When Not to Use Generative AI

19 March 2024 - ID G00806238 - 24 min read

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Initiatives:Artificial Intelligence; Analytics and Artificial Intelligence; Generative AI Resource Center

Using generative AI for the wrong business use cases leads to high failure rates and diminishes the value of AI in organizations. To avoid this, IT leaders can use this guidance to evaluate if GenAI is the right fit for their use case or whether to consider alternative AI techniques.

Overview

Key Findings

- IT leaders struggle in understanding when and when not to apply generative AI (GenAI) for their use cases. The hype surrounding GenAI can lead them to apply it where it is not a good fit, increasing the risk of higher complexity and failure in their AI projects.

- A disproportionate focus on GenAI can lead IT leaders to ignore the broader set of alternative AI techniques, diminishing business value. More established AI techniques are a better fit for the majority of potential AI use cases.

- AI techniques are not mutually exclusive; they can often be combined in a way that makes for a stronger overall system. Organizations that develop an ability to combine the right AI techniques are uniquely positioned to build AI systems that have better accuracy, transparency and performance, while also reducing costs and need for data.

Recommendations

- Systematically categorize each use case and evaluate its relative GenAI feasibility. Use cases in the categories of prediction and forecasting, planning and optimization, decision intelligence, and autonomous systems are not currently a good fit for the use of GenAI models in isolation.

- Utilize alternative AI techniques when GenAI models are not the right fit. The most prominent alternative techniques are the use of nongenerative machine learning (ML), optimization, simulation, rule-based systems and graphs. For many use cases, these alternatives are often more reliable and better-understood than GenAI models.

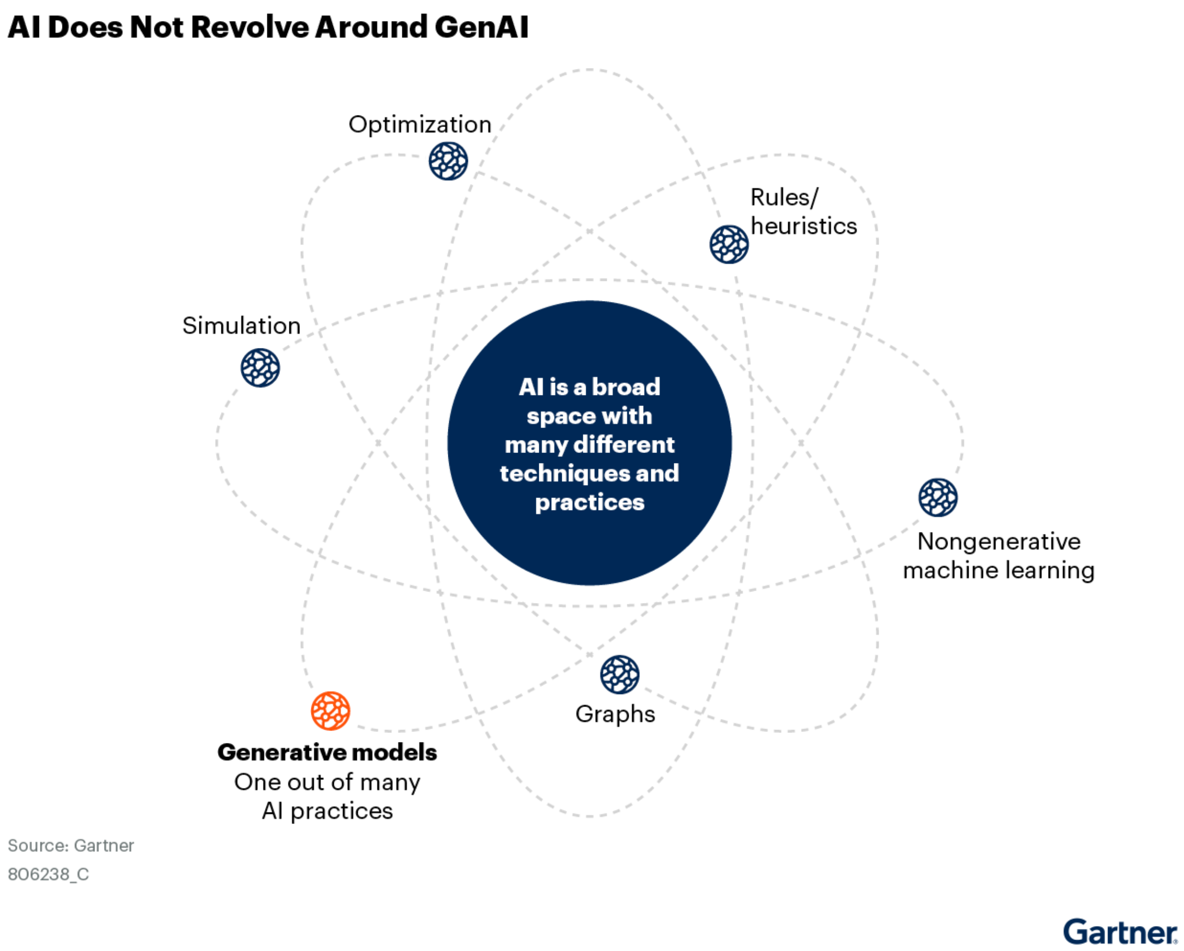
- Combine GenAI models with other AI techniques to create more robust systems that mitigate some of the limitations of GenAI, such as its tendency to generate inaccuracies and hallucinations. Conversely, use GenAI models to support other AI techniques, for instance, by serving as a natural language interface to other AI and software systems.

