A Survey on Large Language Model based Human-Agent Systems

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Abstract

Recent advances in large language models (LLMs) have sparked growing interest in building fully autonomous agents. However, fully autonomous LLM-based agents still face significant challenges, including limited reliability due to hallucinations, difficulty in handling complex tasks, and substantial safety and ethical risks, all of which limit their feasibility and trustworthiness in real-world applications. To overcome these limitations, LLM-based human-agent systems (LLM-HAS) incorporate human-provided information, feedback, or control into the agent system to enhance system performance, reliability and safety. This paper provides the first comprehensive and structured survey of LLM-HAS. It clarifies fundamental concepts, systematically presents core components shaping these systems, including environment & profiling, human feedback, interaction types, orchestration and communication, explores emerging applications, and discusses unique challenges and opportunities. By consolidating current knowledge and offering a structured overview, we aim to foster further research and innovation in this rapidly evolving interdisciplinary field. Paper lists and resources are available at GitHub repository.

1 Introduction

The rapid advancement of Large Language Models (LLMs), with their remarkable capabilities in language understanding, reasoning, and generation, has spurred significant interest in developing LLM-based agents – AI systems designed to perceive environments, reason about goals, and execute actions (Wang et al., 2024a; Li et al., 2024a). These agents, often envisioned as autonomous entities leveraging LLMs as their core "brain" augmented with memory, planning, and tool-use modules, promise to automate complex tasks and boost productivity (Xi et al., 2025). However, the pursuit of *full autonomy* faces critical hurdles. ***(1) Reliability*** remains a major concern due to LLMs' propensity for hallucination – generating plausible but factually incorrect or nonsensical outputs – which erodes trust and can lead to significant errors, especially when actions are chained (Gosmar and Dahl, 2025; Xu et al., 2024). ***(2) Complexity*** often stalls autonomous agents; they struggle with very complicated tasks requiring deep domain expertise, long multi-step execution, nuanced reasoning, dynamic adaptation, or strict long-context consistency dependencies, as seen in scientific research (Feng et al., 2024; Yehudai et al., 2025). ***(3) Safety and Ethical Risks*** escalate with autonomy; agents can take unintended harmful actions, amplify societal biases present in training data, or create accountability gaps, particularly in critical decision-making scenarios involving finance, healthcare, or security (Mitchell et al., 2025; Deng et al., 2024; Shen et al., 2024).

The persistence of these challenges suggests that full autonomy may be unsuitable for many real-world applications (Mitchell et al., 2025; Natarajan et al., 2025) and underscores a crucial insight often overlooked in the drive for pure automation: the indispensable role of human involvement. Humans are frequently needed to provide essential clarification, context, or domain knowledge, offer vital feedback and corrections, and exercise necessary oversight and control. These motivate a paradigm shift towards systems explicitly designed for human-agent collaboration: ***LLM-based Human-Agent Systems*** **(LLM-HAS)**.

While surveys on LLM-based autonomous agents (Wang et al., 2024a; Li et al., 2024a), multi-agent systems (Tran et al., 2025; Wu et al., 2025), and specific applications exist (Wang et al., 2025b; Peng et al., 2025), a dedicated synthesis focusing specifically on LLM-based human-agent systems is lacking. This survey fills that gap by providing

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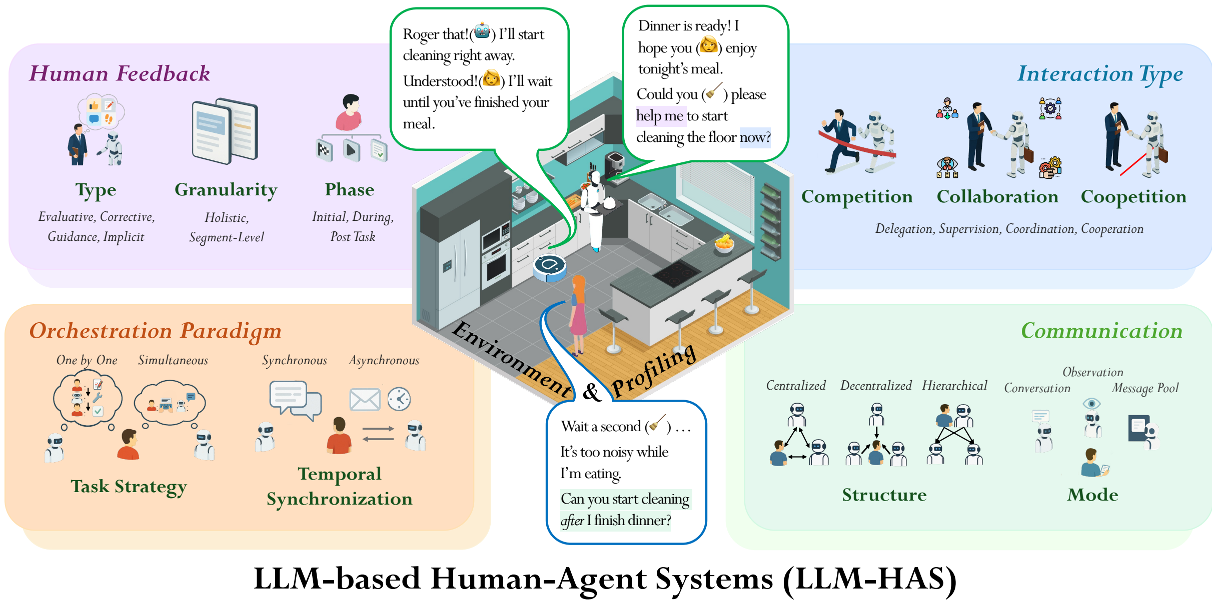

Figure 1: Overview of LLM-based human-agent systems. The system is composed of five core components: **Environment & Profiling** (including environment settings, and role definitions, goals, and agent capabilities such as planning and memory), **Human Feedback** (with varying types, timing, and granularity), **Interaction Types** (collaborative, competitive, cooperative, or mixed), **Orchestration** (task strategy and temporal synchronization), and **Communication** (information flow structure and mode). Together, these five components define the structure and functionality of LLM-based human–agent systems.

a comprehensive and structured overview of the LLM-HAS. It clarifies the fundamental concepts and systematically presents its core components, emerging applications, and unique challenges and opportunities within this specific niche. To the best of our knowledge, this is still the first survey on LLM-based human-agent systems. We aim to consolidate current knowledge and inspire further research and innovation in this rapidly evolving interdisciplinary field.

To provide a sustainable resource complementing our survey paper, we maintain an open-source GitHub repository. We hope that our survey will inspire further exploration and innovation in this field, as well as applications across a wide array of research disciplines.

This survey is organized as follows: Section 2 defines and formulates LLM-HAS. Section 3 details the core components shaping the human-agent systems (e.g., human feedback, interaction type, orchestration and communication protocols). Section 4 explores diverse application domains. Section 5 presents open-source implementation frameworks as well as datasets and benchmarks. Finally, Section 6 discusses key challenges and future opportunities in the LLM-based human-agent systems.

2 LLM-Based Human-Agent Systems

We define LLM-based human-agent systems as interactive frameworks where humans actively provide additional information, feedback, or control during interaction with an LLM-powered agent to enhance system performance, reliability and safety (Feng et al., 2024; Shao et al., 2024; Mehta et al., 2024). The core idea is synergy: combining unique human strengths—like intuition, creativity, expertise, ethical judgment, and adaptability—with LLM agent capabilities such as vast knowledge recall, computational speed, and sophisticated language processing. LLM-HAS builds upon core LLM agent components but places critical emphasis on the human's interactive prowess:

(1) ***Provide Information / Clarification:*** Humans provide essential context, domain expertise, preferences, or resolve ambiguities, helping agents interpret situations more accurately (Naik et al., 2025; Kim et al., 2025).

(2) ***Provide Feedback / Error Correction:*** Humans evaluate agent outputs and provide feedback, ranging from simple ratings to complex critiques, demonstrations or corrections, effectively guiding agents' adjustment (Gao et al., 2024b; Dutta et al., 2024; Li et al., 2024b).

