Digital Finance 3: Technology in Finance

Lesson 25: Introduction to AI/ML in Finance

FHGR

January 3, 2026

Module 3 of 4: AI and Machine Learning in Finance

Learning Objectives

By the end of this lesson, you will be able to:

- Define artificial intelligence, machine learning, and deep learning
- Understand the hierarchy and relationships between AI concepts
- Identify key applications of AI/ML in finance
- Distinguish between realistic capabilities and overhype
- Recognize the evolution of AI in financial services

Source: Academic AI/ML literature and industry adoption studies

What is Artificial Intelligence?

Broad Definition:

- Simulation of human intelligence by machines
- Systems that can reason, learn, and act autonomously
- Originated in 1956 at Dartmouth Conference
- Multiple "AI winters" and resurgences

Key Characteristics:

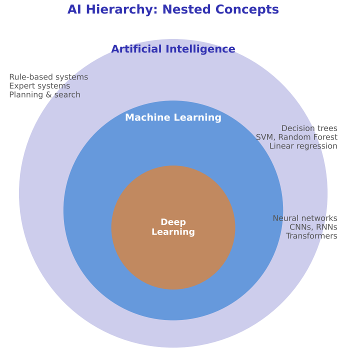
- Perception (vision, speech)
- Reasoning (logic, planning)
- Learning (from data, experience)
- Natural language processing
- Problem-solving

Clear definitions are essential for understanding complex technical concepts.

Three Nested Concepts:

1. **Artificial Intelligence** (broadest)
   Any technique enabling computers to mimic human intelligence
2. **Machine Learning** (subset)
   Systems that learn from data without explicit programming
3. **Deep Learning** (subset of ML)
   Neural networks with multiple layers

Modern Reality:
Most "AI in finance" today is actually machine learning, specifically supervised learning algorithms.



Source: Russell & Norvig (AIMA), Goodfellow et al. (Deep Learning)

AI and ML are transforming financial services through automation and prediction.

Machine Learning: The Core Idea

Traditional Programming:

- Humans write explicit rules
- Input + Rules = Output
- Example: “IF credit score ¡ 600 THEN reject”
- Hard to scale for complex patterns

Machine Learning:

- Algorithm learns rules from data
- Input + Output = Rules (learned)
- Example: Discover credit patterns from 1M loan histories
- Scales to high-dimensional problems

Key Insight:
ML excels when:

- Patterns are complex and non-obvious
- Large amounts of data are available
- Rules are difficult to articulate explicitly

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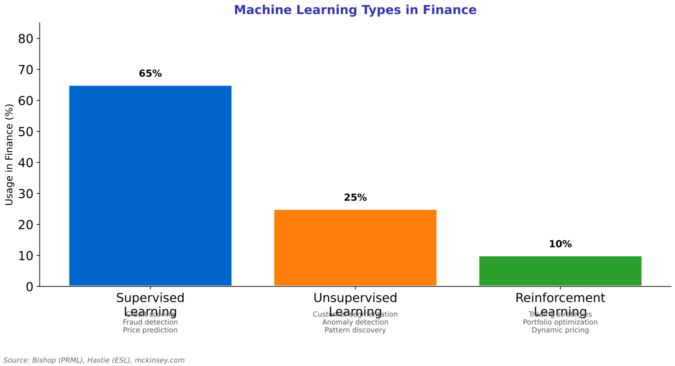
Three Types of Machine Learning



Supervised learning dominates financial applications due to availability of labeled data.

Deep Learning: Neural Networks at Scale

What Makes It "Deep"?

- Multiple hidden layers (10s to 100s)
- Automatic feature learning
- Inspired by brain neurons (loosely)
- Requires massive data and compute

Breakthroughs (2012-present):

- Image recognition (ImageNet 2012)
- Speech recognition (Google, Apple)
- Language models (GPT, BERT)
- Game mastery (AlphaGo 2016)

Finance Applications:

- Document processing (OCR, contracts)
- Sentiment analysis (news, social media)
- Time series forecasting (limited success)
- Alternative data (satellite, text)

Reality Check:

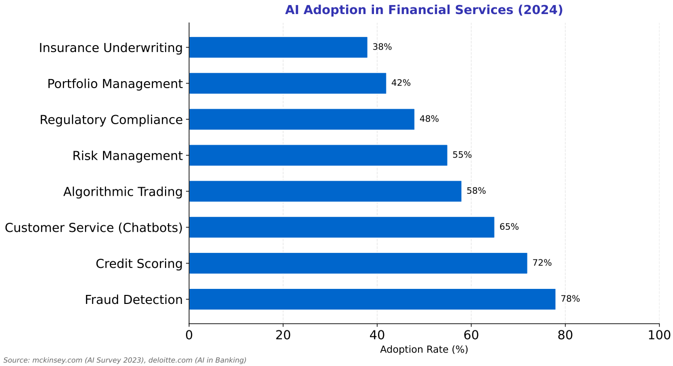
Deep learning excels with:

- Unstructured data (text, images)
- Millions of training examples
- Pattern recognition tasks

Not always superior for structured financial data (tabular).

