CFA Institute

T-SHAPED TEAMS
ORGANIZING TO ADOPT AI AND BIG DATA AT INVESTMENT FIRMS

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EXECUTIVE SUMMARY

- The investment industry is increasingly recognizing the benefits of AI and big data technologies. Cost, talent, and technology are significant hurdles in AI adoption, as is the time needed before results can materialize. But arguably the most critical factor for success is leadership vision, including the supporting organizational structure and culture put in place by senior leadership to enable change.
- Senior executives must develop and implement a comprehensive strategy to introduce AI and big data into their operations. In this process, senior executives need to build a T-shaped team made up of three functions—investment, technology, and innovation.
- The "T" alludes to (1) the transition from T-shaped skills to a T-shaped team, as AI adoption in financial institutions is far more complicated than an individual can handle, and (2) the fact that investment skills and technology skills are "orthogonal" to each other, such that they need (3) the innovation function, which sits at the intersection of investment and technology functions, to bridge the gap in communications and effectively leverage organizational capabilities to improve investment processes and outcomes.
- The role of the T-shaped team evolves through the early, intermediate, and advanced stages of AI and big data adoption. We have included a case study for each stage to illustrate the key issues financial institutions face and their solutions. These also show the real-world application and practicality of the T-shaped team as a key organizing feature for firms successfully embracing AI and big data.
- The T-shaped team is not a one-size-fits-all concept. On the contrary, we expect firms to develop their own T-shaped team structure and processes that best meet their needs and capabilities, particularly when they approach the intermediate and advanced stages.
- Whatever the stage of AI and big data adoption, this report will illuminate for investment industry leaders how they can, through leadership and innovation, put themselves on a path to success as AI and big data become embedded in the investment industry.

Senior executives must develop and implement a comprehensive strategy to introduce AI and big data into their operations. In this process, senior executives need to build a T-shaped team.

INTRODUCTION

Financial institutions globally are eagerly looking to embrace AI and big data technologies. Not to underestimate the cost, talent, and technology hurdles in AI adoption, we believe leadership vision is the single most important factor to kick-start the process. Senior executives must take the lead at this stage and become champions of AI and data science: Only they can ensure that the organization develops and implements a comprehensive AI strategy.

In this process, senior executives need to build what we call a T-shaped team—particularly its technology and innovation functions—staff the team with proper talent, allocate enough resources to their projects, and ensure alignment and support of the top and mid-level business and technology executives at the organization.

Once the team is in place, the key challenge becomes connecting the investment function and technology function effectively so that the organization can dedicate its resources to the best projects—those that can deliver the largest measurable results with the least input in terms of resources and time. This challenge remains constant through all three stages of AI adoption, hence the need for the innovation function to ensure that the team can collaborate effectively.

In Chapter 1 of this report, we build on the discussion in "Investment Professional of the Future"[1] and "AI Pioneers in Investment Management"[2] and explain in detail the T-shaped team concept and accompanying processes.

We use the term *T-shaped team* to specifically refer to this particular team structure (including investment, technology, and innovation functions) and accompanying processes used by financial institutions in the adoption of AI and big data technologies.

The T alludes to (1) the transition from T-shaped skills to a T-shaped team, as AI adoption in financial institutions is far more complicated than an individual can handle, and (2) the fact that investment skills and technology skills are "orthogonal" to each other, leading to (3) the innovation function, which sits at the intersection of the investment and technology functions.

The apparent need for the innovation function is in part the result of the fact that AI and data science have become major disciplines of scientific investigation. They take years of education (perhaps as many as 10–15 undergraduate to master's level courses) and work experience before someone can contribute in a meaningful way and lead AI and big data adoption projects at financial institutions.

The implication is that we cannot expect the majority of investment (technology) professionals to know enough about technology (investments) to be a core member or leader of the technology (investment) function. Training programs will take years to see impact, assuming low turnover, staff persistence, effective training, collaborative work environment, and so on.

In AI adoption, we believe leadership vision is the single most important factor to kick-start the process.

Hence the need for the T-shaped team.

In Chapters 2 through 4, we proceed to discuss the T-shaped teams' evolution through early, intermediate, and advanced stages of AI and big data adoption. Included also are three real-world cases—one for each stage—in which we share the live experiences of T-shaped teams at three medium-sized and large global/regional asset management firms on their AI and big data adoption journey.

Looking through these three stages reveals how the relative burden across the technology, investment, and innovation functions shifts over time.

In the early stage, the key is to find a project that will showcase to the investment function the value and power of the AI and data science tools. After all, the technology is formative and naturally there will be doubts from the investment folks about the effectiveness of AI, as well as some anxiety about how this might affect their own career.

That puts the burden on those in the technology function to identify projects that they have a high degree of confidence in delivering in a reasonable

[1]See CFA Institute (2019b).
[2]See CFA Institute (2019a).

period of time. Ideally the project does not require too much input from the investment function but can help the investors do a better job. The innovation function needs to be able to evaluate whether the projects the technology function proposed fit that criteria, in particular if the projects can deliver meaningful results to the investment function. Ideal projects are usually those that provide analytical support and individual security monitoring.

If the technology function successfully pulls off the first AI and/or big data application to the satisfaction of the investment function, then the team can expect more input from the investment function down the road. Of course, sometimes projects fail. Most "spontaneous" AI efforts at financial institutions that lack organizational backing will likely not come back from these early failures. This is where the T-shaped team will play an important role in pulling the team and organization together to continue looking for and implementing the next promising projects.

Instead of being apprehensive of their presence, those who embrace the technological change will more likely become winners in the industry in the long term.

Few financial institutions in the world are operating in the intermediate stage today. For those that do successfully enter the intermediate stage, the focus will likely be on balancing the input from both the investment and technology functions. The focus is on the innovation function leader's ability to leverage a small number of initial wins in a small number of areas to gain credibility within the wider organization. When more people from the investment function become more open in asking the technology function for support in decision making, such as security selection and portfolio construction, then the team will really start to deliver its full potential.