Introduction

Generative AI (GenAI) adoption has exploded over the last year. According to the 2023 Gartner AI in the Enterprise Survey, generative AI is one of the most deployed AI techniques among survey respondents. [1] Organizations are deploying GenAI in many use cases across many business units (see Executive Pulse: GenAI Initiatives Take Shape Across the Enterprise).

Although this rapid adoption is promising, it also entails the risk of GenAI overshadowing the broader AI space. For many organizations or business units, GenAI will be their first experience with AI and will start conflating GenAI with AI. However, GenAI is only a small part of the AI landscape (see Figure 1).

Figure 1: AI Does Not Revolve Around GenAI



This is an important problem because different use cases may require different AI techniques. GenAI is not a silver bullet: It is often not the right fit for most AI use cases. Moreover, many business problems will require a combination of different AI techniques, which are likely to be ignored if organizations maintain a short-sighted focus on GenAI.

> Organizations that solely focus on GenAI and do not consider other AI techniques risk both an increased failure in their AI projects and missing out on most AI opportunities.

Increased hype can also lead to misplaced expectations: Many GenAI technologies are at the Peak of Inflated Expectations (see Hype Cycle for Generative AI, 2023). Given these increased expectations, IT leaders are at risk of implementing GenAI for use cases that are not a good fit. GenAI amplifies the tendency of business leaders to overestimate AI impacts and underestimate its complexity.

To avoid failure, IT leaders can use the guidance in this research to evaluate when GenAI is not the right fit for their use case, when to consider alternative AI techniques, and when to combine them with GenAI.

Analysis

Evaluate Whether GenAI Is Right for Your Use Case

The question of whether to use GenAI models is a use-case-by-use-case decision. The first step is to determine that the use case is in itself valuable and feasible, regardless of the AI technique being considered. This is important because some use cases are not a good fit for AI and do not merit further consideration. Gartner recommends using a prioritization tool such as Gartner's AI Prism (see: Toolkit: Discover and Prioritize Your Best AI Use Cases With a Gartner Prism).

After prioritizing your use cases, map them against the relevant use-case family in Table 1 to understand the relevant usefulness of GenAI models for your use case. This table simplifies the broad landscape of AI use cases into 12 use-case families, ranking the current utility of GenAI models for each (see Note 1 for detailed rationale and AI Zodiac: Mapping AI Use Cases to Techniques for details on the use-case families).

Table 1: Use-Case Families and Relative Generative Models' Usefulness

(Enlarged table in Appendix)

Use-case family	Generative models' current usefulness	Use-case examples
Prediction/Forecasting	Low	Risk prediction, customer churn prediction, sales/demand forecasting
Planning	Low	Operation research, optimization, route planning
Decision Intelligence	Low	Decision support, augmentation, automation
Autonomous Systems	Low	Self-driving cars, advanced robotics, drones
Segmentation/Classification	Medium	Clustering, customer segmentation, object classification
Recommendation Systems	Medium	Recommendation engine, personalized advice, next best action
Perception	Medium	Object detection, recognition, analysis
Intelligent Automation	Medium	Intelligent document processing, object character recognition, robotic process automation, hyperautomation
Anomaly Detection/Monitoring	Medium	Abnormal transaction detection, outlier detection, monitoring
Content Generation	High	Text generation, image and video generation, synthetic data
Conversational User Interfaces	High	Virtual assistant, chatbot, digital worker
Knowledge Discovery	High	Knowledge store, search, mining

Source: Gartner (March 2024)

The guidance in Table 1 is meant to serve as a good starting point to understand whether GenAI is currently useful as the primary technique for your type of use case. There are a few use-case families for which GenAI models are typically misused in organizations (marked as "Low" in Table 1):

- **Prediction and forecasting:** It is currently a mistake to directly use LLMs and other GenAI models for forecasting use cases, such as demand prediction, sales forecasting, time-of-arrival estimation, weather forecasting and supply chain forecasting. LLMs are not currently designed to do the kind of numerical predictive and statistical modeling required for predicting a continuous variable given input features (known as a regression task). LLMs could be tangentially used to create features that could be useful in predictive tasks, but the prediction/forecasting itself would need to be done by an alternative AI technique.

