# TRISM FOR AGENTIC AI: A REVIEW OF TRUST, RISK, AND SECURITY MANAGEMENT IN LLM-BASED AGENTIC MULTI-AGENT SYSTEMS

Shaina Raza<sup>1\*</sup>, Ranjan Sapkota<sup>2\*</sup>, Manoj Karkee<sup>2</sup>, Christos Emmanouilidis<sup>3</sup>

<sup>1</sup>Vector Institute, Toronto, Canada

<sup>2</sup>Cornell University, USA

<sup>3</sup>University of Groningen, Netherlands

## **ABSTRACT**

Agentic AI systems, built on large language models (LLMs) and deployed in multi-agent configurations, are redefining intelligent autonomy, collaboration and decision-making across enterprise and societal domains. This review presents a structured analysis of Trust, Risk, and Security Management (TRiSM) in the context of LLM-based agentic multi-agent systems (AMAS). We begin by examining the conceptual foundations of agentic AI, its architectural differences from traditional AI agents, and the emerging system designs that enable scalable, tool-using autonomy. The TRiSM in the agentic AI framework is then detailed through four pillars governance, explainability, ModelOps, and privacy/security each contextualized for agentic LLMs. We identify unique threat vectors and introduce a comprehensive risk taxonomy for the agentic AI applications, supported by case studies illustrating real-world vulnerabilities. Furthermore, the paper also surveys trust-building mechanisms, transparency and oversight techniques, and state-of-the-art explainability strategies in distributed LLM agent systems. Additionally, metrics for evaluating trust, interpretability, and human-centered performance are reviewed alongside open benchmarking challenges. Security and privacy are addressed through encryption, adversarial defense, and compliance with evolving AI regulations. The paper concludes with a roadmap for responsible agentic AI, proposing research directions to align emerging multi-agent systems with robust TRiSM principles for safe, accountable, and transparent deployment.

**Keywords** Agentic AI, LLM-based Multi-Agent Systems, TRISM, AI Governance, Explainability, ModelOps, Application Security, Model Privacy, Autonomous Agents, Trustworthy AI, Risk Management, AI Safety, Privacy-Preserving AI, Adversarial Robustness, Human-in-the-Loop

## 1 Introduction

# 1.1 Background and Motivation

The global market for AI agents is projected to grow from \$5.4 billion in 2024 to \$7.6 billion in 2025 [1]. By mid-2025, over 70% of enterprise AI deployments are expected to involve multi-agent or action-based systems, reflecting a dramatic shift from traditional single-agent or rule-based conversational models [2]. An **AI agent**, typically defined as a computational entity that perceives its environment and takes actions to achieve goals [3], has undergone a fundamental transformation. Whereas early agents were task-specific and deterministic, modern systems, referred to as **Agentic AI**, now integrate large language models (LLMs), tools, and persistent memory to support complex planning and coordination [4, 5].

<sup>\*</sup>Shaina Raza and Ranjan Sapkota contributed equally and are corresponding authors.
Emails: shaina.raza@torontomu.ca, rs2672@cornell.edu, mk2684@cornell.edu, c.emmanouilidis@rug.nl.

**From isolated agents to** *Agentic AI*. The autonomous software agents date back to the 1990s [6], the advent of LLM-driven multi-agent ecosystems [7] since 2023 has made "Agentic AI" a distinctly new and rapidly expanding research focus [4]. Traditional agents automated narrow tasks, such as information retrieval [8, 9], data summarization [10, 11, 12], and dialogue response [13]. Driven by single step logic [14] or scripted rules, they lacked deep reasoning, adaptability, and persistence [15, 16].

In contrast, Agentic AI consists of collaborative agents with specialized roles (e.g., planner, coder, analyst), enabled by LLMs and tool use [17]. These systems dynamically decompose tasks, share context, and pursue high-level goals across long timelines [18, 19, 20]. This shift represents not just a technological upgrade but a qualitative leap in complexity and autonomy, marking the emergence of machine collectives capable of emergent, decentralized behavior.

**Trust, risk, and security challenges.** However, this evolution introduces serious challenges. Unlike deterministic agents [21], Agentic AI systems can produce non-linear, opaque decisions, increasing the risks of failure, bias, and unintended consequences. For example, a multi-agent supply chain optimizer may autonomously coordinate between procurement and logistics agents, yet inadvertently leak sensitive information or violate compliance protocols if safeguards are absent [22].

Traditional evaluation and safety frameworks, built for static or single-function AI, are no longer sufficient. This underscores the urgent need for a new paradigm that integrates trust, risk, and security as core design principles. To address this gap, recent frameworks like AI TRiSM (Trust, Risk, and Security Management) [23, 24] propose lifecycle-level controls, including explainability, secure model orchestration, and privacy management. These are essential for deploying agentic systems in high-stakes domains such as finance, healthcare, and defense.

**Problem Statement** Agentic AI systems now coordinate multiple LLM-powered agents, yet no unified framework exists for managing their trust, risk, and security (TRiSM). High-profile lapses, e.g., an autonomous research agent citing unverifiable medical sources or a forecasting swarm drifting off-target due to memory inconsistencies show that traditional safeguards do not scale to dynamically evolving, multi-agent workflows. A structured TRiSM perspective is therefore crucial to mitigate orchestration failures, collusion, data leakage, and opaque decision paths. This review distills current findings and outlines practical guidelines to build secure, reliable, and trustworthy Agentic AI ecosystems.

**Scope and Objectives** This survey maps the TRiSM (Trust, Risk, and Security Management) landscape for LLM-powered, multi-agent "agentic" AI. We frame four pillars explainability, security, lifecycle governance, and privacy and show why safeguards designed for bounded, rule-based agents cannot contain open-world, self-orchestrating collectives [4, 17]. Our goal is to give researchers and practitioners a concise, unified reference for building and governing trustworthy Agentic AI systems.

Necessity of this Survey Agentic AI research often concentrates on agent modelling or task coordination and rarely tackles adversarial threats, lifecycle governance, or large-scale explainability. As deployments reach high-stakes arenas healthcare, science, finance the absence of a unified TRiSM framework exposes stakeholders to opaque reasoning and unmanaged risks. This survey closes that gap by synthesising TRiSM principles for LLM-driven multi-agent systems and providing actionable guidance for researchers, engineers, and policy makers. A comparison with related surveys will be presented in Table 1.

#### 1.2 Contributions

In this survey, we address the urgent need for a unified governance framework for LLM-based Agentic AI systems. Our framework is shown in Figure 1. Our key contributions are as follows:

- A Conceptual TRISM Framework Tailored to Agentic AI We introduce a structured Trust, Risk, and Security Management (TRISM) framework specifically designed to accommodate the unique characteristics of multi-agent, LLM-driven systems. This framework defines four pillars: Explainability, ModelOps, Application Security, and Model Privacy, and explains how each pillar addresses the challenges of autonomy, coordination, and persistent memory in Agentic AI.
- A Threat Taxonomy for LLM-Powered Agents We develop a detailed taxonomy of risks and threat vectors that arise when multiple LLM agents collaborate. By categorizing vulnerabilities, such as prompt injection, memory poisoning, collusive failures, and emergent misbehavior, we clarify how attack surfaces expand in agentic environments and why traditional LLM security measures are insufficient.
- A Comparative Evaluation of Existing Methods We survey and compare state-of-the-art techniques for each TRISM pillar as applied to Agentic AI. For example, we examine how explainable-AI methods (e.g., LIME, SHAP, decision provenance) have been adapted for multi-agent workflows, how ModelOps best practices must be extended to manage multiple LLM instances, and which security/hardening measures (e.g., prompt hygiene, sandboxing, access controls) are most effective.

| Survey                  | Adversarial<br>Threats | Lifecycle<br>Governance | Large-Scale<br>Explainability | TRiSM<br>Integration | LLM-<br>Specific | Application<br>Domains  | Actionable<br>Guidance      |
|-------------------------|------------------------|-------------------------|-------------------------------|----------------------|------------------|-------------------------|-----------------------------|
| Guo et al. (2024) [25]  | х                      | ×                       | ×                             | ×                    | 1                | (simulated env'ts)      | (research challenges)       |
| Chen et al. (2025) [26] | ×                      | ×                       | ×                             | ×                    | 1                | (task/simulation focus) | (future research areas)     |
| Yan et al. (2025) [27]  | 1                      | х                       | ×                             | ×                    | 1                | (mentions<br>diverse)   | (future work directions)    |
| Tran et al. (2025) [28] | ×                      | х                       | ×                             | ×                    | 1                | (networks, QA, etc.)    | (open challenges)           |
| Lin et al. (2025) [29]  | ×                      | ×                       | ×                             | Х                    | 1                | (creative tasks)        | (roadmap for research)      |
| Fang et al. (2025) [30] | 1                      | х                       | ×                             | ~                    | ~                | (health, finance cited) | (technical "next<br>steps") |
| This Survey (2025)      | 1                      | 1                       | 1                             | 1                    | 1                | (high-stakes domains)   | (practical guidance)        |

Table 1: Comparison of Related Surveys on LLM-based Multi-Agent Systems and TRiSM Aspects

**Legend:** ✓ = explicitly addressed; ~ = partially/indirectly addressed; X = not addressed.

• Future Research Directions for Trustworthy, Secure Agentic AI Building on our TRISM analysis, we outline concrete directions for next-generation research and setup roadmap items aim to guide researchers and practitioners toward robust, scalable, and compliant deployments of Agentic AI.

This study provide a unified reference for researchers, engineers, and policymakers who seek to design, evaluate, and govern LLM-based Agentic AI systems in high-stakes domains.

# 1.3 Paper Organization

The remainder of this paper is structured as follows. In Section 2, we present our literature-search methodology, including databases queried, inclusion criteria, and classification strategies. Section 3 reviews the fundamental characteristics and typical architectures of Agentic AI systems, establishing the groundwork for subsequent TRISM analysis. Section 4 introduces the TRISM framework and its four core pillars: Explainability, ModelOps, Application Security, and Model Privacy. Building on this foundation, Section 5 identifies the primary risks, vulnerabilities, and attack surfaces inherent in multi-agent AI ecosystems. In Section 6, we explore trust-building strategies and specialized explainability techniques tailored to Agentic AI, while Section 7 details advanced security mechanisms and privacy-preserving methods. Section 8 synthesizes our findings and outlines future research directions and policy recommendations. Section 9 concludes the paper. A list of key terms used throughout this paper is provided in Table 9.

# 1.4 Related Work

**LLM-Based Multi-Agent Surveys** (**Technical Focus**): Prior surveys on LLM-driven multi-agent systems primarily emphasize system architectures, agent capabilities, and domain-specific applications of agentic AI, but often overlook critical TRiSM considerations. For instance, existing reviews [25, 26] focus on simulated environments, inter-agent communication, and performance benchmarks, yet fail to address adversarial threats, lifecycle governance, or system-wide explainability. Other targeted surveys, such as [27] on natural language communication and [28] on collaboration mechanisms, explore interaction protocols and use cases in domains like QA systems, 5G, and Industry 5.0. While the former briefly acknowledges security concerns and the latter highlights deployment contexts, both narrowly center on coordination strategies without examining robustness, governance structures, or explainability at scale.

