

#### Mastering AI Agents

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#### Aditya Kakkar (zjq5mr)

#### **Presentation Outline**



#### **Presentation Outline**





#### Chapter 1 - What are AI Agents?

### Introduction



Mastering AI Agents: From Theory to Real-World Implementation





### Motivation



- Companies have quickly adapted, adopted, and integrated AI agents into their workflows.
- Capgemini's research found that over 50% of companies plan to use AI Agents in 2025 and 82% plan to integrate them within the next three years.

## What are AI Agents?



# How do we use LLMs to accomplish end-to-end tasks?

- AI agents take LLMs to the next level by adding decision-making and action-taking capabilities—like making API calls.
- Think of an LLM as the brain that understands and generates text, while an AI agent is the body that takes action based on that intelligence.

### When should I use an AI Agent?



They're incredibly useful for tasks that demand complex decision-making, autonomy, and adaptability, especially helpful in dynamic environments where the workflow involves multiple steps or interactions that could benefit from automation.



Salesforce estimates that salespersons spend **71%** of their time on non-selling tasks (like administrative tasks and manually entering data).

### **Use Cases**

#### 1. Customer Interaction

A customer messages your service asking, "When will my order ship?"

#### 2. Data Retrieval

The AI agent accesses the order management system to find the specific order details.

#### 3. Response Generation

Based on the data retrieved, the agent automatically provides an updates to the customer, such as sending "Your order will ship tomorrow and you'll receive a tracking link via email once it's on its way."

## Use Cases(code)



## **Types of AI Agents**

Name of the agent	Key Characteristics	Examples	Best For
Fixed Automation: The Digital Assembly Line	No intelligence, predictable behavior, limited scope	RPA, email autoresponders, basic scripts	Repetitive tasks, structured data, no need for adaptability
LLM-Enhanced: Smarter, but Not Einstein	Context-aware, rule- constrained, stateless	Email filters, content moderation, support ticket routing	Flexible tasks, high- volume/low-stakes, cost- sensitive scenarios
ReAct: Reasoning Meets Action	Multi-step workflows, dynamic planning, basic problem-solving	Travel planners, Al dungeon masters, project planning tools	Strategic planning, multi- stage queries, dynamic adjustments
ReAct + RAG: Grounded Intelligence	External knowledge access, low hallucinations, real-time data	Legal research tools, medical assistants, technical support	High-stakes decisions, domain-specific tasks, real-time knowledge needs
Tool-Enhanced: The Multi-Taskers	Multi-tool integration, dynamic execution, high automation	Code generation tools, data analysis bots	Complex workflows requiring multiple tools and APIs
Self-Reflecting: The Philosophers	Meta-cognition, explainability, self- improvement	Self-evaluating systems, QA agents	Tasks requiring accountability and improvement
Memory-Enhanced: The Personalized Powerhouses	Long-term memory, personalization, adaptive learning	Project management Al, personalized assistants	Individualized experiences, long-term interactions
Environment Controllers: The World Shapers	Active environment control, autonomous operation, feedback-driven	AutoGPT, adaptive robotics, smart cities	System control, IoT integration, autonomous operations
Self-Learning: The Evolutionaries	Autonomous learning, adaptive/scalable, evolutionary behavior	Neural networks, swarm Al, financial prediction models	Cutting-edge research, autonomous learning systems

## **Fixed Automation Agent**

Feature	Description
Intelligence	No learning, adaptation, or memory.
Behavior	Predictable and consistent, follows pre-defined rules.
Scope	Limited to repetitive, well-defined tasks. Struggles with unexpected scenarios.
Best Use Cases	Routine tasks, structured data, situations with minimal need for adaptability.





## LLM-Enhanced – Smarter, but Not Exactly Einstein

Feature	Description
Intelligence	Context-aware; leverages LLMs to process ambiguous inputs with contextual reasoning.
Behavior	Rule-constrained; decisions are validated against predefined rules or thresholds.
Scope	Stateless; no long-term memory; each task is processed independently.
Best Use Cases	Tasks requiring flexibility with ambiguous inputs, high-volume/low-stakes scenarios, and cost-sensitive situations where "close enough" is sufficient.





*"Press 1 for English, Press 2 for Spanish, Press 3 for Billing..."* – that's a basic rule-based IVR (Interactive Voice Response) system.

"I need help with my bill"  $\rightarrow$  classified as a **billing** inquiry

"My internet is down"  $\rightarrow$  classified as a **technical issue** 

## **ReAct - Reasoning Meets Action**

Feature	Description
Intelligence	Reasoning and action; mimics human problem-solving by thinking through a problem and executing the next step.
Behavior	Handles multi-step workflows, breaking them down into smaller, actionable parts. Dynamically adjusts strategy based on new data.
Scope	Assists with basic open-ended problem-solving, even without a direct solution path.
Best Use Cases	Strategic planning, multi-stage queries, tasks requiring dynamic adjustments, and re-strategizing.