- **Planning:** Planning and optimization are some of the key missing elements in current GenAI models. This limits their utility for valuable use cases like inventory optimization, field workforce scheduling, route optimization, financial portfolio optimization, pricing optimization in retail, and resource allocation. All of these use cases require exact calculations, which is not the current strength of generative models. There have been attempts to augment LLMs by embedding them into broader systems that are capable of planning. However, this is far from the explicit optimization, search and planning that is already possible with other classic AI approaches.

- **Decision intelligence:** Decision intelligence leverages AI techniques to augment organizations' decision making. This is a complex activity that requires an ability to model and choose between courses of action to achieve a target outcome (see Tool: Gartner Decision Intelligence Framework to Reengineer Decisions). Current GenAI models are not built for decision making; their output is unreliable, they lack explainability and they are not able to model decisions in an explicit way to achieve outcomes. It is risky for organizations to rely on GenAI outputs to make critical decisions, such as hiring/HR decisions, budget and financial planning, supply chain management, marketing allocation, and strategic decision making. Similarly, LLMs should not be directly used for analytics, but instead, only as a conversational interface to a system capable of analyzing data.

- **Autonomous systems:** GenAI has an autonomy gap — current models are not currently robust enough to be autonomous, requiring close human supervision given the inaccuracies and hallucinations. Developers are pushing to build LLM-based agents, augmenting LLMs with external data and tools, resulting in early assistants such as Microsoft 365 Copilot. However, the current application of LLMs (and other GenAI models) for autonomous systems is limited to narrow domains and typically requires having a "human in the loop." This limits the usefulness of GenAI for use cases such as industrial robotics, delivery drones, smart factories, algorithmic trading and autonomous vehicles.

A broader reason why GenAI might not be a good fit for your use case is that the risks that come with GenAI are unacceptable and cannot be effectively mitigated. GenAI-specific risks include output unreliability, data privacy, intellectual property, liability, cybersecurity and regulatory compliance. These need to be considered for each individual use case (see Tool: Generative AI Policy Kit).

The relative usefulness of GenAI for the types of use cases described in Table 1 will evolve over time as GenAI techniques improve and are combined with other AI techniques. However, for these use cases, IT leaders should explore alternative AI techniques in the next section.

Consider Alternative AI Techniques to GenAI

GenAI has taken focus away from existing and proven AI techniques. Alternative AI techniques, or their combination, may represent the best fit to support specific use cases.

Use Figure 2 to map your use case against the relevant family and to understand the alternative AI techniques that are currently most useful for this type of use case. Figure 2 does not include the combination of techniques (see the Combine GenAI Models With Other AI Techniques section), but gives guidance on the potential usefulness of different AI alternatives as the primary technique to be used in a given use case.

Figure 2: AI Technique Heat Map

AI Techniques Heat Map

AI technique suitability: Low (L), Medium (M), High (H)

	Common AI techniques					
Use-case families	Generative models	Nongenerative machine learning	Optimization	Simulation	Rules/ heuristics	Graphs
Prediction/ forecasting	L	H	L	H	M	L
Planning	L	L	H	M	M	H
Decision intelligence	L	M	H	H	H	M
Autonomous systems	L	M	H	M	M	L
Segmentation/ classification	M	H	L	L	H	H
Recommendation systems	M	H	M	L	M	H
Perception	M	H	L	L	L	L
Intelligent automation	M	H	L	L	H	M
Anomaly detection/ monitoring	M	H	L	M	M	H
Content generation	H	L	L	H	L	L
Conversational user interfaces	H	H	L	L	M	H
Knowledge discovery	H	M	L	L	M	H

Source: Gartner
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Figure 2 is not an exhaustive list, but it represents some of the most widely used AI techniques. There are other emerging techniques — such as causal AI, neuro-symbolic AI and first-principles AI — that are not represented in Figure 2 but are worth tracking (see Hype Cycle for Artificial Intelligence, 2023 for descriptions).

> If all you have is a GenAI hammer, everything looks like a GenAI use-case nail.

As described in Figure 2, some of the main alternative AI techniques to generative AI include:

- **Nongenerative ML:** Also known as "predictive ML," this is a set of techniques that make predictions with ML models that have been trained on historical data. These could be category predictions — for example, an image object classification prediction — or continuous-variable predictions (known as regression tasks), such as a prediction of a customer's lifetime value. This has been the dominant AI paradigm over the last decade, until GenAI became more prominent in 2023. It can be used for all kinds of high-value forecasting use cases, as well as problems like customer segmentation, anomaly detection, recommendation systems, customer churn prediction and predictive maintenance. For many of these cases, nongenerative ML is more suitable than GenAI.

- **Optimization:** Traditionally used by operations research groups, optimization techniques maximize benefits while managing trade-offs between different business objectives. They do this by finding optimal combinations of resources, given a number of constraints in a specified amount of time. They are a key technique for planning use cases such as inventory management, fleet and workforce scheduling, marketing budget allocation, route planning, financial portfolio optimization, and pricing strategy. Optimization and planning techniques can also support decision intelligence by helping to evaluate different courses of action, as well as autonomous systems. They are better-positioned for these use cases than current GenAI techniques.