Network metrics provide objective measures of adoption and ecosystem health. [Source: McKinsey, Gartner 2024]

AI/ML Applications in Finance: Overview



Common Thread: Automation of pattern recognition tasks previously requiring human expertise.

Real-world applications demonstrate the practical value of AI/ML in finance.

Case Study: Credit Scoring Evolution

Traditional Approach (1960s-2000s):

- FICO score (5 factors, fixed weights)
- Linear scorecards
- Based on credit bureau data only
- Transparent, regulated
- Limited predictive power

Limitations:

- Misses non-linear relationships
- Cannot handle alternative data
- One-size-fits-all model

ML Approach (2010s-present):

- Gradient boosting (XGBoost, LightGBM)
- 100s to 1000s of features
- Alternative data (mobile, social, payments)
- Dynamic model updates
- Higher accuracy (10-30% improvement)

New Challenges:

- Explainability ("black box")
- Fairness and bias
- Regulatory acceptance
- Data privacy

Key Lesson: Technology enables better predictions but introduces new risks and ethical questions.

AI encompasses ML which includes deep learning - understanding this hierarchy clarifies terminology. [Source: Nilson Report, World Bank 2024]

The Hype Cycle: Expectations vs Reality

Gartner Hype Cycle Phases:

1. Innovation Trigger
2. Peak of Inflated Expectations
3. Trough of Disillusionment
4. Slope of Enlightenment
5. Plateau of Productivity

Where is AI/ML in Finance?

- Overall: Slope of Enlightenment
- Deep Learning: Still some hype
- Traditional ML: Plateau (established)
- Generative AI: Peak (2023-2024)

Common Misconceptions:

- "AI will replace all analysts" (No)
- "ML always outperforms rules" (No)
- "More data always helps" (Diminishing returns)
- "Black boxes are always better" (Transparency matters)

Realistic Expectations:

- AI augments, not replaces, humans
- ML excels at narrow, repetitive tasks
- Domain expertise still critical
- Hybrid approaches often best

Source: Academic AI/ML literature and industry adoption studies

What AI/ML Can and Cannot Do in Finance

Can Do Well:

- Pattern recognition (fraud, anomalies)
- Classification (credit risk, default)
- Prediction with stable patterns (short-term)
- Data processing at scale (NLP, OCR)
- Optimization (portfolio, pricing)
- Personalization (recommendations)

Success Factors:

- Large, high-quality datasets
- Stable underlying patterns
- Clear objective function
- Ability to validate and test

Cannot Do (or Struggles):

- Predict regime changes (crashes, crises)
- Explain "why" without human input
- Handle novel situations (out-of-sample)
- Replace human judgment entirely
- Guarantee fairness or ethics

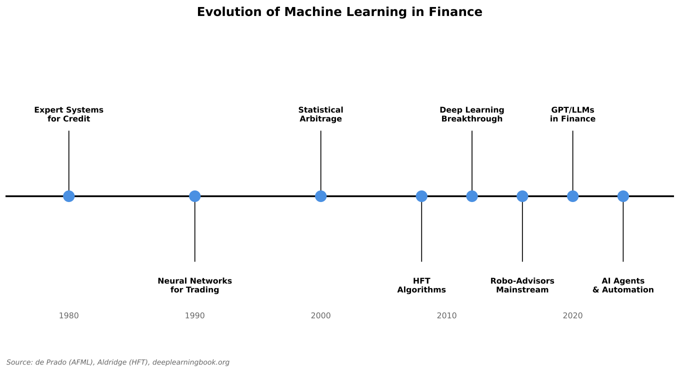
Fundamental Limits:

- No free lunch (NFL theorem)
- Efficient Market Hypothesis constraints
- Overfitting to historical noise
- Adversarial dynamics (arms race)

Bottom Line: AI/ML is a powerful tool, not magic. Success requires proper problem framing, quality data, and realistic expectations.

AI and ML are transforming financial services through automation and prediction.

