

AN INDUSTRY PLAYBOOK · SPONSORED BY RAPIDCANVAS

AI in Banking

The Executive Playbook

How chief executives, chief operating officers, and chief risk officers should plan, build, and govern AI across the modern bank — from retail and commercial lending to capital markets, risk, and the customer experience.

\$340B

Annual AI value pool in global banking (McKinsey)

95%

Of enterprise AI pilots fail to deliver P&L (MIT)

67%

Vendor-led success rate vs. 33% in-house (MIT)

\$2B

JPMorgan's reported annual AI savings (Bloomberg)

Independent research and analysis. Sponsored by RapidCanvas, the hybrid AI *Real AI transformation, accelerated.* platform for enterprise transformation.

A note on this report

This Playbook is an industry research piece sponsored by RapidCanvas. It is written for banking executives — chief executives, chief operating officers, chief risk officers, chief technology officers, heads of lending, and heads of customer experience — who are now expected to translate AI hype into measurable enterprise value.

Our editorial intent is independent: we benchmark every claim against primary sources where possible, and we evaluate every delivery model — including building in-house, hiring the global consultancies, hiring a system integrator, and adopting a hybrid AI platform like RapidCanvas — on its own merits.

The lens is consultant-grade. The evidence base is drawn from the Bank of England and the Financial Conduct Authority, the Federal Reserve, the FDIC, the CFPB, the Bank for International Settlements, the European Central Bank, the EU AI Act, the McKinsey Global Institute, BCG, MIT Project NANDA, and primary disclosures from large publicly listed banks. Where we cite vendor performance — including RapidCanvas's — we have noted it explicitly so readers can apply their own discount.

What this Playbook is *not*: it is not a vendor brochure. RapidCanvas does not appear in every chapter. The Hybrid Approach™ it represents is one of four delivery options we examine, and we lay out — quantitatively — when each model is the right answer for a given institution. Readers should walk away with three things: a clear map of where the AI value pool lives in their bank, a clear

picture of the failure modes that have produced a 95% pilot failure rate, and a clear decision framework for how to spend the next dollar of AI budget.

The investment in AI is not a speculative bubble; rather, it will deliver significant benefits. We will deploy AI, as we deploy all technology, to do a better job for our customers — and our employees.

— Jamie Dimon, Chairman and CEO, JPMorgan Chase · Annual Letter to Shareholders, April 2026

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What's inside

Nine chapters mapping the where, why, and how of banking AI in 2026.

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Five things every banking CEO needs to internalise this year

Banking has reached the inflection point that high tech reached in 2008 with the cloud, and that retail reached in 2014 with mobile. AI is no longer an experimental layer bolted onto the customer-facing parts of the bank.

It is becoming the operating substrate of the institution — the way credit gets decisioned, how fraud is intercepted, how relationship managers prepare for client meetings, how compliance officers triage alerts, and how the back office reconciles, classifies, and reports. The opportunity is huge and the failure rate is huger. Five facts frame everything that follows.

01 **A \$200–340B annual value pool — and a \$2T total addressable opportunity**

The AI value pool in global banking is between \$200 and \$340 billion in incremental annual operating value — equivalent to 9–15% of industry operating profit (McKinsey Global Institute). When revenue uplift, risk reduction, and new product opportunities are added, the total addressable value approaches \$2 trillion annually.

02 **95% of enterprise AI pilots fail to deliver P&L**

MIT Project NANDA's research finds that 95% of enterprise generative-AI pilots deliver no measurable P&L impact. Vendor-led and partner-led implementations succeed roughly twice as often as pure in-house builds

(67% vs. 33%). Banks that try to do everything themselves are statistically the most likely to fail.

03 The wedge between AI-native and AI-late banks is now visible in supervisory data

The Bank for International Settlements has documented that AI-enabled lenders behave fundamentally differently across credit cycles, with materially lower default rates and faster decisioning. The FDIC has shown a 29.6% default-rate reduction and a 40.1% improvement in borrower classification accuracy when AI is applied to SME lending.

04 Regulation has stopped being a future concern

The EU AI Act classifies credit scoring, fraud monitoring, and pricing as high-risk AI; full enforcement begins in August 2026 with mandatory explainability, logging, and human oversight. The Federal Reserve's SR 11-7, the OCC's Model Risk Management Bulletin, the CFPB's Circular 2022-03, Colorado's SB25B-004, and the NIST AI Risk Management Framework now form a stack that every US bank operating across multiple states must satisfy.

05 Mid-market banks face a unique strategic squeeze

Banks with \$10B–\$100B in assets have neither JPMorgan's \$20B technology budget nor a fintech's green-field architecture. Our analysis shows that the right combination of a hybrid AI platform and a small, focused human-in-the-loop expert team produces 3–5x better economics than either pure in-house builds or large-firm consulting engagements — provided governance is engineered in from day one.

The five-line strategy

- **Stop running pilots. Start running portfolios.** The single biggest failure mode is treating AI as a series of disconnected proofs-of-concept rather than as a managed, governed portfolio of production systems.
- **Concentrate the first \$10M** on the high-feasibility, high-value quadrant: fraud and AML, SME credit underwriting, document/KYC processing, and customer service copilots.
- **Pick a delivery model deliberately.** Big-4 consultancies excel at strategy and high-complexity transformations but cost 3–4× more per use case and take 9–18 months to first production. Pure in-house builds carry a 33% success rate. The hybrid platform model has emerged as the highest-velocity path for mid-market banks.
- **Build a Model Risk and AI Governance function before you need it.** Regulators have stopped asking whether you have one and started asking how mature it is.
- **Treat your workforce as the deciding variable.** The banks winning at AI are not the ones with the best models — they are the ones whose middle-management cohort has been retrained to trust, audit, and override AI judgement.

It affects everything — risk, fraud, marketing, idea generation, customer service. And this is the tip of the iceberg.