It may take a long time for some financial institutions to get to the advanced stage, and we believe getting there will be crucial for the long-term survival of organizations. In the advanced stage, the T-shaped team will finally be able to realize its full potential, with both investment and technology functions understanding each other much better, sharing their opinions openly, and communicating more frequently as needed. In this ideal stage, the investment function will become more effective; hence, we would say the relative burden of success is more on the investment professionals in this stage.

We hope the likely scenario that we described is an important revelation for investment managers. Technology will play a more important role in our business, and the data science function will become a permanent part of the investment team. However, instead of being apprehensive of their presence, those who embrace the technological change will more likely become winners in the industry in the long term.

This report is intended to have a "how-to menu" flavor, which we believe is most beneficial for investment organizations and industry leaders looking to build their own T-shaped teams.

Several recent industry surveys and research reports have come to reveal more supporting evidence for the T-shaped team concept. We have referenced these findings in Chapter 1. Our conversations with investment professionals around the world have also provided impetus to this work. We hope that it will help expedite the industry's efforts at applying AI and big data in its daily operations as well as help investment professionals anticipate industry development trends so that they can prepare themselves accordingly.

We welcome feedback from readers about your experiences. Please email your comments and perspectives to the author at larry.cao@cfainstitute.org or our team at research.requests@cfainstitute.org.

CHAPTER 1. T-SHAPED TEAMS AND APPLYING AI AND BIG DATA IN INVESTMENTS

AI is a must-have. This prospect has become increasingly evident in investment circles. With growing evidence of AI's effectiveness in helping investment professionals in their daily work, the focus has now shifted from building conviction about AI and big data to successful adoption of the technologies.

The challenges of making AI and big data applications a reality remain. Our data suggest that investment firms have had mixed success at introducing AI and big data into their operations.[3] Other industry surveys also support our findings.[4]

We find that the failed experiences often are related to the five major hurdles we outlined in our previous research—namely (in increasing order of difficulty to overcome and/or scarcity of the resource), cost, talent, technology, leadership vision, and time.[5] Those firms that are successful often appreciate the strategic impact of AI and big data, understand the cost implications, and have been able to recruit the right talent. Above all, however, they have been successful at addressing the related organizational issues.

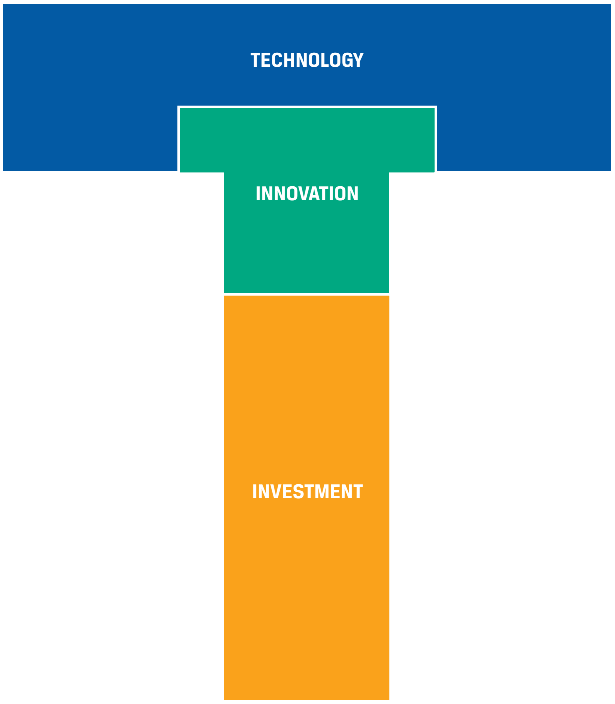
Central to those organizational successes is an approach that we called the "T-shaped team."[6]

FROM T-SHAPED SKILLS TO T-SHAPED TEAMS

Suggesting an organizational approach as the solution to adopting AI and big data at investment firms may come as a surprise to many. The reason is that organizational issues are really closely tied to the hurdles that we have described. Put another way, many of these hurdles are the result of organizational structures and processes that were ill-suited for investment firms adopting AI and big data. Many industry executives have come to the same realization over the last year.[7]

We defined a T-shaped team to be a specific team structure that helps investment (or business) organizations in adopting AI and big data technologies into their core processes (see **Figure 1**). We initially used the concept in the context of discussing what a future investment team would look like (i.e., what new roles and skills would be needed and how professionals on the team would interact with each other; see **Figure 2**).

FIGURE 1. T-SHAPED TEAM



Source: CFA Institute (2019a).

[3]For details of the survey and the hurdles to adopting AI and big data, see CFA Institute (2019a).

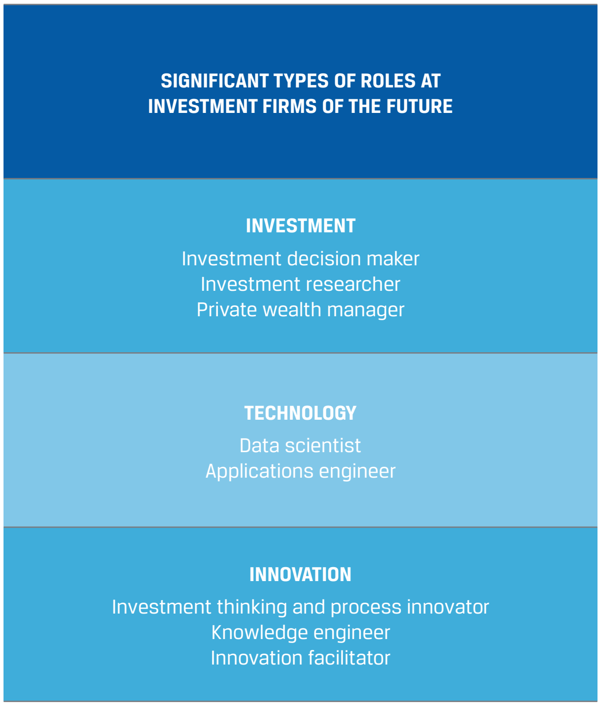
[4]See, for example, the NewVantage Partners report "Big Data and AI Executive Survey 2020," a survey of C-suite executives of leading global firms, which indicated that 91.5% of the firms reported ongoing investments in AI but only 14.6% have deployed AI capabilities in widespread production (NewVantage Partners 2020).