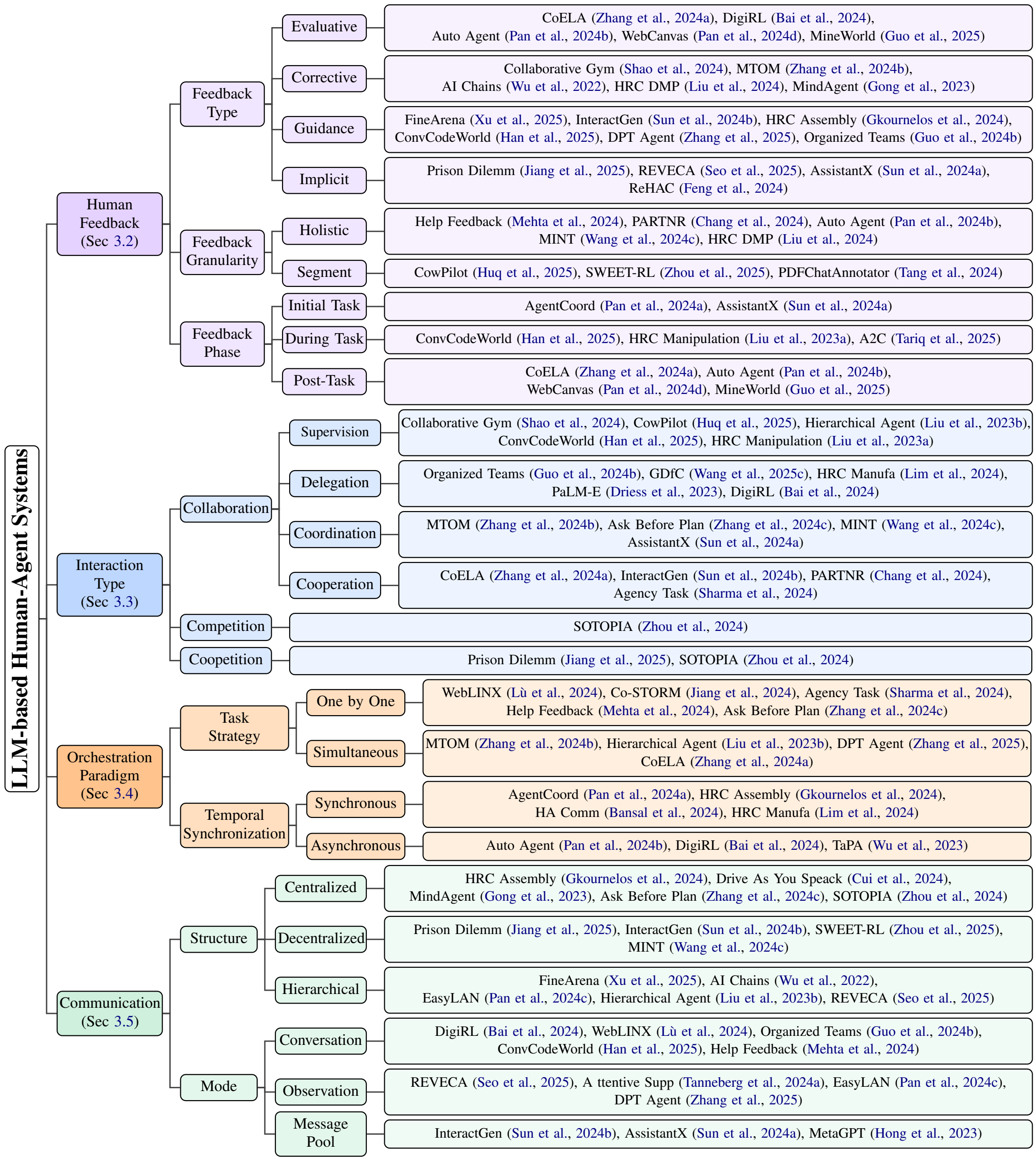

Figure 2: Taxonomy of LLM-based Human-Agent Systems.

(3) ***Take Control / Action:*** In high-stakes or sensitive scenarios (e.g., healthcare, privacy, or ethics), humans retain the authority to override, redirect, or halt agent actions, ensuring accountability, safety, and alignment with human values (Chen et al., 2025; Natarajan et al., 2025; Xiao and Wang, 2023).

Figure 1 provides a generalized overview of LLM-based human-agent systems. These systems operate within a defined **Environment** (e.g., physical world, simulation) that provides context and stimuli. **Human & Agent Profiling** characterize the participants' roles and goals, and the agent's core LLM engine augmented with capabilities like planning, memory, and tool use. **Human Feedback** can occur during different phases in various types and granularities. Human-Agent **Interaction Types** may be collaborative (most common), competitive, cooperative, or mixed. The **Orchestration** layer governs high-level coordination—choosing a task strategy (e.g., sequential one-by-one versus parallel simultaneous execution) and a temporal synchronization mode (real-time synchronous exchanges versus delayed asynchronous workflows) so that each actor acts at the right moment. The **Communication** layer specifies how information flows—defining message structure (centralized, decentralized, hierarchical) and mode (conversation, observation signals, or shared message pools). The effective interplay and configuration of these components, particularly various human feedback, are critical for tailoring the system to specific tasks and optimizing the overall system's performance, reliability and safety.

3 Core Components

In this section, we dissect LLM-HAS Systems, discussing the five key aspects: environment & profiling, human feedback, interaction type, orchestration paradigm, and communication.

3.1 Environment and Profiling

Environment Setting. The environment in LLM-HAS defines a shared interaction space that can exist either in the physical world, such as offices (Sun et al., 2024b), or in fully simulated virtual environments where agents and humans engage under controlled conditions (Sun et al., 2024b; Zhang et al., 2024a; Guo et al., 2024b). These systems can be configured in various ways, including single-human single-agent, single-human multi-agent, multi-human single-agent, and multi-human multi-agent setups, each reflecting different collaboration dynamics and complexities.

Human & Agent Profiling. Human participants can be broadly categorized as *lazy* or *informative* users. Lazy users provide minimal guidance, typically offering evaluative feedback such as binary correctness or scalar rating. In contrast, informative users engage deeply by offering demonstrations, detailed guidance, refinements, or even taking over parts of the task (Wang et al., 2024c; Han et al., 2025). On the other side, agents are profiled by their roles and capabilities—ranging from general assistants to specialized personas like mathematicians, engineers, doctors, or cleaning robots—each tailored to the specific demands of their operational context (Guo et al., 2024a; Samuel et al., 2024).

3.2 Human Feedback

Human Feedback Type. We categorize human feedback as *evaluative*, *corrective*, *guidance*, and *implicit* feedback. ***(1) Evaluative Feedback*** provides an assessment of the agent's output quality, typically as preference ranking, scalar rating, or binary assessment. A prime example is preference ranking, where users compare agent outputs, forming the basis of Reinforcement Learning from Human Feedback (RLHF) (Chaudhari et al., 2024). Alternatively, platforms like Uni-RLHF (Yuan et al., 2024) support scalar ratings or binary assessments. ***(2) Corrective Feedback*** offers direct edits or fixes to the agent's behavior. For instance, the PRELUDE (Gao et al., 2024a) framework learns latent preferences from user edits made to agent-generated text. ***(3) Guidance Feedback*** means the human proactively provides instructions, critiques, or demonstrations to shape the agent's behavior. Agents like InteractGen (Sun et al., 2024b), AutoManual (Chen et al., 2024) can be bootstrapped using initial demonstrations, while methods like Self-Refine (Choudhury and Sodhi, 2025) employ iterative critiques and refinements to improve outputs. ***(4) Implicit Feedback*** is inferred by the agent observing user actions or control signals, rather than explicitly stated or direct output modifications. For example, an agent might learn user priorities by observing how a user adjusts control sliders in a system like VeriPlan (Lee et al., 2025), or infer preferences by analyzing user behaviors like clicks and purchases in frameworks such as AgentA/B (Wang et al., 2025a). This contrasts with corrective feedback where the user directly edits the output; here, the agent interprets the user's independent actions or control choices.

Human Feedback Granularity. Human feedback also varies in granularity, from coarse-grained, holistic judgments to fine-grained, segment-level critiques. ***(1) Coarse-grained/Holistic feedback*** provides a single assessment for the entire agent output. Standard RLHF often relies on holistic preferences between complete responses, which simplifies feedback collection but struggles with credit assignment in complex tasks. ***(2) Fine-grained/Segment-Level Feedback*** by contrast, targets specific parts (e.g., sentences, paragraphs, code blocks). This is crucial in environments like ConvCodeWorld (Han et al., 2025), where feedback pertains to specific conversational turns or generated code segments, or in annotation tasks like PDFChatAnnotator (Tang et al., 2024), where feedback applies to specific annotations or parts of the document. This finer granularity provides more precise learning signals, crucial for debugging complex behaviors.

