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Enterprise AI Agent Adoption: From Pilot to Production

A short decision framework for executives

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For financial institutions and large enterprises with many AI pilots and few production deployments

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Executive summary

Most AI agent initiatives stall for reasons that have nothing to do with the model: **the wrong starting point, no credible measurement, and no path beyond one team.**

Five decisions, in the order they come up, for moving an AI agent from a demo that impresses people to a workflow that can be measured, budgeted and audited:

1. **Map the chain before picking a stage.** Time adds up, reliability multiplies: one stage running 10× faster saves at most 20% of the cycle, while a chain of 20 steps, each at 95%, clears only 36% of the time.
2. **The first pilot must clear three gates**: closed loop, measurable, reversible. Its job is to prove the path cheaply, not to maximise value.
3. **The sweet spot is a process with an SOP that people still execute manually.** The least mature and the most mature processes are both poor starting points.
4. **Prove value with three metric layers and a same-period A/B test.** Efficiency alone, or before/after comparisons, will not survive a budget review.
5. **Draw the integration path on day one, and keep "stop" as an option.** Failure to scale is the real failure.

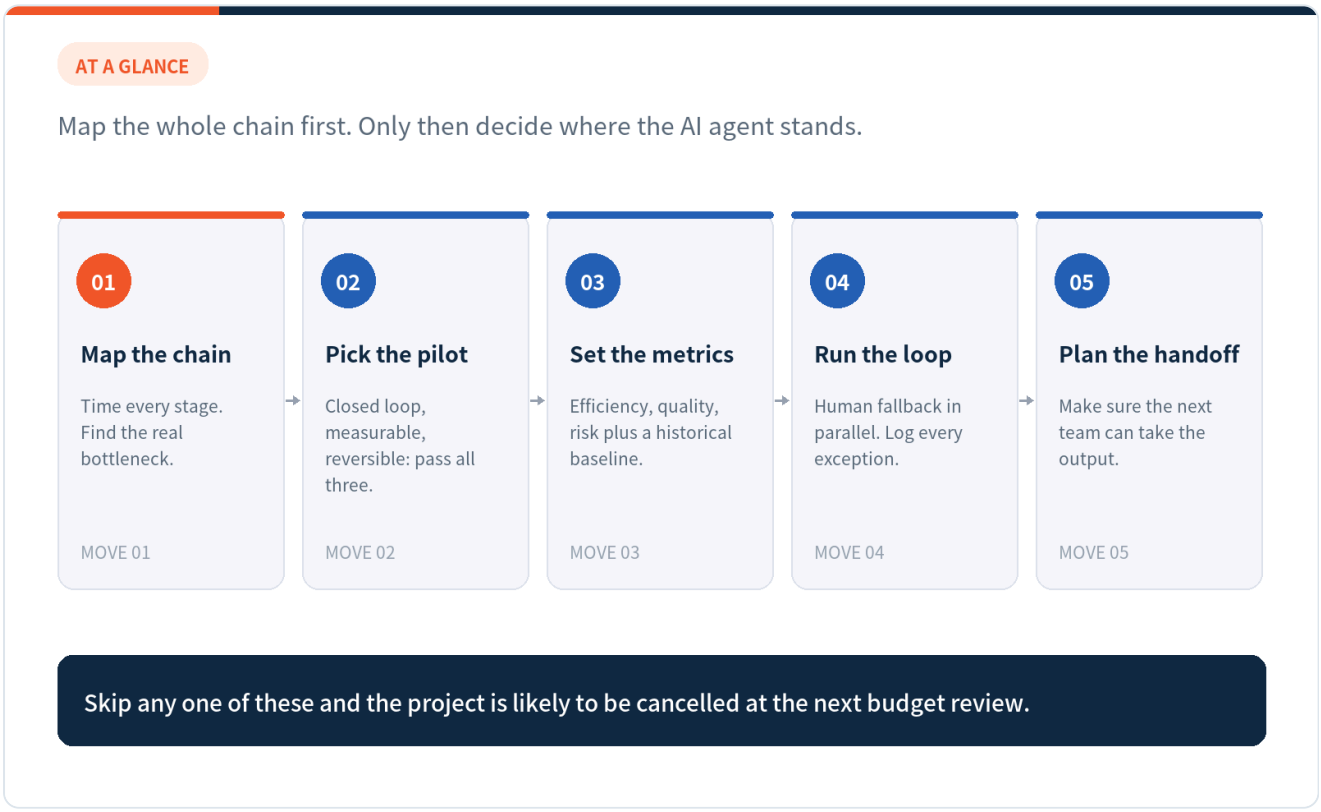


Figure 01 | Five moves from demo to production

01 • Many PoCs, few production systems

Almost every enterprise has run an AI pilot in the last two years. Far fewer have put one into production, into a department's scorecard, or into next year's budget.

The gap is not anecdotal. McKinsey's 2025 global survey (1,993 respondents across 105 countries) finds 88% of organisations using AI in at least one function, yet nearly two-thirds have not begun

scaling AI across the enterprise, and in no single function do more than 10% say they are scaling AI agents. MIT NANDA puts it more bluntly: of the $30–40 billion enterprises have spent on generative AI, 95% of pilots have produced no measurable P&L impact.

The usual causes are three:

- **Only one stage improved.** The local metric looks great; overall cycle time does not move, so the business feels nothing.
- **No way to measure it.** No baseline, no like-for-like comparison, no defensible answer to "how much better?" The budget does not survive.
- **No way to scale.** The single point works, but expansion stalls on data rights, permissions and conflicting departmental KPIs.

None of these are model problems. **Understand the whole chain first, then decide where the AI agent stands**; reverse that order and the first round is wasted.

The industry-level forecast points the same way. Gartner expects more than 40% of agentic AI projects to be cancelled by the end of 2027, citing escalating costs, unclear business value and inadequate risk controls (Gartner, June 2025). The first two are what sections 2 and 5 are for.

02 • Map the chain before picking a stage

A service ticket passes through several hands before it closes. If drafting the reply is 20% of the cycle and the rest is intake, identity checks with cross-system lookups, QA, sending and rework, then making the draft 10× or even 100× faster shortens the whole cycle by at most 20% — that stage is one fifth of it. The bottleneck simply moves. Faster replies produce a queue at QA and follow-up, and resolution time barely changes.

Pilots usually start with drafting the reply, because it demos best: text appears on screen and anyone can judge whether it sounds human. But a good demo and a better chain are two different things — the first shows up inside a single stage, the second only shows up end-to-end.

> **Map the chain, then pick the pilot.** Look at where the time actually goes and where the bottleneck sits, not where automation is easiest.

"The chain" here means the end-to-end path the customer experiences: intake, triage, closure, follow-up, across several systems and several teams. A team's own process can be smooth and still queue at the handover, and that short stretch usually has no owner.

You need no tooling, just one table filled with six to twelve months of real data:

Stage	Avg. time	Share of cycle	Bottleneck today?	Automatable?
Intake / triage	fill in			
Identity + cross-system lookup	fill in			
Draft the reply	fill in			
QA / compliance check	fill in			
Send / follow-up	fill in			
Rework	fill in			

