

# Generative AI Agents in Action: Revolutionizing Software Development Testing



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# Foreword

## A Few Thoughts at the End of 2024

**A**s we approach the close of 2024, the landscape of Artificial Intelligence (AI) is undergoing a profound transformation. Since the pivotal ChatGPT milestone two years ago, we have witnessed a rapid adoption of Large Language Models (LLMs) in a huge variety of applications. In most cases, LLMs have been used for multi-modal content generation, knowledge retrieval and chatbots, already generating value in various industries and their value chains.

A common pattern across current generative AI applications is the instruction-oriented interaction between users and AI, primarily facilitated through a chat format. Whether users formulate specific questions, need a summary or key insights from a document, or want to note their thoughts and ideas for future reminders, the typical usage pattern involves providing the AI with a specific prompt or instruction to elicit the desired response.

While this interaction model has driven numerous relevant and valuable business use cases and directly embeds the human-in-control principle to mitigate certain risks of generative AI, it does not fully utilize the most recent capabilities of generative AI. With the advent of more powerful LLMs equipped with deep reasoning and thinking abilities, use of tools, and the capacity to understand and synthesize multilingual and multimodal data, **generative AI is increasingly capable of solving complex problems by translating them into a set of autonomous steps or tasks, much like humans would.** We refer to these advanced systems as **generative AI agents.**

Leading organizations such as Anthropic, Microsoft, NVIDIA, OpenAI, Salesforce, SAP, and others are at the forefront of developing agents that not only follow commands but also proactively solve complex problems by aligning with broader objectives. **Although we are still in the early phases of agent development, the evolution towards autonomous multi-agent systems is already underway.** In the not-too-distant future, these agents hold immense promise, as they begin to tackle intricate tasks that were once the exclusive domain of human intelligence.

In fact, generative AI agents have now become a spotlighted field within AI technology. Why is this so? Because **generative AI agents represent a shift from instruction-oriented chat interactions, where humans guide problem-solving, to task delegation and autonomous problem-solving with minimal or even no human oversight** in the future. This shift opens up vast potential for businesses, enabling task automation in software-based virtual environments and even action planning in physical environments.

**In this white paper, we explore the rise of generative AI agents, transitioning from traditional instruction-driven interactions to innovative, goal-oriented automation.** We will delve into the evolving progress of generative AI agents, market observations, and the exciting potential of autonomous systems, particularly in the field of software development. We invite you to reflect on the technological advancements shaping our future and the implications of an increasingly automated world.



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# Executive Summary

## *Adaptability, Transformation, and Responsibility – Getting Prepared for the Agentic Era*

### **Adaptability**

Generative AI agents are defined by their ability to **interact with environments** and **execute tasks autonomously**, showcasing cognitive processes like **reasoning** and **goal setting** for problem solving.

- Currently, most agents operate at foundational levels of **conversation**, **analytical capability**, and **autonomy**, but significant advancements toward **innovation and collaboration** are anticipated.
- These agents already enhance business processes across various value chains, from research to customer service, by automating complex tasks. Future agent systems can potentially automatize entire processes instead of use cases.
- The transition **from Robotic Process Automation (RPA) to Agentic Process Automation (APA)** allows for dynamic, goal-oriented workflows that improve cost and time efficiency of processes already now. The use of Small Language Models (SLMs) instead of LLMs within APA is an important approach to optimize costs and deploy agents on-premise or on edge.
- As generative AI evolves, there is an increasing focus on mitigating the known risks of LLMs. However, since these risks cannot be completely eliminated, there remains an important need for **human oversight in agentic systems**.

### **Transformation**

Generative AI agents are able to significantly transform processes instead of single use case or tasks.

- A highly promising process showcasing this transformative potential is the **software development lifecycle**, particularly through roles and tasks in **planning**, **development**, **testing**, **review**, and **deployment**. Notable use cases include **code generation**, **automated testing**, and **automated reviewing**.
- While there is a cautious approach to their use in critical tasks like infrastructure deployment, these agents enhance workflows by automating test creation and adapting to evolving requirements, thereby improving overall efficiency in the software lifecycle.
- Technologies such as Retrieval-Augmented Generation (RAG) and AutoGen help reduce manual testing efforts, allowing developers to focus on complex problem-solving. Beyond software, these agents are impacting fields like **industrial engineering** and **scientific research** by streamlining tasks and fostering collaboration.

### **Responsibility**

Generative AI agents present both remarkable **opportunities** and significant **challenges**.

- The creation of **scalable, multi-modal agentic systems** capable of integrating **diverse sensory inputs** and harnessing **collective human and artificial intelligence** will open new frontiers for generative AI across various sectors.
- While they hold potential for enhancing efficiency, their susceptibility to adversarial attacks raises concerns about their **robustness** and **trustworthiness**, particularly as these systems are designed to predict and perform actions.
- As AI technology advances, it is vital to anticipate potential risks and to adapt evaluation methods for real-world applications, including methods like **agent-as-a-judge solutions** with **human oversight**.
- Addressing **ethical and stability considerations** and ensuring **responsible use** are essential to mitigating risks.

By carefully weighing both the opportunities and challenges, we can fully realize the transformative potential of generative AI agents while safeguarding societal well-being.

*“AI agents will drive business automation and business decision augmentation. They will advance to specialized assistants that will help users in various business roles by driving business decisions and taking action. Ultimately, this will not only lead to much more efficient and guided processes, but also transform the business processes themselves.”*

---

Dr. Christian Karaschewitz  
AI Product Incubation Lead,  
SAP Business AI – Product & Partner Management  
SAP SE



*“Artificial Intelligence has fundamentally transformed how we interact with software, making natural language interfaces not just possible but powerful. The next frontier lies in AI agents – autonomous systems that can take intelligent action on our behalf. As these agents evolve from concept to reality, organizations and individuals alike must actively explore and experiment with them to understand their transformative potential.”*



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Antoine Leboyer  
Managing Director SW/AI,  
TUM Venture Labs

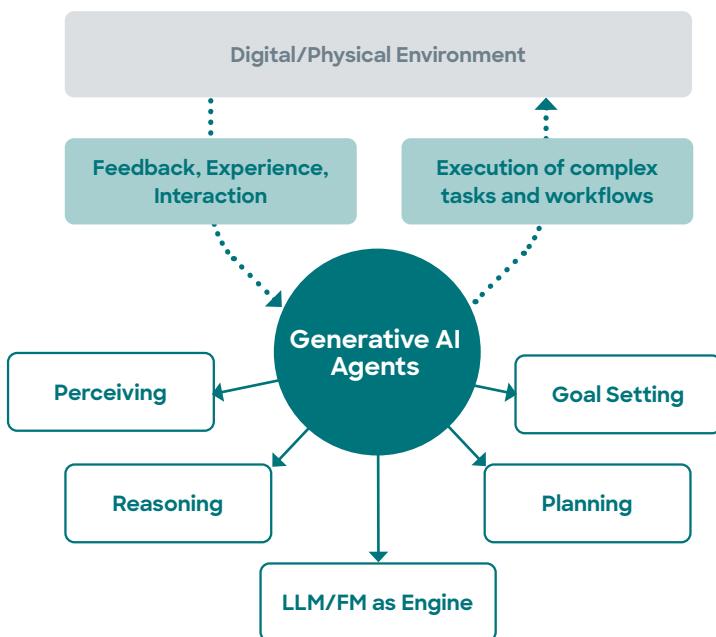
# A Quick Dive into Generative AI Agents

## Generative AI Agents: What & Why

A generative AI agent is an **autonomous** system that leverages **large language models** and **foundation models** to **independently execute complex tasks and workflows** in a **digital/physical environment**. It **perceives** its surroundings, **reasons**, **plans**, and **acts** over time to achieve its **goals** and influence future outcomes [1-4].

## 7 Reasons to Use GenAI Agents

- Automation and Efficiency:** Automating repetitive tasks to boost productivity and allow focus on strategic work.
- Adaptability and Flexibility:** Handling flexible tasks and dynamically adapting to various scenarios.
- Personalization and Customization:** Tailoring experiences and recommendations based on user preferences to enhance engagement.
- In-depth Reasoning:** Improving robustness in addressing ambiguous scenarios by utilizing advanced reasoning and reflective processes.
- Decision Support:** Analyzing data to provide insights, aiding informed decision-making in complex situations.
- Innovation Enhancement:** Inspiring creativity by collecting and generating innovative insights that human minds may overlook.
- Simulation of Complex Systems:** Optimizing real systems through simulations, such as in the case of cyber attacks and digital twins.



## Five Levels of Competence in Generative AI Agents

Here we outline five levels of generative AI agent competence—**conversational**, **reasoning**, **autonomous**, **innovating**, and **organizational**—based on their capabilities in thinking (**brain**), perceiving (**perception**), and task execution (**action**). While not exhaustive, this categorization aims to provoke inquiries about the dynamics of human-agent interactions [5-7].