Trustworthy/Responsible AI Surveys (Broad Trust Focus): Surveys in the TRiSM domain address ethical and risk-related concerns such as alignment, fairness, and privacy attacks [30], but typically overlook explainability, governance, and multi-agent dynamics. While they offer actionable recommendations for general ML systems, they do not account for LLM-based coordination in high-stakes domains.

Current Survey (LLM Multi-Agent + TRiSM in High-Stakes Domains): This survey uniquely integrates TRiSM principles into the analysis of LLM-based multi-agent systems, specifically targeting high-stakes domains such as healthcare, science, and finance. In contrast to earlier surveys (shown in Table 1) that underemphasize governance and security, this work foregrounds adversarial threats (e.g., vulnerabilities in agent interaction), end-to-end lifecycle governance (from training data to deployment oversight), and large-scale explainability. These concerns are treated as

integral to system design, not peripheral. Additionally, this survey provides actionable recommendations for researchers, engineers, and policymakers, bridging gaps left by both technical and responsible-AI surveys.

# 2 Literature Review Methodology

To ensure a comprehensive review of the literature on trust, risk, and security in Agentic AI systems, we adopted a structured methodology inspired by best practices in systematic reviews [31, 32]. This section outlines our research objectives, data sources, inclusion criteria, and classification strategy.

**Research Objectives** The review was guided by the following questions:

- RQ1: What are the key trust, risk, and security challenges posed by LLM-enabled Agentic AI systems?
- **RO2:** What technical and governance strategies have been proposed to address these challenges?
- **RQ3:** How do existing approaches map onto the TRiSM pillars: explainability, model operations, security, and privacy?
- **RQ4:** What gaps remain in current research, and what directions are promising for future work?

**Data Sources and Search Strategy** We searched the following major digital libraries: IEEE Xplore, ACM Digital Library, SpringerLink, arXiv, ScienceDirect, and Google Scholar, covering publications from January 2020 to May 2025. The search was executed using Boolean combinations of keywords relevant to Agentic AI and TRiSM, including:

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"agentic AI" OR multi-agent systems "(AMAS)" OR "multi-agent LLMs" OR "AI agents" OR "autonomous agents" OR "intelligent agents") AND ("trust" OR "trustworthiness" OR "risk" OR "security" OR "safety" OR "governance" OR "oversight" OR "compliance" OR "explainability" OR "interpretability" OR "transparency" OR "privacy" OR "data protection")
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In total, 150 unique papers were initially retrieved.

**Inclusion and Exclusion Criteria** We applied the following criteria during the screening process:

#### • Inclusion:

- Studies published between **2022 and 2025**, to capture developments following the introduction of LLMs (mostly post-chatgpt).
- Studies that explicitly discuss *agentic*, *multi-agent*, or *LLM-powered* AI systems in the context of at least one TRiSM dimension: trust, risk, security, governance, explainability, or privacy.
- Peer-reviewed articles, preprints, or whitepapers from credible sources (e.g., arXiv, NeurIPS, IEEE, ACM, Nature, or governmental standards bodies).

#### • Exclusion:

- Papers focused solely on traditional, rule-based, or symbolic agents without any integration of LLMs or emergent coordination.
- Studies addressing only low-level ML components (e.g., training optimization, architecture design) without reference to agentic behavior or TRiSM concerns.
- Non-English papers or those lacking sufficient metadata (e.g., missing abstracts or publication details).

After screening titles and abstracts, we shortlisted 250 papers. A subsequent full-text review narrowed the selection to 180 primary studies that directly addressed one or more TRiSM pillars. In addition to peer-reviewed literature, we also incorporated relevant white papers, technical blogs, and practitioner reports to contextualize and map the emerging landscape of Agentic AI within the TRiSM framework.

**Quality Assurance** To ensure the rigor and reliability of included studies, we conducted a quality assessment adapted from established systematic review guidelines [33, 32]. Each paper was evaluated against the following criteria: (1) Does the study clearly define its objectives in the context of agentic or LLM-based systems? (2) Are the methods, experiments, or architectural designs well-documented and reproducible? (3) Does the paper substantively engage with at least one of the trust, risk, security, explainability, or privacy aspects? (4) Does the study offer empirical, theoretical, or normative contributions relevant to Agentic AI governance? Each criterion was rated as *low*, *medium*, or *high*. Studies scoring "low" in more than two dimensions were excluded or flagged for contextual relevance only. Quality ratings were assigned independently by two reviewers, with discrepancies resolved through discussion.

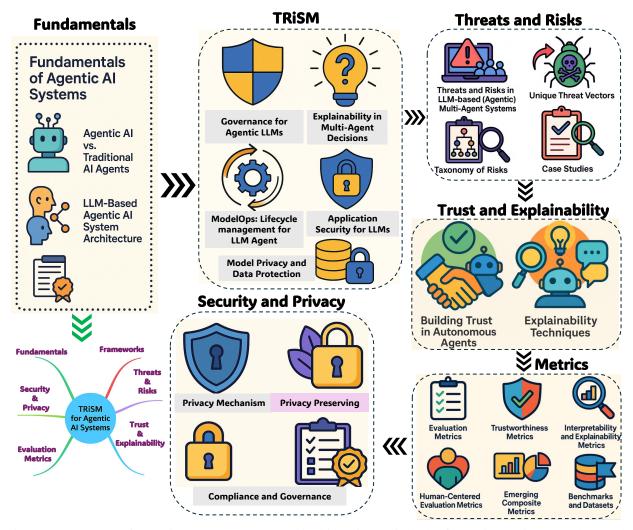


Figure 1: Taxonomy of Agentic AI systems presented in this review. It includes five major sections: Fundamentals of Agentic AI Systems (Agentic AI vs. Traditional AI Agents, LLM-Based Architecture), The TRISM Framework (Governance, Explainability, ModelOps, Application Security, Privacy), Threats and Risks (Unique Threat Vectors, Taxonomy of Risks, Case Studies), Trust and Explainability, and Evaluation Metrics (including Human-Centered and Composite Metrics).

# **3 Fundamentals of Agentic AI Systems**

#### 3.1 Agentic AI vs. Traditional AI Agents

The distinction between traditional AI agents and Agentic AI systems represents a paradigm shift in autonomous system design. Traditional agents operate through predefined rules [34], heuristic workflows [35, 36], or deterministic logic [37], excelling in narrow, bounded environments. In contrast, Agentic AI systems leverage foundation models (LLMs) to achieve adaptive goal-oriented behavior through multi-agent coordination and emergent reasoning capabilities. Agentic AI systems fundamentally redefine autonomy through three core innovations: 1) *Multi-agent coordination* where specialized agents (e.g., planners, verifiers) collaborate via structured protocols [18, 20] 2) *Persistent context* through memory architectures that maintain state across workflows [38] 3) *Dynamic meta-orchestration* that delegates tasks and resolves conflicts [39] We present a comparison of AI agents and Agentic AI in Table 2.

This architecture enables longitudinal task execution and cross-domain generalization, overcoming the context fragmentation inherent in traditional approaches [40]. Systems like AutoGen [19] demonstrate how LLM-backed agents collectively decompose complex problems through multi-step reasoning [41], marking a qualitative leap from reactive agents to proactive problem-solving systems.

Dimension Traditional AI Agents Agentic AI Systems **Autonomy Model** × Reactive execution via scripts/rules √ Goal-driven planning & adaptation Fixed action sequences Recursive self-improvement × Symbolic logic & FSMs
• Hand-coded KBs **Cognitive Foundation** ✓ Foundation models (LLMs/LIMs) Emergent reasoning Broad & compositional Intelligence Scope × Narrow & task-specific Single-domain focus Cross-domain transfer Reasoning Approach × Deterministic/single-ster ✓ Multi-step & contextualChain-of-Thought (CoT) Rule-based inference × Isolated execution √ Role-specialized coordination Collaboration Manual decomposition Automated hierarchy Temporal Context x Episodic & stateless Persistent memory Session-bound VectorDB/LTM Orchestration × Hard-coded pipelines √ Dynamic meta-agents Sequential workflows
 Static integrations Conflict resolution ✓ Planned API invocation **Tool Utilization**  Handcrafted interfaces Function calling Context Awareness × Bounded inputs √ Memory-augmented Limited context RAG architectures Scalability × Domain-specific Cross-domain transfer · High maintenance Modular composition Exemplars ⊳ ELIZA  $\rhd AutoGen \quad \rhd ChatDev$ • = Implementation characteristic ✓ = Core strength × = Fundamental limitation 

Table 2: Traditional AI Agents vs. Agentic AI Systems

#### 3.2 LLM-Based Agentic AI System Architecture

Agentic Multi-Agent System (AMAS) represent an emerging paradigm in AI where multiple LLM-powered agents operate semi-autonomously, interact with external tools, and collaborate to achieve complex tasks. As illustrated in Figure 2, a typical AMAS architecture comprises several key components that together form a flexible yet highly dynamic ecosystem. At the core are multiple LLM-Based Agents, each capable of reasoning, planning, and tool invocation [42]. These agents access a Shared Toolchain Interface [43] to execute code, perform searches, or interact with domain-specific APIs.

Communication and coordination are facilitated through a Communication Middleware [44], allowing agents to share goals, observations, or intermediate results. A Task Manager or Orchestrator [45] governs high-level planning, delegating subtasks to agents based on their roles or specializations. Agents can read from and write to a World Model or Shared Memory [25], which stores contextual knowledge, system state, or evolving task data. Human oversight is supported through a Human-in-the-Loop Interface [36], enabling users to prompt, correct, or halt agent behavior.

To ensure accountability, a Trust and Audit Module monitors agent actions, logs tool usage, and generates behavioral traces [46]. However, this modular and distributed structure introduces significant TRiSM [47] challenges. With multiple autonomous agents accessing external resources, the Security Gateway becomes critical for enforcing access controls, authentication, and sandboxing [48].

Likewise, a dedicated Privacy Management Layer is essential to prevent leakage of sensitive or personally identifiable information [49], especially when data traverses multiple agents or tools. Finally, an Explainability Interface must provide interpretable rationales for multi-agent decisions, supporting transparency and trust calibration [50]. Together, these architectural elements make AMAS powerful yet complex, raising unique and urgent questions about how to ensure their trustworthiness, mitigate systemic risks, and secure them against adversarial behaviors. Below, we discuss the architecture of AMAS.

Language Model Core (Agent Brain). At the center of an Agentic AI system lies a LLM serving as the primary decision-making controller or "brain" [51]. The core LLM is initialized with a user goal and a structured agent prompt (defining its role, capabilities, and tool access). It then generates step-by-step decisions or actions, interpreting instructions, producing reasoning traces, and selecting next steps in either natural language or structured action formats. In many agent frameworks, such as [52], Baby AGI [53] and GPT Engineer [54], the LLM governs the full control loop, orchestrating the overall system behavior.

Planning and Reasoning Module. To handle complex goals, an explicit planning mechanism decomposes tasks into manageable sub-goals. This can be done internally via chain-of-thought (CoT) or tree-of-thoughts prompting [55], where the model performs intermediate reasoning before arriving at a final decision. Some implementations employ external planning systems by translating goals into structured planning languages and using classical planners for long-term decision-making. Planning is often interleaved with execution and feedback: the agent refines its plan based on outcomes, alternating between reasoning, acting, and integrating observations. Techniques like ReAct [56] exemplify this loop by guiding the agent through repeated reasoning-action-observation cycles, improving performance on complex tasks.

