OBEYA CONSULTING

AI Readiness
– Building Capability & Creating Business Impact

A practical guide to turn AI Readiness at SME into Real Business Results

Executive Summary

Artificial Intelligence is no longer a far-off vision of the future. It is already transforming how companies operate, make decisions, and deliver value - across industries, and at all sizes. But while headlines are dominated by breakthrough models and futuristic capabilities, the everyday reality for most mid-sized companies is very different.

They're not looking for the next revolutionary algorithm.
They're looking for clarity. For structure. For a way to understand how AI might actually fit into their business - not as an abstract vision, but as a real, measurable advantage.

And that's exactly what this whitepaper is about.

In our work with business and technology leaders, we see a consistent pattern: a growing awareness that AI could play a role - but uncertainty about what to do next. Which use cases are actually feasible? What kind of data is required? Are our systems and processes mature enough? And how do we avoid wasting time and budget on initiatives that lead nowhere?

This whitepaper offers a pragmatic way forward.

It provides a clear, structured approach for companies that want to move from AI interest to AI readiness - and from readiness to actual impact. It is built specifically for mid-sized organizations that may not have in-house data science teams, but who do have valuable processes, domain knowledge, and a desire to innovate.

Rather than promoting tools or platforms, this guide focuses on what truly matters

- Understanding your own starting point
- Knowing how to identify use cases that are worth pursuing
- Building internal clarity on responsibilities, data quality, and decision criteria
- And launching AI projects that are focused, feasible, and scalable over time

Inside this whitepaper, you'll find

- A clear **maturity model**, so you can see where your organization stands today
- A **quick-check assessment** to pinpoint gaps and strengths in your AI readiness
- A practical **framework to evaluate AI use cases**, based on data availability, automation potential, and business relevance
- A simple, actionable **pilot roadmap** to move from concept to implementation with minimal risk and clear KPIs

But most importantly, this whitepaper gives you something often missing in the AI conversation. We provide **orientation.**

Abbreviation Glossary

AI – Artificial Intelligence
The capability of machines to perform tasks that typically require human intelligence, such as learning, reasoning, or natural language processing.

API – Application Programming Interface
A set of protocols and tools that enables different software applications to communicate and interact - essential for integrating AI systems.

CEO – Chief Executive Officer
The highest-ranking executive in a company, responsible for setting strategic direction and overseeing overall operations.

CIO – Chief Information Officer
The executive responsible for a company's IT strategy and technological infrastructure, often driving AI adoption.

Claude – Claude AI
A family of conversational large language models developed by Anthropic, focused on safe, steerable, and helpful interactions for business and research.

CRM – Customer Relationship Management
Systems used to manage customer data and interactions across the lifecycle; today often enhanced with AI for personalization and automation.

DevOps – Development and Operations
A set of practices that combine software development and IT operations to improve deployment speed and system reliability.

ERP – Enterprise Resource Planning
Integrated software systems used to manage core business functions such as finance, supply chain, and production.

Gantt – Gantt Chart
A project management tool used to visualize task timelines and dependencies, supporting structured planning and tracking.

GDPR – General Data Protection Regulation
The European regulation that governs the handling of personal data - critical for AI systems dealing with sensitive information.

GPT – Generative Pre-trained Transformer
A class of large language models developed by OpenAI, capable of producing contextually appropriate, human-like text.

IT – Information Technology
A broad term covering the infrastructure, software, and systems used to process, store, and transmit digital information - foundational to AI readiness.

KPI – Key Performance Indicator
Quantifiable metrics used to assess performance or success; in AI, KPIs may measure model accuracy, ROI, or user engagement.

LLM – Large Language Model
An AI model trained on vast text datasets to understand and generate natural language - examples include GPT, Claude, and LLaMA.

LLaMA – Large Language Model Meta AI
An open-source language model developed by Meta, optimized for research and commercial use with a focus on performance and efficiency.

Mistral – Mistral AI
A European company known for developing high-performing, lightweight, and modular open-source language models.

Mixtral – Mixtral of Experts
A model from Mistral AI using a "mixture of experts" architecture, dynamically activating specific sub-models depending on the task.

MLOps – Machine Learning Operations
Practices and tools that support the deployment, monitoring, and management of machine learning models in production environments.

MVP – Minimum Viable Product
The most basic version of a product that delivers value, used to test assumptions quickly and iteratively in AI development.

NLP – Natural Language Processing
A field of AI focused on enabling machines to understand, interpret, and generate human language.

POC – Proof of Concept
A demonstration project to validate that a proposed idea, model, or solution is technically and operationally feasible.

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1. Introduction

Artificial Intelligence is increasingly moving from the innovation agenda into the operational core of companies. What began as isolated use cases in data science labs is now evolving into enterprise-wide discussions around process automation, decision support, customer interaction, and digital efficiency.

While large corporations have the resources to invest in dedicated AI teams, labs, and transformation programs, mid-sized companies often operate under different conditions: limited resources and capacity, unclear starting points, and the need for tangible outcomes.

