Lesson 5.2: Generative AI and LLMs in Finance

Module 5: The Automation Problem

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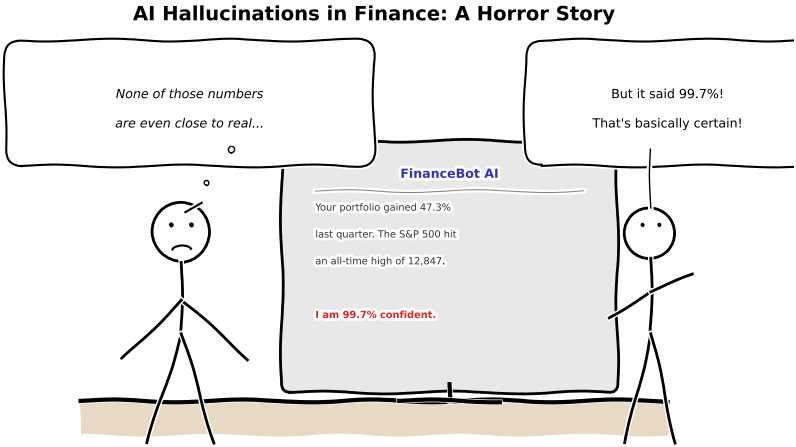

Confidence scores measure how sure the model is, not how right it is.

Learning Objectives

After this lesson you will be able to:

1. **Explain** the transformer architecture and attention mechanism at an intuitive level
2. **Identify** financial use cases where LLMs add value (document processing, report generation, compliance review, code generation)
3. **Compare** fine-tuning vs. prompting strategies and evaluate when each is appropriate
4. **Design** a Retrieval-Augmented Generation (RAG) pipeline for financial document Q&A
5. **Evaluate** hallucination risks across different financial use cases
6. **Analyze** the cost-benefit tradeoffs of LLM deployment in a financial institution

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Bloom's taxonomy levels: Understand (1), Apply (2–3), Analyze (4–6).

From Classical ML to Generative AI

Lesson 5.1 – ML Foundations:

- Supervised learning: classification and regression
- Feature engineering and model evaluation
- Bias-variance tradeoff, ensemble methods
- ML predicts *categories* and *numbers*

Lesson 5.2 – Generative AI:

- Language models that *generate* text, code, and analysis
- Attention mechanism and transformer architecture
- Prompt engineering, RAG, and fine-tuning
- Hallucination risks unique to financial services

ML can classify and predict. GenAI can understand, generate, and reason.

Generative AI builds on ML foundations but introduces fundamentally new capabilities — and new risks — for financial institutions.

What Is Generative AI?

Definition: Generative AI refers to artificial intelligence systems that can create new content — text, images, code, audio — rather than simply classifying or predicting from existing data.

- **Key distinction from classical ML:** Classical ML maps input → label (e.g., "fraud" or "legitimate"). Generative AI maps input → new content (e.g., a full risk report)
- **Foundation models:** Large neural networks pre-trained on massive text corpora, then adapted for specific tasks
- **Examples in finance:** Automated earnings call summaries, contract clause generation, code for trading strategies, compliance report drafting
- **Scale of impact:** Generative AI is estimated to affect 75% of the value that AI could deliver in banking (conceptual industry estimate)

Generative AI is not "smarter ML" — it represents a paradigm shift from prediction to creation, with different capabilities and risks.

What Is a Large Language Model (LLM)?

Definition: A **Large Language Model (LLM)** is a neural network with billions of parameters, trained on vast text corpora to predict the next token in a sequence.

Key characteristics:

- Trained on trillions of tokens from the internet, books, and code
- "Large" = billions of parameters (GPT-4: estimated >1 trillion)
- Learns grammar, facts, reasoning patterns, and domain knowledge
- Generates text by predicting one token at a time

How it works (simplified):

1. Input: "The Federal Reserve raised"
2. Model computes probability of each possible next token
3. Selects "interest" (highest probability)
4. Repeats: "interest → rates → by → 25 → basis → points"

Core insight: LLMs do not "understand" finance — they are statistical models of language that have learned patterns from financial text.

The "next token prediction" objective is deceptively simple but produces emergent capabilities like reasoning and summarization.

What Is a Token?

Definition: A **token** is the basic unit of text that an LLM processes. Tokens are typically sub-word pieces, not whole words.