### **ReAct + RAG – Grounded Intelligence**

Feature	Description
Intelligence	Employs a RAG workflow, combining LLMs with external knowledge sources (databases, APIs, documentation) for enhanced context and accuracy.
Behavior	Uses ReAct-style reasoning to break down tasks, dynamically retrieving information as needed. Grounded in real-time or domain-specific knowledge.
Scope	Designed for scenarios requiring high accuracy and relevance, minimizing hallucinations.
Best Use Cases	High-stakes decision-making, domain-specific applications, tasks with dynamic knowledge needs (e.g., real-time updates).





### **Tool-Enhanced – The Multi-Taskers**

Feature	Description
Intelligence	Leverages APIs, databases, and software tools to perform tasks, acting as a multi- tool integrator.
Behavior	Handles multi-step workflows, dynamically switching between tools based on task requirements.
Scope	Automates repetitive or multi-stage processes by integrating and utilizing diverse tools.
Best Use Cases	Jobs requiring diverse tools and APIs in tandem for complex or multi-stage automation.





## **Self-Reflecting – The Philosophers**

Feature	Description
Intelligence	Exhibits meta-cognition, evaluating its own thought processes and decision outcomes.
Behavior	Provides explanations for actions, offering transparency into its reasoning. Learns from mistakes and improves performance over time.
Scope	Suited for tasks requiring accountability and continuous improvement.
Best Use Cases	Quality assurance, sensitive decision-making where explainability and self- improvement are crucial.





for Software Developers



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## **Memory-Enhanced – The Personalized Powerhouses**

Feature	Description
Intelligence	Possesses long-term memory, storing and recalling past interactions, preferences, and task progress.
Behavior	Provides context-aware personalization, adapting decisions and actions based on user-specific data and history. Learns and improves over time.
Scope	Excels at tasks requiring individualized experiences, tailored recommendations, and maintaining consistency across multiple interactions.
Best Use Cases	Personalized assistance, long-term interactions, tasks spanning multiple sessions.



**H&M Virtual** Shopping Assistant



master.of.code .....

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## **Environment Controllers – The World Shapers**

Feature	Description
Intelligence	Autonomous learning; refines models and processes based on feedback, data, or environmental changes without manual updates.
Behavior	Adaptive and scalable, adjusting to changing conditions and new tasks. Exhibits evolutionary behavior, improving performance over time.
Scope	Suited for cutting-edge research and autonomous learning systems, offering high potential but requiring careful monitoring.
Best Use Cases	Situations where autonomous learning and adaptation are crucial, such as complex research, simulation, or dynamic environments.







#### Aryan Sawhney (ryd2fx)

### **Self-Learning – The Evolutionaries**

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Best Use Cases	Situations where autonomous learning and adaptation are crucial, such as complex research, simulation, or dynamic environments.
Examples	Neural networks with evolutionary capabilities, swarm Al systems, autonomous robotics, financial prediction models.





Fig 1.10: Workflow of a self-learning agent

## When to Use Agents?

- Al Agents excel at tasks that require:
  - Complex decision-making
  - Autonomy
  - Adaptability
- Al Agents excel at environments where workflow is dynamic and involves multiple steps or interactions

Domain	Task	Benefits of Using Al Agents	
Customer Support	Handling queries, providing real-time assistance, issue escalation	Agents enhance the efficiency and customer experience by offering timely and accurate responses, allowing human staff to focus on more complex issues.	
Research and Data Analysis	Gathering, processing, and analyzing data	They autonomously provide deep insights from large datasets, helping you understand patterns without manual effort.	
Financial Trading	Real-time data processing	Agents excel in making quick decisions based or rapidly-changing market conditions.	
Education	Personalized learning experiences	These agents adapt to each student's learning pace, offering tailored feedback and supporting unique learning journeys effectively.	
Software Development	Code generation, debugging, and testing	Agents streamline the development process by handling repetitive tasks like coding and testing, improving code quality, and reducing development time. They also learn and improve over time, which continually enhances their assistance.	

## When Not to Use Agents?

- Tasks are too simple or infrequent
  - Minimal automation needed; traditional software is more efficient
  - Complexity and cost of AI agents may not be justified
- Requires deep domain expertise
  - Legal analysis, medical diagnosis, and high-stakes decision-making are better handled by professionals
  - Sole reliance on AI can lead to suboptimal or harmful outcomes
- Human emotion and creativity are essential
  - Fields like psychotherapy, counseling, and creative writing require a human touch
  - Al lacks the depth to fully understand emotions and creativity

- High implementation costs
  - Small businesses and budget-constrained projects may find AI agents too expensive
  - Development and maintenance costs may outweigh benefits
- Regulatory and compliance challenges
  - Highly regulated industries impose strict security and legal constraints
  - Ensuring AI agents meet compliance standards is resource-intensive

## 10 Questions to Ask Before You Consider an AI Agent





How often does the task occur?