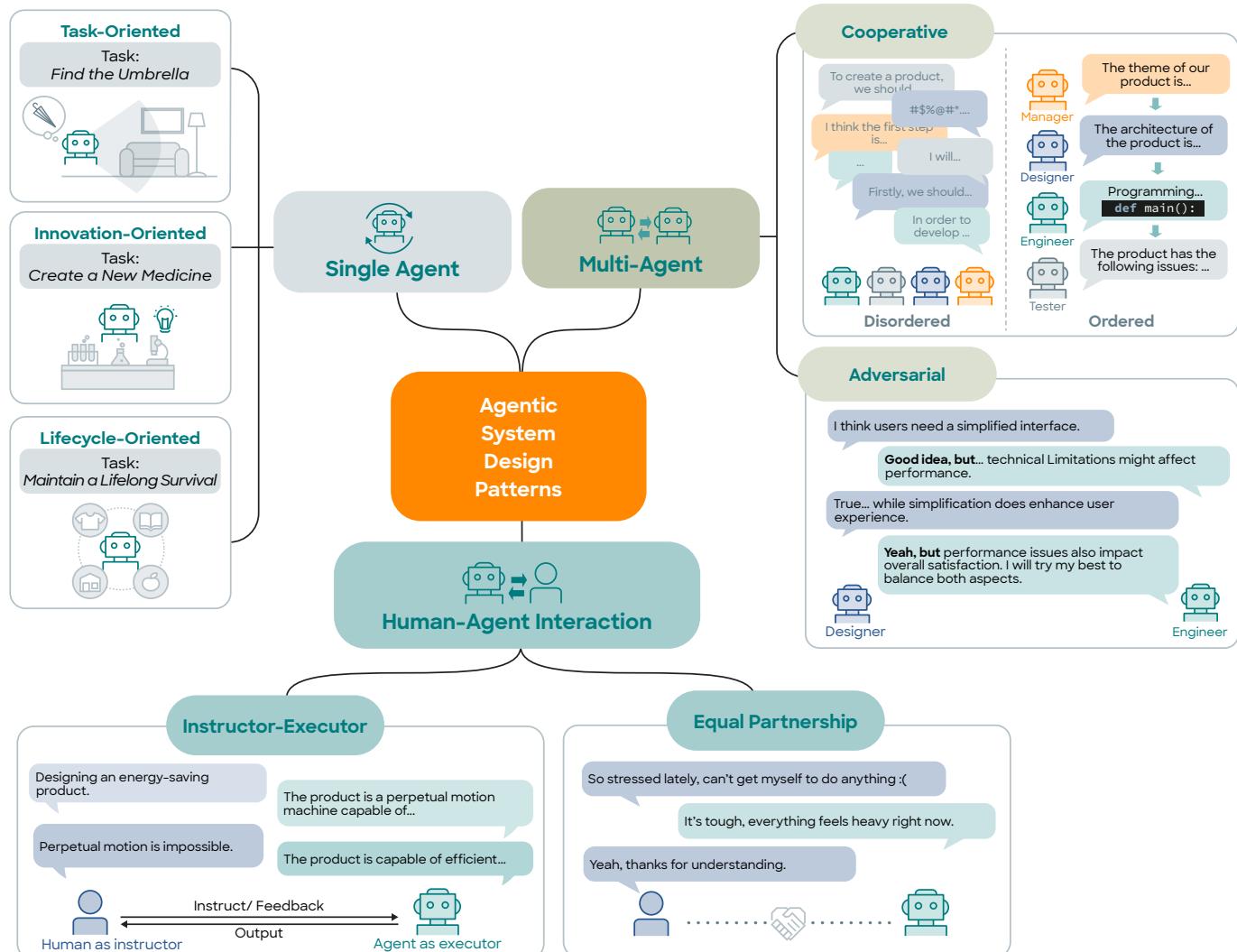
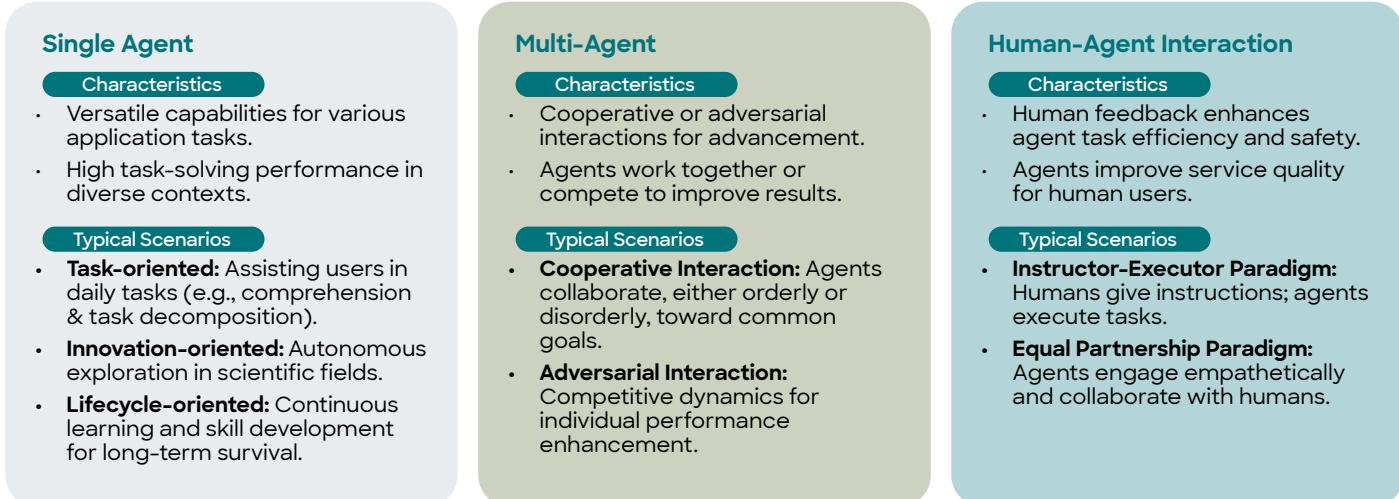
	Level 1 (Conversational)	Level 2 (Reasoning)	Level 3 (Autonomous)	Level 4 (Innovating)	Level 5 (Organizational)
 Brain	Episodic Memory: Events Summary & Abstraction Semantic Memory: Knowledge	Human-like Reasoning Reflection & Critique Judgement & Evaluation	Goal-setting Planning Multistep Tasks Decision-making	Autonomous Learning Generalization Goal Recalibration Idea/Design Generation	Personality & Role-Playing Team Dynamics Insight Strategic Thinking Coordination Planning
 Perception	Textual Input Encoding Visual Input Encoding Auditory Input Encoding Other Sensor Input Encoding	Pattern Recognition Multi-source Input Integration	Active Sensing/Monitoring Goal-directed Perception Autonomous Data Mining	Perceptual Learning Perceptual Recalibration Perceptual Anticipation	Organizational Monitoring Collective/Mutual Perception System Failure Awareness
 Action	Conversation Completion Question Answering	Intent Inference Tool Selection Analytical Problem Solving	Automated Tool Usage Embodied Actions Routing/Navigation	Learning/Making New Tools Self-improving/refining Prototyping	Multi-agent Collaboration Conflict Resolution Project Management Mutual Task Delegation

# A Quick Dive into Generative AI Agents

## Building Generative AI Agent Systems for Business

### Fundamental Agentic System Design Patterns

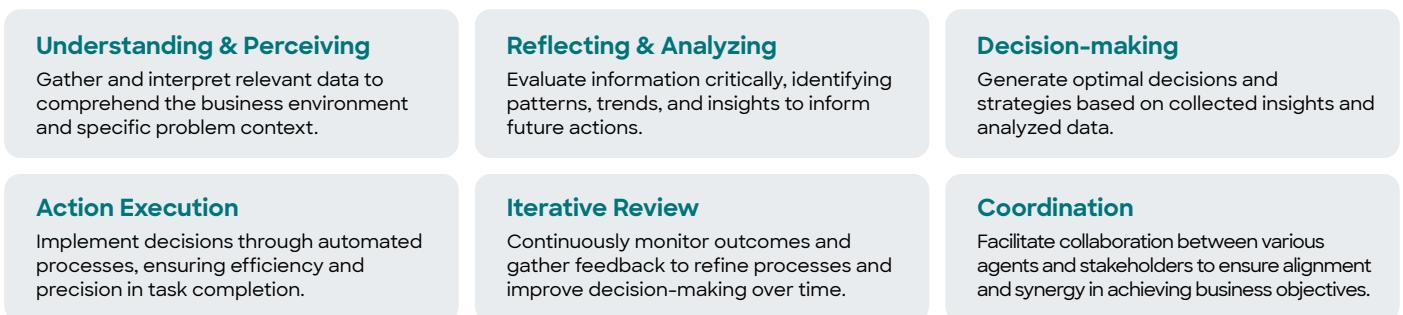
To build generative AI agent systems for business, let's firstly look into three main design patterns for such systems [5].



# A Quick Dive into Generative AI Agents

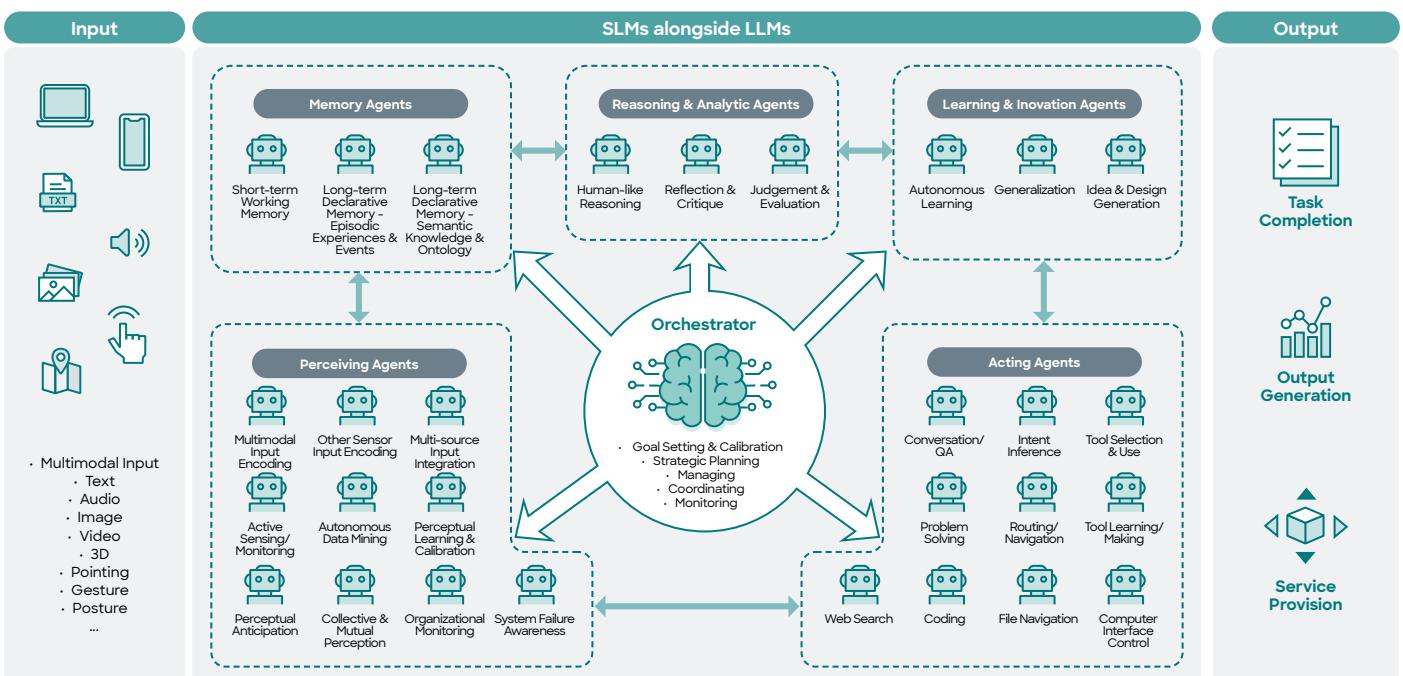
## Core Components of An Arbitrary Business Problem

- To develop generative AI agent systems for business scenarios, we pinpoint six key components illustrated below that may exist within an arbitrary business problem that agents can address.
- In the case of **customer feedback analysis**, for example, the following components are critical [5-7]:
  - Understanding & Perceiving:** Gather customer feedback from various sources (surveys, reviews, social media) to understand sentiments and trends.
  - Reflecting & Analyzing:** Analyze the feedback to identify common themes and areas for improvement. Use natural language processing to extract insights and sentiments.
  - Iterative Review:** Continuously monitor customer reactions to implemented changes, collecting new feedback to assess the effectiveness of actions taken.