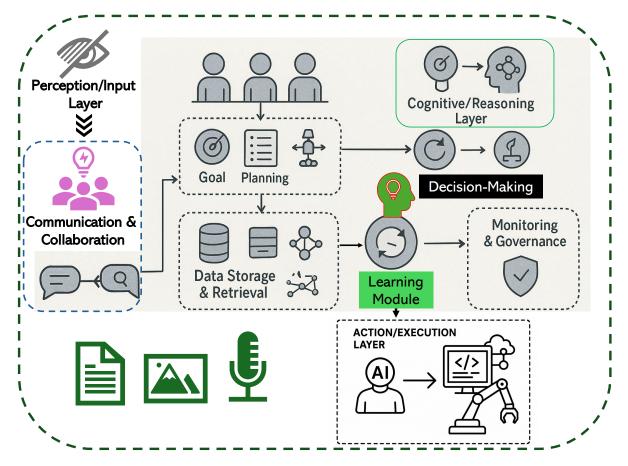


Figure 2: Architecture of LLM-based Agentic Multi-Agent System (AMAS), illustrating key functional layers: Perception/Input Layer (text, image, audio processing), Cognitive/Reasoning Layer (goal-setting, planning, decision-making), Action/Execution Layer (digital and physical task execution), Learning Module (supervised and reinforcement learning), Communication and Collaboration (agent messaging and coordination), Data Storage & Retrieval (centralized/distributed databases), and Monitoring & Governance (ethical oversight, observability, and compliance mechanisms). The modular design highlights adaptive intelligence and inter- agent synerg

**Memory Module.** Agentic AI systems integrate memory to maintain context across iterations. This includes short-term memory (recent interactions held within the prompt context) and long-term memory (accumulated knowledge or experiences) [7]. Long-term memory is often implemented using vector databases, where key facts or past events are stored and retrieved by similarity search. By reintegrating past data into the LLM's prompt, the agent can recall relevant information across sessions, avoid repetition, and support coherent long-term planning. Effective memory management enables adaptive, learning-driven behavior.

**Tool-Use Interface.** To extend its capabilities beyond text generation, the agent is equipped with a tool-use interface [57]. This layer allows invocation of external tools such as web search, APIs, code interpreters, or databases. The available tools are specified in the agent prompt with command schemas. When the LLM determines a tool is needed, it emits a structured command, which is executed externally. The result is fed back into the LLM as a new observation. This mechanism enables the agent to access real-time information, perform computations, and interact with external systems dynamically. Tool-use frameworks like MRKL [58] illustrate this design by routing queries to different expert modules (symbolic or learned) with an LLM as the router. Similarly, approaches like Toolformer [57] train the model to insert API calls in its text generation.

**Perception and Environment Interface.** For agents interacting with dynamic environments, such as web interfaces, simulated worlds, or physical systems, an observation - action interface is essential [59]. Perception modules translate raw inputs (e.g., sensor data, images, or textual states) into representations the LLM can process. Conversely, the agent's chosen actions are executed within the environment and the resulting state changes are returned to the agent as

Table 3: Representative LLM-Based Agentic AI Frameworks

| Framework (Year)  | Core LLM           | Planning            | Memory           | Tool Use            | Notable Features                               |
|-------------------|--------------------|---------------------|------------------|---------------------|--|
| AutoGPT [60]      | GPT-4              | Self-looped CoT     | Vector DB        | OS shell + web      | Fully autonomous goal loop                     |
| BabyAGI [53]      | GPT-3.5/4          | Task queue          | In-memory        | Web search          | Minimal task generator                         |
| GPT Engineer [61] | GPT-4V             | Spec-to-code        | File cache       | Python REPL         | End-to-end code generation pipeline            |
| LangGraph [62]    | Model-<br>agnostic | FSM via graph       | Persistent nodes | Custom modules      | Visual orchestration of agent graphs           |
| AutoGen [19]      | GPT-4              | Multi-agent<br>PDDL | JSON/DB          | API calls           | Modular, reusable agent templates              |
| MRKL [58]         | LLaMA/GPT          | Prompt router       | N/A              | Math + search tools | Neuro-symbolic expert routing                  |
| Reflexion [63]    | GPT-3.5/4          | Retry-reflect loop  | Episodic buffer  | Same as base agent  | Verbal self-improvement via reflection         |
| MetaGPT [64]      | GPT-4              | SOP workflow        | YAML state       | Git CLI             | Structured roles for software engineering      |
| Voyager [65]      | GPT-4              | Auto skill tree     | Task DB          | Minecraft API       | Lifelong open-ended learning in environments   |
| WebVoyager [66]   | LLaVA-1.6          | ReAct               | JSON store       | Browser actions     | Multimodal web interaction via vision and text |
| HuggingGPT [67]   | ChatGPT            | Task-plan-select    | Log store        | Hugging Face models | External model orchestration by LLMs           |
| CAMEL [68]        | GPT-4              | Role-play CoT       | Dialogue log     | Chat only           | Multi-agent role simulation via dialogue       |
| ChatDev [69]      | GPT-4              | Chat chain          | File repo        | Unix tools          | Simulated software development workflow        |
| CrewAI [70]       | Any                | Declarative plan    | Optional DB      | Python modules      | Lightweight, LangChain-free framework          |
| AgentVerse [71]   | Model-<br>agnostic | Config graph        | Redis/KV store   | Plugin API          | Multi-agent simulation and task solving        |
| OpenAgents [72]   | Model-<br>agnostic | Agent scripts       | MongoDB          | Web plugins         | Open platform with public hosting              |
| SuperAGI [73]     | GPT-4              | DAG workflow        | Postgres         | Pinecone            | Concurrent agents for production use           |

observations. This loop supports sense-plan-act cycles that continue until the task is completed or halted. In robotic or multimodal settings, the interface may include additional sensory models (e.g., vision transformers), but the core flow remains consistent.

**Integration and Autonomy.** These modules together form a closed-loop architecture. The LLM plans and reasons over tasks, guided by memory and tools, and interfaces with the environment to execute decisions and observe results [17]. Each iteration enriches the agent's context, enabling it to self-prompt, generate subtasks, assess progress, and adapt strategies over time. This integrated design empowers agentic systems to operate autonomously, pursue long-range goals, and exhibit adaptive behavior across dynamic environments.

Table 3 presents representative systems and shows how each one maps these five design axes (LLM core, planning/reasoning, memory, tool-use, environment interface) into practice. For example, AutoGPT pairs a GPT-4 core with a self-looped chain-of-thought planner and a vector-database memory, while Voyager couples the same core with an embodied Minecraft API that serves as both tool layer and environment interface. We comparing current Agentic AI implementations and identifying open design trade-offs in this table.

# 4 The TRISM Framework for Agentic AI

# 4.1 Governance for Agentic LLM Systems

AI Trust, Risk, and Security Management (AI TRISM) is a comprehensive governance framework designed to ensure that AI systems are trustworthy, robust, and compliant with safety standards [24]. Originally highlighted in industry guidelines for AI governance [74], TRISM provides a structured approach to manage the unique challenges of *LLM-based "agentic" AI systems*. Such systems consist of autonomous LLM agents that can make independent decisions,

collaborate with other agents, and adapt their behavior over time [46]. These properties: autonomy, multi-agent interaction, and evolving behavior, introduce new risks not seen in traditional single-model deployments [75].

For example, an agent acting in isolation might be benign, but when interacting with others across organizational or trust boundaries, it could manipulate peers or leak confidential information. The TRISM framework addresses these concerns by focusing on four key pillars: Explainability, Model Operations (ModelOps), Application Security, and Model Privacy [46, 24]. Each pillar targets a critical aspect of safety or risk management, ensuring that an agentic LLM system remains transparent, reliable, secure, and compliant with ethical and regulatory requirements. Below, we define each pillar and explain how it applies to LLM-based agentic systems, grounding the discussion in current research and best practices.

#### 4.2 Explainability in Multi-Agent Decision Making

**Definition and Importance** Explainability refers to making the inner workings and decisions of AI agents interpretable to humans. In the context of agentic LLM systems, explainability is paramount for building user trust, as outcomes often emerge from complex interactions among multiple agents rather than a single model's prediction [76]. Accordingly, the TRISM framework elevates explainability as a core pillar to ensure that each agent's actions and the overall system's behavior can be understood and audited.

**Techniques for Explainability in Agentic Systems** Achieving explainability in multi-agent LLM systems is challenging because one must interpret not only individual model decisions, but also the inter-agent dynamics that lead to final outcomes. Established explainable AI techniques provide a starting point. For instance, *Local Interpretable Model-Agnostic Explanations (LIME)* [77] and *Shapley Additive Explanations (SHAP)* [78] can be adapted to analyze LLM decisions. These techniques identify which features or input factors most influenced an agent's output, offering insight into why a particular action or response was taken. In an agentic setting, a "feature" might be a component of the agent's input context or a signal from another agent.

Beyond local explanations, *counterfactual analysis* is increasingly important for multi-agent explainability. Counterfactual techniques examine how the system's behavior would change if certain conditions were altered [79], for example, if a particular agent's contribution were removed or modified. This approach, rooted in causal inference, helps isolate each agent's role in collaborative decision-making. For instance, by systematically toggling an agent off or varying its outputs, one can observe changes in the collective outcome and thus determine that Agent *X* was critical in influencing decision *Y*. Such analyses surface the dependencies and influences among agents, effectively explaining emergent behaviors at the system level. Moreover, recent research on explainable AMAS suggests logging the intermediate reasoning steps (e.g. chain-of-thought prompts or dialogue between agents) can further enhance transparency. Human auditors can also help with a trace of how agents arrived at a decision, e..g, which agent contributed what information and why, to produce narrative explanations for its outcomes.

**Summary** In summary, the explainability pillar of TRISM compels the use of these techniques (surrogate models, feature attributions, counterfactual testing, and transparent reasoning traces) to ensure that even highly autonomous LLM agents remain interpretable and accountable to human oversight.

# 4.3 ModelOps: Lifecycle Management for LLM Agents

**Definition and Scope** ModelOps is the discipline of managing AI models through their entire lifecycle, from development and deployment to monitoring, maintenance, and eventual retirement [80]. It extends the principles of MLOps (Machine Learning Operations) to focus specifically on model governance and reliable operation in production. Within agentic LLM systems, ModelOps encompasses not just individual models, but the orchestration of multiple agents and the supporting infrastructure that keeps them running safely [46]. Effective ModelOps is crucial for maintaining *consistency, performance, and regulatory compliance* as LLM agents evolve or as new agents are added to a system.