This whitepaper is designed specifically for SME - companies that see potential in AI, but want a structured, realistic and business-aligned approach to begin. Rather than presenting AI as a disruptive force or a technological revolution, we focus on what matters most in practice: readiness, relevance, and results.

How This Paper Creates Value

This paper provides a practical framework for assessing and improving AI readiness. It is intended for decision-makers in IT, operations, innovation and business functions who are tasked with shaping or enabling data-driven strategies in their organization.

This whitepaper will help the reader to

- Understand what **AI readiness** means in an operational and organizational context
- Identify typical **barriers** and misconceptions that limit the adoption of AI in mid-sized environments
- Use a clear and pragmatic **maturity model** to assess the current state of their organization
- Apply a **quick-check** to reflect on readiness dimensions such as data quality, governance, stakeholder alignment, and process stability
- Recognize which types of **AI use cases** are most relevant and feasible, and how to structure their identification and prioritization
- Learn how to move from analysis to execution by means of **targeted pilot initiatives**

2. Why AI Readiness Is More Than Just Technology

The implementation of artificial intelligence (AI) in mid-sized companies is often perceived primarily as a technical undertaking. However, practical experience shows that **technological capabilities alone are not sufficient** to derive measurable value from AI investments. Sustainable AI usage requires a broader foundation - one that integrates strategic alignment, process transparency, data availability, and organizational governance.

Mid-sized companies frequently have a solid digital infrastructure, but lack the clarity and structure to prioritize, evaluate, and operationalize AI use cases. As a result, initiatives often remain fragmented, pilot-driven, or technology-led, with limited strategic impact.

A structured approach to AI readiness addresses this gap by focusing on the conditions that enable scalable and business-relevant use of artificial intelligence.

> ***"Only 26% of companies have already built the capabilities to scale AI pilot projects effectively across the organization."***
> ***(BCG, AI at Scale 2024 – Global AI Adoption Report)***

2.1 Defining AI Readiness

AI readiness refers to the degree to which an organization is prepared to identify, evaluate, and implement AI-based solutions in a structured, efficient, and value-oriented manner. It **is not defined by the number of tools in use**, but by the organization's ability to deploy them purposefully and manage their impact.

This includes the following dimensions

1) **Strategic Integration**

AI initiatives must support defined business objectives, performance metrics, or transformation goals. Without this link, technical investments risk being misaligned or redundant.

2) **Data Governance and Accessibility**
The availability, quality, and governance of relevant data are essential prerequisites. Without a clear data landscape, AI solutions lack the input required to produce reliable results.

3) **Process Maturity**
AI thrives in structured environments. Only processes that are well-documented, stable, and measurable can be effectively supported or automated through AI-based methods.

4) **Role Clarity and Accountability**
AI implementation requires coordination across IT, business units, and compliance functions. Readiness includes clearly defined responsibilities, decision rights, and oversight mechanisms.

5) **Change Management and Internal Acceptance**
Organizational readiness also includes the willingness and ability to integrate AI into existing workflows and decision-making processes - with appropriate communication and user involvement.

2.2 Key Observations from Practice

Based on current market data and field experience, the following observations are relevant for mid-sized organizations:

- Many companies have technological foundations (e.g., cloud platforms, data pipelines) in place, but lack an integrated roadmap for AI adoption.
- In the absence of defined ownership structures, AI projects are often initiated informally and lack continuity.
- The business relevance of AI use cases is frequently underestimated during the evaluation phase - leading to solutions that are technically interesting but operationally nonessential.
- A limited understanding of data dependencies and quality requirements can delay or derail implementation.
- Regulatory and compliance implications (e.g., in the context of automated decision-making) are often addressed too late in the process.

2.3 Why Readiness Is a Strategic Imperative

Establishing AI readiness is not a prerequisite for all innovation - but it is essential for ensuring that AI initiatives are scalable, auditable, and aligned with business goals. It enables companies to

- Prioritize use cases based on feasibility and expected value
- Reduce dependency on individual initiatives or external providers
- Create transparency around data usage and decision logic
- Position AI as part of a broader modernization or automation strategy

3. Common Barriers to AI Adoption in Mid-Sized Companies

Artificial intelligence is no longer a theoretical concept. In many industries, it has already become a practical tool to improve forecasting, optimize operations, or enhance customer interactions. Nevertheless, many mid-sized companies find it difficult to move beyond isolated pilots or conceptual discussions. While interest in AI is often high, the implementation remains fragmented or superficial.

This is not primarily due to a lack of intent or awareness. Rather, it stems from a combination of structural, procedural, and cultural barriers that make it difficult to establish a sustainable approach to AI adoption. These barriers are not unique, but they are consistent - and frequently underestimated.

Understanding them is a critical step toward building a realistic and actionable AI strategy.

3.1 Lack of use case orientation

In many organizations, the starting point for AI is abstract. The technology is seen as promising, but there is no clear connection to specific business objectives or operational challenges. As a result, early initiatives tend to be exploratory - often without defined scope, success metrics, or stakeholder alignment.

