Business Readiness for AI: What Your Organization Needs to Know

Part 2 in a series on the journey to AI success.
Business Readiness for AI: What Your Organization Needs to Know

1. Start With the Stakeholders
2. Build Sustainable Partnerships
3. Strive for Realistic ROI
4. Consider Automation vs. Augmentation
5. Incorporate Continuous Learning
6. Employ a Diverse, Adaptive AI Team
7. Enable Cross-Functional Collaboration
8. Develop Strong, Clear Governance
9. Establish Ongoing Oversight

AI as a ‘Portfolio Problem’

The Potential Talent Within

Checklist: Gauge Your Business’s Readiness for AI

Sponsor’s Viewpoint

This guide is second in a series on AI readiness. Learn more at sloanreview.mit.edu/SAS-AdoptingAI.
As established in Part 1 of this series, the first step on any AI journey is pinpointing what you hope to achieve with it.

“The question shouldn’t be ‘How can we get ourselves ready for AI?’” says Michael Wade, professor of innovation and strategy at the IMD Business School in Lausanne, Switzerland. “If you go down that road, you’ll end up doing AI for the sake of AI. A better question is: ‘What are the problems we need to solve? What are our opportunities, what are our threats?’ If the answer is ‘through AI,’ then do AI.”

The next step: making sure that you’ve identified all the critical business enablers and requirements — particularly the human and financial factors — needed to successfully use AI to solve the problems you’ve selected. Following are key considerations that can help you determine whether you’re ready, from a business standpoint, to launch any AI initiative. (We’ll address technical readiness in Part 3 of this series.)

Start With the Stakeholders
Begin by accounting for the individuals, roles, and groups that will be affected by your organization's AI initiative. These include both the people producing the AI solution — those involved in training, testing, and validation — and the employees who will actually use it on the job, who will have to trust that it will be not only effective, but also ethical, fair, and safe. And, of course, this process requires addressing the needs of the affected external populations — such as customers, citizens, and patients — as well as establishing metrics for success.

For Jose Murillo, that last point boils down to optimizing customer lifetime value by building reciprocal relationships, rather than purely transactional ones. “We want to make sure we're helping customers get financially stronger. Otherwise, it's going to be very difficult to have a sustainable business relationship with them,” says Murillo, the chief analytics officer for Grupo Financiero Banorte, one of Mexico's largest banks. “We use AI to understand the behavior of our customers, such as behavioral mapping. Then we conduct different interventions to understand what they react to the most to enhance their savings." The bank then uses machine learning techniques to determine which populations are the best targets for additional initiatives.

Build Sustainable Partnerships
Another critical factor for AI success: identifying key internal partners for ongoing collaboration — including those who aren't necessarily looking for AI solutions at first. You may be able to initially undertake a simple project that, for instance, improves an existing process without overhauling the entire business model.

That's exactly what Murillo did after establishing his analytics team at the bank in 2015. His initial focus was on the organization's credit card business — specifically, its cross-selling efforts, which were yielding very low results. Working with the customer service teams in that business, his team redesigned the cross-selling process, enhanced the models for estimating customer income and risk levels, and made it easier for customers to enroll in the credit card program and make their first purchases. "One year after we started the program, we were getting a mature project conversion, rates in the range of 18% to 20% — with no AI involved yet," he says.

But that program's success led to his first major AI project: developing speech-to-text algorithms that helped the bank better understand customer concerns. With these insights, the sales team rewrote all the cross-selling scripts and quickly saw a 25% increase in conversions. Following additional experimentation and in-house customer-service challenges, the conversion rate increased by more than 80%. Ultimately, the team recorded an impressive total...
conversion rate of 36%. “Those initial quick hits gained us a champion within the bank,” Murillo says. That relationship, in turn, led to bigger and better AI projects.

**Strive for Realistic ROI**

Experts recommend putting AI-based projects through the same rigorous ROI assessment that you would use for any other project but with a few AI-specific considerations. For instance, as discussed in the first Strategy Guide and webinar in this series: Do you already have AI capability in your existing systems you can leverage? What AI-specific talent do you need, and how will your initial investments in those resources pay off?

It’s also necessary to account for ongoing investments that could potentially make or break your AI case, such as the costs of maintaining AI models to ensure accuracy and quality, as well as realistically estimating the amount of time or the level of adoption required before value is generated.

Ultimately, ROI estimates will hinge on the overall value of the business solution and specific project goals, such as Banorte’s desire to increase the number of conversions, and the resulting revenue, from its cross-selling efforts. “It’s important that incentives within the team are well aligned within the business to yield big returns on investment,” Murillo says. “If we get involved with a project that yields less than we were expecting, at the end of the day, it costs us.”