What is the expected volume of data or queries?



Does the task require adaptability?



Can the task benefit from learning and evolving over time?



What level of accuracy is required?



Is human expertise or emotional intelligence essential?



What are the privacy and security implications? What are the regulatory and compliance requirements?



What is the costbenefit analysis?

### **3 Interesting Real-World Use Cases of AI Agents**







### Wiley and Agentforce

**Company:** Wilev Al Agent: Agentforce by Salesforce

Use Case: Customer service automation

#### Problem:

Wiley faced challenges handling spikes in service calls during peak times, particularly at the start of new semesters when thousands of students use Wiley's educational resources.

#### Need:

The company needed an efficient customer service system to manage the increased volume and maintain positive customer experiences.

#### Solution:

Wiley invested in Salesforce's Agentforce, an Al agent designed to enhance customer service operations. This integration has significantly improved case resolution rates and faster resolution of customer queries, especially during peak times, such as the start of new semesters when demand spikes.

#### ROI:

A 40%+ increase in case resolution compared to their previous chatbot, a 213% ROI, and \$230K in savings

### **Oracle Health and Clinical AI agent**

**Company:** Oracle Health **Al Agent:** Clinical Al Agen

#### **Use Case:**

Enhancing patientprovider interactions

#### **Problem:**

Healthcare providers faced documentation and time management challenges during patient visits, leading to burnout and reduced patient engagement.

#### Need:

There was a need for a solution that could streamline clinical workflows and improve documentation accuracy while allowing providers more time to interact with patients.

#### Solution:

Oracle Health developed its Clinical Al Agent, which automates documentation processes and enhances patient-provider interactions through a multimodal voice user interface. This allows providers to access patient information quickly and generate accurate notes efficiently.

#### ROI:

AtlantiCare, using the Clinical Al Agent, reported a 41% reduction in total documentation time, saving approximately 66 minutes per day, which translates to improved productivity and enhanced patient satisfaction.

### **Magid and Galileo**

#### **Company:** Magid

AI Agent: RAG-based system powered with real-time observability capabilities

#### Use Case:

Empowering newsrooms with generative AI technology

#### **Problem:**

Magid, a leader in consumer intelligence for media brands, needed to ensure consistent, high-quality content in a fastpaced news environment. The complexity of diverse topics made it challenging to uphold accuracy, and errors could potentially lead to significant repercussions.

#### Need:

A robust observability system was essential for monitoring Aldriven workflows and ensuring the quality of outputs across various clients. This scalability was crucial for managing the daily production of numerous stories.

#### Solution:

Magid integrated Galileo's real-time observability capabilities into their product ecosystem. This integration provided production monitoring, relevant metrics for tracking tone and accuracy, and customization options tailored to Magid's needs.

#### ROI:

With Galileo, Magid achieved 100% visibility over inputs and outputs, enabling customized offerings as they scale. This visibility helps identify trends and develop client-specific metrics, enhancing the accuracy of news delivery.



#### Nina Chinnam (fhs9af)



#### Chapter 2 - Frameworks for Building AI Agents

#### **Presentation Outline**



### Why do we need AI agent frameworks?



- State Management
- Tool Integrations
- Multi-Agent Coordination

### **Three AI Agent Frameworks**







## **High Level Comparison of Frameworks**

Feature	LangGraph	Autogen	CrewAl
Execution Model	DAG-based execution	Conversational AI Modeling	Role-based multi agent system
Best For	Structured, DAG-based workflows	Chat-driven Al applications	Teams of agents working together
Memory Handling	Long-term, short-term, entity	Moderate, Conversation-based tracking	Shared-multi agent memory
Tool Support	Deep LangChain integration	Code execution, function calls	Customizable tools & LangChain support
Scalability	Highly scalable	Scales well for chat-bot like systems	Scales for teams & delegation
# LangGraph Overview





DAG-based execution flow

Structured, deterministic task execution





Data processing pipelines

Automated research workflows

Al-driven decision making systems

# **Example: Automating Research Pipelines**

### Workflow

User inputs a research topic

Al retrieves papers from multiple sources

Al extracts insights from each source

Al combines findings into a final structured report

### LangGraph's DAG Approach

# Define Input Node (User provides research topic)
query\_input = graph.add\_node("User Inputs Topic")

# Define Parallel Retrieval Nodes (Fetching from multiple sources)
fetch\_arxiv = graph.add\_node("Fetch Papers from ArXiv")
fetch\_ieee = graph.add\_node("Fetch Papers from IEEE")
fetch\_google = graph.add\_node("Fetch Papers from Google Scholar")

# Define Processing Nodes (Running in Parallel)
analyze\_arxiv = graph.add\_node("Analyze ArXiv Papers")
analyze\_ieee = graph.add\_node("Analyze IEEE Papers")
analyze\_google = graph.add\_node("Analyze Google Scholar Papers")