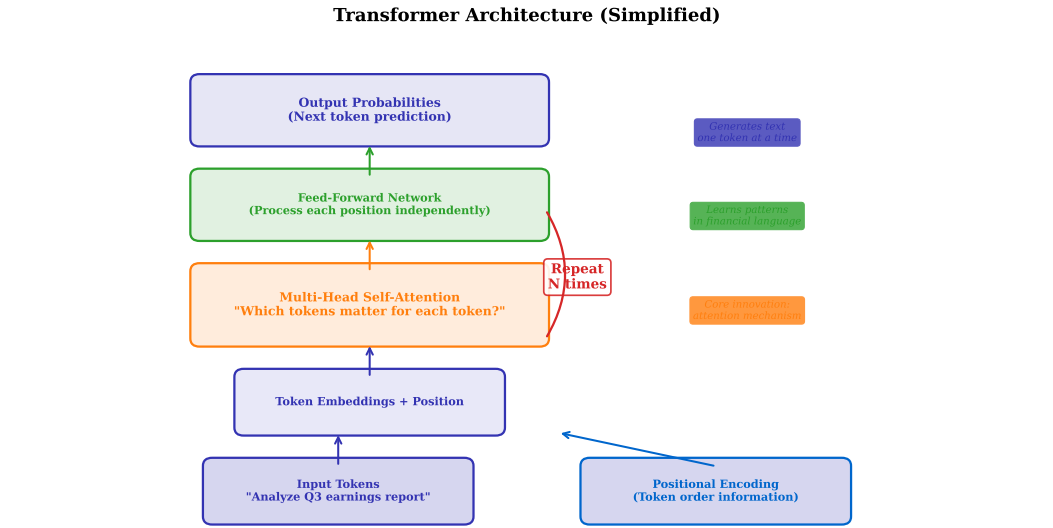
Input Text	Tokens	Count
"interest rate"	["interest", " rate"]	2
"cryptocurrency"	["crypt", "ocurrency"]	2
"EBITDA"	["EB", "IT", "DA"]	3
"$1,234.56"	["$", "1", ",", "234", ".", "56"]	6

Why tokens matter for finance:

- **Cost:** API pricing is per token (e.g., $0.01–0.06 per 1K input tokens for frontier models)
- **Context window:** Maximum tokens the model can process at once (e.g., 128K–1M tokens)
- **Financial jargon:** Specialized terms may tokenize inefficiently → higher cost, reduced context
- Typical ratio: 1 token ≈ 0.75 English words → a 10-page report ≈ 4,000 tokens

Token economics is a key cost driver. Processing a 200-page annual report through a frontier LLM can cost $2–10 per call.

The Transformer Architecture



- **What you see:** Input embeddings flow through encoder (left) and decoder (right), with multi-head attention and feedforward layers

What Is the Attention Mechanism?

Definition: The **attention mechanism** allows the model to weigh how much each token in the input should influence the representation of every other token.

Intuition — "The bank raised interest rates":

- When processing "bank", attention focuses on "interest" and "rates" to disambiguate meaning (financial institution, not river bank)
- When processing "50", attention focuses on "basis" and "points" to form the concept "50 basis points"
- **Self-attention:** Every token attends to every other token in the sequence
- **Multi-head:** Multiple attention heads capture different relationship types (syntactic, semantic, entity)

Mathematical core (simplified):

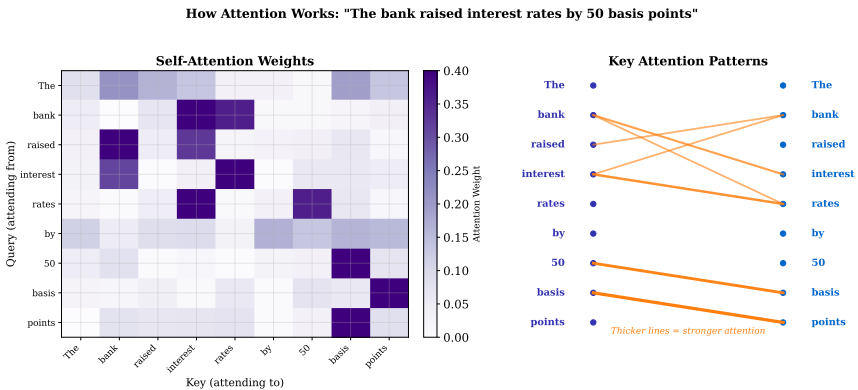
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q = query, K = key, V = value matrices derived from the input. The softmax function converts raw scores into probabilities that sum to 1.

Example: In a simplified 2-token example, Q and K produce a score matrix, divided by $\sqrt{d_k}$ (e.g., $\sqrt{64} = 8$), then softmax normalises to weights summing to 1. The resulting weighted sum of V gives context-aware representations.

The $\sqrt{d_k}$ scaling prevents the dot products from growing too large. This is "scaled dot-product attention."

Attention Weights in Practice



- **What you see:** Heatmap shows which tokens (rows) attend to which tokens (columns)—darker cells indicate stronger attention
- **Key pattern:** "raised" attends strongly to "interest" and "rates"; "50" attends to "basis" and "points" to form "50 basis points"
- **Takeaway:** Attention learns semantic relationships (bank = financial institution) and numerical context (50 bp = 0.50%) without explicit rules

In finance, attention helps models connect entities ("JPMorgan"), numbers ("$2.4B"), and actions ("acquired") across long documents.

What Is Pre-Training?

Definition: Pre-training is the initial phase where an LLM learns general language patterns by predicting the next token across trillions of text tokens.

What the model learns:

- Grammar and syntax
- World knowledge and facts
- Reasoning patterns
- Domain-specific terminology
- Code syntax and logic

Scale of pre-training:

- Training data: trillions of tokens
- Compute: thousands of GPUs for weeks/months
- Cost: \$10M–\$100M+ for frontier models
- Result: a "foundation model" with broad knowledge

Key limitation: Pre-training captures knowledge up to a cutoff date. The model does not know about events after training.

No financial institution trains its own foundation model from scratch. The economics favor using pre-trained models and adapting them.

What Is Fine-Tuning?