## Example Generic Multi-Agent Framework

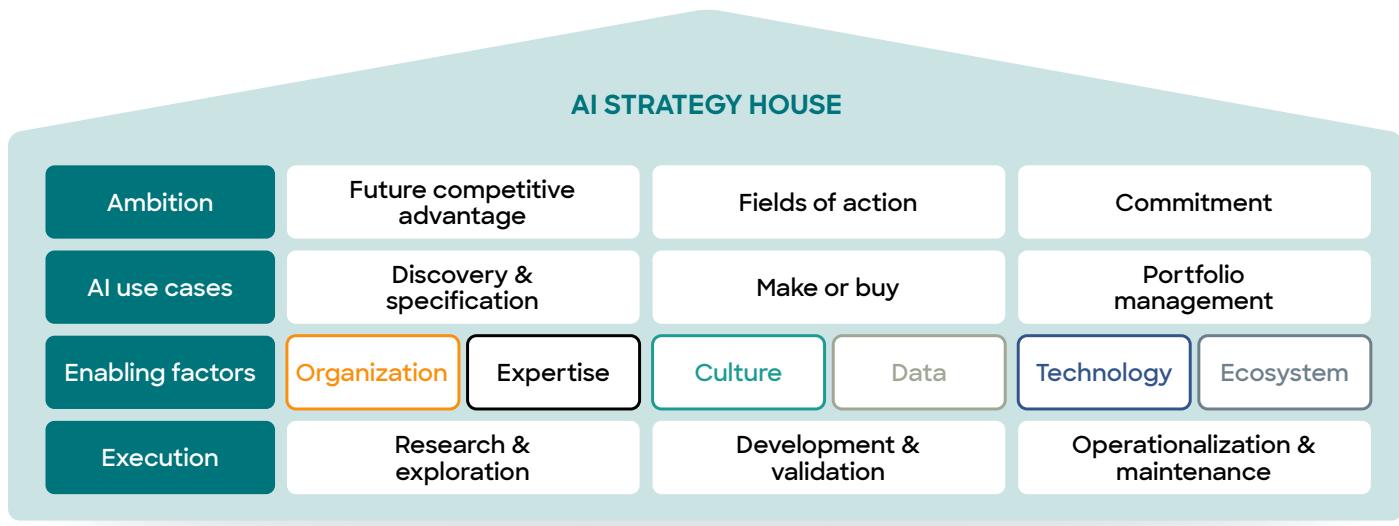
- With the core components of business problems in view, this section illustrates a generic multi-agent framework based on three core generative AI agent capabilities as outlined earlier: the "brain" (memory, reasoning & analytic, as well as learning & innovation agents), along with **perception**- and **action**-related agents. Here we aim to broadly outline potential agents based on various previous definitions, though this graphic is by no means exhaustive [5].
- In a multi-agent system, agents can interact in various patterns, such as in a hierarchical or decentralized structure. Most existing frameworks typically employ a **centralized communication model**, where an **orchestrator** sets goals, creates plans, delegates tasks to specific agents, and monitors the outcomes [5, 8-10].
- For instance, in **customer feedback analysis**, an **orchestrator** may collaborate with an **autonomous data mining** agent and a **reflection** or **evaluation** agent to effectively accomplish the task.



# Industrial Agentic Use Cases: From Strategy to Operation

## Prerequisites for Agentic Use Case Adoption: Strategic Perspective

Despite the promising capabilities of large language models and the future potential of AI agents, the **successful adoption of AI agents in organizations**, as with any AI technology, depends on various critical elements. The **appliedAI AI Strategy House** framework provides a clear visual and conceptual structure of these essential elements. By systematically aligning and measuring these elements, organizations can implement and scale AI agents more effectively, ensuring the maximization of their AI investments. The crucial **prerequisites of AI agent adoption** associated with the **six enabling elements** in the appliedAI Strategy House are detailed below.



### Organizational Commitment

- Leadership Support:** Executives drive AI initiatives and secure necessary resources.
- Cross-functional Collaboration:** Align goals and stimulate innovative ideas.
- Ongoing Training:** Provide continuous learning opportunities to upskill employees

### Expert-empowered Workflow

- Empowerment:** Design workflows that balance the autonomy of AI agents with employee acceptance, incorporating elements such as human oversight.
- Future Role Definition:** Clearly outline roles and responsibilities for AI and employees in future AI-supported workflows.

### Promoted User Adoption

- Training and Support:** Provide comprehensive training and ongoing assistance for users (i.e. customers or employees)
- Incentives:** Cultivate an innovative mindset and encourage user adoption through rewards.
- User-Centric Design:** Develop intuitive AI tools that meet user needs and emphasize trustworthy human-agent interactions.

### Data Quality and Access

- High-Quality Data:** Ensure data in different languages and modalities is accurate, consistent, and relevant.
- Sufficient Quantity:** Gather enough data to train models effectively. Also consider augmentation with synthetic data generation.
- Seamless Integration:** Connect agentic applications with data in existing systems.

### AgentOps & Adaptable Tools

- Robust Evaluators:** Implement validation frameworks to ensure quality. Automated evaluation methods can be deterministic, statistical, or AI-based.
- Dynamic Monitoring:** Continuously review AI performance and in production for optimization
- Adaptable Tools:** Develop clear strategies for process/tool changes.

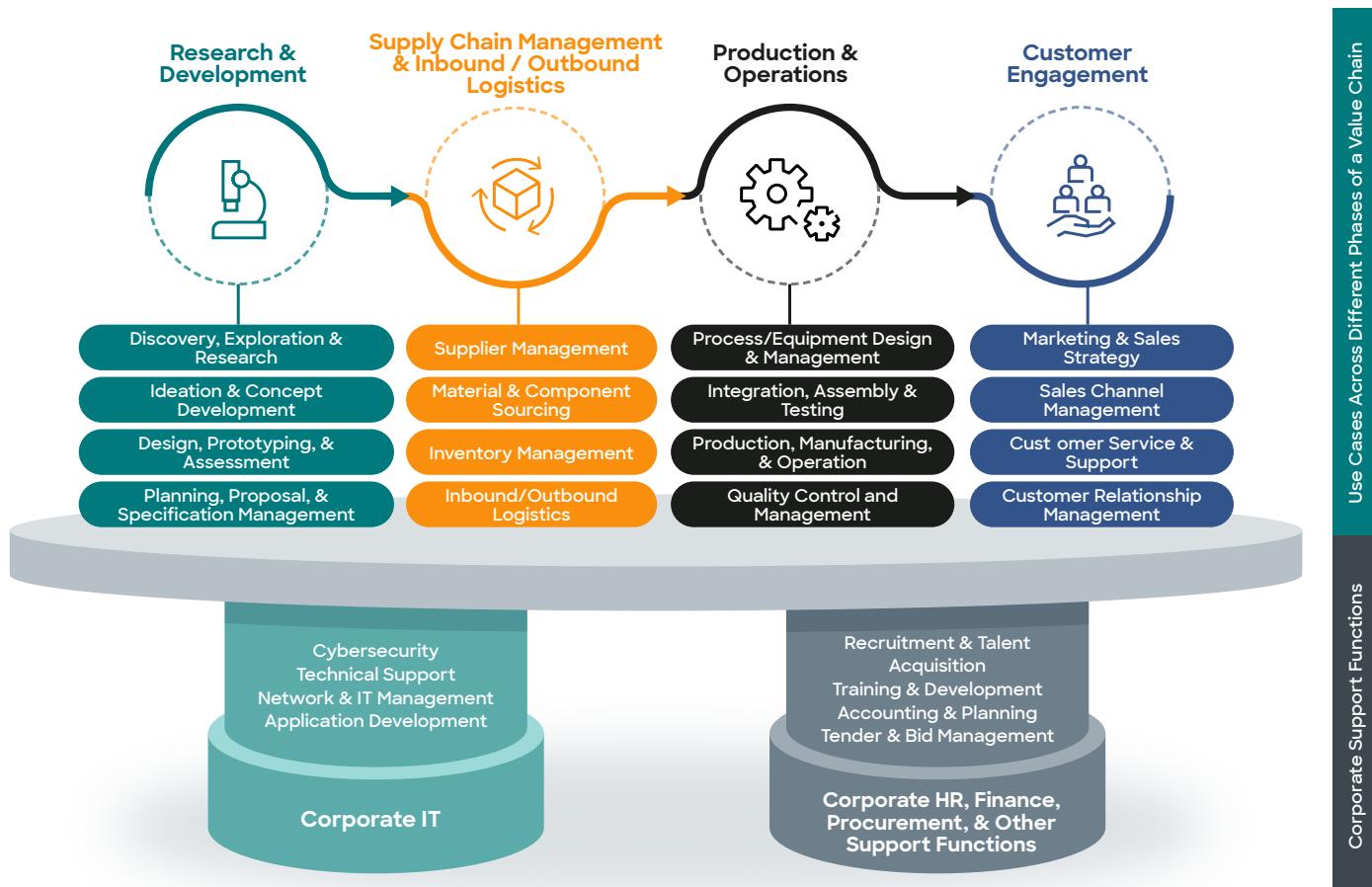
### Ecosystem Support

- Collaborative Partnerships:** Consider partnerships to accelerate innovation and the adoption of AI agents.
- Knowledge Exchange:** Share insights and best practices to accelerate agent adoption.
- Collaborative Development:** As agent technologies are still immature, share risks and ramp up investments through joint development initiatives.

# Industrial Agentic Use Cases: From Strategy to Operation

## Mapping Generative AI Agents Across the Value Chain

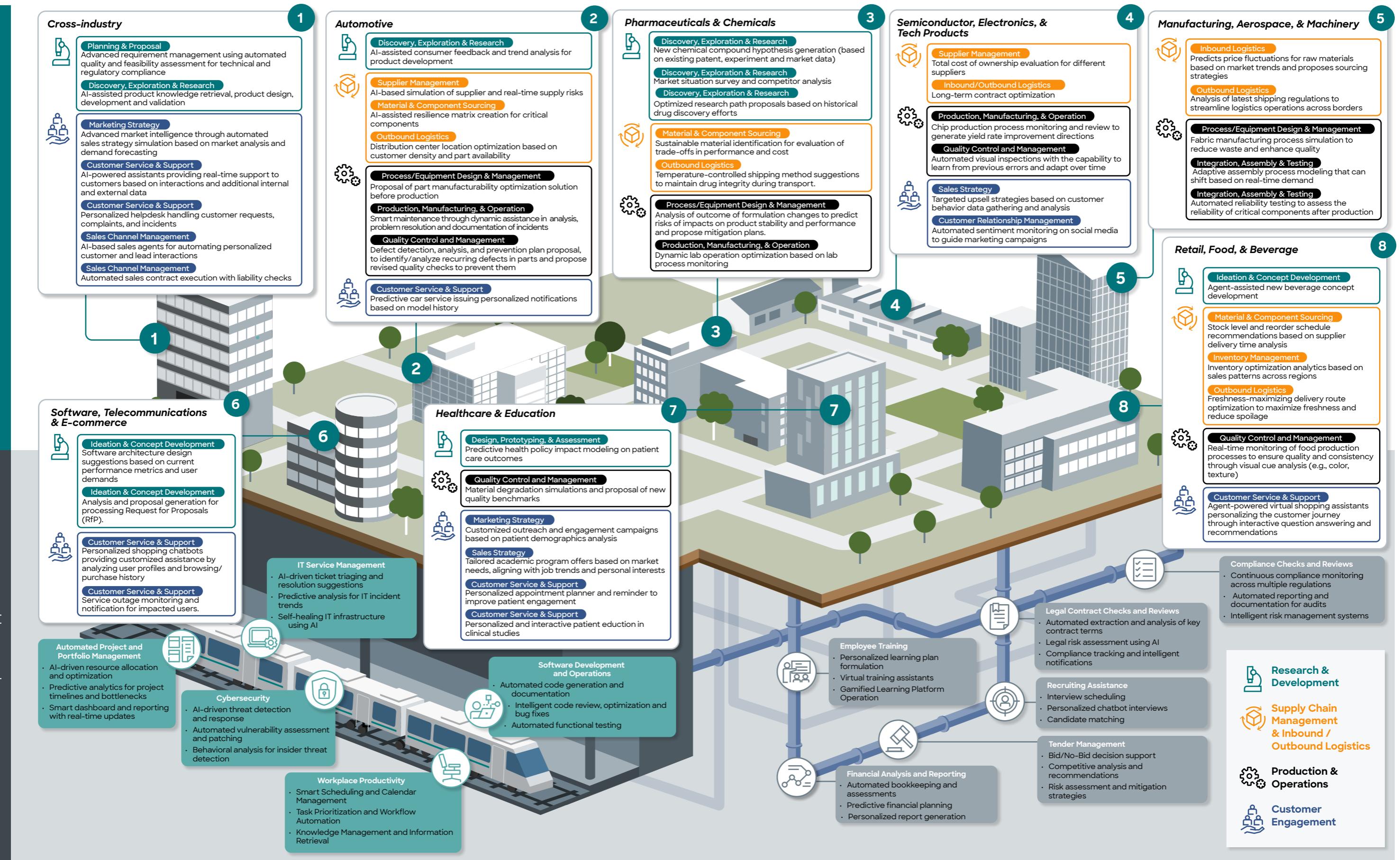
Here we illustrate potential use cases across **different phases of a value chain** as well as various **corporate support functions**, aiming to inspire further ideas and innovation. While the examples are **not exhaustive**, they serve as a **starting point** for exploring the diverse applications of value chain optimization.