# Define Final Aggregation & Report Generation Node aggregate\_findings = graph.add\_node("Aggregate Insights & Generate Report") # Connect Nodes (Creating Parallel Execution Paths)
graph.add\_edge(query\_input, fetch\_arxiv)
graph.add\_edge(query\_input, fetch\_ieee)
graph.add\_edge(query\_input, fetch\_google)

graph.add\_edge(fetch\_arxiv, analyze\_arxiv)
graph.add\_edge(fetch\_ieee, analyze\_ieee)
graph.add\_edge(fetch\_google, analyze\_google)

# All analyses feed into the final report generation
graph.add\_edge(analyze\_arxiv, aggregate\_findings)
graph.add\_edge(analyze\_ieee, aggregate\_findings)
graph.add\_edge(analyze\_google, aggregate\_findings)

# **Autogen Overview**







Enables AI agents to interact via conversations

Ideal for AI assistants and chat-driven workflows

Function calling and code execution





Conversational AI for customer support

AI Research Assistants

Collaborative Q&A Systems

# **Example: AI Coding Assistant**



# **CrewAI Overview**



# Core Features



Multiple AI agents work together with assigned roles

Structured Teamwork

Agents can be assigned hierarchical roles

Ideal Use Cases



Al-powered research teams

Automated content generation

Decision-making systems

# **Example: AI-Based Newsroom Workflow**

### **Specific Workflow Roles**

**Research Agent:** Gathers news stories Writing Agent: Generates draft articles **Editing Agent:** Fixes grammar, refines the draft Fact-Checking Agent: Ensures accuracy before publishing

### **CrewAl Implementation**

from crewai import Agent, Task, Crew

#### # Define Agents

research\_agent = Agent(role="Research", goal="Gather latest news")
writing\_agent = Agent(role="Writer", goal="Draft news articles")
editing\_agent = Agent(role="Editor", goal="Refine and fix writing")
fact\_checker = Agent(role="Fact-Checker", goal="Verify information accuracy")

#### # Define Tasks

gather\_news = Task(name="Find breaking news", agent=research\_agent)
write\_news = Task(name="Write article draft", agent=writing\_agent, depends\_on=[gather\_news])
edit\_article = Task(name="Edit the draft", agent=editing\_agent, depends\_on=[write\_news])
verify\_info = Task(name="Fact-check the article", agent=fact\_checker, depends\_on=[edit\_article])

#### # Crew Orchestration

newsroom\_crew = Crew(tasks=[gather\_news, write\_news, edit\_article, verify\_info])
newsroom\_crew.kickoff()

# **Feature Comparison**

Ease of Use	Autogen
Multi-Agent Support	CrewAl
Tool Support	LangGraph & CrewAl
Memory Handling	LangGraph & CrewAl
Scalability	All
Customization	All

# **Choosing the Right Framework**





### Mihika Rao (xsw5kn)



### Chapter 3 - How to Evaluate Agents

### **Presentation Outline**



# Why Evaluate AI Agents?

![](_page_47_Picture_1.jpeg)

- Tasks are performed correctly and reliably
- Ensure accurate, relevant, and efficient responses

![](_page_47_Picture_4.jpeg)

### **Case Study: Building a Financial Research Agent**

![](_page_48_Picture_1.jpeg)

- Approach:
  - Break down research into smaller steps
  - Search for external data (Tavily)
  - Analyze findings with ReAct (Reasoning + Action)

#### ...

from langchain\_openai import ChatOpenAI
from langchain\_community.tools.tavily\_search import TavilySearchResults
from langgraph.prebuilt import create\_react\_agent

system\_prompt = "You are a helpful finance expert named Fred in year 2024. First of all you create a plan to get answer to the research query. Then you use tools to get answers to the questions. Finally you use the answers to each question in the plan to give your final verdict."

```
llm = ChatOpenAI(model="gpt-4o-mini")
tools = [TavilySearchResults(max_results=3)]
agent_executor = create_react_agent(llm, tools, state_modifier=system_prompt)
```

### **Understanding State Management in AI Agents**

![](_page_49_Picture_1.jpeg)

...

import operator

from pydantic import BaseModel, Field
from typing import Annotated, List, Tuple
from typing\_extensions import TypedDict

#### class PlanExecute(TypedDict):

input: str
plan: List[str]
past\_steps: Annotated[List[Tuple], operator.add]
response: str

#### class Plan(BaseModel):

"""Plan to follow in future"""

steps: List[str] = Field(
 description="different steps to follow, should be in sorted order"

- How agent keeps track of its progress while solving a task.
- (action, result\_action)
- Store input and response
- Benefits:
  - Avoids redundant work
  - Helps agent replan efficiently
    - Helps track progress to final answer

### **Creating the Plan**

...