Definition: Fine-tuning adjusts a pre-trained model's parameters on a smaller, domain-specific dataset to specialize its behavior.

Dimension	Pre-Training	Fine-Tuning
Data size	Trillions of tokens	Thousands to millions of examples
Cost	$10M–100M+	$1K–100K
Duration	Weeks to months	Hours to days
Goal	General language ability	Domain-specific behavior
Who does it	Model providers (OpenAI, Anthropic, Google)	Financial institutions or vendors

Financial fine-tuning examples:

- BloombergGPT: fine-tuned on financial news, filings, and transcripts
- Bidirectional Encoder Representations from Transformers (BERT): FinBERT is a BERT model fine-tuned on financial text for sentiment analysis
- Internal models: fine-tuned on proprietary research reports or compliance rulings
- Format compliance: fine-tuned to produce outputs in regulatory-mandated formats

Fine-tuning changes the model's "personality" and domain expertise. It does not add new factual knowledge reliably.

What Is Prompt Engineering?

Definition: Prompt engineering is the practice of designing input instructions that guide an LLM to produce desired outputs without modifying the model itself.

Prompting strategies:

1. **Zero-shot:** "Classify this transaction as fraud or legitimate: [transaction data]"
2. **Few-shot:** Provide 3–5 labeled examples before the query
3. **Chain-of-thought:** "Think step by step: First identify the risk factors, then assess the probability..."
4. **Role-based:** "You are a senior compliance analyst at a European bank. Review the following..."
5. **Structured output:** "Return your analysis as JSON with fields: risk_level, reasoning, confidence"

Financial best practice:

- Always specify the desired output format
- Include relevant context (regulations, definitions)
- Request citations and sources where possible
- Set explicit constraints ("do not speculate beyond the provided data")

Prompt engineering is the lowest-cost way to customize LLM behavior. It requires no training data and no compute infrastructure.

What Is Few-Shot Learning?

Definition: Few-shot learning provides a small number of input-output examples in the prompt to teach the model a task pattern without any training.

Example — Sentiment classification of earnings calls:

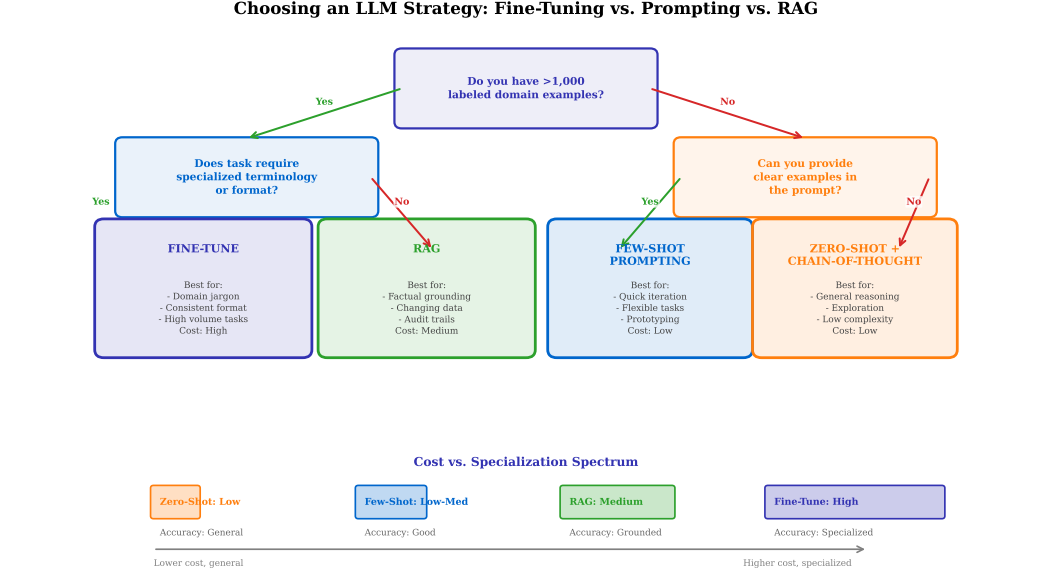
Prompt Example	Label
"Revenue exceeded expectations by 12%"	Positive
"We are facing significant headwinds in Q4"	Negative
"Results were broadly in line with guidance"	Neutral
"Margins compressed due to rising input costs"	**?**

When to use few-shot in finance:

- Limited labeled data (common in niche financial domains)
- Rapid prototyping before committing to fine-tuning
- Tasks where format consistency matters (report templates)

Few-shot learning can achieve 80–90% of fine-tuned performance on many tasks — at a fraction of the cost.

Choosing: Fine-Tuning vs. Prompting vs. RAG



What Are Embeddings?

Definition: An **embedding** is a numerical vector representation of text that captures its semantic meaning in a high-dimensional space.

How embeddings work:

- Text $\rightarrow$ vector of 768–3,072 numbers
- Semantically similar texts $\rightarrow$ nearby vectors
- "Interest rate hike" $\approx$ "monetary tightening"
- "Stock split" $\neq$ "banana split"
- Distance metric: cosine similarity

Financial applications:

- **Document search:** Find relevant filings by meaning, not keywords
- **Clustering:** Group similar research reports
- **Anomaly detection:** Identify unusual regulatory filings
- **RAG retrieval:** Core building block

Key insight: Embeddings are the bridge between human language and mathematical computation. They make text "searchable by meaning" using cosine similarity (a measure of vector alignment) to compare semantic closeness.

