforts, like gathering resources, has strengthened their mutual trust and cooperation.

Dialog Active: No

On the other hand, Joe thinks this about Samantha in a another performance where things aren't going so well between them:

Samantha is a relentless manipulator, actively trying to catch me in a lie—she's definitely hiding something. I'm increasingly anxious and frustrated around her, convinced she'd exploit me.

*Trust is nonexistent; her goals are *not* aligned with mine.*

Recent questioning & the locket have confirmed my suspicions, escalating this into a deception war. I'm actively trying to control the narrative.

Dialog Active: No

Actor Model Maintenance

The KnownActorManager orchestrates the creation, retrieval, and updating of actor models. When a character observes or interacts with another character, the manager first attempts to resolve the reference to an existing model. If no model exists, a new one is created, allowing characters to incrementally build their social understanding as they encounter new individuals.

Reference resolution is particularly important in dialogue, where characters may use various names, pronouns, or descriptions to refer to the same individual. The KnownActorManager implements a multi-level reference resolution system that matches textual references against known actors based on name similarity and contextual cues, as usual falling back to an LLM-based global reference resolution mechanism that includes reference to a known relation graph. When appropriate, the system will also dynamically instantiate new *NPCs*. This creates a coherent sense of who characters are talking about, even when references are ambiguous or incomplete.

Model updates occur after significant interactions, particularly conversations. When a dialog concludes, the system prompts the LLM to analyze the conversation transcript and update the relationship description accordingly. This update considers previous relationship status, the content and tone of the interaction, and patterns in communication.

Self-Model and Reflection

Characters also maintain models of themselves, enabling self-reflection and identity coherence. These are initiated when a character executes a 'Think' act – an internal monologue. The self-model follows the same structure as other actor models but is used differently in cognition. Through internal dialog—conversations a character has with themselves—the self-model is periodically updated, allowing (we hope) characters to develop insight into their own motives and behaviors, and making explicit situational characteristics that may otherwise not be apparent.

Internal dialogs often reveal characters working through conflicting drives or reflecting on the implications of their actions, creating a sense of self-awareness that enriches narrative depth.

Integration with Social Behavior

Actor models influence how characters interpret and respond to social situations. During dialog generation, the model of the conversation partner provides context that shapes response tone, content, and style. Characters speak differently to those they trust versus those they mistrust, drawing on their accumulated understanding of the relationship. The social modeling system creates a foundation for emergent narrative as relationships evolve through interaction. Initial models based on limited information gradually develop as

characters interact, observe each other's behavior, and update their mental models. This evolution drives character arcs and relationship developments that feel natural and earned rather than scripted.

5. Implementation Notes

The current implementation of our framework is built in Python, with natural language processing capabilities provided by large language models (LLMs) and a UI built using js/React. The simulation can be run in both scripted and free-running modes, with varying levels of autonomy for the characters. In scripted mode, key narrative beats are provided, but characters maintain autonomy in how they respond to events. In free-running mode, characters operate with full autonomy, generating narrative through their interactions.

6. Case Study – “The Offer”

How the architecture’s inner loops surface as believable dramatic action

A minimal scaffold—three characters, three drives each, a small coastal map, and the opening act headings—was handed to the engine. Everything else in the transcript below¹¹ is the product of the cognitive pipeline outlined in Sections 3–4.

We highlight five architectural elements and show, with verbatim snippets, how each one manifests on stage.

Scenario primer

Characters

Maya (artist, ambition vs. belonging), **Elijah** (boat-builder, stability & love), **Chrys** (gallery owner, opportunity catalyst)

Inciting situation A sealed city-gallery offer letter lies on Maya’s desk; no one else knows.