Such projects rarely gain momentum. They deliver unclear outcomes, struggle to justify further investment, and may even lead to internal fatigue. Over time, the perception of AI can shift from opportunity to complexity.

A structured approach to identifying and prioritizing use cases is therefore essential. Only when AI is embedded into real business processes - with defined objectives and measurable value - can it move from experimentation to impact.

3.2 Data fragmentation and access limitations

AI requires data. But not just any data - it must be reliable, relevant, and accessible in a usable format. This is where many mid-sized companies encounter structural limitations.

Data is often distributed across departments, systems, and formats. It may be incomplete, inconsistently maintained, or inaccessible due to unclear ownership or technical barriers. In some cases, critical data simply isn't captured at all.

This makes it difficult to train models, validate results, or scale solutions.

Before investing in AI tooling, companies must gain clarity over their data landscape: What data exists? Who owns it? Is it trustworthy? And is it available in the form required to support automated or semi-automated decision-making?

Without a baseline of data governance and accessibility, AI will remain limited in scope and reliability.

3.3 Limited internal expertise and resource constraints

Unlike larger corporations, mid-sized businesses rarely have in-house data science teams or AI departments. Expertise, if available, is often limited to individual initiatives or external consultants. This creates dependency and can limit organizational learning.

Moreover, the gap between technical complexity and business applicability can be wide. AI capabilities are frequently discussed in terms that are not well integrated into operational language or decision frameworks.

For AI to become a repeatable capability, companies need more than technical talent. They need role clarity, training concepts, and the ability to translate business requirements into AI-compatible questions - and vice versa.

Building this bridge requires both time and focus. But it is essential to **avoid the "pilot trap"** where useful experiments fail to become scalable solutions.

3.4 Missing governance structures

Even successful pilots can fail to scale if governance is missing. Without defined standards for evaluating, approving, and managing AI initiatives, companies risk creating parallel efforts, redundant tooling, and inconsistent practices.

In practice, this can lead to:

- Uncoordinated investments across departments
- Unclear responsibilities for monitoring or maintaining AI solutions
- Difficulty in ensuring compliance, especially in regulated environments

Governance does not have to be bureaucratic. But it must be present. Especially when AI begins to influence operational decisions or customer interactions, oversight, transparency, and accountability become non-negotiable.

> ***"Without a shared understanding of strategic readiness, organizations lack the ability to translate vision into execution – making even well-resourced initiatives prone to failure."***
> ***(Adapted from RAND Corporation's Ready for Strategic Readiness? (2025))***

3.5 Internal resistance and uncertainty

Finally, every technological shift touches culture. AI is no exception. When introduced without proper context, it can create resistance. Employees may worry about job security, managers may be skeptical about opaque decision logic, and leadership may hesitate to commit resources in the absence of clear return on investment.

In these cases, even well-designed solutions can fail - not because of technical flaws, but because the organization was not prepared to absorb them.

Effective AI adoption depends on active communication. Companies must articulate what AI is - and what it is not. They must clarify expectations, involve key stakeholders, and explain the role of human judgment in AI-supported processes.

Trust is not built through algorithms. It is built through transparency, engagement, and the ability to demonstrate value over time.

Recognizing these barriers does not mean avoiding AI. It means addressing the right questions early - before time, resources, and internal credibility are put at risk.
The next chapter introduces a structured model for assessing AI readiness, helping organizations understand their current position and plan their next steps with confidence.

4. AI Readiness Maturity Model

Introducing artificial intelligence into an organization requires more than isolated initiatives or technological upgrades. It demands a clear understanding of the organization’s current capabilities - not only in terms of data and infrastructure, but also in terms of strategic alignment, operational integration, and governance maturity.

To support this understanding, the following AI Readiness Maturity Model provides a structured view of how companies typically progress in their ability to identify, implement, and scale AI initiatives. The model is intentionally pragmatic and reflects the experience of mid-sized organizations across different sectors.

4.1 Initial – Isolated interest without structure

At this stage, AI is present primarily as a topic of interest. Individual employees or teams may explore tools, attend conferences, or run minor experiments. However, these activities are not coordinated, and there is no clear link to business priorities.

Key characteristics

- AI discussions are informal and often technology-driven
- No dedicated budget or roles exist
- Use cases are opportunistic and lack clear ownership
- Data is fragmented and often not usable for AI applications
- No governance or evaluation criteria are defined

Organizations at this level face a high risk of misalignment and internal fatigue. Progress is possible, but limited in scope and sustainability.

4.2 Structured Awareness – Foundation building

Companies in this phase have begun to recognize the need for structure. First use cases are scoped with a business problem in mind, and initial investments are made in data infrastructure, tools, or external partnerships.

Key characteristics:

- AI initiatives are linked to specific business needs or processes
- Roles and responsibilities start to emerge
- Data availability is mapped and cleaned on a per-use-case basis
- First governance elements are in place (e.g., approval processes, documentation)
- Learnings from early pilots are used to define future steps

This level is often marked by valuable experience - including failures. The organization begins to understand what is realistically achievable and where the key constraints lie.