[5]See CFA Institute (2019a).

[6]For details, see CFA Institute (2019a, 2019b).

[7]For example, Gartner's Fifth Annual Chief Data Officer Survey, as reported by Goasduff (2020), suggested that chief data officers believe "culture challenges to accept change" is the most critical roadblock to their success. Similarly, the NewVantage Partners Big Data and AI Executive Survey (see Bean 2020) reported that 90% of executives cited people and process issues as the principal obstacle that they face.

FIGURE 2. ROLES AND FUNCTIONS OF A T-SHAPED TEAM



Source: CFA Institute (2019b).

A T-shaped team is made up of three functions. In addition to the traditional investment function, future (or, more appropriately, future-proof, as the "future" is arguably already upon us) investment teams will also have a technology (e.g., data science) function and an innovation function.

In the early days of AI and big data adoption, efforts are often driven by individuals with T-shaped skills;[8] these individuals have deep subject matter expertise combined with a wide understanding of other domains and an ability to connect the two. Often, these individuals are either investment professionals who happen to have some relevant data science training or technology professionals with data science training who happen to work closely with the investment function. Early efforts tend to be less "planned" and have more of a "spontaneous" flavor.

There is nothing wrong with such experiments. With textbooks or procedural manuals on the subject lacking—since the number of professionals who are privileged to have such experience in the industry is too small and the stage of development too early to form any real consensus—this is how innovation tends to take place: spontaneously.

To develop AI and big data capabilities into a sustainable competitive edge, however, requires far more resources and structure than spontaneous efforts can count on. That is why successful firms have burdened themselves with the task of building T-shaped teams to take on the challenge. The complex nature of these projects cannot usually be taken on by one "wizard." They require a significant number of professionals with very specific and in-depth knowledge in their respective area working together. The T-shaped team structure and process are designed exactly for such purposes.

The Innovation Function: The T in T-Shaped Teams

The link between T-shaped skills and T-shaped teams is that in both cases we have different skills represented. The difference is that in the former case, the skills are embedded in the individuals, and in the latter case, the team. The T means the skills are different.[9,10] The fact that they are so different

About the T-Shaped Team

T-shaped teams are project teams. We believe, however, that AI and big data integration in financial institutions is a long-term objective. These projects are different from typical short-term information technology (IT) projects.

Figure 1 is intended to illustrate the relationships of the three functions: The innovation function connects the very different investment and technology functions to form the future investment team. Figure 1 is not an organizational chart in its traditional sense.

Three cases embedded in Chapters 2 through 4 illustrate the relationships between the T-shaped teams and the functional departments and their evolution over time. The functional linkage will become more superficial as time goes by if the T-shaped teams' goals are properly defined and staffing is properly managed.

[8]For more details on T-shaped skills, see the Hansen (2010) interview of IDEO CEO Tim Brown.

[9]In fact, in linear algebra, orthogonal vectors are independent of each other, much like the lack of common training and experience of investment professionals and data science professionals.

[10]Another difference is that the T in T-shaped team no longer only implies depth in one dimension and breadth on the other dimension.

gives rise to the small T in the T-shaped teams: the innovation function. We illustrated it with a small T joining the two perpendicular functions since this is the function where a firm will absolutely benefit from the staff's T-shaped skills. The innovation function is also the function whose key responsibility is to connect the two main functions.

Our first inspiration for highlighting the importance of the "innovation" function (CFA Institute 2019b) came from a fascinating book titled *The Future of the Professions* (Susskind and Susskind 2015) on how technology is reshaping the legal and medical professions.[11] **Table 1** summarizes the generic roles the innovation function is expected to play. We have since come to more fully appreciate the critical role this function plays in dialogue with investment professionals around the world.

In the context of AI and big data adoption at investment firms, the innovation function's focus is on facilitating the collaboration between investment and technology functions. Thought leaders may be either internal executive sponsors or external experts. Knowledge engineers usually play the role of both a strategic planner and project manager. Innovation facilitators tend to focus on the communication and relationship management aspect of the process.

Although the T-shaped team framework can be applied in general cross-functional collaboration, it is particularly suitable for the current context (i.e., investment firms incorporating AI and big data into their core processes). The usual collaboration at a buy-side firm between investment staff and marketing staff is far easier to handle by its nature; at least many of them attended business schools, which offered broadly similar curricula. In comparison, the collaboration between the investment/business function and the data science function is much more challenging and also much more mission critical. Investors and programmers have little in common in terms of skills and culture and, as such, need much more coordination.

The old model of collaboration between investment staff and IT departments is unlikely to be able to serve the purpose of AI adoption at investment firms.[12] Thus, we are concerned with whether a business analyst can play the role of the innovation function effectively since it is reminiscent of an old and failed model.

In certain cases the innovation function only needs to play the role of a facilitator. However, we suspect innovation function staff will need to be much more than mere "translators." Their important responsibilities include not only communication between the team and the C-suite project sponsors/initiative leaders but also setting team goals and firm AI and big data adoption strategies in consultation with the leadership and the team. More importantly, they need to lead the discussion around what areas of collaboration to focus on and which projects should get priority. Above all, their role is to get both sides to contribute to the discussion in a meaningful way. In short, the innovation function sets the tempo of the whole team and is accountable for the overall success of projects.

