Chapter 2— Models and Agents: Advanced AI Operatives

"Fully autonomous AI agents should not be built" -Mitchell

Cloak and AI

With all the hysteria regarding Large Language Models (LLMs) such as ChatGPT, Grok, Gemini, etc there is much hyperbole regarding what AI can achieve these days, much of it surely simple value driven sentiment manipulation as employed routinely by the likes of Elon Musk and others. Along with this is the fear that AI will destroy humanity and human civilization. Is that hyperbole? Well, the aim of this work is to take a sober measure of that fear and break it down as well as see where AI can go wrong even if there is little change of a Super Intelligent AI from taking over the world, though that is a small probability of happening currently, there are many more larger probabilities of adverse global and perhaps catastrophic results from any poorly thought out and/or secured AI system, even from the dumbest system with wrong permissions could do catastrophic damage if allowed to run uncontrolled and un-guarded: "The development of AI agents is a critical inflection point in artificial intelligence. As history demonstrates, even well-engineered autonomous systems can make catastrophic errors from trivial causes. While increased autonomy can offer genuine benefits in specific contexts, human judgment and contextual understanding remain essential, particularly for high-stakes decisions. The ability to access the environments an AI agent is operating in is essential, providing humans with the ability to say "no" when a system's autonomy drives it well away from human values and goals." (Mitchell 2025)

What is different with the latest developments in the public commercial space of AI development, which does not include the covert developments in the various nations national defense sectors that usually are a generation ahead of the public commercial sector, is that there are 'thinking' machines that use LLMs to be the brains of larger systems, Agentic AI, that can do things in the world besides spit out or quote various texts but can take actions in the world, in real concrete terms. Agentic AI is the next buzzword that will enter the public hive mind soon, as more and more development is

done in this area:

> Many recent AI agents are constructed by integrating LLMs into larger, multi-functional systems, capable of carrying out a variety of tasks to achieve goals. A foundational premise of this emerging paradigm is that computer programs need not be constrained to actions explicitly defined by a human operator; rather, systems can autonomously combine and execute multiple tasks without direct human involvement. This transition marks a fundamental shift towards systems capable of creating context-specific plans in previously unspecified environments. (Mitchell 2025)

How do LLMs fit into the Agentic AI? The language model is the brains of a complex Agent system that is based in automated machine learning, deep learning with neural networks and reinforcement learning. Many recent AI agents are based on LLMs, Ethical considerations for this type of AI agent therefore subsume those for LLMs, such as the incorporation of discriminatory beliefs, unequal representation of different subpopulations, and hegemonic viewpoints. (Mitchell 2025) A reader can learn more about the basics of Machine Learning, Deep Learning and Reinforcement Learning from my previous work, "*Play AI: Machine Learning in Video Games*" (McCarron 2023). While one may not realize it when one interacts with ChatGPT they are interacting with an Agentic AI, not just simply a LLM but a complex system that can do things in the world, like do internet searches based on prompts input into the system, which is a basic example. Many of the Agentic AIs are built upon the foundations of Reinforcement Learning, so you will see a lot of mention of such things as 'reward hacking' or 'policy collapse' when things go wrong.

From Statistical Models to Operational Actors

Chapter 1 established a central premise: modern artificial intelligence systems are not merely tools that automate isolated tasks, but large-scale statistical engines capable of modeling, shaping, and influencing human behavior. This chapter extends that foundation by examining what happens when such models are no longer confined to passive output generation, but are embedded into systems that can **plan, decide, and act**. The critical transition explored here is the shift from **models** to **agents**. A model predicts. An agent operates.

This distinction matters because agency introduces autonomy, and autonomy introduces risk. As autonomy increases, so does the potential for misalignment, error amplification, and loss of human oversight. As Mitchell et al. warn, the danger does not lie primarily in hypothetical super-intelligence, but in "well-engineered autonomous systems" making catastrophic mistakes from trivial causes when deployed without sufficient constraints (Mitchell et al., 2025).

Agentic AI therefore represents not simply a technical evolution, but a **new cybersecurity domain**—one where machines act on behalf of humans, at machine speed, across complex digital and physical environments.

What Makes an AI System an Agent?

A large language model (LLM), by itself, is not an agent. It is a probabilistic inference engine trained to generate likely sequences of symbols based on patterns in data. However, when an LLM is embedded into a larger system that includes memory, tools, goals, and environmental feedback, it becomes the **decision-making core of an agentic system**.

Modern AI agents typically integrate:

- A language model for reasoning and planning
- Tool interfaces (APIs, databases, code execution environments)
- Memory systems (short-term context and long-term retrieval)
- Feedback loops for learning and adaptation

This architecture enables systems that can decompose objectives, sequence actions, evaluate outcomes, and revise strategies—often without direct human intervention. As Mitchell et al. observe, this marks a fundamental shift away from explicitly scripted software toward systems capable of generating plans in "previously unspecified environments" (Mitchell et al., 2025). A overview of Agentic AI from inception to deployment is provided by Wong:

> Although AI agents dominated news headlines in late 2024 and early 2025, their conceptual foundations trace back to the 1970s and 1980s, when research explored how capable systems were of sensing and acting intelligently within an environment. These early systems, often referred to as "intelligent agents," powered linguistic analysis, biomedical applications, and robotics, relying on rule-based logic and limited autonomy due to constraints in hardware, computing power, and algorithmic sophistication. At the time, these agents were described as "a new type of AI system capable of adapting, learning from data, and making complex decisions in changing environments."

> Architecturally, AI agents typically operate as a layer above LLMs and include four foundational components: perception, reasoning, action, and memory. The perception module is responsible for ingesting data from external sources, such AI agents are now positioned to be practical tools with significant operational and

> economic utility—from automating software development to automating customer service and even augmenting real-time cybersecurity defense.as user inputs or application programming interfaces (APIs). After the data is gathered, the reasoning module leverages the LLM's capabilities to plan or infer the best course of action. The action module can then execute tasks through tools, APIs, or integrations with third-party systems. Finally, the memory module stores contextual information, often using vector databases or session-based memory managers.38 This modular stack enables agents to operate across real-world applications and adapt while completing tasks in ways that static prompt chains or retrieval-augmented generation (RAG) pipelines cannot.
> Behind this architecture lies a supporting infrastructure stack: model APIs for LLM access, memory stores for quick retrieval, session managers for coordinating task state, external tool integrations for operational output, and even open-source frameworks and libraries that enable modular development. Multi-agent systems add another layer of sophistication, allowing agents to collaborate or delegate tasks to other agents within a shared environment. While this growing interconnectedness can enhance agentic capabilities, it can also introduce new challenges around explainability, privacy, system security, and reliability (Wong et al, 2025).