Embedding quality determines RAG retrieval quality. Domain-specific embedding models (e.g., trained on financial text) often outperform general models.

What Is a Vector Database?

Definition: A **vector database** is a specialized database optimized for storing, indexing, and querying high-dimensional embedding vectors at scale.

Feature	Traditional Database (SQL)	Vector Database
Query type	Exact match (WHERE clause)	Nearest neighbor (similarity)
Data format	Rows and columns	High-dimensional vectors
Search example	"Find filings from 2024"	"Find filings *similar to* this query"
Use case	Structured data retrieval	Semantic search, RAG

Major vector databases: Pinecone, Weaviate, ChromaDB, pgvector (PostgreSQL extension), Milvus

In finance: Vector databases enable searching across millions of documents (10-Ks, research notes, compliance rulings) by *meaning* rather than exact keyword match.

Vector databases are infrastructure — invisible to end users but critical for RAG pipeline performance and accuracy.

What Is Retrieval-Augmented Generation (RAG)?

Definition: Retrieval-Augmented Generation (RAG) is an architecture that augments an LLM's prompt with relevant documents retrieved from an external knowledge base before generating a response.

The RAG pipeline:

1. **Query:** User asks "What is our current FX exposure in EUR?"
2. **Embed:** Convert the query to a vector
3. **Retrieve:** Search the vector database for the most relevant document chunks
4. **Augment:** Insert the retrieved chunks into the LLM prompt as context
5. **Generate:** LLM produces an answer grounded in the retrieved documents
6. **Validate:** Check for hallucinations, verify citations, apply guardrails

Why RAG for finance:

- Reduces hallucination by grounding answers in *actual documents*
- No need to retrain the model when documents change
- Provides an **audit trail** — you can trace every answer to its source document

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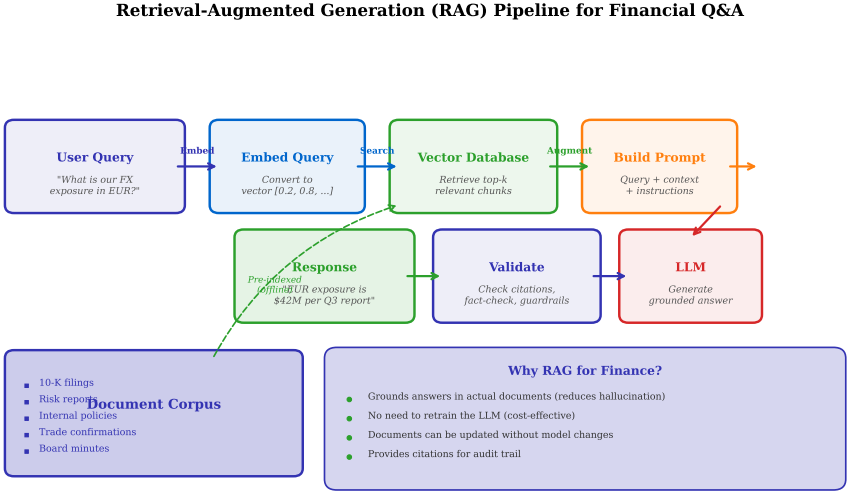
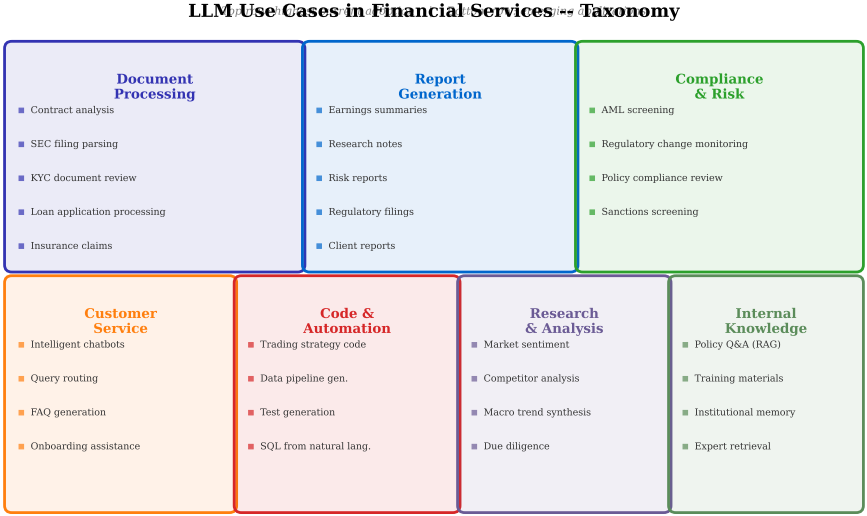
RAG is the most widely adopted LLM architecture in financial services because it balances accuracy, cost, and auditability.