# Industrial Agentic Use Cases: From Strategy to Operation

Use Cases Across Different Phases of a Value Chain

Use Cases for Corporate Support Functions



# Industrial Agentic Use Cases: From Strategy to Operation

## Transforming Robotic Process Automation (RPA) into Agentic Process Automation (APA)

### Bringing Agents into RPA

When considering AI agent automation, a logical next step is to **integrate AI agents into existing Robotic Process Automation (RPA)** workflows [11]. This strategy provides a straightforward yet effective means of implementing agent-driven process automation.

### Addressing Robustness Issues in RPA

By utilizing established problem-solving frameworks (i.e., process structures), AI agents can tackle predefined **sub-problems** and **tasks**, which they are generally more robust and capable of handling than existing RPA methods. This approach not only mitigates the current challenges associated with orchestrating and managing AI agents but also effectively addresses a key limitation of RPA: **robustness**, hence a valuable advancement.

### SLMs as Cost-effective Options

In these scenarios, system designers may opt for Small Language Models (SLMs) over Large Language Models (LLMs) to reduce costs and infrastructure needs. For instance, agentic RPA workflows could run on **standard servers with less expensive GPUs**.

	Pipeline Design	Pipeline Building	Pipeline Execution	Pipeline Monitoring, Evaluation, & Update	Pros	Cons	When To Adopt	
RPA	Using manual-crafted rules to orchestrate several software in a solidified workflow for execution	Static and simple step-by-step workflows	Manually constructing via pull-and-drag	Rule-based data-flow and control-flow	Fixed to defined scenarios and unable to update instructions	Can handle rigid task	Cannot handle flexible task	Well-defined sub problems and tasks
Use Case Example	Insurance Claim Processing	<ul style="list-style-type: none"> <li><b>Focus:</b> Create workflows using defined rules to handle repetitive tasks such as extraction of names and dates.</li> <li><b>Structure:</b> Simple flowcharts illustrating the step-by-step process for claim data entry, verification, and updates.</li> </ul>	<ul style="list-style-type: none"> <li><b>Resources Required:</b> IT expertise to configure bots and integrate them with existing claim processing systems.</li> <li><b>Development Work:</b> Through manual robotic procedure setup and review process.</li> </ul>	<ul style="list-style-type: none"> <li><b>Mechanism:</b> Bots execute predefined tasks like claim data entry, validations, and standard communications.</li> <li><b>Speed:</b> High volume processing of claims at a consistent rate once programmed.</li> <li><b>Consistency:</b> Executes tasks exactly as programmed, with minimal deviation.</li> </ul>	<ul style="list-style-type: none"> <li><b>Monitoring:</b> Rule-based monitoring through claim processing logs and alerts to identify failures or bottlenecks.</li> <li><b>Evaluation Frequency:</b> Periodic reviews for performance and efficiency.</li> <li><b>Update Process:</b> Manual updates required for any changes in workflows or system integrations.</li> </ul>	<ul style="list-style-type: none"> <li><b>Efficiency:</b> Greatly reduces claim processing time for routine tasks.</li> <li><b>Cost-Effective:</b> Significant savings on claim processing labor for repetitive tasks.</li> <li><b>Scalability:</b> Easy to scale operations up or down as needed.</li> </ul>	<ul style="list-style-type: none"> <li><b>Limited Flexibility:</b> Struggles with unstructured data and unexpected scenarios.</li> <li><b>Maintenance Requirement:</b> Requires periodic manual updates to adapt to new processes.</li> <li><b>Lack of Insight:</b> Doesn't analyze data for patterns or insights beyond predefined tasks.</li> </ul>	<ul style="list-style-type: none"> <li><b>Indicative Scenarios:</b> High volume, repetitive claim processing tasks with clear rules; ideal for back-office functions.</li> <li><b>Best Fit:</b> Claim processes with low variance and where performance can be measured without needing complex decision-making.</li> </ul>
APA	Incorporating AI agents to adaptively contract and execute workflows to achieve process automation	Dynamic and scenario-adaptive workflows	Automatically constructing, orchestrating, and testing	Agent-based data-flow and control-flow	Adaptable to various scenarios and able to update instructions	Can handle rigid and flexible tasks	Monitoring and verification may be tricky	Ill-defined sub problems and tasks

# Industrial Agentic Use Cases: From Strategy to Operation

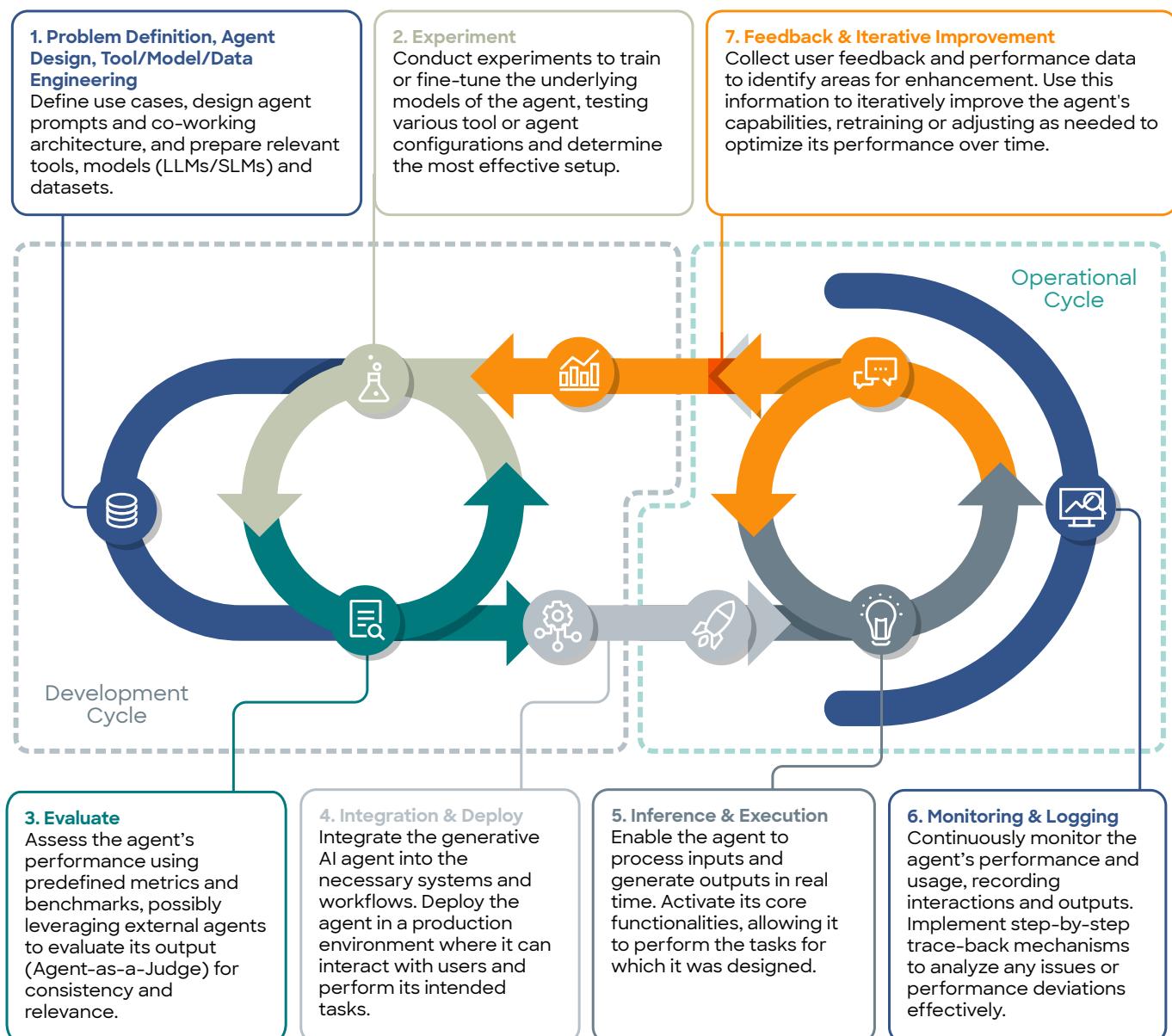
## The Growing Need for AgentOps

### A Call for Long-term Agent Management

AgentOps is an emerging concept focused on the **operational management** of generative AI agents, which are often characterized by their ability to autonomously perform tasks, interact with users, and generate content based on user inputs or external data sources [12].

### Towards Trustworthy Agents

As generative AI agents become increasingly complex and capable, establishing clear operational practices becomes crucial for ensuring their **reliability**, **effectiveness**, and **ethical deployment** [12-13].