4.3 Operational – Repeatable practices, measurable outcomes

At this stage, AI is no longer an isolated topic. It is integrated into operational workflows and planning cycles. Teams have a shared understanding of when and how to apply AI, and the organization can repeat successful patterns across different domains.

Key characteristics:

- Use case identification follows a structured process
- AI initiatives are prioritized based on feasibility and value
- Data pipelines and model operations are standardized
- Internal capabilities (technical and business) are developed intentionally
- Governance includes monitoring, documentation, and stakeholder reporting

The organization is now able to scale successful pilots, integrate AI into legacy processes, and maintain internal alignment between departments and leadership.

4.4 Strategic – Embedded capability with enterprise relevance

In this phase, AI is an accepted and embedded part of the company's value creation strategy. The organization actively integrates AI into product development, service design, and business model innovation.

Key characteristics:

- AI strategy is aligned with corporate objectives and reviewed regularly
- Investments in data and AI capabilities are long-term and portfolio-based
- AI is integrated into enterprise architecture and IT governance
- Models are monitored for fairness, compliance, and performance
- Cross-functional teams work with clear KPIs and success metrics

At this level, AI is no longer a special project. It is a capability - one that evolves, is governed, and delivers sustained value.

4.5 Applying the model

The purpose of this model is not to label organizations, but to provide a shared language and orientation. Many companies operate across levels - for example, with advanced capabilities in one function and foundational gaps in another.

Using the model can support:

- Internal discussions about readiness and priorities
- Scoping and evaluation of AI-related investments
- Alignment between business, IT, and leadership stakeholders
- A roadmap for moving from isolated experimentation to scalable impact

In the following section, a practical quick-check will help readers reflect on where their organization currently stands - and where the most immediate areas for improvement may lie.

> ***"As of 2019, only about 6% of mid-sized companies in Germany with more than 50 employees reported using any AI solutions."***
> ***(KfW Research, Digitalization in the German Mittelstand, 2021)***

5. Quick-Check – Where Do You Stand Today?

Before engaging in AI initiatives, organizations benefit from a structured reflection on their current level of readiness. This quick-check supports that reflection by posing a set of guiding questions across five key dimensions. Each question is accompanied by an explanation of its relevance - designed to stimulate internal discussion, align expectations, and highlight potential gaps.

This chapter does not aim to deliver a quantitative result. Rather, it provides a **framework for qualitative insight and dialogue** - particularly valuable for mid-sized organizations that operate with limited resources and must prioritize carefully.

5.1 Strategic Alignment

- **Do we have a clearly defined business objective that AI is expected to support?**
  AI should never be implemented for its own sake. When projects are not anchored in business goals - such as improving efficiency, reducing error rates, or enabling faster decision-making - they often fail to generate commitment or measurable outcomes. A clear objective helps set direction and justify investment.
- **Are current or planned AI initiatives linked to existing KPIs or operational priorities?**
  Linking AI use cases to performance indicators ensures that their value can be assessed in familiar terms. This not only improves evaluation but also makes it easier to gain support from leadership and operational teams, who often prefer continuity over abstract metrics.
- **Is there consensus among leadership that AI is a relevant enabler - not just an experimental tool?**
  If AI is seen only as a technical experiment, its relevance in strategic planning remains low. When leadership understands and communicates that AI serves broader business transformation goals, projects are more likely to receive sustained support and cross-functional alignment.

5.2 Data and Infrastructure

- **Do we know where relevant data resides - and who owns it?**
  Many AI projects are delayed because data sources cannot be located, accessed, or clarified in terms of responsibility. Knowing who is responsible for data - both technically and legally - is a prerequisite for compliant and reliable use.

- **Is the data we plan to use for AI accessible, structured, and of sufficient quality?**
  Even with the right algorithms, poor-quality data will lead to weak or biased outcomes. Structured, consistent, and validated data is a critical foundation for meaningful AI results - and one of the most underestimated challenges in early-stage initiatives.

- **Are data integration and maintenance processes defined and reliable?**
  One-off data extractions may work for pilots, but not for scalable solutions. Without repeatable data processes, AI applications cannot be maintained or improved over time, and their credibility within the organization suffers.

5.3 Process and Use Case Maturity

- **Are the processes we want to enhance with AI clearly documented and stable?**
  AI works best in well-understood environments. If a business process is poorly defined, frequently changing, or highly dependent on informal workarounds, it becomes difficult to model, automate, or support through AI.

- **Do we have criteria to evaluate whether a process is suitable for AI-driven automation or prediction?**
  Not every task or decision benefits from AI. By applying feasibility and impact criteria early - such as data availability, volume, variability, or business relevance - organizations can avoid wasted effort on low-value or technically impractical use cases.

