



ASSOCIATION FOR
FINANCIAL
PROFESSIONALS

AFP® FP&A GUIDE TO
**AI-Powered
Finance**

OVERVIEW



The hyperbolic growth in data, processing power and sophistication of our technology tools is simultaneously challenging us with more work to do and more tools to work with. Artificial intelligence (AI) is looked to as both a cause and cure for this challenge. Some companies are running with this technology already; this guide is intended for the group milling around the starting line, considering how to approach AI and take their first steps.

2 POSITIONING YOUR AI PROJECT

Seizing the opportunities — and mitigating the challenges — of artificial intelligence requires understanding the categories of the technology in question and the modes of AI encountered in finance, placing it in the context of the CFO's role.

5 ENTERPRISE PLANNING FOR AI

Companies can lay the foundation for success of a broad AI program by developing readiness in the key building blocks of organizational planning, data, policy and skills.

9 PROJECT-LEVEL DECISIONS

At the tactical level, organizations will confront several common decision points and balance their decisions against the extremes of treading too lightly or proceeding too far, too fast. Those decisions can be summarized as Six S's: sourcing ideas, scoping and selecting projects, staffing, scrubbing data, supporting the effort and scaling learnings.

CASE STUDY LINKS:

This guide is supplemented by three case studies that provide a deeper exploration of how companies and individuals are putting AI programs in play. They are accessible through the links below:

- [Case Study: IBM's Enterprise Transformation](#)
- [Case Study: Applying AI to an EPM System](#)
- [Use Cases for Generative AI](#)



POSITIONING YOUR AI PROJECT

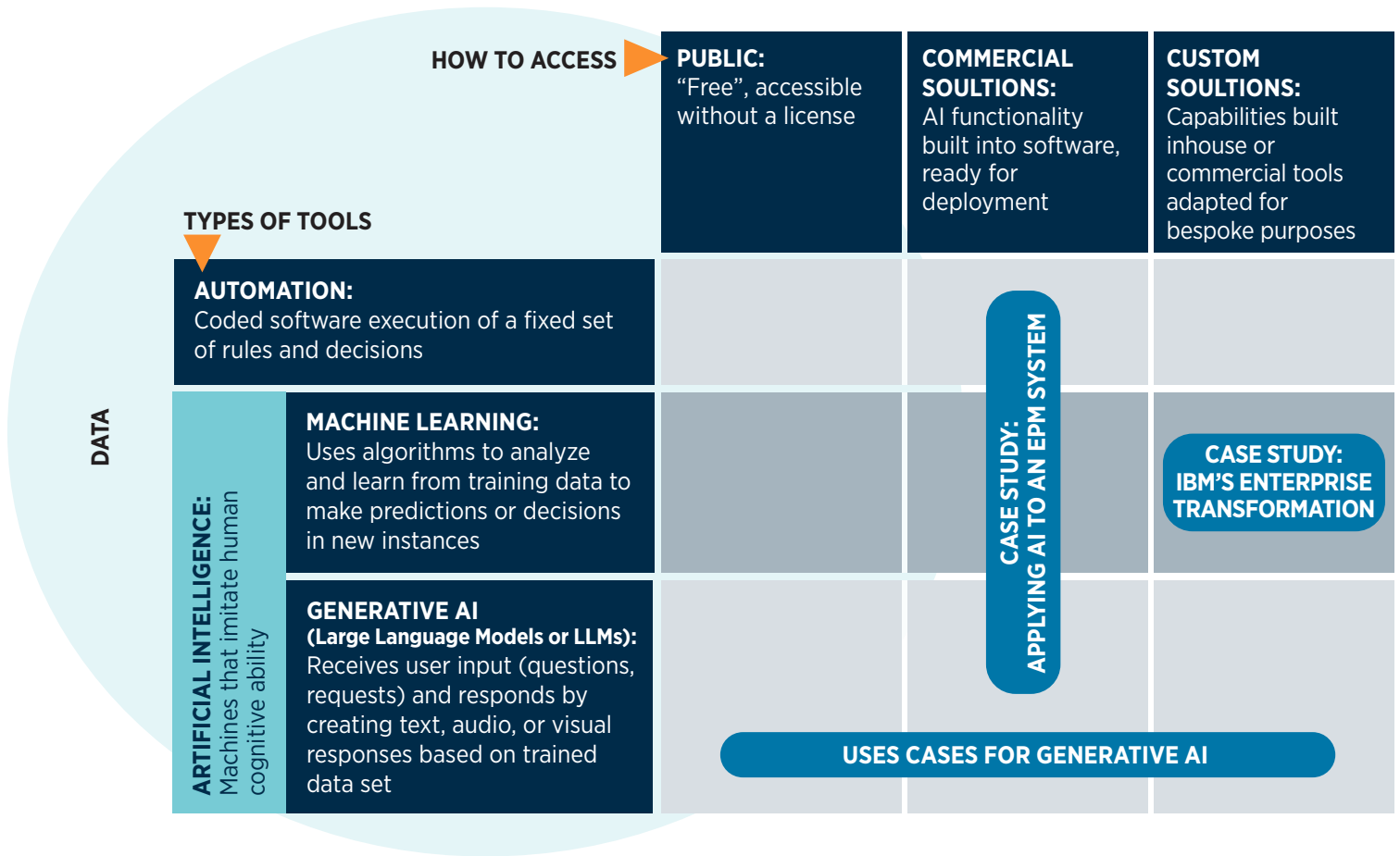
Bryan Lapidus, FPAC, Association for Financial Professionals