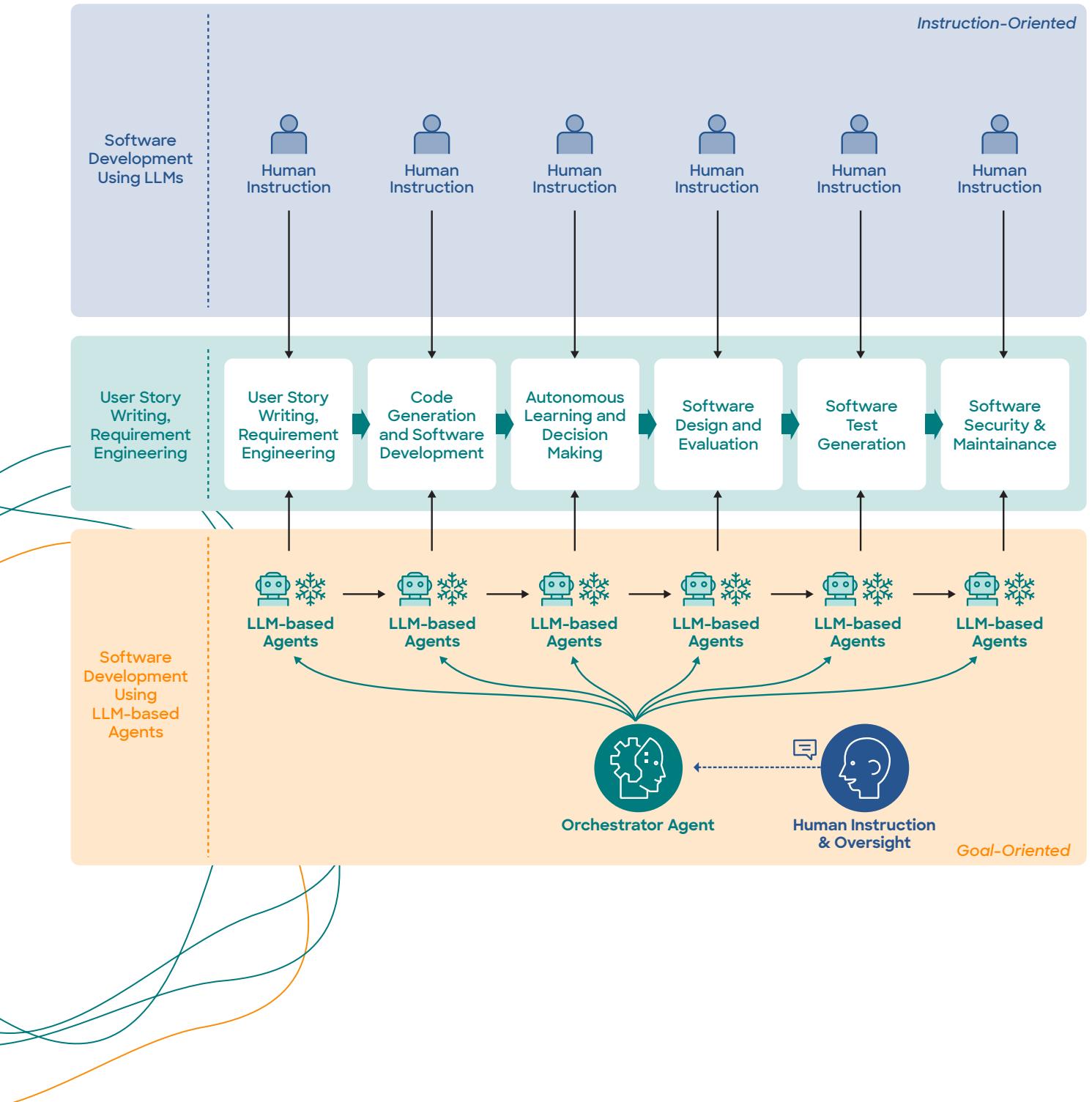


Partially inspired and adapted from: <https://learn.microsoft.com/en-us/ai/playbook/solutions/generative-ai/llmops-promptflow>

# Focusing the Lens: Generative AI Agents in Software Development

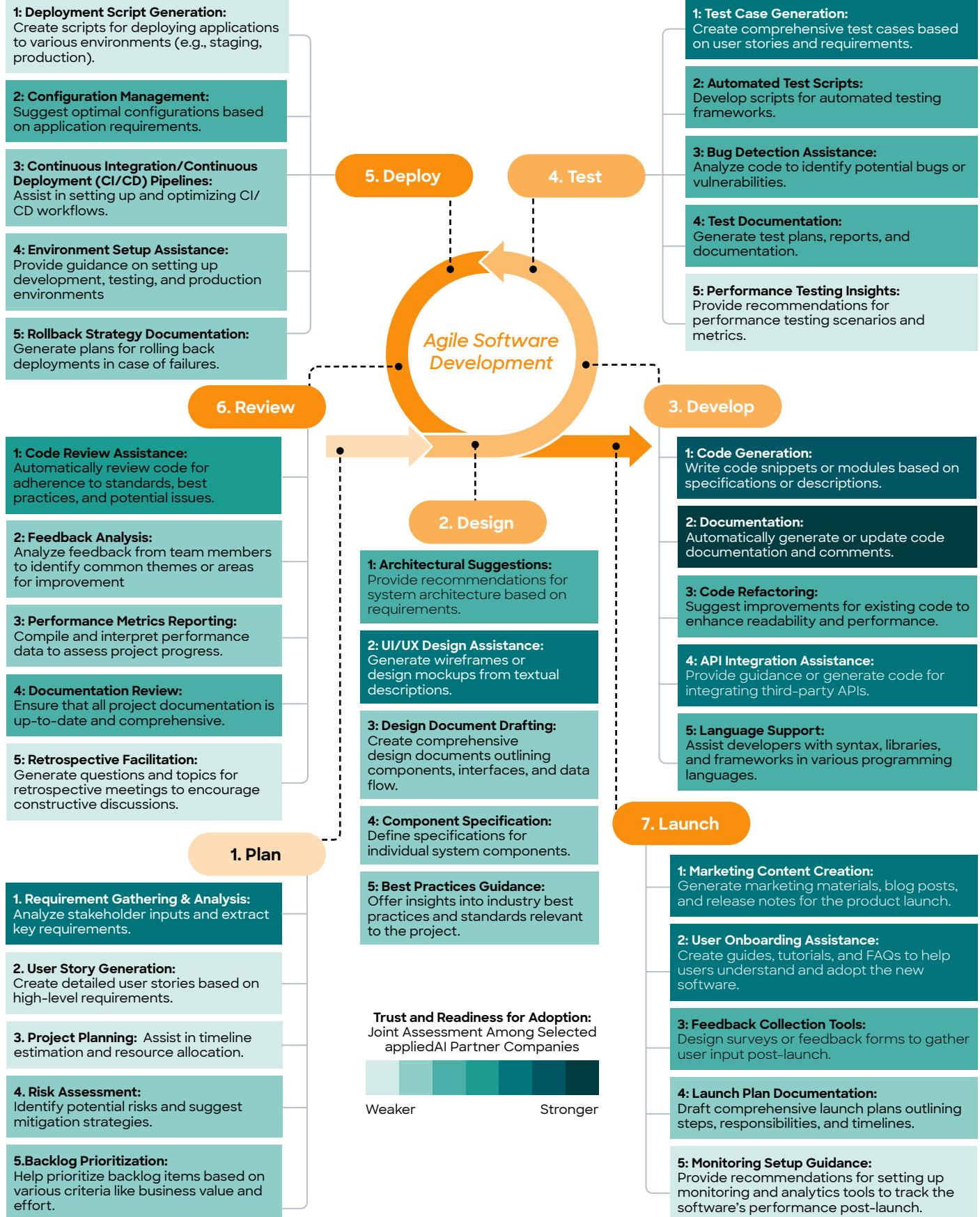
## From LLMs to LLM-based Agents in Software Development

With the emergence of LLMs and generative AI, their applications are being extensively investigated across different industries. A significant area of focus is **software development**, where LLMs have demonstrated impressive capabilities in tasks like **code generation** and **test design**. Despite these achievements, they also face several limitations, particularly regarding autonomy. **LLM-based agents** utilize LLMs as the foundation for **planning**, **designing**, **decision-making**, and **executing actions** during software development, thereby overcoming some of the prior constraints. In this section, we highlight the main distinctions between these two approaches [14].



# Focusing the Lens: Generative AI Agents in Software Development

## Navigating the Agentic Software Development Cycle: Use Cases and Trust Spectrum



# Generative AI Agents in Action for Software Testing

## Enhancing Software Development Testing: Why Generative AI Agents Matter

### Background

**Continuous software testing** is a critical element of the software development lifecycle, especially within agile methodologies, where testing occurs at every stage to ensure system robustness as new code is committed to repositories like GitHub, often facilitated by tools like Jenkins for **CI/CD** processes.

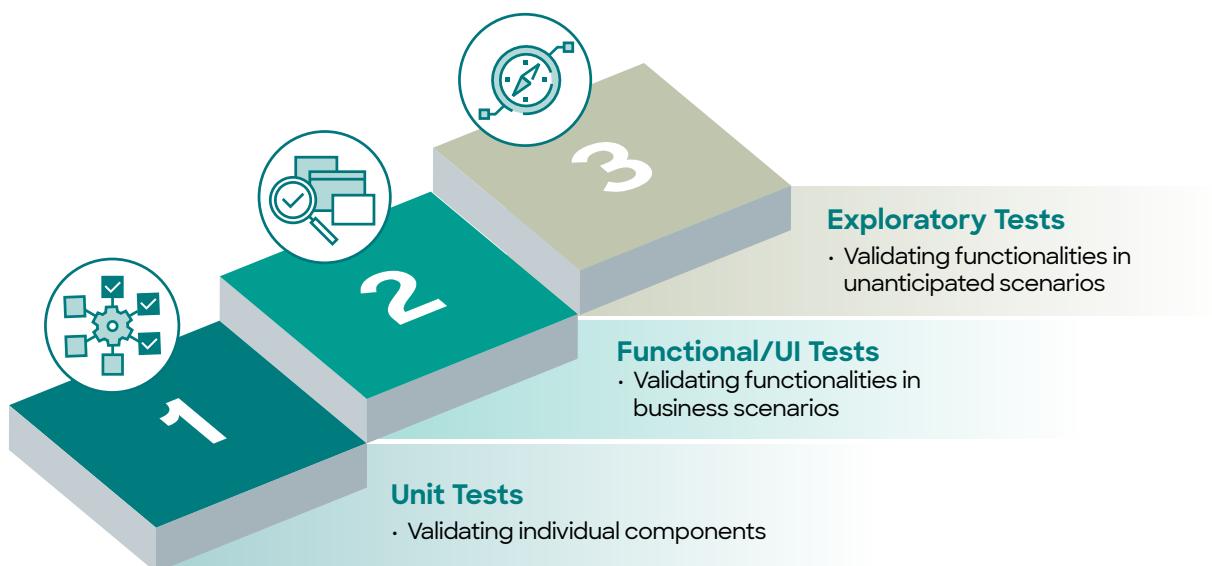
### Challenge

Despite advancements in automation, the creation and refinement of test cases—such as **unit tests** and **functional/UI tests**—still require substantial human effort, leading to inefficiencies and potential gaps in testing coverage.

### Opportunity

There is a significant opportunity to leverage AI to automate the **generation** and **optimization** of test cases, thereby reducing the manual workload on developers, enhancing testing efficiency, and improving the overall quality of software products.