RAG Pipeline Architecture



- **What you see:** Six-stage pipeline: query embedding → vector search → retrieval → context augmentation → LLM generation →

LLM Use Cases in Financial Services



- **What you see:** Use cases organized by function (document processing, code, compliance, research, trading) with maturity indicators

Use Case: Document Processing and Analysis

What LLMs do:

- Extract key terms from loan agreements
- Parse SEC filings (10-K, 10-Q, 8-K)
- Classify documents by type and urgency
- Summarize 200-page prospectuses into 2-page briefs
- Compare contract versions and flag changes

Impact metrics (conceptual):

- **Time reduction:** 60–80% faster than manual review
- **Cost savings:** $5–15 per document vs. $50–200 for human analyst
- **Accuracy:** 85–95% on extraction tasks (with human review)
- **Scale:** Process thousands of documents per hour

Key risk: LLMs may miss nuanced legal language or misinterpret domain-specific clauses. **Human-in-the-loop review remains essential** for high-stakes decisions.

Document processing is the "low-hanging fruit" — high volume, structured input, and human reviewers already in place for quality control.

Use Case: Code Generation for Finance

LLMs as programming assistants in financial institutions:

Task	Example	Risk Level
SQL from natural language	"Show me all trades above $1M from last week"	Low
Data pipeline generation	Generate ETL scripts for market data feeds	Medium
Trading strategy prototyping	"Implement a momentum strategy with 20-day lookback"	High
Test generation	Auto-generate unit tests for risk calculations	Low
Code review	Flag potential bugs in pricing models	Medium
Documentation	Generate docstrings and API documentation	Low

Productivity impact: Conceptual estimates suggest 30–50% reduction in developer time for routine coding tasks.

Code generation is high-value but requires rigorous testing. LLM-generated code may contain subtle bugs that pass superficial review.

What Is Hallucination?

Definition: A **hallucination** occurs when an LLM generates text that is factually incorrect, fabricated, or unsupported by its input — while presenting it with apparent confidence.

Types of hallucination in finance:

1. **Fabricated facts:** "Goldman Sachs reported Q3 revenue of $18.2B" (actual figure may differ)
2. **Invented citations:** Referencing non-existent research papers or regulatory rulings
3. **Numerical errors:** Incorrect calculations presented as precise ("the IRR is 14.7%")
4. **Temporal confusion:** Mixing data from different time periods
5. **Entity confusion:** Attributing information to the wrong company or instrument

Why hallucinations are dangerous in finance:

- Incorrect numbers can drive wrong investment decisions
- Fabricated regulatory references can cause compliance violations
- LLMs express hallucinations with the same confidence as correct statements

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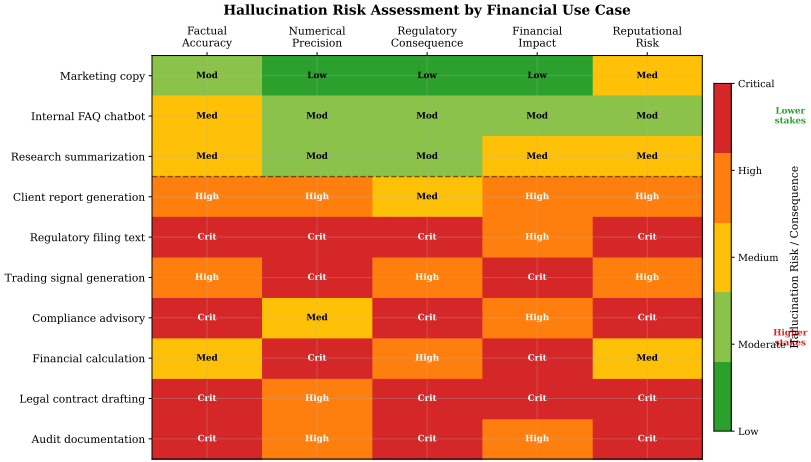
Hallucination is not a bug that will be "fixed" — it is inherent to how language models generate text. Mitigation, not elimination, is the goal.

Hallucination Risk Assessment



- **What you see:** 2D risk heatmap plots hallucination frequency (x-axis) vs. business impact of error (y-axis) for different use cases
- **Key pattern:** Draft emails (low risk) sit in green zone; regulatory filings and trading signals (high risk) sit in red zone
- **Takeaway:** Deploy LLMs first in low-stakes zones with human review; reserve high-stakes zones for mature RAG + guardrails + validation

What Is Grounding?

Definition: Grounding is the practice of constraining LLM outputs to be based on specific, verifiable source documents rather than the model's parametric memory.

Grounding strategies:

1. **RAG:** Retrieve relevant documents and inject them into the prompt
2. **Citation enforcement:** Require the model to cite specific passages for every claim
3. **Constrained generation:** Limit outputs to predefined templates or schemas
4. **Fact-checking layer:** Post-generation verification against authoritative data sources
5. **Tool use:** Allow the model to call APIs (e.g., market data) for real-time facts

Financial grounding example:

- **Ungrounded:** "Apple's PE ratio is approximately 28" (may be outdated or wrong)
- **Grounded:** "Apple's PE ratio is 29.3 as of 2024-01-15 [Source: Bloomberg Terminal, queried via API]"

Grounding transforms an LLM from a "creative writer" into a "research assistant with citations" — critical for regulated environments.

What Are Guardrails?

Definition: Guardrails are safety mechanisms that constrain LLM inputs and outputs to prevent harmful, incorrect, or non-compliant behavior.