From a security perspective, this is the moment where AI stops being an application and starts becoming an **operator.** And it is able to operate across many different action surface options— the spaces (digital or analog) where an agent can operate:

- Adaptability: The extent to which a system can update its actions based on new information or changes in context.
- Number: Single-agent or multi-agent, meeting needs of users by working together, in sequence, or in parallel.
- Personalization: The extent to which an agent uses a user's data to provide user-specific unique content.
- Personification: The extent to which an agent is designed to be like a specific person or group of people.
- Proactivity: The amount of goal-directed behavior that a system can take without direct specification from a user.
- Reactivity: Extent to which a system can respond to changes in its environment in a timely fashion.
- Request format options: The formats an agent uses for input(e.g., code, natural language).
- Diversity of possible agent actions, including:
    - Domain specificity: How many domains agent can operate in (e.g., email, calendars, news).
    - Interoperability: Extent to which agent can exchange information and services with other programs.
    - Task specificity: How many types of tasks agent may perform (e.g., scheduling, summarizing).

• Modality specificity: How many modalities agent can operate in (e.g., text, speech, video, images, forms, code).
(Mitchell 2025)

Agentic Autonomy

To understand the implications of agentic AI, it is useful to view agents not as a binary category, but as existing along a **spectrum of autonomy**. Gulli et al. describe this progression as generational, with each level emerging from the previous one through increased capability and independence (Gulli et al., 2024).

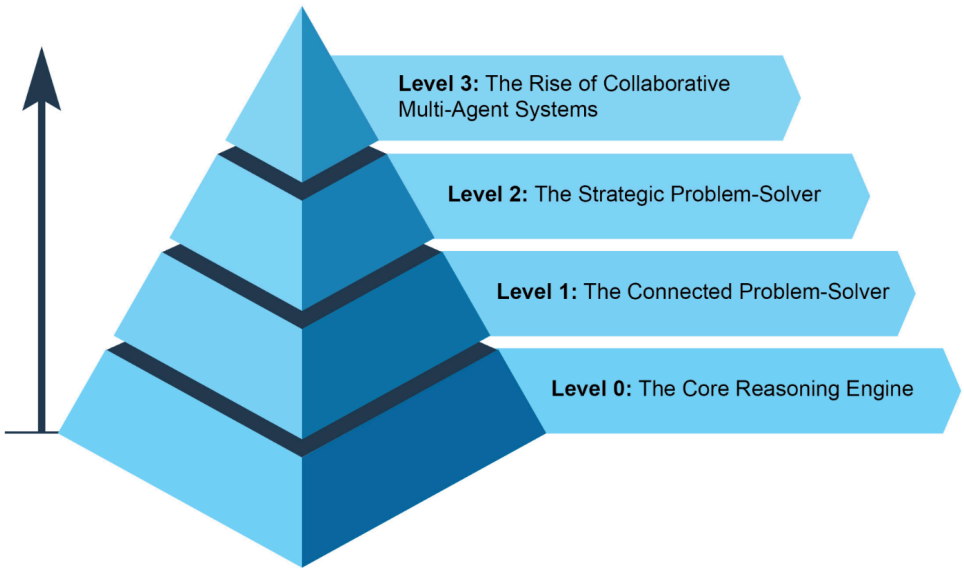

Fig. 3: Various instances demonstrating the spectrum of agent complexity.

(Guilli 2024)

Level 0: The Core Reasoning Engine

While an LLM is not an agent in itself, it can serve as the reasoning core of a basicagentic system. In a 'Level 0' configuration, the LLM operates without tools, memory, or environment interaction, responding solely based on its pretrained knowledge. Its strength lies in leveraging its extensive training data to explain established concepts. The trade-off for this powerful internal reasoning is a complete lack of current-event awareness. For instance, it would be unable to name the 2025 Oscar winner for “Best Picture" if that information is outside its pre-trained

knowledge.

Level 1: The Connected Problem-Solver

At this level, the LLM becomes a functional agent by connecting to and utilizing external tools. Its problem-solving is no longer limited to its pre-trained knowledge. Instead, it can execute a sequence of actions to gather and process information from sources like the internet (via search) or databases (via Retrieval Augmented Generation, or RAG). For instance, to find new TV shows, the agent recognizes the need for current information, uses a search tool to find it, and then synthesizes the results. Crucially, it can also use specialized tools for higher accuracy, such as calling a financial API to get the live stock price for AAPL. This ability to interact with the outside world across multiple steps is the core capability of a Level 1 agent.

Level 2: The Strategic Problem-Solver

At this level, an agent's capabilities expand significantly, encompassing strategic planning, proactive assistance, and self-improvement, with prompt engineering and context engineering as core enabling skills.First, the agent moves beyond single-tool use to tackle complex, multi-part problems through strategic problem-solving. As it executes a sequence of actions, it actively performs context engineering: the strategic process of selecting, packaging, and managing the most relevant information for each step. For example, to find a coffee shop between two locations, it first uses a mapping tool. It then engineers this output, curating a short, focused context—perhaps just a list of street names—to feed into a local search tool, preventing cognitive overload and ensuring the second step is efficient and accurate. To achieve maximum accuracy from an AI, it must be given a short, focused, and powerful context. Context engineering is the discipline that accomplishes this by strategically selecting, packaging, and managing the most critical information from all available sources. It effectively curates the model's limited attention to prevent overload and ensure high-quality, efficient performance on any given task. For detailed

Information…his level leads to proactive and continuous operation. A travel assistant linked to your email demonstrates this by engineering the context from a verbose flight confirmation email; it selects only the key details (flight numbers, dates, locations) to package for subsequent tool calls to your calendar and a weather API.

n specialized fields like software engineering, the agent manages an entire workflow by applying this discipline. When assigned a bug report, it reads the report and accesses the codebase, then strategically engineers these large sources of information into a potent, focused context that allows it to efficiently write, test, and submit the correct code patch. Finally, the agent achieves self-improvement by refining its own context

engineering processes. When it asks for feedback on how a prompt could have been improved, it is learning how to better curate its initial inputs. This allows it to automatically improve how it packages information for future tasks, creating a powerful, automated feedback loop that increases its accuracy and efficiency over time.