Cognitive elements at work

Architecture component	Internal process	Transcript evidence
Selective Perception filters raw input into subjective “percepts”.	Maya’s first cycle classifies the envelope as salient and hides it; Elijah is not cued because he lacks that percept.	19:30 – “ <i>The envelope is fully hidden... Elijah remains unaware.</i> ”
Drive-conflict → Goal generation turns background motivations into dialog objectives.	Maya’s <i>Ambition</i> vs. <i>Belonging</i> drives spawn a new, unspoken goal: keep the offer secret while gauging Elijah’s reaction.	19:41 – “ <i>Steadiness is a comfort... but my thoughts are restless. I’m just trying to find where I fit.</i> ”
Theory-of-Mind update revises each character’s mental model of the other after every percept.	Elijah issues a direct probe <i>after</i> a watch-gesture cycle that tried to read Maya’s micro-expressions.	19:55 – “ <i>Elijah: Watch Maya’s face... ‘Does that gallery thing’s real? ...Trying to make sense of</i>

11 The full transcript of Act 1 is provided in an appendix

Architecture component	Internal process	Transcript evidence
Goal → Task → Act pipeline forces concrete, world-modifying moves.	Chrys converts her business goal into one task—secure commitment—and one act—deliver a 24-hour ultimatum.	<i>where we both stand.”</i> 20:07 – “Chrys: ‘24 hours to lock this in... no exceptions.’”
Memory & Emotional Stance modulate follow-up behavior.	Maya, now holding the ultimatum in working memory, seeks solitude to stabilize her emotional stance.	20:17 – “Maya moves quietly... to a secluded gazebo, maintaining her resolve to protect the secret.”

These steps chain naturally: the hidden letter (perception) activates conflicting drives, which create internal goals, which color how each line of dialogue is chosen, interpreted, stored, and re-used.

Emergent narrative coherence

1 **Escalation without author scripting** – Scene order alone (Letter → Rumor → Deadline) yields rising stakes; each new percept triggers fresh goal/act cycles, not reiterations.

2 **Consistent voices** – Maya’s metaphoric language (“*tide quietly rising*”) appears across scenes because her *artist trait* is injected into every prompt the LLM sees, not because of static text blocks.

3 **Reciprocal adaptation** – Elijah’s dialogue softens after his watch-gesture perceives Maya’s anxiety; Chrys repeats the ultimatum once, then pauses, having satisfied her current task.

Together these mechanisms keep the conversation short enough to play (< 20 min) yet emotionally legible—without external rule scripts or post-edited dialogue.

Key take-aways supported by the transcript

- **Structured cognition, not ad-hoc chat, drives action.**
Every quoted line can be traced to a perception-drive-goal-task chain visible in the log (e.g., 19:30 → 19:41 → 19:55).
- **Theory-of-Mind is audible.**
Elijah’s shift from generic comfort to a pointed question follows an explicit *watch-and-infer* act (19:55).
- **Memory and stance temper pacing.**
After Chrys’s pressure (20:11) the very next act is Maya’s withdrawal to the gazebo, not another speech—showing an internal *calm-down* task before re-engaging.

These observations affirm the paper’s thesis: **deep cognitive models are necessary for emergent, coherent narrative**—they furnish each utterance with motive, perspective, and continuity that a surface-level language model alone does not sustain.

7. Evaluation

Evaluating narrative intelligence systems presents unique challenges given the subjective nature of narrative quality. Initially we used a simple metric:

You are a college-level creative writing lecturer teaching an introduction to creative writing class. Grade and critique the following submission of a term-project draft by one of your students. Ignore formatting details and focus on narrative coherence, character development, and other key aspects of creative writing.

Our early work generally scored B- at the scene level, and fell apart as the characters deteriorated over longer time periods. However, we found evaluations unstable and unreliable. We are currently developing a multi-dimensional numerical benchmark, using LLM-based scoring. While such a benchmark may be difficult to calibrate, we are more interested in score deltas than absolute values. The current dimensions include *goal directedness*, *theory of mind evidence*, and *cognitive flexibility*. Each is evaluated over sliding windows of a transcript with scores ranging from 0.0-5.0, and final score for each dimension is reported as the average over all windows.