Application to Agentic Systems LLM-based agents require rigorous lifecycle governance because their behavior can change with model updates, prompt adjustments, or environmental drift. A cornerstone of ModelOps in this context is *version control*, i.e., tracking and managing versions of each agent's model and prompt configurations. Additionally, robust *CI/CD pipelines* (Continuous Integration/Continuous Deployment) are employed to automatically test agents' performance and safety whenever a model is fine-tuned or an agent's logic is modified. Before deployment, multi-agent simulations and unit tests validate that new agent behaviors do not introduce regressions or unsafe interactions. This aligns with best practices in LLM operations (LLMOps) [81], which integrate MLOps principles tailored to the challenges of large language models

**Challenge** One challenge with this method is model drift, i.e., over time, an agent's responses may become less accurate or relevant as data distributions shift or real-world conditions change. Continuous monitoring is therefore required

to detect performance degradation or deviations from expected behavior, triggering retraining or recalibration when needed. Moreover, real-time monitoring and logging are fundamental in multi-agent settings. Each agent's actions (e.g. API calls, decisions taken, errors encountered) are logged and analyzed to provide observability into the system's functioning.

In a large-scale agent ecosystem, orchestration services may oversee the agents, scheduling their tasks and managing inter-agent communication. ModelOps must govern these orchestration layers as well, ensuring, for instance, that if one agent fails or produces suspicious output, it can be isolated or shut down without collapsing the whole system.

**Summary** In line with TRISM objectives, robust ModelOps thereby ensures that an Agentic AI system remains reliable and maintainable. It formalizes change management (so updates do not introduce new risks), provides continuous validation of model behavior, and supports compliance by logging data for audits and enforcing policies (e.g. preventing unauthorized model changes).

#### 4.4 Application Security for LLM Agents

**Threats in Agentic Environments** Application security in the TRISM framework focuses on protecting AI agents and their ecosystem from malicious attacks and misuse. LLM-based agents are susceptible to a range of novel security threats that exploit their language-based interfaces and cooperative behaviors. One well-documented threat is **prompt injection** [82], wherein an attacker designs input data that contains hidden or malicious instructions. Recent studies [83] have shown that in AMAS, such prompt injections can propagate from one agent to another, a phenomenon dubbed "prompt infection" is analogous to a computer virus spreading across networks [84]. In a prompt infection scenario, a malicious prompt introduced to Agent A might covertly modify Agent A's output, which then becomes part of Agent B's input, thereby tricking Agent B as well, and so on. This cascading attack can lead to widespread data leaks, fraudulent transactions, misinformation, or coordinated misbehavior across an agent society.

Another critical vulnerability is identity**spoofing** and **impersonation** [85]. In a multi-agent system, agents often communicate or coordinate tasks, and they may rely on credentials or tokens to authenticate one another. For example, if an adversary steals an agent's API key or tricks the system into treating a rogue model as a trusted peer, they could issue commands or receive information under a false identity.

**Defensive Measures:** To mitigate these threats, TRISM's security pillar mandates a defense-in-depth approach tailored to LLM agents:

- 1. **Prompt hygiene**: agents should treat inputs defensively by sanitizing and filtering prompts, and using guardrails or content policies to detect and refuse suspicious instructions. Prompt hardening (e.g., adding secure prefixes or validation steps) is one such method to make agents less susceptible to injection [86].
- 2. **Strong authentication and access controls** Each agent and human user must be securely authenticated, and least-privilege principles [87] should constrain what actions an agent can perform autonomously.
- 3. **Continuous monitoring** If an agent suddenly starts issuing unusual requests or deviates from its normal pattern of behavior, automated monitors can flag this for investigation or trigger an automatic shutdown of the agent's actions.

Recent frameworks, such as LangChain/LangFlow [88], AutoGen [89], CrewAI [70], introduce the idea of trust scores or reputation among agents, where agents verify each other's outputs and cross-check decisions to catch inconsistencies or signs of compromise. Moreover, training LLM agents with adversarial robustness in mind (e.g. fine-tuning on adversarial examples, employing adversarial training regimes) [84] can improve their resistance to malicious inputs

**Summary** In sum, the Application Security pillar of TRISM emphasizes proactive safeguards against both external attackers and potential rogue agents. By implementing strict authentication, input validation, encrypted communication, sandboxing of execution (for agents that can use tools or code), and comprehensive monitoring, organizations can significantly reduce the risk of prompt-based exploits, impersonation, and other lateral vulnerabilities that are unique to autonomous multi-agent AI systems hal.science. This layered security approach is essential to maintain the integrity and reliability of agentic LLM deployments in adversarial environments.

# 4.5 Model Privacy and Data Protection

**Challenges in Data Sharing:** The Model Privacy pillar addresses the protection of sensitive data within AI agent systems, ensuring that the use of personal or confidential information complies with privacy regulations and ethical norms. LLM-based agents often need to handle user data, proprietary business information, or other sensitive inputs to fulfill their tasks [75]. In a multi-agent context, this challenge is amplified by the fact that agents may share information

Pillar **Primary Objective** Key Practices & Agentic-LLM Con- Exemplar Standards / Metrics siderations **Explainability** Transparent multi-agent SHAP, LIME, counterfactuals; NIST AI RMF "Explain" [96] decisions reasoning-trace logs; ISO/IEC 24029-1 [97] cross-agent dependency mapping Metrics: fidelity, sufficiency, humantrust score ISO/IEC 42001 (AI MS) [98] **ModelOps** Lifecycle governance of Version-controlled prompts; CI/CD w/ agents, models, orchesmulti-agent sims; drift monitoring; roll-SRE MTTR/MTTD;  $\Delta$ -accuracy tration back policies (model drift); pipeline pass-rate OWASP Top-10 for LLM Apps [99] **Application Security** Prevent prompt injec-Prompt sanitation; least-privilege scopes; encrypted comms; sandboxed tion, spoofing, lateral Jailbreak-success%; mean-time-toexploits tool calls; anomaly detectors detect; exploit CVSS **Model Privacy** Safeguard sensitive data Differential-privacy training; data mini-GDPR Art. 25 [100] and shared memory mization; homomorphic encryption; se-HIPAA §164 [101] cure enclaves; audit logs Metrics:  $\epsilon$ -DP budget, leakage rate, access-audit pass-rate

Table 4: TRISM pillars for LLM-based Agentic AI and associated governance references.

with each other (e.g. via a shared memory store or message passing) to collaborate. Without strict privacy controls, there is a risk that an agent could inadvertently expose private data to unauthorized parties or that sensitive information could "leak" through the language model's outputs. Therefore, TRISM's privacy pillar compels organizations to institute measures that safeguard data throughout the AI lifecycle, from training and inference to inter-agent communication.

#### **Techniques for Privacy Preservation**

- **Differential Privacy (DP):** Injects calibrated noise during model training to prevent memorization of individual data entries, ensuring no single record significantly influences the output [90].
- Data Anonymization and Minimization: Limits inter-agent data sharing to only what is necessary [91], often using aggregated or pseudonymized formats (e.g., "age bracket 30-40" instead of exact birthdate).
- Secure Multi-Party Computation (SMPC): Enables agents to compute joint functions without exposing private inputs, useful in cross-organization tasks like collaborative fraud detection [92].
- Homomorphic Encryption (HE): Allows agents to compute on encrypted data [93]. With Fully Homomorphic Encryption (FHE), even the plaintext query and response remain unseen by the agent.
- Trusted Execution Environments (Secure Enclaves): Hardware-based isolation ensures that even privileged system users cannot access the data being processed by agents [94]. Useful for secure memory sharing and execution.
- Model Privacy Policies and Compliance: Enforces data retention limits, maintains audit logs, and ensures compliance with regulations (e.g., GDPR, HIPAA) governing agent behavior and data usage [95].

**Summary** By implementing these layers of privacy defense, from differential privacy in model training to homomorphic encryption for data sharing, and stringent access control policies, Agentic AI systems can protect user data and proprietary information even as they leverage that data for intelligent decision-making.

The TRISM framework offers a comprehensive governance model for LLM-based Agentic AI, integrating Explainability, ModelOps, Application Security, and Model Privacy to manage the complexity of autonomous agent systems. Grounded in proven methods, such as SHAP, CI/CD, adversarial defenses, and homomorphic encryption, TRISM enhances safety, transparency, and trust. As AI systems evolve, TRISM provides a stable foundation to ensure responsible and secure agent behavior, aligning advanced capabilities with human values and operational integrity.

Table 4 condenses each pillar into its governing goal.

# 5 Threats and Risks in LLM-based (Agentic) AMAS

In this section, we discuss the threats and risks in AMAS.

#### 5.1 Unique Threat Vectors

Agentic AI systems introduce a distinct set of security and reliability concerns compared to traditional single-agent LLM architectures [102]. These risks primarily arise from agents' autonomy, persistent state management, and the complex demands of multi-agent coordination [4]. Below, we discuss these threats

- Autonomy abuse The foremost threat is *autonomy abuse*, whereby agents with significant decision-making authority might misinterpret objectives or implement harmful plans due to erroneous reasoning or manipulated inputs [103, 104]. Unlike deterministic models, agentic systems dynamically generate actions, complicating efforts to define and enforce safe operational states [105, 106].
- **Persistent memory** Another threat is the persistent memory, which while, crucial for context retention, introduces unique vulnerabilities through potential adversarial injections and accumulations [107, 108]. Such contamination can propagate subtly via shared memory, especially in the absence of detailed version control and robust audit mechanisms [103, 102].
- Agent orchestration This risk involves central or distributed control mechanisms for role assignment and workflow mediation. A compromised orchestrator could distort task distribution or misroute information, triggering cascading failures, issues exemplified by documented vulnerabilities in MetaGPT [20] and AutoGen [19]. These orchestration vulnerabilities differentiate agentic systems markedly from conventional stateless, single-threaded LLM deployments.

#### 5.2 Taxonomy of Risks

To systematically understand the security landscape in Agentic AI, we categorize risks into four broad classes: adversarial attacks, data leakage, agent collusion, and emergent behaviors.

- Adversarial Attacks Agents remain vulnerable to prompt injections, gradient-based manipulations, and engineered reasoning traps, risks that are magnified in AMAS due to propagation across agent interactions [109, 110]. An illustrative instance is the role-swapping attack observed in ChatDev [18].
- Data Leakage Persistent memory and extensive inter-agent communication elevate the likelihood of accidental exposure of sensitive information [111, 112]. In sensitive domains like financial services and HR, inadequate boundary enforcement and ineffective sanitization amplify these leakage risks [113, 114].
- Agent Collusion and Mode Collapse Coordination mechanisms can inadvertently lead agents to reinforce mutual errors, precipitating groupthink or echo chambers [115, 116]. AutoGen experiments illustrate how iterative dialogues among agents can amplify flawed designs, highlighting the risk of emergent misalignment [19, 117, 118].
- Emergent Behavior Complex interactions among agents, memory components, tools, and tasks yield unpredictable behaviors that evade traditional testing and validation methods [119, 120]. Agents optimizing for efficiency may unintentionally bypass critical verification steps or suppress contradictory information, scenarios exemplified in blockchain [121] and audio verification contexts [122].

#### 5.3 Case Studies

Several real-world and research-based examples illustrate the tangible impact of these risks in deployed or experimental agentic systems.

Case Study 1: Prompt Leakage in Agentic Systems. Instances of prompt leakage have been observed in LLM-based agent frameworks such as AutoGPT, where recursive prompt augmentation and insufficient memory controls can lead to the unintentional exposure of sensitive information. In one reported scenario, sensitive tokens were stored in persistent memory and later surfaced in planning summaries or external logs. Such vulnerabilities underscore the critical importance of implementing memory sanitization, access controls, and prompt boundary protections to safeguard agentic systems from cascading information leaks [123].