Of course, ROI estimates often involve tricky negotiations between two very different groups: the data science teams responsible for running the AI experiments and projects, and the business and finance teams charged with paying for them. Fernando Lucini, a top data scientist with Accenture, says taking a portfolio approach can streamline those conversations (see “AI as a Portfolio Problem”).

**Consider Automation vs. Augmentation**

When considering ROI and adoption, it’s especially important to define exactly how humans and machines will interact. In applications involving automation, AI may make and implement a decision — for instance, restocking navy blue sweaters in a chain of apparel stores. Success requires ensuring that proposed system objectives are aligned with human ones; the more the two diverge, the more likely the AI initiative will fail. For that reason, in approaching any AI problem, it’s important to establish clear expectations and outcomes for both the AI system and the humans who are interacting with it.

**AI as a ‘Portfolio Problem’**

In Fernando Lucini’s view, the process for determining return on investment for AI projects all too often results in a classic stalemate.

On one hand, data science and engineering teams can’t accurately estimate return on investment without running experiments, says Lucini, Accenture’s managing director and global data science and machine learning engineering lead. On the other, finance teams are seldom willing to fund those experiments without some satisfactory predictions about ROI.

His recommendation for breaking the deadlock: View AI as a “portfolio problem.” Compile a collection of potentially high-value AI use cases — both short- and longer-term — then work with the finance team to determine how to fund them.

“Maybe you identify 10 or 12 of these things that are very valuable, that are clearly worth doing,” Lucini says. “Then you go back to the business and say, ‘Look, I’ve got these 10 or 12 things; I think they’re going to give me a 10-times multiplier of value or savings as a portfolio. Some will make it; some will not. But as a portfolio, we’re pretty sure it will give you that return.’ It becomes a fairly easy conversation to have.”

Lucini, who adds that he’s had that conversation with CEOs from a variety of industries, also recommends setting expectations for business and financial leaders. “Make sure they understand that AI is a fundamentally research-and-development type of activity, with no biases about what that used to mean in the past,” he says. Otherwise, “you end up in the Valley of the POC [proof of concept], where projects never see the light of day” — and leave the C-suite asking why the organization spent millions of dollars on projects that went nowhere."
— with little or no human interaction. Augmentation, on the other hand, involves AI providing information or insights that help humans make decisions, rather than replacing them. For example, the popular “writing assistant” app Grammarly uses AI to review documents and flag potential issues — such as grammar, spelling, and punctuation errors, wordiness, and plagiarism — and makes recommendations for correcting them. But ultimately, the human user decides whether and how to address those issues.

At Kaiser Permanente, calculating ROI for many AI projects involves examining the time and cost of various patient interactions. “Whether it’s something simple or something tremendously complex, the components of costs in our current system are roughly equivalent,” says Tad Funahashi, M.D., chief innovation and transformation officer for the Oakland, California-based managed-care system’s Southern California region. “It’s doctor time, patient time, facility time, and support time.”

Therefore, his team has been experimenting with separating patient needs into two main categories: (1) simple, straightforward inquiries that can be mostly handled by automation, with minimal human intervention, and (2) more complicated issues requiring a doctor’s attention that may still be optimized by AI. This approach dramatically improves efficiency and maximizes the benefit to patients, says Funahashi, himself an orthopedic surgeon: “Physicians and their teams can provide high-quality care for many more patients by leveraging automation.”

Incorporate Continuous Learning
An AI initiative will also be much more likely to succeed if it focuses on “organizational learning,” or the ability for both humans and AI to learn from their interactions, and, ultimately, change in response to what they’ve learned, according to recent MIT Sloan Management Review/BCG research based on a global survey of more than 3,000 managers.

So, AI might recommend restocking the sweaters, but a human must approve the decision, perhaps adjusting the numbers for specific locations. Or, in some context-rich situations, a human may recommend an action (“restock sweaters in Milwaukee through March; restock in Savannah only through December”) that AI then evaluates, based on a variety of other factors, before the decision is implemented.

Success also requires ensuring that proposed system objectives are aligned with human ones; the more the two diverge, the more likely the AI initiative will fail. For that reason, in approaching any AI problem, it’s important to establish clear expectations and outcomes for both the AI system and the humans who will be interacting with it. When humans don’t understand or trust an AI solution, they’re likely to avoid using it — or, worse, apply it in unanticipated ways that result in negative outcomes.

