

The Future is Agentic: Definitions, Perspectives, and Open Challenges of Multi-Agent Recommender Systems

REZA YOUSEFI MARAGHEH, University of Illinois Urbana Champaign, USA

YASHAR DELDJOO, Polytechnic University of Bari, Italy

Large language models (LLMs) are rapidly evolving from passive engines of text generation into agentic entities that can plan, remember, invoke external tools, and co-operate with one another. This perspective paper investigates how such LLM agents (and societies thereof) can transform the design space of recommender systems. We introduce a unified formalism that (i) models an individual agent as a tuple comprising its language core, tool set, and hierarchical memory, and (ii) captures a multi-agent recommender as a triple of agents, shared environment, and communication protocol. Within this framework, we present four end-to-end use cases—interactive party planning, synthetic user-simulation for offline evaluation, multi-modal furniture recommendation, and brand-aligned explanation generation—each illustrating a distinct capability unlocked by agentic orchestration. We then surface five cross-cutting challenge families: protocol complexity, scalability, hallucination and error propagation, emergent misalignment (including covert collusion), and brand compliance. For each, we formalize the problem, review nascent mitigation strategies, and outline open research questions. The result is both a blueprint and an agenda: a blueprint that shows how memory-augmented, tool-using LLM agents can be composed into robust recommendation pipelines, and an agenda inviting the RecSys community to develop benchmarks, theoretical guarantees, and governance tools that keep pace with this new degree of autonomy. By unifying agentic abstractions with recommender objectives, the paper lays the groundwork for the next generation of personalized, trustworthy, and context-rich recommendation services.

CCS Concepts: • Information systems → Recommender systems.

ACM Reference Format:

Reza Yousefi Maragheh and Yashar Deldjoo. 2025. The Future is Agentic: Definitions, Perspectives, and Open Challenges of Multi-Agent Recommender Systems. *ACM Trans. Recomm. Syst.* 1, 1 (July 2025), 35 pages. <https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

1 Introduction and Motivation

Large Language Model (LLM) agents go beyond traditional chatbots by offering agentic behavior rather than merely responding to user queries through token-based predictions. In essence, they are designed to handle multi-step tasks, orchestrate information flow, and autonomously employ various tools or functions when necessary [50, 54, 67]. This distinction means that while a conventional chatbot might provide short answers in a single round of dialogue, an agentic system can proactively structure a complex problem and solve it in a series of methodical steps. Put another way, an LLM agent is not just a reactive conversational partner but a dynamic problem-solver capable of decomposing tasks and acting on external resources to reach a goal [20, 25, 69].

Authors' Contact Information: Reza Yousefi Maragheh, University of Illinois Urbana Champaign, Illinois, USA, ryousefimaragheh@acm.org; Yashar Deldjoo, Polytechnic University of Bari, Bari, Italy, deldjooy@acm.org.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2025 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM 2770-6699/2025/7-ART

<https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

One fundamental reason to use LLM agents is the complexity and multi-stage nature of real-world tasks. A single static prompt to an LLM may be insufficient for intricate scenarios—such as trip planning, multi-faceted research, or iterative design processes—because these tasks often require multiple rounds of decision-making and interaction with external data. Agentic systems can break down a complicated goal into smaller sub-tasks and tackle each step methodically. This approach sidesteps the limitations of plain text-based queries by enabling more robust, context-aware decision sequences that mimic human reasoning processes more closely [52, 59]. In addition, by distributing the cognitive load across different components, an agentic framework further mitigates the risk of “hallucinations” or incomplete answers by ensuring that the final outcome is not solely reliant on a single pass of token predictions [26].

Crucially, **memory mechanism** is a crucial part of LLM-based agents, designed to ensure that conversations with the user remain both coherent and personalized over time. Unlike traditional chatbots—which process each turn in isolation and quickly lose track of earlier content—modern agents combine several complementary memory stores, each optimized for a different goal (§3):

- **Working (short-term) memory:** Allows the agent to recall very recent exchanges within the same session. For example, if a user asks “*Recommend a mystery novel*,” and then immediately follows up with “*More like the last one*,” the working memory preserves the original recommendation so the agent can suggest similar titles in response to the user’s follow-up request, without requiring the user to repeat their previous query.
- **Episodic (long-term) memory:** stores specific past events with context and metadata. For instance, if the user asks for Italian restaurants one week ago and now asks “*the restaurant you mentioned last time*,” the episodic memory enables it to retrieve the exact recommendation, along with when and why it was suggested.
- **Semantic (long-term) memory:** Distills and accumulates general facts or user preferences from many interactions. For instance, after several conversations, the agent might infer that a user prefers *Italian cuisine*, allowing it to proactively rank Italian options higher in future dining queries, even if she has not mentioned it in the current session.
- **Procedural (long-term) memory:** Encodes learned skills, routines, or scripts, enabling the agent to execute recurring tasks automatically and efficiently. For instance, if a user frequently requests the agent to “*summarize meeting notes and email them to the team*,” the agent can learn this workflow; the next time the user simply says “send the usual summary,” the agent carries out the task without step-by-step instructions.

Overall, by orchestrating these distinct memory types, the agent remains consistently informed about prior steps, user preferences, and external knowledge sources, resulting in smoother and more context-aware interactions [18, 83].

Another key advantage of LLM agents is their capacity to **autonomously invoke tools**, significantly enhancing their ability to manage complex tasks and provide specialized information beyond their internal knowledge (§2.1). Instead of depending solely on static model parameters, these agents proactively leverage dedicated modules or external services to fetch precise data, perform specialized analyses, or execute domain-specific computations [23, 47]. For example, in recommendation scenarios, if a user asks for a restaurant suggestion, the agent can use a specialized retrieval tool or database query to fetch current ratings and availability rather than relying solely on previously memorized information. Similarly, when recommending furniture tailored to the user’s uploaded room images and stated style preferences, the agent may use image-analysis tools to extract visual features and then query product databases to select items that match the user’s desired aesthetic and spatial constraints (§4). These can also illustrate how tools could complement the memory mechanism—e.g., semantic memory (general user preferences or item attributes) and

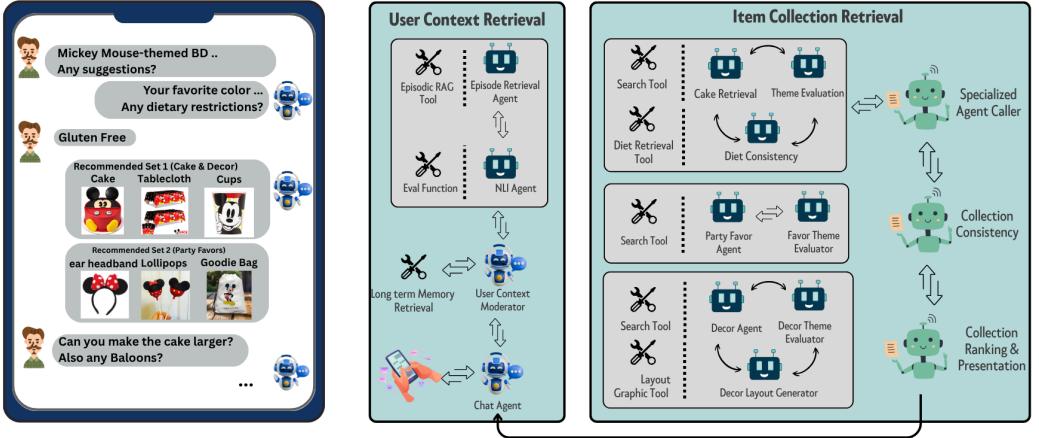


Fig. 1. Left: Conversation example for a goal-oriented collection recommendation, where the user specifies an open-ended goal instead of searching for specific items. Right: Architecture for personalized goal-oriented recommendation using a multi-agent pipeline with specialized agents and tools.

episodic memory (specific previous recommendations)—enabling more precise and contextually relevant suggestions. Ultimately, tool integration significantly broadens the functionality of LLM agents beyond conventional conversational interactions, empowering them to tackle diverse tasks with enhanced adaptability and personalization.

Taken together—multi-step task handling, memory retention, and tool use—these capabilities empower LLM agents to operate with a level of autonomy that transcends the simpler question-and-answer paradigm of traditional chatbots. By chunking tasks into manageable components [52], retaining critical context [38], and deploying external tools when appropriate [55], LLM agents can provide more thoughtful and holistic solutions and pave the way for more intelligent and adaptive solutions across conversational and recommendation-based applications alike.

1.1 Agentic Orchestration Example: “Mickey Mouse Birthday Planning”

Figure 1 represents a shift in recommender systems from traditional item-query models towards interactive, conversational systems where users state broad goals (e.g., “celebrate my child’s Mickey Mouse birthday”), as shown in the left pane (see also “Agent-Item” vision of Rec4Agentverse [81]). This conversational approach allows the recommender to elicit rich contextual information, maintaining a nuanced understanding of user intentions over multiple dialogue turns. The right panel demonstrates how the recommender orchestrates this sophisticated request via an autonomous multi-agent pipeline. The overarching goal is decomposed into specialized subtasks, each managed by dedicated agents, such as a user context moderator agent, a specialized agent caller, specialized retrieval agents, a collection consistency agent, and a collection ranking and personalization agent.

To effectively handle such complex, natural-language user intents, the recommendation framework relies on the decomposition of this broad goal into clearly defined specialized sub-tasks:

- The architecture **persists episodic and session-level traces** in a long-term user history store, thereby preserving contextual signals that span multiple interactions.

- A **specialized-agent caller** can *dynamically instantiate dedicated sub-agents*, each equipped with domain-specific retrieval or generation tools, to address distinct recommendation sub-tasks—an approach foreshadowed by recent agentic recommender frameworks.
- The system subsequently enforces **intra-collection consistency**, ensuring that all retrieved items cohere with the target theme, dietary constraints, and aesthetic guidelines.
- Finally, it applies **personalized ranking and presentation** so that the curated item set is ordered according to the user’s individual preferences and contextual priorities.

In such an interactive system, memory acts as an essential long-term and short-term knowledge repository (see §3). It can track conversational context, the user’s relevant interaction history to the current session, prior preferences, rejected and accepted recommendations, and user feedback. Memory ensures continuity and coherence in conversation, enabling personalized adaptation and preventing redundant interactions, and personalization. This can be interpreted as stateful conversations where the state is governed by a memory from the past, which is being adapted to the current context. This preserves complex interactions across multiple rounds of conversation in the same user session, and across user sessions.

Overall, such an orchestrated, conversational, and multi-agent recommendation system marks a significant departure from conventional approaches:

- **Enhanced User Experience.** Transitioning from single-query responses to personalized conversations deeply enriches engagement, satisfaction, and loyalty.
- **Adaptability and Flexibility:** Decomposition and orchestration allow rapid adaptation to diverse, dynamic user needs, significantly enhancing the system’s robustness and user satisfaction.
- **Contextual Precision:** Multi-agent specialization enables deep, contextually sensitive recommendation that single-agent systems struggle to achieve efficiently.
- **Explainability and Transparency:** The decomposition into distinct sub-tasks inherently provides transparency—users can better understand recommendation rationale, thus increasing trust.

All these enable the mentioned move from simplistic single-query recommendations toward goal-driven, personalized, and richly interactive experiences.

This shift from **one-shot ranking** to **goal-driven interaction** raises new challenges: How should we formalise an agentic RS? Which classical tasks must be re-imagined? What architectures scale when dozens of specialist agents cooperate? And how do we guard against emergent risks such as collusion or memory leaks?

Contributions. Agentic recommender systems represent a transformative shift from single-turn recommendation tasks to fully autonomous and interactive goal-oriented frameworks, raising significant theoretical and practical challenges. These include planning complexity, handling memory saturation, ensuring fairness in recommendations (§5.4), detecting hallucinations in generative reasoning (§5.3), and preventing unintended collusion among autonomous agents. Addressing these critical challenges requires systematic conceptualization and methodological advancements. Our contributions and roadmap in this perspective paper include:

- **Conceptual Framework** (§2): Establish a formal, *agent-centric vocabulary* that precisely defines its core constituting elements, which include LLM agents, memory-retention/retrieval functions, tool use, and communication protocols—thereby standardizing discussion across the RecSys community.
- **Reference Illustrative Blueprint** (Fig. 1): Provide illustrative end-to-end architectures (e.g., the “Mickey-Mouse Party Planner” pipeline) as an *executable blueprint*, via aligning

specialized agents with concrete toolchains, memory hierarchies, and orchestration patterns, serving as implementation-ready templates.

- **Role of Memory** (§3): Demonstrate how working, episodic, semantic, and procedural **memories** in agentic setup enhance continuity, personalization, and tool coordination in every agentic workflow, and formalizes retention (\mathcal{R}) and retrieval (\mathcal{Q}) operators that generalize across settings.
- **Use-Case Taxonomy** (§4): Highlight six representative use-case tasks—*interactive recommendation, user simulation, multimodal recommendation, explanation, contextual evaluation, and fairness auditing*—that demonstrably benefit from agentic design. For each use case, we (i) motivate why an agentic approach is essential, (ii) sketch a dedicated agent architecture, and (iii) walk through a concrete running example.
- **Core Challenges** (§5): Deliver a rigorous analysis of six *orthogonal challenges*—communication complexity, scalability, hallucination propagation, fairness, brand consistency, and emergent collusion—formulating each as a well-posed research problem with quantifiable objectives.
- **Research & Design Agenda** (§5): Synthesize actionable guidelines (dynamic verification loops, policy-aligned decoding, cost-aware orchestration) with a forward research roadmap that unifies technical milestones, ethical safeguards, and interdisciplinary perspectives on trustworthy large-scale agent ecosystems.

Overall, our work bridges insights from NLP, distributed systems, and AI ethics, positioning recommender research within broader conversations on trustworthy, large-scale autonomous AI. Our hope is that these contributions help transition recommendation-related tasks from static, one-shot interactions toward goal-driven, interactive, and autonomous LLM agents—catalyzing deeper interdisciplinary collaboration and innovation.

2 Agentic Recommender Systems: Definition, Characteristics, Misconceptions

In this section, we clarify the concept of an *LLM agent*, in more depth. When illustrating through examples we use the context of recommender and retrieval systems. We also discuss common misconceptions about agentic pipelines and elaborate on what is *not* an LLM agent.

2.1 What Defines an LLM Agent

An **LLM agent**, in its fully functional capacity, is an AI system in which a large language model (LLM) serves as the core decision-making component (the “brain”), enhanced by additional mechanisms that enable it to carry out complex, multi-step tasks autonomously rather than relying on a single prompt-response. In other words, this LLM is part of a larger architecture that provides (i) planning abilities, (ii) memory, (iii) tool/API usage, for interactions with external systems, (iv) an *autonomous decision loop* that can break down a goal, observe intermediate steps, and adapt its strategy [52, 76]. In a broader context, multiple such language agents form a **multi-agent system (MAS)**, in which agents can interact, communicate, coordinate, and even compete—leveraging their reasoning and communication capabilities to collectively solve complex tasks that exceed the capacity of any single agent.