- **Simulation:** Simulations are computational models that emulate the real world. They support decision making by being able to test different scenarios or changes without having to enact them. It has applications in financial modeling, strategic scenario analysis, architecture and building design, workforce planning, supply chain, and manufacturing process simulations. They can also be used to generate synthetic data and train other AI models — for example, using simulation engines to train autonomous vehicles. Simulation can be a great alternative to GenAI for prediction and decision intelligence use cases, as well as for generating content in a more controlled and explainable way.

- **Rules/heuristics:** Rule-based systems aim to capture expert knowledge in a structured manner — often in the form of rules — and use these for decision making (they are also known as "expert systems"). They are used in fraud detection, loan approval, risk assessment, medical diagnosis, quality control, knowledge discovery, anomaly detection and many other use cases. Contrary to GenAI models, rule-based systems are easy to interpret, which makes them a better option for sensitive use cases that require explainable decision making.

- **Graphs:** Knowledge graphs represent entities (for example, customers, products and locations) and their relationships in a network of nodes and links. They are better-suited than LLMs for use cases that require explainability and precise data retrieval to generate exact answers, such as recommendation systems, search engines, fraud detection, data management, planning and optimization. They can also be combined with GenAI to add trusted and verified facts to their outputs (see the Combine GenAI With Other Techniques section).

These alternatives can be more efficient, effective and reliable and better understood than GenAI models for many use cases. It is key to consider what is needed for the specific use case in terms of explainability, performance and reliability. GenAI models tend to be less reliable and explainable than other techniques. Trying a simpler alternative AI technique first can be a good idea because it can be less risky, less expensive and easier to understand.

Combine GenAI Models With Other AI Techniques

AI techniques are not mutually exclusive; they can often be combined in a way that makes for a stronger overall system. The most sophisticated AI systems typically leverage a balanced composition of AI tools that is intended to complement techniques to deliver better accuracy, transparency and performance while also reducing costs and need for data.

> **A combination of AI techniques might be the best choice for your use case.**

The combination of GenAI models with other AI techniques can be particularly powerful.

On one hand, some of the limitations of GenAI models — such as their lack of robustness, inaccuracies and hallucinations — can be mitigated by coupling them with more robust techniques. For example, knowledge graphs can help reduce hallucinations in LLMs.

On the other hand, GenAI models can be helpful additions for established techniques. For example, LLMs can be used to both help build knowledge graphs and more easily access them. A common way in which GenAI models can be useful is by serving as a natural language interface to other AI/software systems. Similarly, GenAI can be used to develop features that are then used in a nongenerative ML model. See How to Use Design Patterns for AI for a collection of reusable solutions to combine LLMs with knowledge graphs, analytics and BI solutions, and other techniques.

The space of potential combinations of AI techniques is endless. However, Table 2 covers some of the typical ways in which GenAI models are combined with the five other alternative AI techniques discussed earlier, together with some examples.

Table 2: Synergies Between GenAI and Other Techniques

(Enlarged table in Appendix)

Combination	Potential use cases of the combination
Nongenerative ML and GenAI models	Segmentation and classification: Pretrained GenAI foundation models can be used as a starting point to build a classifier model for specific applications, such as sentiment analysis, intent recognition, spam and fraud detection, image classification, and many others. This can be done either by using the GenAI model's outputs as features for a separate nongenerative model or by directly building a nongenerative model on top of a pretrained GenAI one (also known as "transfer learning," this requires access to the full GenAI model). Synthetic data: Synthetic data has been used as training data for supervised, nongenerative machine models for many years (see What Should I Know About Synthetic Data?). GenAI models are particularly useful to generate data for infrequent scenarios or to protect data privacy (by generating synthetic versions of real data). Examples include the training of predictive ML models for autonomous driving, object detection, robotics and many other applications. Computer vision: The integration of computer vision techniques with GenAI models facilitates natural language contextual search of unstructured image data and correlation of data on video streams at scale. This unlocks rich multimodal analytics and experiences (see Innovation Guide for Generative AI in Computer Vision).
Optimization/search and GenAI models	**Enterprise search**: GenAI models such as LLMs can be used to augment traditional enterprise search to make its interface more conversational and to improve its accuracy. LLMs can also be used as embedding models in support of vector databases and vector search (see How Generative AI Impacts Knowledge Management).
Simulation and GenAI models	**Simulation acceleration**: High-fidelity simulations can be resource-intensive. GenAI models can substitute parts of a traditional simulation without a need to run step-by-step calculations, accelerating simulations by orders of magnitude. This allows organizations to run simulations that would be too expensive or too slow to run otherwise, with applications in architecture and building design, material design, drug discovery, and weather prediction (see Innovation Insight: AI Simulation).
Graphs and GenAI models	**Knowledge management**: LLMs can be used to extract entities and relationships from unstructured text to populate a graph database. They can also be used to translate natural language questions into structure queries for graph databases. This makes the building and use of knowledge graphs easier for organizations, improving their knowledge management capabilities. Knowledge graphs act as the backbone of a number of products, including smart assistants, recommendation engines and enterprise search. Retrieval augmented generation: Graphs can be used to better ground LLMs by using graph databases as part of a data retrieval system and augmenting prompts with information coming from a curated knowledge graph (see AI Design Patterns for Knowledge Graphs and Generative AI).
Rule-based systems and GenAI models	**Chatbots**: Increasingly, chatbots are a mix of rule-based techniques and generative models, in addition to other ML models and data representation techniques such as graphs and ontologies. Chatbot architectures can leverage components, such as natural language understanding modules, that make use of sophisticated pipelines where several techniques, including rule-based and LLM-driven ones, are combined for entity extraction, intent classification and other inferences that are fundamental for chatbots. LLMs are now leveraged for their speech-to-text, text-to-speech and translation capabilities in chatbots, often in conjunction with other techniques like rule-based systems. **Robo-advisors**: A robo-advisor is a digital platform that provides automated financial planning services with little or no human supervision by collecting information from customers, offering advice and automatically investing assets. Most advanced robo-advisor implementations leverage a composable architecture and use a mix of retrieval-augmented generation (RAG) and rule-based techniques. **Specialized natural language generation**: Platforms supporting natural language generation (NLG) for specific content production requirements (e.g., news articles, product description and marketing copies) are often leveraging both rule-based or data-driven approaches and, for more creative content types, LLMs and image generation models. Such NLG platforms provide rule-based controls for content generation that are customizable and transparent, and that are aimed to maximize quality and reduce the need for human review and postediting.