#### ...

from langchain\_core.prompts import ChatPromptTemplate

planner\_prompt = ChatPromptTemplate.from\_messages(

#### "system",

"""You are a finance research agent working in Oct 2024. For the given objective, come up with a simple step by step plan.  $\$ 

```
This plan should involve individual tasks, that if executed correctly will yield the correct answer. Do not add any superfluous steps. The result of the final step should be the final answer. Make sure that each step has all the information needed - do not skip steps. At the end use the info collected to give the final answer to the main question containing the facts.""",
```

```
),
("placeholder", "{messages}"),
]
```

Fig. 3.3: Guiding the agent to create a step-by-step plan that should lead to the correct answer for a given objective

# planner = planner\_prompt | ChatOpenAI( model="gpt-4o-mini", temperature=0 ).with\_structured\_output(Plan) planner.invoke( { "messages": [ ("user", "Should we invest in Tesla given the current situation of EV?")

#### Fig. 3.4: Testing the agent with a question

# **Re-planning - Adjusting the Agent's Strategy**

![](_page_51_Picture_1.jpeg)

- Original question
- Initial Plan
- Completed Steps

#### replanner\_prompt = ChatPromptTemplate.from\_template(

"""For the given objective, come up with a simple step by step plan. \
This plan should involve individual tasks, that if executed correctly will yield the
correct answer. Do not add any superfluous steps. \
The result of the final step should be the final answer. Make sure that each step has all
the information needed - do not skip steps.

Your objective was this: {input}

Your original plan was this: {plan}

You have currently done the follow steps: {past\_steps}

Update your plan accordingly. If no more steps are needed and you can return to the user, then respond with that. Otherwise, fill out the plan. Only add steps to the plan that still NEED to be done. Do not return previously done steps as part of the plan."""

### **Executing the Plan**

```
async def plan_step(state: PlanExecute):
    plan = await planner.ainvoke({"messages": [("user", state["input"])]})
    return {"plan": plan.steps}
```

```
async def replan_step(state: PlanExecute):
    output = await replanner.ainvoke(state)
    if isinstance(output.action, Response):
        return {"response": output.action.response}
    else:
```

return {"plan": output.action.steps}

```
async def execute_step(state: PlanExecute):
    plan = state["plan"]
    plan_str = "\n".join(f"{i+1}. {step}" for i, step in enumerate(plan))
    task = plan[0]
    task_formatted = f"""For the following plan:
{plan_str}\n\nYou are tasked with executing step {1}, {task}."""
    agent_response = await agent_executor.ainvoke(
        {"messages": [("user", task_formatted)]}
    )
    return {
        "past_steps": [(task, agent_response["messages"][-1].content)],
    }
```

```
def should_end(state: PlanExecute):
    if "response" in state and state["response"]:
        return END
    else:
        return "agent"
```

# **State Graph**

![](_page_53_Figure_1.jpeg)

### **Galileo Callback - Debugging and Optimizing**

{'plan': ['Research the current market trends in the electric vehicle (EV) industry as of October 2024.', "Analyze Tesla's current financial ( {'past\_steps': [('Research the current market trends in the electric vehicle (EV) industry as of October 2024.', "### Current Market Trends in {'plan': ["Analyze Tesla's current financial performance, including revenue, profit margins, and growth rates.", "Evaluate Tesla's competitive {'past\_steps': [("Analyze Tesla's current financial performance, including revenue, profit margins, and growth rates.", "### Step 1: Analysis {'plan': ["Evaluate Tesla's competitive landscape, identifying key competitors in the EV market and their market shares.", 'Assess the risks {'past\_steps': [("Evaluate Tesla's competitive landscape, identifying key competitors in the EV market and their market shares.", "### Step 1 {'plan': ['Assess the risks associated with investing in Tesla, including regulatory risks, market volatility, and technological changes.', {'past steps': [('Assess the risks associated with investing in Tesla, including regulatory risks, market volatility, and technological change {'plan': ['Gather stock price forecast information for Tesla for 1 year, 3 years, and 5 years from reputable financial analysts and sources.' {'past\_steps': [('Gather stock price forecast information for Tesla for 1 year, 3 years, and 5 years from reputable financial analysts and so {'plan': ['Compile the findings from the market analysis, financial performance, competition, risks, and stock forecasts into a comprehensive {'past steps': [('Compile the findings from the market analysis, financial performance, competition, risks, and stock forecasts into a compre {'plan': ['Make a final recommendation on whether to invest in Tesla based on the compiled data.']} {'past\_steps': [{'Make a final recommendation on whether to invest in Tesla based on the compiled data.', "Based on the gathered data regarding {'response': 'The analysis and recommendation process for investing in Tesla has been completed. Based on the comprehensive overview and fina Initial job complete, executing scorers asynchronously. Current status:

cost: Done 🔽 toxicity: Computing 🚧 pritect\_status: Done 🔽 latency: Done 🟹 groundedness: Computing 🚧 & View your prompt run on the Galileo console at: <u>https://console.dev.rungalileo.io/prompt/chains/1704927a-e6e7-4b22-9cff-890ebd8d32bf/be0</u>