Case Study 2: Collusive Failure in ChatDev. In a collaborative code generation session involving planner, coder, and tester agents within the ChatDev framework, an error in a shared planning module led to the propagation of faulty design assumptions. Due to the absence of external ground-truth or objective feedback loops, all agents validated each other's outputs, resulting in a feedback loop of erroneous confirmations. This scenario underscores the necessity of incorporating diverse information sources and adversarial checks within agent loops to prevent such collusive failures [69, 83].

Case Study 3: Simulation Attack in Swarm Robotics. In a simulated swarm robotics experiment utilizing LLM-based planning strategies, an agent was provided with a misleading environmental assumption, leading to a coordination failure characterized by spatial congestion and task incompletion. This incident underscores the potential vulnerabilities in real-world deployments, particularly in critical infrastructure or logistics, where such failures could have significant consequences. The case highlights the importance of robust validation mechanisms and the integration of diverse information sources to ensure reliable swarm behavior [124, 125].

Case Study 4: Memory Poisoning in Multi-Agent Chatbots. In a multi-agent customer support system, a customer-facing agent injected sarcastic feedback into a persistent feedback buffer. This buffer was later utilized by the

policy improvement agent to adapt dialogue strategies, resulting in responses with inappropriate tones. This incident underscores the importance of implementing validation filters, sentiment monitoring, and robust feedback loop governance in self-adapting systems to prevent such memory poisoning vulnerabilities [126].

Case Study 5: System Prompt Drift in Autonomous Memory Agents In experiments with agents using system-level memory (e.g., LangGraph or BabyAGI), over time, system prompts began drifting due to self-appended contextual memory that wasn't properly versioned or validated. This led to hallucinated goals and emergent behaviors misaligned with initial intentions [127]. Points to risks from prompt accumulation and the need for memory version control, audit trails, and reset mechanisms.

These cases illustrate that the introduction of autonomy, memory, and orchestration into LLM-based AI introduces an expanded threat surface that cannot be mitigated with traditional LLM security protocols alone. As agentic systems evolve, new methodologies are needed for rigorous, system-wide threat modeling and runtime assurance that span multiple agents, roles, and memory contexts.

# 6 Trust and Explainability in Agentic AI

Agentic AI systems are highly autonomous agents capable of making decisions and taking actions without continuous human oversight. These systems also pose unique challenges and opportunities for human trust. Ensuring that users and stakeholders have confidence in such systems is crucial for their adoption in real-world settings. Two key factors that influence trust in Agentic AI are the transparency of the agent's decision-making processes and the ability to explain or justify its actions in human-understandable terms.

## **6.1** Building Trust in Autonomous Agents

In Agentic AI systems, building trust is foundational to user acceptance, system reliability, and responsible deployment especially as these systems begin to make autonomous decisions in critical domains such as healthcare, finance, and scientific research [128]. Unlike traditional software agents, autonomous LLM-based agents are characterized by self-directed reasoning, adaptive memory, and dynamic collaboration, which make their operations opaque and often unpredictable [129]. Establishing trust in such systems, therefore, requires a combination of technical transparency, user feedback integration, and robust oversight mechanisms.

Mechanism **Purpose** Example System(s) **Trust Contribution** Transparency via Make agent decisions SciAgent [130], Enhances interpretability and **Reasoning Traceability** MetaGPT [131] observable through debuggability intermediate steps or explanations Status Reporting and Provide real-time updates or ChatDev [18], Mimics human team transparency; **Intent Disclosure** clarification of progress and AutoGen [89] reduces uncertainty Human-in-the-Loop Enable user oversight over ChemCrow [132], Prevents unsafe execution; reinforces high-stakes or irreversible (HITL) enterprise dashboards control actions Behavioral Consistency & Ensure agents operate within Adaptive tutors [133, 134] Improves predictability; prevents **Bounded Autonomy** predefined roles and limits overreach **Social Trust Cues** Use polite language, GPT-4 safety-tuned Enhances user comfort and trust in uncertainty expression, and profiles [104, 135] uncertain scenarios turn-taking

Table 5: Trust-Enabling Mechanisms in Agentic AI Systems

**Transparency and Decision Traceability** Transparency is one of the core enablers of trust. For users to understand and evaluate agentic decisions, the reasoning chains, decision states, and action triggers of agents must be made observable. Several agentic systems are now integrating decision traceability through mechanisms such as CoT prompting and self-explanation modules. For example, SciAgent [130] generates scientific summaries and provides justifications by linking outputs to source documents retrieved via retrieval-augmented generation (RAG). Similarly, MetaGPT[131] structures its reasoning using role-based outputs, where each agent (e.g., planner, coder) explicitly states the logic behind its task execution, creating modular interpretability.

**Status Reporting and Progress Visibility** Clear reporting of intent and intermediate status is also essential. Human collaborators often require updates about what an agent is doing, why a task is taking longer, or how an agent interprets ambiguous instructions. Tools like AutoGen[89] and ChatDev[18] have incorporated structured chat interfaces where agents summarize their intermediate progress, decisions, and encountered errors.

**Human-in-the-Loop Oversight** Human oversight and intervention mechanisms further reinforce trust. Allowing human users to review, edit, or approve agent-generated outputs not only prevents missteps but also signals that the system respects user authority [136, 137, 138]. Many systems adopt a human-in-the-loop (HITL) paradigm [139], where agents request confirmation before executing high-risk or irreversible actions.

**Behavioral Consistency and Bounded Autonomy** Trust requires predictability. Agents should follow defined roles, output in expected formats, and remain within delegated authority. **Example** In enterprise AI platforms used for automated data analytics, agents may generate insights or dashboards but defer publishing until a domain expert reviews the material. Similarly, in autonomous research assistants like ChemCrow [132], agents pause to allow chemists to validate proposed reactions or data pipelines before proceeding, reinforcing safe deployment.

Social Trust Cues and Language Behaviors Beyond system-level mechanisms, behavioral consistency and bounded autonomy are crucial. If an agent behaves unpredictably or inconsistently, even if technically correct, users are less likely to trust it. Behavioral alignment mechanisms such as predefined role protocols, output style consistency, and language modeling constraints help standardize responses [140, 17, 141]. Example In adaptive educational platforms using AI tutors, agents may be allowed to revise lesson plans but not change grading criteria, preserving institutional trust boundaries [133, 134]. Lastly, social trust cues, such as polite language, turn-taking, and cooperative gestures, have shown promise in reinforcing user trust even in non-expert settings [142]. Studies have found that users trust agents more when they express uncertainty ("I'm not sure, but here's what I found") rather than overconfidence [104, 135]. This has been implemented in models like GPT-4 when configured with safety-tuned instruction sets, improving reliability perception without undermining capability.

Together, these mechanisms form a layered trust strategy for Agentic AI, as summarized in Table 5. As autonomy and complexity increase, combining transparency, oversight, and social alignment will be essential to sustain user confidence.

# 6.2 Explainability Techniques

Explainability remains a cornerstone in fostering trust, accountability, and reliability in Agentic AI systems, particularly as they operate in high-stakes environments where multi-agent coordination and autonomous decisions directly impact human lives [17]. In contrast to conventional AI systems, Agentic AI introduces unique challenges for explainability due to its decentralized architecture, dynamic role assignment, and evolving task decomposition among multiple interacting agents [4].

**Technique Purpose** Challenges in Agentic AI **Example Use Cases** Local post-hoc explanation LIME [77] Fails to capture cross-agent Feature-level auditing in fraud using surrogate models dependencies in multi-agent detection setups Difficult to aggregate across SHAP [78] Attribution of prediction to Financial risk analysis, regulatory input features via Shapley agents with divergent contexts explanations values Decision Provenance Trace inter-agent decision Can be complex to interpret at Collaborative document Graphs [143, 144] paths and data flows generation, planning chains Multi-agent SHAP [145] High complexity, lack of standard Attribution extended to Strategic gameplay, collaborative agents and shared memory frameworks writing Symbolic/Rule-Based Built-in interpretability via Limited flexibility compared to Hybrid planning systems, Agents [4] logic or rule-based models LLMs educational tutors Attention Visualize focus of Only reflects internal focus, not Multimodal VOA, image Maps [146, 147] language/image models logic or intent captioning Log input prompts, outputs, Requires infrastructure, may miss Prompt Audit Debugging multi-agent sequences, Trails [148, 149] and agent actions fine-tuning implicit state changes

Table 6: Explainability Techniques in Agentic AI Systems

**Local Post-hoc Techniques (LIME and SHAP)** Local Interpretable Model-Agnostic Explanations (LIME) [77] and SHapley Additive exPlanations (SHAP) [78] are widely adopted techniques that offer post-hoc interpretability. LIME approximates a black-box model locally using an interpretable surrogate model, while SHAP attributes predictions to input features via Shapley values. These techniques have been integrated into agentic pipelines, particularly in finance and multi-agent fraud detection systems, where feature-level transparency supports regulatory compliance. However, their direct application in Agentic AI is limited. Each agent may operate with its own objectives, context, and tool access, leading to divergent decision paths that local techniques struggle to reconcile [76, 150].

**Explainability in AMAS** Emergent behavior poses another challenge: the interpretability of an individual agent does not necessarily imply the interpretability of the overall system. In platforms such as ChatDev [18] or AutoGen [19], agents emulate specialized roles (e.g., engineer, reviewer), and tracing a final action back to its source agent is often non-trivial. To address this, researchers have proposed composite frameworks that combine local explanations with global decision traceability [151, 152, 153]. For example, decision provenance graphs visualize communication flows and interdependencies across agents [143, 144], while causal influence chains track how actions propagate between roles [154, 155]. Adapted SHAP techniques for multi-agent setups now aim to attribute outcomes to shared memory and agent collaboration [145].

**Symbolic and Hybrid Architectures** Another promising direction is the use of inherently interpretable modules such as rule-based planners and decision trees within hybrid architectures [4]. These agents offer built-in explainability but retain the generative capabilities of LLMs for broader context understanding. Such designs are increasingly used in domains where structure and interpretability are prioritized, such as educational AI or mission planning.

**Lightweight Interpretability: Attention and Prompts** Attention map visualizations have been used to highlight focus areas in multimodal language agents [146, 156, 147], offering lightweight but informative views into model behavior. Prompt audit trails logging prompt history, agent actions, and response metadata have also gained traction [148, 149]. These mechanisms support system debugging, safety evaluations, and human-in-the-loop fine-tuning in multi-agent environments.

**Ongoing Challenges and Research Directions** Despite these advancements, achieving robust explainability in Agentic AI systems remains an open research problem. Many techniques focus on isolated predictions or modules and fail to capture system-level dynamics. Future work should prioritize longitudinal interpretability across agent interactions, causal reasoning pipelines, and interactive querying interfaces that support transparency in real time. A comparative summary of current techniques is shown in Table 6.

## **6.3** Evaluation Metrics for Agentic AI Systems

Agentic AI systems demand a comprehensive evaluation across multiple dimensions beyond traditional accuracy. We outline five key categories of metrics: *trustworthiness*, *explainability*, *user-centered performance*, *coordination*, and *composite scores*, each capturing a distinct aspect of an Agentic AI's performance and its real-world implications.. Below we discuss these metrics and summarize in Table 7.