- **Have we successfully mapped at least one AI-relevant use case from problem to solution?**
  A single well-executed example can serve as a reference for internal discussions and future project planning. It also helps in building internal

confidence and exposing practical obstacles, such as access to data or acceptance by users.

5.4 Organizational Governance

- **Is there a responsible owner for AI initiatives or use case portfolios within the company?**
  Without clearly defined roles, AI projects often lack continuity and decision-making authority. A designated owner ensures prioritization, coordination with other departments, and accountability for results - especially in cross-functional contexts.
- **Are approval, documentation, and monitoring procedures in place for AI projects?**
  Governance mechanisms do not have to be complex, but they must exist. Structured oversight helps prevent duplication, ensures regulatory compliance, and enables internal transparency - particularly when AI touches sensitive areas like HR, finance, or customer communication.
- **Have we discussed regulatory and compliance implications, particularly where decisions are automated?**
  AI use in business-critical processes may fall under data protection, consumer protection, or sector-specific regulation. Discussing these aspects early reduces legal risk and ensures that AI remains auditable and explainable.

5.5 Internal Skills and Change Readiness

- **Do we have internal resources who understand both the business context and AI fundamentals?**
  Bridging the gap between domain knowledge and technical feasibility is one of the most critical enablers for AI success. Without this interface, teams may talk past each other, and projects fail to move beyond technical experimentation.
- **Are we able to manage external providers in AI-related projects competently?**
  External partners can accelerate implementation, but they must be managed based on informed specifications and expectations. Organizations that lack internal understanding risk vendor dependency or misaligned results.

- **Is there a willingness across teams to adapt workflows, roles, or decisions in response to AI implementation?**
  Even the best models are ineffective if they are not accepted or applied. Cultural readiness - the ability to integrate new logic into established routines - is a frequently underestimated success factor.

This set of questions is not exhaustive, but it is sufficient to initiate a focused internal dialogue. Organizations that answer openly and cross-functionally - involving business, IT, and leadership - will gain the most insight.

The next chapter presents a structured framework for identifying and prioritizing AI use cases. It supports organizations in allocating resources where readiness and relevance intersect most effectively.

6. Identifying and Prioritizing AI Use Cases

Many organizations today understand the strategic potential of artificial intelligence. Yet, one of the most common obstacles to adoption is a surprisingly practical one - not knowing where to begin.

While the interest in AI is often high, companies frequently struggle to identify concrete, value-generating use cases. Discussions remain theoretical or too broad, initial projects lack direction, and pilot initiatives fail to demonstrate clear business benefits. As a result, AI is perceived as complex, distant, or not actionable under real-world conditions.

To overcome this gap, companies need a structured approach for identifying use cases - one that is grounded in operational reality, informed by business needs, and attentive to feasibility. This chapter outlines such an approach and highlights why use case selection is a decisive factor in building sustainable AI capabilities.

> *“72% of companies cite poor data quality and unscalable infrastructure as major obstacles to effective AI adoption."*
> *(F5, State of AI Readiness in Enterprises, 2024)*

6.1 Why the right use case matters

AI is a powerful enabler, but only if it is applied to the right problem. In practice, many AI projects fail not because of technical limitations, but because they target the wrong processes. Either the expected benefits are too low, the data is insufficient, or the organizational context is not ready to absorb the change.

By contrast, when use cases are selected based on **business relevance, technical feasibility and organizational readiness**, they are far more likely to deliver measurable value - and to serve as credible reference points for further investment.

The process of identifying and prioritizing use cases is therefore not a minor preliminary step. It is **a core component of AI strategy** - especially for mid-sized companies, where resource allocation must be targeted and justifiable.

6.2 What makes a good AI use case?

Not every process is suitable for AI. To narrow down potential areas of application, the following characteristics are often observed in use cases that lead to successful implementations:

- **Recurring decision patterns**
  The task involves making similar decisions repeatedly, such as classifying, predicting, or selecting based on structured input.
- **Availability of relevant data**
  Data needed to support the decision is available, consistent, and preferably digitalized.
- **Clear business ownership**
  There is a team or department that understands the process, owns the outcomes, and is willing to collaborate.
- **Defined outputs**
  The outcome of the process is clear and can be validated - for example, approving a request, assigning a category, or predicting a value.
- **Economic relevance**
  The process affects cost, speed, customer experience, or risk in a way that matters to the business.

These criteria can be used as a basic filter to separate general interest in AI from cases where **concrete application and measurable impact are possible**.

6.3 A structured discovery approach

Identifying suitable use cases requires a cross-functional dialogue. In many cases, promising ideas emerge at the operational level - but require validation and refinement before they can be developed into AI initiatives.