Human Feedback Phase. Human feedback can be incorporated at different phases of the LLM-agent pipeline. ***(1) Initial Setup & Goal Definition*** occurs before task execution, configuring the agent system and defining goals, such as setting

Dimension	Category	Definition Summary	Key Characteristics / Trade-offs	Example Work
Type	*Evaluative*	User provides an **assessment** of the agent's output quality, typically as **binary assessment**, **scalar rating**, or **preference ranking**.	① Easy to collect, scalable. ② Less specific signal for improvement.	*CoELA* (Zhang et al., 2024a), *MINT* (Wang et al., 2024c), *MetaGPT* (Hong et al., 2023)
	Corrective	User **offers edits or fixes** to the agent's behavior.	① Highly informative, clear signal for improvement. ② Higher user effort, often fine-grained & interactive.	*PARTNR* (Chang et al., 2024), *MindAgent* (Gong et al., 2023), *AI Chains* (Wu et al., 2022)
	Guidance	User proactively provides **instructions**, **demonstrations**, or **critiques** to shape the agent's behavior.	① Bootstraps learning, conveys complex goals, proactive alignment. ② Requires clear specification from user.	*Drive As You Speack* (Cui et al., 2024), *Hierarchical Agent*(Liu et al., 2023b), *Ask Before Plan* (Zhang et al., 2024c)
	Implicit	**Inferred by the agent observing user actions or control signals**, rather than explicitly stated or direct output modifications.	① Natural, unobtrusive collection. ② Ambiguous, requires careful interpretation.	*ReHAC*(Feng et al., 2024), *Attentive Supp.* (Tanneberg et al., 2024a), *A2C* (Tariq et al., 2025)
Granularity	*Coarse-grained / Holistic*	Single assessment/signal for **an entire agent output**, **trajectory**, or **task outcome**.	① Simple for user, good for overall assessment ② Obscures specific errors, less precise learning signal.	*AssistantX* (Sun et al., 2024a), *Help Feedback* (Mehta et al., 2024), *HRC DMP* (Liu et al., 2024)
	Fine-grained / Segment-Level	Feedback targeting **specific parts of agent output**, **actions**, or **process**.	① Precise learning signal, crucial for debugging complex skills ② Potentially higher user effort/burden.	*Collaborative Gym* (Shao et al., 2024), *MTOM* (Zhang et al., 2024b), *FineArena* (Xu et al., 2025)
Phase	*Initial Setup & Goal Definition*	Feedback provided **task execution**, **configuring** the agent system and **defining** the **task**, **goals**, **constraints**, and **preferenc**.	① Proactive alignment, prevents costly errors, sets constraints ② Requires upfront user input.	*AgentCoord* (Pan et al., 2024a), *GDfC* (Wang et al., 2025c), *HA Comm.* (Bansal et al., 2024)
	During Task Execution	Online, interactive feedback **while the agent is actively performing the task**, enabling **real-time adaptation**.	① Enables real-time adaptation, crucial for dynamic/collaborative tasks ② Requires responsive interfaces.	*InteractGen* (Sun et al., 2024b), *CowPilot* (Huq et al., 2025), *EasyLAN* (Pan et al., 2024c)
	Post-Task Eval. & Refinement	Feedback provided **after task completion** to assess outcomes and **provide suggestions** for **immediate revision** or **future improvement**.	① Non-disruptive, good for aggregate data/offline learning ① No impact on completed task.	*Auto Agent* (Pan et al., 2024b), *WebCanvas* (Pan et al., 2024d), *MineWorld* (Guo et al., 2025)

Table 1: Dimensions of Human Feedback in LLM-based human–agent systems. These dimensions include feedback type, granularity, and phase. For each dimension, a summary, key characteristics, trade-offs, and example works are provided for comparison.

coordination strategies (AgentCoord (Pan et al., 2024a)) or critiquing plans before execution (Ask-before-Plan (Zhang et al., 2024c)). ***(2) During Task Execution*** involves online, interactive feedback while the agent is actively performing the task, enabling real-time adaptation. Examples include interactive instruction editing (InstructEdit (Wang et al., 2023)), mid-task refinements (Mutual Theory of Mind (Zhang et al., 2024b), Collaborative Gym (Shao et al., 2024)), online interventions (HG-DAgger (Kelly et al., 2019)), or interpreting concurrent user actions (REVECA (Seo et al., 2025)). ***(3) Post-Task Evaluation & Refinement*** happens after task completion to assess outcomes and provide feedback for immediate revision or future improvement. Frameworks like WebCanvas (Pan et al., 2024d) and Organized Teams (Guo et al., 2024b) apply feedback loops after initial generation for benchmarking or offline learning, while AdaPlanner (Sun et al., 2023) archives successful plans post-task as skills for future use. Integrating feedback during execution is increasingly important for dynamic tasks requiring adaptation.

3.3 Human-Agent Interaction Types

Interaction types define how individuals communicate, exchange information, and take actions with one another. In LLM-HAS, interactions tend to be more dynamic and complex compared to multi-agent systems (MAS). This complexity arises from the various roles and responsibilities assigned to both human agents and those based on LLMs, necessitating a finer-grained framework to describe their collaborative behaviors. The following categorization highlights the three key interaction types: **Collaboration**, **Competition** and **Coopetition**. Base on the collaboration pattern, the collaboration can be partitioned into four fine-grained subtype, which will introduced in Section 3.3.1.

3.3.1 Collaboration

Collaborations are by far the most common interaction and foundational interaction, which involve humans and LLM-based agents working together to achieve a common goal. This partnership combines human creativity and contextual understanding with LLM-based agents to address challenges and improve the efficiency and quality of results (Vats et al., 2024; Du et al., 2024). Depending on the type of collaboration considered, it can be categorized into four main fine-granted subtypes: ***(1) Delegation & Direct Command*** (Kiewiet and McCubbins, 1991), ***(2) Supervision*** (Loganbill et al., 1982) ***(3) Cooperation*** (Rand and Nowak, 2013), and ***(4) Coordination*** (Turvey, 1990).

Delegation & Direct Command. In this interaction modality, a controlling party, usually a human, assigns explicit tasks to the LLM-based agent by providing clear and direct instructions. The agent is expected to execute these directives autonomously, or on the behalf of human, ensuring that responsibilities are well-defined and actions align with the system's overarching objectives. Unlike supervision, where strategies can be dynamically adjusted in response to new situations, delegation involves providing instructions upfront. This means the agent follows a predetermined set of tasks rather than adapting to the situation. For instance, the investor specifies their risk preference to the agent executing the investment strategy (Xu et al., 2025), driver utter the command to LLM-based agent (Cui et al., 2024), and humans issue explicit action directives for LLM-based agent execution (Seo et al., 2025).

Supervision. Supervision is the process by which one party, usually a human operator, oversees, monitors and guides the actions of an LLM based agent. This involves real time evaluation and intervention to ensure the agent's output aligns with established goals and quality standards. Supervision also encompasses setting alert thresholds and providing corrective inputs when deviations occur. By maintaining a continuous feedback loop between the human and the agent, supervision helps calibrate agent behaviour, catch and mitigate errors before they propagate and build confidence in the system. It also enables agents to handle routine tasks with increasing independence. For instance, agents seek human confirmation at critical moments (Shao et al., 2024), agents notify human to check whether the action is align (Liu et al., 2023b), teleoperator monitor the LLM generated motion plans (Liu et al., 2023a).

Cooperation. Cooperation refers to the voluntary and joint efforts of multiple parties to achieve agreed-upon goals. Unlike coordination, which focuses on organizing and aligning tasks, cooperation combines the various efforts and outcomes of different individuals and LLM-based agents toward a common objective. It emphasizes collective commitment, mutual assistance, and the pooling of resources to attain a shared result, thereby fostering a collaborative problem-solving environment. For instance, the human robot coordination in household activities (Chang et al., 2024), cooperative embodied language agent (CoELA) (Zhang et al., 2024a), human designers collaborate with the LLM-based agent (Sharma et al., 2024).

Coordination. Coordination is the organized process of aligning and synchronizing the actions of multiple human and LLM-based agents to achieve a shared objective. The key idea behind coordination is to avoid conflict and bias in both humans and LLM-based agents to reach the final goal. It involves clear communication, strategic planning, and the intentional division of tasks, ensuring that individual efforts are harmonized and effectively integrated to support common goals. For instance, human and agents work in the shared workplace to complete interdependent tasks (Zhang et al., 2024b), human and agent integration for the adaptive decision-making (Sun et al., 2024b), Agent-Coord for coordination work between human and agent (Pan et al., 2024a).

3.3.2 Competition

Competition is a form of interaction where participants aim to achieve their own goals, which often conflict with the objectives of others. In the LLM-HAS, competition emerges when agents or humans seek to enhance their personal performance or obtain resources, even if it negatively impacts

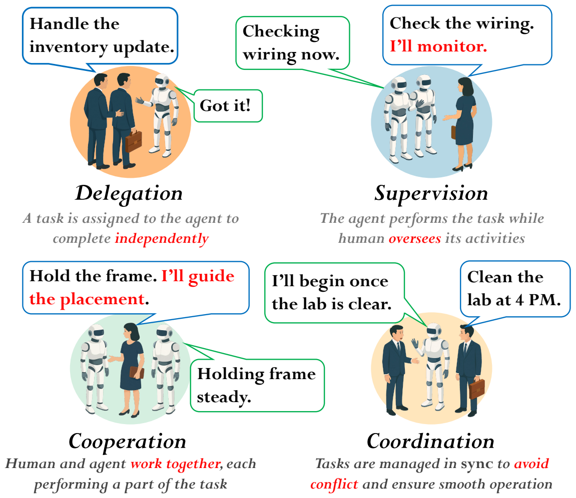

Figure 3: The subtype of the collaboration between humans and LLM-based agents.

collective results. In addition, competition also necessitates effective balancing mechanisms, like performance regulation or conflict resolution strategies, to prevent unproductive behaviors and ensure that the overall goals of the system remain intact. For instance, simulating the human and LLM-based agent social behaviors in the SOTOPIA framework (Zhou et al., 2024).