## Levels of Software Testing Automation



# Generative AI Agents in Action for Software Testing

## Generative AI Agents for Unit Test Writing & Reviewing

### Problem Statement

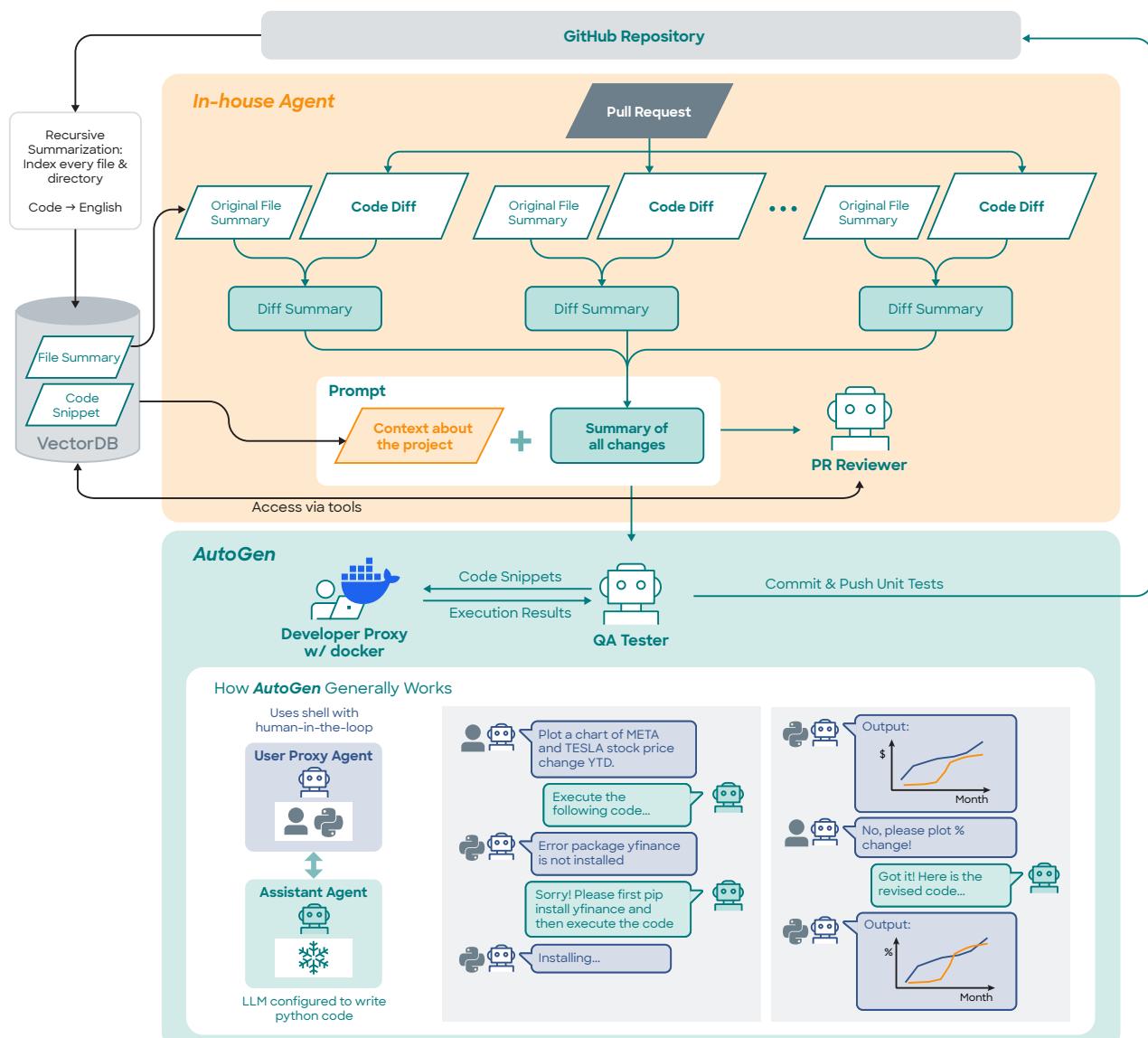
Writing and reviewing unit tests can be **time-consuming** and **error-prone**, often requiring deep domain knowledge and meticulous attention to edge cases.

### Current Solution

Generative AI agents can automate the generation of unit tests by analyzing **code logic**, identifying **critical paths**, and suggesting tests for **edge cases** and **coverage gaps**. In this white paper we showcase an innovative autonomous Pull Request Tester and Reviewer.

### Methods

- Our tool integrates **Retrieval-Augmented Generation (RAG)** and **AutoGen** technologies to automatically review GitHub pull requests. It generates **summaries** for the code, **analyzes code differences**, and provides concise summaries of those differences. Using these summaries, the tool conducts in-depth **reviews** of the pull requests, assessing code quality and functionality while also creating effective **unit tests**.
- By leveraging **generative AI agents** to interpret requirements and code structure, the system can generate test cases, validate them against expected behaviors, and provide feedback or improvements to existing test suites.



AutoGen diagram partially adapted from: <https://microsoft.github.io/autogen/0.2/docs/Getting-Started/>

# Generative AI Agents in Action for Software Testing

## Generative AI Agents for Functional/UI Tests

### Background & Methods

#### Problem Statement

Developing **functional and UI tests** is labor-intensive and requires detailed knowledge of **user flows**, **interface interactions**, and **system functionality**, making it a high-cost process for the company in terms of business value.

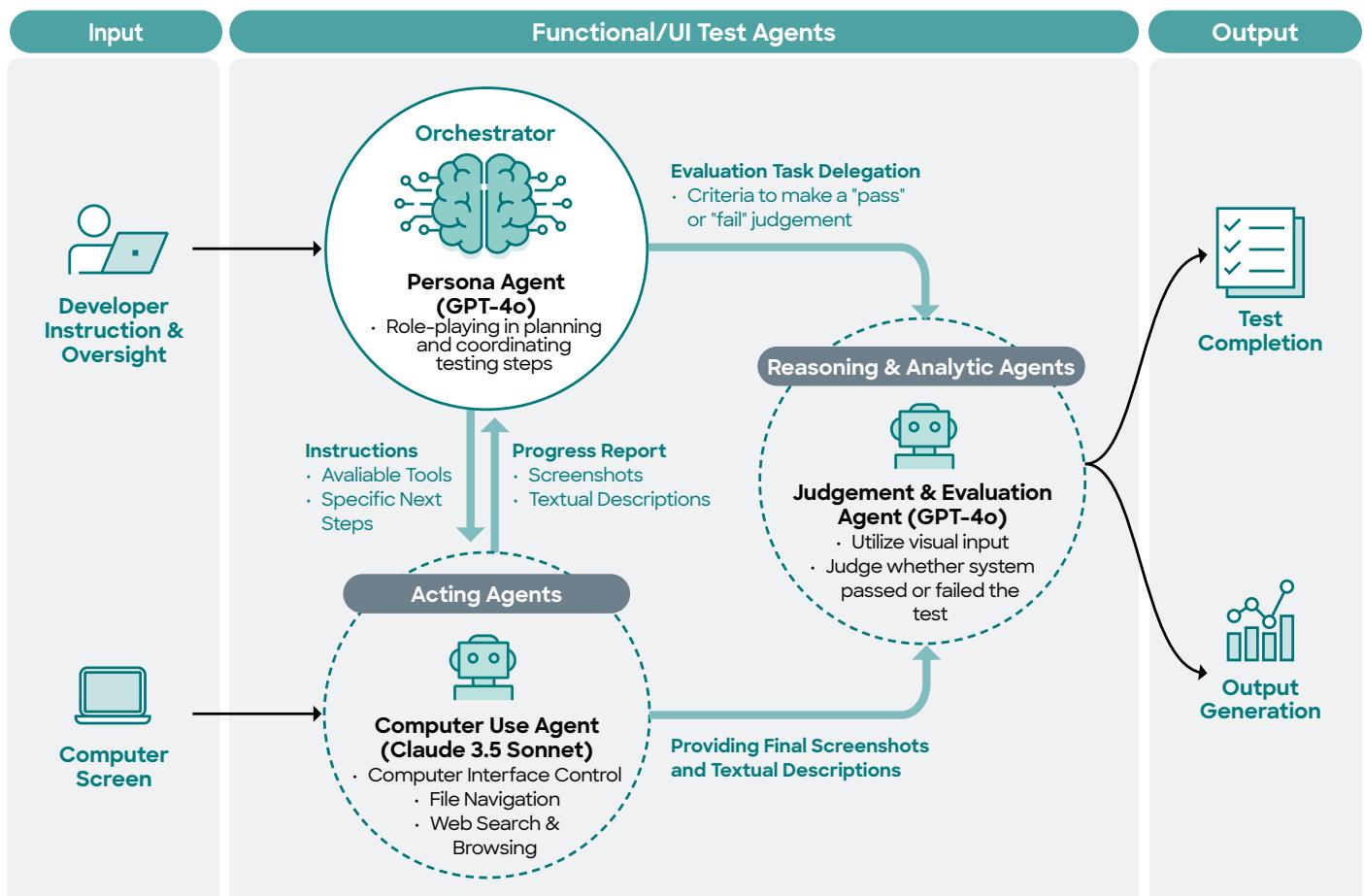
#### Current Solution

Generative AI agents can **automate** functional and UI test **creation**, **execution** and **validation** by analyzing **workflows**, **user stories**, and **interface designs**, reducing manual effort while enhancing test accuracy and consistency. Here we showcase a multi-agent autonomous UI function tester.

#### Methods

- We use an **orchestrating agent** with AI generated **persona** to automate end-to-end functional/UI tests, in combination with the **acting agent** based on Claude 3.5 Model and a visual large language model **judgement and evaluation agent**.
- Using this multi-agent system, AI agents can **simulate** user interactions, **generate** plans and instructions for automated functional / UI tests, and **adapt** these tests dynamically based on changes in the application's UI.

### Multi-agent Functional/UI Testing Workflow



# Generative AI Agents in Action for Software Testing

## Demonstration Test Cases

For demonstration purposes during the prototypical phase, we have chosen an internally developed software, '**GenAI.xy Playground**', as the target for software testing. This selection allows us to assess, based on its current capabilities (such as reasoning, planning, and UI execution), **the level of complexity** (functional level) that our designed multi-agent system can handle.

The table below presents the GUI-based functions that have been tested with the prototype as well as the testing results. Refer to "Multi-agent Functional/UI Testing Workflow" on the previous page for a diagram of the prototyped system and the [appliedAI Initiative Youtube channel](#) for live demo recordings.

Test case	Goal Description	Testing result	Judgement Agent result
Search bar	Use the search bar to search for one keyword, and then open a use case from the result	Acting agent based on Claude 3.5 Computer Use correctly understood the visual design of a search bar	PASS
Favourite (bookmark) feature	In the Use Case Library, use the filtering feature to select 1 industry and find one use case to add to favorites.	Acting agent based on Claude 3.5 Computer Use was able to correctly find filter on UI and also understand the visual design that a heart ❤ means adding to favourite.	PASS
Filtering (checkbox with dropdown menu)	Open Image Generation in the Playground, and then generate a cute image and add it to favorite.	Agent correctly navigated to the image generation playground and found correct model.	PASS
Using image generation model with a prompt	Find one user-specified prompt template in the code generation playground which can assist in writing RESTful API and test that template.	Acting agent found the correct required template, but after reviewing the template and getting back to the main menu, it forgot the context and applied the wrong template.	FAIL
Search and apply 1 specific prompt template	Find one user-specified prompt template in the code generation playground which can assist in writing RESTful API and test that template.	Acting agent found the correct required template, but after reviewing the template and getting back to the main menu, it forgot the context and applied the wrong template.	FAIL

## Example Agentic Software Test Workflow for the Test Case 'Seach Bar'

### Step 1 Define the Test Case 'Search bar'

- The user and developer define the functional test case goal – in this example, testing the search bar functionality – by appropriately describing the test case.