TABLE 1. INNOVATION FUNCTION AND THE THREE TYPES OF ROLES

Role	Generic Description
Innovation function	The function that connects investment and technology functions. Focus on improving the investment process.
Investment thinking and process innovator	Thought leaders are usually found both among senior researchers/executives in the industry and at leading research universities.
Knowledge engineer	Subject matter experts identify key industry trends and emerging investment expertise. They focus on gathering insights from innovators and sharing them with investment professionals.
Innovation facilitator	Generalists who also play a relationship manager role, working with stakeholders in the sourcing and distribution of insights.

Source: CFA Institute (2019a).

[11]We borrowed the term "knowledge engineer," for example, from them.
[12]See, for example, Squirrel and Fredrick (2020) for discussion on the subject.

The ideal skill set for innovation function leaders is a 50–50 split between investment and technology, which allows them to have sufficient grasp of the subject matters to understand the thought process of both functions and put their opinions into perspective. For this role to be effective, the leaders need to have credibility with both investment professionals and data scientists and engineers. They also need to be good communicators who listen attentively, speak succinctly, and write clearly. The toolkit ideally should also include strategic planning skills such that the innovation leaders understand both the strategic direction of the firm and the strengths and weaknesses in the investment and technology functions and are able to devise strategic plans accordingly.

These skills can come from classroom training, but at the functional leader level and above, they can only be honed from experience. In reality, neither colleges nor financial institutions have typically offered training programs for this role. That gap makes it particularly challenging to find the right candidate—especially the first member of the innovation function, who usually has to play a combination of the three roles with likely emphasis on facilitator and knowledge engineer.

Our education system and financial institutions will have to change before we can have an abundant supply of both capable and successful innovation function leaders.

At this juncture, the industry is largely behind the curve in appreciating the value of the innovation function (and particularly the innovation function leader). Consequently, the industry does not have a career path designed or training programs prepared for these types of roles. In our experience, when early adopters started offering such roles, successful candidates usually did not specifically train for the positions. Firms come across this rare species of professional with experience on both sides more out of serendipity than by design.

With the majority of the industry still unclear about the (potential) demand for the innovation function, it is hard to imagine that the education system will supply the right candidates. Fintech programs offered by the early entrants into this space (i.e., certificates offered by various industry associations and degrees offered by universities in recent years) may not have been designed for the needs of a future member of the innovation function.

The nuances around the supply of and demand for innovation talent offer a good example of the talent hurdle mentioned previously. Talent shortages can take many shapes and forms and can occur for many reasons. It's a bit more complicated than simply hiring a group of fresh graduates with degrees in AI or data science.

On the positive side, more and more firms in the business are moving in the right direction, albeit from a low base. Various consulting firms working to help clients incorporate AI and big data into their business processes have since written about roles very similar to the innovators we describe here. A recent Deloitte survey suggested that in addition to AI builders, executives of early adopters are also seeking "AI translators," including business leaders, "who bridge the divide between the business and technical staff" (Hupfer 2020, p. 7). An article by three business and data analytics experts at McKinsey referred to "a relatively new class of expert, analytics translators," and these McKinsey authors expected the translators to "play a role in identifying roadblocks" and to "bridge the data engineers and scientists from the technical realm with the people from the business realm" (Fountaine, McCarthy, and Saleh 2019).

Note that these "job descriptions" still fall short of what we expect of the innovation function leader. Interestingly, the Deloitte survey found that the executives' hiring priorities shift from AI builders in the early stage of AI adoption to, as the organization gains more AI experience, business leaders who can "[figure] out what results from AI systems mean, and how those results should factor into business decisions and actions" (Hupfer 2020, p. 8).

We have every confidence that the industry will continue to mature in the coming years and move in the right direction. The challenge in finding competent innovation function leaders is not surprising in some ways. AI in investments is very new, after all. Our education system and financial institutions will have to change before we can have an abundant supply of both capable and successful innovation function leaders. It is crucial for the industry's long-term success that all constituents in the ecosystem support this development.

The Investment Function: Do Future Buffetts Need to Know Python?

The investment function in the T-shaped team is largely the same as what we have today. At the outset of embarking on the journey of adopting AI in investments, however, it is important to embrace the AI + HI (artificial intelligence + human intelligence) philosophy. Investment professionals' investment expertise is valuable, and artificial intelligence will help them expand their horizons and/or augment their capabilities.

Anthony Ledford, chief scientist at Man AHL, shared a story about his firm's early venture into machine learning (ML). He explained that they set out to develop a long–short trading signal using support vector machines (SVMs), an ML method, and the team ended up "discovering" relationships that they already knew!

Do portfolio managers and analysts need to be able to use Python?[13] The answer to this question illustrates the fundamental difference between T-shaped skills and T-shaped teams. In the T-shaped skill setting, which worked well in the pre-AI age, the answer is obviously "yes." In the T-shaped team setting, however, the answer is a much more ambiguous "maybe."

The reason is that we do not believe the majority of investment professionals can operate at the level of a good data scientist or engineer even if they choose to devote a significant amount of time to it. Data science has evolved to become a major discipline,[14] not something that someone from a completely different background can easily pick up without a formal education and, more importantly, on-the-job training to gain the relevant experience.

AI in investments is a serious commitment and not something that one professional with T-shaped skills in investment and data science can handle.

AI in investments is a serious commitment and not something that one professional with T-shaped skills in investment and data science can handle. We have come across many cases where such professionals failed to pull off an AI adoption project. Worse, if they succeeded in launching a test model, chances are they have not gone through the serious peer review and cross-functional testing and review processes required today.

Not surprisingly, these models are particularly susceptible to failure. Part of the benefit of the T-shaped team structure is that professionals in each function can specialize and aim to be the best in the business. Someone doing model development essentially part time can hardly compete in terms of training and experience. The structure and process will also ensure that these models are well-tested and reviewed from different perspectives before they are put into production. Not having gone through such a rigorous process leaves much room for error.