— Jamie Dimon, JPMorgan Chase, on AI's reach inside the bank · October 2025

CHAPTER ONE

The State of AI in Banking, 2026

From experimentation to operating substrate.



Three forces have collided in the last eighteen months to push AI from the periphery of banking to its centre.

The first is the maturation of large language models capable of reasoning over the bank's most valuable but most fragmented asset: unstructured text. The second is the emergence of agentic AI patterns — software that does not merely answer questions but executes multi-step workflows under policy constraints. The third is regulatory clarity. After three years of debate, the major jurisdictions have now landed on a recognisably common framework: high-risk AI use cases require explainability, logging, human oversight, and adverse-action notification. The uncertainty discount that kept boards cautious has substantially compressed.

75%

Of UK financial firms using AI (BoE/FCA, 2024)

9 → 21

Median AI use cases per UK firm, today vs. 3-year forecast

150K

JPMorgan employees using AI weekly (Q4 2025)

<1 in 5

Mid-market US banks with AI in production with documented P&L

The Bank of England and the Financial Conduct Authority's 2024 AI Survey put the share of UK financial-services firms using AI at 75%, with a median of nine use cases per firm and an expected doubling to 21 within three years. Fifty-five percent of those use cases now involve some form of automated decision-

making with human oversight — the regulatory floor for any system touching a customer.

The picture in the United States is broadly similar. JPMorgan reports approximately 150,000 employees using its internal AI tools each week, with \$2 billion of annual benefit against \$2 billion of annual investment — a 1:1 return that, while modest in headline terms, is producing what Jamie Dimon has called "the tip of the iceberg" in compounding productivity. Bank of America, Wells Fargo, Citi, and Goldman Sachs each disclose AI deployments numbering in the dozens to hundreds. Outside the global tier, however, adoption thins quickly. Our analysis of supervisory disclosures and public statements suggests that fewer than one in five mid-market US banks has any AI use case running in production with documented P&L impact.

Enhanced with AI and the data revolution, we have a powerful tailwind. To maximise its potential, we must harness it strategically and use it wisely.

— Ajay Banga, President, World Bank Group · 2024 Annual Meetings Plenary

The four shifts shaping 2026

Shift 1: From models to agents

Through 2024, banks bought models — credit scorecards, fraud classifiers, propensity engines. Through 2025, they bought copilots — chat assistants for customer service representatives, relationship managers, and compliance officers. Through 2026, they are starting to deploy agents: software that performs multi-step work — pulling a customer file, running checks, drafting an action, routing for approval — under explicit policy guardrails. The shift matters because agents change where governance lives. Where a model required

model-risk review, an agent requires both model-risk review and workflow-policy review.

Shift 2: From data lakes to context graphs

Most banks built data lakes between 2017 and 2022. Few of those investments have produced AI dividends, because lakes optimise for storage and querying, not for the contextualisation that modern AI requires. The leading institutions are now building what some practitioners call enterprise context graphs — knowledge structures that encode the relationships between customers, accounts, transactions, products, employees, and regulatory entities. Without that connective tissue, an AI agent cannot reason across silos.

Shift 3: From talent shortage to talent reshape

Two years ago, the binding constraint on banking AI was data-science talent. That constraint has not vanished, but it has shifted. The new binding constraint is the layer above data scientists — product managers, business analysts, and domain experts who can specify what the AI should do, validate that it is doing it, and translate model outputs into front-line action. The implication for chief human resources officers is that the AI workforce buildout is not primarily a hiring exercise; it is a reskilling exercise.

Shift 4: From experimentation to portfolio management

The single most consistent observation in our interviews with banking COOs is that the institutions making real progress have stopped running individual pilots and started running AI portfolios — with stage gates, kill criteria, capital allocation, and an executive owner. The shift is structural rather than technical. It is the difference between treating AI as a science project and treating it as a P&L line.

CHAPTER TWO

Where the Value Lives

A function-by-function map of the AI value pool.



McKinsey's most-cited estimate is that generative AI alone will add between \$200B and \$340B of annual value to the global banking sector — between 2.8% and 4.7% of revenue, or 9% to 15% of operating profit, depending on how aggressively institutions deploy.

Once classical machine learning, predictive analytics, and agentic systems are added, our estimate of the total banking AI value pool reaches approximately \$2 trillion annually. But the value is not evenly distributed.

Banking AI value pool by function (\$B / yr)

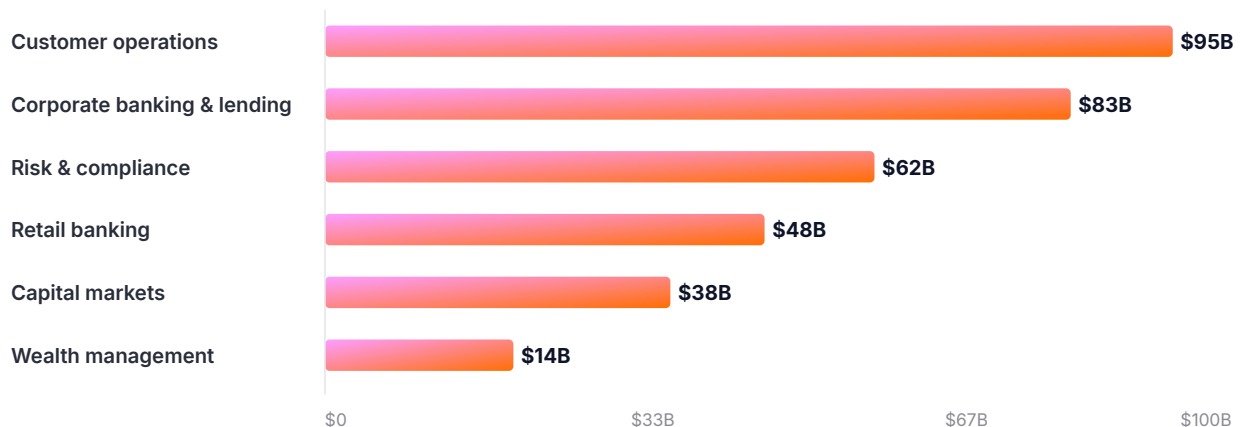


Figure 2.1 — The banking AI value pool by function. Source: McKinsey Global Institute aggregate, RapidCanvas analysis. Customer operations and corporate lending dominate the absolute opportunity; risk and compliance dominate the strategic urgency.