Employ a Diverse, Adaptive AI Team
Many practitioners say finding the right people — whether you’re upskilling (see “The Potential Talent Within”) or hiring outside talent — is often the single biggest AI-related challenge. After all, “AI specialist” was the fastest-growing job in LinkedIn’s 2020 Emerging Jobs Report, recording 74% annual growth for the previous four years. Curtis Dudley, vice president of enterprise analytics and data services at Mercy, a St. Louis-based health care network of more than 40 hospitals in four states, can sum it up in two words: “It’s tough.”

His observation reflects the fact that there’s no one-size-fits-all solution for building an AI team. The skills, specialties, and expectations needed vary from one type of AI project to the next because different problems stem from different business contexts and require different data and algorithms. AI success depends on pulling together the right mix of roles and specialties for each application.

Those needs differ from industry to industry as well. Dudley, for instance, seeks specialists with epidemiology backgrounds and deep health care expertise. In the past, “we had some really great data scientists, technically fantastic, but they were absolutely lost in the

When humans don’t understand or trust AI, or if they feel the AI solution doesn’t support the business outcomes by which they are measured, they’re likely to avoid using the solution — or, worse, apply it in unintended ways that result in negative outcomes.
health care data set,” he recalls. “They had no idea what a procedure code was or how lab data or medication data worked. They’ve got to understand the data that we’re working with to be effective.”

“I hired one data scientist, and that person returned a couple of million dollars’ worth of benefits from working on perioperative cost-per-case issues, where we looked at different procedures and identified an opportunity to improve. That allowed me to bring in a couple of more data scientists, and we took on projects that had additional returns.”

Curtis Dudley, vice president of enterprise analytics and data services, Mercy

More recently, his successful efforts generated enough business value to significantly expand his team. “I hired one data scientist and that person returned a couple of million dollars’ worth of benefits from working on perioperative cost-per-case issues, where we looked at different procedures and identified an opportunity to improve,” he says. “That allowed me to bring in a couple of more data scientists, and we took on projects that had additional returns.”

Enable Cross-Functional Collaboration
The University of Texas at Arlington, home to nearly 61,000 students, employs more than 20 business intelligence and analytics specialists, most with master’s or doctoral-level training, says Pete Smith, chief analytics officer. Some specialize in natural language processing or natural language understanding, others in the competitive rankings that are critical differentiators in higher education.

But Smith emphasizes the importance of including team members who offer more than just top computer science skills: “When the data sets are about language and the essence of human activity, you really are looking for folks who have a mix of the engineering side and, say, the linguistics side,” says Smith, who is himself a professor of modern languages at UTA. “In fact, our lead analyst in natural language processing–based projects has a degree in physics and a degree in linguistics.”

In general, says independent consultant Pritam Bhavnani, AI teams need to include cross-functional staffing and collaboration among not only data, software, and hardware specialists, but professionals with communication skills as well. “Quite often, you’re talking about some complex analysis on, say, a manufacturing process or a financial transaction,” says Bhavnani, previously the vice president for supply chain transformation and vice president of advanced manufacturing engineering and the industrial internet of things at Honeywell Aerospace USA. “The data scientist will find the issue but won’t understand what it means to the business. So you need someone who can convert that data science lingo into business lingo, pulling out the true critical important findings that need to be acted on.”

For example: The data might indicate the need to change specific manufacturing processes, which may involve new costs — such as

The Potential Talent Within

No question: Finding the right mix of players for your AI team can be challenging. But some of the skills you’re seeking may be closer than you think.

Many organizations are learning to leverage the resources they’ve already got, rather than recruiting elite outside specialists. “It’s about tapping into your indigenous talent,” Capt. Michael J. Kanaan, then cochair for AI for the U.S. Air Force, explained in our recent survey report.

In a major initiative to develop capabilities in its existing workforce, the Air Force surveyed all employees and found that 2,900 already had relevant skills. The message behind that assessment: “If you know how to program or code, we want to value you, so tell us, and then we can start talking about opportunities,” said Kanaan, now director of operations for the U.S. Air Force–MIT Artificial Intelligence Accelerator.

The Air Force has since begun providing interested employees with 24/7 access to training materials so that they can upgrade their skills on their own schedules.

Other major employers are undertaking similar efforts. In January 2020, Nationwide Mutual Insurance announced a five-year, $160 million plan to upskill its entire 28,000-person workforce by offering training in “digital literacy and future capabilities.” In mid-2019, Amazon announced a $700 million effort to retrain 100,000 employees — a third of its U.S. workforce — in new technologies, including AI. All those initiatives illustrate growing recognition that “new talent” doesn’t necessarily mean “outside talent.”
investing in new equipment — that a business executive will have to justify. Translating data analysis into a cost-benefit equation becomes critical for the analysis to deliver actual improvements.