Source: Gartner (March 2024)

Organizations that develop an ability to combine the right AI techniques are uniquely positioned to build AI systems that have better accuracy, transparency and performance, while also reducing costs and need for data.

Evidence

[1] **2023 Gartner AI in the Enterprise Survey.** This study was conducted to understand the keys to successful AI implementations and their impact on the broader AI that has been brought by generative AI. The research was conducted online from 19 October through 21 December 2023 among 703 respondents from organizations in the U.S., Germany and the U.K. The *main sample* consisted of 645 out of the 703: Organizations in this sample were required to have developed or intended to deploy at least two AI initiatives within the next three years; respondents were required to be part of the organization's corporate leadership or report to corporate leadership roles. Fifty-eight out of 703 are the *business intelligence (BI) sample*: Organizations in this sample were required to have developed or intended to deploy at least one AI initiative within the next three years; respondents were required to be part of the organization's corporate leadership or report to corporate leadership roles or below (senior manager and above) and to be primarily responsible for BI in their organizations.

Both the main sample and the BI sample respondents were required to have a high level of involvement with at least one AI initiative, and they were required to have one of the following roles when related to AI in their organizations: determine AI business objectives, measure the value derived from AI initiatives, or manage AI initiatives development and implementation. Quotas among the main sample were established for company size and for industries to ensure a good representation across the sample. No quotas were established for the BI sample. Disclaimer: The results of this survey do not represent global findings or the market as a whole, but reflect the sentiments of the respondents and companies surveyed.

Contributors

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Note 1: Rationale for Generative Models' Usefulness for Different Use-Case Families

Table 3: Rationale for Generative Models' Usefulness for Different Use-Case Families

(Enlarged table in Appendix)