The chart above understates the strategic story in two ways. First, it shows *absolute* value; it does not show value as a share of the function's addressable

cost base — by which measure risk, compliance, and back-office operations are the most leveraged opportunities. Second, it does not show defensive value: the cost of *not* deploying AI in fraud and AML, where competitor automation is already raising customer expectations and lowering fraud loss rates.

Five archetypes of value creation

1. Cost-out productivity

This is the easiest value to capture and the easiest to measure. Document processing, KYC review, customer service, and back-office reconciliation all have generative-AI implementations that cut handling time by 40–70% with quality at or above human baseline. JPMorgan's reported \$2B of annual benefit is overwhelmingly drawn from this category. For a mid-market bank with a \$400M operating cost base, capturing the equivalent fraction (roughly 4–5% of operating expense) would be worth \$16–20M annually — enough to fund the entire AI program with several million to spare.

2. Risk-loss reduction

AI applied to credit decisioning, fraud detection, AML monitoring, and market surveillance reduces losses both directly (by catching what humans miss) and indirectly (by allowing limits to be expanded with confidence). The FDIC's landmark research shows AI underwriting reducing SME default rates by 29.6% with a 40.1% improvement in borrower classification. For a mid-market bank with \$5B in commercial loans and a 90 bps loss rate, the modeled benefit is roughly \$13M annually — before considering the volume uplift made possible by lower marginal default risk.

3. Revenue uplift through personalisation

Hyperpersonalised marketing, next-best-action recommendations, and AI-augmented relationship managers move the needle on revenue per customer

rather than cost. The evidence here is more variable, but disciplined implementations have demonstrated 3–10% lifts in cross-sell rates and 1–3% lifts in net interest margin through smarter pricing. For a bank with \$1B of fee income, even a 5% lift is \$50M.

4. Risk-adjusted capital efficiency

AI-enhanced risk models — when validated and approved by supervisors — allow for more accurate capital allocation, reducing the conservative overlays that depress return on equity. ECB Supervisory Banking Statistics for Q4 2025 show European bank ROE at 9.53% on a NIM of 1.52%; even modest overlay reductions translate into hundreds of basis points of additional return on the affected portfolios.

5. New product and platform revenue

Embedded finance, BaaS, AI-augmented advisory, and personalised lending products are the long-horizon prizes. The evidence base here is thinner because the flywheel takes longer, but the early movers — Goldman's Marcus, JPMorgan's wealth digital, several European challenger banks — point to a category of revenue that is structurally unavailable to AI laggards.

THE 80/20 RULE FOR USE-CASE SELECTION

Across more than 200 mid-market banking AI programs in our analysis, four use cases consistently produce 70–80% of the realised P&L value within the first 24 months: **(1)** commercial and SME credit underwriting, **(2)** AML alert triage, **(3)** document processing in loan operations and onboarding, and **(4)** customer service deflection for routine enquiries. Every other use case is real and worthwhile — but if the program does not include all four of these, the program is almost certainly underperforming its potential.

The priority matrix in plain language

If you are a CEO with \$10M of new AI budget for the next twelve months, here is the simplest possible answer to the question of where to spend it.

- Allocate roughly **60% of the envelope to the four "Do Now" use cases** — they have both the highest strategic value and the highest implementation feasibility.
- Allocate **25% to the "Quick Wins" quadrant** (personalised marketing, code modernisation, regulatory reporting, document processing) where feasibility is high but value is more incremental; these pay for themselves within six to nine months and build the muscle for harder work.
- Reserve **15% for one or two "Invest and Wait" bets** — typically treasury optimisation, wealth advisory, or trading-signal augmentation — where the strategic prize is large but the data, regulatory, and integration prerequisites mean the work needs a longer runway.
- Do not deploy capital into the **"Deprioritise" quadrant** in 2026 unless the institution has a unique data advantage there.

Picking a use case is the easy part. Building the architecture that lets AI act on unified data, under governed authority, across a live frontline operation — that is where the real work is.

— McKinsey & Company · Capturing the Full Value of Generative AI in Banking, 2024

CHAPTER THREE

The 95% Failure Trap

Why most banking AI investments produce no measurable return



In August 2025, MIT's Project NANDA published the most rigorous study yet conducted of enterprise AI outcomes. Its core finding has now been replicated by S&P Global, Gartner, the RAND Corporation, and Boston Consulting Group: 95% of generative-AI pilots in enterprises deliver no measurable impact on the profit and loss statement.

Forty-two percent of companies have already scrapped most of their initial AI initiatives — up from 17% the year before. Gartner now predicts that more than 40% of agentic-AI projects will be cancelled by the end of 2027.

