Agents (are back)

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"The aim of marketing is to know and understand the customer so well the product or service fits him and sells itself" — Peter F. Drucker (1967)

This is not about 007, the fictional British secret service agent created by Ian Fleming, known for his espionage missions and sophisticated style. It is about software agents, now experiencing a resurgence as Agentic Artificial Intelligence (AI)—AI-driven entities capable of autonomous action, decision-making, and collaboration. Unlike traditional AI systems like generative AI (e.g., ChatGPT), which primarily answer questions or provide recommendations, these agents actively perform tasks, execute workflows, and orchestrate complex digital interactions. How to win quickly: Avoid reinventing the wheel—build on a proven foundation, and approach Agentic AI, or AI-powered software agents, as a three-phase evolution: from multi-agent systems (MAS) to smart devices and the Internet of Things (IoT). By leveraging past advancements and best practices, organizations can accelerate learning, reduce inefficiencies, and drive smarter, more effective solutions.

What is a software agent

Merriam-Webster, a widely recognized dictionary and authority on meaning, defines an agent as someone who acts on behalf of another. For example, a stockbroker serves as a living agent, executing stock orders on behalf of a client:

> Agent (Merriam Webster Collegiate Dictionary 2025)
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> - Pronunciation: 'A-j&nt; Function: noun; Date: 15th century
> - Etymology: Middle English, from Medieval Latin agent-, agens, from Latin, present participle of agere to drive, lead, act, do
>
> 1 : one that acts or exerts power
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> [...]
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> 4 : one who is authorized to act for or in the place of another: as a : a representative, emissary, or official of a government <crown agent> <federal agent> b : one engaged in undercover activities (as espionage) : SPY <secret agent> c : a business representative (as of an athlete or entertainer) <a theatrical agent>

In software systems, AI scholar and genetic algorithms pioneer John Holland did not conceive software agents in isolation. Instead, he adapted and grounded the concept in economic science, which provides template solutions for the numerous challenges arising from the interaction and coordination of parties with differing economic interests (Holland 1995, pp. 6–7). Instead of handling financial transactions, software agents in computing automate tasks, analyze data, and facilitate decision-making in digital environments.

Roots in agency theory from economics

The field of economics Holland referred to is agency theory, which defines best practices for structuring relationships and behavior between two parties: the principal, who assigns the work, and the agent, who performs it (Ross 1973; Grossman and Hart 1983; and for a survey, see Sappington 1991). The agency theory literature provides foundational frameworks for interaction and behavioral design—eliminating the need to reinvent—by analyzing the costs of resolving two types of conflicts that arise between principals and agents under conditions of incomplete information and uncertainty: adverse selection and moral hazard. Adverse selection occurs when the principal cannot determine whether the agent accurately represents their ability to perform the work for which they are paid, while moral hazard arises when the principal cannot verify whether the agent is exerting maximum effort (Eisenhardt, 1989).

Phase 1: Multi-agent systems (MAS)

The evolution of Holland's software agents can be divided into three phases. The first marked the rise of multi-agent systems (MAS) as a key methodology for supply chain and market analysis using business simulation (Sikora & Shaw 1998, Malone et al. 1987; for simulation, please see SIM 1: From Impossible to Probable – Compendium). Initially, software agents were used to model supply chains (with agents representing a manufacturer and its parts suppliers, for example; Wooldridge & Jennings 1995) and later market dynamics as complex adaptive systems–with agents as a marketplace, for example (CAS; Holland 1995). Rather than relying on monolithic software applications, MAS introduced a distributed approach where autonomous agents interacted to produce emergent behaviors. This advancement enabled researchers to move beyond traditional algorithmic solutions, including analytically intractable problems, offering a computational framework to examine business phenomena that had eluded traditional scientific inquiry, particularly those based on laws and axiomatic reasoning (Kimbrough, 2003). Researchers implemented business scenarios as MAS, running simulations to conduct A-B-type testing of strategies by observing outcomes and analyze both individual agent and overall system performance (Schlueter Langdon & Sikora 2006, Schlueter Langdon 2000).