Even in an AI world, the role of the CFO remains constant: managing the sources and uses of capital for the company by reporting where it was, optimizing circulation for deployment and supporting decisions of where the next unit should go. AI is a tool and capability that can support this goal, and, as with other investments, companies must weigh the costs and benefits to determine how it can add value.

“Not all problems are AI problems, and not all solutions are AI solutions.”

– Ashok Manthana, Founder, ChatFin

DATA IS EVERYWHERE; WE ARE MANAGING IT THROUGH AUTOMATION AND AI



The diagram above provides a simplification of the categories of technology and the modes where finance encounters them.

Looking down the left side of the diagram:

- **AUTOMATION** (or robotic process automation, also known as RPA) is the deterministic application of rules to produce a knowable outcome. Automation is often applied to repetitive tasks such as invoice matching or data entry; the rules may be used to manage data pipelines that feed into the AI application, execute a script such as building a dashboard, or make decisions. An example of automation is software that is coded to create a dozen trend lines to explain historical data, selects the best approximation as determined by the lowest variance to actuals, and creates a forecast based on that selected trend. While the software is making a decision, the rules are already proscribed.
- **MACHINE LEARNING AI** applies computer algorithms to training data, often historical data, where it learns to identify patterns; it then applies these inferences to other data sets (i.e., current data) to make predictions. This form of AI applies advanced math, analytics, computer science and logical flows and may require data science to bring it to use in scale.

- **GENERATIVE AI** uses enormous foundation models for its knowledge base and human interface because it approximates our understanding of text, voice and images. The numerous open-access GenAI tools have allowed people to test these tools on their own, and they are being built into commercial tools as assistants or co-pilots that unlock deeper applications behind the scenes. Ideas of how to deploy GenAI are given in the section [Use Cases for Generative AI](#).

“We are already seeing in the market evidence that, as many say, ‘AI may not replace managers, but the managers that use AI will replace those who do not.’”

– Josephine Schweiloch, Director of Data Science & Technology, IBM Finance

Today, finance generally encounters these forms of AI and automation across three modalities:

- Some companies have made their AI software **publicly available** so users can access it without specific licenses. This includes ChatGPT, Bing, Gemini and IBM watsonx for generative AI, and SageMaker and Profit for machine learning AI.
- **Commercial solutions** are analogous to purchasing software today, and the AI functionality is part of what you are purchasing. The **Case Study: Applying AI to an EPM System** explores how one company deployed forecasting AI within a tool already used in-house for tax, consolidation, etc.
- **Custom solutions** are tools applied to customize challenges. The staff could be in-house, such as in the **Case Study: IBM's Enterprise Transformation**, or a partner, such as a consultant who provides expertise to the internal team.