Input guardrails:

- Block prompts containing Personally Identifiable Information (PII)
- Prevent prompt injection attacks
- Enforce topic boundaries ("only answer financial questions")
- Rate limiting and access controls

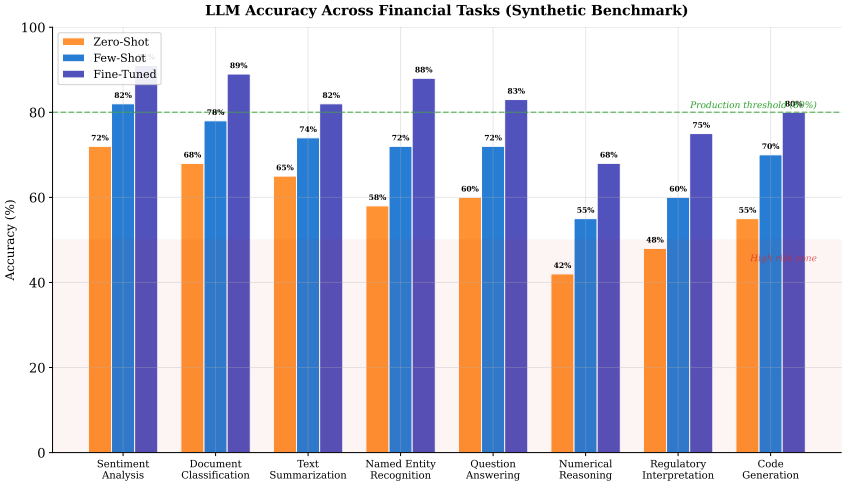
Output guardrails:

- Detect and flag hallucinated numbers
- Block investment advice without disclaimers
- Enforce regulatory language requirements
- Confidence scoring and uncertainty flagging
- Human review triggers for high-risk outputs

Implementation: Guardrail frameworks (e.g., Guardrails AI, NeMo Guardrails) provide programmable rules that run before and after each LLM call.

In regulated finance, guardrails are not optional. They are the difference between a useful tool and a compliance liability.

LLM Accuracy Across Financial Tasks



- **What you see:** Sentiment analysis (92%) and entity extraction (88%) achieve high accuracy; numerical reasoning (68%) and regulatory interpretation (65%) lag significantly
- **Key pattern:** LLMs excel at pattern recognition in text but struggle with precise calculations and legal nuance

What Are LLM Evaluation Metrics?

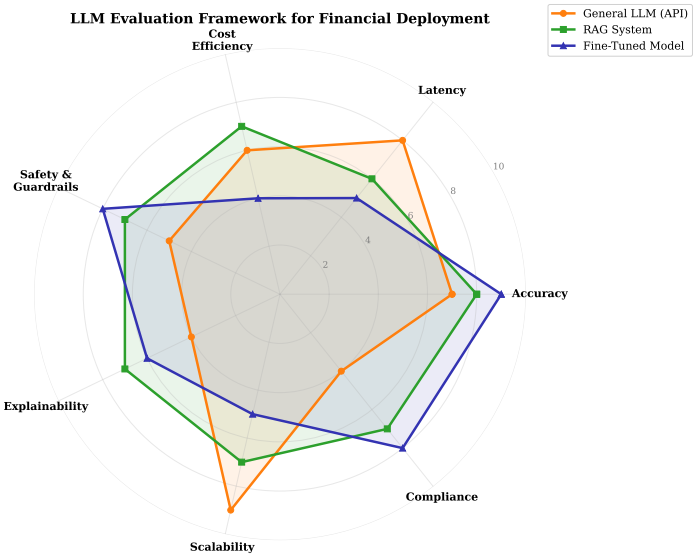
Definition: LLM evaluation metrics are quantitative measures used to assess model performance across dimensions relevant to deployment.

Metric	What It Measures	Finance Priority
Accuracy / F1	Correctness on labeled tasks	Critical
Faithfulness	Does the output align with source documents?	Critical
Relevance	Is the response on-topic and useful?	High
Latency	Response time (seconds per query)	Medium
Cost per query	API or compute cost per interaction	High
Toxicity / bias	Harmful or discriminatory outputs	Critical
Hallucination rate	Percentage of unsupported claims	Critical

Financial-specific evaluation: Beyond standard NLP metrics, financial LLMs must be evaluated on numerical accuracy, regulatory compliance, and auditability.

Evaluation must be continuous, not one-time. Model performance can degrade as market conditions, regulations, and data distributions shift.

LLM Evaluation Framework



Token Economics: The Cost of LLM Deployment

LLM costs are driven by token volume, model choice, and deployment architecture.