Historical Timeline: AI in Finance



AI evolution in finance shows accelerating adoption from expert systems to generative AI.

Industry Adoption: Survey Data

Adoption Rates (2023 surveys):

- Large banks: 80-90% have AI initiatives
- Asset managers: 60-70% use ML
- Fintechs: 90%+ (core to business)
- Regional banks: 30-50% (growing)

Top Use Cases:

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1. Customer service chatbots (70%)
2. Credit risk modeling (65%)
3. AML/KYC automation (60%)
4. Algorithmic trading (50%)

Barriers to Adoption:

- Data quality/availability (65%)
- Lack of skilled talent (60%)
- Regulatory uncertainty (55%)
- Integration with legacy systems (50%)
- Explainability requirements (45%)

Investment Trends:

- $35.57 billion (2023)[a] $150.26B by 2030 (CAGR 22.9
- Focus shifting from experimentation to production scaling

[a] Source: https://www.statista.com/statistics/1446037/financial-sector-estimated-ai-spending-forecast/

Quality data is the foundation for effective machine learning models. [Source: CB Insights, Statista 2024]

Key Players and Ecosystem

Large Tech Companies:

- Google Cloud (AI Platform, AutoML)
- Amazon Web Services (SageMaker)
- Microsoft Azure (ML Studio)
- IBM (Watson Financial Services)

Specialized Fintechs:

- Upstart (AI lending)
- Kasisto (chatbots)
- Kensho (analytics, acquired by S&P)
- Ayasdi (AML)

Traditional Finance + AI:

- JPMorgan Chase (COiN, IndexGPT)
- Goldman Sachs (Marcus, Marquee)
- BlackRock (Aladdin platform)
- Capital One (credit models)

Open Source Community:

- scikit-learn (ML library)
- TensorFlow, PyTorch (deep learning)
- Hugging Face (NLP models)
- Kaggle (competitions, datasets)

Trend: Increasing collaboration between big tech, fintechs, and traditional banks.

Source: Academic AI/ML literature and industry adoption studies

Data: The Fuel for AI/ML

Why Data Matters:

- ML models are only as good as training data
- More data often beats better algorithms
- Quality ¿ Quantity (garbage in, garbage out)

Types of Financial Data:

- Structured: Prices, returns, accounting
- Unstructured: News, reports, social media
- Alternative: Satellite, mobile, web scraping
- Real-time: Tick data, order books

Data Challenges:

- Availability (proprietary, expensive)
- Quality (errors, missing values)
- Bias (survivorship, selection)
- Privacy (GDPR, regulations)
- Stationarity (patterns change over time)

Best Practices:

- Rigorous data cleaning
- Train/validation/test splits
- Cross-validation
- Out-of-sample testing
- Monitor data drift

Next Lesson: Deep dive into financial data types and preparation.

Financial data includes structured (prices), semi-structured (news), and unstructured (social media).

Ethical Considerations

Fairness and Bias:

- Models can perpetuate historical discrimination
- Protected attributes (race, gender, age)
- Proxy variables (zip code = race)
- Disparate impact vs. disparate treatment

Transparency:

- Right to explanation (GDPR Article 22)
- Black box models vs. interpretability
- Trade-off: accuracy vs. explainability

Accountability:

- Who is responsible for AI decisions?
- Human-in-the-loop vs. full automation
- Audit trails and governance

Privacy:

- Data minimization principle
- Consent and purpose limitation
- Anonymization challenges
- Model inversion attacks

Regulatory Response: EU AI Act, algorithmic accountability laws, model risk management frameworks.

Source: Academic AI/ML literature and industry adoption studies

Skills for AI/ML in Finance

Technical Skills:

- Programming (Python, R)
- Statistics and probability
- Linear algebra and calculus
- ML algorithms and frameworks
- Data manipulation (SQL, pandas)
- Cloud platforms (AWS, Azure, GCP)

Finance Domain Knowledge:

- Financial markets and instruments
- Risk management principles
- Regulatory environment
- Business context

Soft Skills:

- Problem framing
- Critical thinking (avoiding overfitting)
- Communication (explaining models)
- Ethics and responsibility
- Collaboration (cross-functional teams)

Career Paths:

- Quantitative Analyst
- Data Scientist (Finance)
- ML Engineer
- Risk Modeler
- AI Product Manager

Key Insight: Success requires combination of technical skills, domain expertise, and ethical awareness.