To focus on the business deployment, it is helpful to think about operating at two distinct levels, and this paper is organized as such. First, at the **enterprise level**, the organization thinks broadly and holistically about the role of AI and automation to create the necessary and sufficient conditions to be applied across all your efforts. Second, the **project level** has a set of tactical decisions to help you apply the techniques and gather your learnings. In addition, this links to three case studies to provide an intimate look at how companies have implemented their AI programs.

“When it comes to AI, I believe that the technology problem has largely been solved. Although you do need technology to do this, so much of this is about the business deployment and the way that this is integrated into the business and adopted by the business.”

– Justin Croft, VP, Data Science & Architecture, QueBIT





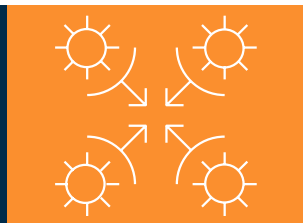
ENTERPRISE PLANNING FOR AI

Based on the AFP FP&A Series presentation “Ready, Set, AI: Embracing AI in the Finance World” by Justin Kuzma, FPAC, Senior Director of FP&A at U.S. Steel, and Ashok Manthana, Founder of ChatFin.

Working at the enterprise level of a company requires thinking across the functions and silos that exist, establishing controls — or constraints — around what the teams do, and providing enabling resources. The elements listed below are relevant for all parts of managing a business but take on an extra dimension when considering your AI program. Whether you approach AI through public sites, commercial software or custom solutions, these elements are all relevant, but the scope and amount of work in each area may change.

Organizational Planning

Expertise and the Skills Journey



Data

Policies

ORGANIZATIONAL PLANNING

Your organization **will set and re-set its AI goals at multiple points** in its AI adoption and adaptation. Those at the beginning stages of the journey are prioritizing what they learn over what they earn and may look for strategic — non-financial — evaluations, such as decision-tree analysis and appropriate benchmarks to measure progress. Manthena observes, “We all think AI is going to be dominant, but we don’t know how and we don’t know when, so a lot of companies are exploring various use cases and gaining advantages by being the early adopters of the technology.” As the capability matures, the organization becomes ready to harvest the benefit of the investments with a new set of goals that mirrors overall corporate investment objectives, such as defined ROI goals. Defining the goals is critical to how you structure your teams, set expectations of what will be delivered, create a mandate for change, and establish the overall appetite for risk with allocated resources.

Budgets are a statement of corporate intent, and the **funding strategy should reflect your goals**. “We developed a pool of funding for AI projects that was distinct from a department leader’s P&Ls (profit and loss),” says Kuzma. This separates the growth and earnings incentives inherent in running a business from the strategic goals that don’t have defined returns. “When exploring and experimenting with technology applications, and the outcomes are unclear, we want people to come up with ideas that may be a bit risky. We have dedicated funding for this” like an internal venture investment firm.

Executive leadership is key to sustained commitment to your AI strategy, and one step below that, **companies take various organizational structures to address the AI goals**. Kuzma says at U.S. Steel, “Finance is a very strong partner, but IT governs our AI programs because we’re looking at an enterprise-wide rollout of AI. Having IT lead centralizes the incorporation of cyber, legal and compliance issues as we navigate through this.” Finance needs to be at or near the driver’s seat, but the specifics of leadership depend on company risk tolerance, executive capacity and capability, and power dynamics.

Conversely, Manthena prefers finance or the business in the lead role because he has often seen challenges when IT juggles responsibility for multiple teams, projects and customers. “It can be difficult to bring attention to finance’s specific needs because IT deals with everything out there. More common in successful implementations or explorations is having a champion within finance, a CFO or a VP of finance who really understands how it will be used.”

What is clear is that **AI implementations require both functional leadership to deliver on business objectives and technical leadership to deliver on consistent application of capabilities** across the organization. Success requires definition of the issues, representation from multiple groups, clear guidance from the top and an understanding of its authority. Who sits in the primary seat may be less important than having a complete supporting cast.