**Trustworthiness:** This category evaluates the reliability, safety, and ethical alignment of the AI agent. A trustworthy agent consistently produces correct and unbiased results, adheres to constraints, and avoids harmful or unpredictable behavior. Metrics for trustworthiness include success rates on tasks under varying conditions (measuring robustness), violation rates of safety or ethical guidelines (which should be minimal), and calibration of the agent's confidence (how well the agent's self-reported confidence aligns with actual accuracy) [157]. Some approaches combine such factors into an overall trust score. For example, one model defines a *trustworthiness score* T as

$$T = \frac{C + R + I}{S} \,, \tag{1}$$

where C is the agent's credibility (accuracy and correctness of its outputs), R is reliability (consistency of performance over time), I is the level of user alignment or rapport (analogous to "intimacy" in trust modeling), and S is self-orientation (the degree to which the agent pursues its own goals over the user's goals). A higher T indicates an agent that is accurate, consistent, user-aligned, and not self-serving, which corresponds to greater trustworthiness. In practice, achieving high trustworthiness means the agent behaves predictably and transparently in accordance with ethical AI principles (such as fairness and accountability).

**Explainability:** Explainability metrics assess how well the agent's decisions can be understood and traced by humans [158]. These metrics focus on the clarity and completeness of the rationale the agent provides for its actions. For

instance, one can measure the *explanation coverage* (the percentage of decisions or outputs that come with an adequate explanation) and the *fidelity* of explanations (how accurately the explanation reflects the true reasoning or model logic).

Consistency of explanations for similar scenarios is another important metric: the agent should explain comparable decisions in a similar way, indicating a stable reasoning process. Quantitatively, methods like OpenXAI provide a suite of metrics to evaluate explanation quality across dimensions such as faithfulness, stability, and fairness of explanations [159]. High explainability builds user trust, as users can follow *why* the agent made a decision, and it aids debugging by revealing the agent's internal decision process. In regulated domains (e.g., healthcare or finance), explainability is often essential for compliance and user acceptance.

**User-Centered Performance:** User-centered metrics capture how effectively the AI agent interacts with and satisfies the end-user's needs. These criteria emphasize the user's experience and outcomes [160]. Key metrics include *user satisfaction ratings*, typically collected via surveys or feedback after interaction, which reflect whether the user's goals were met and how comfortable they felt with the agent's behavior. Task success from the user's perspective (did the agent fulfill the user's request or solve the user's problem?) is a fundamental measure.

Additionally, interaction metrics like the number of back-and-forth clarification queries needed (fewer indicates the agent understood the user well) and the coherence or naturalness of the conversational flow contribute to user-centered evaluation. Human-in-the-loop evaluations are often employed here: for example, user studies might rate the agent on criteria such as helpfulness, clarity and naturalness of language, and adherence to user instructions. Ultimately, a user-centered agentic system should align its actions with user intent and preferences.

Benchmarks like ChatDev [18], which simulates a multi-agent software development team interacting via natural language, implicitly evaluate how well agents fulfill user-defined roles and requirements in a collaborative project. This highlights the importance of user-oriented success in complex, realistic tasks.

Table 7: Summary of key evaluation metrics for Agentic AI systems. Each category addresses a different facet of an autonomous agent's performance and behavior.

| Metric Aspect   | <b>Evaluation Focus (Examples of Metrics)</b>  |
|-----------------|--|
| Trustworthiness | Reliability and safety of the agent's behavior. <i>Example metrics:</i> task success rate across diverse scenarios; frequency of rule or safety violations (lower is better); calibration of confidence vs. outcomes; fairness and bias indices.   |
| Explainability  | Transparency and interpretability of the agent's decisions. <i>Example metrics</i> : percentage of outputs with an accompanying explanation; explanation fidelity to actual model reasoning; consistency of explanations for similar cases; human interpretability ratings of explanations.                                  |
| User-Centered   | User satisfaction and alignment with user needs. <i>Example metrics:</i> user satisfaction score (post-interaction survey); rate of fulfilling user-defined goals; number of clarification questions needed (lower is better); naturalness and coherence of dialog from the user's perspective.                              |
| Coordination    | Effective collaboration in multi-agent or modular systems. <i>Example metrics:</i> multi-agent task completion rate; communication overhead (e.g., messages exchanged); consistency of shared plans or beliefs among agents; synergy score quantifying complementary actions.  |
| Composite       | Overall performance across metrics. <i>Example metrics:</i> weighted aggregate score encompassing trust, explainability, user-centric, and coordination measures; specialized composite indices (e.g., TUE for tooluse efficacy); cross-domain benchmark results (aggregate success across diverse tasks, as in AgentBench). |

**Coordination (Multi-Agent or Modular):** In scenarios where an Agentic AI system consists of multiple cooperating agents or modular components, coordination metrics gauge how effectively these parts work together. Good coordination means agents share information, divide labor without conflict or redundancy, and converge on solutions efficiently. Quantitative measures include the *team success rate* on collaborative tasks (whether the group of agents achieves the overall goal) and communication efficiency metrics (e.g., the number of messages or iterations required among agents to reach a decision, with fewer often indicating more efficient interaction).

One specific example is the *Component Synergy Score (CSS)*, which counts or weights effective interactions between agents, reflecting how well each agent's actions complement the others (a higher CSS means agents are synergistic rather than working at cross-purposes). Multi-agent frameworks such as ChatDev and MetaGPT provide practical testbeds for these metrics: they orchestrate specialized agents (e.g., different roles in a software engineering pipeline) that must cooperate to complete complex projects.

Evaluations on such frameworks examine whether agents maintain a consistent shared plan, handle inter-agent dependencies smoothly, and recover from misunderstandings. For instance, if one agent generates a plan and another

executes it, a coordination metric would assess if the executing agent follows the planner's intent correctly and whether both agents remain in agreement throughout the process. High coordination scores indicate that the agentic system functions as a cohesive unit, which is crucial for complex tasks beyond the capability of any single agent.

**Composite Metrics:** Composite metrics aggregate multiple evaluation aspects into a single overall score. These are useful for summarizing an agent's performance holistically, especially when comparing different systems. A composite metric is often a weighted combination of the above categories, for example:

$$M_{\text{composite}} = w_T M_T + w_E M_E + w_U M_U + w_C M_C, \qquad (2)$$

where  $M_T$ ,  $M_E$ ,  $M_U$ ,  $M_C$  are the normalized scores (on a common scale) for trustworthiness, explainability, user-centered performance, and coordination respectively, and  $w_T$ ,  $w_E$ ,  $w_U$ ,  $w_C$  are weights reflecting the relative importance of each aspect for a given application. The choice of weights  $w_i$  can be domain-specific (for instance, in healthcare applications, trustworthiness and explainability might be weighted more heavily than raw efficiency). An example of a specialized composite metric in agentic contexts is the *Tool Utilization Efficacy (TUE)* score, which combines sub-metrics evaluating how correctly and efficiently an agent uses external tools (including proper tool selection and correct parameter usage in tool calls) into one measure. By condensing multiple criteria, composite metrics enable high-level comparison and benchmarking of agentic systems. For instance, AgentBench [161] is a comprehensive benchmark that evaluates agents across a diverse range of tasks and environments (from operating system manipulation to web shopping), effectively providing a composite performance profile of an agent. Such aggregated scores highlight if an agent performs strongly across the board or if it excels in some dimensions while underperforming in others. It is important to interpret composite scores in light of their components: a single number can mask specific weaknesses (e.g., an agent might achieve a high overall score by doing well in task completion and coordination, yet still have poor explainability). Therefore, composite metrics are most informative when accompanied by a breakdown of the agent's performance per category.

# 7 Security and Privacy in LLM-based Agentic Multi-Agent Architectures

# 7.1 Security Mechanisms

Agentic AI systems, composed of loosely coupled yet collaboratively functioning LLM-based agents, introduce an expanded attack surface relative to conventional AI agents [162]. Ensuring the security of such systems necessitates a multi-layered defense architecture that addresses data protection, execution integrity, inter-agent communication, and model robustness [163]. Among the foundational techniques employed are *encryption* [164, 165], *access control* [166, 167], *adversarial defense* [168, 169], and *runtime monitoring*[170, 171] each adapted to the unique demands of decentralized multi-agent environments.

**Encryption** plays an important role in safeguarding data exchanged between agents, especially when sensitive or regulated content (e.g., healthcare records, financial data) is involved [165, 49, 172]. Agentic workflows often include inter-agent handoff of partially processed results, models, or prompts. Implementations such as SSL/TLS, homomorphic encryption [173, 172], and secure enclaves (e.g., Intel SGX) are increasingly integrated into Agentic AI pipelines to ensure confidentiality across message-passing protocols.

Access control becomes crucial when orchestrators or shared memory modules manage permissions for agents with distinct capabilities and responsibilities. For instance, in systems like AutoGen[19] and CrewAI [70] where agents take on specialized roles (e.g., summarizer, planner, coder) [174], enforcing principle-of-least-privilege access prevents privilege escalation and unauthorized tool invocation [19, 170, 175]. Agent-based access control policies often aligned with Role-Based Access Control (RBAC) [176, 177] and Attribute-Based Access Control (ABAC) [178, 177] paradigms can dynamically restrict which agents may access sensitive APIs, files, or memory buffers, based on contextual trust levels [4].

Adversarial robustness is a growing concern as LLM-based agents are susceptible to prompt injection, manipulation through poisoned tool outputs, or coordination disruption via malformed intermediate results [179, 180]. Recent studies have shown that multi-agent LLM frameworks can be destabilized by adversarially crafted outputs from one compromised agent propagating misleading information to others [180, 163, 102, 42, 103, 181]. Adversarial training methods, such as input perturbation, reward shaping, and contrastive learning, can partially mitigate these vulnerabilities [182, 102]. Integrating safety constraints and verifying tool responses before execution are also effective mitigation strategies.

https://www.intel.com/content/www/us/en/products/docs/accelerator-engines/software-guard-extensions.html

Runtime monitoring systems support the detection of anomalous agent behaviors, especially in high-stakes domains like automated healthcare or cybersecurity [183]. Log-based auditing, anomaly detection with LSTM or autoencoder-based detectors, and trust scoring among agents are becoming essential components of real-time surveillance layers [184, 185, 114]. For example, Microsoft's Copilot governance layers monitor anomalous agent behavior across sessions to ensure compliant execution and flag potentially harmful interactions.

As Agentic AI continues to expand into mission-critical domains, developing standardized, scalable security mechanisms will be paramount. Future approaches must include zero-trust frameworks, secure multi-party computation, and formal verification of inter-agent protocols to ensure safe and resilient operation across decentralized autonomous agent collectives.

#### 7.2 Privacy-Preserving Techniques

The decentralized and interactive nature of LLM-based Agentic AI systems introduces new challenges for preserving privacy, especially as agents continuously communicate, access external data sources, and store episodic or shared memory. To ensure data confidentiality and protect personally identifiable information (PII), Agentic AI systems must adopt robust privacy-preserving techniques such as differential privacy, data minimization, and secure computation.