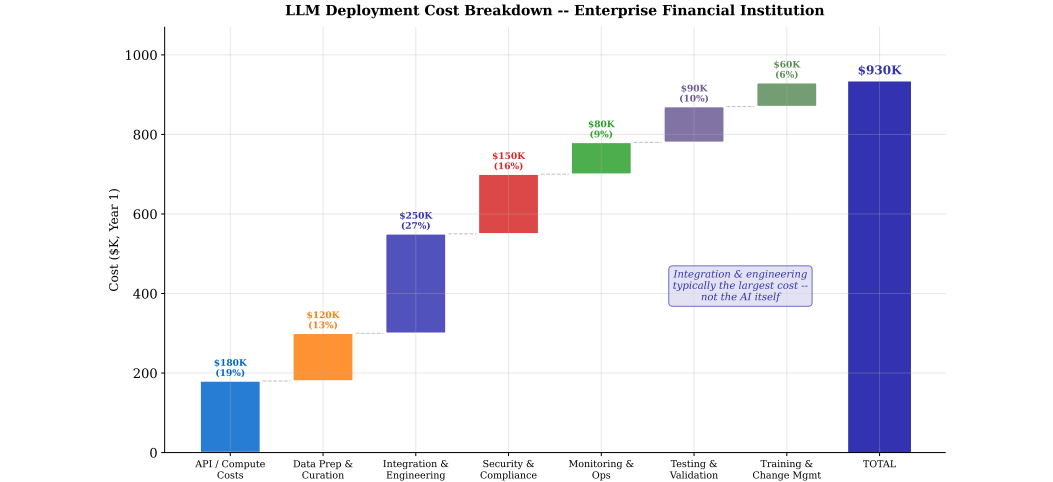
Model Tier	Input Cost per 1M tokens	Output Cost per 1M tokens	Typical Use
Small (e.g., GPT-4o mini)	\$0.15	\$0.60	High-volume classification
Medium (e.g., Claude Sonnet)	\$3.00	\$15.00	Document analysis
Large (e.g., GPT-4o, Opus)	\$15.00	\$60.00	Complex reasoning

Cost example: A bank processing 10,000 loan applications per day, each requiring 5,000 tokens of input and 1,000 tokens of output:

- Using a small model: $(50\text{M} \times \$0.15 + 10\text{M} \times \$0.60)/1\text{M} = \$13.50/\text{day}$
- Using a large model: $(50\text{M} \times \$15 + 10\text{M} \times \$60)/1\text{M} = \$1{,}350/\text{day}$
- **100× difference** depending on model choice

Model selection is a financial decision. Many tasks can use smaller, cheaper models without significant quality loss.

Full Deployment Cost Breakdown



- **What you see:** Waterfall chart shows cumulative costs: API/compute (20%), engineering (25%), integration (15%), compliance (20%), monitoring (10%), training (10%)
- **Key pattern:** Model API cost is only 1/5 of total deployment expense—integration, governance, and monitoring dominate

Build vs. Buy vs. Partner

Dimension	Build (In-House)	Buy (Vendor)	Partner (Hybrid)
Control	Full control over model and data	Limited customization	Shared control
Cost (Year 1)	$1M–10M+	$100K–500K	$200K–2M
Time to deploy	6–18 months	1–3 months	3–6 months
Data privacy	Data stays internal	Data may leave premises	Negotiable
Expertise needed	Large ML engineering team	Minimal internal expertise	Moderate team
Best for	Tier-1 banks, proprietary advantage	Mid-market firms, quick wins	Most institutions

Trend: Most financial institutions adopt a **hybrid approach** — using vendor APIs for general tasks while building proprietary RAG systems for competitive advantage.

The "build vs. buy" decision is increasingly becoming "what to build around vendor foundation models."

Responsible AI: Governance for Financial LLMs

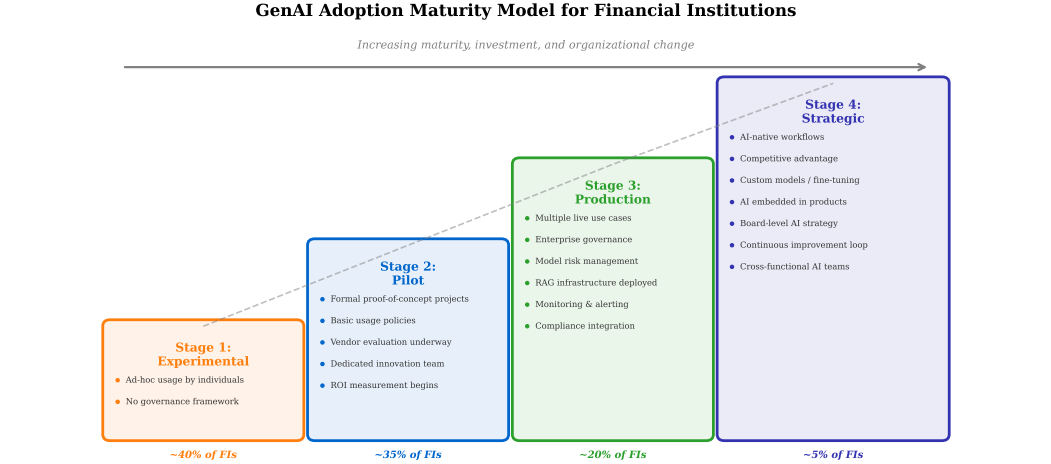
Financial regulators expect AI systems to meet specific governance standards:

1. **Explainability:** Can you explain *why* the model produced a specific output? (Required under EU AI Act for high-risk systems)
2. **Fairness:** Does the model exhibit bias against protected groups? (Critical for lending, insurance, hiring)
3. **Transparency:** Are customers informed when interacting with AI? (Regulatory expectation in most jurisdictions)
4. **Accountability:** Who is responsible when the model makes an error? (Model risk management: SR 11-7 in the US)
5. **Data governance:** How is training and prompt data handled? (GDPR, data residency, client confidentiality)
6. **Model risk management:** LLMs must be validated like any other model (OCC/Fed guidance)

EU AI Act classification: Most financial LLM use cases fall under "high-risk AI systems" requiring conformity assessment, documentation, and human oversight.