DATA

Organizations of any size that have good data on their customers, products and processes can make use of AI. Data is the source material for the algorithms and outcomes; here are a few specific things to consider at the enterprise level:

Kuzma describes a multi-phased approach to data in their AI projects. “Step one is starting with lower risk data, the publicly available SEC investor relations presentations, government data and federal reserve data. It is standardized, easily accessible and in the public domain. After building some AI muscle, step two would be applying tools to internal data, such as linking back to our enterprise performance management system, which is our version of a data lake for finance.” However, all tools and data would remain internal to retain security and privacy of company data.

Having **good enterprise data requires enterprise-level efforts to clean and consolidate data.** It may take years of cross-company efforts to standardize what is variously called data dictionaries, data taxonomies or analytical frameworks. Kuzma describes it this way: “Within our business segment, we leveraged a great enterprise performance management (EPM) project over the past couple of years where we have defined from the bottom up our KPIs by units, divisions, manufacturing plants, operating segments and through our sales, so that all those stats numerically tie out to our

financials. This was a large undertaking, and FP&A played a critical role because it understands the dynamics of the metrics at each level. Now that we have pristine data that everyone accepts as fact, we can build good predictive analytics and minimize ‘hallucinations,’” i.e., instances where the AI thinks it’s giving you a good answer, but in reality, it is guessing at an answer.

Kuzma is describing the approach of bringing all the data into one place, like a data warehouse or a data lake. Manthena posits that if a company has a competent data dictionary, it can grant the AI tool access to data sets where they currently reside, and not have to create a central repository. Smaller deployments may use smaller, narrowly targeted data sets, such as a commercial solution applying AI to data within its existing system (see [Case Study: Applying AI to an EPM System.](#))

Data is rarely perfect, but Manthena notes that you can do a lot with imperfect data. “There’s no shortcut for having clean data, but if we wait to clean everything, it will be a forever project that neither starts nor ends. Machine learning and predictive analytics projects have a high threshold for clean data, but it is lower for generative AI. Generative AI is about discovering the data that exists and running operations on that data right now. You can still run a generative AI project data as it is.”



POLICY

Companies are adopting a variety of postures as AI comes online, trying to find the **right balance between promoting adoption and experimentation while not exposing themselves to risk** at the same time, such as sharing or misapplication of data, cyber security, compliance or intellectual property.

At U.S. Steel, Kuzma says, “We’re very concerned about protecting our intellectual property and our data, so we have an enterprise generative AI that’s protected that people can use more widely in the organization. We also ask our colleagues not to expose our internal data to external AI tools. We’re very structured and communicate what tools can be used and which ones to avoid.”

Manthena sees companies operating on opposite ends of the spectrum: Some are very restrictive in using generative AI in any part of the business process, and others have an open-door policy that encourages users to explore and find finance use cases. He provides another example of a challenge: “There’s a finance team that’s very active in terms of exploring AI in their finance processes. They asked their AI team leaders

if they could use an external tool, but the AI leaders said, ‘No, because we are building our own models and you should use that.’ Finance asked to use it, but the AI team said, ‘We are building it. It’s going to be ready in two years.’”

Manthena advises having an open conversation about the balancing act required: “I think it is important to have a policy that promotes a culture of experimentation and experiential learning with these tools. Even if the initial model, tools and data sets are limited, you want your employees to get their hands on the tools, to develop the imagination to think about applications and the habit of thinking about ways to resolve the pain points in their work.”

Companies need a centralized group or steering committee at the enterprise level who can review current policies around data governance and create guidelines applicable at the project level. The individual titles will differ from company to company, but the enterprise roles should include information security, privacy, generalized data governance, compliance, legal, audit, and of course, finance.

EXPERTISE AND THE SKILLS JOURNEY

AI tools today are relatively inexpensive; the human resources are the expensive part. That includes training, change management and specialized technical skills, especially for machine learning projects: data governance, analytics, technology and infrastructure. People with these skills and the understanding of the capabilities — and limitations — of AI are hard to find and very expensive. However, once the first project is complete, subsequent efforts become easier, so it is important to make the investment upfront. Companies are approaching the skills challenge in several ways:

- **RENT:** Partner with a vendor to develop your projects.
- **BUY:** Increasingly, AI is built into software packages or has narrowly defined applications that can harness your internal data sets.
- **BUILD:** Develop the expertise among your current staff; expand or duplicate projects to new areas within your company.