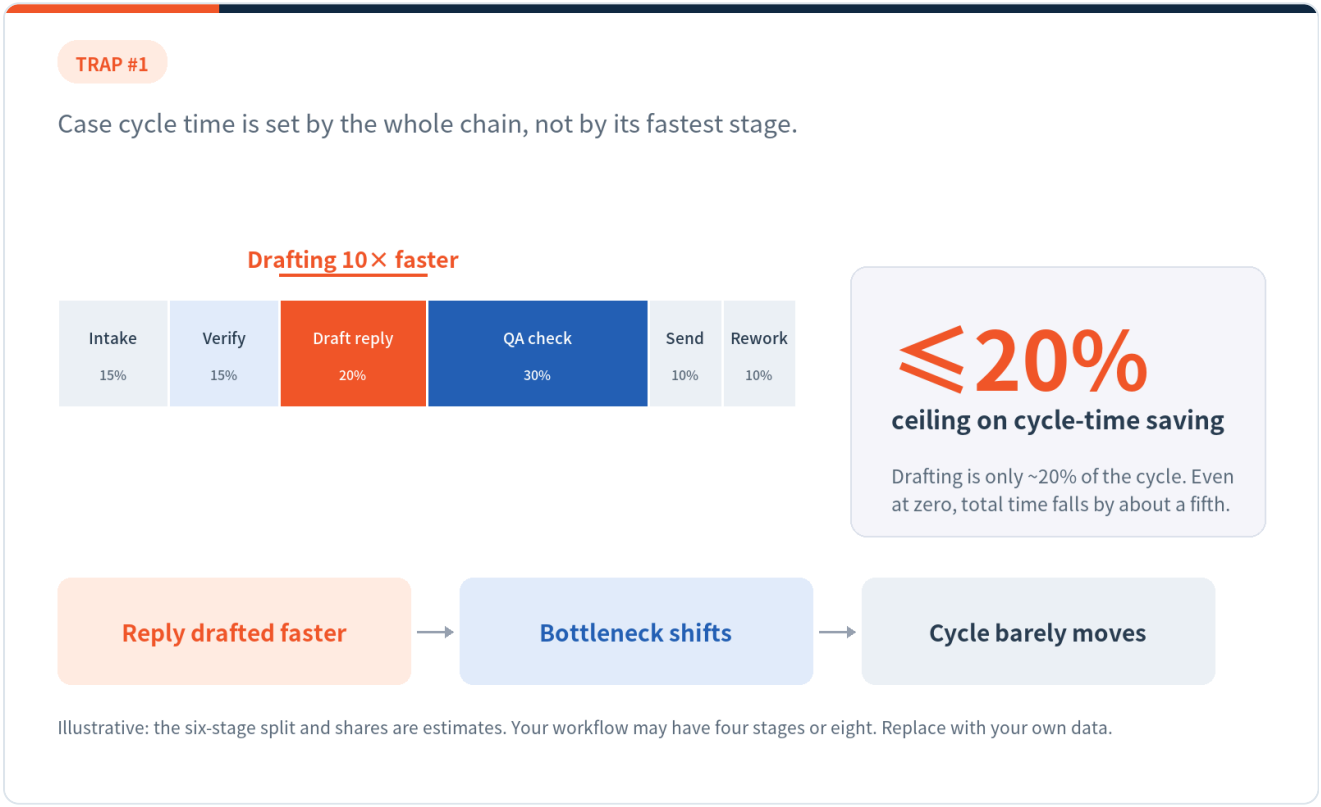


Figure 02 | A 10× speed-up that nobody feels

Most teams find, once the table is filled, that **the stage they most want to automate is not the stage that eats the time.** A drafted reply gets picked first precisely because its result is easy to judge; yet it is one fifth of the chain, and the hours sit on either side of it.

The six stages follow a common ticket workflow. Yours may have four stages or eight, and the count need not match. What matters is that rework gets its own line: it is the first thing a time study drops, and often the real bottleneck. Waiting time belongs inside each stage, not off to the side.

Time adds up. Reliability multiplies.

The six stages above are business stages, and each one breaks down into system actions: open the case, verify identity, look up the order, pull history, check the rules, draft the reply, run the compliance scan, send, receipt, close. A cross-system workflow runs anywhere from a dozen to thirty steps; take 20 as an example. At 95% success per step, only about 36% of cases finish end-to-end on the first pass (0.95^{20}), before retries or human fallback.

From that 36%, there are two routes. Both start from 95% per step — they are not one cumulative line:

- **Make each step more accurate.** Push the per-step failure rate from 5% to 0.5%, and the chain reaches roughly 90%.
- **Let the failed attempt run again.** Add one automated check and retry per step: the step succeeds $1 - 0.05^2 = 99.75\%$ of the time, and 20 steps land at roughly 95%.