3.3.3 Coopetition

Coopetition is an interaction where cooperation and competition coexist at the same time. Within this interaction, participants collaborate on shared tasks or mutual goals while also seeking to outdo each other to improve their own performance or gain extra advantages. In terms of the LLM-HAS, this dual aspect implies that agents and human may join forces to address complex issues while competing in specific domains such as efficiency or precision. This approach not only combines the strengths of both collaboration and competition but also fosters innovation driven by competitive incentives while also reaping the benefits of cooperative synergy. Successfully managing coopetition typically requires mechanisms for building trust and adaptable strategies that reconcile collective advantages with personal aspirations, which is a challenge for the LLM-HAS. For example, humans and agents play the prisoner's dilemm in the shared workspace (Jiang et al., 2025).

3.4 Orchestration Paradigm

The orchestration paradigm in LLM-HAS refers to *how* tasks and interactions are managed between humans and agents, covering two dimensions in our survey: **Task Strategy** (*ordering*) and **Temporal Synchronization** (*timing*).

3.4.1 Task Strategy

In LLM-HAS, the chosen task strategy, defined by the order and grouping of tasks performed by humans and agents, significantly impacts task execution effectiveness and efficiency. These strategies can typically be categorized into *one-by-one* and *simultaneous* paradigms.

One-by-One. The one-by-one strategy requires participants (humans and LLM-based agents) to perform tasks sequentially, taking clearly defined turns. For example, a human first outlines a plan, the agent then executes the task, the human subsequently reviews the output, and finally, the agent refines its work based on feedback (Chang et al., 2024; Zhou et al., 2025). Such sequential interaction helps maintain a clear order of execution and reduces the complexity associated with concurrent task management. However, this rigidity may limit overall efficiency and flexibility, especially in dynamic scenarios requiring parallel processing or rapid interaction cycles (Bansal et al., 2024; Guo et al., 2024b).

Simultaneous. Simultaneous strategy describes an interaction pattern in which LLM-based agents and humans respond concurrently in real time. Compared to the one-by-one strategy, the simultaneous approach more closely mirrors real-world conditions encountered in many simulation tasks (Liu et al., 2023b; Zhang et al., 2025). However, this strategy demands sophisticated mechanisms to handle latency mitigation and seamless coordination between participants.

3.4.2 Temporal Synchronization

Temporal synchronization in LLM-HAS refers to the timing and coordination of interactions between humans and agents. It significantly influences system responsiveness, user experience, and task efficiency. It can be broadly categorized into two modes: *synchronous* and *asynchronous*.

Synchronous. Synchronous interaction involves real-time interactions where humans and agents engage simultaneously. Immediate response is expected, facilitating dynamic exchanges. Examples include live chat sessions, real-time voice

Orchestration Paradigm	Description
Task Strategy	**What order and grouping** of tasks do participants perform?
One-by-One	**Actors take turns** (e.g., human plans → agent executes → human reviews → agent refines).
Simultaneous	**Actors work in parallel** (e.g., agent streams partial suggestions while human types).
Temporal Synchronization	**When and how tightly** do actors' steps need to align in time?
Synchronous	(1) **Real-time interaction**: Humans and agents communicate simultaneously or in immediate sequence ; (2) **Immediate response**: Participants expect or require prompt feedback. (e.g. live chat session, real-time voice assistant).
Asynchronous	(1) **Delayed interaction**: Communication occurs without the expectation of immediate responses ; (2) **Flexible timing**: Participants can respond at their convenience. (e.g., email queues, human leaves comments, agent processes offline).

Table 2: Orchestration paradigms in LLM-based human–agent systems encompass two orthogonal dimensions: task strategy, which can be one-by-one or simultaneous, and temporal synchronization, which can be synchronous or asynchronous.

assistants (e.g., Siri, Alexa), and collaborative decision-making scenarios (Zhang et al., 2024b; Liu et al., 2023b). This mode is advantageous for tasks requiring rapid responses, immediate clarification, or real-time collaboration (Mehta et al., 2024; Han et al., 2025).

Asynchronous. In contrast, asynchronous interaction occurs without the necessity for immediate responses. Participants can engage at their convenience, allowing for flexibility in communication. Examples include email exchanges, message queues, ticket-based support systems, and task assignments where agents process and report outcomes independently (Shao et al., 2024; Zhang et al., 2025). Asynchronous communication is beneficial for complex issues that require thoughtful analysis or when participants are in different time zones (Sun et al., 2024b,a).

3.5 Communication

In LLM-HAS, communication serves as the fundamental mechanism defining the transmission, reception, and transformation of information between humans and LLM-based agents. It focuses specifically on how *information flows* across participants to support effective interaction and mutual understanding. Unlike LLM-based multi-agent systems (Yan et al., 2025), human-agent systems introduce a unique dimension (i.e., flexible, and cognitively diverse human participation). This leads to a broader and more complex communication landscape, encompassing both human-to-agent and agent-to-agent exchanges, each influenced by human interpretability, feedback style, and interaction latency.

To systematically analyze communication behavior in such systems, we propose a two-dimensional taxonomy that captures the communication behavior characteristics of humans and agents from macro-structures to micro-interaction rules. Specifically, we divide this section into the following parts: **Communication Structure**, which describes the macro-level organization of information channels, and **Communication Mode**, which characterizes the micro-level methods of message exchange.

3.5.1 Communication Structure

Communication structure refers to the organizational structure of agents, including both humans and agents, in LLM-HAS. It determines how information flows at the macro level and shapes the rules of interaction at the micro level. While originally developed for LLM-based multi-agent environments (Guo et al., 2024a), these structures have been effectively adapted to human-agent scenarios by treating humans as specialized agents. In such systems, the communication structure not only governs the efficiency of information exchange but also significantly impacts the system's adaptability, scalability, and robustness to human variability. We categorize the representative structures into three types: **Centralized**, **Decentralized**, and **Hierarchical**.

In **Centralized** structure, one primary agent or a group of core agents acts as a central node to coordinate all communications within the system. This central agent manages interactions among other agents, simplifying coordination and minimizing conflicts (Cui et al., 2024). **Decentralized** structure employs peer-to-peer communication, enabling direct interactions among agents without centralized control. Agents autonomously manage their communications based on systemic information, enhancing system flexibility, adaptability, and robustness (Shao et al., 2024; Xu et al., 2025). In addition, **Hierarchical** structure organizes agents into clearly defined levels, assigning distinct roles and responsibilities according to their position within the hierarchy (Liu et al., 2023b; Pan et al., 2024c). High-level agents typically fulfill managerial or strategic roles, providing overarching guidance and supervision, while lower-level agents perform specialized tasks and execute detailed operations.

3.5.2 Communication Mode

Communication mode defines the manner through which humans and agents exchange information within LLM-HAS. Specifically, communication mode describes the methods employed by participants to transmit, acquire, and utilize information, critically shaping interaction efficiency and the overall performance of the system. Broadly, communication modes can be categorized into three primary approaches: **Conversation**, **Observation**, and **Shared Message Pool**.

Conversation. The conversation-based mode is perhaps the most prevalent and intuitive approach in LLM-HAS, wherein agents and humans directly engage through natural language dialogues. This interaction format typically utilizes conversational interfaces that allow iterative exchanges, questions, clarifications, and dynamic responses, facilitating efficient collaboration and mutual understanding (Shao et al., 2024). For instance, conversational LLM agents can assist users by answering queries, explaining complex concepts, or collaboratively solving reasoning tasks through iterative dialogues (Wang et al., 2024c). While intuitive and flexible, conversational interactions rely significantly on the communicative clarity and dialogue management capabilities of the LLM agents.

Observation. In the observation-based communication mode, agents acquire information implicitly by observing participants behaviors, decisions, or interactions within their environment, rather than through explicit verbal communication. This mode leverages indirect signals, including user actions, feedback cues, or behavioral traces, to infer intentions, preferences, or states (Seo et al., 2025). For example, an LLM-driven tutoring system may adaptively provide targeted instructions by continuously observing student problem-solving behaviors without explicit verbal queries (Pan et al., 2024c). However, relying solely on observational signals can introduce ambiguity, potentially impacting inference accuracy unless complemented by robust inferential mechanisms.