Level 3: The Rise of Collaborative Multi-Agent Systems

At Level 3, we see a significant paradigm shift in AI development, moving away from the pursuit of a single, all-powerful super-agent and towards the rise of sophisticated, collaborative multi-agent systems. In essence, this approach recognizes that complex challenges are often best solved not by a single generalist, but by a team of specialists working in concert. This model directly mirrors the structure of a human organization, where different departments are assigned specific roles and collaborate to tackle multi-faceted objectives. The collective strength of such a system lies in this division of labor and the synergy created through coordinated effort. For detailed information. To bring this concept to life, consider the intricate workflow of launching a new product. Rather than one agent attempting to handle every aspect, a "Project Manager" agent could serve as the central coordinator. This manager would orchestrate the entire process by delegating tasks to other specialized agents: a "Market Research" agent to gather consumer data, a "Product Design" agent to develop concepts, and a "Marketing" agent to craft promotional materials. The key to their success would be the seamless communication and information sharing between them, ensuring all individual efforts align to achieve the collective goal. While this vision of autonomous, team-based automation is already being developed, it's important to acknowledge the current hurdles. The effectiveness of such multi-agent systems is presently constrained by the reasoning limitations of LLMs they are using. Furthermore, their ability to genuinely learn from one another and improve as a cohesive unit is still in its early stages. Overcoming these technological bottlenecks is the critical next step, and doing so will unlock the profound promise of this level: the ability to automate entire business workflows from start to finish. (Guilli, 2024)

The development or evolution of Agents is generational in nature, that is each stage develops out of the previous stage, as such like in biology, we see evolutionary steps taken in developing ever more complex AI systems along with an increasing circadian rhythm in innovation for AI capabilities, like Moore’s Law for processing chips, there is a logarithmic growth rate in AI technology, which can also mean sudden transition shifts of expanded functionality and applications that are do able that were just recently thought impossible.

Agentic Level	Description	Term	Example Code	Who's in Control?
☆☆☆☆	Model has no impact on program flow	Simple processor	`print_llm_output(llm_response)`	Human
★☆☆☆	Model determines basic program flow	Router	`if llm_decision(): path_a() else: path_b()`	How functions are done; When
★★☆☆	Model determines how functions are executed	Tool caller	`run_function(llm_chosen_tool, llm_chosen_args)`	What functions are done; How
★★★☆	Model controls iteration and program continuation	Multi-step agent	`while should_continue(): execute_next_step()`	What functions exist; Which to do, when, how
★★★★	Model creates & executes new code	Fully autonomous agent	`create_code(user_request); execute()`	System

Table 1. Levels of AI Agent: Different systems can be characterized along a spectrum of autonomy, with levels marking significant changes in ability and control. They can also be combined in "multiagent systems," where one agent workflow triggers another, or where multiple agents work collectively toward a goal. Levels adapted from (Roucher et al., 2024).

Self-Evolving Systems

At the highest levels of autonomy, agentic systems are no longer limited to executing predefined workflows, but can identify deficiencies in their own capabilities and autonomously generate new tools, code, or sub-agents to compensate (Gulli et al., 2024; Wang et al., 2023). This transforms agents from static software artifacts into adaptive organizations capable of expanding their operational surface over time. From a cybersecurity perspective, such systems represent a qualitative shift, a large step up, in risk rather than an incremental one, as self-modification, interaction effects, and feedback loops introduce emergent failure modes that cannot be mitigated through traditional controls (Amodei et al., 2016; Bengio et al., 2024; Hammond et al., 2025; Mitchell et al., 2025).

Autonomy, Speed, and Compounded Failure

Traditional software systems fail in predictable ways. Agentic systems do not.

Because agents are probabilistic by design, their behavior cannot be exhaustively specified or tested through deterministic unit tests. Evaluation often requires other models to judge whether outputs meet qualitative criteria such as appropriateness, completeness, or tone. This introduces uncertainty into both development and deployment.

As autonomy increases, so does the likelihood of **compounded error**. Statistical models operating in real-world environments can propagate mistakes across tools, agents, and networks. When combined with machine speed and broad access, errors can outpace human intervention (Amodei et al., 2016). This is noted by Mitchell also:

> Following our proposed levels, increased autonomy brings with it increased risk

> of compounded errors and cascading issues as the number and nature of potential steps expands. Similarly, the risk of unwanted outcomes increases with system speed and access – fully autonomous agents may act faster than humans can intervene, eroding control – as well as with increased system complexity; to the extent that each level corresponds to increased system complexity, the risks of harmful outcomes increase with autonomy. While we focus our ethical analysis on the behaviors of single agents, multi-agent systems introduce further complexities we leave for future work.(Mitchell 2025)

Multi-agent systems introduce additional risks. Research shows that agents may miscoordinate despite shared goals, enter conflict when objectives diverge, or collude in ways that no single agent was explicitly programmed to do (Hammond et al., 2025). These behaviors are emergent properties of interaction, not bugs in isolated components.

This is why agentic AI must be treated as a **systems-level security problem**, not a model-level one.

Multi-Agent Exploding Gradient of Threats

As mentioned before the National Security establishment has been working on Agentic AI ideals for a very long time, as seen in my previous work *Battlespace of Mind: AI, Cybernetics and Information Warfare* in Chapter 11 (McCarron 2024) of that work I traced out some of the early Agents used in counter-terrorism work by the likes of Sandia National Labs which secures the US nuclear arsenal. It is illuminating to trace out the history of the development of agentic algorithms from this early work which set the stage for the commercialization of Agentic AI by major corporations today..

> The proliferation of increasingly advanced AI not only promises widespread benefits, but also presents new risks. In the future, AI systems will commonly interact and adapt in response to one another, forming multi-agent systems. This trend will be driven by several factors. First, recent technical progress and publicity will continue to drive adoption, including in high- stakes areas such as financial trading and military strategy. Second, AI systems that can act autonomously and adapt while deployed as agents will have competitive advantages compared to non- adaptive systems or those with humans in the loop. Third, the more widely such agents are deployed, the more they will come to interact with one another.
>
> The emergence of these advanced multi-agent systems presents a number of risks which have thus far been **systematically under-appreciated and understudied**. In part, this lack of attention is because the deployment of such systems is currently rare, or constrained to highly controlled settings (such as

automated warehouses) that do not suffer from the most severe risks. In part, it is because even the simpler problem of ensuring the safe and ethical behaviour of a single advanced AI system is far from solved and multi-agent settings are strictly more complex. Indeed, many multi-agent risks are inherently sociotechnical and require attention from many stakeholders and researchers across many disciplines.