Phase 2: Smart products and Internet of Things (IoT)

The second phase of software agents emerged with ubiquitous computing and the Internet of Things (IoT), transforming connected physical devices into intelligent, adaptive systems (Luck et al. 2005, Weiser 1991). At its core, this phase involves adding (1) sensors to collect input (e.g., measuring the actual temperature), (2) processing to compare the actual state with a desired setpoint (e.g., actual vs. desired temperature), and (3) actuators to adjust the system accordingly (e.g., activating heating or cooling). As Crosby & Schlueter Langdon (2017) describe, IoT-driven smart products leverage AI and real-time analytics to enhance decision-making, automate interactions, and minimize friction in operations, customer journeys and user experience (UX).

Phase 3: Agentic AI

Now, in the third phase, agentic AI integrates generative AI into autonomous agents. Conceptually, take a software agent from a phase 1 multi-agent system (MAS), evolve it into a "processing element" of a phase 2 smart product, and then upgrade its rule-based comparison algorithm to decision-making powered by a generativ AI engine, such as a Large Language Model (LLM). Finally, feed results back into the agent as performance feedback through local training data, a practice known as Retrieval-Augmented Generation (RAG). These advancements enhance overall system performance, allowing autonomous systems to pursue complex goals with minimal human intervention. Now, software agents exhibit adaptability, advanced reasoning, and self-sufficiency, enabling dynamic operation in evolving environments (Hu et al., 2025; Gabora et al., 2024; Shapiro et al., 2023). With today's expansive generative AI models trained on vast, global datasets, software agents could move beyond closed platforms into more open, global ecosystem networks.

CEO playbook: Agentic AI + Dataspace = Ecosystem power

The game is changing. Competing in today's world means keeping pace with "China speed" innovation, where technology evolves faster than most companies can adapt on their own. The proposed solution is inherently more adaptive and resilient—designed to accommodate unforeseen developments more effectively and efficiently. It shifts value creation from siloed business models to one centered around a proprietary core, complemented by best-in-class solutions within a mix-and-match ecosystem. This is where agentic AI plays a crucial role, enabling scaling on two levels: (a) agents acting on behalf of an entity facilitate scalability across multiple relationships, while (b) AI-powered optimization enhances mix-and-match efficiency. The final piece of the puzzle is dataspace technology, which provides the right data to fuel AI-powered agents. Success with generative AI is a prime example: without cats in the training data, generative AI cannot generate cats. Likewise, for generative AI to understand your business and deliver market-differentiating results, it must be fueled with proprietary insights and historical data from your business and supply chain and market channels. Just as James Bond needed high-tech gadgets, your agentic AI needs high-quality, relevant data as its fuel. This is where dataspace technology comes in (please see Data 0: README). It enables cross-organizational data transactions with built-in governance, allowing data to be shared across internal silos and between organizations while preserving data sovereignty: The data provider retains full control over rights to the data. Dataspaces perfectly complement generative AI by supplying the right training data and supporting Retrieval-Augmented Generation (RAG). For CEOs, the choice is clear: remain trapped in fragmented systems or harness generative AI and dataspace-powered data sharing to drive value creation in an ecosystem constellation—one that is inherently more adaptive and resilient.

Accelerate from insight to action

The rise of agentic AI and dataspaces presents both opportunities and challenges for businesses aiming to harness intelligent automation, data-driven decision-making, and ecosystem collaboration. The right response? Leading organizations are already recalibrating:

1. **Strategic Direction** – Peer-to-Peer Exchange for Actionable Insights: Engage with industry leaders to navigate emerging opportunities:
   a. Exclusive Roundtables – High-level discussions on AI-powered business ecosystems
   b. Executive Peer Workshops – Tackling real-world AI challenges with proven strategies
2. **Capability Building** – Master Classes with Playbooks for Action: Equip your management team with expertise refined through decades of executive education at USC Marshall School of Business and Drucker School of Management:
   a. MGT 505 Data Analytics – Develop analytics-powered solutionss in three steps
   b. MGT 317 Smart Products & IoT – Leverage data and AI to create intelligent products
3. **Rapid Prototyping** – From Strategy to Execution: Move beyond theory with hands-on experimentation in our Drucker Customer Lab: Build, test, and validate first pilots with expert guidance

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