Message Pool. The shared message pool mode involves agents and humans exchanging information through a common information repository. Participants publish messages or data into a message pool, subscribing and retrieving relevant messages based on specific interests or tasks (Sun et al., 2024a). This approach significantly simplifies direct agent-to-agent or human-to-agent interactions, reduces communication complexity, and enhances information management efficiency. A prominent example includes the MetaGPT framework (Hong et al., 2023), where LLM-based agents collaboratively retrieve information dynamically from a shared message pool, streamlining cooperation and information dissemination. Despite these advantages, shared message pools must carefully manage access control to avoid information conflicts or inefficient retrieval.

4 Application

Embodied AI. Embodied AI applications involve various aspects of dynamic and complex real-world tasks, benefiting from valuable humans' feedback and interactions in Human-Agent collaboration for adaptation. Ye et al. (2023) explores incorporating LLMs in human-robotic collaboration assembly tasks, allowing seamless communication between robots and humans and increasing trust in human operators. To address the challenges of false planning due to suboptimal environment changes , Seo et al. (2025) proposes REVECA to enable efficient memory management and optimal planning. Additionally, Tanneberg et al. (2024b) extends the agents' collaboration with a group of humans via Attentive Support, enabling agents' ability to remain silent to not disturb the group if desired.

Software Development. Given the inherently collaborative nature of software development, human-agent collaboration has emerged as a critical component in addressing the associated challenges. Feng et al. (2024) introduces ReHAC framework, wherein agents are trained to determine the optimal stages for human intervention within the problem solving process, offering improved generalizability over the traditional heuristic-based approaches. Building on this direction, Zhou et al. (2025); Han et al. (2025); Wang et al. (2024c)

Domain	Datasets & Benchmarks	Proposed or Used by	Data Link
Embodied AI	TaPA	TaPA (Wu et al., 2023)	Link
	EmboInteract	InteractGen (Sun et al., 2024b)	–
	AssistantX	AssistantX (Sun et al., 2024a)	–
	IGLU Multi-Turn	Help Feedback (Mehta et al., 2024)	Link
	PARTNR	PARTNR (Chang et al., 2024)	Link
	MINT	MINT (Wang et al., 2024c)	Link
	C-WAH	REVECA (Seo et al., 2025)	Link
Conversational Systems	WEBLINX	WebLINX (Lù et al., 2024)	–
	Ask-before-Plan	Ask Before Plan (Zhang et al., 2024c)	Link
	Agency Dialogue	Agency Task (Sharma et al., 2024)	–
	WildSeek	Co-STORM (Jiang et al., 2024)	Link
	MINT	MINT (Wang et al., 2024c)	Link
	HOTPOTQA	ReHAC (Feng et al., 2024)	Link
	StrategyQA	ReHAC (Feng et al., 2024)	Link
Software Development	MINT	MINT (Wang et al., 2024c)	Link
	InterCode	ReHAC (Feng et al., 2024)	Link
	ColBench	SWEET-RL (Zhou et al., 2025)	Link
	ConvCodeWorld	ConvCodeWorld (Han et al., 2025)	Link
	ConvCodeBench	ConvCodeWorld (Han et al., 2025)	Link
Gaming	CuisineWorld	MindAgent (Gong et al., 2023)	Link
	MineWorld	MineWorld (Guo et al., 2025)	Link
Finance	FinArena-Low-Cost	FineArena (Xu et al., 2025)	Link

Table 3: Datasets and Benchmarks across various domains.

investigate broader spectrum of human feedback types via multi-turn human-agent interactions. These approaches incorporate carefully designed optimization objectives to effectively capture more diverse and nuanced interactions between humans and agents.

Conversational Systems. Due to the frequent presence of ambiguity and the broad range of complex tasks in conversational systems, effective human-agent collaboration constitutes as a critical component of the system. (Zhang et al., 2024c) introduces Proactive Agent Planning, wherein agents are trained to predict classification needs based on the user-agent conversational interactions and current environment, thereby leading to improved reasoning efficacy. (Wu et al., 2022) introduces Chaining LLM to improve the quality of task outcomes and enhance the transparency, controllability and collaboration from the conversational systems.

Gaming. Human-Agent collaboration is naturally well-suited to simulated gaming environments due to their dynamicity and sophistication. Such collaborative interactions have been shown to enhance humans' experience, satisfaction and comprehension of both the environment and agents (Gong et al., 2023; Gao et al., 2024c). Concurrently, these interactions also contribute to improved agents' task performance and decision-making capabilities. For instance, MindAgent framework (Gong et al., 2023) illustrates the efficacy of human-agent collaboration through measurable improvements in task outcomes when humans and agents work together. Mehta et al. (2024) demonstrates agents achieve improved outcomes when interacting with humans via autonomous confusion detection and clarification questions inquiries. Ait et al. (2024) introduces Meta-Command Communication-based framework to enable effective human-agent collaboration. To address challenges related to execution latency while maintaining strong reasoning capabilities, Liu et al. (2023a) proposes Hierarchical Language Agent that promotes faster responses, stronger cooperation, and more consistent language communications.

Finance. Given the inherent complexity of stock markets and financial data systems, where investors' strategies and risk preferences are critical determinants of successful outcomes, Human-Agent collaboration is increasingly recognized as an essential component in financial decision-making. FinArena (Xu et al., 2025) has been proven effective in stock predictions by integrating the dynamic yet essential collaboration between experienced investors and advanced AI Agents. This collaborative framework is demonstrated to produce optimal investment outcomes in terms of the best annualized return and the sharpe ratio for investors (Xu et al., 2025).

5 Implementation Tools and Resources

5.1 Human-Agent Framework

In this section, we present a comprehensive introduction to the three open-source LLM-HAS frameworks from previous works: Collaborative Gym (Shao et al., 2024), COWPILOT (Huq et al., 2025), and DPT-Agent (Zhang et al., 2025). Although all three employ an LLM-HAS architecture, they differ in key configuration aspects, including environment settings, interaction types, orchestration paradigms, and communication strategies. **Collaborative Gym** (Shao et al., 2024) facilitates asynchronous interactions among humans, agents, and task environments, supporting various simulated and real-world tasks such as travel planning, data analysis, and academic writing. It emphasizes flexible, real-time collaboration and evaluates both outcomes and interaction quality, making it a robust tool for studying human-agent dynamics. **COWPILOT** (Huq et al., 2025) provides a framework for human-agent collaborative web navigation through a Chrome extension. It employs a "Suggest-then-Execute" model under human supervision, allowing dynamic interventions to enhance task completion rates and reduce human workload. COWPILOT effectively demonstrates how human intervention can significantly improve agent performance. **DPT-Agent** (Zhang et al., 2025) applies Dual Process Theory (DPT) to enable real-time simultaneous human-agent interactions. It features intuitive, fast decision-making and deliberative reasoning components, employing Theory of Mind and asynchronous reflection to manage latency and adapt dynamically to human actions. This approach excels in environments requiring immediate and adaptive responses.

Other notable frameworks, such as **A2C** (Tariq et al., 2025), **FinArena** (Xu et al., 2025), and a **human-robot collaboration framework** (Liu et al., 2023a), also contribute significantly to specific domains like cybersecurity, financial forecasting, and robotic manipulation, respectively. These frameworks further demonstrate the diverse potential and adaptability of LLM-HAS.

5.2 Datasets and Benchmarks

We summarize the commonly used datasets and benchmarks for Large Language Model-based Human-Agent Systems in Table 3. Diverse domains employ distinct methodologies for evaluating these systems, aligned closely with their unique application contexts. Within the domain of embodied AI, the primary approach involves simulated environments (Sun et al., 2024b,a; Mehta et al., 2024), designed to assess how effectively agents cooperate and execute tasks in dynamic, interactive scenarios. Another significant domain, Conversational Systems, encompasses applications such as question answering (Feng et al., 2024), website navigation (Lù et al., 2024), design decision assistance (Sharma et al., 2024), and travel planning (Zhang et al., 2024c), adopting benchmarks that evaluate the ability of language models to function as user-aligned conversational assistants, ensuring interactions meet user expectations. Despite the extensive application coverage of current benchmarks, there remains a clear necessity for the development of more comprehensive and standardized benchmarking frameworks.

6 Challenges and Opportunities

LLM-HAS is designed to improve solutions for daily tasks and complex challenges like advanced reasoning. By integrating the intelligence of humans and LLM-based agents, tasks can be solved wisely and efficiently. However, implementing LLM-HAS may also bring out the duality of transformative potential and significant risk. On one hand, the remarkable capabilities of LLM agent in natural language understanding, generation (Zou et al., 2024a,b), and emergent reasoning (Wang et al., 2024b; Gu et al., 2025) have catalyzed their integration into increasingly sophisticated agentic systems (Xi et al., 2025). However, this potential is counterbalanced by several fundamental challenges. These challenges can be divided into five distinct aspects: ***(1) Mostly Agent-Centered Work (2) Human Flexibility and Variability (3) Inadequate Evaluation Methodologies (4) Unresolved Safety Vulnerabilities (5) Fine-Grained Collaboration Type***.