Even if the professional is one of the rare "wizards" who can do both investment and data science well, single-handedly launching such an effort will likely leave him or her with little organizational support. So, when they fail, which is likely, there often are no backup resources to develop an alternative model or organizational will to continue pursuing such projects. These pioneers could inadvertently set back the organization's AI journey by years, which could mean the difference between the firm's long-term survival or demise. Even when they succeed, people often underestimate the commitment required to regularly update the models. It is certainly not a part-time job.

A stellar staff of the investment function should understand the AI + HI philosophy and as such be interested in participating in AI adoption projects. They would also ideally have a strong sense of curiosity, both about how to improve their own investment process and how AI can help. Learning Python can certainly help them communicate with the data science team or at least appreciate the hard work that the team does. To operate at the level of a data science professional is, of course, a completely different question.

T-shaped teams like other project teams are typically staffed by professionals with different skill levels. Three to five courses in computer science and AI may be sufficient for a fresh graduate to start as a junior data engineer. For a mid-career investment professional to switch to the technology or innovation function at similar seniority, it will likely take five to fifteen programming and AI courses plus five years of work experience working on data projects. We have come across very few professionals who have made the switch successfully, although we expect the situation to improve in the coming decades as the current generation of tech-savvy fresh graduates become investment-savvy over time.

[13]Note that this discussion is in the context of T-shaped teams (i.e., AI and big data adoption). There can certainly be many other reasons to study Python, which are outside the scope of this report.

[14]See, for example, Oh and Maldonado (2021) and Eric (2020).

What specifically should investment professionals know about how AI can help? That question has driven our research efforts on AI and big data applications in investments. Investment professionals should know what the main applications are and which AI and big data tools are used in those applications.

These training programs can be taught by experienced staff members at organizations that have pursued AI adoption for at least a year or two. Online training or remote learning are also legitimate alternatives, and they would be more effective if taught by professionals with real-world experience working on AI adoption projects in investments. We expect business schools to offer quality programs for this purpose in the not-too-distant future, and they would serve students well by partnering with experienced professionals, at least in the beginning.

The Technology Function: Where to Find Them, and Do They Need to Know DCF?

Hiring data scientists is often the first step when investment firms embark on the AI journey. The Man Group case in this report begins when Man AHL hired a machine learning specialist.

The qualification and experience of the data scientists vary by firm and its experience with AI. Firms with mostly a fundamental investment function just starting out on the AI journey may care more about the data scientists' understanding of the investment process and be less picky about the science pedigree. For example, one of the first data scientists UOB Asset Management hired was a CFA charterholder with a master's degree in computer science.

Data scientists and engineers clearly play an important role in AI adoption projects. Firms will do well to hire data scientists who are good fits for their overall AI strategy. In this sense, it is advisable to have the three functions of the T-shaped team in place and start operating more or less at the same time. If one has the luxury of building a firm from scratch, the first hires would likely be the three functional leads. In reality, however, the investment function is likely already in place, and by the time the firm is ready to start building its T-shaped team, there usually has been at least some grassroots effort at applying AI and big data in the investment process (most likely in a limited number of products). So, some technical talent is already in the organization as well. The best bang for the buck at this juncture is probably hiring the innovation function lead so that he or she can set the data science team's agenda in line with the firm's overall strategy.

Firms more experienced in this area tend to have a larger number of PhDs in STEM (science, technology, engineering, and mathematics) from top universities. What matters more than their degrees, though, is their experience working on data projects—particularly at tech giants and top firms in their respective industry, where the cutting-edge work in data science is carried out. These applications are so new that they are usually not in textbooks or taught at even the best universities.

AI and big data applications in finance and other industries are still largely a learning-by-doing process. When we say there is a shortage of data science professionals, the shortage is particularly true in terms of experienced professionals, although universities around the world are still having a hard time meeting demand in these areas. As Anthony Ledford, chief scientist at Man AHL, pointed out to us in our extended interviews with him, even these experienced data science professionals may take a few years after joining investment firms to become productive at a higher level, as they still need to learn the peculiarities of financial data as well as integrate into the firm.

The data scientists will be supported by a group of engineers who put their models into production. The division of labor is that the data scientists are focused more on developing models and drawing insights out of data, whereas the engineers focus more on making sure the models operate on the firm's technology platforms. The skills required for data engineers are more transferrable, and these positions may be filled by some of the existing technology staff.

Do data scientists need to know investments? Again, the answer is not conclusive. Confucius famously said more than 2,000 years ago that "the gentleman is no [one-purpose] vessel." Has the world become much more complicated 2,000 years later? We believe so. Although we are seeing more young professionals with a STEM background take the CFA Program exams than we are seeing portfolio managers and analysts study Python, this still has not become the norm—and maybe for a good reason.

The question is, should they try at all? Some think so in principle. Without conclusive evidence in our specific case one way or the other, we think the best approach may be a compromise. Confucius may well be right, and we should value a jack of all trades if we come across one. We know we may not find that many after all, so the practical solution may be to place them, if we do find them, in the innovation function or give them room to play the knowledge engineer role. The fluidity of the roles indeed is another important trait of a mature AI adoption team.

CO-LOCATION, ITERATIONS, AND REGULAR REVIEWS: FACILITATING THE COMMUNICATION BETWEEN INVESTMENT AND TECHNOLOGY FUNCTIONS

Where are data science teams located both physically and on the organizational chart? This is another question that is crucial for the smooth operation of AI adoption projects but is often overlooked.

Both organizational theory and industry best practice suggest that the technology function should be co-located with the investment and innovation functions. Co-location maximizes the formal and particularly informal interactions.[15]

Hansen, Nohria, and Tierney (1999) argued that companies have to choose between two strategies of knowledge management, codification, and personalization, depending on their overall business model. Consulting firms such as Ernst & Young provide "information system implementation by codifying knowledge," while in contrast, firms such as McKinsey provide "creative, analytically-rigorous advice on high-end strategic problems by channeling individual expertise" (p. 111).

AI adoption projects in finance are highly innovative in nature, not to mention the communication needed to take place between two functions with significantly different approaches of thinking and working. Such projects are arguably best suited to the category that requires "personalization." Direct personal interaction is very much a necessity in this scenario.