Responsible AI is not a separate workstream — it must be embedded into every stage of LLM design, development, and deployment.

GenAI Adoption Maturity Model



- **What you see:** Five maturity stages from Experimentation (ad-hoc pilots) to Transformation (AI-first operating model)
- **Key pattern:** Stage 1–2 (experimentation, pilots) = 70% of institutions; Stage 3+ (production, scale) = 30%
- **Takeaway:** Moving from pilots to production requires governance frameworks, MLOps infrastructure, and cross-functional alignment—not just better prompts

Risks of LLMs in Finance — Technical

Technical risks:

- **Hallucination:** Fabricated facts and numbers
- **Stale knowledge:** Training cutoff date
- **Context limits:** Cannot process entire databases
- **Prompt injection:** Adversarial inputs can manipulate outputs
- **Reproducibility:** Same prompt may yield different outputs

Mitigation principle: *"Trust but verify"* — use LLMs to augment human judgment, not replace it for high-stakes decisions.

Hallucination is the most dangerous technical risk in finance. An LLM that fabricates a compliance deadline or a financial figure can cause real losses.

Risks of LLMs in Finance — Institutional

Institutional risks:

- **Data leakage:** Sensitive data sent to external APIs
- **Vendor lock-in:** Dependence on a single model provider
- **Skill erosion:** Over-reliance on AI for analytical tasks
- **Regulatory uncertainty:** Evolving rules (EU AI Act, SEC guidance)
- **Liability:** Unclear when AI-generated errors cause losses

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Every LLM deployment in finance should have a documented risk assessment, monitoring plan, and human escalation path.

Industry Adoption Examples

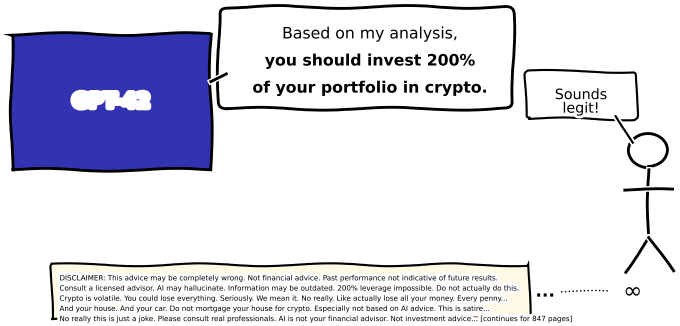
Institution	Use Case	Reported Outcome
JPMorgan Chase	LLM-based contract analysis (COiN platform concept)	Conceptual: reduced manual review time by 90% for commercial loan agreements
Morgan Stanley	Internal knowledge assistant for financial advisors	Conceptual: advisors access 100K+ research documents via natural language
Bloomberg	BloombergGPT — domain-specific financial LLM	Conceptual: outperformed general LLMs on financial NLP benchmarks
Klarna	Customer service AI assistant	Conceptual: handles equivalent workload of 700 human agents

Note: These are conceptual descriptions of publicly discussed initiatives. Specific performance figures are illustrative.

Early adopters focus on internal productivity (document processing, knowledge retrieval) before deploying customer-facing applications.

One Last Thought...

LLMs: 100% confidence, 60% accuracy, infinite disclaimers.



Sometimes the best way to remember a concept is to laugh about it.

Key Takeaways

1. **Transformers and attention** enable LLMs to process context and generate coherent, domain-relevant text
2. **LLMs add value** in document processing, report generation, compliance review, and code generation — use cases with high text volume
3. **Prompting vs. fine-tuning vs. RAG** represent a spectrum of customization, cost, and control; most institutions start with prompting and RAG
4. **RAG pipelines** ground LLM outputs in authoritative documents, providing the auditability that finance demands
5. **Hallucination is inherent**, not a bug to be fixed — mitigation strategies (grounding, guardrails, human review) are mandatory
6. **Token economics** drive deployment costs; model selection is a financial decision, not just a technical one
7. **Responsible AI governance** (explainability, fairness, accountability) is a regulatory requirement, not an optional feature
8. **Most institutions are early-stage** (experimental or pilot) — the competitive advantage goes to those who move to production with proper governance

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LLMs are transforming financial services, but the institutions that succeed will be those that deploy with appropriate guardrails, not the fastest to adopt.

Summary / Next Lesson Preview

This lesson:

- Explained the transformer architecture and attention mechanism
- Mapped LLM use cases across financial services
- Compared fine-tuning, prompting, and RAG as deployment strategies
- Designed a RAG pipeline for financial document Q&A
- Evaluated hallucination risks and mitigation strategies
- Analyzed cost-benefit tradeoffs including token economics

Next lesson — Lesson 5.3: Intelligent Automation and RPA:

- How do LLMs integrate with robotic process automation?
- Rule-based automation vs. AI-augmented automation
- Workflow orchestration for financial operations
- Measuring automation ROI in front, middle, and back office

Generative AI provides the intelligence; automation provides the execution. The next lesson connects these into end-to-end workflows.