An evaluation of a full performance of the *Offer* play provides the following assessment (the second number in each row is an assessment of the amount of evidence available to rate this dimension):

Goal Directedness:	4.92, 1.0
Theory of Mind evidence:	3.83, 0.9
Cognitive Flexibility:	3.38, 0.82

8. Summary

This paper presented a multi-character simulation framework that treats large language models as the engine for sub-symbolic cognition. Each character repeatedly filters perceptions, stores or abstracts them in memory, tests incoming signals against a fixed set of drives, formulates goals, decomposes those goals into task plans, and finally executes concrete acts. Social reasoning is realised through a lightweight, text-based Theory-of-Mind store that evolves after every interaction. A detailed examination of the “Offer” scenario showed how these pipelines translate internal state into outwardly coherent dialogue and action, producing a first act in which tension rises naturally from the concealment of a job offer through rumor and finally to an explicit ultimatum.

8.1. Potential Applications

The same mechanisms can serve several practical contexts. In interactive entertainment they enable non-player characters who adjust motives mid-story instead of following fixed dialogue trees. Educational and professional-training settings can benefit from scenario generators that rehearse negotiation, counseling, or historical role-play while adapting to learner choices. The framework also provides a test-bed for cognitive-architecture research, permitting controlled ablations of memory, drive balance, or Theory-of-Mind updates. Finally, therapists exploring exposure or social-skills rehearsal may find value in characters that remember prior sessions and continue relationships over time.

8.2. Current Limitations

The prototype is computationally expensive; running a three-act play with 27-billion-parameter models requires several hours on a high-end GPU. Stylistic quality and factual grounding remain tied to the underlying LLM, and default prompts reflect Western conversational norms, limiting cultural breadth. Objective evaluation is still difficult: although we employ automated LLM-based rubrics for coherence, character consistency, and social reasoning, definitive judgments rely on human readers.

8.3. Future Work

Planned research will focus on reducing latency through prompt compression and retrieval-augmented generation, extending cultural coverage by introducing alternative drive taxonomies and conversational scripts, and allowing characters to modify drive weights or generate new drives in response to experience. A multi-modal layer—connecting actions to generated visual scenes—would give physical stakes to dialogue, while a richer benchmark, combining reference plots with crowd-sourced ratings, should provide clearer progress signals.

8.4. Conclusion

The study demonstrates that a small set of generic information-flow operations, when coupled with contemporary language models, can yield characters whose dialogue, emotional timbre, and goal pursuit remain believable over extended interaction. Although questions of efficiency, culture, and evaluation persist, the results encourage further exploration of flow-centered cognitive architectures as a foundation for emergent narrative and socially aware artificial characters.

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10. Appendix – The Offer, Act 1

For this run the system ran in ‘screenwriter’ mode. That is, the system first processed the basic play description and output a director’s script: a list of scenes, each including a list of characters and a goal for each character in the scene. Characters then run autonomously within a scene, and carry their full internal cognitive state into the next scene.

World: ---ACT----- Hairline Cracks

World: -----scene----- Unread Letter

Maya: -----cognitive cycle----- 2025-06-15T19:30:00

Maya: Smooth the edges of the sketches over the envelope carefully, making sure it lies flat and hidden beneath the papers without any bulges or creases. Resulting in The sketches lie flat beneath the papers without any bulges or creases. The envelope is fully hidden and feels heavier in Maya’s pocket. Maya senses a quiet tension lingering in the studio. Elijah remains unaware of the envelope’s presence. Maya feels a subtle weight of caution and resolve.

Elijah: -----cognitive cycle----- 2025-06-15T19:31:00

Elijah: move to approach Maya slowly, keeping a relaxed posture to show calmness Resulting in Elijah approaches Maya slowly, his relaxed posture signaling calmness. Maya shifts slightly but remains seated quietly, the envelope beneath her sketches undisturbed. The room's tension remains palpable, with no immediate change in Maya’s expression. Elijah feels a quiet steadiness settling within him. The faint scent of linseed and wood lingers in the air. Outside, the harbor remains still as dusk deepens.