The second is usually cheaper. It does not need a better model, only output that a machine can check.

Step count is the exponent here. At the same 95% per step, 10 steps give about 60%, 20 give 36%, and 30 give about 21%. Count your own steps rather than borrowing this number.



Figure 03 | 20 steps in series: two routes out of 36%

Verifiable output matters more than faster output. It is the common precondition for retries, human fallback and QA sampling — and it is what section 3 really asks when it asks about a closed loop.

03 • Three gates, plus process maturity

A function qualifies as the first pilot only if it clears all three gates. Miss one and you may build something you cannot evaluate.

Gate	In one line	If it fails
Closed loop	Defined input, verifiable output	No way to judge success
Measurable	An existing KPI can serve as baseline	Improvement cannot be proven
Reversible	Errors are cheap, recoverable, auditable	One incident ends the programme

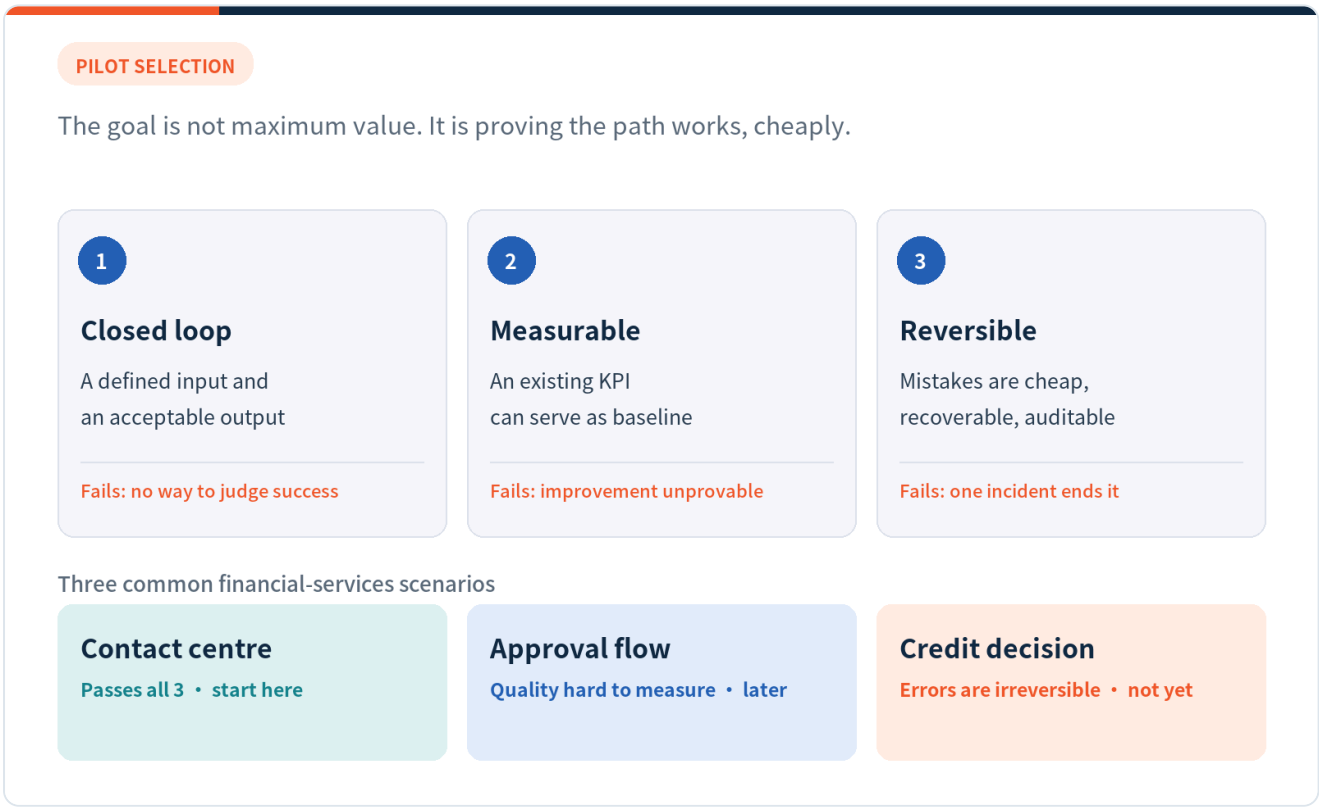


Figure 04 | Three gates: contact centre passes, credit decisions wait

In financial services: contact centres clear all three and are the natural first choice; approval workflows are measurable on time but weak on quality, so they come second; credit decisions are irreversible when wrong and should not be first.

Customer service is the default starting point because it is often the only place where all three gates hold at once. Value has little to do with it.

The same gates behave differently across departments, and the difference is process maturity, not technology. AI agents need executable rules and verifiable output. Where the process is immature, nobody can even define what "done correctly" means.

Five checkable signals: a living written SOP; a system of record with exportable logs; explicit roles and handoff points; quantified KPIs with sampled QA scoring; and six to twelve months of retrievable history. Missing two or more? Fix the process first.