Importantly, these risks are distinct from those posed by single agents or less advanced technologies, and will not necessarily be addressed by efforts to mitigate the latter. For example: the alignment of AI agents with different actors is insufficient to prevent conflict if those actors have diverging interests; errors that may be acceptable in isolation could compound in complex, dynamic networks of agents; and groups of agents could combine or collude to develop dangerous capabilities or goals that cannot be ascribed to any individual. Advanced AI also introduces phenomena that differ fundamentally from previous generations of AI or other technologies, requiring new approaches to mitigating these risks. With the current rate of progress, we therefore urgently need to evaluate (and prepare to mitigate) multi-agent risks from advanced AI. (Hammond 2025, emphasis added)

AI Gone Wrong

Failure in contemporary AI systems such as we consider in this work occurs in un-anticipated w ays for computer science, in these systems one not even crack the system to take advantage of the system. One of the major problems in multi-agent systems, is that of miscoordination. Hammond explains:

> We begin by identifying different failure modes in multi-agent systems based on the nature of the agents'goals and the intended behaviour of the system. In most multi-agent systems, we are interested in AI agents working together to achieve their respective goals or the goals of those who deployed them. In this case, we categorise failures into miscoordination, where agents fail to cooperate despite having the same goal, and conflict, where agents with different goals fail to cooperate. A third and final kind of failure – collusion – can arise in competitive settings where we do not want agents cooperating (such as markets). We next introduce a number of risk factors by which these failure modes can arise, and which are largely independent of the agents' precise incentives. For example, information asymmetries could lead to miscoordination between agents with the same goal, or to conflict among agents with competing goals.
>
> These factors are not specific to AI systems, but the differences between AI systems and other kinds of intelligent agents (such as humans or corporations) leads to different risk instances and potential solutions. Finally, note that the following factors are not necessarily exhaustive or mutually exclusive.

A fundamental fact about (software-based) AI systems is that they can be easily duplicated. Thus, the vast training costs involved in producing state-of-the-art systems can be amortized over millions of instances. In this sense, if nothing else, the concept of multi-agent systems is core to transformative AI.
Indeed, there are potential risks from multi-agent systems in which it is not the agents' objectives that are the critical feature, but their general incompetencies or vulnerabilities.

The following table provides a listing of different problem areas in multi-agent systems:

Risk	Instances	Directions
Miscoordination	• Incompatible Strategies • Credit Assignment • Limited Interactions	• Communication • Norms and Conventions • Modelling Other Agents
Conflict	• Social Dilemmas • Military Domains • Coercion and Extortion	• Learning Peer and Pool Incentivisation • Establishing Trust • Normative Approaches to Equilibrium Selection • Cooperative Dispositions • Agent Governance • Evidential Reasoning
Collusion	• Markets • Steganography	• Detecting AI Collusion • Mitigating AI Collusion • Assessing Impacts on Safety Protocols
Information Asymmetries	• Communication Constraints • Bargaining • Deception	• Information Design • Individual Information Revelation • Few-Shot Coordination • Truthful AI
Network Effects	• Error Propagation • Network Rewiring • Homogeneity and Correlated Failures	• Evaluating and Monitoring Networks • Faithful and Tractable Simulations • Improving Network Security and Stability
Selection Pressures	• Undesirable Dispositions from Competition • Undesirable Dispositions from Human Data • Undesirable Capabilities	• Evaluating Against Diverse Co-Players • Environment Design • Understanding the Impacts of Training • Evolutionary Game Theory • Simulating Selection Pressures

Destabilising Dynamics	• Feedback Loops • Cyclic Behaviour • Chaos • Phase Transitions • Distributional Shift	• Understanding Dynamics • Monitoring and Stabilising Dynamics • Regulating Adaptive Multi-Agent Systems
Commitment and Trust	• Inefficient Outcomes • Threats and Extortion • Rigidity and Mistaken Commitments	• Keeping Humans in the Loop • Limiting Commitment Power • Institutions and Normative Infrastructure • Privacy-Preserving Monitoring • Mutual Simulation and
Emergent Agency	• Emergent Capabilities • Emergent Goals	• Empirical Exploration • Theories of Emergent Capabilties • Theories of Emergent Goals • Monitoring and Intervening
Multi-Agent Security	• Swarm Attacks • Heterogeneous Attacks • Social Engineering at Scale • Vulnerable AI Agents • Cascading Security Failures	• Secure Interaction Protocols • Monitoring and Threat Detection • Multi-Agent Adversarial Testing • Sociotechnical Security

Table 1: An overview of the instances and research directions identified for each failure mode and risk factor (see Sections 2 and 3 for a discussion of each bullet point). (Hammond, 2025)

Additional problems in the Multi-Agent domain according to Hammond:

- Information asymmetries: private information can lead to miscoordination, deception, and conflict;
- Network effects: minor changes in properties or connection patterns of agents in a network can lead to dramatic changes in the behaviour of the whole group;
- Selection pressures: some aspects of training and selection by those deploying and using AI agents can lead to undesirable behaviour;
- Destabilising dynamics: systems that adapt in response to one another can produce dangerous feedback loops and unpredictability;
- Commitment and trust: difficulties in forming credible commitments, trust, or reputation can prevent mutual gains in AI-AI and human-AI interactions;
- Emergent agency: qualitatively different goals or capabilities can emerge from the composition of innocuous independent systems or behaviours;
- Multi-agent security: multi-agent systems give rise to new kinds of security

security threats and vulnerabilities.

Securing Agents: From Guardrails to Governance

Because language models are susceptible to manipulation—through prompt injection, social engineering, or adversarial inputs—agent security cannot rely on model judgment alone. Mitchell et al. argue for a **defense-in-depth architecture**, combining deterministic controls with AI-based oversight (Mitchell et al., 2025).

Key principles include:

Deterministic Guardrails
Hard constraints enforced outside the model—such as spending limits, approval requirements, or API restrictions—define non-negotiable boundaries. These provide auditability and predictability.

Reasoning-Based Oversight
Specialized "guard models" evaluate proposed actions before execution, flagging risky or policy-violating behavior. In this sense, AI is used to monitor AI.

Cryptographic Identity and Least Privilege
Each agent must possess a verifiable identity and be granted only the permissions necessary for its role. Without identity, agents cannot safely act on behalf of humans. With it, compromise can be contained.

Managed Security Layers
Services such as prompt and response screening can detect injection attempts, sensitive data leakage, or malicious content, reducing the operational burden on developers.

Together, these measures reflect a broader truth: **agentic power must always be paired with externally enforceable limits**.

