

ML LABS INTELLIGENCE

# How to Find Your First AI Use Case

Most teams start with AI ideas that sound impressive but do not survive delivery or ROI scrutiny. Use this framework to find a first use case worth shipping.

STRATEGIC

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Every executive feels the pressure. Competitors are announcing AI initiatives. Board members are asking about your AI strategy. The temptation is to pick something — anything — just to get started. That urgency is exactly how organizations waste their first AI investment on a use case that sounds impressive in a pitch but cannot survive delivery, data reality, or ROI scrutiny.

This is exactly how most organizations waste their first AI investment. [Research on organizational AI adoption](#) (McKinsey, 2024) shows 72% of organizations have adopted AI, yet [research on AI value realization](#) (BCG, 2024) finds only a minority report meaningful value from their initial deployment. The gap almost always traces back to use case selection.

## The Use Case Selection Trap

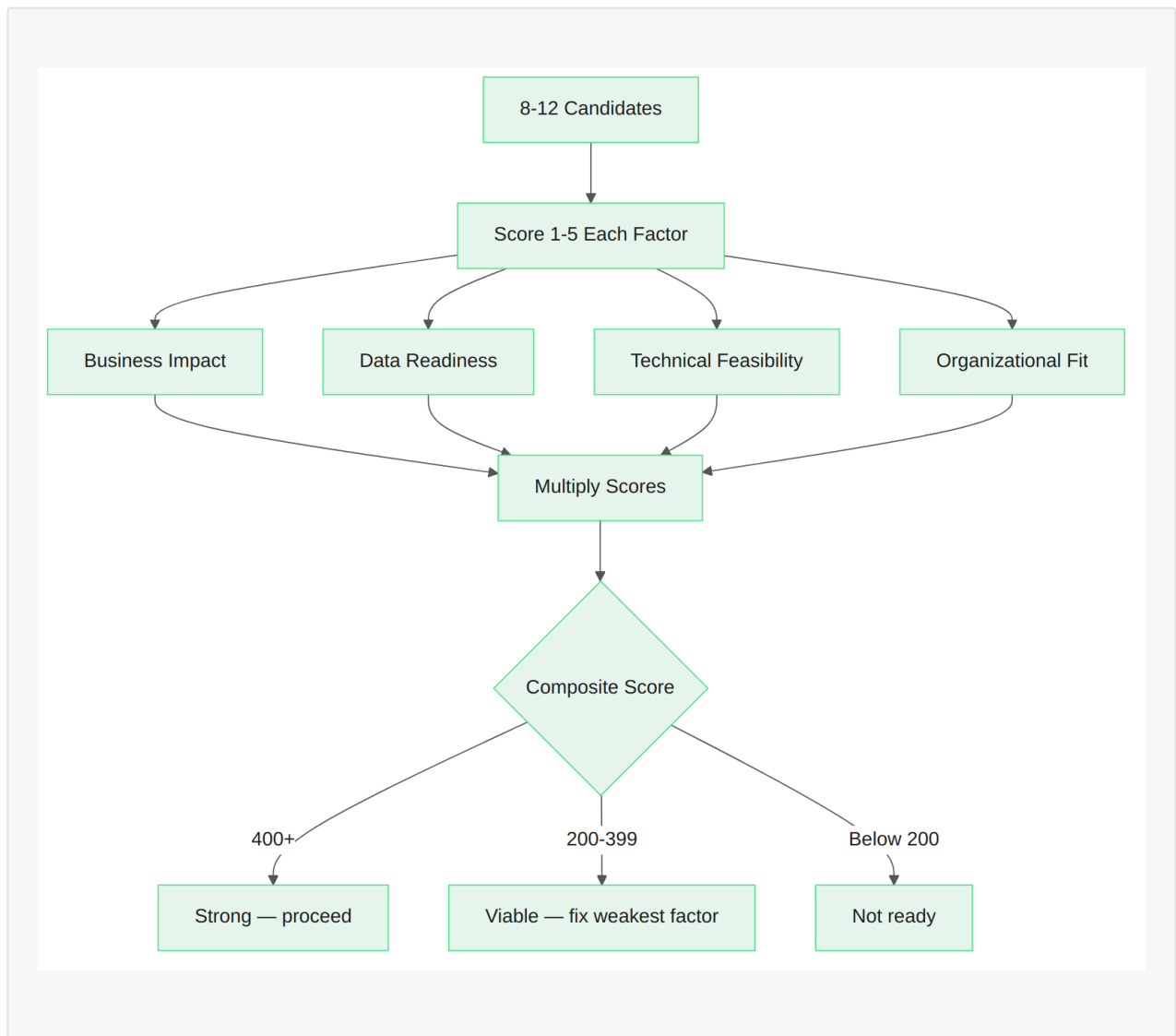
The most common mistake isn't picking the wrong technology. It's picking the wrong problem.

- **The Shiny Object Trap:** choosing a use case because it sounds impressive rather than because it solves a real problem
- **The Boil the Ocean Trap:** automating an entire process when a narrow application would deliver value faster
- **The Data Fairy Tale Trap:** assuming the needed data exists and is clean when it's fragmented or missing

Each leads to the same outcome: significant spend and a demo that never becomes a product.

# The Use Case Evaluation Framework

A four-factor scoring model helps evaluate potential AI use cases. Each factor is scored 1-5 and the four scores are multiplied together. The maximum possible score is 625 ( $5 \times 5 \times 5 \times 5$ ). Multiplication penalizes weakness — a single low score drags the composite down hard.