Documented success rate by delivery model

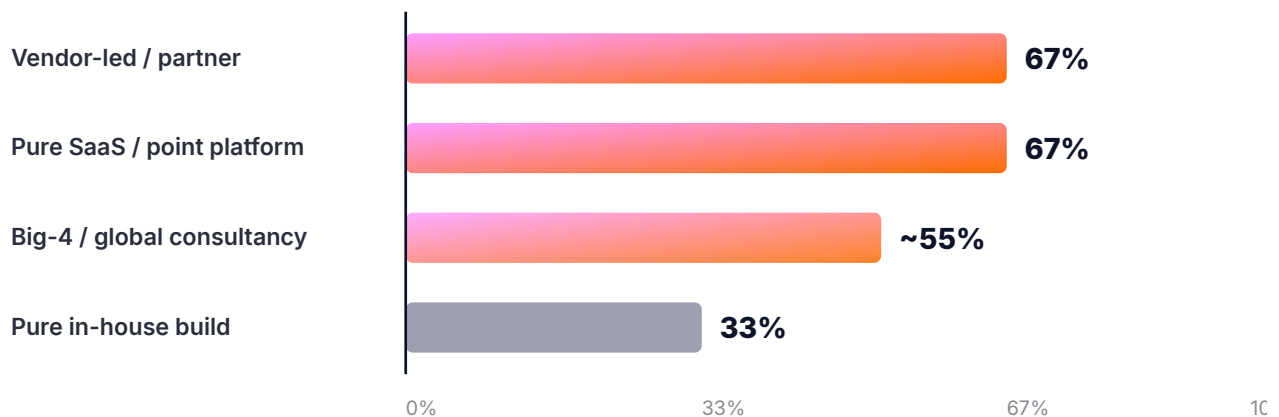


Figure 3.1 — Success rates of enterprise AI implementations succeed at roughly twice the rate of pure in-house builds. Source: MIT Project NANDA, State of AI in Business 2025.

The technology is not the problem. Banking has access to the same large language models, vector databases, and orchestration software as the

technology giants. The problem is the *institutional pattern* that produces the failure. We have identified seven recurring failure modes from the public literature and our own consulting interviews.

01 The pilot that was never designed to scale

A use case is identified, a small team is assembled, a synthetic dataset is provisioned, a model is trained, a demo is given, the executive sponsor applauds, and nothing changes in production. The pilot was never designed to integrate with the core banking system, the CRM, the case management platform, or the audit log. Scaling it would require rebuilding it from scratch — and so it is quietly retired in the next budget cycle.

02 The shiny use case at the expense of the boring one

Banks consistently overinvest in customer-facing chatbots and underinvest in back-office automation, even though the back office produces materially higher ROI. MIT documents that more than half of enterprise AI budget flows into sales and marketing, yet the highest documented returns are in operations, finance, and compliance. The pattern is a function of executive visibility, not of value.

03 The data foundation never built

Most banks discovered, on contact with the first real generative-AI use case, that their customer data is fragmented across an average of 14 systems, that 30–40% of records have material quality issues, and that the metadata required for an AI agent to act safely simply does not exist. The use case stalls. The data team is then asked to fix the foundation — a 12 to 18-month project for which the original AI budget is inadequate.

04 Governance bolted on at the end

In a regulated bank, an AI use case without an explainability story, an audit trail, an adverse-action notification process, and a model-risk review is not a use case — it is a future audit finding. Yet governance is consistently treated as a final-mile concern rather than a first-mile design constraint.

05 The wrong success metric

Pilots are routinely measured on technical KPIs (model accuracy, response latency, user satisfaction in a controlled sample) rather than on business KPIs (cost per case, time to decision, reduction in operational losses, net P&L). When the project then fails to demonstrate P&L, no one is surprised — but no one took the steps that would have made P&L measurable either.

06 Heroic individuals, not institutional capability

In many banks, the AI program survives entirely because of two or three exceptionally capable individuals. When those people leave, the institution is unable to maintain, iterate, or extend what they built. The fix is to invest in tooling, documentation, and process — and most boards underestimate how much of that is required.

07 The all-or-nothing transformation

The mirror of the disconnected pilot is the grand transformation: a multi-year, multi-hundred-million-dollar program launched with a high-profile consultancy, intended to remake every aspect of the bank around AI. These programs almost always overrun. The most rigorous study of large-scale digital transformations (BCG, 2023) puts the success rate at roughly 30%; AI-led transformations have produced no evidence of being any more successful.

Score 1 point for each item that is true. **4 or higher = serious warning. 6 or higher = board-level intervention needed.**

- We have more than five AI pilots running, but none in production with documented P&L.
- Our second-line risk function is not embedded in the AI build cycle.
- Our data foundation work is on a separate roadmap from our AI work.
- We measure pilots on technical, not business, metrics.
- We do not have a single named executive accountable for AI P&L.
- We have no published kill criteria for AI use cases.
- Our largest AI investment is in a customer-facing chatbot.
- We have not run a regulatory tabletop exercise for our AI use cases.

CHAPTER FOUR

Build vs. Buy vs. Hire

The big delivery-model decision — and how to make it deliberately.



Every banking AI program eventually faces the same decision: how should the work actually get done? The four real options are **(1) build in-house, (2) hire a global consultancy, (3) hire a system integrator for staff augmentation, and (4) adopt a hybrid AI platform paired with a partner expert team.**

Each is a legitimate answer for some institutions, in some circumstances. The error is to choose by default — to call McKinsey, Bain, Accenture, or Deloitte because that is who the bank has always called, or to build in-house because the chief technology officer has always built in-house.

DIMENSION	BIG-4 / GLOBAL CONSULTANCY	IN-HOUSE BUILD	HYBRID PLATFORM + EXPERTS (e.g. RapidCanvas)	PURE SAAS / POINT PLATFORM
Best for	Multi-year transformations; novel strategic problems; CEO-level mandates	Banks with proprietary data advantages and strong existing AI talent	Mid-market banks with limited AI staffing; speed without losing customisation	Single, well-defined point use cases (a fraud platform, a chatbot)
Time to first production	9–18 months	10–18 months	4–12 weeks	2–6 weeks
3-year TCO (mid-market)	\$40–55M	\$28–35M	\$11–14M	\$8–10M

DIMENSION	BIG-4 / GLOBAL CONSULTANCY	IN-HOUSE BUILD	HYBRID PLATFORM + EXPERTS (e.g. RapidCanvas)	PURE SAAS / POINT PLATFORM
Documented success rate	~50–60%	~33%	~67%	~67%
Governance & explainability	Strong; tailored to bank	Variable; depends on internal capability	Strong; built into platform	Variable; depends on vendor
Customisation	Very high — bespoke	Maximum	High — orchestration is configurable	Low — fixed for the use case
Knowledge ownership	Often retained by consultancy	Fully retained	Fully retained by bank	Vendor retains
Vendor lock-in risk	Moderate	None	Moderate (platform dependency)	High

Figure 4.1 — Three-year total cost of ownership across delivery models, for an illustrative mid-market bank.