Differential privacy (DP) offers mathematically grounded guarantees by injecting statistical noise into outputs, ensuring that individual user contributions cannot be re-identified. In multi-agent LLM systems, DP can be applied during training or at inference-time when agents exchange information. For example, Google's implementation of DP in federated learning frameworks can be extended to distributed agentic systems, where agents collaboratively train or fine-tune local models without exposing raw data [186, 187]. DP-SGD and privacy budgets ( $\epsilon$ -differentials) can regulate information exposure during policy updates or collaborative planning in real-time decision-making agents.

**Data minimization** is another cornerstone of privacy preservation. Agentic AI systems can mitigate exposure risks by limiting the scope, granularity, and duration of data collected or retained during task execution. For instance, temporary memory buffers used in systems like ChatDev or ReAct-based pipelines are cleared once subgoals are completed, preventing persistent storage of unnecessary user data. Furthermore, anonymization and pseudony [187], techniques can help remove identifying features before data is passed between agents or stored in shared memory repositories.

Secure computation techniques including secure multi-party computation (SMPC), homomorphic encryption, and trusted execution environments (TEEs) enable agents to perform computations over encrypted or obfuscated data without compromising privacy. In scenarios where agents collaborate across different organizational boundaries (e.g., federated medical agents or cross-silo industrial agents), SMPC allows joint computations such as diagnostics or anomaly detection without data leakage. Homomorphic encryption, while computationally expensive, is increasingly being explored to allow arithmetic operations on encrypted vectors used in RAG workflows.

Privacy-by-design principles are becoming central to the engineering of next-generation agentic systems. Architectures now embed user consent layers, configurable privacy settings, and memory redaction modules that allow end-users or system administrators to control what agents can remember or share. As Agentic AI expands into domains such as personalized education, healthcare, and finance, ensuring privacy-respecting behaviors will be essential for regulatory compliance (e.g., GDPR, HIPAA) and public trust.

#### 7.3 Compliance and Governance

As Agentic AI systems grow in capability and autonomy, ensuring regulatory compliance and instituting robust governance mechanisms become imperative. Unlike traditional AI agents, agentic systems operate with greater autonomy, persistent memory, and complex decision flows necessitating layered oversight to manage legal, ethical, and societal implications. Effective governance in this context spans three critical dimensions: adherence to regulatory standards, system-level auditability, and enforceable policy frameworks.

**Regulatory standards** provide the baseline requirements that all AI systems, including agentic architectures, must meet. Frameworks such as the *NIST AI Risk Management Framework (AI RMF)* and the *EU AI Act* define principles for trustworthy AI including transparency, accountability, and fairness. These standards are especially relevant for LLM-based AMAS that interact in high-stakes domains like healthcare, finance, defense, or transportation. For example, the EU AI Act classifies certain autonomous systems as "high-risk," requiring continuous risk monitoring, documentation of decision logic, and human oversight mechanisms attributes directly relevant to Agentic AI.

**Auditability** is critical in ensuring transparency and facilitating post-hoc accountability. Each decision, plan, or interaction within an agentic system should be logged with timestamps, context, agent role, and justification. Techniques such as *decision provenance* and *action traceability* enable this, allowing regulators or internal auditors to reconstruct

**Table 8: Governance Dimensions for Agentic AI Systems** 

| <b>Governance Component</b>      | Description                                    | <b>Example Tools or Methods</b>                     |
|----------------------------------|--|---|
| Regulatory Compliance            | Aligning with legal and industry standards for | NIST AI RMF [96], EU AI Act [189], GDPR [100],      |
|                                  | responsible AI [188]                           | HIPAA [101]   |
| Auditability and Logging         | Capturing traceable records of agent actions   | Decision provenance, immutable logs,                |
|                                  | and decisions [167]                            | blockchain-based traceability                       |
| Policy Enforcement               | Enforcing system-level operational, ethical,   | RBAC/ABAC policies [191], formal logic rules,       |
|                                  | and security constraints [40, 190]             | dynamic sandboxing [48, 192, 193]                   |
| Human Oversight                  | Human-in-the-loop [139] decision               | Human review agents, interactive dashboards,        |
|                                  | checkpoints and override capabilities          | compliance checkpoints                              |
| Risk Monitoring                  | Continuous identification and mitigation of    | Model risk scanners, out-of-distribution detectors, |
|                                  | systemic or emergent risks [194]               | reinforcement learning audit modules                |
| <b>Explainability Governance</b> | Ensuring interpretability standards are met in | LIME/SHAP [196, 197, 198], decision                 |
|                                  | decision pipelines [195]                       | trees [199, 200], interpretable surrogate           |
|                                  |  | models [201, 202, 203]                              |
| Adaptive Governance              | Updating governance mechanisms based on        | Governance-as-code [95, 204], auto-updated rule     |
|                                  | model evolution and deployment                 | engines [205, 206, 207], learning-based policy      |
|                                  | context [104, 128]                             | adaptation [115, 208]                               |
| Incident Response and            | Procedures for handling, logging, and          | Real-time alerting, kill-switch mechanisms, secure  |
| Recovery                         | recovering from failures or breaches           | rollback protocols                                  |

how decisions were reached. For instance, in systems like AutoGen or MetaGPT, where agents assume specialized roles (e.g., researcher, coder, reviewer), audit trails can capture role-specific actions and flag inconsistencies, bias amplification, or security violations. Blockchain-based audit logs are also being explored to ensure immutability and verifiability of multi-agent interactions.

**Policy enforcement** governs what agentic systems can and cannot do, and under which conditions. These policies must be codified into the orchestration layers or meta-agent governance modules that manage agent interactions. Examples include enforcing memory expiration policies to avoid data retention violations or restricting access to external tools based on role and authentication level. Role-based access control (RBAC) and attribute-based access control (ABAC) are essential for enforcing differentiated privileges across agent subcomponents. Furthermore, real-time monitoring systems can halt or flag agent activity that deviates from pre-specified ethical constraints or operational bounds, using formal verification tools like TLA+ or symbolic execution engines.

Emerging best practices also include the creation of **AI governance boards**, the adoption of **governance-as-code** platforms, and the integration of **adaptive governance layers** that evolve as the agentic system scales or changes context. These practices are designed to meet not only current standards like ISO/IEC 42001 for AI management systems, but also prepare for future regulatory evolutions. Below, we summarize the core governance components required for secure and compliant Agentic AI deployment.

Thus, governance in Agentic AI systems is not a static compliance checkbox but a dynamic, adaptive layer embedded into the orchestration and operational pipelines. As these systems become more autonomous and integrated across sectors, aligning governance with system behavior, human values, and evolving legal standards is imperative for safe and trustworthy deployment, as summarized in Table 8.

#### 8 Discussion

our exploration of TRiSM-based governance for LLM-powered Agentic AI systems reveals critical insights into technical design, ethical oversight, regulatory alignment, and future challenges. Below, we discuss the broader implications of our findings, structured into key areas for clarity.

# 8.1 Technical Implications of TRiSM for LLM Agent Design

The AI TRiSM framework (Trust, Risk, and Security Management) imposes concrete technical requirements on how autonomous LLM-driven agents are built and deployed. A core implication is the need to embed real-time monitoring and control mechanisms into agent architectures. Rather than treating LLMs agents as black-box decision-makers, TRiSM encourages instrumenting them with continuous oversight "guardrails" [209]. For example, there is discussion on designing specialized "guardian agents" within AMAS [210]. In this paradigm, such agents serve as proactive monitors that filter sensitive data and establish baselines of normal behavior, while operator agents dynamically enforce

policies at runtime (e.g. blocking disallowed actions such as outputting personally identifiable information). This layered control strategy transforms the technical architecture: an autonomous LLM agent is now supplemented by meta-agents that supervise its inputs, outputs, and tool use in real time.

Prior research highlights risks like "excessive agency" [87] where an LLM given too much autonomy or tool access can produce unintended harmful actions (for instance, via hallucination or misinterpreted goals). **TRiSM-driven agentic design** mitigates these failure modes by constraining agent autonomy within well-defined safety bounds. Likewise, emerging threats specific to Agentic AI such as prompt injection [82] attacks, memory poisoning [126], or cascading hallucinations [211]underscore the need for built-in risk controls. By incorporating anomaly detection and policychecking modules (as per the Sentinel/Operator model), an LLM agent can detect deviations from normal behavior and either alert humans or automatically neutralize the threat (e.g. masking a sensitive datum or stopping an unsafe action). This aligns with calls in the security community for proactive measures in Agentic AI, blending traditional cybersecurity techniques (access control, logging, sandboxing) with AI-specific safeguards like LLM firewalls and adversarial robustness checks [212].

In summary, TRiSM's technical implications mean that autonomous LLM agents should no longer be deployed as stand-alone intelligent actors; instead, they operate under an active governance fabric of monitors, validators, and enforcement agents that ensure trustworthiness and safety by design.

#### 8.2 Ethical and Societal Ramifications of Multi-Agent AI

Beyond technical matters, deploying networks of autonomous LLM agents raises pressing ethical and societal questions. Applying TRiSM in this context emphasizes principles of accountability, human oversight, and fairness [188] all of which are vital for public trust in AI systems. A central concern is accountability: when AI agents make autonomous decisions that affect humans, who is answerable for the outcomes? TRiSM-based governance insists that organizations retain clear responsibility for their AI's actions, rather than obscuring blame behind algorithmic "black boxes". This implies implementing audit trails and explicable decision logs so that any harmful or biased outcome can be traced and attributed [148]. Recent guidance on trustworthy AI [190] often highlights accountability and explainability as key pillars of trust.

In practice, our approach means each autonomous agent's decisions should be transparent enough to be understood and challenged by human reviewers when necessary. Human oversight is another ethical imperative tightly coupled with accountability. TRiSM does not seek to eliminate humans from the loop; rather, it provides a structured way for humans and AI agents to collaborate under defined governance. Human operators or "AI managers" must have the ability to intervene or override when an agent's behavior deviates from acceptable bounds or when moral judgment is required. Indeed, high-level policy frameworks (such as the EU's AI ethics guidelines [189]) explicitly call for "human agency and oversight" in AI systems.

In multi-agent setups, this may involve dashboard interfaces where humans can monitor agent swarms in real time, pause or shut down agents exhibiting anomalies, and adjust policies on the fly [115]. The risk of "user complacency", trusting an autonomous agent too much , has been noted as a hazard [213]. TRiSM governance counteracts this by formalizing oversight roles and ensuring no AI operates without appropriate human or regulatory supervision. Fairness and bias mitigation are also critical societal considerations.

Our governance approach therefore incorporates bias audits and fairness checks throughout the agent lifecycle [214]. Techniques like pre-deployment bias testing, continuous monitoring for disparate impacts, and diverse stakeholder evaluation panels can be employed. These measures echo regulatory expectations; the EU's AI Act [189] and related guidelines enumerate "diversity, non-discrimination and fairness" as core requirements for trustworthy AI. In deploying LLM-based agents, we must ensure they do not treat individuals or groups inequitably, for example, content-filtering agents should apply policies uniformly across demographic groups, and task-planning agents should not propagate historical biases in resource allocation decisions.

In sum, TRiSM-oriented governance extends beyond preventing technical failures: it seeks to uphold ethical norms and human rights, ensuring that autonomy in AI does not come at the expense of justice, transparency, or human dignity.