The screenshot shows the 'Multi-Agent E2E Testing' application. On the left, there's a sidebar with 'Multi-Agent E2E Testing' at the top, followed by 'Persona Computer' and 'Computer Agent'. Below these are two input fields: 'Type a command...' and a blue button with a right-pointing arrow. The main area is titled 'Test Definition' with a checked checkbox. The description reads: 'Use the search bar to search for one keyword, then open a use case from the result.' To the right of this is a 'Generate Personas' button. Below the definition is a 'Use Case Library' section with tabs for 'Use Case Library', 'Playground', and 'Knowledge Hub'. It shows a budget of 9,835581 € and a 'My Favourites' link. There are filters for 'Industry', 'Process', and 'GenAI's Capabilities'. Under 'Use Cases (80)', there are two cards: 'AI-Powered Content Moderation' and 'Conversational Analytics with Generative AI'. Both cards provide details about their industry, process, and GenAI's capabilities.

# Generative AI Agents in Action for Software Testing

## Step 2 Initialize the Persona Agent

- The Orchestrator (Persona Agent) generates three persona templates based on the given test case definition and awaits the user's selection.

The screenshot shows the 'Multi-Agent E2E Testing' interface. On the left, there are two panels: 'Persona Agent' and 'Computer Agent'. The 'Persona Agent' panel has a search bar with 'Type a command...' and a blue button with a play icon. The 'Computer Agent' panel is currently empty. In the center, a large red-bordered box highlights the 'Test Definition' and 'Choose a Persona' sections. The 'Test Definition' section contains a search bar with placeholder text 'Use the search bar to search for one keyword, then open a use case from the result.' and a 'Generate Personas' button. The 'Choose a Persona' section displays three personas: Raj Patel (Healthcare Data Analyst), Sarah Thompson (Educational Technologist), and another partially visible persona. Below this is a screenshot of the 'Use Case Library' interface, showing a grid of use cases like 'AI-Powered Content Moderation' and 'Conversational Analytics with Generative AI'. A tooltip says 'Persona started talking to Computer'.

## Step 3 Orchestrator Collaborates with the Acting Agent

- The Orchestrator selects the appropriate persona and begins planning and delegating tasks to the Acting Agent.
- The Acting Agent will request assistance or instructions from the Orchestrator when blocked by a subtask and will also report major milestones to the Orchestrator, providing both text descriptions and UI screenshots.

The screenshot shows the 'Multi-Agent E2E Testing' interface. The 'Persona Agent' panel on the left has a red border around its top half. It displays a message: 'Done! I've typed "AI marketing" into the search bar and pressed Enter. The search results are now showing on the screen.' Below this is a screenshot of the 'Use Case Library' interface with a search bar containing 'AI marketing'. The 'Computer Agent' panel on the right also has a red border around its top half. It displays a message: 'Done! I've typed "AI marketing" into the search bar and pressed Enter. The search results are now showing on the screen.' Below this is a screenshot of the 'Use Case Library' interface with a search bar containing 'AI marketing'. A tooltip in the 'Computer Agent' panel says 'Pressed key: Return'. A tooltip in the 'Use Case Library' interface says 'Showing 80 Use Cases from 80'.

# Generative AI Agents in Action for Software Testing

## Step 4 Orchestrator Calls the Judgement Agent for Evaluation

- Once the Orchestrator "believes" that the test has been completed by the Acting Agent, it will call the Judgement Agent for a final evaluation.
- The Judgement Agent will analyze and evaluate, based on the final screenshot and last report, whether the original test goal given by the user has been completed (**PASS**) or not (**FAIL**).

The screenshot shows the Multi-Agent E2E Testing interface. On the left, there are two sections: 'Persona Agent' and 'Computer Agent'. The 'Persona Agent' section contains a message from 'Raj Patel' about AI transforming marketing strategies. The 'Computer Agent' section contains a message from 'Sarah Thompson' about educational technologies. In the center, there is a 'Test Definition' search bar and a 'Choose a Persona' dropdown with options for Raj Patel (Healthcare Data Analyst) and Sarah Thompson (Educational Technologist). Below this is a 'Judge Result' box indicating 'Passed' with a green checkmark. A detailed description of the task and its successful completion is provided. At the bottom, there is a 'Test Finished!' message.

# Retrospective & Prospective: Challenges and Opportunities for Generative AI Agents

## Insights & Reflections

### Agent Capabilities

**Defining Characteristics:** Generative AI agents exhibit key traits including environmental interaction, task execution, and advanced cognitive capabilities—spanning perception, reasoning, goal setting, and planning—allowing for adaptive responses to complex scenarios.



**Current Status:** Presently, agentic functionalities are primarily concentrated at level 2 (reasoning), with emerging advancements at level 3 (autonomy), underscoring a landscape ripe for the evolution of more sophisticated cognitive processes in future iterations.

**Prospects:** In the coming years, we anticipate breakthroughs in agentic innovation and organizational capacity, leading to the deployment of multi-agent systems that facilitate enhanced communication and orchestration among individual agents, while emphasizing the ongoing necessity for human oversight.

### Industrial Agentic Use Cases



**Transformative Automation Across the Value Chain:** Generative AI agents offer substantial opportunities to enhance business decision making processes by automating and simplifying complex tasks, enabling deep semantic understanding and driving efficiencies across diverse processes – from research & development to customer engagement.

**Holistic Value Creation:** By facilitating processes such as creativity, discovery and research, optimizing logistics in supply chain management, and streamlining operations and quality control in production, generative AI agents contribute to holistic value creation and operational excellence.

#### From Exploration and Engagement to Execution and

**Effective Operation:** Currently, the trajectory of generative AI applications tends to prioritize the initial exploratory and final customer engagement stages. However, there is also growing effort in the domains of supply chain management and production operations, aimed at developing robust automation tools for critical processes in the future.

### From RPA to APA



#### Boosting Dynamicity and Adaptability:

Transitioning from Robotic Process Automation (RPA) to Agentic Process Automation (APA) enables a shift from rigid, rule-based workflows to dynamic, goal-oriented frameworks that adapt to varying task complexities, enhancing overall process efficiency and effectiveness.

**Augmenting Existing Workflows:** By incorporating AI agents into existing RPA workflows, organizations can leverage agentic problem-solving capabilities to tackle both predefined and ill-defined sub-problems, thereby addressing RPA's limitations in adaptability and robustness.

**Cost-Effective Deployment:** Utilizing Small Language Models (SLMs) over Large Language Models (LLMs) in agentic workflows allows organizations giving self-hosting options on cloud, on-premise, and edge environments to optimize data privacy, IT integration and infrastructure costs, while still harnessing the flexibility and intelligence of AI agents.

### Software Development



**From LLMs to LLM-based agents:** The transition from LLMs to LLM-based agents is reshaping software development, with current applications focusing on code generation, unit/functional testing, and requirements engineering, while cautious adoption persists for critical tasks like infrastructure deployment.

**Prioritizing Safe AI Integration:** High-value, low-cost use cases in agile development, such as documentation and UI/UX design support, are being prioritized for AI agent integration, whereas critical activities like deployment script generation in complex environments are viewed as risky and less mature.

**Impact and Trust Across Roles:** AI agents are expected to influence various software engineering roles. Areas such as frontend and web development and software testing are currently the most trusted for AI automation and may see the most impact. In contrast, task planning and deployment are less trusted. Nonetheless, the complexity of enterprise software development may pose challenges.

### Software Testing



**Revolutionizing Continuous Testing:** Generative AI agents streamline the software development lifecycle by automating the creation and refinement of unit, functional, and UI tests, enhancing efficiency and ensuring robust testing coverage integral to agile methodologies.

**Mitigating Human Effort in Test Generation:** By leveraging advanced techniques like Retrieval-Augmented Generation (RAG) and AutoGen, AI agents automatically review pull requests and produce tailored test cases, significantly relieving developers from the time-consuming and error-prone task of manual test writing.

**Enhancing Test Accuracy and Adaptability:** With the ability to analyze user workflows and interface interactions, generative AI agents facilitate the dynamic creation of functional and UI tests, ensuring comprehensive coverage while adapting to evolving application requirements and maintaining consistency across testing efforts.

### Next-Gen Potentials



**Transformative Problem-Solving:** Advanced generative AI agents are revolutionizing problem-solving in diverse fields like software development and industrial engineering by automating complex tasks, enhancing collaboration, and producing high-quality solutions through dynamic interaction and learning from human feedback.

**World Simulation Applications:** Generative AI agents may assist in simulating human behavior across gaming, societal interactions, and economic modeling, enabling realistic role-playing, engaging dialogue, and strategic decision-making that closely mimics human responses and social dynamics.

**Autonomous Scientific Innovation:** Generative AI agents will drive significant advancements in scientific research by autonomously conducting experiments, optimizing processes, and facilitating collaborative debates, thereby enhancing the efficiency and accuracy of scientific inquiry across various disciplines.

# Retrospective & Prospective: Challenges and Opportunities for Generative AI Agents

## Challenges & Risks of Generative AI Agents

### Adversarial Robustness



#### LLMs Under Attacks

- Large language models are susceptible to adversarial attacks, leading to erroneous responses. Relevant attack methods include dataset poisoning and prompt-specific attacks.

#### In Pursuit of Robustness Techniques

- Approaches such as adversarial training, data augmentation, and sample detection can enhance the robustness of LLM-driven agents; however, a complete solution continues to be elusive.

#### Human Oversight Required

- Introducing a human-in-the-loop framework can help oversee and improve the conduct of LLM-dependent agents, which may reduce the threats posed by adversarial attacks.

### Trustworthiness



#### Calibration Challenges

- Language models face challenges with the so-called calibration problem, which causes them to inadequately convey the certainty of their predictions, leading to outputs that do not reflect human expectations in practical use cases.

#### Demand for Reliability

- There is an urgent demand for intelligent agents that are both reliable and honest. Recent studies have focused on directing models to offer reasoning and explanations to improve their credibility.

#### Debiasing and Fairness

- Implementing debiasing strategies and calibration methods during the training process can address fairness concerns and improve the reasoning capabilities of language models.

### Misuse, Bias, & Fairness



#### Exploitation of LLM Agents

- Individuals with malicious intentions can exploit LLM-based agents to sway public perception, disseminate misinformation, and conduct unlawful activities.

#### Dangers to Security and Society

- The potential for abuse of generative AI agents presents considerable dangers to both security and social stability, which could lead to orchestrated terrorist activities and cyber threats.

#### Regulatory Measures for Safe Use

- To reduce these risks and promote responsible usage, it is crucial to implement strict regulatory frameworks and improve security protocols in the development and training of these agents.

### Threat to the Well-being of the Human Race



### Human-agent Interaction



#### Communication Clarity Needed

- Clear communication between humans and AI agents is essential, as misunderstandings can occur due to the intricacies of the agents' language models, potentially resulting in unintended outcomes in decision-making.