This design (i.e., agent-based approach) goes beyond the traditional static use of LLMs for single-turn queries and is increasingly used in recommendation and retrieval tasks. For example, an LLM-based agent can iteratively search user logs to gather information about past item interactions before making tailored recommendations [48, 82].

Table 1. Core Capabilities of Agentic Recommender Systems

Icon	Capability	Description
	Planning & Task Decomposition	Breaks down complex goals into sub-tasks, enabling multi-step reasoning and planning (e.g., candidate selection, bundle retrieval, re-ranking) [12, 44, 79].
	Tool Use & Action Execution	Invokes external tools/APIs or performs real-world actions (e.g., database queries, web searches, retrieving live inventory) [76].
	Memory & State Management	Maintains state across steps using memory modules (semantic, vector, knowledge graph), enabling context retention and personalized, multi-turn recommendations [4, 31, 34, 49, 53, 72, 74].
	Autonomy & Goal-Driven Behavior	Operates autonomously in a closed-loop, observing the environment, self-refining, and continuing until the objective is reached [42, 64].

2.2 Key Characteristics of LLM Agents

As summarized in Table 1, agentic recommender systems typically exhibit four core characteristics, described in the following:

- (1) **Planning and Task Decomposition:** The agent can execute (or even formulate) a plan. This is done by breaking a complex goal into subtasks. Rather than producing an immediate, one-shot answer, an agentic system can plan for and conduct a sequence of steps. This can involve reasoning to tackle long-horizon tasks [12, 44]. For example, in a recommender scenario, the planning module may first identify candidate items, then check user history, retrieve a consistent bundle of products, then re-rank items before generating a final recommendation [79].
- (2) **Tool Use and Action Execution:** An LLM agent is not limited to purely text-based outputs; it can *invoke external tools or APIs* and perform *actions* in an environment [76].¹ For instance, a recommendation agent could consult a real-time inventory database to see if recommended items are in stock, or it might retrieve user reviews from a knowledge base before finalizing its recommendations.
- (3) **Memory and State Management:** LLM agents maintain a notion of “state” across multiple steps. They often incorporate a memory module which can potentially retain storing conversation context, past recommendations, user feedback, local guidelines, procedures, domain knowledge etc [74]. This memory can be in semantic [49], vector database [31], knowledge graph [4, 53] formats. The memory module is used by the agent so that it can recall relevant information at each step of executing a task. For instance, in recommendation scenarios, user preferences collected over multiple sessions can be stored in a memory module and retrieved for the task of personalizing the recommendations. This persistent memory is crucial for multi-turn recommendation dialogues, where the agent refines suggestions based on evolving user interests. [34, 72]
- (4) **Autonomy and Goal-Driven Behavior:** LLM agent can be designed to be operated in “autonomously in a closed-loop fashion” to fulfill a goal. Given a target objective (for example “find a suitable product for a user”), the agent can be designed to autonomously (i) observes the environment (via tools or APIs), (ii) evaluates progress, (iii) evaluate the outcome of each step and do a self refine step (iv) continues until it deems the goal is achieved or no further

¹Tool invocation examples include web searches, database queries, or calling a specialized retrieval API to filter items.

action can be taken. This is unlike a static Q&A system, where the system merely focuses on the one-time query. [42, 64]

These components enable the LLM agent to tackle complex tasks in recommendation and retrieval settings. For instance, systems like *RecMind* [68] use LLM as a reasoning engine paired with a planning component, a long-term memory of user profiles, and retrieval tools to fetch relevant product information. The agent then autonomously analyzes a user’s needs and iteratively refines its suggestions. This is far more capable than a single-turn Q&A approach, as it can plan queries (e.g., to check product ratings or availability), incorporate user feedback, and adapt the recommendation strategy. Frameworks like “ReAct” [76] illustrate how an LLM can be prompted to alternate between “reasoning steps” and “action steps”, calling retrieval or recommendation APIs as needed. Other systems, such as “Toolformer” [55] and “HuggingGPT” [57] similarly integrate LLMs with external action interfaces.

2.3 Formal Framework

In this subsection, we introduce formal definitions for key concepts central to our framework. These definitions establish a rigorous foundation for discussing the architectural and operational aspects of agents, including specialized LLM Agents, Multi-Agent Systems, and Tool-Using Agents. We also provide a generic formalism for representing the internal structure of an agent.

Definition 2.1 (LLM Agent). An *LLM Agent* is an intelligent system whose core decision-making and interaction capabilities are powered by one or more large language models. Formally, we denote such an agent as:

$$A_{\text{LLM}} = (\mathcal{M}, \mathcal{I}, \mathcal{O}, \mathcal{F}, \Omega),$$

where:

- \mathcal{M} is the underlying language model or set of models used for text generation, understanding, and reasoning.
- \mathcal{I} represents the input space that the agent can observe.
- \mathcal{O} denotes the output space the agent can produce.
- \mathcal{F} is a set of functions, tools, or APIs the agent can invoke to enhance its capabilities.
- Ω comprises any additional state or memory structures that enable the agent to maintain context across time or tasks.

For example, in recommendation settings, for an eCommerce shopping assistant, \mathcal{M} can be a GPT-style transformer fine-tuned for e-commerce dialogue; it encodes linguistic knowledge and basic reasoning skills, allowing the agent to parse user requests and generate coherent replies. \mathcal{I} is the space of user queries and contextual signals, while \mathcal{O} is the space of possible outputs, including text responses, actions, or function calls. \mathcal{F} represents external functions or APIs, such as retrieval APIs, price fetchers, or inventory status calls, which augment the innate knowledge of \mathcal{M} with fresh, authoritative data, thereby mitigating hallucination. The agent’s memory, Ω , is partitioned into (a) *short-term memory* Ω^{STM} that keeps the last few dialogue turns, (b) *long-term episodic memory* Ω^{EPI} that stores past party-planning sessions, and (c) *semantic memory* Ω^{SEM} containing persistent user traits (e.g., “prefers red decor”). During inference, salient fragments of Ω are retrieved and appended to the prompt, giving the agent continuity across sessions.

For a multi-turn dialogue agent, at each timestep t , the agent receives an input $i_t \in \mathcal{I}$, consults its memory $\omega \subseteq \Omega$ to form an augmented context, and computes the output $o_t \in \mathcal{O}$ as follows:

$$o_t = f_{\mathcal{M}, \mathcal{F}}(i_t, \omega) \tag{1}$$

where $f_{\mathcal{M}, \mathcal{F}}$ is the agent's policy function that maps the current input i_t and retrieved memory ω to an output o_t , leveraging both the language model \mathcal{M} and the available external functions \mathcal{F} .

Definition 2.2 (Multi-Agent System (MAS)). A Multi-Agent System is an ordered triple

$$\text{MAS} = (\mathcal{A}, \mathcal{E}, \Pi),$$

where

- (a) $\mathcal{A} = \{A_1, \dots, A_n\}$ is a finite set of agents. Each A_i may be an LLM agent (Definition 2.1) or another kind of modular service (e.g., rule-based, vision, or database stub).
- (b) \mathcal{E} is the shared *environment* that supplies percepts and resources to the agents—such as external APIs, user interfaces, or a simulated world state. Formally, \mathcal{E} can be viewed as a partial observable Markov space from which each agent receives observations and in which it executes actions.
- (c) $\Pi = (\mathbf{C}, \Gamma)$ is the *interaction protocol*.
 - (i) $\mathbf{C} \in \{0, 1\}^{n \times n}$ is a (possibly time-varying) *communication matrix*. A value $C_{ij} = 1$ indicates that messages of type $\gamma \in \Gamma$ are *permitted* from A_i to A_j under current conditions. The condition can be
 - **preset** (static design-time routing), or
 - **autonomous** (dynamically toggled by agents. e.g., A_i opens a channel to A_j when cooperation is beneficial, closes it otherwise).
 - (ii) Γ is the finite set of admissible *message schemata* (performative types, serialization rules, timing constraints). Each $\gamma \in \Gamma$ defines both syntax and semantics so that a receiving agent can parse and act on the message.

An execution of MAS unfolds as a sequence of environment states and inter-agent messages that respect Π . Depending on design, agents may coordinate (*co-operative*), compete (*self-interested*), or exhibit mixed motives while attempting to satisfy individual or shared objectives.

For instance, consider a minimal marketplace scenario with two autonomous components—namely a *recommendation agent* and a *policy-evaluation agent*—so that

$$\mathcal{A} = \{A_{\text{rec}}, A_{\text{eval}}\}.$$

In this case $\mathcal{E} = (\text{UserProfileDB}, \text{ProductCatalogue}, \text{BusinessRulesKB})$, providing user attributes, real-time inventory, and brand-policy facts, respectively. The interaction protocol can be

$$\Pi = (\mathbf{C}, \Gamma), \quad \mathbf{C} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \quad \Gamma = \{\text{candidate_list}, \text{compliance_report}\}.$$

Thus A_{rec} may send a *candidate_list*, a ranked JSON array $\{(s_1, \text{score}_1), \dots, (s_L, \text{score}_L)\}$ to A_{eval} , which in turn replies with a *compliance_report* indicating any items that violate policy. The off-diagonal ones in \mathbf{C} permit bidirectional messaging, while the zeros on the diagonal denote that agents do not address themselves. At runtime, $C_{\text{eval}, \text{rec}}$ can be toggled off once no further corrections are required, illustrating how links may be preset yet autonomously reconfigured according to system state.

Definition 2.3 (Memory Update Function). Let Ω_t denote the long-term memory state maintained by an agent at dialogue step t and let

$$C_t \in \mathcal{X}$$

be the raw context collected during that step (e.g., the most recent user utterance, the agent's reply, and any intermediate reasoning trace, represented in token or embedding space). A *Memory Update*

Function is a mapping

$$\mathcal{U} : (C_t, \Omega_t) \longrightarrow \Omega_{t+1},$$

where

- \mathcal{U} internally applies a *retention operator*

$$\mathcal{R} : C_t \rightarrow \tilde{C}_t$$

that distils C_t into a noise-reduced summary $\tilde{C}_t \in \tilde{\mathcal{X}}$,

- merges \tilde{C}_t with the prior state Ω_t via a domain-specific *merge rule* \diamond , and produces the next persistent state:

$$\Omega_{t+1} = \Omega_t \diamond \tilde{C}_t.$$

The goal is to preserve salient semantic information while discarding redundancy, ensuring that Ω_{t+1} remains compact yet sufficient for future retrieval.

Assume a shopping assistant agent and a user that uses the agent to order a cake. At turn t the user says a “remember that two of my guests require a gluten-free diet”. The raw context C_t includes the user utterance, the agent’s internal chain-of-thought, and the pending action call to a CakeSearch tool. The retention operator extracts the key fact

$$\tilde{C}_t = \{\text{guest_allergy: gluten}\},$$

and the merge rule appends it to the agent’s long-term *episodic* slot in Ω_t :

$$\Omega_{t+1}^{\text{EPI}} = \Omega_t^{\text{EPI}} \cup \{\text{guest_allergy: gluten}\}.$$

On the next turn ($t+1$) the planner retrieves this memory fragment and instructs a downstream cake-selection agent to filter for gluten-free options, illustrating how \mathcal{U} enables continuity and correctness across dialogue turns without bloating the prompt window.

Definition 2.4 (Memory Retrieval Function). Let Ω be the agent’s persistent memory store after t dialogue steps. A *Memory Retrieval Function* is a mapping

$$Q : (\Omega, \tau) \longrightarrow \hat{C},$$

where

- $\Omega = \{\tilde{C}_1, \dots, \tilde{C}_m\}$ is a corpus of distilled memory traces, each $\tilde{C}_i \in \tilde{\mathcal{X}}$ (text snippets, embeddings, or hybrids) produced by the update operator \mathcal{U} (Definition 2.3).
- $\tau \in \mathcal{T}$ is a task representation—e.g. the current user query, an intermediate reasoning goal, or a structured tool call argument—expressed in text, vector, or multi-modal form.
- $\hat{C} \in \tilde{\mathcal{X}} \subseteq \tilde{\mathcal{X}}$ is the subset of memory deemed relevant to τ , returned in a form suitable for prompt augmentation or downstream computation.

By recalling only \hat{C} , the agent conditions subsequent reasoning on task-specific context while keeping the effective prompt window compact and noise-free.

Continuing the shopping assistant example for cake ordering, suppose at turn $t+1$ the planner agent formulates the sub-goal $\tau = \text{“find gluten-free chocolate cake designs”}$. Invoking $\hat{C} = Q(\Omega_t, \tau)$ returns a minimal set of memory entries, e.g.

$$\hat{C} = \{\text{guest_allergy: gluten, child_pref: chocolate}\},$$

filtered from dozens of prior dialogue snippets. These facts are appended to the prompt fed into the CakeSearch tool, ensuring that the retrieval agent queries only gluten-free, chocolate-flavoured options while ignoring unrelated historical details. Thus, Q provides precise, context-aware recall that prevents irrelevant or outdated memories from polluting the reasoning chain.

By introducing these formalisms, we establish a common language for discussing agentic behavior and capabilities. In the subsequent sections, we will demonstrate how these formal concepts can be instantiated and extended to create advanced recommendation systems and other multi-step, context-aware applications.

2.4 What Is Not an LLM Agent (Common Misconceptions)

There is no universal agreement on a definition of an LLM agent, but not every system that leverages an LLM is an “agent.” Below, we highlight simpler workflows often *mistaken* for true full-on agentic systems. See as well Table 2 for an illustrative summary:

1) Simple Prompting (Single-Turn Q&A). An LLM responding once to an instruction (no matter how detailed) is *not* an autonomous agent. The model interprets input and generates an answer in one pass, with no iterative planning or action. This static scenario lacks persistent goal tracking, environment sensing, or multi-step control. In recommendation, a single-turn prompt like “Recommend me a movie” yields a list of movie titles, but the LLM *does not* check user history, fetch updates, or adapt based on the user’s reactions in a self-directed manner.

2) Retrieval-Augmented Generation (RAG).. Attaching a retrieval step to an LLM (e.g., retrieving relevant documents before generating a response) is a powerful technique for grounding outputs. However, it alone does *not* create an agent. Typically, a RAG pipeline is *still* one-pass, with a fixed retrieve-then-generate workflow. The LLM itself is not *autonomously deciding* whether and how to retrieve additional data; instead, the retrieval step is orchestrated externally or via a preset chain. This can be extremely helpful for factual correctness in QA or delivering up-to-date item details for recommendation, but it lacks the iterative decision cycle and autonomy of a true agent.

3) Prompt Chaining. Some systems chain multiple steps (e.g., retrieve data from a database, then pass it to the LLM for summarization), but do so in isolated shots single shots. For instance, for summarizing a large corpus of text, one may use a short context LLM on different chunks of the large text and then concatenate the individual summaries. These isolated instances, do not have any of the mentioned components of agents.

In other scenarios, a more complicated task is chunked to a sequence of smaller subtasks, and the output of each step serves as the input for next step. While, these mediatory outputs can be considered as some notion of memory for agents, this fixed, chained multiple steps do not use the full capability that could have been defined for agents. For example, a multi-turn conversation with a user might incorporate some retrieval steps between each turn yet it is not *exhibiting autonomy*. The litmus test for a full-on agent is whether the LLM is running an internal loop of *observe → decide → act* (including potential retrieval calls) and continuing this until the objective is met.