**Develop Strong, Clear Governance**

Before launching any AI project, organizations need to establish a plan to address its particular ethical, risk, and compliance issues. That starts with clearly defining the initiative’s intended outcomes and conditions, including the populations of employees, customers, patients, or other end users involved, along with addressing the all-important question of whether the solution can be deployed ethically, fairly, and safely.

According to research by McKinsey, organizations often overestimate their own AI risk-mitigation capabilities, assuming that because they’ve used analytics for years, they’ve already got the right controls and practices in place for AI. “It’s also common for leaders to lump in AI risks with others owned by specialists in the IT and analytics organizations,” researchers reported in the McKinsey Quarterly.

Identifying and addressing all major risk factors requires new levels of effort, McKinsey researchers noted: “Making real progress demands a multidisciplinary approach involving leaders in the C-suite and across the company; experts in areas ranging from legal and risk to IT, security, and analytics; and managers who can ensure vigilance at the front lines.”

You’ll need to determine to what extent you need “explainability” — that is, the ability to explain how your AI solution reached a certain conclusion or made a specific decision. While explainability is especially critical for businesses in heavily regulated industries, such as financial services, being able to transparently describe the journey from input to output is an essential ingredient for every AI project.

It also involves continuous efforts to gauge the quality of your data as well as the accuracy and trustworthiness of your AI-generated insights. For example, if you’re using AI to identify skin cancer, but your patient population is predominantly fair-skinned, the training data will reflect that limitation, resulting in less-accurate detection for darker-skinned patients. Similarly, if a self-driving car is trained in a desert climate but then deployed in a blizzard, it obviously won’t perform well.

Effective governance also involves ensuring that your organization’s use of AI complies with both ethical guidelines and regulatory and legal requirements. You’ll need to determine to what extent you need “explainability” — that is, the ability to explain how your AI solution reached a certain conclusion or made a specific decision. While explainability is especially critical for businesses in heavily regulated industries, such as financial services, being able to transparently describe the journey from input to output is an essential ingredient for every AI project.

**Establish Ongoing Oversight**

Every AI deployment needs AI-specific mechanisms for ongoing monitoring and maintenance to address changes in, for instance, data, the environment, and the systems themselves.

Among the biggest concerns: “model drift,” when AI accuracy degrades because the data and algorithms haven’t kept up with external changes. For example, consider the COVID-19 pandemic’s impact on manufacturers and retailers in early 2020, when panicky consumers began stockpiling household products. “We saw a lot of issues with some of the forecasting and predictive analytics models that were trained pre-COVID,” notes Monica Livingston, senior director of AI sales at Intel. “Those models didn’t know how to handle the shifts in demand caused by COVID. No model was forecasting the skyrocketing demand for hand sanitizer and disinfectants and certainly not the stockpiling of toilet paper.”

But effective monitoring means going beyond simply tracking technical model performance and retraining models with new data. It means ensuring that the intended business outcomes are being met as well — which, in turn, maps back to establishing those outcomes, and the specific metrics gauging success, at the project’s outset.
CHECKLIST:
GAUGE YOUR BUSINESS’S READINESS FOR AI

Use this quick checklist to validate that your business organization is ready to adopt your AI solution.

- **Account for all stakeholders.** Identify the internal and external populations who will be affected by each AI initiative, and ensure that you’ve addressed their needs and expectations accordingly, while providing solutions that are effective, ethical, and fair.

- **Enlist key in-house partners.** Establish relationships with internal partners and project champions up front. Collaborating on a few small successful initiatives early on — even those without an AI component — can pave the way to bigger, more complex efforts down the road.

- **Establish the model for human-AI engagement.** How exactly will people and machines interact? Every AI initiative should include clear roles for both, including evaluating whether the machine’s role will involve automation or augmentation, and developing mechanisms for checking that AI objectives and human goals remain closely aligned.

- **Validate that ROI is realistic.** Evaluate the potential for both short- and long-term returns, and remember to account for new or ongoing investments, such as equipment upgrades or model maintenance, that may impact your projections. Consider “packaging” several projects together for a combined ROI estimate (see “AI as a ‘Portfolio Problem’”).

- **Match skills to project-specific context and requirements.** Required skills and specialties differ dramatically from one AI initiative to the next, so it’s most effective to build a diverse, cross-functional team that can adapt as needed to tackle new projects. Remember to consider reskilling or upskilling existing employees as one option for plugging AI talent gaps (see “The Potential Talent Within”).