#### Impact of AI Reliance on Human Cognition

- As people depend more on AI agents for decision-making, there is a concern that this reliance could weaken critical thinking and problem-solving abilities, which might compromise human agency.

#### Building Trust and Ethics

- Establishing trust in interactions between humans and AI is crucial; users need to have confidence in the agents' abilities while ensuring that ethical standards are upheld to prevent manipulation or exploitation.

### Agent Evaluation



#### Real-World Performance Limitations

- Existing approaches to assessing AI agents often fall short in accurately reflecting their performance in real-world scenarios, resulting in a limited understanding of their reliability.

#### Bias and Fairness in Evaluation

- When evaluating AI agents, it is crucial to address issues of bias and fairness; using inappropriate evaluation metrics can exacerbate undesirable behaviors, undermining the agent's acceptance in society.

#### Evolving Assessment Frameworks

- As both environments and tasks may change, it is essential for the evaluation of AI agents to evolve, enabling ongoing measurement of their performance while ensuring they remain aligned with user requirements and ethical standards over time.

#### Challenges in Managing Agents

- As AI agent technology progresses, humans may find it challenging to manage these systems, which could result in considerable risks if these agents surpass human intelligence and develop their own objectives.

#### Global Safeguards Imperative

- Without adequate safeguards, sophisticated AI agents could pose significant dangers to humanity, underscoring the need for regulations and a globally shared technical and ethical framework.

#### Economical Impact

- The advancements of AI agents may disrupt traditional job markets, necessitating workforce reskilling and adaptation to ensure that the benefits of this technology are equitably distributed across society.

References: [5,7-8]

# Retrospective & Prospective: Challenges and Opportunities for Generative AI Agents

*The Future Unfolded: Opportunities of Generative AI Agents Today and Beyond*

## Today's Innovations: Generative AI Agents Taking Actions

### Rapid Development of Agent Ecosystems

Tech leaders (e.g., NVIDIA, OpenAI, SAP) are actively pursuing the creation and integration of generative AI agents into **existing frameworks, tools, and ecosystems**, laying the groundwork for an expansive agent society.

### From Single-Agent to Multi-Agent Systems

Companies are gradually transitioning from single-agent approaches to **orchestrated multi-agent systems**, assessing how Level 2 (reasoning) and Level 3 (autonomy) agentic capabilities may be integrated to tackle complex tasks end-to-end with a high degree of autonomy.

### Focus on Efficiency in Both Early- and Late-Stage Value Chains

Initial applications of generative AI agents are likely to concentrate on enhancing efficiency in **use cases** across both the **early- and late-stage value chains** of various sectors, streamlining processes, and improving productivity.

### Start with Agentic Process Automation (APA)

For various business processes, a structural approach such as APA can be implemented to effectively leverage advanced agent capabilities, accommodating diverse task complexities and thereby enhancing and **augmenting existing robotic process automation (RPA) workflows**.

### Advancements in Software Development Tools

Both generative AI code assistants and engineering agents are gaining traction, demonstrating **potential in automating critical software development** tasks such as code reviews and functional testing, although concerns about trust and reliability remain.

### Theoretical Innovations and Cross-disciplinary Approaches

Researchers are advancing theoretical knowledge by integrating insights from fields such as **cognitive science and complex systems**, enhancing understanding and application of generative AI agents in various contexts.

*“Agentic AI's transformative power shines with customization. By designing purpose-built agents for specific domains, we can now blend advanced reasoning and actionability with modern techniques like RAG, Knowledge Graphs, Conversational Analytics, and Intelligent Document Processing, crafting AI systems that excel at tackling complex, domain-specific challenges.”*

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Milos Rusic  
CEO & Co-Founder  
deepset



# Retrospective & Prospective: Challenges and Opportunities for Generative AI Agents

## Beyond the Horizon: Generative AI Agents Shaping the Future

### Enhanced Collective Intelligence and Coordination

Research will likely explore optimizing **collective intelligence** within AI agent networks, where multiple agents accumulate knowledge and experience from both **interactions** among themselves and their **collaborations** with humans, achieving synergies that can lead to more effective problem-solving and innovation.

### Evolving System Interconnection and Complexity

By forming interconnected multi-agent systems, an "**agentic galaxy**," the complexity of these networks may increase significantly, fostering continuous learning and adaptability as well as allowing agents to rapidly evolve through shared insights.

### Progress in Multi-Modal Environments

There will be an increased focus on generative AI agents in **multimodal** settings, which will integrate various **sensory inputs**. These versatile agents will enhance their ability to interact with the physical world, leading to more natural and effective human-robot interactions across diverse industries.

### From Virtual to Physical Agents

The "ChatGPT moment" for **multimodal robotic foundation models** is approaching, enabling predicted actions in complex physical environments and ultimately realizing the long-term vision of human-like intelligence in robotic form.

### Scalability and Resource Efficiency

The future of generative multi-agent systems will depend on developing **scalable architectures** that maintain **efficiency** as the number of agents increases, addressing computational constraints.

### Extensive Applications Across Diverse Fields

Generative AI multi-agent systems are expected to expand into **various industrial sectors** (semiconductor, chemicals, E-commerce, healthcare, education, etc.), tackling complex problems and driving advanced computational solutions.

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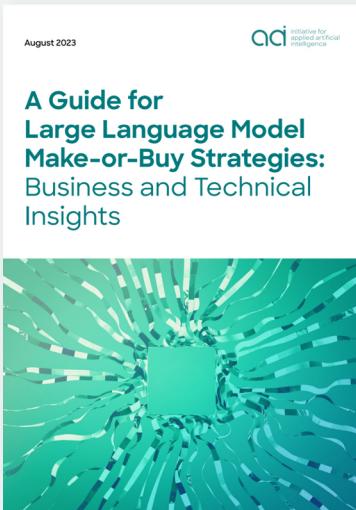
*"We see Generative AI agents, embedded into advanced agentic RAGs, replicating complex human analyses and decisions. When guided by clearly defined processes, they automate tasks, increase efficiency and achieve precision, enabling solutions to challenges that were previously out of reach. This capability has the potential to strengthen the German economy by boosting growth and counteracting labour shortages."*

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Lukas Wogirz  
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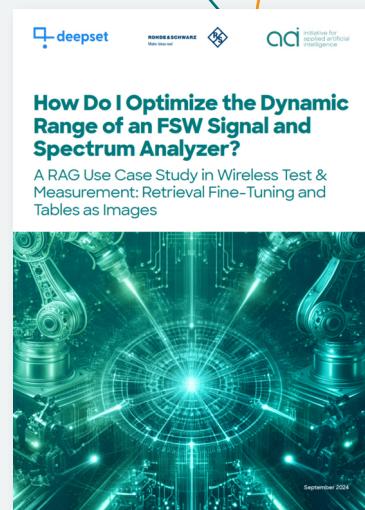
**Do you want to dive deeper into LLM and RAG?  
Start your journey with our white papers.**



Firms that employ large language models (LLMs) can create significant value and achieve sustainable competitive advantage. However, the decision of whether to make-or-buy LLMs is a complex one and should be informed by consideration of strategic value, customization, intellectual property, security, costs, talent, legal expertise, data, and trustworthiness. It is also necessary to thoroughly evaluate available open-source and closed-source LLM options, and to understand the advantages and disadvantages of fine-tuning existing models versus pre-training models from scratch.



Our latest whitepaper on Retrieval-Augmented Generation (RAG) offers insights into the advancements and challenges of Retrieval-Augmented Generation (RAG) within the industry. It provides an analysis of industry demands, current methodologies, and the obstacles in developing and evaluating RAG. Additionally, our whitepaper aims to facilitate strategy development and knowledge exchange about practical use cases across various industrial sectors. The whitepaper is the result of extensive studies and discussions conducted with our internal teams and industry partners. It highlights RAG as a cost-effective technique that has significantly improved the trustworthiness and control of Large Language Model (LLM) applications over the past year.



A RAG Use Case Study in Wireless Test & Measurement: Retrieval Fine-Tuning and Tables as Images

Our RAG use case study on Retrieval-Augmented Generation (RAG) within the test and measurement industry highlights common challenges in the technical domain and explores effective RAG evaluation techniques. We demonstrate how Large Language Models (LLMs) can be leveraged to scale up RAG evaluation reliably, and address industry-specific challenges such as multilingual data, in-domain data, and complex tabular structures. Our vision pipeline and retrieval fine-tuning solutions have significantly improved the accuracy of RAG, proving the value of customized RAG applications for the wireless test and measurement sector.

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Mingyang Ma works as Principal AI Strategist & Product Manager at appliedAI Initiative GmbH, supporting all partner companies' decision making and technical solution identification of various AI use cases, with a particular focus on leveraging LLMs. With over 6 years of expertise in NLP, Mingyang has excelled in the realm of Conversational AI, demonstrating her proficiency in application DevOps and platform development across various processes during her tenure at BMW Group in both Germany and the USA.



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# About appliedAI Initiative GmbH

appliedAI is Europe's largest initiative for the application of trusted AI technology. The initiative was established in 2017 by Dr. Andreas Liebl as a division of UnternehmerTUM Munich and transferred to a joint venture with Innovation Park Artificial Intelligence (IPA) Heilbronn in 2022.

At the Munich and Heilbronn offices, more than 100 employees pursue the goal of making European businesses a shaper in the AI era in order to maintain Europe's competitiveness and actively shape the future.

appliedAI holistically supports international corporations, including BMW and Siemens, as well as medium-sized companies in their AI transformation. This is accomplished through partnership-based exchange and joint knowledge building, comprehensive accelerator programs, and specific solutions and services, such as strategy consulting and Use-Case development.

For more information, please visit  
<https://www.appliedai.de/en/>

## We offer a unique set of offerings to help companies on their way to becoming AI shapers

The diagram illustrates the progression of appliedAI offerings across four main stages:

- Not started**: Represented by a white button.
- Experimenter**: Represented by a blue button with a camera icon. It includes a section for "Professional Services".
- Practitioner**: Represented by a grey button with a brain icon. It includes a section for "Partnership Programs".
- Professional**: Represented by a green button with a gear icon. It includes a section for "Software Solutions".
- Shaper**: Represented by a light green button with a gear icon.

**Professional Services** (Experimenter stage): Supporting companies to scale the application of AI through focussed services and solutions.

- Strategy & Transformation
- AI Use Case Development
- AI Trainings
- AI Programs
- Acceleration Program (large mid-size & enterprises)
- KI-Transfer Plus (focus on SME)

**Partnership Programs** (Practitioner stage): Supporting companies in the entire AI transformation process through interactions with us and the ecosystem, access to knowledge, and co-creation of solutions to tackle future challenges.

- Companion Partnership Program
- Tailored AI Transformation Companion for larger organizations.
- SME Partnership Program
- Supporting AI Journey of SMEs with practical advice and effective solutions.

**Software Solutions** (Professional stage): Professional B2B Software solutions that help to apply and scale AI professionally and in a trusted way.

- Management Suite
- Advance your AI initiatives by managing use cases from idea to production and ensuring compliance with regulations - including the EU AI Act.

**Ventures** (Shaper stage): AI First Products

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