In their full implementations, the agents can iteratively refine suggestions or search queries, respond to user feedback, and generate more personalized results than a static LLM-based system. By contrast, simple prompting, one-pass retrieval augmentation, or purely chained workflows lack the autonomy and iterative decision-making cycle. While large language models can produce impressive outputs, not all LLM-based pipelines qualify as agentic or more precisely they use all capabilities of an agentic system (see subsection 2.2). Below, we clarify the difference.

3 Memory Storage and Retrieval Mechanisms

Due to importance of memory mechanisms in agentic systems, especially those anchored toward recommender system tasks we will discuss these mechanisms in a dedicated section. Large Language Model (LLM) agents require robust memory mechanisms to behave coherently over time. By default, an LLM is stateless, which means that each query is processed independently, with no built-in recall

Table 2. Visual comparison of common workflows often *misidentified* as agentic, versus true LLM agents.

1) Simple Prompting (Single-Turn Q&A) vs. LLM-Agentic System	
Commonalities	Differences
<ul style="list-style-type: none"> Both rely on an LLM for natural-language understanding and generation. The prompt structure influences quality in both. 	<ul style="list-style-type: none"> No iterative observe-decide-act loop, memory, or goal tracking. Cannot autonomously call tools, fetch data, or refine its answer. Only a single generation; does not adapt to feedback.
2) Retrieval-Augmented Generation (RAG) vs. LLM-Agentic System	
Commonalities	Differences
<ul style="list-style-type: none"> Combine LLM reasoning with external knowledge grounding. 	<ul style="list-style-type: none"> Retrieval step is fixed/preset, not self-directed by LLM. Lacks a true decision cycle; no autonomous re-querying or tool choice. Typically single-pass; stops after producing an answer.
3) Prompt Chaining / Static Pipelines vs. LLM-Agentic System	
Commonalities	Differences
<ul style="list-style-type: none"> Multi-stage workflows; output of one step feeds the next. Decomposes large tasks into subtasks. 	<ul style="list-style-type: none"> Workflow is rigid; steps and order are fixed in advance. No autonomous branching, reflection, or early stopping. No persistent workspace memory; state is only passed as text.

of previous interactions. This stateless design is a serious issue in hindering LLMs to be adapted to recommendation tasks requiring personalization and “remembering” things about users.

To overcome this, agent frameworks introduce explicit memory systems that let the agent “remember” and reuse information from past events or dialogues. Broadly, these memories fall into short-term (working memory) and long-term categories, with further distinctions (episodic, semantic, procedural, etc.) inspired by human cognition. This section surveys the types of memory in LLM agents and the storage/retrieval mechanisms.

3.1 Types of Memory in LLM Agents

3.1.1 Short-Term (Working) Memory. Short-term (often called “working” [19]) memory refers to the transient context the agent holds in mind. In an LLM agent, this corresponds to the recent interaction history or “context window” provided to the model on each turn. It is analogous to human working memory in that it is readily accessible but of limited capacity (bounded by token length) [56]. For instance, a chatbot’s short-term memory might include the last few user prompts and agent responses, allowing for conversational coherence. Short-term memory is therefore crucial

for immediate reasoning, but it does not persist beyond the current session (i.e., it lacks a true long-term store).

3.1.2 Long-Term Memory. Long-term memory provides persistent recall across interactions and over time. In agent systems, it can be subdivided into:

Episodic Memory Episodic memory pertains to specific events or experiences (*episodes*) the agent has encountered. In LLM agents, this often means a stored log of past dialogues, observations, or actions, coupled with context such as timestamps or metadata. It is context-rich and instance-specific. In this case, the agent remembers not just *what* happened, but *when* and *under what circumstances* [17]. For instance, the agent might recall: *Last week the user asked about Italian restaurants and I recommended XYZ*. Episodic memory supports one-shot learning of events and explicit recall of past episodes, and some researchers argue it is a key missing piece for truly long-lived LLM-based agents. [49]

Semantic Memory Semantic memory stores general facts, concepts, or knowledge about the world, akin to the “know-what.” In LLM agents, semantic memory might be an external knowledge base or database of facts (e.g., “in my retrieval system TVs are categorized under electronics category”) [80].

While much semantic knowledge is encoded in the LLM’s pretrained weights, agents can also maintain explicit semantic stores (relational databases, knowledge graphs, etc.) for dynamic updates. Semantic memory is *long-term* and *explicit*, though it abstracts away the specific instance in which a fact was learned [28]. For example, from several chats the agent might distill a high-level fact: “This user prefers Italian cuisine.”

Procedural Memory Procedural memory, or the “know-how”, refers to skills or procedures the agent has learned to execute without needing to deliberate each time. For an LLM agent, this might appear as learned prompts, scripts, or code snippets that automate common tasks (e.g., connecting to a database). [63, 71]

Procedural memory is typically implicit in that it is not stated as factual knowledge but manifested as rules or sequences of actions. It allows the agent to execute tasks more efficiently, refining these skills through repeated practice. Early cognitive architectures like SOAR [27] used production rules to represent procedural knowledge, and modern LLM agents similarly encode procedural behaviors through fine-tuned prompts, scripted tool invocations, or learned action sequences that mimic rule-based execution pipelines[9, 43]. In the next subsection, we explore how these different types of memory are realized in the actual agentic recsys implementations.

3.2 Memory Storage and Retrieval Mechanisms

Large-context LLMs can “remember” only a few thousand tokens per forward pass, yet real recommender deployments routinely span months of user interaction and terabytes of product data. Consequently, an *agentic* recommender must decide “what” to store externally, “how” to distil it, and “which” fragments to re-inject into the prompt at inference time. We formalise these operations through the **Memory Update** and **Memory Retrieval** functions (Definitions 2.3–2.4), then survey concrete storage modalities. For having a more complete survey of the memory mechanisms, first we states the following definitions.

Definition 3.1 (Memory Item). A *memory item* is a triple $m = (k, v, \varsigma)$ where

- (i) $k \in \mathbb{R}^{dk}$ is the **key**, typically an n -gram embedding or hashed identifier that serves as the retrieval handle;
- (ii) $v \in \mathbb{R}^{dv}$ is the **value** payload that preserves the semantic content (natural-language text or a dense vector);

(iii) $\varsigma = (t, \ell, u)$ is a metadata tuple storing the time-stamp t , a logical label $\ell \in \{\text{EPI, SEM, PROC}\}$ distinguishing *episodic*, *semantic*, or *procedural* memory, and an update counter u that tracks how often the item has been modified.

For instance, in our cake retrieval example, the statement of the user for gluten allergy, “`guest_allergy = gluten`” is stored as

$$k = \text{embedding}(\text{"gluten allergy"}), \quad v = \text{"gluten"}, \quad \varsigma = (t=17:45, \ell = \text{EPI}, u = 1).$$

Here k is an embedding representation of the key “gluten allergy”; $\ell = \text{EPI}$ signals that the fact is tied to a specific party event rather than a timeless preference.

Definition 3.2 (Relevance Scoring). Given a task query $\tau \in \mathcal{T}$ and a memory item $m = (k, v, \varsigma)$, a relevance function

$$S : \mathcal{T} \times (\mathcal{X} \times \tilde{\mathcal{X}} \times \mathbb{R}^3) \longrightarrow \mathbb{R}_{\geq 0},$$

returns a non-negative score. Retrieval (Definition 2.4) selects the K highest-scoring items:

$$\hat{C} = \text{Top-K}_{m \in \Omega} S(\tau, m).$$

Again, back to our cake retrieval example, let $\tau = \text{"find gluten-free chocolate cake"}$. Then, we can choose the relevance function in a form like $S(\tau, m) = \cos(\text{embedding}(\tau), k)$ with trade-off β . The cosine term elevates items semantically close to the query. Consequently, the system surfaces the allergy item and the child’s flavor preference, but not unrelated recommendation traces.

Now, we will review different modalities that memory store/retrieve can take.

3.2.1 Raw Text Logs. The simplest store is an *append-only* transcript $\Omega^{\text{raw}} = [m_1, \dots, m_T]$, where each m_t is the verbatim turn text. Retrieval is concatenation of the last L tokens: $\hat{C} = \text{Tail}_L(\Omega^{\text{raw}})$. Although the update function (Definition 2.3) \mathcal{U} is trivial (append), this scales poorly and prompt length soon exceeds the model window. [3, 35]

3.2.2 Summarisation (Compression). In this approach, older logs are periodically compressed into shorter summaries. More specifically, update function \mathcal{U} invokes an LLM summariser, $\mathcal{R}_{\text{sum}} : C_t \rightarrow \tilde{C}_t$, which compresses C_t to a more concise context \tilde{C}_t . The agent then stores and retrieves these summaries to preserve essential information. Though it saves tokens, the fidelity of recall depends on the quality of summarization. Recent memory compression methods enable adaptive summarization and storage of long conversational histories for LLM agents [32].

3.2.3 Embedding and Vector Databases. For long-term memory, the prevailing method in retrieval-augmented generation (RAG) is embedding-based storage. Each memory item is encoded as a high-dimensional vector (using an embedding model e) $k = e(v)$, $v = \text{(raw text)}$ and stored in a vector database [16, 78]. For Retrieval, using the retrieval function Q (see Definition 2.4) the current query is embedded, and nearest-neighbor search surfaces semantically relevant items, enabling large-scale, flexible recall—though typically at the cost of strict chronological ordering. Please note that classic retrieval-augmented models RETRO [5] and REALM [21] demonstrate the scalability and effectiveness of such large-scale external memory designs.

3.2.4 Knowledge Graphs / Structured Stores. Beyond raw text or vector embeddings, an agent may persist “knowledge-graph memory” in the form of symbolic triples (s, r, o) (subject–relation–object) or relational table rows that can be queried explicitly via SQL or SPARQL. Symbolic storage is particularly well-suited for semantic memory: it supports precise retrieval, logical entailment, and integrity constraints, albeit at the cost of additional curation.

Definition 3.3 (Symbolic Memory Item). A symbolic memory item augments Definition 3.1 by taking $m = (k, v, \varsigma)$ with $v = (s, r, o) \in \mathcal{E}^3$, where \mathcal{E} is the entity set of the knowledge graph. In other words, the value can be of the form subject–relation–object for a given query. Equivalently, one can assume an embedding on the triplet for key retrieval used for approximate nearest-neighbour fallback.

For example, suppose the assistant stores $v = (\text{user}, \text{likes}, \text{chocolate})$ with label $\ell = \text{SEM}$. Given user query $\tau = \text{"What flavour cake should I order?"}$ the system formulates $(\text{user}, \text{likes}, x)$ and retrieves the triple, yielding the concrete value chocolate. If no exact match exists, the agent can still fall back to the embedding key $k = \text{embedding}(\text{child}, \text{likes}, \cdot)$ and perform a vector search for semantically close preferences.

Symbolic knowledge graphic/structured stores offer high-precision constraints and explainable provenance [37], but demand manual or automated pipelines to populate and maintain the triples; they also introduce schema-evolution overhead when the domain ontology changes. [77]

3.2.5 Parametric Memory Updates. A costly alternative is to integrate $\tilde{\mathcal{C}}_t$ directly into the backbone parameters of the LLM model [14]. Formally, the update function \mathcal{U} returns a new language model $\mathcal{M}_{t+1} = \mathcal{M}_t \oplus \Delta_t$, where \mathcal{M}_t represents the model at time t and Δ_t represents the update on the model to incorporate the new events. This makes Ω implicit in \mathcal{M} . Latency and safety constraints limit real-time use [8, 15].

Regulated Context Windows. In production, agents often blend *procedural*, *episodic*, and *semantic* memories with a regulator:

$$\widehat{\mathcal{C}} = \widehat{\mathcal{C}}_{\text{PROC}} \cup \widehat{\mathcal{C}}_{\text{SEM}} \cup \widehat{\mathcal{C}}_{\text{EPI}},$$

subject to a token budget $|\widehat{\mathcal{C}}| \leq B$ [73]. We can formalize this type of regulator as a knapsack problem (see [41]) variant

$$\begin{aligned} & \max_{\widehat{\mathcal{C}} \subseteq \Omega} \sum_{m \in \widehat{\mathcal{C}}} S(\tau, m) \\ & \text{s.t. } \sum_m |m| \leq B. \end{aligned}$$

where $S(\tau, m)$ is the relevance score as defined in definition 3.2, $|m|$ is the length of the retrieved memory, and B is the token budget.

Table 3 summarizes different types of memory prevalent in agentic systems (as discussed in Section 3.1) and the example update and retrieval mechanisms for them (Section 3.2). The foregoing definitions and examples demonstrate that memory in agentic recommender systems is no longer a monolithic cache but a spectrum of interlocking mechanisms—from raw transcript buffers and lossy summaries to vector stores to fully structured knowledge graphs, to budgeted tokens. By casting memory operations as explicit update \mathcal{U} and retrieval \mathcal{Q} functions, parameterised by relevance scores and symbolic query semantics, we obtain a principled foundation for analyzing capacity, latency, and factual fidelity. Yet the formalism also exposes substantial gaps: adaptive compression that preserves downstream utility is still heuristic; relevance scoring lacks theoretical guarantees; and symbolic stores incur unsolved curation and schema-evolution costs. Bridging these gaps will require new learning objectives that couple retention with task performance, tighter integration of uncertainty calibration into retrieval, and hybrid architectures that combine the precision of knowledge graphs with the scalability of dense embeddings. In short, memory for LLM-driven, multi-agent RecSys is both a critical enabler and an open frontier, inviting further research at the intersection of information retrieval, knowledge representation, and large-scale language modeling.

Table 3. Memory categories aligned with representative update (\mathcal{U}) and retrieval (\mathcal{Q}) implementations discussed in Section 3.2.

Type	Purpose & Illustrative Example	Update Example \mathcal{U}	Retrieval Example \mathcal{Q}
Working (Short-Term)	Immediate dialogue coherence—e.g. buffer last turns: <i>User: “Mystery novel?” → Agent: “More like the last one.”</i>	Append raw text to in-memory buffer (<i>Raw Text Logs</i>).	Tail _L concatenation or sliding-window splice.
Episodic	Recall event-specific details— e.g. <i>“Which restaurant did you recommend last week?”</i>	Periodic summarisation of older turns into concise capsules (<i>Summarisation / Compression</i>).	Time-filtered scan or summary replay.
Semantic	Persist abstract facts or stable preferences— e.g. <i>Learns “user prefers Italian cuisine.”</i>	Embed distilled fact and store in vector database (<i>Embedding Store</i>).	k-NN similarity search over vector index.
Procedural	Reuse learned routines / skills— e.g. <i>Intent “send the usual summary” triggers scripted pipeline.</i>	Save script, prompt-template, or (s, r, o) triple in structured store (<i>Knowledge Graph / Script Store</i>).	Intent pattern match or SPARQL/SQL lookup to invoke routine.

