A Project Sponsor's Warp-Speed Guide:
Improving project performance

Appendix M – When AI is not the right tool for the project

Introduction

This appendix lists project characteristics that indicate artificial intelligence (AI) is not the right tool for the proposed project. These characteristics are intended to help project sponsors and project managers avoid proceeding with a project that will likely fail, or at least disappoint, during the feasibility phase.

AI has rapidly emerged as one of the most powerful tools for improving performance in most enterprises. Examples include:

- Predictive maintenance and supply chain management in manufacturing.
- Autonomous systems in distribution and customer service.
- Software development almost everywhere.
- Improved data-driven decision-making across departments.

AI techniques, particularly machine learning and chatbots, are transforming industries at an incredible pace.

However, AI is not a universal solution. In many scenarios, AI is unnecessary, inefficient, risky, or even counterproductive. Knowing when *not* to use AI is as important as knowing when to use it.

Project sponsors should ask how many of the characteristics below apply to their problem space. The more characteristics below that apply, the less likely AI techniques should be considered as part of the solution.

When simpler solutions are sufficient

A common mistake is overengineering a solution. Sometimes, a straightforward rule-based system, threshold logic, or a statistical model can solve the problem effectively.

For example, basing a business process improvement on Robotic Process Automation (RPA) software may be cheaper and faster to implement while fulfilling the requirements. RPA uses software "robots" or scripts to automate repetitive, rule-based digital tasks.

For example, a temperature control system in a manufacturing plant may only require a Proportional–integral–derivative (PID) controller, a well-established feedback control technique. Introducing a reinforcement learning model would increase development time, validation effort, and maintenance complexity without delivering incremental benefits.

Solution sophistication should match the problem's complexity. If a simpler method achieves the required accuracy and reliability, AI is excessive.

When data is scarce, of poor quality, or biased

AI systems, especially deep learning approaches, depend heavily on large, high-quality datasets. Without sufficient data, models may overfit, generalize poorly, or produce unreliable outputs, often labelled as hallucinations.

In niche domains, such as specialized manufacturing or complex distribution, data is often extremely limited. Training a model under such conditions will lead to unwarranted confidence in inaccurate predictions. In these cases, expert knowledge, simulations, and physics-based reasoning are more dependable.

Additionally, if data is biased or systematically flawed, AI systems can amplify those flaws. Because safety is almost always a concern, relying on biased data can lead to unsafe decisions. Without robust, representative datasets, AI is often the wrong tool.

When the problem is deterministic and well-understood

AI excels at identifying patterns in complex, high-dimensional data where explicit rules are difficult to define. However, if well-understood business processes and physical laws govern a system, traditional procedural methods usually outperform AI.

For example, even complicated invoice processing and revenue allocations are well understood. AI will add more complexity and cost than value to these processes.

For example, structural load calculations for a bridge rely on established principles of mechanics and materials science. Engineers can use analytical equations and finite element methods to produce precise, explainable results. Replacing these with a machine learning model would introduce unnecessary uncertainty. Deterministic methods are faster to validate, easier to certify, and more transparent.

If project teams can solve a business problem reliably with classical algorithms, optimization techniques, or physics-based modeling, AI often adds complexity without meaningful benefit.

When the problem is primarily organizational, not technical

Not every business problem or engineering challenge is technical. Sometimes inefficiencies stem from insufficient training, poor communication, unclear requirements, or process misalignment. Introducing AI into such problem spaces will mask underlying issues rather than solve them.

For example, predictive analytics cannot compensate for flawed maintenance workflows, poorly designed material flow in a manufacturing facility or inadequate staffing. Addressing root organizational causes may be more impactful than deploying AI tools.

When interpretability and accountability are critical

Many AI systems, especially deep neural networks, function as black boxes. In safety-critical industries, such as aviation, medical devices, nuclear energy, or autonomous vehicles, the project team must explain why a system made a particular decision.

For example, regulators overseeing pharmaceutical development or aircraft systems require traceability and validation of every component. Engineers can formally verify a rule-based control system. However, neural networks are often difficult to explain because their black-box internal decision-making logic is opaque.

If the project team cannot justify how or why a model produced a result, certification becomes difficult. In high-liability environments, accountability and explainability may outweigh predictive accuracy. In such cases, simpler, interpretable models, or conventional documentation methods, are more appropriate.

When costs outweigh benefits

Developing AI systems involves data collection, labeling, model training, deployment infrastructure, ongoing monitoring, and maintenance. For small-scale projects or low-margin applications, these costs may exceed the value AI provides.

For example, in a vehicle dispatch system, the trained staff won't improve their performance if an AI system supports their decision-making.

For example, manufacturing simple consumer items with high consistency and a low defect rate is well understood. When an AI system controls such a process, costs outweigh benefits.

Many AI systems require significant long-term support: retraining models as conditions change, updating datasets, and upgrading cybersecurity defenses. If the return on investment is low or questionable, traditional methods are more economical.

When real-time constraints demand predictable performance

Many automated systems require strict timing guarantees. Embedded control systems in industrial automation systems, building operations, or electricity distribution grids must respond within precise time bounds.

AI models, especially large or complex ones, often introduce unpredictable latency or require hardware acceleration. Deterministic control algorithms, by contrast, offer predictable execution times and well-characterized performance.

In applications where milliseconds matter and failure can cause physical harm, predictability often takes precedence over adaptability. AI is too resource-intensive or variable in responsiveness for such environments.

When safety and risk tolerance are extremely low

In critical infrastructure systems, such as nuclear reactor controls or life-support systems, unexpected behavior is unacceptable. AI systems, especially those that adapt or learn over time, sometimes exhibit unpredictable edge-case behavior.

While AI can enhance monitoring or anomaly detection in such environments, it is often unsuitable as the primary decision-maker. System developers and management generally prefer fail-safe, deterministic systems with extensive testing histories.

When failure has catastrophic consequences, proven reliability often outweighs potential performance gains.

When ethical or regulatory constraints limit deployment

AI systems can raise concerns about fairness, privacy, and compliance. In sectors governed by strict regulatory frameworks, deploying AI demands extensive validation and documentation.

For example, these industries require robust privacy frameworks, like GDPR, and data protection because they handle large amounts of personal information:

- Healthcare and life sciences
- Financial services
- Software-as-a-Service (SaaS)
- Marketing, Advertising, Social Media
- Education
- Utilities

- Retail and e-commerce
- Transportation and travel

If regulatory approval processes are lengthy or uncertain, organizations can likely implement simpler process-improvement solutions faster while still meeting compliance standards.

Conclusion

AI is a transformative tool that organizations are rapidly applying in almost every sector of the economy. However, it is not a universal remedy. It works best for complex, data-rich, pattern-based problems that resist explicit modeling.

However, when problems are deterministic, data is scarce, interpretability is essential, timing constraints are strict, safety risks are extreme, costs are high, or organizational issues dominate, AI may be the wrong choice.

Good management judgment involves selecting the right tool for the job. Sometimes that tool is AI. Other times, it is mathematics, physics, control theory, or simply better process design. The goal is not to use the most advanced technology available—but to use the most appropriate one.