Use-case family	Generative models' current usefulness	Description and rationale for usefulness
Prediction/forecasting	**Low**	This use-case family leverages data and predictive analytics for accurate forecasting and precise prediction. Despite GenAI models' impressive capabilities, they fall short in making accurate predictions for real-world situations that necessitate probabilistic thinking. They are not currently designed to do the kind of numerical predictive and statistical modeling required for predicting a continuous variable. LLMs could be tangentially used to create features that could be useful in predictive tasks, but the prediction/forecasting itself would need to be done by an alternative AI technique.
Planning	**Low**	Optimization and planning techniques are vital for industries to improve efficiency, resource allocation and decision making. Planning and optimization are some of the key missing elements in current GenAI models. Attempts have been made to augment LLMs via prompt engineering or by embedding them into broader systems with an orchestration logic to help LLMs break down problems into tasks and execute them. However, this is far from the explicit optimization, search and planning that is already possible with other AI approaches. This limits GenAI models' utility for valuable use cases such as inventory optimization, field workforce scheduling, route optimization, financial portfolio optimization, pricing optimization in retail, and resource allocation. All of these use cases require exact calculations, which is not the current strength of generative models.
Decision intelligence	**Low**	Decision intelligence leverages AI techniques to augment organizations' decision making. This is a complex activity that requires an ability to model and choose between different courses of action to achieve a target outcome. Current GenAI models are not built for decision making. Their output is unreliable, they lack explainability and are not able to model decisions in an explicit way to achieve outcomes. It is risky for organizations to rely on GenAI outputs to make critical decisions, such as hiring/HR decisions, budget and financial planning, supply chain management, marketing allocation, and strategic decision making.
Autonomous systems	**Low**	An autonomous system is a system (such as a robot, a vehicle or a software agent) that is goal-oriented and acts on behalf of users, with minimum human intervention. GenAI models are not currently robust enough to be autonomous, requiring close human supervision, especially given the inaccuracies and hallucinations. Developers are pushing to build LLM-based agents, augmenting LLMs with external data and tools; this has resulted in early assistants such as Microsoft 365 Copilot. However, the current application of LLMs/other GenAI models for autonomous systems is limited to narrow domains and typically requires having a "human in the loop." This significantly limits the usefulness of GenAI for use cases such as industrial robotics, delivery drones, smart factories, algorithmic trading and autonomous vehicles.
Segmentation/classification	Medium	Segmentation and classification unlock valuable insights from complex datasets, which supports data-driven decision making. GenAI models can be used for classification. For example, LLMs can be used for classification tasks such as sentiment analysis via prompt engineering (e.g., few-shot learning). However, their performance in these tasks depends on whether their training data is informative enough to generate good classifications, as well as the additional context/examples that can be provided by the prompt. Overall, current GenAI models (LLMs and image generation) used in isolation are not ideal for many enterprise classification tasks, including for customer segmentation in retail, medical diagnosis in healthcare and credit risk assessment in finance.
Recommendation systems	Medium	Recommendation systems use AI techniques to predict items (products, content, actions, etc.) that are likely to be relevant for a user. LLMs and other GenAI models can be used as embedding models that capture the semantic content of data. These embedding models can potentially be used to find items (such as products, actions or users) that are similar to previous items that relate to the customer, which can then be used as part of a broader recommendation system. However, this is only an emerging approach, and there are other more established techniques, such as rule-based systems (collaborative filtering) and nongenerative ML approaches for use cases such as e-commerce, content, and product recommendations (e.g., next best actions, offers and so on)
Perception	Medium	Perception systems capture and digest different types of data, including audio, visual, language and other unstructured data. Emerging multimodal GenAI models that are trained with many of these modalities could become a key part of how GenAI-based systems perceive their environment (see Innovation Insight: Multimodal AI Explained) to enable use cases like visual search in e-commerce, production line inspection in manufacturing and closed-circuit TV (CCTV) video analytics.
Intelligent automation	Medium	Intelligent automation uses AI techniques to automate business or IT processes, thus accelerating speed, reducing cost and minimizing human errors. GenAI models can help perform tasks, such as optical character recognition, that can save human time and effort. LLMs can also serve as orchestrators of other components to automate tasks that once were not feasible. However, GenAI models suffer from hallucinations and inaccuracies, and they typically require direct human supervision, which limits their current potential for intelligent automation use cases such as automated claims processing.
Anomaly detection/monitoring	Medium	Anomaly detection identifies data points that deviate significantly from normal or expected behavior. GenAI models can be used for anomaly detection, especially when supervised learning approaches suffer from data class imbalance problems. For example, a variational autoencoder (VAE) can be used to learn the underlying distribution of the data and detect inputs that fall outside of this distribution, which may indicate the presence of anomalies. However, other AI techniques are more robust and widely used for anomaly detection use cases, including fraud detection in finance, fault/defect detection in manufacturing and attack detection in cybersecurity.
Content generation	High	This family of use cases leverages AI techniques to generate digital assets, such as text, images, video, audio, code, product designs and even multimodal data. Generative AI models can create new and unique outputs based on user or program input. These models are trained on representative (and often vast) data, and depending on the model and training data, they can generate text, code, images, audio, video or other data. There are other techniques, such as simulation, that can create new content, but GenAI models are widely used for use cases such as marketing materials generation (both text and images), code generation, video generation for media and entertainment, augmented product design, and digital human/avatar.
Conversational user interfaces	High	Conversational user interfaces (CUIs) are human-computer interfaces that enable natural language interactions for the purpose of fulfilling a request, such as answering a question or completing a task. Conversational UIs are one of the primary use cases for LLMs and GenAI. Many organizations and vendors are upgrading their existing conversational AI capabilities with new generative models. The flexibility of the new approaches may augment or even replace existing conversational approaches in coming years. Both internal and customer-facing applications will likely be updated with GenAI capabilities (see Impact of Generative AI on the Conversational AI Market).
Knowledge discovery	High	Knowledge discovery techniques are aimed at exploring, analyzing, describing and organizing content and data. LLMs and GenAI can facilitate knowledge capture, improve enterprise search capabilities, and extract data from documents and messages to produce new content (see How Generative AI Impacts Knowledge Management). This has applications in enterprise knowledge repositories, enterprise search, customer service, digital workplace, and drug discovery and clinical trials in life science manufacturing, as well as many other knowledge management use cases.