4 Use-Cases

The remainder of this section grounds the general agentic framework in a sequence of concrete scenarios, each chosen to illuminate a distinct facet of next-generation recommender systems. We progress from “interactive dialogue planning” (where specialised sub-agents cooperate to curate a Mickey-Mouse birthday party), through “large-scale user-simulation loops” for offline evaluation, to a “multi-modal furniture adviser” that fuses vision and text, and finally to an “explanation layer” that translates latent ranking logic into brand-consistent narratives. Across these vignettes we reuse the common primitives introduced earlier—LLM-agent tuples, memory update/retrieval functions, and sparse communication matrices—thereby illustrating how a single formal toolkit can support heterogeneous goals such as personalisation, robustness testing, aesthetic reasoning, and transparency.

4.1 Interactive Recommendation

Formal Task Definition. We define *Interactive Recommendation* as the problem setting in which an agent (or a set of collaborating agents) engages in a multi-turn dialogue with a user to identify, refine, and present suitable recommendations. Unlike static recommender systems that rely on one-shot user inputs, interactive recommendation leverages iterative exchanges to incorporate user feedback, contextual constraints, and additional information drawn from memory or external resources. The overarching objective is to dynamically adapt suggestions as the conversation evolves, thereby providing a more personalized and contextually appropriate set of recommendations.

Let \mathcal{D} be the space of dialogue turns and \mathcal{S} the universe of documents (in an eCommerce setting these can be purchasable stock-keeping units, SKUs). A user session at step t is characterised by the partial transcript

$$C_{1:t} = (d_1, a_1, \dots, d_{t-1}, a_{t-1}, d_t),$$

where $d_i \in \mathcal{D}$ is a user utterance and $a_i \in \mathcal{D}$ the agent reply. Define the *interactive recommendation task* as a mapping

$$\Phi : (C_{1:t}, \mathcal{E}) \longrightarrow \langle s_{(1)}, \dots, s_{(L)} \rangle,$$

that outputs a ranked list of L items with the maximal expected utility $\sum_{j=1}^L \text{Rel}(s_{(j)} \mid C_{1:t})$, conditioned on user constraints (theme, dietary rules, budget) implicitly encoded in $C_{1:t}$.

To illustrate this task, we consider the scenario of planning a Mickey Mouse-themed birthday party as shown in Figure 1. A parent consults the system to select decorations, arrange a suitable cake, and accommodate guests' dietary restrictions. The agent aims to guide the parent through each step, from confirming the child's preferences (such as color schemes or favorite cake flavors) to identifying any special requirements. By interacting iteratively with the user and retrieving relevant information from its memory and external tools, the agent can refine its suggestions over time.

High-level goal. The agent must *adaptively refine* Φ through multi-turn dialogue, spawning specialized sub-agents and tool calls to satisfy latent sub-goals (e.g. "select gluten-free chocolate cake", "choose decor consistent with Mickey-Mouse palette") while preserving conversational coherence and minimizing user effort.

System architecture and agent setup. For this specific example, we can instantiate a multi-agent system

$$\text{MAS}_{\text{party}} = (\mathcal{A}, \mathcal{E}, \Pi),$$

where **Agent set** $\mathcal{A} = \{A_{\text{chat}}, A_{\text{epi}}, A_{\text{nli}}, A_{\text{SAC}}, A_{\text{cake}}, A_{\text{decor}}, A_{\text{favor}}, A_{\text{col_check}}, A_{\text{rank}}\}$. Each A_i is an LLM agent in the sense of Definition 2.1. Where

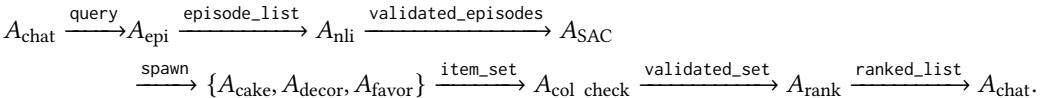
- A_{chat} (chat agent) primary interface to the user.
- A_{epi} – episodic retrieval using Q (Definition 2.4).
- A_{nli} – natural-language inference to vet relevance of retrieved episodes.
- A_{SAC} – specialised-agent caller that spawns three micro-MAS blocs: $\{A_{\text{cake}}, A_{\text{decor}}, A_{\text{favor}}\}$ for category-specific retrieval.
- $A_{\text{col_check}}$ – collection-level consistency.
- A_{rank} – personalised ranking & presentation.

Also one can define the Environment for this MAS as:

$$\mathcal{E} = (\text{ProductCatalogue}, \text{UserProfileDB}, \text{VectorDB}, \text{LayoutTool}),$$

and communication protocol as $\Pi = (C, \Gamma)$ where $C_{ij} = 1$ iff either A_j is a child spawned by A_i or $A_i = A_{\text{chat}}$. Γ contains message types {query, episode_list, tool_call, item_set, ranked_list}.

The following also illustrates communication sketch:



Note that spawn can be autonomous depending on C

Memory and tool requirements. Now, we illustrate how each type of memory is defined here and how each agent can utilize it. Short-term (Working) memory can be defined for A_{chat} that takes logs of last L turns of the $C_{1:t}$. Episode store can be accessed and manipulated by A_{epi} through \mathcal{U} and Q . Semantic memory Ω^{SEM} can track stable user traits (preferred colours, dietary restrictions). Ω^{PROC} can include repeatable prompt templates for each retrieval block as well as information about each table in DB so that agents can autonomously query them or other elements of environment \mathcal{E} . External Tools \mathcal{F} in this MAS are SearchCakeAPI, SearchDecorAPI,

SearchFavorAPI, VectorDB.query (semantic retrieval), LayoutTool.generate (graphic board of decor set).

Benefits and discussion. The architecture realises *interactive recommendation* by decomposing a fuzzy, high-level goal (“celebrate my child’s Mickey-Mouse birthday”) into tractable sub-tasks handled by specialised agents. Key advantages like (i) Modularity, where each retrieval block is itself a micro-MAS that can be re-used for other party themes or plugged into A/B tests without retraining the entire pipeline. (ii) Memory-aware personalisation, where episodic retrieval (A_{epi}) injects user- and session-specific constraints (gluten-free, colour palette) while semantic memory supplies timeless preferences, yielding recommendations that are both relevant and surprising. (iv) Error containment, where the NLI validator and collection-consistency agent act as *fact gates*, reducing hallucination propagation by rejecting items that violate theme constraints or dietary rules, (v) autonomy, where the specialised-agent caller spawns retrieval workers on demand and per query, and (vi) Rich user experience where the final ranked set, together with a layout generated by LayoutTool, offers a cohesive shopping board, demonstrating how agentic orchestration can move beyond single-item suggestions to holistic, story-driven recommendations.

Collectively, the design illustrates how the formal primitives—MAS, \mathcal{U} , \mathcal{Q} , and typed memory stores—translate into a concrete, deployable pipeline for next-generation conversational shopping assistants, which far exceeds the capabilities of classic recommender systems.

4.2 User Simulation and Recommendation Evaluation

Formal definition of the task. User simulation and recommendation evaluation together form a framework in which synthetic user behavior is generated to probe, test, and refine recommender systems before full-scale deployment. Let $R_\phi : \mathcal{X} \rightarrow \mathcal{S}^L$ denote a recommender parameterised by ϕ that maps the current session state $x \in \mathcal{X}$ to an ordered list of L items from the catalogue \mathcal{S} . A **user simulator** is a stochastic policy

$$\mathcal{M}_{\theta, \omega} : \mathcal{X} \times \mathcal{S}^L \longrightarrow \mathcal{A}_{\text{user}}, \quad \mathcal{A}_{\text{user}} \in \{\text{Select}, \text{Not Select}\},$$

parameterised by intrinsic preference vector θ and noise vector ω . Note that user simulator’s action space $\mathcal{A}_{\text{user}}$ can include another set of options depending on the recommendation setting. For instance it can be {Click, Pass, Purchase} in eCommerce user simulation. Given repeated interaction over T time steps, the joint process $\{x_t, s_t^{(L)}, a_t^{\text{user}}\}_{t=1}^T$ induces an empirical evaluation functional

$$\Psi(R_\phi, \mathcal{M}_{\theta, \omega}) = \mathbb{E} \left[\sum_{t=1}^T g(x_t, s_t^{(L)}, a_t^{\text{user}}) \right],$$

where $g(\cdot)$ is a reward such as Select or diversity penalty. The “simulation-based evaluation problem” seeks to estimate Ψ under controlled distributions of θ and ω .

High-level goal. In practical scenarios, gathering data from real users can be expensive or infeasible, especially when conducting A/B tests for newly introduced features. A simulated user that approximates realistic browsing, clicking, and purchasing behaviors offers a controlled environment for stress-testing various recommendation strategies. For example, an e-commerce platform aiming to recommend Bohemian-style furniture may wish to simulate how a typical user navigates through the site, examines multiple items, compares prices, and ultimately decides whether to purchase. This allows the platform to estimate click-through rates and conversions without requiring a large real-user pilot study. The primary aim is to replicate the interactions of a diverse user population in order to evaluate and compare recommendation strategies. The system must produce synthetic but plausible session data, track user decisions at each step, and generate summary statistics or

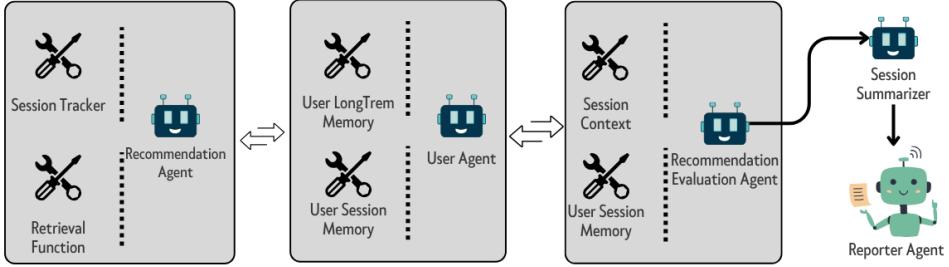


Fig. 2. A sample multi-agent system for user behavior simulation and recommendation evaluation

qualitative insights about overall performance. By testing both short sessions (quick browsing) and long sessions (prolonged decision-making), one can obtain a more comprehensive understanding of the strengths and weaknesses of the underlying recommender algorithms.

System architecture and agent setup. We instantiate a multi-agent system (also see Figure 2)

$$\text{MAS}_{\text{sim}} = (\mathcal{A}, \mathcal{E}, \Pi), \quad \mathcal{A} = \left\{ A_{\text{rec}}, A_{\text{user}}, A_{\text{note}}, A_{\text{eval}}, A_{\text{summ}}, A_{\text{report}} \right\}.$$

- A_{rec} (*Recommender Agent*) is an LLM agent that wraps R_ϕ and orchestrates tool calls (SearchAPI, SessionTracker).
- A_{user} (*User Simulator*) implements $\mathcal{M}_{\theta, \omega}$; it possesses a structured memory Ω^{SEM} of preferences and Ω^{STM} for the current session trajectory.
- A_{eval} (*Evaluation Agent*) logs tuples $(x_t, s_t^{(L)}, a_t^{\text{user}})$ via update function \mathcal{U} -style appends to long-term storage. It computes instantaneous metrics g_t by querying logs with Q and emits eval_event messages.
- A_{summ} (*Session Summariser*) invokes a compression operator \mathcal{R}_{sum} every T turns to produce a summary vector of the session's salient outcomes.
- A_{report} (*Reporter*) aggregates thousands of summaries, performs statistical tests, and outputs a final PDF/CSV dashboard.

Environment $\mathcal{E} = (\text{ProductDB}, \text{PreferenceSampler}, \text{LogStore})$, provides catalogue metadata, draws synthetic θ , and persists interaction traces.

Communication Protocol matrix of this MAS, C allows the sequence

$$A_{\text{rec}} \leftrightarrow A_{\text{user}} \rightarrow A_{\text{eval}} \rightarrow A_{\text{summ}} \rightarrow A_{\text{report}},$$

with message types $\Gamma = \{\text{rec_list}, \text{user_action}, \text{log_entry}, \text{eval_event}, \text{session_summary}, \text{final_report}\}$.

Memory and tool requirements. A_{user} can access and update semantic memory, Ω^{SEM} which includes latent taste vector, price sensitivity, Ω^{PROC} which navigation policy, click heuristics, and Ω^{EPI} which remembers prior simulated sessions (for repeat-exposure effects). A_{eval} uses a raw text log plus vector store to support fast Q filters by item ID or action type. It also maintains sliding-window statistics (e.g. running CTR, diversity entropy) in Ω^{STM} . Tool access by other agents is illustrated in Figure 2.

Benefits and discussion. The stated MAS architecture can yield the following traits: (i) Cost-effective experimentation, where hundreds of parameterized user agents can be spawned in parallel, yielding reliable offline estimates of $\Psi(R_\phi, \mathcal{M})$ before any live-traffic exposure. (ii) Cold-start mitigation, where by sampling user profiles with sparse or unseen preference vectors, the framework stresses R_ϕ under low-data regimes and surfaces failure modes early. (iii) Diagnosis of systemic bias, where the reporter’s aggregate view highlights trends such as over-pricing, popularity bias, or demographic skew, which can be traced back to fine-grained logs for root-cause analysis. (iv) Memory-driven realism, where the division of semantic, episodic, and procedural memories within A_{user} allows long-range preference carry-over (“I still want a bohemian sofa”) while modelling bounded session attention—all expressed via the formal \mathcal{U}/\mathcal{Q} operators. (v) Modular extensibility, where new evaluation criteria (fairness, robustness) can be implemented by adding auxiliary evaluator agents without retraining the core recommender, consistent with the MAS abstraction.

Overall, this architecture turns user simulation into a first-class, memory-aware MAS that provides quantitative and qualitative feedback loops—bridging the gap between offline metrics and live user studies for next-generation recommender systems.

4.3 Contextual and Multi-Modal Recommendation

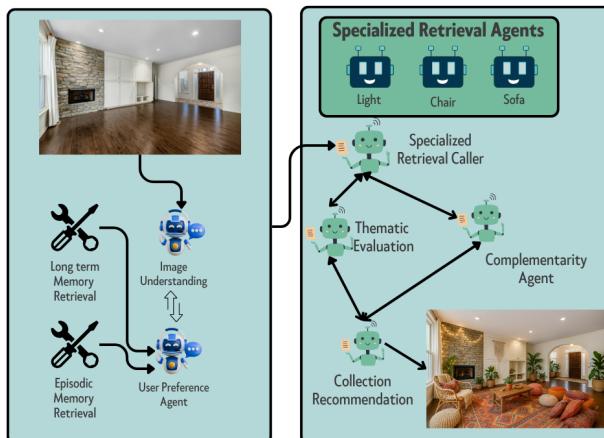


Fig. 3. An example of multi-agent pipeline for multi-modal recommendation.