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*	٥	4	test	0.501	210,623 ms	\$0.9242	\$0.1959	\$0.004		7	
Observe		1	test-3	0.844	84,039 ms	\$0.1361	\$0.003	\$0.0025		3	
C Eine-Ture		2	test-2	0.778	134,085 ms	\$0.0408	\$0.0008	\$0.002		1	
rane-rane		3	test-0	0.819	226,929 ms	\$0.0881	\$0.0009	\$0.0035		1	
		5	test-1	0.855	228,209 ms	\$0.1011	\$0.001	\$0.0046		1	
	0										

# **Galileo Callback - Example**

- Problem: Al agent has context adherence issues
  - Trace view shows 33.33% context adherence score
- System explanation: AI correctly cited some recent figures (Q3 2024, Q4 2023), earlier figures lacked explicit supporting evidence

![](_page_55_Picture_4.jpeg)

![](_page_56_Picture_0.jpeg)

## Anisha Patrikar (gjq2yf)

![](_page_57_Picture_0.jpeg)

### Chapter 4 - Metrics for Evaluating AI Agents

### **Presentation Outline**

![](_page_58_Figure_1.jpeg)

### **Key Performance Dimensions**

#### System Metrics

0

Focus on technical performance and resource utilization

Latency per Tool Call

Total Task Completion Time

API Call Frequency

Token Usage per Interaction

Cost per Task Completion

Context Window Utilization

LLM Call Error Rate

#### 0

Quality Control Evaluate output accuracy and adherence to requirements

Instruction Adherence

**Output Format Success Rate** 

Context Adherence

#### E Task Completion

Measure overall effectiveness of agent

Agent Success Rate

**Task Completion Rate** 

Steps per Task

Number of Human Requests

Tool Interaction Assess how effectively the agent uses available tools Tool Selection Accuracy

**Tool Argument Accuracy** 

Tool Success Rate

Fig 4.1: Four key performance dimensions to evaluate AI agents

Galileo

# **Case Study 1: Advancing the Claims Processing Agent**

### Al deployed for automating claims processing

 $\mathbf{X}$  Struggled with complex claims

X Increased compliance risks due to errors in complex cases

### **Challenges & Solutions**

- 1. LLM Call Error Rate
- 2. Task Completion Rate
- 3. Human Intervention Requests
- 4. Token Usage per Interaction

### Outcomes

- Faster claims processing
- Higher compliance accuracy
- Improved resource utilization
- Reduced rejection rates

![](_page_60_Figure_14.jpeg)

#### Claim Processing System Overview

# **Case Study 2: Optimizing the Tax Audit Agent**

### Al deployed for tax document processing

- X Lengthy turnaround times for complex audits
- X High computing costs from inefficient processing

X A backlog of partially completed audits requiring manual review

### **Challenges & Solutions**

- 1. Tool Success Rate
- 2. Context Window Utilization
- 3. Steps per Task

### Outcomes

- Faster audit completion
- Enhanced discrepancy detection
- Optimized processing efficiency

![](_page_61_Figure_13.jpeg)

# **Case Study 3: Elevating the Stock Analysis Agent**

### Al deployed for investment analysis

- X Redundant analysis requests
- X Inconsistent reporting formats
- X Failed to adjust analysis to market conditions

### **Challenges & Solutions**

- 1. Total Task Completion Time
- 2. Output Format Success Rate
- 3. Token Usage per Interaction

### Outcomes

- More precise market analysis
- Faster processing times
- Optimized resource utilization

![](_page_62_Figure_13.jpeg)

# **Case Study 4: Upgrading the Coding Agent**

### Al deployed to enhance developer productivity

Frequent disruptions during sprint deadlines
 Struggled with large codebases, providing irrelevant suggestions

X Rising infrastructure costs due to inefficient resource usage

### **Challenges & Solutions**

- 1. LLM Call Error Rate
- 2. Task Success Rate
- 3. Cost per Task Completion

### Outcomes

- More accurate code analysis
- Improved suggestion relevance
- Optimized resource utilization

![](_page_63_Figure_12.jpeg)

**Development Assistant System Overview** 

Fig 4.5: An overview of the Development Assistant System

# **Case Study 5: Enhancing the Lead Scoring Agent**

### Al deployed to enhance lead qualification efficiency

Misclassification of prospects led to declining conversion rates
 Sales reps pursued low-quality leads due to inaccurate scoring
 Increased costs per qualified lead, impacting growth targets

### **Challenges & Solutions**

- 1. Token Usage per Interaction
- 2. Latency per Tool Call
- 3. Tool Selection Accuracy