Source: Gartner (March 2024)

Recommended by the Authors

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Table 2: Synergies Between GenAI and Other Techniques

Combination	Potential use cases of the combination
Nongenerative ML and GenAI models	Segmentation and classification: Pretrained GenAI foundation models can be used as a starting point to build a classifier model for specific applications, such as sentiment analysis, intent recognition, spam and fraud detection, image classification, and many others. This can be done either by using the GenAI model's outputs as features for a separate nongenerative model or by directly building a nongenerative model on top of a pretrained GenAI one (also known as "transfer learning," this requires access to the full GenAI model). Synthetic data: Synthetic data has been used as training data for supervised, nongenerative machine models for many years (see What Should I Know About Synthetic Data?). GenAI models are particularly useful to generate data for infrequent scenarios or to protect data privacy (by generating synthetic versions of real data). Examples include the training of predictive ML models for autonomous driving, object detection, robotics and many other applications. Computer vision: The integration of computer vision techniques with GenAI models facilitates natural language contextual search of unstructured image data and correlation of data on video streams at scale. This unlocks rich multimodal analytics and experiences (see Innovation Guide for Generative AI in Computer Vision).
Optimization/search and GenAI models	**Enterprise search:** GenAI models such as LLMs can be used to augment traditional enterprise search to make its interface more conversational and to improve its accuracy. LLMs can also be used as embedding models in

	support of vector databases and vector search (see How Generative AI Impacts Knowledge Management).
Simulation and GenAI models	**Simulation acceleration:** High-fidelity simulations can be resource-intensive. GenAI models can substitute parts of a traditional simulation without a need to run step-by-step calculations, accelerating simulations by orders of magnitude. This allows organizations to run simulations that would be too expensive or too slow to run otherwise, with applications in architecture and building design, material design, drug discovery, and weather prediction (see Innovation Insight: AI Simulation).
Graphs and GenAI models	**Knowledge management:** LLMs can be used to extract entities and relationships from unstructured text to populate a graph database. They can also be used to translate natural language questions into structure queries for graph databases. This makes the building and use of knowledge graphs easier for organizations, improving their knowledge management capabilities. Knowledge graphs act as the backbone of a number of products, including smart assistants, recommendation engines and enterprise search. Retrieval augmented generation: Graphs can be used to better ground LLMs by using graph databases as part of a data retrieval system and augmenting prompts with information coming from a curated knowledge graph (see AI Design Patterns for Knowledge Graphs and Generative AI).
Rule-based systems and GenAI models	**Chatbots:** Increasingly, chatbots are a mix of rule-based techniques and generative models, in addition to other ML models and data representation techniques such as graphs and ontologies. Chatbot architectures can leverage components, such as natural language understanding modules, that make use of sophisticated pipelines where several techniques, including rule-based and LLM-driven ones, are combined for entity extraction, intent

classification and other inferences that are fundamental for chatbots. LLMs are now leveraged for their speech-to-text, text-to-speech and translation capabilities in chatbots, often in conjunction with other techniques like rule-based systems.

Robo-advisors: A robo-advisor is a digital platform that provides automated financial planning services with little or no human supervision by collecting information from customers, offering advice and automatically investing assets. Most advanced robo-advisor implementations leverage a composable architecture and use a mix of retrieval-augmented generation (RAG) and rule-based techniques.

Specialized natural language generation: Platforms supporting natural language generation (NLG) for specific content production requirements (e.g., news articles, product description and marketing copies) are often leveraging both rule-based or data-driven approaches and, for more creative content types, LLMs and image generation models. Such NLG platforms provide rule-based controls for content generation that are customizable and transparent, and that are aimed to maximize quality and reduce the need for human review and postediting.

Source: Gartner (March 2024)

Table 3: Rationale for Generative Models' Usefulness for Different Use-Case Families

Use-case family	Generative models' current usefulness	Description and rationale for usefulness
Prediction/forecasting	Low	This use-case family leverages data and predictive analytics for accurate forecasting and precise prediction. Despite GenAI models' impressive capabilities, they fall short in making accurate predictions for real-world situations that necessitate probabilistic thinking. They are not currently designed to do the kind of numerical predictive and statistical modeling required for predicting a continuous variable. LLMs could be tangentially used to create features that could be useful in predictive tasks, but the prediction/forecasting itself would need to be done by an alternative AI technique.
Planning	Low	Optimization and planning techniques are vital for industries to improve efficiency, resource allocation and decision making. Planning and optimization are some of the key missing elements in current GenAI models. Attempts have been made to augment LLMs via prompt engineering or by embedding them into broader systems with an orchestration logic to help LLMs break down problems into tasks and execute them. However, this is far from the explicit

		optimization, search and planning that is already possible with other AI approaches. This limits GenAI models' utility for valuable use cases such as inventory optimization, field workforce scheduling, route optimization, financial portfolio optimization, pricing optimization in retail, and resource allocation. All of these use cases require exact calculations, which is not the current strength of generative models.
Decision intelligence	Low	Decision intelligence leverages AI techniques to augment organizations' decision making. This is a complex activity that requires an ability to model and choose between different courses of action to achieve a target outcome. Current GenAI models are not built for decision making. Their output is unreliable, they lack explainability and are not able to model decisions in an explicit way to achieve outcomes. It is risky for organizations to rely on GenAI outputs to make critical decisions, such as hiring/HR decisions, budget and financial planning, supply chain management, marketing allocation, and strategic decision making.
Autonomous systems	Low	An autonomous system is a system (such as a robot, a vehicle or a software agent) that is goal-oriented and acts on behalf of users, with minimum human intervention.

