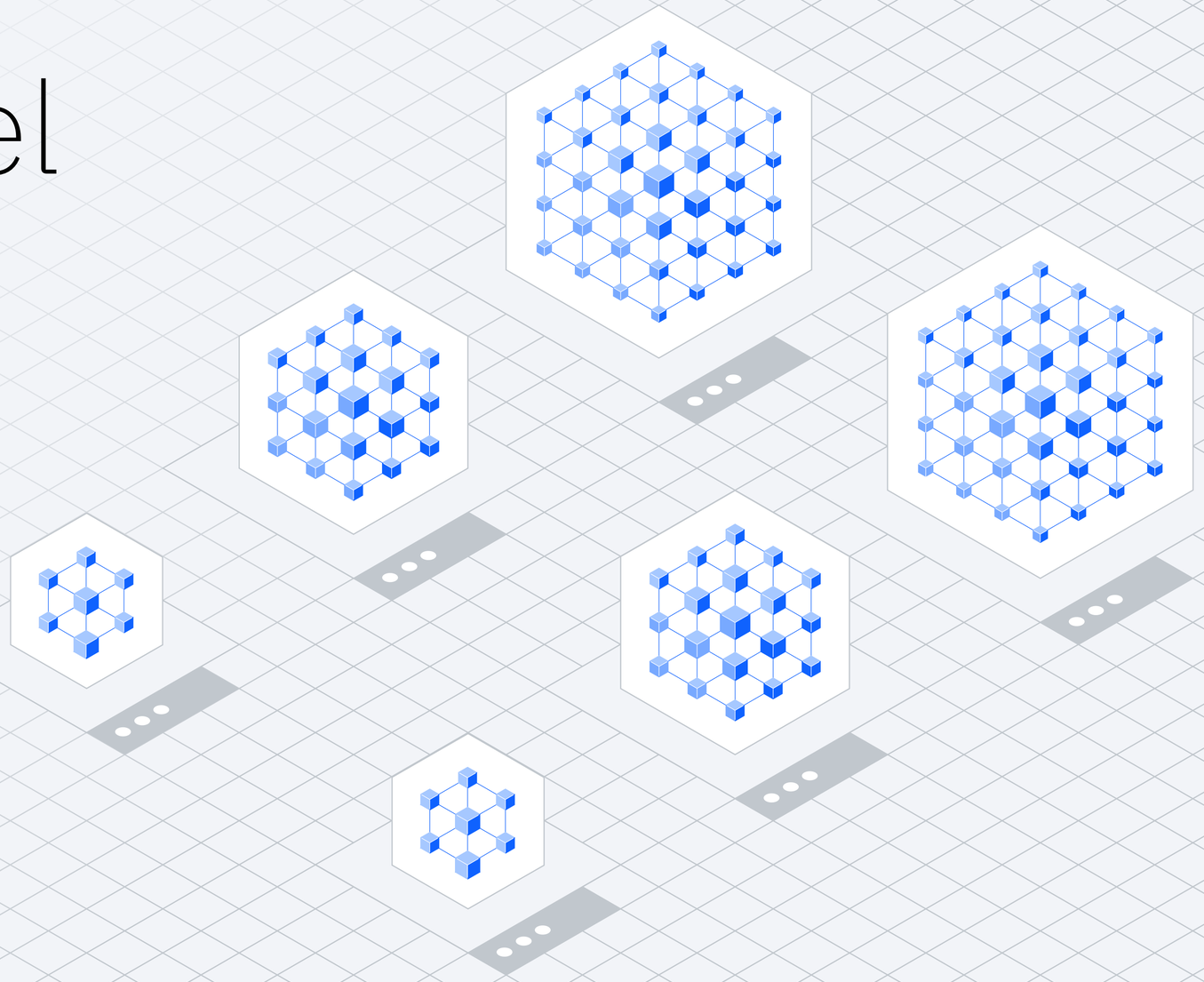
How to choose the right AI foundation model