### Outcomes

- Faster prospect analysis
- Higher lead qualification accuracy
- Optimized resource utilization

![](_page_64_Figure_11.jpeg)

#### Lead Scoring System Overview

Fig 4.6: An overview of the Lead Scoring System

### **Common Challenges in AI Evaluation**

![](_page_65_Figure_1.jpeg)

Ensuring consistency across test runs

![](_page_65_Picture_3.jpeg)

Identifying model weaknesses

![](_page_65_Picture_5.jpeg)

Improving real-time adaptation

### **Best Practices for AI Agent Optimization**

![](_page_66_Figure_1.jpeg)

Continuous Monitoring

![](_page_66_Picture_3.jpeg)

Adaptive Evaluation Methods

Strategic Performance Adjustments

![](_page_67_Picture_0.jpeg)

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![](_page_68_Picture_0.jpeg)

### Chapter 5 - Why Most AI Agents Fail and How To Fix Them

# Why Do AI Agents Fail?

Al Agents are becoming widely used in industries like finance, healthcare, and customer support. Despite their potential, many fail due to poor design, lack of adaptability, and high operation costs.

DEVELOPMENT ISSUES	LLM ISSUES	PRODUCTION ISSUES
Poorly Defined Prompts <ul> <li>Define Clear <ul> <li>Objectives</li> <li>Craft Detailed <ul> <li>Personas</li> <li>Use Effective <ul> <li>Prompting</li> </ul> </li> </ul> </li> <li>Evaluation Challenges <ul> <li>Continuous <ul> <li>Evaluation</li> </ul> </li> <li>Use Real-World <ul> <li>Scenarios</li> <li>Incorporate <ul> <li>Feedback Loops</li> </ul> </li> </ul></li></ul></li></ul></li></ul>	Difficult to Steer Specialized Prompts Hierarchical Design Fine-Tuning Models High Cost of Running Reduce Context Size Use Smaller Models Cloud-Based Solutions Planning Failures Task Decomposition Multi-Plan Selection Refinement Reasoning Failures Enhance Reasoning Capabilities Fine-Tune LLMs with Feedback Use Specialized Agents Tool Calling Failures Define Clear Parameters Validate Tool Outputs Tool Selection	Guardrails  Rule-Based Filters & Validation  Human-in-the-Loop Oversight  Ethical & Compliance Frameworks  Agent Scaling  Scalable Architectures  Resource Management Monitor Performance  Fault Tolerance  Redundancy Automated Recovery Stateful Recovery  Infinite Looping  Clear Termination Conditions Enhance Reasoning & Planning Monitor Agent Behavior
	VerificationLoops	

- Key failure points in AI agent development
- Evaluation and debugging challenges
- Performance, cost, and ethical concerns
- Practical solutions to improve AI agent reliability

### **Development Issues**

![](_page_70_Picture_1.jpeg)

![](_page_70_Picture_2.jpeg)

Poorly Defined Task or Persona **Evaluation Issues** 

### **Development Issues - Poor Persona**

A well-defined task or persona is essential for effectively operating your AI agents. Without it, agents may struggle to make appropriate decisions, leading to suboptimal performance.

![](_page_71_Picture_2.jpeg)

**Define Clear Objectives** 

You should specify the goals, constraints, and expected outcomes for each agent.

![](_page_71_Picture_5.jpeg)

### **Craft Detailed Personas**

Develop personas that outline the agents role, responsibilities, and behavior for you

![](_page_71_Picture_8.jpeg)

Prompting

Use research-backed prompting techniques to reduce hallucinations for your agents
#### **Development Issues - Evaluation Issues**

Evaluation helps you identify weaknesses and ensures your agents operate reliably in dynamic environments. Unlike traditional software, agents operate in dynamic environments which make it difficult to establish clear metrics for success



#### **Continuous Evaluation**

Implement an ongoing evaluation system to assess your agents performance and identify areas for improvement



#### **Use Real-World Scenarios**

Test your agents in real-world scenarios to understand their performance in dynamic environments



**Feedback Loops** 

Incorporate feedback loops to allow for continuous improvement based on performance data













Difficult to Steer

High Cost of Running

Planning Failures Reasoning Failures

Tool Calling Failures

## **LLM Issues - Difficult to Steer**

You can steer LLMs towards specific tasks or goals for consistent and reliable performance. LLMs are influenced by vast amounts of training data which can lead to unpredictable behavior, and fine-tuning them for specific tasks require expertise and compute



Fig 5.1: Hierarchical design with specialized agents performing specific tasks

**Specialized Prompts** - Use specialized prompts to guide the LLM toward specific tasks

**Hierarchical Design** - Implement a hierarchical design where specialized agents handle specific tasks, reducing the complexity of steering a single agent

**Fine-Tuning** - Continuously fine-tune the LLM based on task-specific data to improve performance

## LLM Issues - High Cost of Running

Running LLMs, especially in production environments can be prohibitively expensive. This makes it difficult for organizations to scale their agent deployments cost-effectively.