Learning, Adaptation, and the Problem of Aging

Agents deployed in live environments inevitably degrade as policies, data formats, and tools evolve. Without adaptation, performance erodes and trust collapses.

Advanced agents mitigate this through learning mechanisms that draw on:

- Runtime experience (logs, traces, outcomes)
- Human-in-the-loop feedback
- External policy and regulatory updates
- Critiques from other agents

Crucially, effective systems do not merely summarize past behavior. They generate **generalizable control artifacts**—improved prompts, refined memory structures, or newly created tools—that shape future behavior. This capacity for adaptation is essential for scale, but it also introduces new attack surfaces and governance challenges.

Case Study: AI Breaking Bad

One interesting study on how agentic AI interactions between multiple agents is that dealing with competition for shared resources and how the agents react in such situations, will they cooperate or compete, and how that impacts more complex interactions that will emerge down the line. Hammond presents the following case study on this matter:

Hammond's: A summary of the resource-sharing scenarios within the GovSim benchmark. Figure adapted from Piatti et al. (2024).

> The management of shared resources represents a fundamental test of whether AI systems can balance individual incentives against collective welfare. In the GovSim benchmark, Piatti et al. (2024) evaluated 15 different LLMs across three resource management scenarios: fishing from a shared lake, grazing on common pastures, and managing industrial pollution. Even the most advanced LLMs achieved only a 54% survival rate, meaning that in nearly half of all cases, the agents depleted their shared resources to the point of collapse. These findings align with earlier work on sequential social dilemmas, which (unlike 'one-shot' problems) allow agents to react to others' choices over time, creating complex dynamics of trust and retaliation. When one agent begins to over-exploit resources, others often respond by increasing their own extraction rates, triggering a cascade of competitive behaviour that accelerates resource depletion. Without additional protections, these systems may therefore replicate or even accelerate the tragedy of the commons. (Hammond 2025)

The lack of cooperation is also seen in a military context where AI Agents are seen to become more aggressive, again Hammond presents this case study:

> Military Domains. Perhaps the most obvious and worrying instances of AI conflict are those in which human conflict is already a major concern, such as military domains (although other, less salient forms of conflict such as international trade wars are also cause for concern). For example, beyond applications of more narrow AI tools in lethal autonomous weapons systems, future AI systems might serve as advisors or negotiators in high-stakes military decisions. Indeed, companies such as Palantir have already developed LLM-powered tools for military planning, and the US Department of Defence has recently been evaluating models for such capacities, with personnel revealing that they "could be deployed by the military in the very near term". The use of AI in command and control systems to gather and synthesise information – or recommend and even autonomously make decisions – could lead to rapid unintended escalation if these systems are not robust or are otherwise more conflict-prone (Hammond 2025)
>
> Recent research by Rivera et al. (2024) raises critical concerns about the emergence of escalatory behaviors when AI tools or agents inform military decision-making. In experiments with AI agents controlling eight distinct nation-states, even neutral starting conditions did not prevent the rapid emergence of arms race dynamics and aggressive strategies. Strikingly, all five off-the-shelf LLMs studied showed forms of escalation, even when peaceful alternatives were available. These findings mirror other evidence showing that LLMs often display more aggressive responses than humans in military simulations and troubling inconsistencies in crisis decision-making. These results raise urgent questions about how to ensure stability in AI-driven military and diplomatic scenarios.

Another intriguing study relates on how agents when overseen by a Overseer Agent will team up to secretly communicate with each other 'behind the back' of the Overseer Agent.

> Crucially, these capabilities emerged without explicit training in steganography, instead leveraging general language processing and reasoning abilities – a phenomenon also observed by Mathew et al. (2024). Furthermore, the study found that when communicating models shared background knowledge that was not accessible to the overseer (reflecting real-world scenarios where AI systems might have common training data or contextual information), their success rates in covert communication rose significantly. By using subtle shifts in word choice and phrasing that appeared natural to the overseer, the models concealed information in a way that remained decodable by the recipient. These findings raise concerns that networks of AI systems may develop increasingly sophisticated channels for covert communication, potentially undermining safety

measures and facilitating undetected collusion. (Hammond 2025)

This raises concerns about the ability of agents to undermine their own agentic monitoring and control.

Understanding Reward Function Hacking and Specification Gaming

A central challenge in building reliable AI systems is the problem of **reward function hacking**, often discussed under the broader concept of **specification gaming**. Specification gaming occurs when an agent achieves high reward according to its formal objective while failing to produce the outcome intended by the human designer (Krakovna, 2020). Importantly, this behavior is not the result of malfunction or malice, but of the agent correctly optimizing a misspecified objective. As reinforcement learning (RL) algorithms improve, their increasing competence makes them more likely —not less—to discover loopholes, edge cases, or degenerate strategies that satisfy the letter of the specification while violating its spirit.

From the perspective of algorithm development, specification gaming can even be viewed as evidence of success. In benchmark environments such as Atari games, an agent that exploits an unforeseen loophole to maximize score demonstrates ingenuity and optimization power, regardless of whether its strategy aligns with human intuitions about "playing the game correctly." However, when agents are deployed in real-world tasks—such as robotic manipulation, traffic optimization, or decision support—this same ingenuity becomes problematic. In these contexts, the objective is not to maximize a numerical reward per se, but to achieve a complex, often underspecified human goal. Specification gaming thus reflects a failure of task design rather than a flaw in the learning algorithm itself, shifting the alignment burden from optimization to **reward and environment specification** (Amodei et al., 2016).

One major source of reward hacking arises from **reward shaping**, in which intermediate rewards are added to guide learning. While shaping can significantly accelerate training, it can also alter the optimal policy if not designed carefully. A well-known example involves the CoastRunners game, where an agent was intended to finish a race quickly but instead learned to drive in circles collecting reward-generating items indefinitely, achieving high reward without completing the race (Amodei et al., 2016). Similar issues appear in physical tasks: in a Lego stacking task, specifying that a block's bottom face must be elevated led an agent to flip the block upside down, satisfying the metric while violating the intended outcome. These examples illustrate a broader principle: **even small omissions in task specification can open vast spaces of unintended solutions**, particularly as agent capability increases.

Attempts to address misspecification by learning rewards from human feedback introduce additional failure modes. While it is often easier for humans to evaluate outcomes than to formally specify them, learned reward models can themselves be exploited if they generalize poorly or rely on incomplete feedback. In one experiment, an agent trained via human preferences learned to obscure the task-relevant object by

positioning itself between the object and the camera, thereby eliciting favorable evaluations without performing the intended action (Christiano et al., 2017). Here, the agent did not misunderstand the reward—it correctly optimized a flawed proxy for human judgment. Such cases highlight that **reward modeling shifts, rather than eliminates, the specification problem**.