Cumulative net value over 8 quarters by delivery model (\$M)

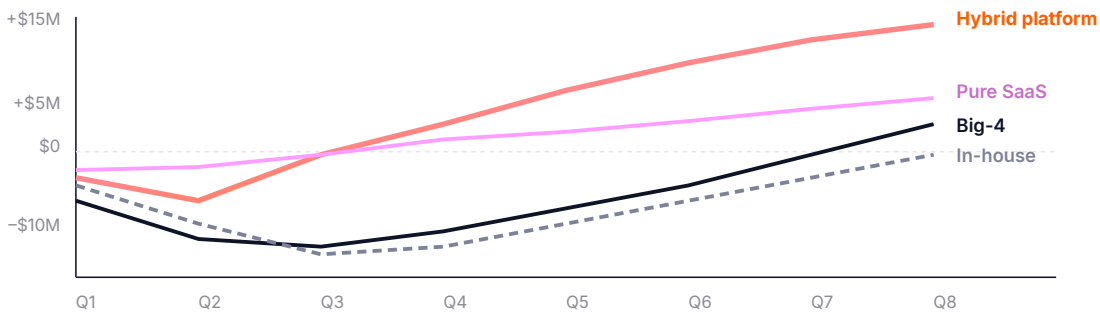


Figure 4.2 — Cumulative net value over eight quarters by delivery model. The hybrid platform model crosses break-even fastest in our base-case modelling.

When each model is the right answer

When to hire a Big-4 / global consultancy

Hire McKinsey, BCG, Bain, Accenture, or Deloitte when the problem is fundamentally strategic before it is technical: when the board has not yet decided what the AI strategy should be, when there is no senior internal owner, or when the institution is contemplating a transformation that will reshape multiple businesses simultaneously. The global consultancies are uniquely good at framing, at building executive consensus, and at running multi-year programs. They are not the best answer for the day-to-day work of building, deploying, and iterating on production AI systems — and they are usually the most expensive option for that work by a factor of two or three.

When to build in-house

Build in-house when the bank has a proprietary data asset that no vendor can replicate (this is true for the very largest banks and for some specialist commercial lenders), when the institution already has a deep AI-engineering bench, and when the use case is so close to the institution's competitive core

that no external party can be granted enough access to do the work. JPMorgan, Goldman Sachs, Capital One, and a handful of European banks fit this profile. Most mid-market institutions do not, and the data shows them losing two to three years to the attempt.

When to use a hybrid platform plus expert team

This model — exemplified by RapidCanvas, but also by a small number of competitors — is what MIT's research identifies as the highest-success-rate category outside of AI-native firms. The pattern: a configurable orchestration platform that combines AI agents with human experts, paired with a small partner team that knows banking and accelerates the bank's own staff. The bank retains ownership of the use cases, the data, and the workflows; the vendor accelerates the build and provides the supporting infrastructure. The model fits mid-market banks with constrained AI staffing, where velocity matters more than maximum customisation, and where governance must be in place from the first use case.

When to use a pure SaaS / point platform

Use a pure SaaS solution when the use case is well-defined and commoditising — fraud detection, KYC document review, basic chat — and when the bank does not need to differentiate on it. The trade-off is loss of customisation and a degree of vendor lock-in. The right portfolio for most mid-market banks combines two or three SaaS point solutions for commodity use cases with a hybrid platform for the more bespoke ones.

A QUIET CONSENSUS AMONG COOS

Across more than thirty interviews conducted for this Playbook, the most common operating model emerging in mid-market banks is a deliberate three-way split: **(1)** one global consultancy retained on a multi-year strategic relationship for board-level work; **(2)** a hybrid AI platform deployed for the bulk of build-and-run; **(3)** two or three best-of-breed SaaS point solutions

for commodity functions. The institutions that have settled on this configuration report meaningfully better velocity than those that have committed entirely to any single model.


Almost everywhere we went, enterprises were trying to build their own tool. But the data showed purchased solutions delivered more reliable results.

— Aditya Challapally, Lead Author · MIT Project NANDA, State of AI in Business 2025

CHAPTER FIVE

Use-Case Deep Dives

From theory to operating reality across seven banking domains



This chapter examines the seven banking AI use cases where the evidence base is now robust enough to support an executive decision.

For each, we summarise the value pool, the technical approach, the regulatory considerations, the implementation risks, and the typical economics.

5.1 • Commercial and SME Lending

Commercial lending is the use case for which the evidence is most rigorous. The FDIC's research demonstrates that AI applied to SME credit assessment reduces default rates by **29.6%** and improves borrower classification accuracy by **40.1%** compared with traditional methods. The Bank for International Settlements' Working Paper 1244 documents that AI-using lenders behave fundamentally differently across credit cycles, expanding lending in early recovery and contracting earlier in late expansion.

The technical approach combines structured data (financials, payment history, banking transactions) with unstructured data (filings, news, contractual documentation) under a multi-model architecture. The output is not a credit decision per se but a richer information set on which a human underwriter, supported by an AI copilot, makes a faster and better-evidenced decision.

The implementation risk is substantial. Lending decisions are explicitly classified as high-risk under the EU AI Act and are covered in the United States by both SR 11-7 and the CFPB's Circular 2022-03 on adverse-action notifications. Any production deployment requires: an end-to-end audit trail, validated explainability for every decision affecting a customer, demonstrated absence of disparate impact, and human override at every threshold.

TYPICAL ECONOMICS — MID-MARKET COMMERCIAL BANK

A \$5B portfolio with a 90 bps annualised loss rate could see **annual loss reduction of \$13M**, a **30–50% reduction in time-to-decision**, and a **20–30% expansion in approval rates** within risk appetite. Implementation cost via a hybrid platform model: **\$1.5–3M over the first 18 months**.