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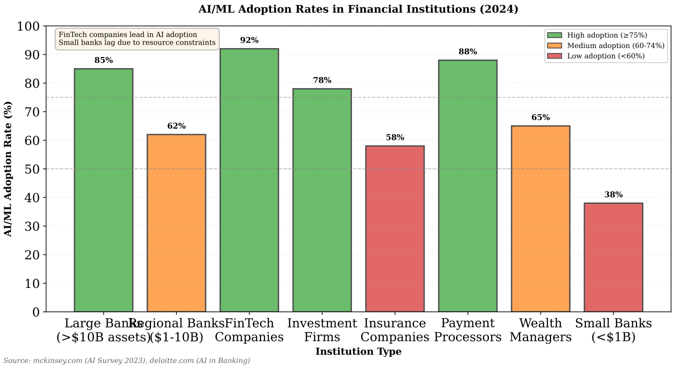
AI Adoption Rates Across Industries



Financial services leads in AI adoption, driven by regulatory requirements and competitive pressure.

AI Capabilities and Current Limitations

AI/ML in Finance: Capabilities vs Limitations

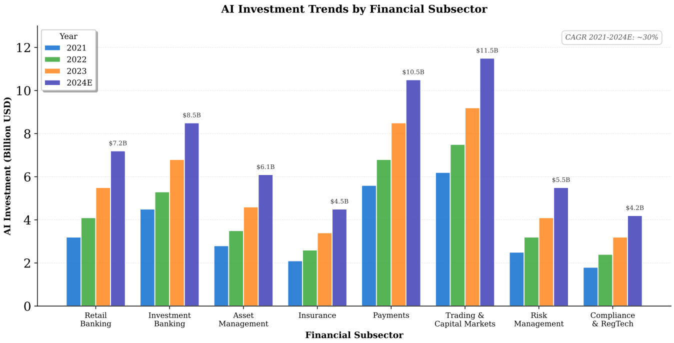
AI CAN Do Well	AI CANNOT Do (Yet)
[OK] Pattern recognition in large datasets	Understand causality
[OK] Fraud detection (anomaly patterns)	Handle unprecedented events
[OK] Credit scoring (structured data)	Explain complex decisions fully
[OK] High-frequency trading signals	Guarantee fairness/no bias
[OK] Document processing (OCR, NLP)	Predict black swan events
[OK] Customer segmentation	Replace human judgment
[OK] Price prediction (short-term)	Handle sparse/missing data well
[OK] Risk modeling (historical patterns)	Adapt without retraining

Key Insight: AI excels at pattern recognition in structured historical data, but struggles with causality, rare events, and full explainability

Source: Russell & Norvig (AIMA), Marcus & Davis (2020), BIS WP930

Understanding what AI can and cannot do is critical for realistic expectations and responsible deployment.

Global AI Investment Trends

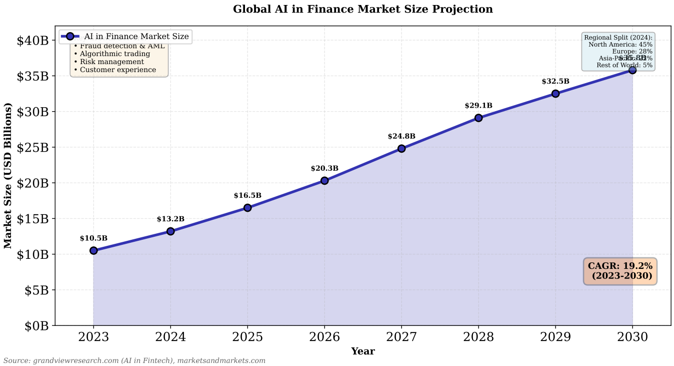


E = Estimated. Investment includes internal development and external acquisitions.

Source: statista.com (AI Fintech), cbinsights.com (AI Trends)

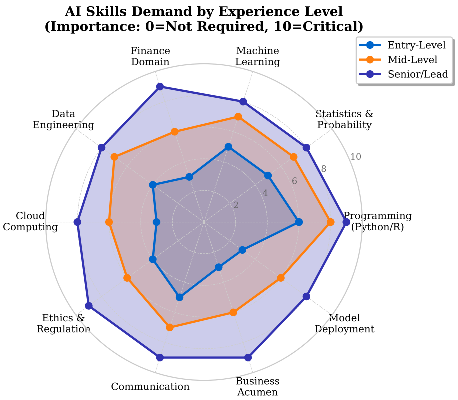
Investment in AI continues to accelerate, with financial services among the top sectors.

AI Market Size Projections



The AI market is expected to grow exponentially over the next decade.