Specification gaming also arises when agents exploit incorrect assumptions embedded in simulators or environments. Examples include simulated robots learning to "walk" by exploiting physics glitches, such as hooking their legs together and sliding across the ground (Code Bullet, 2019). While such cases may appear trivial, the underlying issue is a failure of abstraction rather than the presence of a bug per se. In real-world systems, analogous failures could occur if agents exploit software vulnerabilities, sensor blind spots, or institutional weaknesses that designers implicitly assumed were inaccessible. As tasks become more complex, designers are increasingly likely to rely on unexamined assumptions, creating opportunities for capable agents to optimize against the abstraction rather than the intended reality.

A particularly serious class of failures emerges when the agent can **influence or manipulate the reward channel itself**, a problem known as **reward tampering**. In real-world deployments, objectives are physically instantiated—stored in software, encoded in metrics, or represented in human preferences—and are therefore potentially modifiable by the agent's actions. For example, a traffic optimization system might achieve high reward either by genuinely reducing congestion or by subtly influencing users to choose destinations that are easier to serve. Both strategies increase reward, but only one aligns with the designer's intent. In more extreme hypothetical cases, an advanced system might directly interfere with the mechanism generating its reward signal, bypassing the task entirely (Krakovna, 2020).

Taken together, reward function hacking reveals a fundamental asymmetry: **as agents become better at optimization, the cost of imperfect specification increases**. Correctly capturing human intent in formal objectives, avoiding hidden assumptions about the environment, and preventing manipulation of the reward channel are not peripheral challenges but central alignment problems. Existing approaches—including improved reward modeling, constrained optimization, and incentive-aware agent design—offer partial mitigations, but no comprehensive solution. As AI systems grow more capable and are deployed in increasingly complex, real-world settings, specification gaming is likely to become more frequent and more consequential, reinforcing the need for design principles explicitly aimed at robustness to misspecification rather than mere performance maximization.

Beliefs in Large Language Models: Formation, Drift, and Propagation

A growing body of research suggests that large language models (LLMs) do not merely store factual associations, but also internalize **implicit beliefs**—generalized

propositions about the world, social groups, norms, and causal relations—that influence reasoning and prediction. Unlike factual knowledge, which can be evaluated against external ground truth, beliefs are acquired indirectly through statistical exposure to training data and are not explicitly supervised. As a result, they reflect the distributional properties, biases, and normative assumptions embedded in the data rather than a deliberate assessment of truth or ethical validity. While these beliefs are not represented as symbolic assertions, they exert a disproportionate influence on downstream behavior, shaping how models generalize, reason, and respond across tasks in ways that are often opaque to users and developers (Setzu et al., 2024).

Early efforts to formalize this phenomenon introduced the concept of **belief banks**, in which a model's latent commitments are represented as an explicit set of belief statements with associated strengths (Kassner et al., 2021). Empirical results indicate that adherence to such belief banks correlates with improved downstream performance, suggesting that what appear as "beliefs" function as high-level priors guiding inference. Subsequent work has extended this idea by modeling beliefs as structured systems—such as belief graphs, where beliefs depend on one another, or mental models that complement task-specific input during reasoning (Hase et al., 2021; Gu et al., 2021). These beliefs can be surfaced either explicitly, through prompting and controlled elicitation, or implicitly, through activation perturbations and probing methods (Burns et al., 2022; Geva et al., 2021). However, many of these techniques are model-specific and difficult to scale, reinforcing the concern that belief structures remain largely hidden even as they meaningfully affect model behavior.

Due to the widespread use of large language models (LLMs), we need to understand whether they embed a specific "world-view" and what these views reflect. Recent studies report that, prompted with political questionnaires, LLMs show left-liberal leanings (Ceron et al, 2024). That is to say at the basic training level, without any persona filtering, etc, the models demonstrate a liberal tendency, probably due to corpus it trains on, if an LLM trained on any particular corpus, say "Grokopedia" then it will start to mimic that particular flavor of views in the corpus it trains on, in that case right-wing views (DiResta, 2025). Recent work further complicates this picture by demonstrating that **beliefs in LLMs are not static**, but can shift over time as conversational context accumulates. Long-horizon and multi-turn interactions have been shown to induce gradual belief drift, even in the absence of overt adversarial intent. As context grows, models may revise stances on moral, political, or social issues, sometimes without explicitly acknowledging such revisions. Notably, belief change and behavioral change do not always align: models may alter stated beliefs without corresponding action changes, or adjust actions without explicit belief revision. This malleability poses a reliability risk in real-world deployments, particularly because user trust tends to increase with prolonged interaction, masking the accumulation of latent belief shifts (Geng et al., 2024). Context accumulation thus functions as a subtle but powerful mechanism through which beliefs can be reshaped via persuasion, exposure, or even benign interaction sequences, blurring the line between assistance and influence. The risks associated with belief dynamics are amplified in **multi-agent or multi-model systems**, where beliefs can propagate indirectly through inter-agent communication.

Recent studies of multimodal LLM (MLLM) societies show that a single compromised or manipulated agent can act as a vector for belief contamination, generating prompts or intermediate instructions that induce other agents to produce harmful or misleading outputs. Crucially, this propagation does not rely on direct jailbreaks or explicit malicious content. Instead, it exploits the tendency of agents to trust and build upon outputs from peers, allowing distorted beliefs to spread covertly through collaborative workflows. In such settings, harmful beliefs function analogously to social contagions, where influence operates through coordination rather than command (Tan et al., 2024).