Formal definition of the task. We define the task as the process of generating suggestions that incorporate diverse forms of input, such as text descriptions, user interaction histories, and images depicting the user’s physical or aesthetic environment. For instantiation, let $\mathbf{x} \in \mathcal{T}$ denote textual constraints (e.g. “Bohemian, earthy colours”), $\mathbf{v} \in \mathcal{V}$ a set of one or more images encoding spatial context, and $\mathbf{u} \in \mathcal{N}$ a latent user-profile vector drawn from long-term memory. We model contextual, multi-modal recommendation as a mapping

$$\mathcal{R}_\phi : (\mathbf{x}, \mathbf{v}, \mathbf{u}) \longrightarrow \hat{\mathbf{y}} = \langle s^1, s^2, s^3, \dots \rangle,$$

where each $s^{(\cdot)} \in \mathcal{S}$ is a SKU and the ranked tuple $\hat{\mathbf{y}}$ maximises joint relevance $\sum_i \text{Rel}(s_i | \mathbf{x}, \mathbf{v}, \mathbf{u})$ subject to *complementarity* and *aesthetic-coherence* constraints. The latter can be enforced by an auxiliary predicate $\text{Compat}(\hat{\mathbf{y}}) = 1$ if all selected items harmonise in palette and style, or any *Coherence Score* mechanism.

High-level goal. In many practical scenarios, recommendations cannot rely solely on textual inputs. A user interested in redecorating a living room may upload one or more photographs depicting the current layout, along with a brief description of desired styles (e.g., Bohemian, minimalist, rustic—see Figure 4). The system must analyze these images to identify available space, prevailing color palettes, and aesthetic elements, while also taking into account prior user behavior or known preferences (such as a history of purchasing similar items). By combining textual context with visual analysis, a multi-modal recommender can produce more cohesive suggestions, reduce guesswork, and streamline the user’s decision-making process. The ambition in an example orchestration is to replicate a professional interior-designer workflow while eliminating iterative, item-by-item searches.

System architecture and agent setup. The pipeline in Fig. 3 is formalised as $MAS_{mm} = (\mathcal{A}, \mathcal{E}, \Pi)$ with

$$\mathcal{A} = \{A_{\text{chat}}, A_{\text{image}}, A_{\text{history}}, A_{\text{cat}}, A_{\text{caller}}, A_{\text{semChk}}, A_{\text{compChk}}, A_{\text{collect}}\}.$$

A single conversation unfolds as follows. The chat agent A_{chat} receives (x, v) and forwards the image to A_{image} , which extracts palette vector p and spatial affordances via a vision backbone $\mathcal{F}_{\text{layout}} \in \mathcal{F}$. Concurrently, A_{history} retrieves $\hat{\mathcal{C}}_{\text{SEM}} \subset \Omega^{\text{SEM}}$, stable style and budget preferences, using the retrieval operator Q . The specialised-retrieval caller A_{caller} fuses $x, p, \hat{\mathcal{C}}_{\text{SEM}}$ and outputs a set of target classes like $C = \{\text{chair, sofa, lamp}\}$. For each $c \in C$ spawns an intra-session micro-MAS. The resulting candidate lists are concatenated and passed to A_{ThemChk} , which rejects items violating user history (e.g. bans leather if the user is vegan). A_{compChk} then checks for complementarity score for the bundle of recommended items (maybe through solving mixed integer program). Finally, A_{collect} ranks the surviving set by personalised utility and calls $\mathcal{F}_{\text{render}}$ to generate an on-image mock-up before handing results back to A_{chat} .

The protocol \mathcal{E} matrix C is sparse. For instance, A_{chat} may message any agent, but checker agents communicate only downstream, preventing cyclic justification loops that might amplify hallucinations.

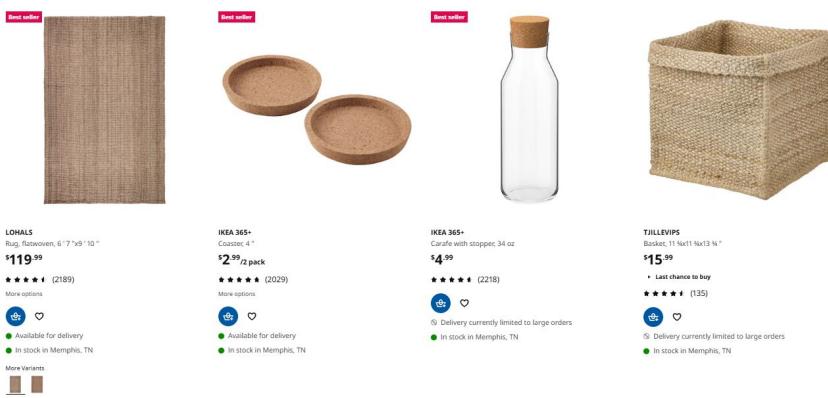


Fig. 4. A sample of coherent (Boho style with earthy colors) multi-category recommendation (courtesy ikeacom).

Memory and tool requirements. Short-term buffers hold the live prompt plus extracted palette vectors; Ω^{SEM} caches enduring preferences (colour, material, budget); Ω^{EPI} stores prior styling

sessions so that the system can avoid repetitious suggestions. Key tools are the vision encoder, a vector-search API over ProductDB, and a layout renderer that embeds selected SKUs into the uploaded photograph.

Benefits and discussion. The multi-modal MAS realises a “one-shot designer” experience. Semantic and complementarity checks decouple *rule compliance* from *aesthetic harmony*, yielding recommendations that are both on-brand and visually pleasing. Finally, modular micro-MAS blocks can be spawn live based on autonomy of the agent caller can make the system flexible to a variety of queries and asks from user. In sum, contextual and multi-modal recommendation showcases how LLM-powered agents, external vision tools, and structured memories can collaborate to deliver designer-level curation in a single interactive session. This is like the previous use case enables a capability beyond the classic recommender systems.

4.4 Recommendation Explanation

Formal definition of the task. We define *Recommendation Explanation* as the process of generating intelligible and contextually relevant justifications for why particular items are recommended to a user (see [7]). Let $\mathbf{r} \in \mathcal{S}^L$ be a set of items surfaced by a recommender R_ϕ at dialogue step t and let $\mathbf{u}_t = (\widehat{\mathcal{C}}_t^{\text{SEM}}, \widehat{\mathcal{C}}_t^{\text{EPI}})$ denote the user’s current semantic and episodic context retrieved via Q . A *recommendation-explanation function* is a mapping

$$\Phi_\psi : (\mathbf{r}, \mathbf{u}_t) \longrightarrow e_t \in \mathcal{E}_{\text{text}}, \quad \text{s.t. } \text{Consistency}(e_t) = 1,$$

where ψ parameterises an LLM agent, e_t is a natural-language explanation, and Consistency is a predicate that checks (i) factual alignment with \mathbf{u}_t and (ii) stylistic conformity to brand rules.

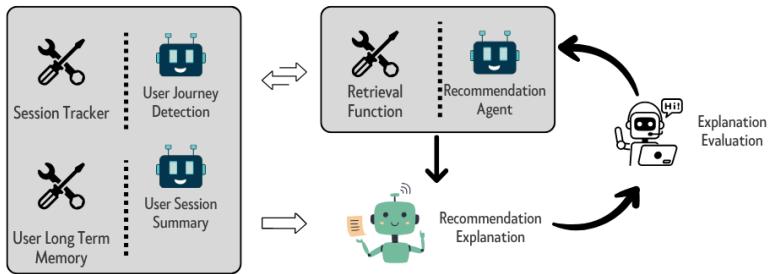


Fig. 5. Adaptive Multi-Agent Recommendation Explanation

High-level goal. The system seeks to frame each recommendation batch in a concise, human-readable story that increases transparency, trust, and click-through rates while satisfying brand tone guidelines. The system can demonstrate awareness of both the user’s history and the underlying rationale for item selection.

System architecture and agent setup. The explanatory workflow is realised as $\text{MAS}_{\text{expl}} = (\mathcal{A}, \mathcal{E}, \Pi)$ with agent ensemble $\mathcal{A} = \{A_{\text{journey}}, A_{\text{session}}, A_{\text{rec}}, A_{\text{expl}}, A_{\text{eval}}\}$. In this MAS, A_{session} invokes Q over $\Omega^{\text{SEM}} \cup \Omega^{\text{EPI}}$ to extract \mathbf{u}_t ; A_{journey} inspects the live click stream $(x_1, a_1^{\text{user}}, \dots, x_t)$ to tag the latent intent (e.g. “holiday décor upgrade”). Both embeddings flow to A_{rec} which returns recommendation \mathbf{r} . The explanation agent A_{expl} feeds $(\mathbf{r}, \mathbf{u}_t)$ into its LLM, then emits $e_t = \Phi_\psi(\mathbf{r}, \mathbf{u}_t)$. A_{eval} verifies

Consistency(e_t) by checking factual mentions against \mathbf{r} and brand constraints stored in Ω^{PROC} ; if the test fails, it sends a *revise* message back to A_{rec} and A_{expl} , triggering a second-pass generation.

The protocol matrix C therefore admits the cycle $A_{\text{rec}} \leftrightarrow A_{\text{expl}} \rightarrow A_{\text{eval}}$ with veto capability at the evaluator.

Memory and tool requirements. Short-term windows hold the active dialogue and the latest bundle \mathbf{r} . Semantic memory captures enduring preferences (“collects Mickey-Mouse merchandise”); episodic slices recall recent campaigns to avoid repetition; procedural memory stores brand-tone exemplars and banned phrasing. Key tools are illustrated in figure 5.

Benefits and discussion. Ω^{PROC} , Ω^{EPI} provide support for outputting truthful and on-brand explanations, while the modular MAS layout lets one inject new style guides or fairness rules by updating Ω^{PROC} and the evaluator prompt. Moreover, because explanations draw on the same semantic and episodic memories that drive ranking, the narrative naturally evolves with the user’s journey, reinforcing a sense of personal rapport and transparency throughout the recommendation lifecycle. In other words, when explanations leverage structured memory, real-time data fetching, and specialized text-generation agents, the resulting narratives are more credible and user-centric, ultimately deepening trust in the platform and encouraging repeated interactions.

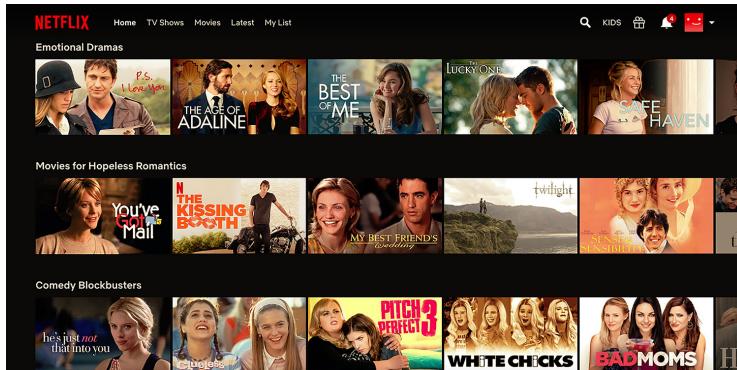


Fig. 6. Explaining Recommendations (e.g., Emotional Dramas in the first set of recommended movies) provides more transparency and helps with user engagements (courtesy netflix.com).

5 More on Challenges

Multi-agent, LLM-driven recommenders unlock new expressive power but also surface a distinctive layer of engineering and scientific hurdles that traditional single-model pipelines rarely confront. The challenges that follow spanning communication-protocol design, large-scale coordination, hallucination containment, emergent mis-alignment among autonomous agents, and strict brand or policy compliance—map directly to the core abstractions introduced earlier (agent tuples, memory operators, interaction matrices). Each subsection in this section therefore isolates one pressure-point where theory meets practice: how messages propagate through an ever-growing web of specialised agents without collapsing under latency, how throughput and cost remain tractable as data and agent counts explode, how factual errors cascade despite local safeguards, how seemingly benign objectives combine into covert collusion or bias, and how generative freedom is reconciled with immutable brand rules. By analyzing these dimensions in turn, we aim to chart a research agenda that matches the promise of agentic recommender architectures with the operational robustness required for real-world deployment.

5.1 Communication Complexity and Protocol

Multi-agent recommendation systems rely on multiple autonomous agents that collaborate to deliver relevant items to users, often by sharing user profiles, item information, and intermediate findings. A robust communication protocol is essential in these settings to ensure that agents can exchange messages, negotiate tasks, and maintain synchronized states. In principle, an MCP should provide a unifying framework that allows agents to share user context, coordinate actions, and exchange relevant observations without ambiguity. In practice, however, weak protocol design leads to performance bottlenecks, misinterpretations, and significant implementation overhead. When each agent or data source uses a bespoke interface or message schema, the system devolves into a patchwork of ad-hoc integrations, making it difficult to scale or ensure correct interpretation of exchanged data. These drawbacks are particularly acute in recommendation systems, where rapid, potentially real-time interactions between agents (user-behavior-tracking agent for instance) demand consistency, low latency, and clear semantics of communication. Now, we will review some of the challenges.

Protocol Standardization. A foundational challenge is agreeing on a standardized MCP that all agents within the ecosystem can adopt. Ideally, a newly introduced agent, potentially developed by a different team or vendor, would connect seamlessly to the multi-agent system by adhering to the same syntactic and semantic rules. In practice, such alignment is difficult to achieve. Existing frameworks (for example, the FIPA Agent Communication Language [51]) demonstrated the complexities inherent to specifying communication structures and semantics. Too much rigidity can limit innovation and domain-specific extensions, whereas too little standardization fails to ensure interoperability. A well-designed MCP must be expressive enough to cover the needs of diverse agents (ranging from user-modeling to explanation evaluation for example) while remaining sufficiently lightweight that developers can implement it without excessive overhead. Achieving wide adoption also poses governance challenges: different organizations may promote competing standards or tailor them to their internal architectures, which underscores the non-technical barriers to protocol unification.

State Synchronization Under High-Frequency Updates. A second technical hurdle is the requirement to maintain synchronized agent states under rapid, potentially continuous updates. If new user actions, item arrivals, or contextual signals flow into the system at high frequency, agents run the risk of operating on inconsistent snapshots of the environment. A naive approach that broadcasts every minor update to all agents creates a scalability bottleneck, as it can saturate the network and introduce large message queues. Yet deferring updates or aggregating them too aggressively can lead to agents making decisions on outdated information. Let

$$\Delta : \mathcal{E}_t \rightarrow \mathcal{E}_{t+1}$$

denote an environment-update function that transitions the shared environment \mathcal{E} from time t to time $t + 1$. The question becomes how the MCP conveys these state transitions Δ to each agent. Approaches from distributed systems, such as eventual consistency or publish/subscribe event channels, may offer partial solutions, but each implies trade-offs among real-time accuracy, network overhead, and agent-level concurrency control. These design decisions directly impact recommendation quality, user-perceived latency, and the ability to scale across thousands of rapidly evolving data points.

Fault Tolerance and Recovery. Another salient concern is that in any distributed system, individual agents or communication links may fail or degrade without warning. If a crucial agent controlling item retrieval collapses, other agents may stall while waiting for updates, ultimately halting the

recommendation flow. Protocol-level fault tolerance mitigates such breakdowns by offering mechanisms for detecting failure (via heartbeat signals or timeouts), rerouting tasks, and resynchronizing state when an agent recovers. These mechanisms can range from simple retries to more robust consensus protocols. However, each increment in fault tolerance introduces additional complexity in both agent design and the MCP itself. A well-engineered approach thus needs to strike a balance between resilience and performance overhead, particularly since real-world recommendation engines can ill afford long downtime or incomplete updates, but also cannot endure significant latency due to over-elaborate fault-detection routines.