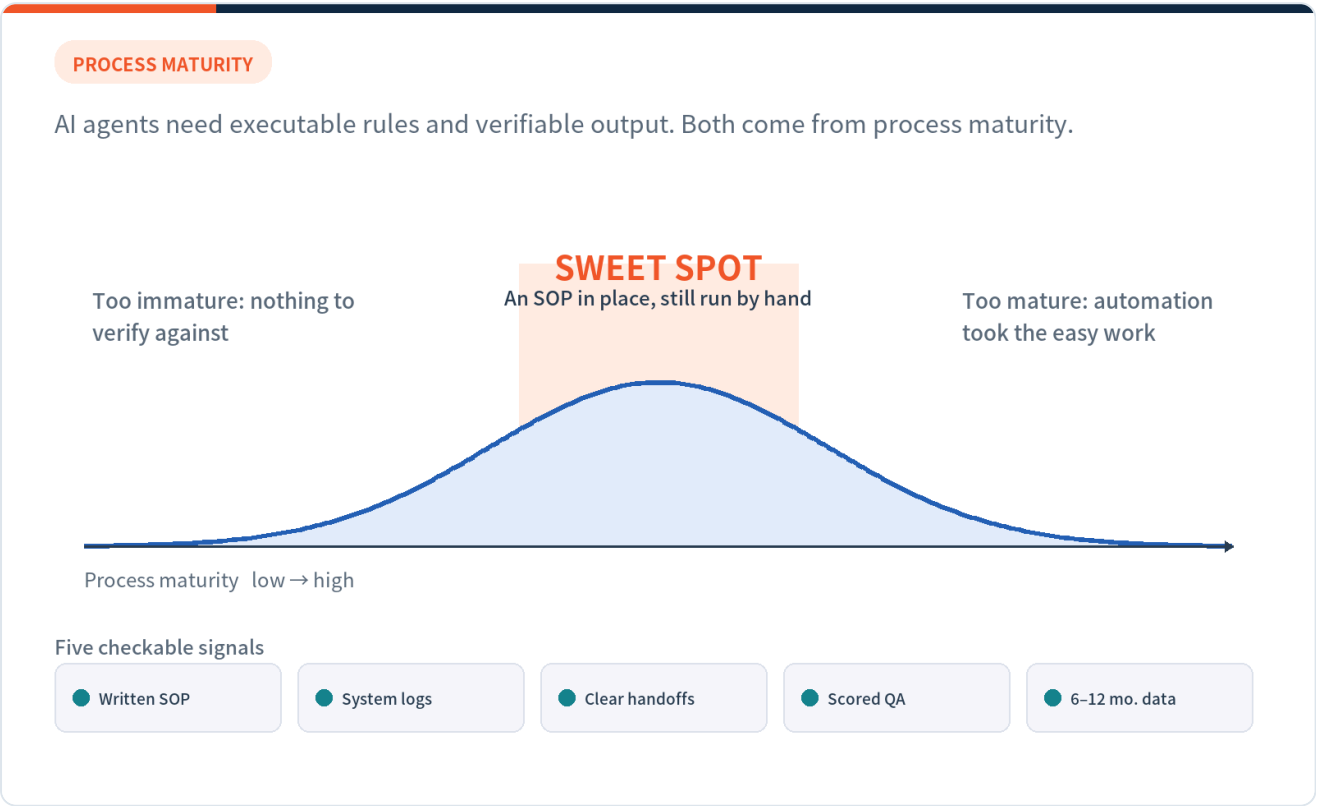


Figure 05 | The sweet spot is not the most mature process

The best target is not the most mature process, either. Mature areas have already been optimised for years by interactive voice response (IVR), rules engines and robotic process automation (RPA). What remains is the long tail of exceptions that rules never covered: the hardest work with the lowest marginal return. The sweet spot is specific: **high volume, enumerable rules, an SOP in place, still executed manually, with humans judging the edge cases.**

04 • Customer service is four businesses

Treating "customer service" as one block is why investment often lands in the wrong place. Ranked by **rule certainty × emotional load**, the four sub-chains are very different.

Order	Sub-chain	Why it sits here
1	After-sales	Return/repair rules are enumerable, closure is clear, emotion is moderate. Best first cut
2	Pre-sales	Scripts can be trained, but persuasion is involved and the KPI is conversion
3	Tech support	Knowledge-base dependent, long tail of complex cases; fix knowledge governance first
4	Complaints	Case-by-case, highest emotional load. Do last, or not at all

How to split it: bucket six to twelve months of tickets by their case-type field rather than by org chart — a single ticket often crosses sub-chains, a pre-sales question turning into an after-sales claim, so the unit of measurement is the sub-chain, not the department. For the first cut take only the three to five highest-frequency after-sales scenarios, and write the hand-over triggers down before launch: no rule matched, amount above threshold, or the customer asks for a person.



Figure 06 | After-sales → pre-sales → tech support → complaints

Prove the loop on the hardest rules and calmest conversations, then widen.

05 • Proving value: three layers, one fair comparison