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Introduction

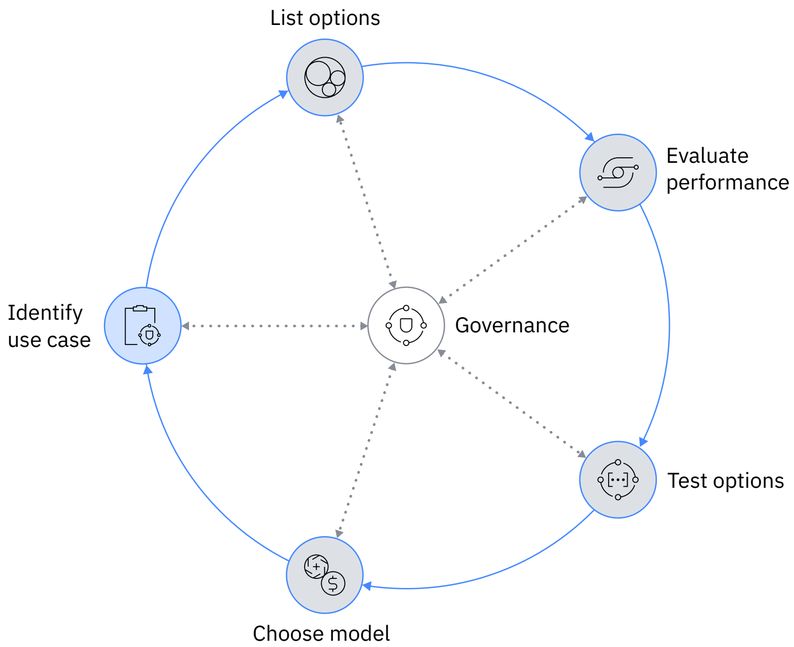
While most organizations are clear about the outcomes they expect from generative AI, what’s not so well understood is the way to go about realizing these outcomes. Different outcomes require different approaches—in terms of the datasets you prepare and the AI models you employ.

Choosing the right AI model can have a positive impact on your brand and your bottom line, speeding up innovation and improving performance for its particular use case. However, you need to be aware of the potential risks of choosing a model that isn't fit for your enterprise, risks that might be financial, strategic or legal.

An evaluation framework will help you consider the diverse needs and skill sets of all kinds of AI decision makers and users in your organization. The end users of AI models could range from data scientists and machine learning (ML) engineers to business analysts, legal and compliance teams, and decision-makers. It’s important to take all of their specific requirements into account so you can identify the right model for each use case and successfully implement AI to drive ROI.

AI model selection framework

This five-step cyclical process for model selection has governance at its core.



Clearly articulate your use case
Text generation, for example. Let's say you want the AI to write personalized emails for a sales or marketing campaign.

List all model options and identify each model's size, performance and risks
Let's compare two models designed for text generation for this example: A 70B general purpose large model and an 8B specialized general purpose model.

Evaluate model size, performance and risks
One of the downsides of the 70B general-purpose model is its slower speed. The 8B specialized model is faster and more cost-effective. In general, more parameters are tied to higher-quality outputs, but this can come with slower speed and higher costs. Depending on the use case, a small model can produce similar results to the larger model.

Test options
Select the model that's likely to deliver the desired output. Prompt to see if it works. Assess model performance and the quality of the output, using metrics such as perplexity or BLEU (Bilingual Evaluation Understudy) score. Try to achieve the same performance by customizing smaller models, using techniques such as prompt engineering, RAG or fine tuning. Add your datasets to the stack and prompt the models to improve accuracy.

Choose the option that provides most value
Whether you need high speed or high accuracy depends on the use case, your cost constraints and deployment methods. In the end you might select the 8B specialized model, because the most important aspect is generating text quickly.

In the following chapters, we'll examine in detail the key considerations for selecting an AI model: Use case, size, performance, risk, cost and deployment needs.