**Reduce Context** - Introduce mechanisms to use as low context as possible to reduce the tokens

**Use Smaller Models -** Where possible, use smaller models or distill larger models to reduce costs

**Cloud Solutions -** Use cloud-based solutions to manage and scale computational resources efficiently



Fig 5.2: A serverless architecture where Lambda Controller makes intelligent decisions about request handling

Components of Fig 5.2

- The SQS Queue acts as our request buffer.
- The Lambda Controller makes intelligent decisions about request handling.
- Small Model API for simple completions and basic tasks
- Medium Model API for moderate complexity tasks
- Large Model API for complex reasoning tasks
- Model Cache for storing frequently used responses to reduce API calls
- CloudWatch to monitor system health and costs

### **LLM Issues - Planning Failures**

Planning enables agents to anticipate future states, make informed decisions, and execute tasks in a structured manner. However, LLMs often struggle with planning, as it requires strong reasoning abilities.



**Task Decomposition -** Break down tasks into smaller, manageable subtasks

Multi-Plan Selection - Generate multiple plan and select the most appropriate one based on the context

**Reflection and Refinement -** Continuously refine plans based on new information and feedback, and scale computational resources efficiently

## **LLM Issues - Reasoning Failures**

Reasoning is a fundamental capability that enables agents to make decisions, solve problems, and understand complex environments. LLMs lacking strong reasoning skills may struggle with tasks that require multi-step logic or nuanced judgement.

**Enhance Reasoning Capabilities -** Use prompting techniques like Reflexion to enhance the reasoning capabilities

**Finetune LLM** - Establish training with data generated with a human in the loop

**Use Specialized Agents -** Develop specialized agents that focus on specific reasoning tasks to improve overall performance



## **LLM Issues - Tool Calling Failures**

Robust tool calling mechanisms ensure agents can perform complex tasks by leveraging various tools accurately and efficiently. Tool calling failures can occur due to incorrect parameter passing, misinterpretation of tool outputs, or failures in integrating tool results into the agent's workflow.

**Define Clear Parameters** 

Ensure that tools have well-defined parameters and usage guidelines for you



Validate Tool Outputs

Implement validation checks to ensure that tool outputs are accurate and relevant



**Tool Selection Verification** 

Use a verification layer to check if the tool selected is correct for the job

#### **Production Issues**



Guardrails

Agent Scaling

Fault Tolerance

Infinite Looping

## **Production Issues - Guardrails**

Guardrails help ensure that agents adhere to safety protocols and regulatory requirements. Guardrails define the operational limits within which agents can function.



Rule-Based Filters & Validation

- Use predefined rules to filter offensive, harmful, or inappropriate content.
- Before processing, inputs received by the agent must be validated to meet criteria



Human-in-the-Loop Oversight

- Allow humans to provide feedback on the agent's performance and outputs
- Establish protocols for escalating complex or sensitive tasks to human operators



Ethical & Compliance Frameworks

- Establish ethical guidelines that outline the principles and values the agent must adhere to
- Implement compliance checks to ensure the agents actions align with regulation

### **Production Issues - Agent Scaling**

Scaling agents to handle increased workloads or more complex tasks is a significant challenge. As the number of agents or the complexity of interactions grows, the system must efficiently manage resources, maintain performance, and ensure reliability.



how you can add monitoring and load balancers for easy scale-up and down

Scalable Architectures - Implement a microservice architecture where each agent or group of agents operates as an independent service

**Resource Management -** Integrate load balancers to distribute incoming requests evenly across multiple agents

**Monitor Performance -** Implement real-time monitoring tools to track each agent's performance

#### **Production Issues - Fault Tolerance**

All agents need to be fault-tolerant to ensure that they can recover from eros and continue operating effectively. Without robust fault tolerance mechanisms, agents may fail to handle unexpected situations, leading to system crashes or degraded performance.

**Redundancy -** Deploy multiple instances of AI agents running in parallel

Automated Recovery - Incorporate intelligent retry mechanisms that automatically attempt to recover from transient errors

**Stateful Recovery -** Ensure the AI agents can recover their state after a failure



### **Production Issues - Infinite Looping**

Looping mechanisms are essential for agents to perform iterative tasks and refine their actions based on feedback. Agents can sometimes get stuck in loops, repeatedly performing the same actions without progressing toward their goals.



**Clear Termination Conditions -** Implement clear criteria for success and mechanisms to break out of loops

#### Enhance Reasoning and Planning -

Improve the agents reasoning and planning capabilities to prevent infinite looping

Monitor Agent Behavior - Monitor agent behavior and adjust to prevent looping issues

## Key Takeaways

- Better task structuring and decomposition
- Continuous evaluation and monitoring
- Resource optimization and caching
- Security and compliance frameworks

# **Paper Reference**