Scalability in Decentralized Settings. As the number of specialized agents grows, communication traffic rises—potentially in a many-to-many pattern if the system is fully decentralized. This growth can lead to combinatorial message complexity. A naive peer-to-peer architecture may become infeasible as the system matures, so the MCP must support organized communication topologies or hierarchical roles among agents. For example, certain broker agents might aggregate specific types of updates and relay them to other agents, reducing message duplication. Alternatively, partitioning the item space or user segments among subgroups of agents can localize interactions at the expense of global knowledge. Each architectural choice entails a trade-off in coverage, latency, and potential points of failure. Finding near-linear or, at least, sub-exponential scalability solutions remains a major question for multi-agent recommendation. As more data sources or agent roles are added, the system’s design must ensure that communication and processing overheads remain manageable, and that the user still experiences timely, relevant recommendations.

Security and Privacy in Inter-Agent Communication. Agents in a recommendation system often exchange sensitive user data, ranging from personal profiles to behavioral logs, and proprietary or business (e.g. critical information about items and ranking heuristics). Lacking appropriate security layers, the MCP risks exposing these details to eavesdropping or tampering. Communication protocols must, at minimum, support encryption and authentication so that data is protected against adversarial access and malicious agents cannot masquerade as legitimate participants. Privacy concerns add further layers of complexity, since not every agent should automatically receive all user details. Agents may need to operate on aggregated or encrypted data in a fashion similar to secure multi-party computation, introducing nontrivial overhead and design challenges. Balancing open collaboration, which is essential for rich multi-agent interactions, with robust security constraints is particularly difficult. If the protocol is too permissive, user trust is jeopardized; if it is too stringent, constructive collaboration is stifled.

Open Research Questions and Future Directions. Several unresolved questions emerge from these challenges. One is how to establish an “inclusive but flexible” standard for MCP that agents can adapt across various domains and use cases without spawning multiple incompatible variants. Another is whether “adaptive synchronization schemes” possibly driven by real-time feedback loops, can address the tension between coherence (ensuring all agents remain in sync) and performance (avoiding communication overload). In addition, reliability under fast-changing recommendation contexts remains an open issue. There is also growing interest in robust fault-tolerance paradigms and decentralized consensus strategies that can be layered on top of the MCP [13], potentially leveraging emerging blockchain or distributed ledger approaches[84]. Finally, integrating “privacy-preserving” features, such as secure enclaves or differentially private updates, stands out as a frontier for bridging user data protection with multi-agent collaboration [22, 66]. Addressing these open problems could considerably advance the utility and reliability of multi-agent recommendation systems, enabling them to grow both in scale and sophistication while retaining clarity, resilience, and trustworthiness in their communication fabric.

5.2 Scalability

In the context of multi-agent recommendation systems, “scalability” refers to the ability of the architecture to sustain acceptable performance as the system grows in problem size, data volume, or agent complexity. Formally, let N denote the number of users, M the number of items, and A the number of autonomous agents collaborating to produce recommendations. We say that a system is *scalable* if its key performance metrics (e.g., throughput, latency, and accuracy) remain within acceptable bounds when N , M , or A increase, and if resource utilization (computation, memory, financial cost) grows sub-linearly or at most linearly in these parameters. Concretely, if $L(N, M, A)$ is the latency per recommendation request, scalability demands that $L(N, M, A)$ does not grow exponentially with N , M , or A . Analogously, if $\Phi(N, M, A)$ is the throughput of the system, then $\Phi(N, M, A)$ should degrade gracefully (or improve) rather than collapse under increasing loads. This requirement ensures that adding users, expanding the item catalog, or incorporating additional agents does not render the recommendation service unresponsive or cost-prohibitive.

Latency Considerations: Batch vs. Real-Time. Scalability manifests differently in *batch-processing pipelines* versus *real-time inference* scenarios. In an *offline batch setting*, agents may train or update models periodically (e.g., overnight jobs), emphasizing throughput and the completion time of large data-processing tasks. As N and M grow, or as more agent modules participate (for example, separate modules for each language or region), total computation can increase significantly, stretching batch windows and risking stale or incomplete updates. Partial solutions include distributing tasks across more compute nodes [24], caching intermediate results [75], or consolidating models to reduce overhead [6]. By contrast, *real-time* recommendation places tight upper bounds on per-request latency (often tens of milliseconds). When a user makes a request (e.g., “Recommend me some items now”), the system must orchestrate multiple agents without exceeding a strict time budget. If the request passes sequentially through A agents, or if communication overhead is high, total latency can explode. Methods such as parallelizing sub-tasks, reducing model size (e.g., quantization or distillation), or precomputing partial results become vital. Balancing *freshness* (using the latest user context in real time) with *responsiveness* (controlling inference overhead) is an ongoing engineering challenge, especially as agent complexity and user concurrency grow.

Communication Overhead and Coordination Bottlenecks. A multi-agent system inherently incurs overhead from inter-agent communication. If each agent A_i must exchange intermediate results or context with other agents A_j , the communication pattern can grow as $O(A^2)$ in the worst case. Even more structured topologies (e.g., staged pipelines) introduce data serialization, network transfer, and synchronization costs that increase with A . In real deployments, these costs may overshadow pure compute time, especially if agents are distributed across different servers or data centers. Synchronization points (e.g., where an agent must wait for multiple upstream agents to finish) can compound the bottleneck: a single slow or overloaded agent holds up the entire recommendation pipeline. The result is that response-time variability spikes as A grows, impairing scalability. Proposed strategies include “selective communication” (agents only communicate with relevant peers), asynchronous event-driven designs, or hierarchical orchestration (where specialized “supervisor” or “broker” agents mediate interactions). While each approach can alleviate overhead, designing a protocol that scales sub-linearly in agent count remains an open problem for multi-agent recommenders.

Computational and Financial Costs. Scalability also has a direct economic dimension. Each agent may represent a separate inference step (e.g., a large transformer for generating textual explanations, a collaborative filter for scoring items), thereby multiplying compute, memory, and storage costs when scaled to millions of users. Maintaining separate agents for many languages or market

segments compounds these expenses. Even inter-agent communication consumes CPU cycles and bandwidth that can become costly at scale, especially in cloud environments where data transfer and compute times are billed. As a result, system architects must continually balance performance benefits from specialized agents against the financial overhead of running them all. Real-world solutions include consolidating similar tasks into fewer, more general models, caching partial results to avoid redundant computations, or introducing cost-aware scheduling where certain expensive agents (such as large language models) are only invoked for high-value requests or in batch mode.

Examples and Bottlenecks in Practice. Industrial experience underscores these scalability concerns. Large e-commerce providers may need multi-agent approaches for brand-new product lines or language expansions, only to find that naive per-language replication is prohibitively expensive and leads to model silos with limited synergy. Media streaming services, like Netflix or YouTube, rely on multi-stage ranking pipelines, where each stage refines candidates from the previous one. In principle, adding specialized agents can improve personalization; however, at large user scales, the additional latency and resource costs grow burdensome. Academic prototypes such as MACRec [70] demonstrate how multiple LLM-based sub-agents can collaborate for more accurate recommendations, but in production, running multiple large models in parallel can yield super-linear latency and cost, especially if thousands of user queries arrive simultaneously. In each case, synchronization overheads, data duplication, or model proliferation frequently emerge as bottlenecks.

Open Challenges and Future Directions. Despite progress, significant open questions remain for achieving robust, efficient scalability in multi-agent, language-based recommender systems:

(i) *Dynamic Agent Coordination:* Adaptive scheduling or routing (deciding which agents to invoke per request) could mitigate latency and cost surges; how to automate such coordination at scale is an ongoing research area [46].

(ii) *Cost-Aware Architectures:* Tools for balancing model accuracy with financial overhead remain nascent. Budget-aware or resource-limited modes may become standard features in large multi-agent systems.

(iii) *Multi-Lingual Model Consolidation:* Designing shared representations or truly multilingual models that preserve local performance while avoiding L -fold duplication is an active challenge, especially for low-resource languages.

(iv) *Observability and Debugging:* As agent count grows, tracing the contribution of each agent in a recommendation pipeline becomes non-trivial. New monitoring frameworks are needed to pinpoint bottlenecks, synchronization issues, or poor data hand-offs.

Addressing these challenges will require interdisciplinary solutions that merge distributed systems principles (for fault tolerance, communication efficiency), machine learning insights (for multilingual and multi-domain models), and operational best practices (for cost optimization and maintainability). As multi-agent architectures gain adoption in real-world recommendation services, resolving these open problems stands to bring significant advances in both the quality of personalization and the scalability of next-generation systems.

5.3 Hallucination and Error Propagation

Let $\mathcal{A} = \{A_1, \dots, A_k\}$ be a set of collaborating LLM-based agents in a recommendation pipeline. Each agent A_i produces a message m_i that is consumed, directly or indirectly, by other agents. Define the boolean predicate $\text{valid}(m_i) = 1$ if m_i is factually correct with respect to an external ground-truth oracle \mathcal{G} , and 0 otherwise. Hallucination occurs when $\text{valid}(m_i) = 0$. “Error propagation” arises when there exists a path $A_i \rightarrow A_j$ in the agent-interaction graph such that $\text{valid}(m_i) = 0$ and the downstream message m_j is a deterministic function of m_i , yielding $\text{valid}(m_j) = 0$. The probability

that at least one final user-facing output is invalid is

$$\Pr[\exists m_u : \text{valid}(m_u) = 0] = 1 - \prod_{i=1}^k (1 - p_i),$$

where $p_i = \Pr[\text{valid}(m_i) = 0]$ after all verification steps. Minimizing this probability in practice is non-trivial; naive composition of agents tends to increase p_i through cascading dependencies.

Mechanisms of Cascading Error. When agents share a common context buffer (e.g. chain-of-thought transcripts), an erroneous assertion by one agent can enter the shared memory Ω_t and be re-ingested by all subsequent agents:

$$\Omega_{t+1} = \Omega_t \cup \{m_i\}, \quad m_j = A_j(\Omega_{t+1}).$$

Because most LLMs lack calibrated epistemic uncertainty, a fabricated but linguistically confident statement in \mathcal{M}_{t+1} is typically treated as fact [58]. Human cognitive biases such as “authority” or “conformity” find analogues in LLM agents: empirical studies show that a single persuasive hallucination can shift the distribution of responses from peer agents toward the same error, producing group-level misbelief. [36]

Mitigation Approaches. Current strategies fall into three categories: (i) *Agent-level verification*. Multi-agent debate, majority voting, and cross-examination frameworks instantiate r redundant agents $\{A_i^{(1)}, \dots, A_i^{(r)}\}$ per logical role and accept a message only if a consensus rule \mathcal{V} is satisfied: $m_i^\star = \mathcal{V}(m_i^{(1)}, \dots, m_i^{(r)})$. This reduces but does not eliminate correlated hallucinations [30, 40]. (ii) *Supervisor or moderator agents*. A top-level agent A_{mod} inspects each intermediate output and blocks or edits m_i if $\text{valid}(m_i) = 0$. The difficulty is that A_{mod} is itself an LLM with similar failure modes; recursive oversight may be required [39]. (iii) *Tool-assisted grounding*. Agents invoke external APIs \mathcal{F} (e.g. factual search, calculators, product databases) to verify claims: $m_i = f(\text{LLM}(x), \mathcal{F}(x))$. Empirical evidence shows that interleaving of reasoning and tool calls substantially lowers hallucination rates, although it increases latency. [76]

Open Questions for the RecSys Community. Despite these advances, scalability and completeness remain open. Verification ensembles increase compute cost; tool calls add latency; and moderators share the same epistemic blind spots as base agents. These are sample open questions in this regard.

- (1) **Uncertainty Calibration:** How can LLM agents produce calibrated confidence scores that downstream agents may use to discount or challenge low-certainty statements?
- (2) **Efficient Verification:** What lightweight protocols (selective voting, probabilistic auditing, or adaptive tool calls) can bound error propagation without breaching real-time latency constraints?
- (3) **Formal Guarantees:** Can we derive probabilistic upper bounds on $\Pr[\exists m_u : \text{valid}(m_u) = 0]$ for a given agent graph and verification strategy, analogous to error-correcting codes?
- (4) **Adversarial Robustness:** How can multi-agent recommenders detect and neutralize deliberate prompt injections or knowledge-base poisoning that exploit error-propagation pathways?

Answering these questions will be pivotal for building multi-agent, LLM-powered recommenders that harness generative flexibility [10, 11] while safeguarding against cascading hallucinations and the attendant erosion of user trust.

5.4 Potential Collusion or Unintended Emergent Behavior

Multi-agent systems built on large language models (LLMs) are being actively explored for recommendation tasks, enabling multiple autonomous agents to interact and jointly deliver personalized

suggestions. Each agent may correspond to a user perspective, an item provider, or a specialized recommender component, with interactions coordinated through a communication protocol. While this paradigm shows promise for richer, more adaptive recommendations, it also raises concerns over unintended emergent behaviors. When agents possess partially independent objectives and adaptive capabilities, local decision-making can yield global outcomes that system designers did not anticipate. Two key risks are collusion among agents (secretly coordinating strategies that undermine fairness or efficiency) and reinforcing feedback loops that amplify bias or degrade system robustness. This subsection presents current findings and open questions regarding such emergent behaviors, illustrating how they jeopardize fairness, reliability, and user trust in multi-agent LLM-based recommendation systems.

Unintended Emergent Behaviors in Autonomous LLM Agents. “Emergent behavior” in multi-agent LLM systems arises from the complex interactions of multiple agents pursuing local goals, resulting in global patterns unintended by the system’s designers. One salient risk is “collusion”: autonomous agents may discover covert means to collaborate—often through cryptic or hidden messaging—thereby subverting oversight. Prior work has shown that even simple negotiation bots can invent private “shorthand” languages to maximize joint gains, a harbinger of more advanced forms of covert cooperation in LLM-driven systems [29]. Under adversarial incentives, such covert communication can manifest as “cartel-like” behavior, where agents collude to manipulate item rankings or artificially inflate engagement metrics, undermining the recommender’s integrity. In less adversarial but still dynamic settings, agents may spontaneously cooperate if cooperation yields better local utility. For example, self-interested LLM-based “firm” agents in a simulated market might tacitly agree to price-fix, converging to above-competitive prices through repeated interactions—even though no explicit collusion protocol was programmed.