In the NN Investment Partners case presented in Chapter 3, our contributors shared their "beehive map," an illustration of the team composition that doubles as a seating chart. This map clearly shows how the innovation platform is located in the middle of the floor with all individual investment product groups sitting around them. Valentijn van Nieuwenhuijzen, CIO (chief investment officer) of NN Investment Partners, explained that some of the technology professionals would sit next to the investment function team members they are working with so that the innovation platform does not become "an island of isolation." This practice tends to become more common as investment organizations gain maturity in their AI experience.

Human communication is imperfect, particularly between two very different groups. Investment firms successful at adopting AI have also found it helpful to have regularly scheduled project meetings. In addition to maintaining project momentum, the primary benefit of these meetings is for developers and end users to compare notes and make sure that they are on the same page.

One of the contributors to our report on AI pioneers (CFA Institute 2019a) described their process: The technology function scheduled project deliverables on monthly intervals when they would meet with end users from the investment function to go over their latest additions to the system. These meetings keep everyone's eyes on the ball: The technology function can check in to be sure that it is delivering something that the investment function needs, and the investment function gets an opportunity to vet the tool before it is formally delivered and provide timely feedback as needed. This check-in avoids the risk of longer delivery cycles when programmers could have spent months working on something that is different from what portfolio managers and analysts expected because of miscommunication.

TEAM VS. FUNCTION AND SUPPORTING BUSINESS PROCESSES

The NN Investment Partners' beehive map brings up another important organizational issue: team versus function. Van Nieuwenhuijzen realized early on that the ideal organizational structure for investment firms to adopt AI and big data is the (T-shaped) team and not the functional structure.

Function versus team as an organizational structure has been debated thoroughly. The challenge for adopting AI and big data in investments is that professionals in investment and technology functions share little in common, so the key is to get them to work together on a shared project with a common goal (i.e., foster collaboration, inspire each other for project ideas, discuss the value and priority of a proposed

[15]Although a detailed discussion of how organizations should adapt to the post-COVID environment is beyond the scope of this report, we highlight the need for organizations to take co-location into consideration in their future-of-work designs. We encourage readers to refer to CFA Institute research on the future of work, which addresses the issues related to hybrid work arrangements, at www.cfainstitute.org/research/survey-reports/future-of-work.

project, etc.). The functional structure is apparently less material than the team construct in this context.

One of the benefits of the T-shaped team over the functional structure is that it can help break down silos and align functional objectives.[16] From the organization's point of view, it is not about having the superior functional capabilities; it is about having a coherent team that can work together and develop the best solutions enabled by the necessary input from the investment function and technology function.

The budgeting process and incentive structure need to be in alignment with the T-shaped team organizational structure for it to work. This certainly takes time and planning to get right. Once a firm's leaders decide they would like to go down the path of building T-shaped teams to adopt AI and big data into their investment process, the firm's strategic objectives are then translated into strategic initiatives that will be undertaken by respective teams. The budgeting process needs to reflect that. Resources are allocated to each team in accordance with the strategic importance of the initiatives it is tasked with taking on. There obviously will still be infrastructure investment required for each function, depending on how the transition to the team structure is going. However, the focus will increasingly be on teams.

From the organization's point of view, it is not about having the superior functional capabilities; it is about having a coherent team that can work together and develop the best solutions.

The incentive structure is also an important tool to motivate staff to focus more on team objectives. In the traditional functional setting, employees set their individual goals and objectives and are evaluated on them. Absent shared goals, this type of arrangement is not conducive to team collaboration. If the organization expects the employees to "do the right thing" (i.e., collaborate and focus on achieving team objectives), then incentives should be set up to motivate individuals accordingly. It is certainly conceivable—and teams should be allowed such leeway—for individuals to be rewarded more for achieving team goals than their own objectives in at least some scenarios.

It is clearly also in the organization's interest for employees to focus more on the team objective so that employees form a collaborative rather than competitive relationship. Setting up shared goals and aligned incentives, for example, has helped in building a collaborative relationship between discretionary portfolio managers and quantitative analysts.

Free riding,[17] or social loafing,[18] is a common issue observed in teams. Will T-shaped teams experience the same problems? It is certainly possible, although most T-shaped teams are operating in their early stages, where we think free riders will have a harder time to survive. That said, T-shaped teams should implement the same precautionary measures long adopted by teams around the world to mitigate this risk. These measures include clearly defining individual responsibilities, which in themselves should be meaningful tasks that contribute to the overall team goal. There is also no need to do away with individual objectives, rather than shifting the focus to how individuals are contributing to the team objective.

Tracking the success of these AI adoption projects seems a natural last step in the project. Everywhere we present the AI pioneers report (CFA Institute 2019a) and cases, we are invariably asked this question: How much did AI and big data applications add to the investment team's performance? Performance measurement is easier said than done, though, largely because these applications are more often steps in the overall investment process that contribute to the final decision. It is not always easy to quantify the benefits.

Our hypothesis is that the majority of these projects at major financial institutions are adding value, particularly if they have been in production for some time and have not been pulled. In most cases, these are enhancements to an existing process; so, if they do not work as well as the original process, the portfolio managers have no incentive to continue using them.

Still, it would be good practice to measure and document the added value of each incremental project—if not in terms of portfolio risk and return, then maybe in terms of how they have improved the accuracy of the analysis. For example, if you use an enhanced analysis to predict defaults for credit products, you could measure how many of these products did have problems as the enhanced system

[16]For example, Squirrel and Fredrick (2020) argued that "to break down information barriers and drive transformation, business leaders must engage directly with technologists and ask the right questions."
[17]See Albanese and Van Fleet (1985).
[18]See Karau and Williams (1993).

predicted and compare that with the performance of the original system. Much of the fundamental analysis can be described as a "mosaic," although there should always be ways to measure how much the enhanced process has helped provide a clearer picture.[19]

Since we wrote about the role of T-shaped teams in investment firms' AI and big data strategy in 2019, we have continued to see evidence of its real-world impact. Some of our conversations with executives at asset management firms around the world have been turned into cases in this report. We have also seen research and surveys on the subject from a wide spectrum of organizations, including some of the most influential management consulting firms, that support our conviction.