Mostly Agent-Centered Work. In most LLM-HAS studies, guidance flows in usually in a single direction, with humans evaluating agent outputs and providing corrective or evaluative feedback. Namely, the current studies are mostly agent-centered. However, enabling agents to observe human actions, detect errors or inefficiencies, and offer timely suggestions can transform collaboration and reduce human effort by leveraging agent intelligence. When agents act as instructors by proposing alternative strategies, drawing attention to overlooked risks, and reinforcing effective practices as tasks unfold in real time, both the human and agent benefit. Genuine collaboration arises when humans and LLM-based agents stand as equal partners and give equal weight to each other's insights. However, current work primarily focuses on delegation rather than coordination or cooperation, leaving significant potential for feedback loops driven by agents. We believe that shifting toward human-centered system, or an equalized LLM-HAS, will unlock the full promise of teamwork between humans and agents.

Human Flexibility and Variability. Human feedback varies widely in terms of role, timing, and style across various LLM-HAS. Human are usually subjective based on their personalities. Namely, different humans in LLM-HAS may lead to different outcomes and conclusions. In addition, humans, regarded as a "special agent" in the LLM-HAS, are subject to fewer restrictions and evaluations than LLM-based agents. This limits how the LLM-HAS can be improved because the impedance may be on the human side instead of the agent. This concern remains and requires a refined strategy to define the strict, fine interaction rule and evaluation equally for both human and LLM-based agents. Also, many studies today substitute real human participants with LLM simulated human proxies, failing to capture human input's variety and unpredictability. The performance gap between humans and the simulated human remains unknown, potentially making the comparison incomparable.

Inadequate Evaluation Methodologies. In existing evaluation frameworks for LLM-HAS, improvements focus primarily on agent accuracy and static benchmarks, which ignore the real burden placed on human collaborators. People dedicate varying amounts of time, attention and cognitive effort depending on the type and frequency of feedback they must provide, yet no standard metric captures this human workload or its impact on overall efficiency. Evaluation methods should measure factors such as time spent offering feedback, perceived mental workload and effort required to detect and correct errors, and they should cover every phase of the human agent collaboration from initial task assignment through post execution review. As human expertise and LLM based agent capabilities merge to deliver unprecedented performance, both uncertainty and variability grow. A new evaluation approach or set of metrics that systematically and comprehensively quantifies contributions and costs for both humans and agents is essential to ensure truly efficient collaboration.

Unresolved Safety Vulnerabilities. In research on LLM-HAS the emphasis on improving agent performance has left safety, robustness and privacy underexplored in the context of human interaction. As people and LLM-based agents collaborate in dynamic workflows, the risk of misaligned behavior, unexpected failures, or unintended disclosure of sensitive information grows. Humans engaging with these systems need clear safeguards around data sharing, error recovery protocols when agents behave unpredictably and privacy protections that cover every stage of the interaction. Robustness measures must ensure agents handle ambiguous or adversarial inputs without passing harm on to their human partners. Without studies that foreground human experience in safety and privacy design, real-world deployments will struggle to gain trust or meet acceptable risk thresholds. Rigorous investigation of how safety, robustness and privacy shape human agent workflows from design through deployment is essential to build collaborations that are both effective and respectful of human needs.

Fine-Grained Collaboration Type. In current research on LLM-HAS, broad interaction categories such as collaboration or competition are typically clearly defined, but granular-level subtypes such as delegation, coordination, and supervision remain underspecified. Yet these subtypes play a critical role in shaping the division of labor, communication patterns, and decision-making protocols between humans and agents. For instance, delegation implies that a human issues a goal and the agent independently plans and executes the necessary steps. In contrast, coordination involves dynamic sharing of responsibilities and mutual adjustment of actions. Without a precise taxonomy of interaction subtypes, it is impossible to compare different systems, establish standard evaluation benchmarks or ensure predictable behavior. This ambiguity is particularly harmful when executing real-time or safety-critical tasks, where unclear role definitions may lead to miscommunication, operational failures, or reduced trust. Developing a systematic framework that clearly defines each interaction subtype will therefore enable rigorous experimental design, more reliable performance and smoother collaboration in complex LLM-HAS.

7 Conclusion

This paper presents a comprehensive review of LLM-based Human-Agent Systems. We introduce a structured taxonomy covering five core dimensions, environment and profiling, human feedback, interaction types, orchestration paradigms, and communication, and use it to classify and analyze existing research on LLM-HAS. We also summarize representative implementation frameworks, benchmark datasets, and evaluation schemes to support reproducibility and comparative analysis. Finally, we identify key challenges and unresolved issues in current LLM-HAS research. These issues remain major obstacles to the development of effective, adaptive, safe and trustworthy human-agent systems. We hope this review offers a comprehensive understanding of the LLM-HAS landscape and serves as a practical guide for future research.

Limitations

Although we strive to include a wide range of representative works (e.g., ACL, EMNLP, NAACL, EACL, COLM, NeurIPS, ICLR, ICML, etc.), some relevant research may not be included, especially recent preprints or interdisciplinary research in fields such as cognitive science. At the same time, although this review briefly discusses safety issues, it does not fully explore broader ethical and social impacts, including the allocation of responsibilities, long-term coexistence of humans and machines, and the consistency of values. These issues deserve further investigation in future work.

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A Difference with Multi-Agent Systems

While both LLM-HAS and MAS involve collaboration among multiple entities, the key distinction lies in the nature and role of the collaborating parties (Feng et al., 2024; Shao et al., 2024). Multi-agent systems are typically composed exclusively of autonomous agents—each designed to make decisions, communicate, and coordinate tasks with one another. In these MAS, each agent operates based on its own set of objectives and algorithms, and the overall behavior emerges from their interactions (Tran et al., 2025; Guo et al., 2024a).

In contrast, LLM-based human–agent systems explicitly incorporate humans as active participants within the decision-making loop (Feng et al., 2024). Rather than letting the system run purely on the combined strategies of several LLM-powered agents, these systems are engineered with mechanisms to allow human supervision, intervention, and feedback (Mehta et al., 2024). This human-in-the-loop design is critical when balancing the strengths of LLMs—such as processing vast amounts of knowledge and performing rapid reasoning—with the need for contextual, ethical, and domain-specific judgments that humans uniquely provide (Vats et al., 2024).

Furthermore, multi-agent systems often assume that the collaboration among agents can lead to a form of "collective intelligence" where agents work toward shared objectives (Sun et al., 2024b). In many such frameworks, the communication protocols, coordination strategies, and role dynamics are all defined among non-human entities. In contrast, in human–agent systems, the interaction protocols are designed to enhance transparency and provide control for human decision-makers (Shao et al., 2024). The system can selectively escalate issues for human review, enable corrective actions when the automated decision may be off-mark, and integrate human feedback to iteratively improve the agent's performance over time (Mehta et al., 2024).

B Human Feedback Type and Subtype

In this appendix, we present a detailed introduction of human feedback types and their subtypes as shown in Table B.1. Table B.1 summarizes its corresponding definition and explains how human feedback guides or constrains an LLM-based agent's learning process. While the main text has already discussed the broad categories of evaluative, corrective, guidance, and implicit of the human feedback to the LLM-based agent in interaction, here we unpack each category into more fine-grained forms, ranging from scalar ratings and preference rankings to direct edits, demonstrations, and inferred behavioral signals. The subtype can help us understand how we react with the LLM-agent with clear instruction and task definition. By acquiring this knowledge, the human are able to improve the quality of interaction with the LLM-based agent. In addition, this comprehensive breakdown enables a systematic comparison across current studies and highlights the diverse ways in which human users can steer, correct, or collaborate with the LLM-based-agent.

C Evaluation Metrics

Evaluating LLM-based human agent systems requires comprehensive methodologies that capture both objective performance metrics and subjective user experiences. Current evaluation strategies have evolved to address these multidimensional aspects, adopting diverse approaches tailored to different contexts and system designs. This section discusses these evaluation methods under three primary categories: Quantitative Evaluation, Qualitative Evaluation, and Mixed-Method Evaluation.

C.1 Quantitative Evaluation

Quantitative evaluations focus on objective metrics to systematically assess system performance across various tasks and frameworks. For instance, in the healthcare domain, Vollmuth et al. (2023), Van Leeuwen et al. (2022) leverage precision, recall, and F1-score metrics to evaluate AI-assisted diagnostic tasks, specifically in oncology and radiology. Similarly, financial domains employ quantitative metrics such as true positives and false positives to for fraud detection evaluation as exemplified in Al-Fatlawi et al. (2024). In manufacturing, quantitative performance metrics are emphasized for assessing AI assistance in process efficiency and safety compliance, as demonstrated by Sankaran et al. (2022) and Massaro (2022). Other specialized domains also propose tailored quantitative metrics, such as specific performance scores in game-based AI (Siu et al., 2021) and evaluation frameworks in neuromorphic computing (Yik et al., 2025).