If you cannot say whether it worked, the programme will not survive the next budget cycle. That is not rhetoric: in McKinsey's 2025 survey only 39% of respondents attribute any EBIT impact to AI, and most of those put it below 5%. Measure three layers together. Efficiency alone is the classic way to fail:

- **Efficiency**: handle time, cost per case, throughput. On its own, efficiency can rise while quality falls, a net loss.
- **Quality**: accuracy, first-contact resolution, rework rate, complaint rate.
- **Risk**: out-of-scope actions, failed compliance audits. One incident wipes out every earlier gain.

Three layers are necessary but not sufficient. Two further questions decide whether the conclusion holds: **is the sample big enough, and is the comparison genuinely like-for-like?**

Sample size and observation window. "Run a full cycle, then compare" is too vague. To resolve a 3-point difference you need several hundred cases per arm and at least eight consecutive weeks. Below that, sampling noise exceeds the agent's real effect, and whichever arm wins may simply have been lucky. On a thin sample, report direction and a confidence interval rather than a point estimate such as "30% better".

Four conditions for like-for-like: the same case pool, the same period, the same scoring rubric, the same reviewer. Change any one of them and the gap between arms is a gap in measurement, not in the agent.

Compliance narrows what can be randomised. In financial services an A/B split is not purely random: high-stakes decisions — credit approval, pricing, disbursement — cannot run unattended, and a human must review afterwards. What can be randomised is the *preparatory* work: lookups, drafting, reconciliation, comparison. The *decision* can be assisted, never replaced. The measurable gain therefore tops out at whatever share those preparatory steps hold in the chain.