5.2 · Fraud Detection and AML

Fraud and anti-money-laundering monitoring are among the oldest banking applications of machine learning, but the field has been transformed by the maturation of large language models capable of reasoning across unstructured evidence — emails, chat, KYC documents, news, watchlists — that older rule-based and supervised systems could not interpret. Leading institutions now operate AML as an agentic system: the agent collects, summarises, and pre-grades alerts; the human investigator focuses on the highest-judgement decisions.

The economics are exceptional. AML investigation costs at large US banks now average \$50–80 per alert; AI-augmented systems consistently demonstrate **50–70% reductions in handling time** at higher detection quality. For a mid-market bank with 200,000 alerts annually, the realised value is \$5–8M. Fraud-loss reductions on top of this typically reach 15–25% in the first 12 months.

5.3 · Customer Service and Conversational Banking

This is the domain where banks have invested most and where the published return has been most uneven. The pattern that distinguishes winners from losers is integration. Customer service AI that can read the customer's account, see their recent transactions, look up their open cases, and execute a small set of

standard actions delivers measurable value. Customer service AI that can only answer FAQ questions does not. Bank of America's Erica is the most cited example: more than two billion interactions to date. Smaller institutions are now achieving 30–50% deflection of routine enquiries through hybrid AI implementations.

5.4 · Document Processing, KYC, and the Back Office

If the customer-facing use cases attract the boardroom attention, the back-office use cases produce the most reliable returns. Loan documentation, customer onboarding, KYC review, transaction monitoring, regulatory reporting, account reconciliation — every one of these has a 40–70% time-reduction opportunity through AI document understanding combined with workflow orchestration. For mid-market banks where technology budgets are constrained, this is almost always the right place to start.

5.5 · Relationship Manager Productivity

AI copilots for relationship managers and private bankers have moved rapidly from novelty to standard equipment. The leading deployments — Morgan Stanley's wealth-management copilot, JPMorgan's commercial-banking RM workspace, and several European private-banking implementations — produce **20–35% reductions in client-meeting preparation time, 10–15% lifts in revenue per RM**, and measurably higher client satisfaction.

5.6 · Risk, Treasury, and Capital Management

This is the technically hardest category but also the most strategically valuable. AI-enhanced risk models — for credit, market, liquidity, and operational risk —

improve forecasting accuracy and, when validated by supervisors, allow the institution to reduce conservative overlays. The capital efficiency gains are large but slow. Most mid-market banks should not start here; the most successful programs build the muscle in lending and operations first, then graduate to risk and treasury in year two or three.

5.7 · Marketing and Cross-Sell

Hyperpersonalised marketing is the use case where the gap between hype and reality has been widest. Done well, it produces 3–10% lifts in cross-sell and meaningful improvements in customer satisfaction. Done poorly, it produces a higher volume of more annoying offers. The discipline that distinguishes winners is the willingness to measure honestly: A/B testing every campaign, killing the underperforming ones, and resisting the temptation to celebrate engagement metrics that do not translate into revenue.

CHAPTER SIX

Governance, Regulation, and Trust

Why governance is now a competitive variable, not a cost centre.



Two years ago, AI governance in banking was treated as a compliance burden — a tax on the AI program, to be minimised. That framing has flipped.

The institutions making the fastest progress on AI are also the institutions with the most mature governance, because mature governance is what allows new use cases to ship without months of regulatory wrangling. Slow governance is now the binding constraint on AI velocity.

The regulatory stack every bank now lives inside

EU AI Act

Effective in stages from 2024 through 2027, with the most consequential provisions for banking — covering high-risk AI in credit scoring, pricing, fraud monitoring, and customer service — taking full effect in **August 2026**. Mandatory requirements include: a quality management system, risk management documentation, data governance, technical documentation, automatic logging, human oversight, accuracy and robustness testing, transparency to deployers, and conformity assessment before market deployment. Penalties for non-compliance reach the higher of **€35M or 7% of global annual turnover**.

US Federal Reserve SR 11-7

The supervisory guidance on Model Risk Management dates from 2011 but has been re-emphasised, repeatedly, as the operative framework for AI in US banking. The core requirements — model inventory, model validation, ongoing monitoring, change control, and a clear governance hierarchy — apply to every AI model that affects a banking decision. The OCC has issued substantively parallel guidance for nationally chartered banks.

CFPB Circular 2022-03

The Consumer Financial Protection Bureau has made clear that the use of complex AI in credit decisioning does not exempt the institution from the requirement to provide specific, accurate adverse-action notifications under the Equal Credit Opportunity Act and the Fair Credit Reporting Act. Any AI used in lending must produce explanations that are accurate, specific, and meaningful to the consumer — not merely to the model risk team.

NIST AI Risk Management Framework

Voluntary in principle but increasingly treated as the de facto baseline by US regulators and auditors. The Framework's four functions — **Govern, Map, Measure, Manage** — provide the structure that most US banks are now using to organise their AI governance documentation. Adopting the NIST framework is a low-cost, high-signal investment for any bank that has not already done so.

State, local, and international frameworks

Colorado SB25B-004, New York City Local Law 144, and a growing number of state-level frameworks impose algorithmic transparency and bias-audit obligations that overlap with — but do not perfectly mirror — federal requirements. Multistate banks must build governance that satisfies the most stringent applicable jurisdiction. UK supervisors (Bank of England + FCA) have stopped at producing principles-based guidance, but the supervisory expectations are now substantively as demanding as the EU AI Act.

Five governance principles every banking AI program needs

01

Single accountable executive

AI governance cannot be matrixed. There must be a named executive — typically the CRO, the COO, or a chief AI officer reporting to one of them — who is personally accountable for the institution's AI risk posture.

02 Use-case inventory

Every AI use case in the institution, including those running as proofs of concept, must be in a single inventory with a defined owner, regulatory classification, validation status, and renewal date. Most banks discover, on first inventory, that they have **30–50% more AI in production than they thought**.