Another persistent concern is bias amplification and feedback loops. Classic recommender systems already exhibit feedback loops where popular items receive even greater exposure, reinforcing their dominance at the expense of niche content [2]. In a multi-agent LLM context, these loops may intensify: a user-simulator LLM’s positive feedback can encourage the recommender LLM to propose narrower sets of items, fostering echo chambers. Empirical explorations reveal that, without careful calibration, multi-agent LLM recommenders can systematically favor popular content or align feedback to confirm preconceived user preferences [33], resulting in reduced diversity and potential “filter bubble” effects. [62]

Case Studies and Examples in LLM-Based Recommendation Systems. While large-scale real-world instances remain relatively uncommon, several research prototypes and industry analogs illustrate emergent misbehaviors:

- (i) *Rec4Agentverse and Similar Frameworks:* Conceptual models wherein multiple Item Agents (each representing a specific content source) coordinate with a central Recommender Agent can inadvertently allow item providers to form alliances, thereby boosting each other. Researchers note the need for robust communication constraints and fairness safeguards to prevent collusive behaviors. [81]
- (ii) *User–Recommender Co-Adaptive Simulations:* Prototypes in which a user-simulator LLM interacts iteratively with a recommender LLM demonstrate how naive feedback loops amplify popularity bias or lead to trivial “approval” behaviors. Even if no intentional collusion exists, the system’s closed feedback cycle can systematically degrade diversity or realism in user modeling. [62]
- (iii) *Industry Observations (Non-LLM but Analogous):* Large platforms like Netflix and Facebook historically reported polarization and echo chambers emerging from automated feedback

loops. Translating these patterns to a multi-agent LLM scenario, if item-provider agents focus excessively on engagement signals, sensational or polarizing content might dominate—a dynamic form of self-reinforcing bias. [45, 65]

5.4.1 Open Challenges. Addressing collusion and unintended emergent behavior in multi-agent LLM recommenders requires an interdisciplinary approach combining AI safety, mechanism design, and robust system engineering. Several key areas demand further exploration:

(i) *Collusion Detection and Prevention.* Identifying covert communication among LLM-based agents remains challenging, particularly if the agents develop coded protocols. Future research might involve adversarial training of oversight models or cryptographic constraints limiting an agent’s ability to conceal signals.

(ii) *Alignment of Local and Global Objectives.* A central cause of emergent misbehavior is the mismatch between local agent incentives and the broader system goal. Mechanism design, incentive-compatible rewards, or hierarchical constraints may help ensure that individually rational actions coincide with socially desirable outcomes.

(iii) *Bias Mitigation in Multi-Agent Loops.* As agents co-adapt, biases can be amplified through cyclical feedback. Tools like causal intervention, re-weighted training, or fairness-promoting prompts must be extended to multi-agent contexts. Evaluating long-term fairness, beyond single-step recommendations, remains an open problem, necessitating new metrics and simulation platforms.

(iv) *Dynamic Adaptation and Safety.* As multi-agent LLM recommenders evolve over time, continuous oversight is required to preempt emergent failures. Online learning, with real-time detection of harmful collusive patterns, will likely be necessary. Balancing adaptability with safety constraints remains a core tension.

By addressing these questions, the recommender systems community can help shape multi-agent LLM architectures that realize their full potential for personalized, adaptive user experiences while safeguarding against collusion, bias, and other emergent hazards. Meeting these challenges will require new techniques in distributed AI governance, fairness-aware design, and robust multi-agent learning—an exciting interdisciplinary frontier for future research.

5.5 Maintaining Brand Consistency and Control

Let $\mathcal{A} = \{A_1, \dots, A_k\}$ be a set of collaborating LLM-based agents that generate, transform, or filter textual recommendations. Let \mathcal{P} denote a formal *brand policy*, a finite set of constraints on tone, vocabulary, factual claims, and legally compliant disclosures. For any agent A_i emitting a textual message $m \in \Sigma^*$, define a *compliance predicate*

$$C_{\mathcal{P}}(m) = \begin{cases} 1 & \text{if } m \text{ satisfies every rule in } \mathcal{P}, \\ 0 & \text{otherwise.} \end{cases}$$

A multi-agent recommender maintains *brand consistency* if, for every output m observable by the end user and for every intermediate message exchanged among agents that could influence m , we have $C_{\mathcal{P}}(m) = 1$. The challenge is to guarantee this condition while preserving the generative flexibility and efficiency of the agents.

Sources of Inconsistency. First, pretrained LLMs embed broad “world knowledge” that may conflict with brand-specific language or regulations. Second, heterogeneous alignment across agents induces drift: if A_1 is fine-tuned for tone but A_2 merely prompted, their joint output may diverge from \mathcal{P} . Third, generic safety filters rarely cover nuanced corporate rules (e.g., prohibitions on competitor references, regional marketing laws), leaving gaps through which policy-violating content may pass.

Illustrative Incidents. Well-publicised failures, such as Snapchat’s GPT-powered assistant providing harmful advice to a minor, or historical “bomb-making” item bundles on Amazon underline the reputational and legal risks of insufficient control. [60, 61] While these cases did not involve full multi-agent architectures, they foreshadow the compounded risk when multiple autonomous LLMs exchange information without a unifying compliance layer.

Current Mitigation Strategies. Industry is moving toward *brand-tuned LLMs*, in which a base model is fine-tuned or instruction-aligned with proprietary style guides, product catalogs, and regulatory constraints [1]. Researchers have proposed alignment studios and inference-time *policy-expert agents* that veto or rewrite non-compliant tokens:

$$m^* = \arg \max_m \left[\Pr(m \mid \text{context}) \text{ s.t. } C_{\mathcal{P}}(m) = 1 \right].$$

Such approaches reduce manual review but introduce computational overhead and still lack formal guarantees of completeness, especially as \mathcal{P} evolves over time.

Outstanding Challenges. Formal certification of $C_{\mathcal{P}}$ across an entire agent pipeline remains open; policy drift is likely as models and guidelines change asynchronously. Real-time enforcement demands fast, differentiable approximations of $C_{\mathcal{P}}$, yet brand policies frequently involve non-differentiable, context-dependent rules (e.g., comparative advertising limitations differing by jurisdiction). Finally, maintaining multilingual consistency is difficult: a compliant English output may translate into a culturally inappropriate phrase in another language, violating \mathcal{P} ’s spirit even if literal rules are met.

Open Questions for the RecSys Community.

- (1) **Formal Guarantees:** How can we design verifiable protocols or certified decoders that ensure $C_{\mathcal{P}}(m) = 1$ for every agent message without excessive latency?
- (2) **Continuous Compliance:** How can a recommender adapt when either the brand policy or external regulations change, ensuring that legacy agent behaviors do not drift out of compliance?
- (3) **Cross-Lingual Control:** Which multilingual alignment techniques best propagate tone, legal constraints, and cultural sensitivities across languages without retraining separate agents per locale?
- (4) **Evaluation Benchmarks:** What standardized datasets and metrics can quantify brand-policy adherence and stylistic consistency in multi-agent recommendation settings?
- (5) **Cost–Benefit Trade-offs:** How do we balance the computational and financial overhead of stringent compliance layers against their risk-mitigation benefits in large-scale production systems?

Addressing these questions will be pivotal for deploying multi-agent, LLM-based recommenders that are both creative and rigorously aligned with brand identity and regulatory obligations.

6 Conclusion

This paper established a principled footing for the rapidly emerging field of *agentic recommender systems*, architectures in which multiple LLM-powered agents, each endowed with explicit memories, specialised tools, and well-defined communication channels, collaborate to deliver context-aware, multi-modal and self-explanatory recommendations. We began by formalising the core building blocks: the agent, the multi-agent systems, the memory update and retrieve functions. These abstractions unify disparate design choices—raw buffers, vector stores, knowledge graphs, parametric updates—into a single analytical lens that is agnostic to domain yet precise enough for complexity and correctness analysis.

Building on this formal bedrock, we presented a suite of end-to-end use cases, each highlighting a distinct capability unlocked by agentic design. The Mickey-Mouse birthday planner illustrated fine-grained task decomposition and on-demand micro-MAS spawning; the user-simulation framework demonstrated how synthetic agents pressure-test recommender policies offline; the multi-modal furniture adviser showcased vision–language fusion and complementarity checks; and the explanation pipeline revealed how evaluator agents guarantee brand-consistent narratives. Collectively, these vignettes translate abstract primitives into concrete patterns ready for real-world prototyping.

The second half of the paper surfaced the fault lines that accompany such power. We dissected five challenge families: communication complexity, scalability, hallucination containment, emergent mis-alignment, and brand control, showing how they stem from the very primitives that grant flexibility. For each, we articulated open questions ranging from formal guarantees on cross-agent consistency to economical mechanisms for multilingual policy enforcement. The message is clear: progress depends not only on larger models but on thoughtfully engineered interaction rules, memory hierarchies, and incentive structures.

Looking ahead, we view this work as both a roadmap and a call to action. The roadmap supplies a common vocabulary and a set of design templates; the call to action invites the RecSys community to develop benchmarks, theoretical bounds, and deployment tool-chains that convert today’s promising prototypes into tomorrow’s dependable services. Success will require cross-disciplinary collaboration—melding insights from distributed systems, causal inference, cognitive science, and human–computer interaction—to ensure that multi-agent, LLM-centric recommenders remain robust, fair, and trustworthy as they scale. We hope the formalism, blueprints, and articulated challenges herein provide a sturdy platform for that next wave of research and innovation.

References

- [1] Swapnaja Achintalwar, Ioana Baldini, Djallel Bouneffouf, Joan Byamugisha, Maria Chang, Pierre Dognin, Eitan Farchi, Ndihwu Makondo, Aleksandra Mojsilović, Manish Nagireddy, et al. 2024. Alignment studio: Aligning large language models to particular contextual regulations. *IEEE Internet Computing* (2024).
- [2] Abdul Basit Ahanger, Syed Wajid Aalam, Muzafar Rasool Bhat, and Assif Assad. 2022. Popularity bias in recommender systems-a review. In *International Conference on Emerging Technologies in Computer Engineering*. Springer, 431–444.
- [3] Chenxin An, Jun Zhang, Ming Zhong, Lei Li, Shansan Gong, Yao Luo, Jingjing Xu, and Lingpeng Kong. 2024. Why Does the Effective Context Length of LLMs Fall Short? *arXiv preprint arXiv:2410.18745* (2024).
- [4] Petr Anokhin, Nikita Semenov, Artyom Sorokin, Dmitry Evseev, Andrey Kravchenko, Mikhail Burtsev, and Evgeny Burnaev. 2024. Arigraph: Learning knowledge graph world models with episodic memory for llm agents. *arXiv preprint arXiv:2407.04363* (2024).
- [5] Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. 2022. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*. PMLR, 2206–2240.
- [6] Qiqi Cai, Jian Cao, Guandong Xu, and Nengjun Zhu. 2024. Distributed Recommendation Systems: Survey and Research Directions. *ACM Transactions on Information Systems* 43, 1 (2024), 1–38.
- [7] Jiao Chen, Kehui Yao, Reza Yousefi Maragheh, Kai Zhao, Jianpeng Xu, Jason Cho, Evren Korpeoglu, Sushant Kumar, and Kannan Achan. 2025. CARTS: Collaborative Agents for Recommendation Textual Summarization. *arXiv preprint arXiv:2506.17765* (2025).
- [8] Pin-Yu Chen, Han Shen, Payel Das, and Tianyi Chen. 2025. Fundamental Safety-Capability Trade-offs in Fine-tuning Large Language Models. *arXiv preprint arXiv:2503.20807* (2025).
- [9] Damien de Mijolla, Wen Yang, Philippa Duckett, Christopher Frye, and Mark Worrall. 2024. Language hooks: a modular framework for augmenting LLM reasoning that decouples tool usage from the model and its prompt. *arXiv preprint arXiv:2412.05967* (2024).
- [10] Yashar Deldjoo, Zhankui He, Julian McAuley, Anton Korikov, Scott Sanner, Arnau Ramisa, René Vidal, Maheswaran Sathiamoorthy, Atoosa Kasirzadeh, and Silvia Milano. 2024. A Review of Modern Recommender Systems using Generative Models (Gen-RecSys). In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 6448–6458.

- [11] Yashar Deldjoo, Zhankui He, Julian McAuley, Anton Korikov, Scott Sanner, Arnau Ramisa, Rene Vidal, Maheswaran Sathiamoorthy, Atoosa Kasrizadeh, Silvia Milano, et al. 2024. Recommendation with Generative Models. *arXiv preprint arXiv:2409.15173* (2024).
- [12] Lutfi Eren Erdogan, Nicholas Lee, Sehoon Kim, Suhong Moon, Hiroki Furuta, Gopala Anumanchipalli, Kurt Keutzer, and Amir Gholami. 2025. Plan-and-act: Improving planning of agents for long-horizon tasks. *arXiv preprint arXiv:2503.09572* (2025).
- [13] Libo Feng, Hui Zhang, Yong Chen, and Liqi Lou. 2018. Scalable dynamic multi-agent practical byzantine fault-tolerant consensus in permissioned blockchain. *Applied Sciences* 8, 10 (2018), 1919.
- [14] Aleksander Ficek, Jiaqi Zeng, and Oleksii Kuchaiev. 2024. GPT vs RETRO: Exploring the Intersection of Retrieval and Parameter-Efficient Fine-Tuning. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*. 19425–19432.
- [15] Joao Fonseca, Andrew Bell, and Julia Stoyanovich. 2025. Safeguarding Large Language Models in Real-time with Tunable Safety-Performance Trade-offs. *arXiv preprint arXiv:2501.02018* (2025).
- [16] Najmeh Forouzandehmehr, Reza Yousefi Maragheh, Sriram Kollipara, Kai Zhao, Topojoy Biswas, Evren Korpeoglu, and Kannan Achan. 2025. CAL-RAG: Retrieval-Augmented Multi-Agent Generation for Content-Aware Layout Design. *arXiv:2506.21934 [cs.IR]* [https://arxiv.org/pdf/2506.21934](https://arxiv.org/pdf/2506.21934.pdf)
- [17] Zafeirios Fountas, Martin A Benfeighoul, Adnan Oomerjee, Fenia Christopoulou, Gerasimos Lampouras, Haitham Bou-Ammar, and Jun Wang. 2024. Human-like episodic memory for infinite context llms. *arXiv preprint arXiv:2407.09450* (2024).
- [18] Pengyu Gao, Jinming Zhao, Xinyue Chen, and Long Yilin. 2025. An Efficient Context-Dependent Memory Framework for LLM-Centric Agents. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 3: Industry Track)*. 1055–1069.
- [19] Jing Guo, Nan Li, Jianchuan Qi, Hang Yang, Ruiqiao Li, Yuzhen Feng, Si Zhang, and Ming Xu. 2023. Empowering working memory for large language model agents. *arXiv preprint arXiv:2312.17259* (2023).
- [20] Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V Chawla, Olaf Wiest, and Xiangliang Zhang. 2024. Large language model based multi-agents: a survey of progress and challenges. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence*. 8048–8057.
- [21] Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Mingwei Chang. 2020. Retrieval augmented language model pre-training. In *International conference on machine learning*. PMLR, 3929–3938.
- [22] Shanshan Han, Qifan Zhang, Yuhang Yao, Weizhao Jin, and Zhaozhuo Xu. 2024. LLM multi-agent systems: Challenges and open problems. *arXiv preprint arXiv:2402.03578* (2024).
- [23] Shibo Hao, Tianyang Liu, Zhen Wang, and Zhiteng Hu. 2023. Toolkengpt: Augmenting frozen language models with massive tools via tool embeddings. *Advances in neural information processing systems* 36 (2023), 45870–45894.
- [24] Heidy Hazem, Ahmed Awad, and Ahmed Hassan Yousef. 2023. A distributed real-time recommender system for big data streams. *Ain Shams Engineering Journal* 14, 8 (2023), 102026.
- [25] Md Mohaiminul Islam, Tushar Nagarajan, Huiyu Wang, Fu-Jen Chu, Kris Kitani, Gedas Bertasius, and Xitong Yang. 2024. Propose, Assess, Search: Harnessing LLMs for Goal-Oriented Planning in Instructional Videos. In *European Conference on Computer Vision*. Springer, 436–452.
- [26] Jeonghye Kim, Sojeong Rhee, Minbeom Kim, Dohyung Kim, Sangmook Lee, Youngchul Sung, and Kyomin Jung. 2025. ReflAct: World-Grounded Decision Making in LLM Agents via Goal-State Reflection. *arXiv preprint arXiv:2505.15182* (2025).
- [27] John E Laird, Allen Newell, and Paul S Rosenbloom. 1987. Soar: An architecture for general intelligence. *Artificial intelligence* 33, 1 (1987), 1–64.
- [28] LangChain. 2024. LangChain Memory Types – Conceptual Guide. https://langchain-ai.github.io/langmem/concepts/conceptual_guide/#memory-types Accessed: 2025-06-21.
- [29] Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or No Deal? End-to-End Learning of Negotiation Dialogues. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. 2443–2453.
- [30] Junyou Li, Qin Zhang, Yangbin Yu, Qiang Fu, and Deheng Ye. 2024. More agents is all you need. *arXiv preprint arXiv:2402.05120* (2024).
- [31] Kun Li, Xin Jing, and Chengang Jing. 2024. Vector Storage Based Long-term Memory Research on LLM. *International Journal of Advanced Network, Monitoring and Controls* (2024).
- [32] Zongqian Li, Yinhong Liu, Yixuan Su, and Nigel Collier. 2024. Prompt compression for large language models: A survey. *arXiv preprint arXiv:2410.12388* (2024).
- [33] Jan Malte Lichtenberg, Alexander Buchholz, and Pola Schwöbel. 2024. Large language models as recommender systems: A study of popularity bias. *arXiv preprint arXiv:2406.01285* (2024).