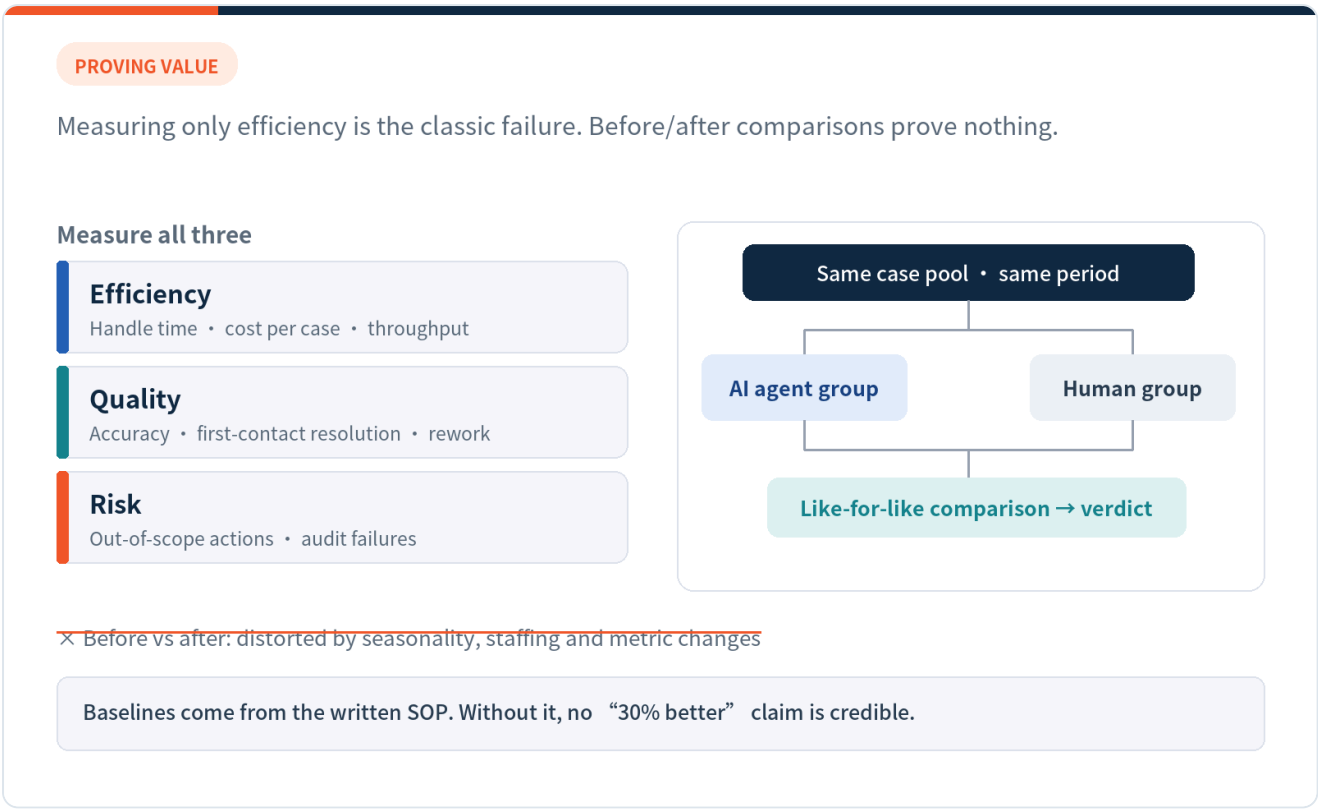


Figure 07 | Three metric layers + same-period A/B

The comparison design matters just as much: **use a same-period A/B split, not before/after.** Before/after is distorted by seasonality, staffing changes and metric redefinitions. Route comparable cases randomly to an AI agent group and a human group over the same period, then compare.

Baselines come from the written SOP, not from estimates. Without a reproducible baseline, no "30% improvement" claim is credible. Process documentation is what gives an AI programme something to measure against.