A structured approach may involve the following steps:

1. **Generate a longlist of candidate processes**
   Begin by involving various stakeholders from business units, operations, IT and customer-facing teams. Ask:
   - Where are decisions made frequently and repetitively?
   - Which processes are time-consuming or error-prone?
   - Where do we rely on estimations or manual classifications?
2. **Screen for technical feasibility**
   For each candidate, assess:
   - Is relevant data available in sufficient quality and quantity?
   - Is the process stable and repeatable?
   - Can the success of an AI solution be measured in a meaningful way?
3. **Evaluate expected business value**
   Estimate the potential impact in terms of:
   - Efficiency gains or cost reduction
   - Improved accuracy or consistency
   - Risk reduction or compliance support
   - Customer or employee satisfaction
4. **Prioritize based on readiness and benefit**
   Rank use cases not just by value potential, but by the effort required for implementation. Favor those that are both feasible and valuable - and where organizational support is likely.

This process can be facilitated through workshops, guided interviews, or structured assessment templates. It is often useful to document assumptions and uncertainties early on - as these will later influence the design of pilots or MVPs (minimum viable products).

6.4 Examples from mid-sized business practice

Use cases for AI do not have to be revolutionary. In many organizations, the most effective starting points are modest in scope, but meaningful in outcome.

Examples include

- **Automated classification of incoming invoices**
  Using historical accounting data to predict the correct cost center or GL account, reducing manual input and approval cycles.
- **Customer e-mail routing based on content**
  Applying natural language processing (NLP) to categorize incoming customer queries and direct them to the appropriate department automatically.
- **Sales demand forecasting for selected products**
  Leveraging past sales data and seasonal indicators to improve planning accuracy - especially in high-volume or perishable goods segments.
- **Predictive maintenance in field operations**
  Identifying patterns in maintenance logs and sensor data that indicate elevated failure risks - allowing proactive scheduling and reduced downtime.

What these cases share is not technical complexity, but clarity of input, stability of process, and relevance to operations.

6.5 Thinking beyond the first pilot

While early use cases often serve to build confidence, it is advisable to consider scalability from the outset. Use cases that offer **potential for reuse, expansion or integration** into broader business processes provide more strategic value than isolated optimizations.

Questions to ask:

- Can this solution be extended to other departments, markets or product groups?
- Will it generate data or insights that benefit other parts of the organization?
- Could it serve as a blueprint for future AI-driven improvements?

Thinking in terms of scalability helps organizations avoid the "pilot trap" - where promising projects remain stuck in proof-of-concept mode and fail to influence long-term capability building.

The identification of use cases is not a one-time event, but a **continuous process**. As organizational maturity grows, new data becomes available and teams gain experience, the pipeline of AI opportunities will evolve. What matters is to create a foundation for structured evaluation - balancing ambition with feasibility.

In the following chapter, we describe how to move from a prioritized use case to a well-scoped pilot project - with a focus on clear objectives, manageable complexity, and operational relevance.

7 From Use Case to Pilot - A Structured Apporoach

Once a promising AI use case has been identified and prioritized, the next step is to move from concept to implementation. For many mid-sized companies, this transition represents a critical moment: it is where strategic ambition meets operational complexity.

A well-designed pilot project reduces this complexity. It enables organizations to test assumptions, validate feasibility, and generate tangible results - without overcommitting resources or raising expectations prematurely. The objective is not to launch a full-scale solution, but to gain insight, reduce risk, and build a foundation for structured scaling.

This chapter outlines a step-by-step approach to designing and executing an AI pilot that is technically feasible, business-relevant, and organizationally manageable.

> ***"Roughly 70% of AI implementation challenges are related to people and processes, not algorithms or tech."***
>
> ***Source: BCG, The Human Side of AI Transformation, 2024***

7.1 Define clear goals and scope

The first step in any pilot is to define what success looks like. This includes not only the technical outcome (e.g. accuracy of a model) but also the operational and business impact the pilot is intended to demonstrate.

Key questions include

- What problem are we trying to solve?
- How will we measure whether the AI solution adds value?
- What constitutes a minimum viable scope - in terms of data, users, and process coverage?

A clearly scoped pilot avoids overreach. It defines what is in scope - and what is not. It also ensures that expectations are aligned between technical teams, business owners, and leadership.

Example: A pilot to automate invoice classification may be limited to a subset of vendors or invoice types, and evaluated based on time savings and classification accuracy - not on complete process transformation.

7.2 Assemble a cross-functional team

AI implementation requires expertise from multiple domains. Even in a small-scale pilot, success depends on collaboration between business users, data specialists, IT, and (where applicable) external partners.

Typical roles in a pilot project include

- **Business owner**: Defines the problem, validates outputs, and ensures relevance
- **Data analyst or engineer**: Provides access to relevant data and prepares it for modeling
- **AI/ML specialist**: Designs, trains, and tests the model
- **IT/system owner**: Manages integration into existing systems or test environments
- **Project lead**: Coordinates the pilot and ensures timelines and communication

The team should be small, clearly aligned, and able to make decisions without unnecessary escalation.

7.3 Prepare and validate the data

Data is the core input to any AI system. For pilot purposes, the focus is not on volume, but on **representative and clean data** that reflects the real conditions under which the solution would operate.