It is impossible to make everyone AI-capable simultaneously; it is better to develop a core group of enthusiasts with hands-on experience and have them become the experimenters and ambassadors throughout the organization. Kuzma says, “One of the things that we did was to **develop digital agents** where we solicited volunteers from across the organization to learn about emerging technologies and use cases. When they returned to their organizations, we had ready-made liaisons to interact with our technical teams, our operations teams and our business groups to accelerate that adoption and push AI projects forward.”

Manthena has turned this into a call to action: “I always tell finance people, this is your chance! If there’s no one right now in your company, you be the org champion. Go explore some of the use cases, build a presentation and present it to your finance leadership. That’s how you can drive this new technology.”

“Every company is going to have a unique journey. Don’t just take cases from someone else, but really make them your own and make sure they fit what you want to achieve. And don’t wait; start iteratively progressing.”

– Justin Kuzma,
Senior Director of FP&A,
U.S. Steel



PROJECT-LEVEL DECISIONS

This section is based on the AFP FP&A Series presentations “Touchless Financial Planning Through Data Science and Automation” by Josephine Schweiloch, Director of Data Science & Technology, IBM Finance, titled, and “AI Projects: Four Rules for Success” by Kendell Churchwell, Senior Data Scientist, Southern Farm Bureau Life; and Justin Croft, VP, Data Science & Architecture, QueBIT. The structure of this section, as a series of decisions between two extremes, is based on Schweiloch’s presentation.

With the enterprise-wide building blocks in place, this section moves to the tactical level of specific AI projects and presents a series of decisions for the project teams to consider. If navigated correctly, teams can avoid the pitfalls on either end of the spectrum in these key areas:

SOURCING IDEAS	SCOPING & SELECTING	STAFFING	SCRUBBING DATA	SUPPORT IN THE EFFORT	SCALING LEARNINGS
Decentralized	Start too small	“Extra-curricular” projects	Prototype with as-is data	Limited advocacy	One-time experiment
↕	↕	↕	↕	↕	↕
Overly centralized	Start too big	Over-invest before proving value	“Perfect data” paralysis	Wait for full-stack alignment	All-at-once deployment

SOURCING IDEAS

Management author Stephen Denning is quoted as saying, “Innovation that happens from the top down tends to be orderly but dumb. Innovation that happens from the bottom up tends to be chaotic but smart.” This can be applied to the sourcing of ideas for AI projects. There are many ways to gather ideas, but in companies where the resources for successful implementation are scarce and have to be rationed, it is important to cull the ideas to ensure they come to success. Over time, the tools and skills will be widespread (like spreadsheet skills), and the level of central control will be less.

SOURCING IDEAS

Decentralized



Ask your team: “We asked the team for different ways that they foresee potentially applying generative AI in their finance roles; we received back a list of over 200 different use cases!” says Jesse Todd, Director, Cross-Industry Transformation, Microsoft, in [Use Cases for Generative AI](#).

Ask your vendors: Vendors can suggest use cases, share other clients’ experiences, and know what is practical.

Ask around: Stay on top of emerging trends in your industry, reach out to partners and advisors at your company, and attend conferences.

Ask yourself: “I like to ask people, ‘What is the most painful part of a process or a job? These challenges tend to be high-impact opportunities for automation and innovation?’” says Schweiloch.

Manage the process: There are inevitably more ideas than capacity; define a participatory process that engages people and ideas and builds followership.

Overly centralized

SCOPING & SELECTING

Create projects with a defined and manageable scope that are aligned with strategy and metrics; they should be big enough to matter to your CFO but not so big that you will become paralyzed trying to complete them. “Do not try to forecast your entire P&L as your first project. You’re going to get stymied,” Schweiloch advises. Focus your efforts on illustrating the potential value of predictive analytics or artificial intelligence.