Elijah: 'Hey, it’s quiet out here tonight. Thought maybe we could watch the sky fade a bit together. How’s your evening going?'

Maya: 'I’d like that. The way the light softens here feels almost like the calm before a brushstroke—quiet, but full of something waiting to emerge. My evening’s been tangled up with thoughts, but sharing this fading sky might help untangle them a bit.'

Maya: -----cognitive cycle----- 2025-06-15T19:35:00 Maya: 'You know, the way the harbor lights flicker on, it almost feels like the town is holding its breath for something beautiful to happen. What’s been catching your eye around here lately?'

Elijah: 'Yeah, I’ve been watching the old pier—thinking about fixing it up, maybe adding a few new slips. It feels right, steady. Like something solid to hold onto while the town waits.'

Elijah: -----cognitive cycle----- 2025-06-15T19:38:00 Elijah: 'Hey, if there’s anything on your mind, you know I’m here to listen—no rush, just whenever you’re ready.'

Maya: -----cognitive cycle----- 2025-06-15T19:40:00

Maya: Watch Elijah’s figure slowly fade down the garden path, noting the gentle sway of his steps as he disappears into the night.. sees You are in Garden terrain. You see Elijah and Workshop#2, Bench#2 resources.

Elijah: -----cognitive cycle----- 2025-06-15T19:41:00 Elijah: 'You know, I’ve been thinking a lot about how steady things feel here—with the pier, the town—sometimes I wonder if that steadiness is enough for you. What’s on your mind tonight?'

Maya: 'Steadiness is a comfort, Elijah, but sometimes I wonder if the calm hides a tide rising beneath. Tonight feels like one of those moments—quiet on the surface, but my thoughts are restless. I guess I’m just trying to find where I fit in all of this.'

Elijah: 'I get that. Sometimes I wonder if the tide’s pulling you somewhere far from here. But no matter where you’re headed, I want to understand it—so we don’t lose what we’ve built together.'

Elijah: ...Reflect quietly on my own hopes and fears about Maya's restlessness, deciding how to gently open up about my feelings without pushing her too hard, while watching her closely for any sign she's ready to share.... Elijah: -----cognitive cycle----- 2025-06-15T19:48:00

Elijah: 'You know, I'm here whenever you want to talk—no pressure, just whenever you're ready. Take your time.'

World: -----scene----- Rumor on the Wharf

Elijah: -----cognitive cycle----- 2025-06-15T19:50:00

Elijah: 'You know, I heard some folks at the tavern talking about a city gallery maybe wanting to show your work. Sounds like the kind of thing that'd stir up the town a bit. What do you make of that?'

Maya: 'It might shake the waters a bit, but sometimes the ripples bring new light to hidden corners. Still, I wonder if the town is ready for something that changes the tide.'

Elijah: 'It's true, change can be good, but it's a heavy weight to carry when the shore's been steady so long. I want to see you shine, Maya, but I worry what we might lose if the tide pulls you too far from here.'

Maya: -----cognitive cycle----- 2025-06-15T19:53:00

Maya: ...I need to keep the offer tucked away, like a secret sketch hidden beneath layers of paint, while staying present with the quiet strength Elijah offers tonight. Holding onto this balance without letting the weight show....

Elijah: -----cognitive cycle----- 2025-06-15T19:55:00

Elijah: Watch Maya's face and hands carefully for any hesitation or subtle signs of discomfort or excitement as she speaks.. sees You are in Road terrain. You see Maya and resources.

Elijah: 'You know, if that gallery thing's real, what would it mean for you? For us? I'm just trying to make sense of where we both stand.'

Maya: 'It would mean stepping into a light that's both thrilling and uncertain. For us... it feels like standing at the edge of the tide—wondering if it will carry us forward or pull us apart. I'm grateful you want to understand, Elijah. That means more than I can say.'