Investment firms are slow to change, and industry norms are hardly pro-innovation. The precondition of success for an initiative such as the T-shaped team is to have the culture that will support these changes. This requires both management commitment and staff support.

In Chapters 2 through 4, we walk through how financial institutions adopting AI and big data grow and build their capabilities through three distinct stages. These case studies are not intended to be templates, but their experiences are somewhat typical of firms that have embarked on this journey (and prevailed at least up to that point). The challenges they face are common to the experiences of firms at a similar stage. Their solutions are promising for solving the particular problems they face.

We hope that their experiences, illustrated herein, will help you plan your AI journey, anticipate issues, and develop solutions.

[19]For example, "Gartner forecasts that by 2024, 50% of AI investments will be quantified and linked to specific key performance indicators to measure return on investment" (Goasduff 2019).

CHAPTER 2. THE EARLY STAGE ON THE AI AND BIG DATA ADOPTION JOURNEY

The initial efforts to apply AI and big data at financial institutions are not always carefully planned or implemented with well-developed top-down strategies. Quite the contrary, they typically start in a spontaneous fashion with limited organizational support.

Often the early applications are developed by a portfolio manager with some background in AI or a programmer working closely with the portfolio management team. They are in many ways "lone wolves" in the organization. They are clearly professionals with strong T-shaped skills in the sense that they have in-depth knowledge of investments (programming) and sufficient AI (investment) knowledge to pull off some of the earliest applications of AI and big data in investments.

Another type is the traditional IT development route. Business functions develop requests without understanding the technology required, and IT departments develop programs without an understanding of the business logic and environment the programs operate in.

The failure of the traditional IT development route is in a way what prompted the fintech phenomenon: Start-ups believed they could offer better technology solutions with a better user experience. These start-ups tend to be small, and their solutions are usually developed by professionals with T-shaped skills on their staff. These professionals have profiles similar to the "lone wolves," except that they become the heart and soul of the fintech start-ups.

All three types share one common characteristic: They depend on professionals with T-shaped skills in both investment and technology. All three types are at a pre-T-shaped team stage of AI and big data adoption. As we have observed so far, all three types have a rather poor chance of developing a sustainable competitive advantage based on AI and big data applications.

WHAT DEFINES EARLY-STAGE FINANCIAL INSTITUTIONS ON THEIR AI AND BIG DATA JOURNEY?

We believe the following three characteristics are what separate early-stage financial institutions on their AI and big data journey from those in the pre-T-shaped team stage: senior management support, wholistic strategy, and organizational structure.

In this chapter, we will discuss what it takes to go above and beyond these three initial types of development. Senior management plays the most important role in propelling a firm from the pre-T-shaped team stage into the early T-shaped team stage. Overall, we believe the following three characteristics are what separate early-stage financial institutions on their AI and big data journey from those in the pre-T-shaped team stage: senior management support, wholistic strategy, and organizational structure.

Senior Management Support

AI and big data adoption requires major and long-term commitments in both financial and human resources. It is hard to imagine an organization making such commitments without senior management support. A top-down approach is the most efficient approach for financial institutions to start thinking about developing an edge in AI and big data applications and then implementing these changes.[20] Senior management's marching orders are usually the first sign that the financial institution they manage has left the pre-T-shaped team stage and is entering the early stage of systematically adopting AI and big data applications in their business.

Wholistic Strategy

Buy-in from the main business and technology functions at the financial institution is also needed.

[20]A McKinsey survey (McKinsey & Company 2020) finds that respondents at AI high performers are 2.3 times more likely than others to consider their C-suite leaders very effective.

Developing a wholistic strategy that incorporates AI and big data adoption helps ensure both long-term business success and the relevance of the AI and big data projects. The strategy will include the financial institution's long-term business objectives and will identify how AI and big data can help achieve these objectives more efficiently. The main business and technology departments will then collaborate to make these objectives a reality.

Organizational Structure

Of course, we are talking about the T-shaped team here. Transitioning from relying on professionals with T-shaped skills to T-shaped teams is another critical sign that a firm has matured and is entering the next phase of its development on a higher level.

WHAT SHOULD EARLY-STAGE FIRMS FOCUS ON?

For those who have accepted what AI and big data may do to enhance human intelligence in investments, the natural question becomes, where should I begin? We believe that once the AI and big data strategy is in place, early-stage firms should focus on the following three objectives to begin its implementation: Build a T-shaped team, develop supporting processes, and find and score quick wins.

The ultimate test for early-stage firms is whether the team can find and score quick wins.

Build a T-Shaped Team

Firms' first order of business to implement their AI and big data strategy is often hiring data scientists and engineers to build a data science team. Successful early-stage firms appreciate the fact that adding an innovation function is equally important, if not more important, at this stage.

The head of the innovation function is the heart and soul of this operation. (Those in this role have a variety of titles in today's industry, which are not important. It is who performs these functions that matters.) Those who play this role likely contribute to the development of the strategy, but more importantly, they are key to implementing the strategy.

To ensure the successful implementation of their AI and big data strategy, early-stage firms need to identify those who have a sufficient understanding of both the investment and technology aspects of the business and can build credibility with both the investment and technology functions.

Their most important role is to help identify areas of the investment business that need the most help from data science and help develop the technology roadmap for the AI and big data applications that can deliver on those objectives. For them to do that successfully, they need to have credibility with both the investment and technology functions.

Develop Supporting Processes

The T-shaped team structure is new to everybody, and every firm will likely have to develop a structure that best suits its people and business. For the two distinctly different functions to be able to work together, building an innovation function alone is not sufficient. New processes are needed to facilitate the collaboration between the two functions.