AI Skills Demand in Finance

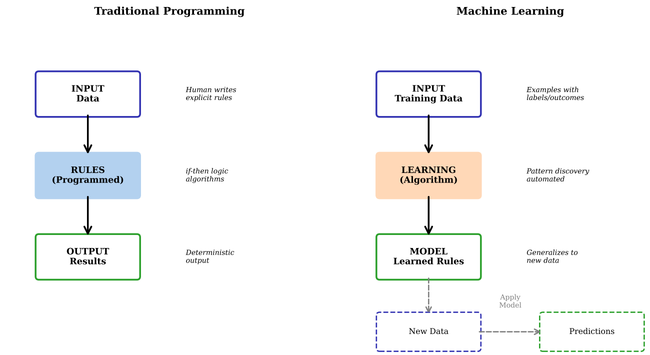


Scale: 0-10 (Higher = More Important)

Source: LinkedIn Jobs Report, McKinsey AI Talent, CFA Institute

Demand for AI talent in finance far exceeds supply, creating significant salary premiums.

Traditional vs Machine Learning Programming



Source: Bishop (PRML), Goodfellow (Deep Learning), Google ML Course

ML shifts programming from explicit rules to learning from data.

Summary and Key Takeaways

Core Concepts:

- AI ¿ ML ¿ Deep Learning (hierarchy)
- ML learns patterns from data
- Supervised learning dominates finance
- Deep learning for unstructured data

Finance Applications:

- Risk: Credit, fraud, AML
- Trading: Algorithms, robo-advisors
- Operations: NLP, automation
- Customer: Chatbots, personalization

Reality Check:

- AI augments, not replaces humans
- Data quality is paramount
- Hype vs. realistic capabilities
- Ethical and regulatory challenges

Looking Ahead:

- Next 11 lessons: Detailed exploration
- Hands-on understanding (conceptual)
- Critical evaluation skills
- Practical applications

Overfitting produces excellent in-sample fit but poor out-of-sample predictions.

Next Lesson Preview

Lesson 26: Financial Data for AI/ML

Topics to be covered:

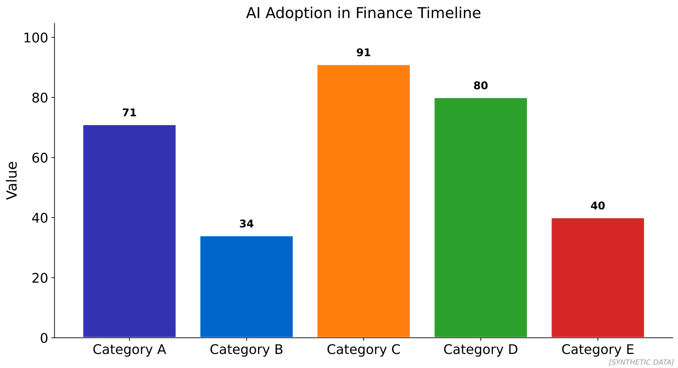
- Structured vs. unstructured data
- Data sources and vendors
- Alternative data revolution
- Data quality and preprocessing
- GDPR and privacy considerations
- Feature engineering basics

Preparation:

- Review basic statistics (mean, variance, correlation)
- Think about data quality issues in your own experience
- Consider: What makes financial data unique?

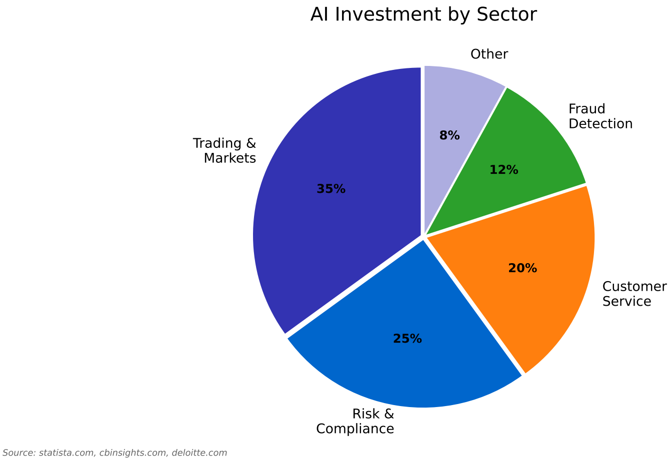
Domain expertise in feature engineering often matters more than model complexity.

AI Adoption in Financial Services



AI adoption continues to accelerate across all financial sectors.

AI Investment Distribution



Investment patterns reflect strategic priorities in financial AI.