		GenAI models are not currently robust enough to be autonomous, requiring close human supervision, especially given the inaccuracies and hallucinations. Developers are pushing to build LLM-based agents, augmenting LLMs with external data and tools; this has resulted in early assistants such as Microsoft 365 Copilot. However, the current application of LLMs/other GenAI models for autonomous systems is limited to narrow domains and typically requires having a "human in the loop." This significantly limits the usefulness of GenAI for use cases such as industrial robotics, delivery drones, smart factories, algorithmic trading and autonomous vehicles.
Segmentation/classification	Medium	Segmentation and classification unlock valuable insights from complex datasets, which supports data-driven decision making. GenAI models can be used for classification. For example, LLMs can be used for classification tasks such as sentiment analysis via prompt engineering (e.g., few-shot learning). However, their performance in these tasks depends on whether their training data is informative enough to generate good classifications, as well as the additional context/examples that can be provided by the prompt. Overall, current GenAI models

		(LLMs and image generation) used in isolation are not ideal for many enterprise classification tasks, including for customer segmentation in retail, medical diagnosis in healthcare and credit risk assessment in finance.
Recommendation systems	Medium	Recommendation systems use AI techniques to predict items (products, content, actions, etc.) that are likely to be relevant for a user. LLMs and other GenAI models can be used as embedding models that capture the semantic content of data. These embedding models can potentially be used to find items (such as products, actions or users) that are similar to previous items that relate to the customer, which can then be used as part of a broader recommendation system. However, this is only an emerging approach, and there are other more established techniques, such as rule-based systems (collaborative filtering) and nongenerative ML approaches for use cases such as e-commerce, content, and product recommendations (e.g., next best actions, offers and so on)
Perception	Medium	Perception systems capture and digest different types of data, including audio, visual, language and other unstructured data. Emerging multimodal GenAI models that are trained with many of these modalities could

		become a key part of how GenAI-based systems perceive their environment (see Innovation Insight: Multimodal AI Explained) to enable use cases like visual search in e-commerce, production line inspection in manufacturing and closed-circuit TV (CCTV) video analytics.
Intelligent automation	Medium	Intelligent automation uses AI techniques to automate business or IT processes, thus accelerating speed, reducing cost and minimizing human errors. GenAI models can help perform tasks, such as optical character recognition, that can save human time and effort. LLMs can also serve as orchestrators of other components to automate tasks that once were not feasible. However, GenAI models suffer from hallucinations and inaccuracies, and they typically require direct human supervision, which limits their current potential for intelligent automation use cases such as automated claims processing.
Anomaly detection/monitoring	Medium	Anomaly detection identifies data points that deviate significantly from normal or expected behavior. GenAI models can be used for anomaly detection, especially when supervised learning approaches suffer from data class imbalance problems. For example, a variational autoencoder (VAE) can be

		used to learn the underlying distribution of the data and detect inputs that fall outside of this distribution, which may indicate the presence of anomalies. However, other AI techniques are more robust and widely used for anomaly detection use cases, including fraud detection in finance, fault/defect detection in manufacturing and attack detection in cybersecurity.
Content generation	High	This family of use cases leverages AI techniques to generate digital assets, such as text, images, video, audio, code, product designs and even multimodal data. Generative AI models can create new and unique outputs based on user or program input. These models are trained on representative (and often vast) data, and depending on the model and training data, they can generate text, code, images, audio, video or other data. There are other techniques, such as simulation, that can create new content, but GenAI models are widely used for use cases such as marketing materials generation (both text and images), code generation, video generation for media and entertainment, augmented product design, and digital human/avatar.
Conversational user interfaces	High	Conversational user interfaces (CUIs) are human-computer interfaces that enable natural language

		interactions for the purpose of fulfilling a request, such as answering a question or completing a task. Conversational UIs are one of the primary use cases for LLMs and GenAI. Many organizations and vendors are upgrading their existing conversational AI capabilities with new generative models. The flexibility of the new approaches may augment or even replace existing conversational approaches in coming years. Both internal and customer-facing applications will likely be updated with GenAI capabilities (see Impact of Generative AI on the Conversational AI Market).
Knowledge discovery	High	Knowledge discovery techniques are aimed at exploring, analyzing, describing and organizing content and data. LLMs and GenAI can facilitate knowledge capture, improve enterprise search capabilities, and extract data from documents and messages to produce new content (see How Generative AI Impacts Knowledge Management). This has applications in enterprise knowledge repositories, enterprise search, customer service, digital workplace, and drug discovery and clinical trials in life science manufacturing, as well as many other knowledge management use cases.

Source: Gartner (March 2024)