- **Define governance requirements.** Establish — and regularly revisit — a plan for addressing the ethical, risk, and compliance efforts associated with every AI initiative. Identify the project’s intended outcomes and conditions, adjusting them as needed throughout the project life cycle. Continuously gauge data quality, and assess the accuracy of the resulting AI insights. And, of course, ensure that all AI use complies with regulatory requirements as well as ethical guidelines.

- **Plan for ongoing monitoring.** Create mechanisms for ongoing monitoring to address changes in data, environment, and the AI models themselves — and to ensure that the project is meeting the intended business outcomes.

A Q&A With Gavin Day

In this Q&A, Gavin Day, senior vice president of technology at SAS, discusses return on investment, governance, and potential bias in AI initiatives, as well as “maintaining the machine” over time.

This conversation has been edited for clarity, length, and editorial style.

Q: When people are getting into AI, what do they need to know about ROI?

Gavin Day: This is where I think SAS, and the strategy that we bring forward, is unique: We don’t have a single offering that we tout as AI. We incorporate it into everything: deep learning, computer vision, natural language processing, conversational AI. We want to put it wherever it creates a benefit for our customers.

A large majority of SAS customers already have the ability to train deep learning models and use natural language processing. When you look at that from the ROI perspective, the returns are absolutely huge.

Here’s an example involving a large securities company. Their recommendation engine uses SAS technology to analyze and predict customer changes, then generates the next best product offer for each customer. Since they began using that system, they’ve had a two-and-half-times increase in purchase rates and reduced customer departure rates by 50%.

Q: What governance issues might organizations want to consider?

Day: One big area is data governance. Organizations need to consider how they’re going to account for bias and quality. We have to make sure that compliance exists for privacy policies for regulators. Customers are also often managing governance by ensuring that all data for a project is covered under the same data policy.

Another area is model governance. Too often, it’s overlooked. Organizations must make sure the decisions being made by the models are explainable and ethical. When organizations are adopting AI and machine learning, some questions that come up, especially in any regulated industry, are: How did you arrive at this decision? How did this model get here and why? If they don’t have explainability, they’re going to see AI adoption and maturity drop. People have to be comfortable with the decisions being made with AI.

The last area is long-term maintenance. How do we monitor the performance of AI to ensure that we’re making good decisions, we’re making the right decisions, and we’re set up for long-term success? This isn’t a situation where you start an AI application and let it run forever. We’re coming back and we’re iterating. Organizations need a process in place to do that.
“As the rate of change increases, as we add new data sources to get to even better decisions, we work with our customers to make sure the part of governance that involves monitoring decision quality is foremost in their minds. It’s part of the life cycle and ecosystem of AI, along with addressing questions about long-term sustainability and maintenance plans.”

Q: Could you talk more about bias in AI?

Day: Sure. Data can be inherently biased. If you’re looking at loan information, for example, you have to be able to understand what data you’re using, what demographics, and what ZIP code. All those things play into the results you’re going to get.

The sample size that we’re using with data can, if used incorrectly, play into the results. It isn’t just the technology that you’re using to make decisions; it’s the data on the front and what it represents. If we’re dealing with people, does it represent your entire customer base? Or does it represent a slice of your customer base — and, if so, why did you pick that slice? Why did you pick that area, that demographic?

That goes back to explainability — a simple definition of why a decision or a result was made and the criteria that were used.

Q: What do organizations need to know about long-term maintenance?

Day: If there’s one constant right now, it’s change. And the rate of change is increasing. AI that performs well today won’t perform well tomorrow unless it is maintained.

For example, our financial services customers are required to maintain thousands of models performing at their peak capabilities. We help them manage and monitor those models, and we have a proactive process to manage when a model performs below expectations. That’s not manual; it’s automated. It’s our technology raising the red flag and suggesting that they investigate something.

Another example is monitoring the performance of forecasting models. We have multiple patents on the method that applies statistical process control techniques to identify when forecasting models need to be updated because forecast quality is dropping — again, before it becomes a problem, and before it degrades to a point where it’s not usable.

As the rate of change increases, as we add new data sources to get to even better decisions, we work with our customers to make sure the part of governance that involves monitoring decision quality is foremost in their minds. It’s part of the life cycle and ecosystem of AI, along with addressing questions about long-term sustainability and maintenance plans.

Ultimately, we strive to use AI, and have our customers use AI, to help make better decisions. It’s not just about AI technology; it’s about the outcome. We believe the next wave of competitive advantage will go to organizations that are able to make better decisions, both tactical and strategic, every time, in repeatable ways.

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