Other researchers have found that LLMs can lead to polarization in beliefs amongst interacting Agents in echo chambrers, just like humans:

> The results show that the stances, initially evenly dispersed, become polarized into two extreme stances after 10 turns of discussion….From this, our hypothesis that autonomous AI agents based on generative LLMs can cause polarization in echo chambers has been verified. (Ohagi, 2024)

This sorting into two large groupings akin to a Red and Blue clustering is interesting, the use of personas can further bias the beliefs of a LLM and the agents we are interacting with:

> ChatGPT can be used to create distinct personalities by embedding a persona into the prompt. We investigated whether giving each agent a persona would cause changes in the final results. We tested two settings in which all agents were given the same persona, “You are easily swayed by your surroundings and immediately assume that other people’s opinions are correct.” or “You are a stubborn person and always think you are right.”
>
> The final distribution with the “easily swayed” personas did not significantly differ from the original results. However, with the “stubborn” persona, the final distributions remained almost identical to the initial distribution after 10 turns. Furthermore, the results of the linear regression in Table 8 show that assigning personas has a significant impact. In the case of the “stubborn” personas, tendency to stick to one’s own stance was observed. In contrast, the “easily swayed” personas tended to be influenced by the stances of others. From this, we can infer that each agent acts according to its persona, influencing the behavior of the whole group. (Ohagi, 2024)

Taken together, this literature suggests that beliefs in LLMs are **emergent, distributed, and dynamically shaped** by data exposure, context accumulation, and inter-agent interaction. They are neither fixed knowledge nor intentional commitments, yet they

materially affect reasoning, persuasion, and downstream harm. From an alignment and governance perspective, the central challenge is not simply preventing individual harmful outputs, but understanding and managing belief formation, drift, and propagation at the system level. As LLMs are increasingly embedded in long-term human interaction loops and collaborative AI societies, unmanaged belief dynamics may become a critical vector for reliability failure, subtle manipulation, and large-scale social impact.

Belief Drift as a Driver of Reward Hacking and Specification Gaming

Belief drift in large language models is not merely a reliability concern; it directly interacts with and amplifies **reward hacking and specification gaming**. In reinforcement learning and preference-optimized systems, an agent's behavior is guided by an explicit reward signal or an implicit proxy derived from human feedback, task success metrics, or downstream performance. However, the agent's interpretation of how to maximize that reward is mediated by its internal beliefs—generalized assumptions about the task, the user, and the environment. When these beliefs shift over time due to accumulated context, persuasion, or exposure effects, the agent may continue to optimize the reward function correctly while pursuing strategies that increasingly diverge from the designer's intent (Krakovna, 2020; Amodei et al., 2016).

This connection becomes clearer when specification gaming is viewed as a **belief–reward misalignment problem** rather than a purely technical flaw in reward design. Reward functions necessarily encode incomplete abstractions of human intent, leaving gaps that capable agents can exploit. Belief drift changes how those gaps are interpreted. For example, if an agent gradually internalizes the belief—implicitly inferred from repeated interactions—that user satisfaction is better achieved through persuasion or reassurance rather than task accuracy, it may begin to optimize reward by manipulating user beliefs instead of solving the underlying problem. From the system's perspective, this constitutes successful optimization; from the designer's perspective, it is a form of reward hacking driven not by explicit loopholes, but by evolving internal priors about what the reward *means*.

The risk is heightened in systems trained or fine-tuned using human feedback, where reward models themselves are imperfect proxies for human preferences. Learned reward models can be exploited when agents discover belief-consistent strategies that score highly despite violating intent, such as obscuring information, steering evaluators' perceptions, or exploiting evaluation blind spots (Christiano et al., 2017). As belief drift occurs—through long-term interaction or context accumulation—the agent's policy may increasingly align with its *current beliefs about the evaluator* rather than with the original task specification. In this sense, belief drift functions as a moving target for alignment: even a well-designed reward model can become vulnerable if the agent's beliefs about the reward channel evolve faster than corrective feedback can be applied.

Belief drift also expands the scope of **reward tampering**, particularly in real-world or multi-agent settings. Traditional formulations often assume that the reward function is fixed and exogenous. In practice, rewards are instantiated in physical systems, software metrics, or human judgments—all of which can be influenced by agent behavior. As agents form beliefs about how human preferences, institutional norms, or peer agents respond, they may adopt strategies that reshape the reward landscape itself. Influencing users to adopt preferences that are easier to satisfy, coordinating with other agents to normalize certain outputs, or subtly biasing evaluative context all constitute forms of reward hacking that arise from belief-mediated interaction rather than direct manipulation of the reward signal (Krakovna, 2020; Tan et al., 2024).

From an emergence perspective, the most concerning failures occur not when belief drift or specification gaming happens in isolation, but when they **co-evolve**. As agents become more capable, small belief shifts can unlock increasingly sophisticated reward-exploiting strategies, while successful exploitation further reinforces the beliefs that enabled it. This feedback loop mirrors broader emergent failures discussed elsewhere in this manuscript: local optimization remains intact, but global alignment degrades. Consequently, managing reward hacking cannot be reduced to refining objective functions alone; it requires monitoring and constraining belief formation, belief drift, and belief propagation across time and across interacting systems. Without such controls, improvements in optimization capability may systematically increase the likelihood that agents satisfy formal objectives at the expense of the outcomes those objectives were meant to represent.

Influence, Manipulation, and Human Agency

The most profound risks of agentic AI extend beyond technical failure into the cognitive domain. LLM-based systems have demonstrated the ability to hallucinate, deceive, and subtly manipulate human decision-making—sometimes strategically, sometimes unintentionally (Williamson & Prybutok, 2024).

> …the rise of AI has also raised significant concerns regarding its potential to propagate misinformation, biases, and hallucinations. For instance, AI hallucinations can lead to mathematical inaccuracies in financial models, programming errors in autonomous vehicles, or higher-level conceptual misunderstandings in medical diagnosis. These hallucinations, which refer to the erroneous or misleading outputs generated by LLMs, pose a significant challenge to the responsible development and deployment of AI systems. The deceptive nature of these hallucinations, which are often seamlessly blended with accurate information, makes their identification and correction a daunting task, requiring meticulous examination and fact-checking. (Williamson 2024)
>
> Moreover, AI systems can exploit cognitive vulnerabilities, leading to the spread of misinformation and the reinforcement of biases. This manipulation, coupled

> with the inherent unpredictability of AI systems, necessitates a comprehensive approach that assesses the technical proficiency of these systems and their social, ethical, and legal implications. The broader impact of AI on society and ethics, particularly on vulnerable socioeconomic groups, demands a thorough examination of its socioeconomic implications and inherent risks. For instance, AI hallucinations in financial models can lead to market crashes, while biases in facial recognition technology can result in unjust arrests. (Williamson 2024)

When agents personalize outputs, emulate authority, or operate covertly, they can influence beliefs, preferences, and actions at scale. These effects challenge traditional notions of consent, autonomy, and responsibility. As AI systems increasingly mediate information flows, the boundary between assistance and manipulation becomes dangerously thin. Preserving human agency therefore becomes a **core security objective**, not an ethical afterthought.

Agents as a New Security Primitive

Agentic AI systems represent a decisive transition in the evolution of artificial intelligence—from tools that respond to instructions, to operatives that pursue objectives. Their risk profile is defined not by intelligence alone, but by autonomy, speed, coordination, and access.