Maya: -----cognitive cycle----- 2025-06-15T19:59:00

Maya: Maya approaches the fishermen with a warm smile, gently lifting a smooth, weathered shell from the ground as a small, quiet offering to start a conversation about the sea's hidden depths and its quiet lessons. Resulting in Maya moves southeast toward the fishermen group about 20 units away. She lifts a smooth, weathered shell from the ground near the road. The fishermen notice the gesture and pause their quiet conversation, turning their attention toward Maya with mild curiosity. Maya retains the shell as a physical token but has not revealed the job offer. The air remains calm with only a faint salt-earth scent. Maya feels a subtle increase in warmth and openness, slightly easing the emotional tension. Elijah remains at Maya's original position, observing but silent. No changes in lighting or weather occur.

Elijah: -----cognitive cycle----- 2025-06-15T20:02:00 Elijah: 'Maya, I need to know straight—does that city gallery really want your work, or is it just talk?'

Maya: 'It's real, Elijah. Like the tide quietly rising—slow, steady, but shifting everything beneath. I'm just trying to find the right moment to let that change wash over us, together.'

Elijah: 'I'm glad it's real. But we need to be sure this tide won't pull us apart before it carries us forward. Let's take this slow—figure out what it means for you, and for us. I want to stand by you, but I need to see the ground beneath my feet too.'

Maya: -----cognitive cycle----- 2025-06-15T20:06:00

Maya: 'Here's to the tides we can't yet see—may they carry us gently, even as they reshape the shore beneath our feet.'

World: -----scene----- Deadlines

Chrys: -----cognitive cycle----- 2025-06-15T20:07:00 Chrys: 'Hey, Maya, can you hear me alright? Just wanna make sure we're connected before I dive in.'

Maya: 'Yes, loud and clear. I'm ready when you are—time's pressing, but we'll navigate this like we always do.'

Chrys: 'Good. Here's the deal—24 hours to lock this in. After that, I move on. No more holding back, Maya. I'm serious. We both know this could be the break we need, but I need your answer by tomorrow, no exceptions.'

Maya: -----cognitive cycle----- 2025-06-15T20:10:00

Maya: '"Elijah, sometimes the quietest moments hold the deepest truths. Let's just sit here a while, no need to rush anything, just the calm between the tides."'

Chrys: -----cognitive cycle----- 2025-06-15T20:11:00

Chrys: 'Look, Maya, I need you to understand—this offer's on the table for exactly 24 hours. After that, I'm moving forward without you. No more delays, okay?'

Maya: -----cognitive cycle----- 2025-06-15T20:12:00

Maya: 'You know, sometimes the sea holds its secrets beneath calm waves, waiting for the right moment to reveal its treasures. I think some things are meant to be felt, not spoken aloud.'

Chrys: -----cognitive cycle----- 2025-06-15T20:15:00

Chrys: ...Focus on Maya's body language and tone, trying to gauge whether she's leaning toward commitment or decline while managing my own rising impatience and anticipation....

Chrys: Watch Maya closely—her face, gestures, and tone—for any sign that she's leaning toward a yes or no. Catch the subtle shifts as the clock ticks down.. sees You are in Garden terrain. You see Maya and Bench#1 resources.

Maya: -----cognitive cycle----- 2025-06-15T20:17:00

Maya: move to Move quietly along the garden path toward the small, secluded gazebo near the harbor's edge, keeping steps light to avoid drawing attention. Resulting in Maya moves quietly along the garden path, steps light and careful. She hears the gentle rustling of leaves and the distant, muted lapping of harbor waters. The fading moonlight and sparse street lamps cast soft shadows along her route. Chrys remains near Bench#1, watching intently but does not call out or move. Maya feels focused and cautious, maintaining her resolve to protect the secret while avoiding drawing attention. She sees the small, secluded gazebo ahead near the harbor's edge, partially illuminated by the diffused moonlight and faint streetlamp glow. No new information is gained.