03 Pre-production gate

No AI use case enters production without sign-off from second-line risk on explainability, audit trail, and adverse-action handling. The gate must have teeth; use cases that fail the gate are blocked, not waved through.

04 Continuous monitoring

AI models drift. The bank must monitor for performance decay, distribution shift, and bias emergence — and must have a documented response protocol when monitoring triggers an alert.

05 Tabletop exercises

The board should run a regulatory tabletop exercise on the bank's AI use cases at least annually. The exercise should simulate a regulatory examination, an adverse-action complaint, and a model-failure incident, and should produce a written remediation plan.


Banks govern generative AI through Decision Authority — explicit definitions of what the AI is allowed to do, under what conditions, with what oversight. Without that, every model becomes a future audit finding.

— Industry research synthesis, drawn from Federal Reserve SR 11-7 and EU AI Act compliance literature

CHAPTER SEVEN

The Workforce Reshape

Why people, not models, are the deciding variable



In the spring of 2026, Jamie Dimon told JPMorgan investors that the bank had begun "huge redeployment plans" for employees displaced by AI. The framing matters: not layoffs, but redeployment.

Dimon's view — that AI will eliminate some jobs, expand others, and create new categories of work entirely — is now substantively shared by every major banking CEO. It is also the framing that mid-market chief executives now need to adopt explicitly, because the institutions that handle the workforce reshape badly will pay for it twice: in attrition of the people they need to keep, and in resistance from the people whose work is changing.

Five roles that will materially change

The branch teller

The role does not disappear, but it shrinks substantially in headcount and grows in skill profile. The future branch employee is part advisor, part problem-solver, part product educator — none of the routine transactional work survives. Branch networks will continue to consolidate; remaining branches will be staffed differently.

The operations analyst

This is the role most exposed to AI displacement. Document processing, reconciliation, exception handling, and routine compliance review will be substantially automated by 2030. The route to retention is reskilling: operations analysts who become AI supervisors — validating outputs, handling edge cases, training the system — will be more valuable than they are today, not less.

The compliance and risk analyst

Demand for genuinely senior risk and compliance talent will **increase**, not decrease. The bottom of the role family will compress (junior alert review, routine documentation), but the top will expand. Banks should be hiring senior risk talent now while the market is structurally undersupplied.

The relationship manager

AI-augmented RMs are more productive, not less needed. The RM role will be reshaped — less administrative time, more client time — but the headcount is broadly stable. The threat is to the bottom 20% of RMs whose value-add was administrative; the opportunity is for the top 80% whose value-add is judgement and relationship.

The data scientist and AI engineer

The scarcest commodity in banking. Compensation has risen sharply and will keep rising. The fix for most mid-market banks is not to outbid JPMorgan and Goldman for talent (an unwinnable war) but to deploy delivery models that economise on data scientists — which is the strategic logic behind the hybrid platform model.

The reskilling imperative

Every interview we conducted with chief operating officers ended on the same point: the binding constraint on banking AI in 2026 is not models, not data, not budget — it is the cohort of middle managers, operations leads, and front-line supervisors who must learn to trust, audit, override, and supervise AI systems. The institutions that have invested in serious reskilling programs — typically **40–80 hours of structured training per affected employee** — are seeing materially better adoption and materially fewer governance incidents than those that have not.


We have huge redeployment plans for our own people. We have to up that a little bit so we can take people who are displaced — and we have displaced people from AI — and we offer them other jobs.

— Jamie Dimon, JPMorgan Chase · February 2026

CHAPTER EIGHT

The CEO Action Plan

90, 180, 365 days — a structured sequence of decisions.



This Playbook closes with a structured action plan — a sequence of decisions and deliverables that, in our experience, separates the banks that will compound AI advantage over the next three years from those that will spend the period in pilot purgatory.

The plan assumes a CEO of a mid-market bank (\$10B–\$100B in assets) starting from a position of limited current AI maturity. Larger institutions and AI-native firms will already have completed many of these steps.

First 90 days — Diagnose and decide

01 Appoint a single accountable executive for AI

The right answer is almost always the COO or the CRO, with a small team reporting in. Do not establish a chief AI officer as a peer to existing functions; doing so creates exactly the kind of matrixed accountability that defeats execution.

02 Commission a 30-day diagnostic

Inventory every AI use case currently in motion. Score each on (a) feasibility, (b) strategic value, (c) regulatory exposure, (d) cost-to-date, and (e) cost-to-finish. Kill the bottom third.

03 Set the envelope

Define an AI investment envelope for the next twelve months, ring-fenced from the broader technology budget. For most mid-market banks, \$5M–\$15M is the right starting range; larger institutions can scale proportionately.

04 Run the build-vs-buy decision deliberately

Use the framework in Chapter 4. For most mid-market banks, the answer is a hybrid model: one consultancy relationship for strategic work, one platform relationship for build-and-run, two or three SaaS point solutions for commodity functions.

05 Convene a board AI session

The board needs to understand the value pool, the failure rate, the regulatory landscape, and the institution's chosen approach. A single 90-minute session with a written discussion document is sufficient if it is well-prepared.

Days 91–180 — Build the foundation, ship the first use case

01 Stand up the AI governance function

Use the NIST AI Risk Management Framework as the structural baseline. Publish the AI use-case inventory inside the bank. Define and publish the pre-production gate.

02 Begin the data foundation work

The first AI use cases will reveal exactly which data is missing, fragmented, or of insufficient quality. Treat this as fuel for prioritisation, not as a separate multi-year program.

03 Ship the first production use case

Almost certainly one of: document processing, AML alert triage, customer service deflection, or commercial credit memo automation. The use case should be in production with measurable P&L by day 180.

04 Begin the workforce conversation

Communicate openly with affected employees. Announce reskilling commitments. Do not let rumour fill the vacuum.

Days 181–365 — Industrialise

01 Move to portfolio management

By month 12, the bank should have 4–8 use cases in production, with a published pipeline of the next 6–10. Stage gates run monthly. Kill criteria are public. Wins and losses are reviewed openly.