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Identify a clear use case

When assessing AI models, a key evaluation criterion is how well the model's functionalities intersect with your use case requirements.

The easiest way to identify the right model for your use case is to craft the prompt and ideal answer, and then work backward from there to find the data needed to provide the desired answer.

Work closely with the product and engineering teams and the business sponsors to understand the actual prompts you'd need to solve the business problems at hand. Factor in the specifics of your business—such as industry terminology and standard definitions—as part of the prompt experience and make the prompts as specific to the use cases as possible. Can you break down the use case into prompts? Can you build the particulars of your business into the prompts at multiple points?

All of this matters, because even subtle nuances in the prompts can make a big difference when it comes to selecting a very specific model. To illustrate this point, consider the prompt, "Give me John Doe's ID number." In an HR function, it would mean the employee ID, but in customer service it could be the customer loyalty number. So, the more specific the prompt is, the more accurate the response. And a more specific prompt could lead you to selecting a model that already knows how to distinguish between different personal IDs without needing any additional training.

Finding the right fit
When evaluating whether a model is right for you, review the model card to see if there's a model that has been trained on data specifically for your purpose. Pretrained foundation models are fine tuned for specific use cases, such as sentiment analysis or document summarization, enabling your team to use zero-shot prompting to obtain the desired results. This approach also allows for rapid experimentation with targeted, domain-specific models. Because it takes less internal training and expertise to adapt the models to your needs, you can achieve accelerated time to value and build competitive advantage.

The most dominant generative AI use cases in the enterprise, according to Menlo Ventures[1]:

- Code generation (51%)
- Support chatbots (31%)
- Enterprise search and retrieval (28%)
- Data extraction and transformation (27%)
- Meeting summarization (25%)

Functions with the most advanced generative AI initiatives, according to Deloitte[2]:

- IT (28%)
- Operations (11%)
- Marketing (10%)
- Customer service (8%)
- Cybersecurity (8%)
- Product development (7%)
- R&D (6%)
- Sales (5%)
- Strategy (5%)
- Supply chain (4%)

Ask yourself: Do I need a massive model to execute my task?

The answer, in most cases, is no. The better approach is to right-size the model for the specific use case you have.

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Evaluate size, performance and risks

Right-sizing a model to your use case

AI models with more parameters need more processing power, cost more to run, take longer to provide an output and, depending on the use case, aren't always more accurate. So, the question you have to ask yourself is, do I need a massive model to execute my task? The answer, in most cases, is no.

The best approach here is to right-size the model for the specific use case you have. Start out with the biggest or the best-performing model and use a basic prompt to get your ideal performance. Now scale down to a smaller model and customize it with fine tuning, prompt tuning, retrieval-augmented generation (RAG), and enhancement in InstructLab (with taxonomy-driven data curation, large-scale synthetic data generation and a multiphase tuning framework) to see if you can get the same results.

Prompt tuning involves designing and optimizing input prompts to steer the model's responses without modifying its weights. It's different from fine tuning, because the latter implies adapting a pretrained model for specific tasks or use cases. This technique adjusts the model's weights by training on task-specific data, creating a specialized version of the base model.

RAG is an architecture for optimizing the performance of an AI model by connecting it to external knowledge bases and retrieving relevant documents at inference time.

InstructLab is created for instruction tuning, involving a structured approach to fine tuning by using diverse tasks-specific instructions. This can improve generalization across multiple tasks with minimal examples.

Evaluating model performance

When evaluating a model for performance, the key criteria are accuracy, reliability and speed. The weightage accorded to each of these criteria varies from one use case to another. A trade-off between these factors is often necessary, depending on the specific needs of the use case.

Accuracy
Accuracy denotes how close the generated output is to the desired output and can be measured objectively and repeatedly. It's the primary way of evaluating a model—against industry benchmarks. Choose evaluation metrics that are relevant to your use cases. For instance, content summarization or RAG performance can be assessed by ROUGE (Recall-Oriented Understudy for Gisting Evaluation) while BLEU indicates the quality of text translation.