SCOPING & SELECTING

Start too small



Align with corporate strategy and metrics: Ensure your project lies in the path that the business is headed; frame the outcomes in the vernacular and metrics of business drivers.

Consider high-frequency applications. “It’s absolutely fine to use AI for large, infrequent decisions, but small, frequently made decisions are where we’ve seen predictive really scale up and give you the biggest bang for your buck,” says Croft.

Use a minimum viable product (MVP) mindset. “Don’t wait to build the perfect project; build something small, iterate, be agile, prove success and grow,” says Schweiloch.

Have a workflow orientation: Choose a project with a well-defined actionable workflow and build process maps as you go. Support your team without reinventing the work.

Start too big

It is useful to have a consistent framework to evaluate how your project aligns with the goals of your company and the AI program. The US Steel framework shared below creates a filter for the company to consider all the ideas through a set of company criteria. “Over the life cycle of our AI program, as we gain experience and maturity, we may change the weightings and prioritize differently. We have found it to be a good starting point that we’ve used to rank and judge our projects,” says Kuzma. Companies should personalize the criteria and weights to suit their needs and maturity levels. Often the program managers set the criteria and weights, and the project teams assign the assessment scores.

VALUE DELIVERY	Weight	* Assessment	= Score
Value delivered: both financial value and learning value	X%	1-10	##
Total cost of the project	X%	1-10	##
Distribution of projects: spread that adoption across the organization to upskill across the organization and have a broad set of use cases	X%	1-10	##
Scalability: ability to apply this idea, methodology or technology elsewhere within the organization with minimal rework	X%	1-10	##
			Total score: ####
LIKELIHOOD OF SUCCESS	Weight	* Assessment	= Score
Digital readiness: preparedness of the data, talent, and tools of the team implementing the project; success of the AI elsewhere	X% *	1-10	##
Project complexity. How impactful is it going to be to that business unit? Is there going to need to be a lot of training or is it minimally invasive? And how many groups are involved?	X%	1-10	##
Duration: short time-to-implementation because industry adoption and technology change are so fast	X%	1-10	##
Executive sponsorship: a senior-level champion who can provide time and resources for the project team	X%	1-10	##
Complexity: amount of training, disruption and challenge to implement	X%	1-10	##
			Total score: ####

* For U. S. Steel, this was the most heavily weighted in this section.

STAFFING

Invest in the people you have and look for outside experts who can guide and augment your team. “Once you go through one project, you get the hang of what all is needed. And the size does not really matter, as long as it’s a full-blown predictive analytics project. Spend the money to do that, bring the knowledge and the understanding of what needs to take place during the project after that,” says Churchwell.

STAFFING

“Extra-curricular” projects



Build your team incrementally, not with a big bang: “Don’t over-invest before you’ve proved value. I’m at a big tech company, and we still started small with two data scientists because this is an expensive resource on the market, and you want to show that it works before you grow,” says Schweiloch.

Cultivate unicorns: “Most companies have people who are keeping up with the trends in technology and are based in the business. Assemble those people and make it a clear mission to cultivate these ‘unicorns.’ Invest in their data science education, introduce them to experts and spend some money on upskilling the team,” says Schweiloch.

Get people who know the data: “I think you want to start with people who have the data experience, SQL, Excel or reporting experience,” says Churchwell. Schweiloch goes further: “Data scientists are amazing, but to get something into production, you also need data engineers and machine learning engineers who understand the data and how systems connect.” As you get into production, consider using robotic process automation to connect systems together.

Build experience: There is no substitute for hands-on experience. If working with consultants, stipulate that knowledge transfer is part of the goals.

Over-invest before proving value



SCRUBBING DATA

Rarely does the right data already exist for you; expect data prep to be the 80% of the time you spend on your initial projects. Paradoxically, data is the essence of AI projects but waiting on data perfection will stop you from starting. Schweiloch advises, “Don’t wait for perfect data. Perfect data is never actually coming. Data is complex; it’s volatile. Leverage a data scientist to start with a good baseline, but don’t get hung up here or you won’t ever start.” Work on your data as you work on your AI methods.