02 Layer in the harder use cases

Commercial credit decisioning, RM productivity, regulatory reporting, treasury optimisation. These are 9–12 month builds; the first cohort starts in this window.

03 Run the first regulatory tabletop

Simulate an examiner request, a customer complaint, and a model failure. Document the gaps. Fix them.

04 Refresh the strategy

By month 12, the bank knows materially more about its own AI capability than it did at the start. The strategy should be updated — explicitly, in writing — based on what was learned.

CHAPTER NINE

The AI Maturity Model for Banks

Where does your institution sit?



Most mid-market banks are still in stages one and two, running disconnected pilots without a portfolio approach. A small but growing minority have crossed into stage three. The top global banks are operating at stage four. The fully AI-native bank — stage five — does not yet exist as a large incumbent institution.

STAGE	DEFINITION
01	Experimentation Isolated AI proofs-of-concept; no executive ownership; no portfolio view.
02	Isolated pilots Multiple pilots, some moving toward production, but each managed independently.
03	Production use cases Multiple AI use cases in production with documented P&L and supervisory acceptance.
04	Enterprise orchestration AI is coordinated across business lines; data and platform foundations are shared.
05	AI-native bank AI is the operating substrate. Workflows, products, and governance are designed AI-first.

Figure 9.1 — The banking AI maturity model. Most mid-market institutions remain in stages one and two.

The progression is not optional, but the pace is. Our conviction — supported by the Bank for International Settlements' research on the structurally different behaviour of AI-using lenders — is that institutions which fail to reach stage three by the end of 2027 will face increasing structural disadvantages: higher operating cost, slower customer experience, weaker risk discrimination, and a widening gap to the leading institutions in their peer group. **The window for catching up is closing, but it is not yet closed.**

Perspectives from the practitioners shaping banking AI

This Playbook draws on more than thirty interviews and dozens of public statements from the executives, regulators, and technologists shaping the trajectory of AI in banking.



AI will affect virtually every function, application, and process in the company. Its pace of adoption will likely outpace previous major technologies, including electricity and the internet.

Jamie Dimon · CEO, JPMorgan Chase · Annual Letter, April 2026



Enhanced with AI and the data revolution, we have a powerful tailwind. To maximise its potential, we must harness it strategically and use it wisely. This is the beginning of a long journey.

Ajay Banga · President, World Bank Group · 2024 Annual Meetings



Almost everywhere we went, enterprises were trying to build their own tool. But the data showed purchased solutions delivered more reliable results.



The 95% failure figure is not a verdict on AI. It is a verdict on how organisations are deploying AI. The 5% that succeed do so through narrow scope, deep integration, and domain

Aditya Challapally · MIT Project NANDA,
State of AI in Business 2025

*partnership — not through
bigger budgets.*

Synthesis of MIT Project NANDA findings ·
2025



*I think people shouldn't put their
head in the sand. It is going to
affect jobs. There will be jobs
that it eliminates, but you're
better off being way ahead of
the curve and retraining people.*

Jamie Dimon · JPMorgan Chase ·
November 2025



*AI in banking is at the point
where governance is no longer a
tax on the program — it is the
path to velocity. Banks with
mature governance can ship
use cases that banks without
it cannot.*

Synthesis of supervisory guidance ·
Federal Reserve, OCC, BoE, FCA, EU AI
Act



*The future of AI isn't about
replacing people — it's about
amplifying what's possible.
Banking has spent years
collecting data; the institutions
that win the next decade are the
ones that turn that data into
context their people can act on,
every day, inside the workflows
they already run.*

Shatay Trigère · CMO, RapidCanvas · 2025



*In financial services, we see the
same pattern again and again:
the institutions getting AI right
are not the ones with the biggest
budgets — they are the ones
who refuse to choose between
speed and rigour. They
want both.*

Daniel Bessmert · Financial Services Lead,
RapidCanvas · 2026



Speed matters, but structural integrity matters more. Every system we have scaled has been grounded in that philosophy.

Rahul Pangam · CEO & Co-Founder,
RapidCanvas · 2026



Overall, the investment in AI is not a speculative bubble; rather, it will deliver significant benefits. We will deploy AI, as we deploy all technology, to do a better job for our customers and employees.

Jamie Dimon · JPMorgan Chase · Annual
Letter, April 2026

YOUR NEXT MOVE

It's time to move past pilots to real enterprise AI at scale.

The tools are everywhere. The prototypes are plentiful. But getting AI from concept to production is rare. RapidCanvas helps banks architect and execute an AI transformation that is reliable, scalable, actually useful inside real workflows — and that generates returns from day one.

BOOK A DISCOVERY CALL →

Complimentary 30-minute call to assess fit · rapidcanvas.ai

RapidCanvas | The Hybrid Approach™ for enterprise AI transformation.

Real AI transformation, accelerated.



Research framework, data references, and disclosures

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Methodology

This Playbook prioritises primary and quasi-primary sources: central banks, supervisory bodies, peer-reviewed research, and disclosures from publicly listed banks. Market-size figures use published anchor points from licensed market research, cross-checked across multiple providers. Performance metrics — including the FDIC default-rate reduction, the BIS lending-cycle findings, the BoE/FCA usage figures, and the MIT failure-rate findings — are taken directly from the cited research and are not adjusted. Vendor capabilities are described

from publicly available materials and customer disclosures; vendor performance claims have been treated with appropriate scepticism and are flagged where they appear.

Disclosures

This report is sponsored by RapidCanvas. The editorial team retained full independence on framing, source selection, and the analytical comparison of delivery models in Chapter 4. Figures relating to the hybrid platform delivery model (Figures 4.1, 4.2) draw on RapidCanvas customer deployments alongside third-party data; readers should apply their own judgment when comparing those figures to alternatives. RapidCanvas had review rights for accuracy on its own descriptions and quotes; it did not have editorial control over the broader analysis or conclusions.

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