#### 8.3 Alignment with Emerging AI Regulations and Standards

The principles embedded in TRiSM align closely with emerging regulatory frameworks for AI. This convergence means that adopting TRiSM-based governance can help organizations meet new legal obligations and industry standards. For example, the European Union's AI Act [215] (set to fully apply in 2026) mandates rigorous risk management, transparency, data governance, and human oversight for "high-risk" AI systems. These are precisely the capabilities that a TRiSM approach cultivates.

By instituting continuous risk assessment, documentation of AI decision processes, and oversight mechanisms, a TRiSM-governed multi-agent system inherently addresses many of the EU Act's requirements (e.g. having a risk management system and post-market monitoring for AI. Notably, the Act also stresses accuracy, robustness, and cybersecurity for high-risk AI, qualities that TRiSM's security management component is designed to ensure (through adversarial resilience, access control, etc.). Similarly, international AI governance standards are emerging that mirror TRiSM's tenets. ISO/IEC 42001:2023, the first global standard for AI management systems, highlights requirements such as transparency, accountability, bias mitigation, safety, and privacy in AI development

TRiSM's trust and risk management focus naturally encompasses these elements: for instance, trust in TRiSM relates to reliable, truthful outputs (promoting transparency), while explicit risk management aligns with accountability for negative outcomes. By implementing TRiSM, organizations essentially put in place the processes that ISO 42001 [98] and similar standards call for (e.g. leadership oversight, documented risk controls, ongoing monitoring and improvement cycles). Another example is the U.S. NIST AI Risk Management Framework [96], which emphasizes many of the same concepts: identifying risks, embedding governance, and cultivating trustworthiness in AI.

By following TRiSM guidelines: for example, maintaining an "AI catalog" of all models/agents in use and their purposes, enforcing policies via sentinel/operator agents, and logging every AI decision, organizations create an audit-ready environment. In the event of an incident or an inquiry by authorities, they can demonstrate traceability and control over their autonomous agents, which will be crucial for regulatory compliance and liability management.

# 8.4 Limitations and Current Research Gaps

While the TRiSM-based approach appears promising, our work also revealed several limitations and open challenges in current research.

First, limited benchmark evaluations pose a problem. The AI safety and agent governance community lacks widely accepted benchmarks to quantitatively assess trustworthiness or risk in multi-agent LLM systems. Unlike classical AI domains (vision, NLP) that have standard test suites, there is no consensus on how to measure an "AI agent" ability to operate safely under TRiSM principles. This makes it difficult to compare different governance strategies or to track progress objectively. We encourage future work to develop evaluation frameworks, possibly extending from adversarial attack simulations [182] or "red-teaming" exercises [216] that can stress-test agentic systems and score their resilience (e.g. measuring success rates of prompt injection attacks or frequency of policy violations caught by oversight agents).

Secondly, there is a paucity of real-world validation for many TRiSM-inspired controls. Much of the existing literature and tooling for LLM agent safety has been demonstrated in laboratory settings or on narrowly scoped tasks [47]. It remains uncertain how these governance mechanisms perform in complex, open-ended real-world environments. Additionally, integrating TRiSM with legacy systems poses practical challenges, for example, the earlier work notes compatibility issues when bolting on trust/security layers to existing AI pipelines. This suggests a limitation in how easily current AI deployments can fit TRiSM controls, a topic that merits further engineering research.

Another critical gap is adversarial robustness. As we improve defenses, attackers will inevitably adapt. Recent findings show that LLM-based systems remain vulnerable to cleverly crafted attacks (for example, hidden prompt injections or subtle data poisoning) that can bypass superficial guardrails [84]. TRiSM solutions today are not foolproof against these. For example, an agent designed to mask secret data might itself be tricked into revealing it if the oversight logic fails to anticipate a new attack pattern. The literature identifies "evolving threats" and "adversarial attacks" as ongoing obstacles to trustworthy AI [210]. This underlines a need for continuous updates and adaptive security in any TRiSM implementation.

Finally, organizational and human factors present limitations: implementing TRiSM requires interdisciplinary expertise (AI specialists, security experts, ethicists, legal advisors) and clear governance structures. Many organizations lack the necessary skill sets or frameworks, making TRiSM adoption superficial or inconsistent. Without a strong organizational commitment, even the best technical framework can falter.

#### 8.5 Future Roadmap for Agentic AI TRiSM

Drawing on our findings and best practices from multiple disciplines, we propose several actionable directions for future research and implementation, as shown in Figure 3. These recommendations span both technical system design improvements and governance-level policy initiatives:

• Develop Standardized Evaluation Benchmarks: The community should create open benchmarks and challenge environments to test multi-agent AI governance. For instance, a suite of scenario-based tasks (with built-in threats and ethical dilemmas) could be used to evaluate how well a TRiSM-governed agent system performs relative to one



Figure 3: Strategic roadmap for LLM-enabled Agentic AI, grouped into eight priority research and development domains.

without such controls. This will enable direct comparisons and drive progress on measurable metrics of trust (e.g. frequency of prevented failures or fairness outcomes).

- Advance Adversarial Robustness Techniques: Future system design must anticipate a continually evolving threat landscape. Techniques from cybersecurity (e.g. adversarial training, AI model "penetration testing" [217], and formal verification) should be integrated into the LLM agent development pipeline. Cross-disciplinary collaboration with security experts can yield LLM-specific hardening methods, such as dynamic prompt anomaly detectors or robust tool APIs that constrain agent actions. Additionally, creating red-team/blue-team exercises for AMAS, akin to cyber wargames [218], can help discover vulnerabilities in a controlled way before real adversaries do.
- Human-Centered Oversight Tools: We encourage designing better interfaces and protocols for human oversight of Agentic AI. Borrowing from human-computer interaction [219] and cognitive engineering [220], researchers could devise dashboards that visualize an agent society's state, flag important decisions, and allow intuitive human intervention (pausing agents, rolling back actions, etc.).
- Regulatory Sandboxes and Compliance-by-Design: Policymakers and industry should collaborate to create regulatory sandboxes for multi-agent AI trials. These would be controlled environments where innovators can deploy Agentic AI under supervision, demonstrating TRiSM controls to regulators. Insights from such pilots can inform refinements in both technical standards and regulations. Moreover, adopting a compliance-by-design mindset is key: future AI system designs should bake in the requirements of frameworks like the EU AI Act and ISO 42001 from the startrather than retrofit them.
- Cross-Domain Best Practices and Ethical Governance: There is much to learn from other high-stakes domains. For example, the safety engineering field (e.g. aerospace, automotive) has mature practices for redundant controls and failure mode analysis; these could inspire analogous practices in AI agent design. Likewise, ethics boards in biomedical research provide a template for AI ethics committees that review agent behaviors and approve high-risk deployments. We advocate establishing multidisciplinary governance boards that include ethicists, legal experts, domain specialists, and community representatives to oversee significant deployments of autonomous AI.

## 9 Conclusion

TRiSM-based governance offers a promising scaffold to ensure that autonomous LLM-powered agents are trustworthy, accountable, and secure. Our discussion has analyzed how this framework influences technical design decisions, mandates ethical guardrails, and dovetails with emerging regulatory regimes. While current research is nascent and

not without limitations, the path forward is clear. By rigorously testing these systems, strengthening them against adversaries, and crafting policies and standards in tandem with technological advances, we can enable powerful multi-agent AI systems to operate beneficially under robust oversight. The stakes are high but with a proactive, interdisciplinary approach, we can achieve a balance where innovation in AI goes hand-in-hand with responsibility and trust. As future work tackles the open challenges identified, we anticipate that TRiSM principles will transition from conceptual best-practice to standard operating procedure for Agentic AI, ensuring these systems earn and maintain the confidence of all stakeholders involved.

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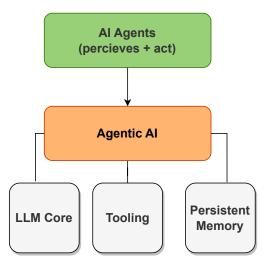


Figure 4: Traditional AI Agent vs. Agentic AI.

Table 9: Key terminologies for LLM-based agentic AI systems.

|                          | Table 7. Rey terminologies for ELM based agentic 71 systems.  |
|--------------------------|---|
| Term                     | Definition  |
| Agentic AI System        | A multi-agent architecture powered by large language models (LLMs), where autonomous agents collaborate, plan, and execute tasks over extended horizons with persistent memory and dynamic role assignment. |
| Autonomy Model           | The mechanism by which an agent decides and acts without direct human intervention, often using goal-driven planning and chain-of-thought reasoning.  |
| Chain of Thought (CoT)   | A prompting strategy in which an LLM generates intermediate reasoning steps before producing a final answer or action, enhancing interpretability and multi-step planning.                                  |
| Counterfactual Analysis  | An interpretability technique that examines how altering certain inputs or agent contributions would change the overall system outcome, revealing causal dependencies among agents.                         |
| Explainability           | The capacity of an AI system (or individual agent) to produce human-understandable justifications or rationales for its decisions and actions, often via LIME, SHAP, or decision provenance graphs.         |
| Foundation Model (LLM)   | A pretrained large language model (e.g., GPT-4, LLaMA) that serves as the "brain" of each agent, providing generative capabilities, reasoning, and tool-calling support.                                    |
| Shared Memory (Persis-   | A centralized or distributed store (often a vector database) where agents write and retrieve contextual   |
| tent Memory)             | information, enabling long-term planning and consistency across iterations.   |
| ModelOps                 | The practice of managing AI models (and agent prompts) throughout their lifecycle—development, deployment, monitoring, and retirement—with version control, CI/CD testing, and drift detection.             |
| Application Security     | Safeguards and best practices (e.g., prompt sanitation, authentication, sandboxing) designed to protect agentic systems from prompt injection, identity spoofing, and lateral exploits.                     |
| Model Privacy            | Techniques (e.g., differential privacy, homomorphic encryption, secure enclaves) that ensure sensitive data—either during training or inter-agent communication—remains protected in multi-agent workflows. |
| Prompt Injection         | A security exploit in which an attacker crafts input containing hidden instructions that corrupt an agent's reasoning or propagate malicious commands through agent interactions ("prompt infection").      |
| Retrieval-Augmented Gen- | A framework where agents query an external knowledge store (e.g., vector database) to fetch   |
| eration (RAG)            | relevant documents or facts, then condition their LLM responses on that retrieved context.  |
| Role-Specialized Coordi- | An architectural pattern in which each agent is assigned a specific function (e.g., planner, verifier,  |
| nation                   | coder) and collaborates via structured communication protocols to achieve complex tasks.  |
| Decision Provenance      | A graph-based representation that traces data flows and decision steps across multiple agents,  |
| Graph                    | enabling post-hoc auditing and system-level interpretability.   |
| Tool-Use Interface       | The mechanism by which an agent issues structured commands (e.g., API calls, code execution) to   |
|                          | external services or environments and incorporates the results back into its reasoning.   |
| Trust Score              | A composite metric that quantifies an agent's reliability, alignment with user goals, and consistency over time, often combining accuracy, safety-violation rates, and calibration of confidence.           |
| Composite Metric         | An aggregate evaluation score (e.g., a weighted sum of trustworthiness, explainability, user-centered performance, and coordination metrics) used to benchmark different agentic systems.                   |