SCRUBBING DATA

Prototype with as-is data



“Perfect data” paralysis

Build in time for data: Don’t overlook this step in your race for results.

Begin with the cleanest data you have: Often that will be historical actuals.

Create data management agreements: Document the sources, uses, security constraints, etc., even within your own company.

Build a consistent taxonomy: Common definitions and unique identifiers are critical. (See [Case Study: IBM’s Enterprise Transformation.](#))

Examine the dataset: Understand its structure format and quality. Look for missing values, outliers and inconsistent taxonomies.

SUPPORT THE PROJECTS

“Having business buy-in is really critical to making your modeling activities successful,” says Croft. “Recognize that somebody is going to have to change something, like the way they operate, make decisions, prioritize work. Therefore, it is your job as the project manager to align the model with the incentives and direction of the organization.”

Individuals move through AI and automation projects at different paces. “Don’t wait for everyone to agree,” says Schweiloch, “You’re going to have people who love their pivot tables and are going to keep loving their pivot tables. That’s okay, you can bring them on the journey later.” The key thing is to continuously build momentum so that you move from mixed support to full corporate alignment.

SUPPORT THE PROJECTS

Limited advocacy



Wait for full-stack alignment

Begin with at least two champions who are really excited about this effort: “You need someone at the senior level who’s going to consume the results, and you need someone at the analyst level who’s going to actually live with the outcome and do the work to get there. A lot of these projects originate at the middle management level, and they never get the momentum they need to be successful,” says Schweiloch.

Product management mindset: Prioritize customer needs, experiment to determine usage patterns, develop incremental releases and change as needed.

Integrate your model into the way business works: “Our models helped the sales team to sell more or earn more. And we made the predictions easy to consume by incorporating them into the tools they already used,” says Croft.

Explain your AI: Strive for a “glass box” instead of a “black box” (i.e., people can understand the rules and logic). “Stakeholders range from curious to skeptical, so you must be able to explain how it works, how you use the data and why you have made the decisions,” says Croft.

SCALING LEARNINGS

When the project is finished, capitalize on what you have learned by conducting a project review, sharing the learnings and planning how to expand to a new project in a way that leverages new institutional learnings.

SCALING LEARNINGS

One-time experiment



All-at-once deployment

Expand horizontally: Replicate projects in similar circumstances.

Expand vertically: Extend the project upstream or downstream within the same process flow.

Build your followership: Expand the circle of people who come in contact with the project or the people who worked on the project.

Institutionalize successes. “We’ve created two new departments: one for pulling the data in – and for this, we got people from our quality assurance department as they are very skilled with SQL – and a second department for managing the data – and here we needed ETL expertise,” says Churchwell.



THE COSTS OF AI

Eva Cruz, PhD, MBA, FRM, Principal Consultant, QuantDI

Beware of colleagues — management, data scientists or enthusiasts — who fall in love with the technology and ignore the business case. The life cycle costs of owning and operating AI models are significant and sometimes hidden. Here are some costs to be aware of:

PHASE	COST COMPONENTS
DATA READINESS	Without the appropriate data infrastructure and sufficient data of good quality, there is no path to success. Even if licensing a third-party model, internal data systems and processes are a prerequisite to ensure the appropriate format, reliability for model testing or tuning, and availability for production.
MODEL DEVELOPMENT	Model development is an iterative process that requires rounds of experimentation and testing; development platforms and skilled personnel are expensive. Even if licensing a third-party model, extensive testing is required to prove the model is appropriate for the intended use.
DEPLOYMENT TO PRODUCTION	Internal platforms require IT integration costs while external platforms charge based on usage.
MODEL MAINTENANCE	Annual costs include technology and personnel for retraining (or retesting a retrained model), code maintenance and enhancements, and data and infrastructure support.
MODEL MONITORING	All models in use must have ongoing monitoring to assess performance degradation, shifts in external environment, drifts in input data, obsolescence, bias, etc. Annual costs involve maintenance, execution and reporting.
GOVERNANCE & COMPLIANCE	Model management requires dedicated personnel for reviews; these costs are higher in heavily regulated industries.