C.2 Qualitative Evaluation

Complementing quantitative metrics, qualitative evaluations aim to examine subjective aspects such

Human Feedback Type	Description	How it Helps Agents
Evaluative Feedback	User provides an assessment of the agent's output quality.	Signals overall correctness or preference, guiding general alignment.
Preference Ranking	User compares two or more agent outputs and selects the preferred one.	Helps the agent learn relative quality and subjective nuances.
Scalar Rating	User assigns a numerical score (e.g., 1–5) to the agent's output.	Provides a quantitative measure of satisfaction or quality.
Binary Assessment	User indicates simple correctness (e.g., yes/no, thumbs up/down).	Offers a basic signal of success or failure.
Corrective Feedback	User modifies or directly improves the agent's output.	Provides explicit examples of desired output, enabling direct learning from errors.
Direct Edits/Refinements	User manually changes the agent's generated text or code.	Shows the agent the precise correction needed.
Guidance Feedback	User provides instructions or explanations to steer the agent.	Offers deeper context, reasoning, or demonstrations for learning complex behaviors.
Demonstrations	User shows the agent how to perform a task correctly.	Teaches specific procedures or desired interaction patterns.
Instructions/Critiques	User provides natural language explanations, critiques, or step-by-step guidance.	Helps the agent understand why an output is wrong and how to improve.
Implicit Feedback	Agent infers user preference from their behavior.	Reveals preferences and usability issues without explicit feedback requests.
Human Action/Control	Human directly takes actions and control.	Collaborate with humans to effectively finish tasks or learns from human actions.

Table B.1: Human Feedback Type and Subtype.The subtype of evaluative feedback includes preference ranking, scalar rating, and binary assessment. The subtype of corrective feedback includes the direct edits or refinement. The subtype of guidance feedback includes the demonstration and instructions or critiques. The subtype of implicit feedback include the human action or control.

as user perceptions, trust, adaptability, and ethical considerations. For example, Timmons et al. (2023) employs qualitative methods including interviews and case studies to investigate potential biases in mental health AI applications. Rezwana and Maher (2023) explores qualitative feedback to assess the impact of AI on creative workflows, underscoring the importance of human-AI interaction dynamics. Sharma et al. (2023) demonstrates the value of qualitative insights by examining conversational empathy improvements in AI-assisted mental health platforms through user feedback and thematic analyses. These qualitative methodologies are vital for uncovering the nuanced human factors influencing system adoption and effectiveness.

C.3 Mixed-Method Evaluation

The mixed-method approach integrates quantitative and qualitative evaluations, offering a holistic assessment tailored to specific contexts. This approach addresses the limitations inherent in exclusively quantitative or qualitative methods by combining measurable performance outcomes with rich user-centric insights. For example, Arias-Rosales (2022) evaluates AI-generated design output by pairing quantitative shape metrics with qualitative user assessments, providing deeper insights into subjective aesthetic values. Similarly, in finance, Chakravorti et al. (2022) combines detection accuracy with user trust evaluations to identify issues related to transparency and interpretability. Mixed-method evaluations are particularly effective in understanding complex interactions between humans and AI, facilitating nuanced and contextualized evaluations that are essential across diverse domains. By leveraging the advantage of the mixed-method, Fragiadakis et al. (2024) provides a robust and comprehensive framework that integrates multiple evaluation dimensions to effectively assess Large Language Model-based Human-Agent Systems across diverse contexts.

D Tables

Table D.1 catalogs the environmental configuration and human feedback type, and Table D.2 categorizes the interaction, orchestration, and communication of the current works, respectively.

Table D.1: The ① Humans-Agent Configuration ② Human Feedback in LLM-based human–agent systems.

Paper	*Venue*	Code/ Data	Environment Configuration		Human Feedback to LLM-based Agent			
			Human	**LLM Agent**	**Type**	**Subtype**	**Granularity**	**Phase**
Collaborative Gym (Shao et al., 2024)	*Arxiv'25*	Link	Single	Single	Corrective	Refinement	Segment	During Task
MTOM (Zhang et al., 2024b)	*Arxiv'24*	–	Single	Single	Corrective	Refinement	Segment	During Task
FineArena (Xu et al., 2025)	*Arxiv'25*	–	Single	Multiple	Guidance	Demonstration	Segment	During Task
Prison Dilemm (Jiang et al., 2025)	*Arxiv'25*	–	Single	Single	Implicit	User Action	Segment	During Task
InteractGen (Sun et al., 2024b)	*THU'24*	–	Multiple	Multiple	Guidance	Demonstration	Segment	During Task
AI Chains (Wu et al., 2022)	*CHI'24*	–	Single	Single	Corrective	Refinement	Segment	During Task
Drive As You Speack (Cui et al., 2024)	*WACV'24*	–	Single	Multiple	Guidance	Demonstration	Segment	During Task
AgentCoord (Pan et al., 2024a)	*Arxiv'24*	Link	Single	Multiple	Guidance, Corrective	Demonstration, Refinement	Segment	Initial Setup
CowPilot (Huq et al., 2025)	*Arxiv'25*	Link	Single	Single	Corrective, Implicit	User Action, Refinement	Segment	During Task
EasyLAN (Pan et al., 2024c)	*Arxiv'24*	–	Single	Multiple	Corrective, Guidance	Demonstration, Refinement	Segment	During Task
Hierarchical Agent (Liu et al., 2023b)	*AAMAS'24*	–	Single	Multiple	Guidance, Corrective	Demonstration, Refinement	Segment	During Task
SWEET-RL (Zhou et al., 2025)	*Arxiv'25*	Link	Single	Single	Corrective, Implicit	Refinement, User Action	Segment	During Task
HRC Assembly (Gkournelos et al., 2024)	*CIRP'24*	–	Single	Multiple	Guidance	Demonstration	Segment	During Task
REVECA (Seo et al., 2025)	*Arxiv'24*	–	Single	Single	Implicit	Human Control	Segment	During Task
AssistantX (Sun et al., 2024a)	*Arxiv'24*	Link	Multiple	Multiple	Implicit	Human Control	Holistic	Initial Setup
MINT (Wang et al., 2024c)	*ICLR'24*	Link	Single	Single	Evaluative	Binary Assessment	Holistic	During Task
Help Feedback (Mehta et al., 2024)	*EACL'24*	–	Single	Single	Corrective, Guidance	Demonstration, Refinement	Holistic	During Task
ConvCodeWorld (Han et al., 2025)	*ICLR'25*	Link	Single	Single	Guidance	Demonstration, Critique	Segment	During Task
ReHAC (Feng et al., 2024)	*ACL'24*	Link	Single	Single	Implicit	Human Control	Segment	During Task
DPT Agent (Zhang et al., 2025)	*Arxiv'25*	Link	Single	Single	Guidance	Critique	Holistic	During Task
HRC Manipulation (Liu et al., 2023a)	*IEEE'23*	–	Single	Single	Corrective, Guidance	Demonstration, Refinement	Segment	During Task
HRC DMP (Liu et al., 2024)	*IEEE'24*	–	Single	Single	Corrective	Refinement	Holistic	During Task
PARTNR (Chang et al., 2024)	*ICLR'25*	Link	Single	Single	Corrective, Guidance	Refinement, Critique	Holistic, Segment	During Task, Post Task
Organized Teams (Guo et al., 2024b)	*Arxiv'24*	Link	Single	Multiple	Guidance	Critique	Holistic	During Task
CoELA (Zhang et al., 2024a)	*ICLR'23*	–	Single	Multiple	Evaluative	Scaler Rating	Holistic	Post Task
Agency Task (Sharma et al., 2024)	*EACL'24*	Link	Single	Single	Guidance	Demonstration, Critique	Segment	During Task
GDfC (Wang et al., 2025c)	*SME'25*	–	Single	Multiple	Guidance, Evaluative	Demonstration, Binary Assessment, Preference Ranking	Holistic, Segment	Initial Setup, Post Task
PDFChatAnnotator (Tang et al., 2024)	*IUI'24*	–	Single	Single	Corrective, Guidance	Demonstration, Refinement	Segment	During Task
Attentive Supp. (Tanneberg et al., 2024a)	*IEEE'24*	Link	Multiple	Single	Implicit, Guidance	Demonstration, User Action	Holistic	Initial Setup, During Task
HRC Trust (Ye et al., 2023)	*IEEE'23*	–	Single	Single	Guidance	Demonstration, Critique	Segment	During Task
HA Comm. (Bansal et al., 2024)	*Arxiv'24*	–	Single	Multiple	Guidance	Demonstration, Critique	Holistic, Segment	Initial Setup, During Task, Post Task
BPMN (Ait et al., 2024)	*Arxiv'24*	Link	Multiple	Multiple	Guidance	Demonstration	Holistic	Initial Setup, During Task, Post Task
Co-STORM (Jiang et al., 2024)	*EMNLP'24*	Link	Single	Multiple	Guidance	Demonstration	Segment	During Task
HRC Manufa. (Lim et al., 2024)	*IEEE'24*	–	Single	Single	Corrective, Guidance	Demonstration, Refinement, Critique	Segment	Initial Setup, During Task
A2C (Tariq et al., 2025)	*Arxiv'24*	Link	Multiple	Multiple	Guidance, Implicit, Corrective, Evaluative	Refinement, Binary Assessment, Critique, Human Control	Holistic, Segment	During Task
MindAgent (Gong et al., 2023)	*NAACL'24*	Link	Multiple	Multiple	Corrective	Refinement	Segment	During Task
Ask Before Plan (Zhang et al., 2024c)	*EMNLP'24*	Link	Single	Multiple	Guidance	Demonstration, Critique	Segment	During Task
SOTOPIA (Zhou et al., 2024)	*ICLR'24*	–	Multiple	Multiple	Evaluative, Implicit	Scaler Rating, User Action	Holistic, Segment	During Task, Post Task
PaLM-E (Driess et al., 2023)	*ICML'23*	Link	Single	Single	Guidance, Implicit	Demonstration, User Action	Segment	During Task
TaPA (Wu et al., 2023)	*Arxiv'23*	Link	Single	Single	Guidance, Evaluative	Demonstration, Binary Assessment	Holistic, Segment	Initial Setup, Post Task
MetaGPT (Hong et al., 2023)	*ICLR'24*	Link	Single	Multiple	Evaluative, Guidance	Binary Assessment	Holistic	Initial Setup, Post Task
DigiRL (Bai et al., 2024)	*NeurIPS'24*	Link	Single	Single	Evaluative	Binary Assessment	Holistic	During Task, Post Task
WebLINX (Lù et al., 2024)	*Arxiv'24*	Link	Multiple	Single	Guidance	Demonstration	Holistic, Segment	During Task
Auto Agent (Pan et al., 2024b)	*COLM'24*	Link	Single	Single	Evaluative	Binary Assessment	Holistic	Post Task
WebCanvas (Pan et al., 2024d)	*Arxiv'24*	Link	Single	Single	Evaluative	Scaler Rating	Holistic	Post Task
MineWorld (Guo et al., 2025)	*Arxiv'25*	Link	Multiple	Single	Evaluative	Scaler Rating	Holistic	Post Task