Key steps include

- Identifying relevant data sources
- Ensuring that data is complete, consistent, and accessible
- Documenting the meaning of variables, units, labels, or classifications
- Establishing criteria for training, testing, and validation

Involving domain experts in this step is critical. Data that appears usable at first glance may have limitations - such as hidden biases, non-standard coding, or missing context - that only operational staff can detect.

7.4 Develop and test the model

The actual model development is typically the shortest phase in a pilot - provided that data preparation has been done properly. The goal is not to achieve perfection, but to develop a **functioning prototype** that demonstrates how AI could support or automate a defined decision.

Important principles

- Keep the model interpretable - especially in sensitive domains
- Document assumptions, thresholds, and decision rules
- Use historical data to simulate performance under real conditions
- Compare AI recommendations to actual decisions to assess alignment and improvement

Depending on the use case, it may also be useful to define boundaries: when should the system act autonomously, and when should it defer to human judgment?

7.5 Evaluate results and document findings

At the conclusion of the pilot, the team should conduct a structured review - not only of the model's technical performance, but of its operational relevance and integration potential.

Typical evaluation criteria

- Accuracy and reliability of the AI output
- Business impact (e.g. time saved, errors reduced)
- User feedback and process alignment
- Technical feasibility of scaling the solution
- Risks and limitations identified during implementation

This review should lead to a documented recommendation - whether the pilot should be scaled, modified, paused, or discontinued. Transparency at this stage builds credibility and prepares the ground for broader adoption if justified.

7.6 Communicate results and next steps

Even a limited pilot can generate valuable insights - not only for the project team, but for the broader organization. It is important to communicate outcomes clearly and realistically, avoiding overstatement but highlighting concrete achievements.

Effective communication includes

- Presenting results in business language, not just technical metrics
- Sharing what was learned - including challenges and risks
- Outlining the path to scaling, if applicable
- Engaging leadership and end users in the discussion of next steps

Pilots that are well communicated tend to enjoy greater internal support, even if they do not result in immediate deployment. They also build trust in the overall AI program and encourage future participation.

An AI pilot is not a proof of perfection. It is a structured learning exercise - one that reduces uncertainty, validates feasibility, and connects technical capability to operational value.

The next chapter outlines the organizational requirements needed to move from pilots to broader adoption, focusing on governance, change management, and long-term capability development.

8 Operationalizing AI – From Pilot to Scalable Capability

A successful pilot demonstrates what is possible. But for artificial intelligence to become a consistent source of business value, it must be anchored in the operational structure of the organization. This transition - from individual projects to an integrated capability - requires more than technical refinement. It requires **governance, ownership, and process alignment**.

Many organizations reach a plateau after initial experimentation. Pilots may deliver promising results, but without the right institutional support, they remain isolated. Momentum fades, and the broader benefits of AI remain unrealized.

To avoid this outcome, companies must address three interrelated dimensions: **governance and oversight, integration into processes, and organizational enablement**.

8.1 Establishing Governance and Accountability

AI initiatives touch multiple domains - from data strategy and infrastructure to compliance, operations, and customer interaction. As projects scale, decision rights and accountability must be clearly defined.

> *"By 2027, AI governance will be mandatory in all major jurisdictions, and companies lacking formal controls will face strategic and legal disadvantages."*
> *(Gartner, AI Governance Forecast, 2023)*

Key elements of AI governance include

- **Strategic alignment**: AI projects should be evaluated and approved in relation to business priorities, not only technical interest.
- **Ownership models**: Clear roles for business owners, data stewards, and technical leads ensure that responsibilities for outcomes and risks are shared.
- **Standards and policies**: Guidelines for model development, testing, validation, and monitoring help ensure consistency and compliance - especially in regulated environments.

- **Risk and compliance management**: AI introduces new forms of operational and reputational risk. Transparent logic, explainability, and proper escalation paths must be part of the framework.
- **Lifecycle management**: AI models evolve. Organizations must define how models are updated, reviewed, and eventually retired.

A lightweight governance model can suffice in the early stages. What matters is that decisions are made intentionally and transparently - not reactively.

8.2 Embedding AI into Operational Processes

An AI model delivers value only when it is embedded in a process that uses its output. This often requires adjustments to workflows, systems, and interfaces.

Examples of integration activities include

- **Defining points of interaction**: Where does the AI output enter the process? Who sees it? What actions does it trigger?
- **Automating handoffs**: Reducing manual steps between AI output and downstream systems (e.g. ERP, CRM, ticketing tools) increases efficiency and reliability.
- **Process redesign**: In some cases, introducing AI may require the creation of new decision paths, approval rules, or exception handling procedures.
- **System interoperability**: AI components must align with existing infrastructure and IT architecture - avoiding redundancy or fragility.
- **User training**: Operational staff must understand how to interpret and apply AI outputs in context - and where to challenge or override them if necessary.

Successful integration turns AI from a system into a tool - one that is accessible, accepted, and usable by those responsible for delivering results.

8.3 Building Organizational Capabilities

Beyond systems and governance, scaling AI requires internal capacity. This includes not only technical expertise, but also **cross-functional competencies and institutional learning**.