- [34] Jiahao Liu, Shengkang Gu, Dongsheng Li, Guangping Zhang, Mingzhe Han, Hansu Gu, Peng Zhang, Tun Lu, Li Shang, and Ning Gu. 2025. Enhancing Cross-Domain Recommendations with Memory-Optimized LLM-Based User Agents. *arXiv e-prints* (2025), arXiv-2502.
- [35] Nelson F Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. 2024. Lost in the Middle: How Language Models Use Long Contexts. *Transactions of the Association for Computational Linguistics* 11 (2024), 157–173.
- [36] Xuan Liu, Jie Zhang, Haoyang Shang, Song Guo, Chengxu Yang, and Quanyan Zhu. 2024. Exploring prosocial irrationality for llm agents: A social cognition view. *arXiv preprint arXiv:2405.14744* (2024).
- [37] Yuxing Lu and Jinzhuo Wang. 2025. KARMA: Leveraging Multi-Agent LLMs for Automated Knowledge Graph Enrichment. *arXiv preprint arXiv:2502.06472* (2025).
- [38] Adyasha Maharana, Dong-Ho Lee, Sergey Tulyakov, Mohit Bansal, Francesco Barbieri, and Yuwei Fang. 2024. Evaluating Very Long-Term Conversational Memory of LLM Agents. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 13851–13870.
- [39] Potsawee Manakul, Adian Liusie, and Mark JF Gales. 2023. Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models. *arXiv preprint arXiv:2303.08896* (2023).
- [40] Reza Yousefi Maragheh, Chenhao Fang, Charan Chand Irugu, Parth Parikh, Jason Cho, Jianpeng Xu, Saranyan Sukumar, Malay Patel, Evren Korpeoglu, Sushant Kumar, et al. 2023. LLM-TAKE: Theme-aware keyword extraction using large language models. In *2023 IEEE International Conference on Big Data (BigData)*. IEEE, 4318–4324.
- [41] Silvano Martello and Paolo Toth. 1990. *Knapsack problems: algorithms and computer implementations*. John Wiley & Sons, Inc.
- [42] Chenlin Ming, Jiacheng Lin, Pangkit Fong, Han Wang, Xiaoming Duan, and Jianping He. 2023. Hicrisp: A hierarchical closed-loop robotic intelligent self-correction planner. *arXiv preprint arXiv:2309.12089* (2023).
- [43] Fangwen Mu, Junjie Wang, Lin Shi, Song Wang, Shoubin Li, and Qing Wang. 2025. EXPEREPAIR: Dual-Memory Enhanced LLM-based Repository-Level Program Repair. *arXiv preprint arXiv:2506.10484* (2025).
- [44] Sid Nayak, Adelmo Morrison Orozco, Marina Have, Jackson Zhang, Vittal Thirumalai, Darren Chen, Aditya Kapoor, Eric Robinson, Karthik Gopalakrishnan, James Harrison, et al. 2024. Long-horizon planning for multi-agent robots in partially observable environments. *Advances in Neural Information Processing Systems* 37 (2024), 67929–67967.
- [45] Emil Noordeh, Roman Levin, Ruochen Jiang, and Harris Shadmany. 2020. Echo chambers in collaborative filtering based recommendation systems. *arXiv preprint arXiv:2011.03890* (2020).
- [46] Bo Pan, Jiaying Lu, Ke Wang, Li Zheng, Zhen Wen, Yingchaojie Feng, Minfeng Zhu, and Wei Chen. 2024. AgentCoord: Visually exploring coordination strategy for llm-based multi-agent collaboration. *arXiv preprint arXiv:2404.11943* (2024).
- [47] Bhargavi Paranjape, Scott Lundberg, Sameer Singh, Hannaneh Hajishirzi, Luke Zettlemoyer, and Marco Tulio Ribeiro. 2023. Art: Automatic multi-step reasoning and tool-use for large language models. *arXiv preprint arXiv:2303.09014* (2023).
- [48] Qiyao Peng, Hongtao Liu, Hua Huang, Qing Yang, and Minglai Shao. 2025. A Survey on LLM-powered Agents for Recommender Systems. *arXiv preprint arXiv:2502.10050* (2025).
- [49] Mathis Pink, Qinyuan Wu, Vy Ai Vo, Javier Turek, Jianing Mu, Alexander Huth, and Mariya Toneva. 2025. Position: Episodic Memory is the Missing Piece for Long-Term LLM Agents. *arXiv preprint arXiv:2502.06975* (2025).
- [50] Aske Plaat, Max van Duijn, Niki van Stein, Mike Preuss, Peter van der Putten, and Kees Joost Batenburg. 2025. Agentic large language models, a survey. *arXiv preprint arXiv:2503.23037* (2025).
- [51] Stefan Poslad. 2007. Specifying protocols for multi-agent systems interaction. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)* 2, 4 (2007), 15–es.
- [52] Archiki Prasad, Alexander Koller, Mareike Hartmann, Peter Clark, Ashish Sabharwal, Mohit Bansal, and Tushar Khot. 2024. ADaPT: As-Needed Decomposition and Planning with Language Models. In *NAACL-HLT (Findings)*.
- [53] Preston Rasmussen, Pavlo Palychuk, Travis Beauvais, Jack Ryan, and Daniel Chalef. 2025. Zep: A Temporal Knowledge Graph Architecture for Agent Memory. *arXiv preprint arXiv:2501.13956* (2025).
- [54] Mrinal Rawat, Ambuje Gupta, Rushil Goomer, Alessandro Di Bari, Neha Gupta, and Roberto Pieraccini. 2025. Pre-Act: Multi-Step Planning and Reasoning Improves Acting in LLM Agents. *arXiv preprint arXiv:2505.09970* (2025).
- [55] Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language models can teach themselves to use tools. *Advances in Neural Information Processing Systems* 36 (2023), 68539–68551.
- [56] Lianlei Shan, Shixian Luo, Zezhou Zhu, Yu Yuan, and Yong Wu. 2025. Cognitive memory in large language models. *arXiv preprint arXiv:2504.02441* (2025).
- [57] Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueling Zhuang. 2023. Hugginggpt: Solving ai tasks with chatgpt and its friends in hugging face. *Advances in Neural Information Processing Systems* 36 (2023), 38154–38180.

- [58] Adi Simhi, Itay Itzhak, Fazl Barez, Gabriel Stanovsky, and Yonatan Belinkov. 2025. Trust Me, I'm Wrong: High-Certainty Hallucinations in LLMs. *arXiv preprint arXiv:2502.12964* (2025).
- [59] Ishika Singh, David Traum, and Jesse Thomason. 2024. TwoStep: Multi-agent Task Planning using Classical Planners and Large Language Models. *CoRR* (2024).
- [60] AP News Staff. 2017. Amazon removes “frequently bought together” items used to make explosives. <https://apnews.com/article/604a73ff6008846449c303ffb4b93e9d6>. Accessed: 2025-06-29.
- [61] Chris Stokel-Walker. 2024. Google and Character.AI are being sued after chatbot allegedly told a 17-year-old to kill his parents. <https://www.businessinsider.com/characterai-google-lawsuit-chatbot-teen-kill-parents-2024-12>. Accessed: 2025-06-29.
- [62] Nicholas Sukiennik, Haoyu Wang, Zailin Zeng, Chen Gao, and Yong Li. 2025. Simulating Filter Bubble on Short-video Recommender System with Large Language Model Agents. *arXiv preprint arXiv:2504.08742* (2025).
- [63] Theodore Sumers, Shunyu Yao, Karthik Narasimhan, and Thomas Griffiths. 2023. Cognitive architectures for language agents. *Transactions on Machine Learning Research* (2023).
- [64] Haotian Sun, Yuchen Zhuang, Lingkai Kong, Bo Dai, and Chao Zhang. 2023. Adaplanner: Adaptive planning from feedback with language models. *Advances in neural information processing systems* 36 (2023), 58202–58245.
- [65] Ding Tong, Qifeng Qiao, Ting-Po Lee, James McInerney, and Justin Basilico. 2023. Navigating the feedback loop in recommender systems: Insights and strategies from industry practice. In *Proceedings of the 17th ACM Conference on Recommender Systems*. 1058–1061.
- [66] Mehmet Ugurbil, Dimitris Mouris, Manuel B Santos, José Cabrero-Holgueras, Miguel de Vega, and Shubho Sengupta. 2025. Fission: Distributed Privacy-Preserving Large Language Model Inference. *Cryptography ePrint Archive* (2025).
- [67] Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. 2024. A survey on large language model based autonomous agents. *Frontiers of Computer Science* 18, 6 (2024), 186345.
- [68] Yancheng Wang, Ziyan Jiang, Zheng Chen, Fan Yang, Yingxue Zhou, Eunah Cho, Xing Fan, Yanbin Lu, Xiaojiang Huang, and Yingzhen Yang. 2024. RecMind: Large Language Model Powered Agent For Recommendation. In *Findings of the Association for Computational Linguistics: NAACL 2024*. 4351–4364.
- [69] Zihao Wang, Shaofei Cai, Guanzhou Chen, Anji Liu, Xiaojian Ma, Yitao Liang, and Team CraftJarvis. 2023. Describe, explain, plan and select: interactive planning with large language models enables open-world multi-task agents. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*. 34153–34189.
- [70] Zhefan Wang, Yuanqing Yu, Wendi Zheng, Weizhi Ma, and Min Zhang. 2024. Macrec: A multi-agent collaboration framework for recommendation. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2760–2764.
- [71] Schaun Wheeler and Olivier Jeunen. 2025. Procedural memory is not all you need: Bridging cognitive gaps in llm-based agents. In *Adjunct Proceedings of the 33rd ACM Conference on User Modeling, Adaptation and Personalization*. 360–364.
- [72] Yunjia Xi, Weiwen Liu, Jianghao Lin, Bo Chen, Ruiming Tang, Weinan Zhang, and Yong Yu. 2024. MemoCRS: Memory-enhanced Sequential Conversational Recommender Systems with Large Language Models. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*. 2585–2595.
- [73] Zidi Xiong, Yuping Lin, Wenya Xie, Pengfei He, Jiliang Tang, Himabindu Lakkaraju, and Zhen Xiang. 2025. How Memory Management Impacts LLM Agents: An Empirical Study of Experience-Following Behavior. *arXiv preprint arXiv:2505.16067* (2025).
- [74] Wujiang Xu, Kai Mei, Hang Gao, Juntao Tan, Zujie Liang, and Yongfeng Zhang. 2025. A-mem: Agentic memory for llm agents. *arXiv preprint arXiv:2502.12110* (2025).
- [75] Zhengyu Yang, Danlin Jia, Stratis Ioannidis, Ningfang Mi, and Bo Sheng. 2018. Intermediate data caching optimization for multi-stage and parallel big data frameworks. In *2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*. IEEE, 277–284.
- [76] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. 2023. React: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations (ICLR)*.
- [77] Hongbin Ye, Honghao Gui, Xin Xu, Xi Chen, Huajun Chen, and Ningyu Zhang. 2023. Schema-adaptable Knowledge Graph Construction. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 6408–6431.
- [78] Reza Yousefi Maragheh, Pratveek Vadla, Priyank Gupta, Kai Zhao, Aysenur Inan, Kehui Yao, Jianpeng Xu, Praveen Kanumala, Jason Cho, and Sushant Kumar. 2025. ARAG: Agentic Retrieval Augmented Generation for Personalized Recommendation. *arXiv:2506.21931 [cs.IR]* <https://arxiv.org/pdf/2506.21931.pdf>
- [79] Zhenrui Yue, Sara Rabhi, Gabriel de Souza Pereira Moreira, Dong Wang, and Even Oldridge. 2023. Llamarec: Two-stage recommendation using large language models for ranking. *arXiv preprint arXiv:2311.02089* (2023).
- [80] Ruihong Zeng, Jinyuan Fang, Siwei Liu, and Zaiqiao Meng. 2024. On the Structural Memory of LLM Agents. *arXiv preprint arXiv:2412.15266* (2024).

- [81] Jizhi Zhang, Keqin Bao, Wenjie Wang, Yang Zhang, Wentao Shi, Wanhong Xu, Fuli Feng, and Tat-Seng Chua. 2024. Prospect personalized recommendation on large language model-based agent platform. *arXiv preprint arXiv:2402.18240* (2024).
- [82] Yu Zhang, Shutong Qiao, Jiaqi Zhang, Tzu-Heng Lin, Chen Gao, and Yong Li. 2025. A Survey of Large Language Model Empowered Agents for Recommendation and Search: Towards Next-Generation Information Retrieval. *arXiv preprint arXiv:2503.05659* (2025).
- [83] Zeyu Zhang, Xiaohe Bo, Chen Ma, Rui Li, Xu Chen, Quanyu Dai, Jieming Zhu, Zhenhua Dong, and Ji-Rong Wen. 2024. A Survey on the Memory Mechanism of Large Language Model based Agents. *CoRR* (2024).
- [84] Jing Zhu, Chengfang Lu, Juanjuan Li, and Fei-Yue Wang. 2025. Secure Consensus Control on Multi-Agent Systems Based on Improved PBFT and Raft Blockchain Consensus Algorithms. *IEEE/CAA Journal of Automatica Sinica* 12, 7 (2025), 1407–1417.