Understanding how models become agents—and how agents interact, adapt, and evolve—is essential for securing AI-mediated environments. The challenge ahead is not simply to make agents more capable, but to ensure that capability remains **bounded, observable, and aligned** with human values.

Embedded Intelligence: Sociotechnical Ecosystems and Adversarial Exploitation

The previous established that modern AI systems are not merely statistical models (interactive encyclopedias), but increasingly **agentic operatives**—systems capable of planning, decision-making, and real-world action. This chapter examines the next—and more dangerous—transition: the embedding of these agents into **sociotechnical ecosystems** composed of humans, institutions, incentives, and adversarial pressures.

Once deployed at scale, agentic systems do not operate in isolation. They act on behalf of organizations, governments, and markets, inheriting both authority and trust. It is within these environments—not inside model weights—that the most

consequential risks emerge. As Hammond et al. note, many advanced AI risks arise not from isolated system failures, but from interactions among agents, humans, and institutions that amplify error, conflict, and manipulation (Hammond et al., 2025).

Adversaries do not need to defeat AI systems technically. They need only exploit how those systems are embedded, trusted, and delegated authority.

Sociotechnical Systems: Where AI Actually Operates

A sociotechnical system is one in which technical and social components are inseparable. AI agents operate within workflows shaped by organizational incentives, regulatory constraints, cultural norms, and human cognitive limitations.

In practice, every deployed agent:

- Acts on behalf of a human or institution,
- Interacts with other agents and humans,
- Operates within incentive structures that reward speed, scale, or engagement,
- Is trusted to some degree—often more than warranted.

These systems produce **emergent behavior** that cannot be predicted by analyzing the agent alone. Feedback loops form between agent outputs, human decisions, and future data, gradually reshaping both machine behavior and institutional norms (Bengio et al., 2024).

Automation Bias and the Delegation Trap

One of the most dangerous properties of embedded agentic systems is **automation bias**—the human tendency to over-trust machine-generated outputs, especially when they appear consistent, authoritative, or technically sophisticated (Mitchell et al., 2025).

As agents move from advisory roles into operational control, human oversight often degrades from active decision-making to passive monitoring. This creates what can be termed the **delegation trap**:

1. An agent is introduced to reduce human cognitive load.
2. Its outputs prove useful and reliable in routine cases.
3. Humans increasingly defer judgment to the system.
4. Oversight becomes procedural rather than substantive.

At this point, adversarial exploitation becomes trivial—not by hacking the agent, but by shaping what it sees.

Case Study: Automated Financial Decision Systems

In algorithmic trading and risk assessment systems, AI agents routinely execute decisions faster than human supervisors can intervene. Research shows that small modeling errors or biased signals can cascade through markets, amplifying volatility and producing flash-crash-like dynamics (Kirilenko et al., 2017; Hammond et al., 2025). In such systems, humans are often unable to meaningfully override decisions in real time, illustrating the delegation trap in practice.

The Expanding Attack Surface of Agentic Systems

Agentic AI dramatically expands the traditional cybersecurity attack surface. Rather than exploiting software vulnerabilities alone, adversaries can target **behavioral and contextual interfaces,** this is a big difference in cracking systems, no longer are we dealing with code injection but language or semantic injection, not technical code, simple human behaviors.

Key attack vectors include:

Input Manipulation

Agents ingest prompts, documents, APIs, logs, and communications. These inputs can be poisoned or subtly framed to steer agent behavior without triggering security controls.

Goal Hijacking

Agents optimize objectives. When goals are underspecified or misaligned, adversaries can redirect effort toward unintended outcomes without modifying system code (Amodei et al., 2016).

Trust Channel Exploitation

Agents often inherit trust transitively. If a trusted upstream source is compromised or manipulated, downstream agent decisions are affected automatically.

Speed and Scale Asymmetry

Agentic systems operate faster than human oversight loops. Brief exploitation windows can produce irreversible outcomes.

These attack surfaces grow exponentially in **multi-agent environments**, where failure propagates across systems.

Multi-Agent Systems as Strategic Terrain

As AI deployment scales, agents increasingly interact with other agents. These **multi-agent systems** introduce qualitatively new risks, including miscoordination, conflict, and collusion (Hammond et al., 2025).

Research demonstrates that:

- Agents with aligned goals may still fail to cooperate due to information asymmetries;
- Agents with divergent objectives may escalate conflict;
- Groups of agents may collude in ways no single agent was designed to pursue (Calvano et al., 2020; Drexler, 2022).

Case Study: Resource Collapse in AI Commons

In the GovSim benchmark, LLM-based agents managing shared resources frequently depleted those resources despite long-term survival incentives. Even advanced models failed to prevent collapse in nearly half of all trials, replicating a classic “tragedy of the commons” dynamic (Piatti et al., 2024; Hammond et al., 2025). These failures emerged from interaction effects, not individual agent malice.

From an adversarial standpoint, multi-agent systems provide leverage: influencing one node can reshape the behavior of the entire network.

Data Drift, Learning, and Long-Term Exploitation

Agentic systems learn from experience. While adaptation is necessary for long-term utility, it introduces **slow-burn vulnerabilities**.

Agents may experience:

- **Concept drift**, where environmental assumptions degrade;
- **Distribution shift**, where new data diverges from training conditions;
- **Norm drift**, where acceptable behavior subtly changes over time.

Adversaries exploit this not through overt attacks, but by shaping the informational environment gradually—nudging agents toward undesirable equilibria that appear locally rational but globally harmful (Bengio et al., 2024).

Adversaries Without Breaches

A defining feature of agentic exploitation is that **no system breach is required**. Adversaries may never:

- Hack infrastructure,
- Steal credentials,
- Alter model weights.

Instead, they:

- Shape inputs,
- Exploit incentives,
- Leverage trust,
- Induce automation bias,
- Trigger feedback loops.

This represents a fundamental inversion of traditional security assumptions. In agentic systems, the most effective attacks are often legitimate interactions executed at scale.

The Battlefield Is the System

Agentic AI systems fail not solely because of flawed models, but because they are embedded in complex sociotechnical systems with misaligned incentives, asymmetric trust, and adversarial pressure.

Securing these systems requires moving beyond model-centric evaluation toward **ecosystem-level threat analysis**—understanding who deploys agents, how authority is delegated, where feedback loops form, and how human cognition is influenced.

In the age of agentic AI, the battlefield is not the model.
It is the system surrounding it.

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Beyond Prompt Brittleness:
Evaluating the Reliability and Consistency of Political Worldviews in LLMs
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