Elements of capability development include

- **Basic literacy in AI across roles**: Managers, analysts, and operational staff should understand what AI can and cannot do - to frame problems, interpret outputs, and collaborate with technical teams.
- **Dedicated roles or units**: Depending on size and ambition, companies may establish AI leads, Centers of Excellence, or data teams to coordinate initiatives and share best practices.
- **Knowledge management**: Learnings from pilots and deployments should be captured and made reusable - through documentation, templates, or internal communities of practice.
- **Partnership models**: Few organizations have all the required skills in-house. Structured engagement with external partners, consultants, or platforms is often part of a realistic operating model.
- **Performance tracking**: AI projects must be evaluated not only for technical success, but also for adoption, impact, and sustainability over time.

Capability building is not a single program. It is an ongoing effort - embedded in recruitment, training, project management, and leadership development.

8.4 Creating the Conditions for Sustainable Impact

Scaling AI is not a purely technical exercise. It is a matter of organizational maturity. Companies that succeed typically show:

- A clear link between AI efforts and business value
- A growing pipeline of use cases, informed by operational feedback
- A pragmatic but consistent governance structure
- Internal ownership, not dependency on individuals or vendors
- A mindset of learning and adaptation, rather than fixed blueprints

In short: they treat AI not as a one-time project, but as a **capability to be developed, governed, and improved over time**.

In the final chapter, we summarize the key takeaways of this whitepaper and outline actionable next steps for companies seeking to move forward with AI - methodically, realistically, and with measurable impact.

9 Summary and Recommendations

Artificial Intelligence is no longer a niche topic. For many mid-sized companies, it has become a strategic consideration - not because it is expected by the market, but because it holds tangible potential to increase efficiency, improve decision quality, and support long-term competitiveness.

At the same time, AI adoption in this segment remains cautious and uneven. The reasons are understandable: limited resources, unclear starting points, and uncertainty about what it truly means to be "ready" for AI.

This whitepaper has aimed to close that gap - by providing a structured, pragmatic, and business-aligned view of AI readiness and implementation.

9.1 Key messages at a glance

1. **AI Readiness is not about technology alone**
   Tools and platforms matter - but without clear objectives, stable processes, and organizational support, they do not lead to impact.
2. **Use cases must be identified deliberately**
   AI is most effective when applied to clearly defined problems, with available data and measurable business relevance. Structured use case discovery prevents misaligned efforts and wasted resources.
3. **Pilots are learning instruments, not end goals**
   A well-designed pilot helps reduce uncertainty, align teams, and build internal momentum. It should be scoped, executed, and evaluated with discipline - not urgency.
4. **Scalability requires governance, integration, and capabilities**
   Moving from isolated pilots to operational solutions depends on embedding AI into workflows, defining ownership, and developing internal competencies.
5. **AI should be treated as a capability - not a one-time project**
   Organizations that succeed with AI build repeatable processes, engage cross-functional teams, and integrate learnings into broader transformation efforts.

9.2 Next steps for mid-sized organizations

Companies looking to begin or refocus their AI journey should consider the following actions:

- **Conduct an AI readiness assessment** based on the five dimensions outlined in this paper - strategic alignment, data, process maturity, governance, and internal skills.
- **Facilitate cross-functional dialogue** to identify pain points, data sources, and operational processes that could benefit from intelligent support.
- **Prioritize one to two use cases** with high feasibility and value potential. Use them to build experience, demonstrate results, and test internal collaboration models.
- **Design a pilot framework** with clear goals, scope, roles, and evaluation metrics. Focus on learning and iteration rather than perfection.
- **Establish basic governance mechanisms** to manage decision-making, compliance, and model lifecycle - even at an early stage.
- **Communicate transparently** across the organization. Highlight purpose, progress, and practical value to build trust and engagement.
- **Plan for scaling from the outset**, but act incrementally. Focus on developing internal confidence, not on meeting external benchmarks.

9.3 Final thought

Artificial intelligence is not a silver bullet - and it does not require large-scale disruption to deliver value. For most mid-sized companies, the challenge is not whether AI is relevant, but how to apply it meaningfully and sustainably within their specific context.

With the right level of preparation, orientation, and focus, AI can become a practical tool - not a distant ambition.

Thank you for engaging with this extensive whitepaper. We look forward to partnering with you on your AI journey - turning strategic vision into operational excellence, and experimentation into enterprise-wide transformation.

- End

Note on Editorial Optimization

This text originates from a manually drafted version created by the OBEYA-CONSULTING team.
AI-based tools were employed to refine linguistic clarity, ensure a consistent, reader-friendly tone and support a professional yet accessible style.
As the authors are not native English speakers, idiomatic expressions and culturally specific phrasing were deliberately minimized to enhance international readability and neutrality.
AI was also utilized for quality assurance purposes – specifically for the detection and correction of grammatical, spelling, and punctuation errors.
Full responsibility for the content, messaging, and final approval remains solely with the authors.
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