Reliability
Reliability is a measure of how best the model generates the same output. It's a function of several factors, such as consistency, explainability and trustworthiness, as well as how well a model avoids toxicity (hate speech, harmful language) and bias. It's a crucial consideration, especially in the case of external-facing applications. Typically, a model that offers transparency into its training methodology and data tends to be more reliable as it addresses key issues, including governance, risk and privacy concerns.

Speed
Speed is about how quickly a user gets an answer to a question. It's especially critical in the case of real-time applications that demand a low-latency response. Consider use cases ranging from chatbots to financial trading—where timely answers can make all the difference—compared to financial forecasting where accuracy is more important. The speed versus accuracy trade-off is a crucial consideration here and prioritizing one factor over the other is a decision that's dependent entirely on the use case at hand.

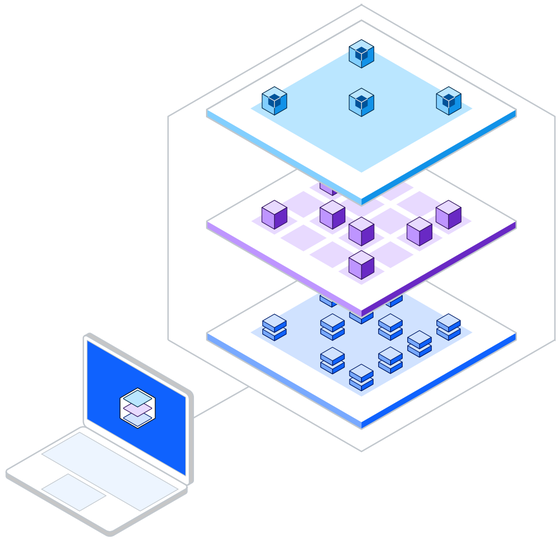
Evaluating risks and governance

For any organization, data privacy and security are key considerations, irrespective of the use case. Similarly, transparency and traceability of the training data and accuracy and reliability of the output—which should be free of bias, toxicity and hallucination—are all crucial aspects in model selection.

As a result, AI governance applies throughout the whole selection process—from performance evaluation and optimization through customization to validation and cost control. It's that one essential ingredient you need to select the right model for your use case with attributes such as risk, transparency, reliability and trustworthiness, and it should remain an ongoing effort as the model goes through continuous monitoring and evaluation.

In almost all use cases, full transparency into the training methodology is critical to enable responsible deployment of the models and to address key issues including governance, risk assessment, privacy concerns and bias mitigation. A model that's highly transparent will enable users to achieve greater reliability and trustworthiness as they can easily monitor and optimize for performance and operational risks.

Lastly, if there are data gaps in your ecosystem or data privacy risks based on your use case, you'll want to look for a model that can generate synthetic tabular data to help address the gaps and enable users to adapt the model with minimal risk to privacy or of bias.



US Open managed to scale the productivity of their editorial team and to offer a world-class digital experience for more than 15 million fans around the globe with the help of AI-powered IBM solutions.[3]

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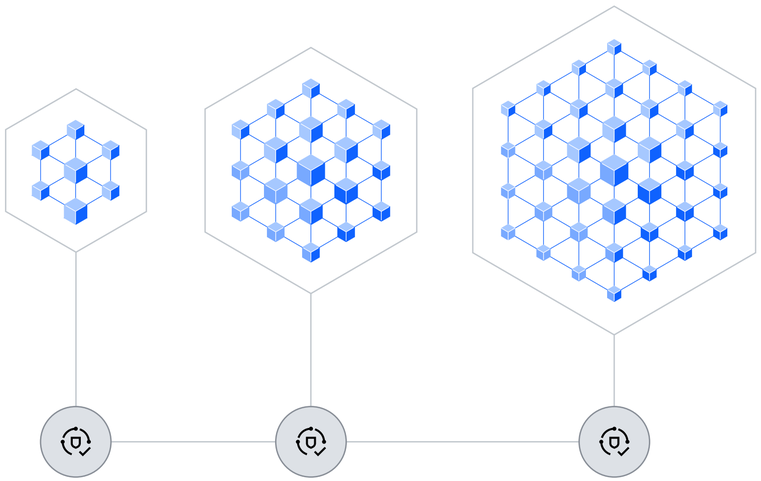
Refine selection based on cost and deployment needs