06 • Two assumptions worth checking

Data governance follows use, not the other way round. Planning two or three years of data governance before AI rarely works: without an AI use case, governance has no ROI, business teams will not fund it, and the engineering work has no finish line. **AI is the trigger for data governance, not its reward.** A concrete AI agent target turns governance into "to reach this resolution rate, we must fix these fields in these tables": bounded, testable, fundable. Skip the standalone governance programme; attach a **minimum viable dataset** to the pilot, then widen it once the loop works.

Draw the integration path before choosing the pilot. Single-point pilots usually succeed; scaling is where programmes break. Three recurring failure points: data sovereignty (a one-off authorisation that expires across departments), KPI conflict (better first-contact resolution in service changes the downstream ticket mix and hurts another team's scorecard), and the handoff gap (SOPs inside a team, none between teams, which is exactly where AI agents die).

> **When this pilot succeeds, can the next team actually take its output?**

Ask this before asking which department is keenest. Otherwise you build a beautiful island that gets switched off in year two.

07 • A 90-day path



Figure 08 | 90 days, four phases, one decision

Phase	When	Key actions	Deliverable
Map	Weeks 1–2	Time the chain; run the five questions on candidate teams	Bottleneck + ranked pilots
Baseline	Weeks 3–4	Pick one stage; define three metric layers; pull 6–12 months of history	Metric definitions + baseline values
Run the loop	Weeks 5–10	Go live on that stage with human fallback; log every exception	First working loop + incident log
Compare & decide	Weeks 11–12	Same-period A/B; map the next team's interface and data rights	Decision report: scale / fix / stop

Weeks 11–12 must leave "stop" on the table. A project that is allowed to be stopped gets evaluated honestly. A project that can only succeed will produce polished numbers.

What this paper does not cover. Security and compliance (data classification, masking, audit trails), explainability (why a given step decided what it did) and model risk management (versioning, drift, rollback) are preconditions for putting an agent into production, but each is a discipline of its own and is out of scope here. They decide whether a project can go live; this paper is about proving value once it has. Teams currently in a security review should scope those three as separate workstreams rather than folding them into the pilot.

Appendix • Five questions before you start

Answer these before approving a first pilot. If you cannot answer three of them, do not start yet.

Done	Question	Why it comes first
☐	**Is there a written SOP? When was it last updated?**	Without a reproducible baseline, no "30% improvement" is credible
☐	**Is there a system of record? Can the data be exported, and for how long?**	No exportable data, no starting point for any estimate
☐	**How many people do this work, and what is the daily volume per person?**	That number sets the ROI ceiling
☐	**What is the KPI? Who does QA, and is the standard quantified?**	If improvement cannot be measured, the budget stops
☐	**In-house or outsourced? Priced per head or per case?**	That basis decides how the saving is counted

These five are not a scorecard but a veto filter: any one left blank means the function is not yet measurable.

Third-party figures here are sourced; unsourced proportions and calculations are illustrative. Replace them with your own 6–12 months of operational data before committing to a target.

Sources

1. MIT NANDA, *The GenAI Divide: State of AI in Business 2025*, August 2025. Sample: 300 public AI deployments, 150 executive interviews, 350 employee surveys. Cited here for "95% of pilots show no measurable P&L impact" and "$30–40 billion spent".
2. McKinsey & Company, *The State of AI in 2025: Agents, Innovation, and Transformation*, 5 November 2025. Sample: 1,993 respondents across 105 countries. Cited here for "88% use AI in at least one function", "nearly two-thirds have not begun scaling", "no more than 10% scaling agents in any function", and "39% report any EBIT impact, most below 5%".
3. Gartner, *Gartner Predicts Over 40% of Agentic AI Projects Will Be Canceled by End of 2027*, press release, 25 June 2025.

Third-party figures describe the industry, not this framework. The proportions, calculations and table values here still need replacing with your own data.

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A pilot is not production. Prove one loop, then scale.

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