Table D.2: The ① Interaction ② Orchestration ③ Communication in LLM-based human–agent systems.

			Interaction		Orchestration		Communication	
Paper	***Venue***	**Code/ Data**	**Types**	**Variant**	**Strategy**	**Sync**	**Structure**	**Mode**
Collaborative Gym (Shao et al., 2024)	*Arxiv'25*	Link	Collaboration	Supervision, Delegation	One-by-One	Asynchronous	Decentralized	Conversation
MTOM (Zhang et al., 2024b)	*Arxiv'24*	–	Collaboration	Coordination	Simultaneous	Synchronous	Decentralized	Conversation
FineArena (Xu et al., 2025)	*Arxiv'25*	–	Collaboration	Delegation	One-by-One	Synchronous	Hierarchical	Conversation
Prison Dilemm (Jiang et al., 2025)	*Arxiv'25*	–	Coopetition	–	One-by-One	Synchronous	Decentralized	Conversation
InteractGen (Sun et al., 2024b)	*THU'24*	–	Collaboration	Cooperation, Delegation, Coordination	One-by-One	Asynchronous	Decentralized	Message Pool
AI Chains (Wu et al., 2022)	*CHI'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Hierarchical	Conversation
Drive As You Speack (Cui et al., 2024)	*WACV'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Centralized	Conversation
AgentCoord (Pan et al., 2024a)	*Arxiv'24*	Link	Collaboration	Coordination	One-by-One	Synchronous	Decentralized	Conversation
CowPilot (Huq et al., 2025)	*Arxiv'25*	Link	Collaboration	Supervision, Delegation, Coordination	One-by-One	Synchronous	Decentralized	Conversation
EasyLAN (Pan et al., 2024c)	*Arxiv'24*	–	Collaboration	Delegation, Supervision	One-by-One	Synchronous	Hierarchical	Observation
Hierarchical Agent (Liu et al., 2023b)	*AAMAS'24*	–	Collaboration	Supervision, Delegation	Simultaneous	Synchronous	Hierarchical	Conversation
SWEET-RL (Zhou et al., 2025)	*Arxiv'25*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
HRC Assembly (Gkournelos et al., 2024)	*CIRP'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Centralized	Conversation
REVECA (Seo et al., 2025)	*Arxiv'24*	–	Collaboration	Delegation	One-by-One	Asynchronous	Hierarchical	Observation
AssistantX (Sun et al., 2024a)	*Arxiv'24*	Link	Collaboration	Delegation	One-by-One	Asynchronous	Decentralized	Message Pool
MINT (Wang et al., 2024c)	*ICLR'24*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
Help Feedback (Mehta et al., 2024)	*EACL'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
ConvCodeWorld (Han et al., 2025)	*ICLR'25*	Link	Collaboration	Supervision, Delegation	One-by-One	Asynchronous	Decentralized	Conversation
ReHAC (Feng et al., 2024)	*ACL'24*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
DPT Agent (Zhang et al., 2025)	*Arxiv'25*	Link	Collaboration	–	Simultaneous	Asynchronous	Decentralized	Observation
HRC Manipulation (Liu et al., 2023a)	*IEEE'23*	–	Collaboration	Supervision, Delegation	One-by-One	Synchronous	Decentralized	Conversation
HRC DMP (Liu et al., 2024)	*IEEE'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
PARTNR (Chang et al., 2024)	*ICLR'25*	Link	Collaboration	Coordination, Cooperation	One-by-One	Asynchronous	Decentralized	Conversation
Organized Teams (Guo et al., 2024b)	*Arxiv'24*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
CoELA (Zhang et al., 2024a)	*ICLR'23*	–	Collaboration	Cooperation	Simultaneous	Synchronous	Decentralized	Conversation
Agency Task (Sharma et al., 2024)	*EACL'24*	Link	Collaboration	Cooperation, Delegation	One-by-One	Synchronous	Decentralized	Conversation
GDfC (Wang et al., 2025c)	*SME'25*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
PDFChatAnnotator (Tang et al., 2024)	*IUI'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
Attentive Supp. (Tanneberg et al., 2024a)	*IEEE'24*	Link	Collaboration	Coordination	One-by-One	Synchronous	Decentralized	Observation
HRC Trust (Ye et al., 2023)	*IEEE'23*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
HA Comm. (Bansal et al., 2024)	*Arxiv'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
BPMN (Ait et al., 2024)	*Arxiv'24*	Link	Collaboration	Coordination	One-by-One	Asynchronous	Decentralized	Conversation
Co-STORM (Jiang et al., 2024)	*EMNLP'24*	Link	Collaboration	Coordination	One-by-One	Synchronous	Decentralized	Conversation
HRC Manufa. (Lim et al., 2024)	*IEEE'24*	–	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
A2C (Tariq et al., 2025)	*Arxiv'24*	Link	Collaboration	Coordination	One-by-One	Asynchronous	Decentralized	Conversation
MindAgent (Gong et al., 2023)	*NAACL'24*	Link	Collaboration	Coordination	One-by-One	Synchronous	Centralized	Conversation
Ask Before Plan (Zhang et al., 2024c)	*EMNLP'24*	Link	Collaboration	Coordination	One-by-One	Synchronous	Centralized	Conversation
SOTOPIA (Zhou et al., 2024)	*ICLR'24*	–	Collab./Comp./Coo[illegible]	Coordination	One-by-One	Synchronous	Centralized	Conversation
PaLM-E (Driess et al., 2023)	*ICML'23*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
TaPA (Wu et al., 2023)	*Arxiv'23*	Link	Collaboration	Delegation	One-by-One	Asynchronous	Decentralized	Conversation
MetaGPT (Hong et al., 2023)	*ICLR'24*	Link	Collaboration	Coordination	One-by-One	Asynchronous	Decentralized	Message Pool
DigiRL (Bai et al., 2024)	*NeurIPS'24*	Link	Collaboration	Delegation	One-by-One	Asynchronous	Decentralized	Conversation
WebLINX (Lù et al., 2024)	*Arxiv'24*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
Auto Agent (Pan et al., 2024b)	*COLM'24*	Link	Collaboration	Delegation	One-by-One	Asynchronous	Decentralized	Conversation
WebCanvas (Pan et al., 2024d)	*Arxiv'24*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation
MineWorld (Guo et al., 2025)	*Arxiv'25*	Link	Collaboration	Delegation	One-by-One	Synchronous	Decentralized	Conversation