In model selection, while the key criteria are the use case, the size and performance of the model and the mode of deployment, there's a common throughline of costs and ROI.



Typically, the objective is not just about accomplishing task accuracy, it's also about figuring out the practicalities of ROI and cost effectiveness. The cost factor is important as you discern between models. A more expensive, larger model might be slightly more accurate than a significantly smaller, less expensive one. However, the question is, will the expensive model provide you the ROI to justify its use for that particular use case? The answer isn't always yes.

It really comes down to finding the sweet spot between performance, speed and cost. A smaller, less expensive model might not offer performance or accuracy metrics on par with an expensive one, but it would still be preferable over the latter if you consider any additional benefits the model might deliver, such as lower latency and greater transparency into the model inputs and outputs.

For example, the smaller model could be scaled across your organization for multiple use cases, increasing its overall value. On the flip side, if your use case requires a high degree of accuracy and precision in your outputs, you might opt for the larger model. However, there's a point at which you might hit diminishing returns with ROI, so in the end it's a game of trade-offs.

Another way to approach the size versus performance trade-off is to use customization techniques on a smaller model to achieve the same or better results than on a larger, more expensive model. Prompt tuning is an efficient, low-cost method of adapting a model to a specific use case, because it doesn't require retraining the model and can be performed using your existing resources.

Lastly, one other critical factor that influences overall costs and energy consumption is the model deployment method and the corresponding infrastructure and GPU requirements.

LLMs, no doubt, are resource intensive. So, how do you incorporate these models into your business without substantially impacting your ESG goals? It's important to consider how the models can be deployed sustainably to keep the total cost of ownership lower.

The deployment decision
Another important consideration in evaluating model selection costs is where and how you want the model and data to be deployed. The AI models you select should be compatible with your applications, existing vendor and partner footprint, and your overall AI and data platform—whether it's on premises, in the cloud or in a hybrid environment.

For example, you might want to work with an open-source model like IBM® Granite®, Meta Llama or Mistral AI models. If you've customized it with your own enterprise data, though, you might need to deploy it on premises. Open-source models offer the freedom to choose your deployment location, be it on premises, in private cloud or public cloud environments, or at the edge. If you'd rather deploy on premises, take smaller models into consideration, because they're more efficient due to lower resource requirements. So, when deciding on the right model and deployment method, it all comes down to balancing the performance, security and governance aspects of the model.

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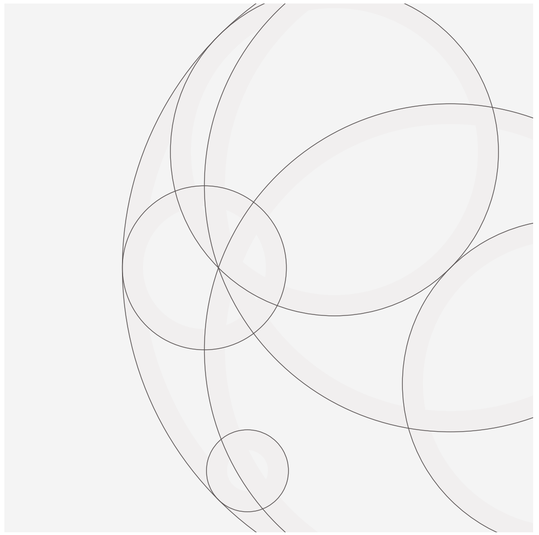
How an AI and data platform helps

To harness the true potential of AI, enterprises should stop looking at AI as an add-on to existing systems, and instead embed it into the core of their business.