The cost structure is different when using commercial solutions: **MODEL DEVELOPMENT** is a service offered by the vendor, and the client is responsible for testing to ensure a generic model works for them.

DEPLOYMENT TO PRODUCTION and **MODEL MAINTENANCE** can vary along a spectrum. On one end, you may have a model that resides in the vendor's server infrastructure and the client accesses through an API, just sending data and receiving an output; in that case, there is still testing to be done initially, but costs of infrastructure and maintenance reside with the vendor. On the other end, you may have models developed by the vendor but that need to be implemented by an IT team in the client's systems.

2024 AFP FP&A Guide to AI-Powered Finance

Copyright © 2024 by the Association for Financial Professionals (AFP).

All Rights Reserved.

This work is intended solely for the personal and noncommercial use of the reader. All other uses of this work, or the information included therein, is strictly prohibited absent prior express written consent of the Association for Financial Professionals. The *2024 AFP FP&A Guide to AI-Powered Finance* or the information included therein, may not be reproduced, publicly displayed, or transmitted in any form or by any means, electronic or mechanical, including but not limited to photocopy, recording, dissemination through online networks or through any other information storage or retrieval system known now or in the future, without the express written permission of the Association for Financial Professionals. In addition, this work may not be embedded in or distributed through commercial software or applications without appropriate licensing agreements with the Association for Financial Professionals.

Each violation of this copyright notice or the copyright owner's other rights, may result in legal action by the copyright owner and enforcement of the owner's rights to the full extent permitted by law, which may include financial penalties of up to \$150,000 per violation.

This publication is not intended to offer or provide accounting, legal or other professional advice. The Association for Financial Professionals recommends that you seek accounting, legal or other professional advice as may be necessary based on your knowledge of the subject matter.



ASSOCIATION FOR
FINANCIAL
PROFESSIONALS

All inquiries should be addressed to:

Association for Financial Professionals

Phone: 301.907.2862

E-mail: AFP@AFPonline.org

Web: www.AFPonline.org

References and Appreciation

AFP would like to thank the presenters from the AFP FP&A Series event in March 2024, *AI-Powered Finance*, who contributed their insight and expertise that became this guide.

In addition, AFP would like to thank the FP&A Advisory Council members who provided technical editing: **Majid Darvishan**, Clinical Assistant Professor, Indiana University, Kelley School of Business; **Rosemary Linden**, President, Momentum CFO; **Larry Maisel**, President, DecisionVu; and **Jesse Todd**, Director, Cross-Industry Finance Transformation, Microsoft.



About the Author

Bryan Lapidus, FPAC, director of FP&A Practice for the Association for Finance Professionals (AFP), has more than 20 years of experience in the corporate FP&A and treasury space working at organizations such as American Express, Fannie Mae and private equity-owned companies. He is the staff subject-matter expert on FP&A for AFP, which includes designing content to meet the needs of the profession and helping keep members current on developing topics. Lapidus also manages the FP&A Advisory Councils in North American, Asia Pacific and the Middle East and Africa, which act as a voice to align AFP with the needs of the profession.



CERTIFIED CORPORATE
FINANCIAL PLANNING &
ANALYSIS PROFESSIONAL

The topics in this guide are intended for education and reflect the state of practice for corporate finance. While not intended as study materials for the Certified Corporate FP&A Professional exam, it does relate exam knowledge domains.

FPAC, Certified Corporate FP&A Professional and the FPAC logo are registered trademarks of the Association for Financial Professionals.

Learn more about the FPAC [HERE](#).



ASSOCIATION FOR
FINANCIAL
PROFESSIONALS

About AFP®

As the certifying body in treasury and finance, the Association for Financial Professionals (AFP) established and administers the Certified Treasury Professional (CTP) and Certified Corporate Financial Planning and Analysis Professional (FPAC) credentials, setting the standard of excellence in the profession globally. AFP's mission is to drive the future of finance and treasury and develop the leaders of tomorrow through certification, training, and the premier event for corporate treasury and finance. Learn more at www.AFPonline.org.