## Factor 1: Business Impact

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Score based on quantifiable impact. [Research on AI investment outcomes](#) (MIT Sloan, 2024) shows that first AI projects with quantifiable ROI are significantly more likely to receive follow-on investment.

- How often does this process run, and what does each execution cost?
- What would a 30% improvement be worth annually?
- Can you define a concrete measurement milestone?

## Factor 2: Data Readiness

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This is where most evaluations fall apart. A [study on AI-ready data](#) (Gartner, 2025) found that organizations will abandon 60% of AI projects unsupported by AI-ready data.

- **Is the data structured and in one place?** Tabular data in a single source beats text scattered across spreadsheets and SaaS tools
- **How much history exists?** Supervised learning needs thousands of labeled examples — 50 records requires a different approach
- **Is it accurate?** Self-reported quality assessments are almost always optimistic — audit a sample before committing

// Data readiness is the single highest-risk factor in first AI projects. A technically sound use case with no accessible data is the most common and most expensive failure pattern.

## Factor 3: Technical Feasibility

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Not all AI problems are equal. Some are well-solved patterns with off-the-shelf solutions. Others require cutting-edge research. For a first use case, stick with proven patterns:

- **Classification:** sorting items into categories (email routing, document classification, lead scoring)
- **Regression:** predicting a number (demand forecasting, pricing optimization, risk scoring)
- **Extraction:** pulling structured data from unstructured sources (invoice processing, contract analysis)

Avoid as a first project: generative AI for creative tasks, multi-agent systems, real-time computer vision, or anything described as "state of the art" in recent [peer-reviewed research](#) (IEEE).

## Factor 4: Organizational Fit

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The best first AI project changes how people work as little as possible. A system that augments an existing decision faces far less resistance than one that automates a role. [Research on AI adoption approaches](#) (Deloitte, 2024) shows that augmentation-first approaches achieve higher adoption rates and faster time to value.

## Scoring and Prioritization

**Score each candidate and multiply.** [Research on AI in project success](#) (MDPI, 2025) confirms that structured evaluation before implementation significantly improves time and cost outcomes.

- **400+:** Strong first use case — proceed with confidence
- **200-399:** Viable — address the lowest-scoring factor first
- **Below 200:** Not ready — foundational gaps need work before AI

## Common High-Scoring First Use Cases

Based on patterns across hundreds of evaluations, certain use cases consistently score well because they combine high volume, structured data, proven ML patterns, and minimal workflow disruption.

- **Financial Services:** transaction anomaly detection (high volume, structured data, proven pattern)
- **Manufacturing:** predictive quality (sensor data already collected, clear cost of defects, fast feedback loop)
- **Professional Services:** document classification and routing (high volume, measurable time savings)
- **Retail/Logistics:** demand forecasting and route optimization (historical data exists, direct cost impact)
- **Healthcare/Insurance:** clinical note extraction and claims triage (high volume, augments existing workflow)

## The Evaluation Workshop Format

A half-day structured workshop accelerates scoring and builds alignment. [Research on AI initiative failure](#) (RAND, 2024) found that misunderstandings about project intent are the most common reason AI initiatives fail — workshops surface these misalignments before investment.

**Participants:** operations managers, department leads, one or two technical people. Diversity of perspective matters more than seniority.

1. **Brainstorm:** each participant submits 2-3 candidates (aim for 15-25 total)
2. **Deduplicate:** merge overlaps down to 8-12 candidates
3. **Score independently:** no discussion until scores are in
4. **Discuss outliers:** divergent scores reveal hidden constraints
5. **Rank and select:** average scores, select the top 3 for deeper validation

## When This Approach Does Not Apply

This framework assumes scoring drives the final decision. When a senior executive overrides the data to push their preferred project, expected success rates decline regardless of framework quality. The symptoms: scores adjusted after the fact, low factors dismissed as "we'll figure it out later," and the workshop becomes theater. As [research on organizational barriers to AI adoption](#) (HBR, 2025) confirms, a single committed sponsor who defends the framework's output matters more than perfect methodology.

## First Steps

1. **Gather 8-12 candidate use cases** from across the business, including front-line employees who see operational pain daily.
2. **Run a focused evaluation workshop** using the four-factor framework — be brutally honest on data readiness.
3. **Validate the top candidate** — examine the actual data and define a tightly scoped pilot with clear success criteria.

## Practical Solution Pattern

Score candidates 1-5 on business impact, data readiness, technical feasibility, and organizational fit. Multiply for a composite score and reject anything below 200 before committing resources. Run a focused evaluation workshop to surface operational reality that top-down decisions routinely miss.

This works because data readiness is the single highest-risk factor in first AI projects — requiring a score before funding prevents the most common failure pattern. The organizational fit factor prevents the second pattern: choosing a technically feasible use case that requires cultural change to adopt. Use cases that augment existing workflows reach production faster and sustain adoption longer than those demanding process redesign alongside model deployment.

Organizations evaluating multiple AI opportunities can accelerate scoring through a **Strategic Scoping Session** that maps candidates to the framework and produces a written recommendation with feasibility, approach, and timeline.

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## USE CASE CANDIDATES

- Use case candidates
  - Flow enriched
  - Support assignment
  - Work, rating system (pointing)
- Case model or events
  - Add options/constraints
  - User by changing attributes
- Priority markings
  - Lifecycle when enter
  - User assignment model
  - Data in https/ice

- To use priority
- To use priority
- To use priority

## PRIORITY RANKING