There are several challenges to implementing AI, ranging from data quality and availability to data security and privacy, interoperability with existing systems, scalability for enterprise-wide adoption and, of course, cost. While selecting a model, how do you monitor its accuracy and trustworthiness—especially if it's a closed, proprietary model? What can you do to minimize the cost and energy consumption of large-scale models? How do you make your AI responsible, transparent and explainable?

To address these concerns and to drive AI adoption enterprise wide, you need the right AI and data platform. IBM watsonx® is an end-to-end AI and data platform that enables you to scale and accelerate the impact of AI with trusted data.

With watsonx, you can train, tune and deploy AI across your business, using critical data wherever it resides. The core components of the watsonx AI and data platform include:

- IBM watsonx.ai®, a studio for foundation models, generative AI and machine learning. The watsonx.ai studio offers a variety of foundation models—including proprietary, open source and third party.
- IBM watsonx.data®, a fit-for-purpose data store built on an open data lakehouse architecture.
- IBM watsonx.governance®, a solution that provides organizations with the toolkit they need to manage risk, embrace transparency and anticipate compliance with future AI-focused regulation.

The watsonx.ai studio is designed for a multi-model approach. To make the selection and scaling of models easier, the studio offers a hybrid, full-stack approach that includes:

- Library with open-source models, either from third-party providers or from the IBM Granite family
- Prompt lab to experiment with foundation models and build prompts for various use cases and tasks
- Tuning studio to help tune your foundation models with labeled data for better performance and accuracy
- Data science and MLOps toolkit to build ML models automatically with model training, development, visual modeling and synthetic data generation

The watsonx.ai studio offers a variety of model sizes trained to serve multiple use cases. These models can be deployed on premises, in the cloud or in a hybrid environment, providing great flexibility. You can explore the benefits of working with the studio, the foundation models currently available and their specific use cases.

Explore foundation models within the watsonx platform →

Discover the IBM Granite models →

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Conclusion

Not all AI models are the same, and neither are your use cases.

Each specific use case demands an AI model that's a right match, which explains why a multi-model approach is pivotal to achieving success with generative AI. Ultimately, you need trusted, performant and cost-effective foundation models that enable you to optimize for various parameters, such as cost, performance and risk, based on your use cases.

With the flexibility to curate the right model mix, you can:

- **Reduce the total cost of ownership** across model training, inferencing, tuning, hosting, compute and production.
- **Optimize compute and costs** as well as scalability of models across use cases and domains for optimal ROI.
- **Make use of intuitive interfaces** that facilitate human-in-the-loop learning to improve the relevancy and accuracy scores and the performance of models based on your needs.
- **Choose models that provide transparency** into the training methodology and offer contractual IP protection to enable responsible deployment and use.
- **Curate models with built-in guardrails** and establish best practices to address key issues, including governance, risk assessment, privacy concerns and bias mitigation—and deliver outputs that can be trusted for optimal performance, accuracy, safety and reliability.

Adoption of generative AI can shape business strategy, product roadmaps, talent management, customer experiences and several other areas of business. However, model selection and optimization are by no means a one-and-done process. It’s important that you continually revisit each AI use case in terms of relevancy, model size and performance, and deployment methods to achieve optimal ROI and business outcomes.

Next steps
The AI and automation experts at IBM can work with you to curate an AI model mix—and operationalize models—to address your specific use cases and business requirements. You can start by learning more about the models offered on the watsonx.ai studio and the advantages of choosing IBM watsonx, the end-to-end AI and data platform that’s built for business.

Discover IBM Granite →
Learn more about watsonx.ai →

1. 2024: The State of Generative AI in the Enterprise, Menlo Ventures, November 2024.

2. Now Decides Next: Generating a New Future, Deloitte, January 2025.

3. Acing the US Open Digital Experience, IBM, 2024.