

## Peer response 1 (Georgios)

Georgios defines intelligent agents and emphasizes their growing importance, particularly in situations like disaster management, due to their ability to reason in complex ways and work together without a central control.

A major driver for the rise of autonomous agents has been the exponential increase in computing power, which allows the development of complex simulations and models of complicated systems (Russel and Norvig, 2021). As organisations deal with more complicated environments, agent-based models (ABMs) can provide important strategic value by simulating possible scenarios and establishing connections that are difficult to handle using traditional methods.

At the same time, the focus on data-driven decision making across many fields has encouraged the growth and use of agent-based systems, supported by the growing availability of big data since the early 2010s. By using these large datasets, agents can evolve and improve their behaviour over time, providing insights that support strategic planning, complex reasoning, and efficient operations (Grimm and Railsback, 2005). This aspect is crucial for organisations seeking to maintain a competitive edge in rapidly changing markets.

Additionally, the integration of machine learning techniques with agent-based systems enhances their capability to learn and adapt autonomously, addressing novel problems without explicit programming. This versatility is particularly beneficial in scenarios where environmental conditions or requirements may shift rapidly or unpredictably (Reynolds, 1987; Macal and North, 2010).

Finally, agent-based systems also facilitate scalability. Organisations can implement these systems across various domains, such as logistics, finance, and healthcare, creating a decentralised yet coordinated approach to problem-solving (Maes, 1991; Bonabeau, 2002). By distributing tasks among multiple autonomous agents, organisations can achieve more efficient resource utilisation and enhance overall system resilience.

In conclusion, the inherent flexibility, adaptability, and scalability of agent-based systems contribute significantly to their rising adoption, offering organisations robust tools for navigating complexity and optimising outcomes in diverse and dynamic operational landscapes.

## References:

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