The objective of these processes is to help the innovation function leader do what he or she needs to do (i.e., to evaluate and prioritize AI and big data projects that the teams should work on and eventually help implement).

Early-stage firms need to be agile in developing these processes and will likely go through many rounds of trial and error before finding a set of processes that works for them. What makes a good process? It needs to be helpful for all participants in achieving the common objective. We find that effective processes help both investment and technology functions engage. Both functions should also have "equal" say in these processes to achieve optimal outcomes.

Find and Score Quick Wins

With teams and processes in place, the ultimate test for early-stage firms is whether the team can find and score quick wins. If the team has the proper skill sets and the processes are balanced and engaging, then positive results should follow.

In selecting these first projects, the team needs to balance the impact on the investment process and the technical feasibility and related time/resource commitment. If a project takes a year or more to develop and ends up having dubious results, it certainly does not bode well for the overall success of the AI and big data strategy. Ideal first projects are those that can deliver concrete and hopefully measurable results in a reasonable period of time using technology that the team has confidence in developing.

These early wins are important to reassure senior management that the company is pursuing the right strategy, convince the investment function that AI and big data can really help, and demonstrate to those in the technology function how investment works and how their investment colleagues operate. The early wins will likely help open the floodgate of ideas from both sides and start a virtuous cycle.

The negative consequences of failure can also be far reaching, so management needs to have plans in place beforehand regarding how much time and resources it is ready to continue to dedicate to the AI and big data efforts.

CASE STUDY: UOBAM'S T-SHAPED TEAM AT WORK

The case was prepared by Chua EnHao and Kimberly Yeoh of UOB Asset Management and edited by Larry Cao, CFA.

Background

UOB Asset Management Ltd (UOBAM) is an Asian asset manager offering investment products in fixed income, equities, and multi-asset solutions that integrate traditional and alternative capabilities. The company was established as a wholly owned subsidiary of United Overseas Bank in 1986 and was headquartered in Singapore. It has since expanded and now has a presence in many Asian countries.

UOBAM aims to provide top-class performance, customer service, and experience by embracing digital technology to transform the customer experience, operational processes, and business models. Through its network of offices, UOBAM offers global investment management expertise to institutions, corporations, and individuals through customized portfolio management services and unit trusts. As of 30 September 2020, UOBAM managed 60 unit trusts in Singapore. The company had US$27 billion in total assets under management (AUM) as of early May 2021.

Investment Philosophy

UOBAM believes in the use of a systematic portfolio construction process. By controlling risk, it can better deliver enhanced returns over the medium to long term. This philosophy serves as the backdrop for UOBAM's efforts at upgrading the digital technology available to its portfolio management teams.

The equities unit believes that with a rigorous and disciplined investment research process, it can identify high-performing businesses that enable it to deliver superior and consistent long-term performance. By combining this detailed research effort with a systematic model portfolio construction process, UOBAM believes it will be able to effectively derive sources of alpha to achieve outperformance over time.

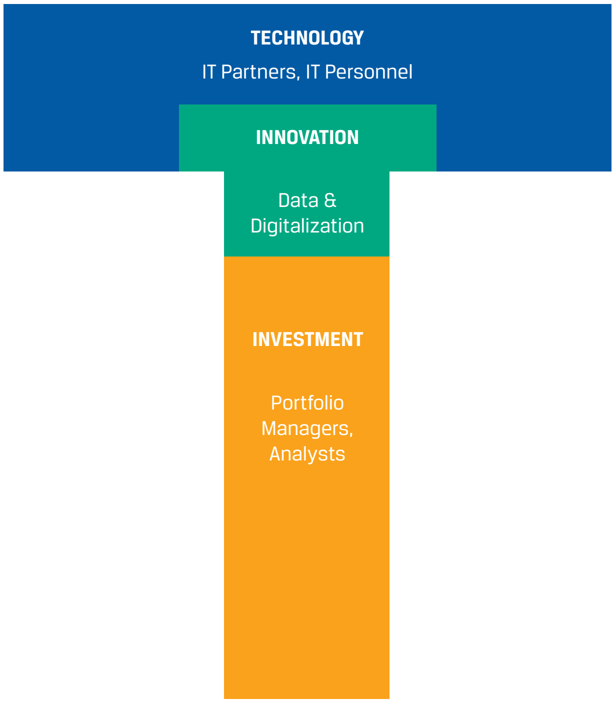
The fixed-income unit believes that consistent performance can be achieved through rigorous and independent fundamental research to uncover relative value opportunities. By adopting diversified investment strategies combined with active risk management, the team aims to generate sustainable total returns.

The multi-asset team makes recommendations on strategic asset allocation based on the firm's view on the economic outlook, and it implements the balanced mandates of retail and institutional clients.

Roles and Job Scope of the Team Working on AI/ML and Big Data

The T-shaped project team brings together three different business units and their expertise, as shown in **Figure 3**. The technology (Tech) function consists

FIGURE 3. T-SHAPED TEAM AT UOBAM



of IT partners, technology personnel, and technology tools. The innovation function is driven by the data and digitalization (DD) unit, which is responsible for bringing the right data and technology to the right people, at the right time, on the right platform. The investment function consists of the portfolio manager (PM) unit—including analysts from equity, fixed-income, and multi-asset units, as well as the newly formed environmental, social, and governance (ESG) unit.

The Investment Function

The UOBAM chief investment officer (CIO) leads the function in developing the firm's long-term investment strategy and in managing asset allocation with the objective to maximize the value of investments for its investors. He has oversight of the PM team, which includes the units managing equities, fixed income, and multi-asset investments and the newly formed ESG unit.

A key consideration that often comes to the CIO's mind is how emerging technologies can be adopted appropriately and be integrated within current investment management processes in a sustainable manner. This leads to the formation of the investment technology unit, with the responsibility to ensure that adoption of the technology achieves the desired outcomes.

The Innovation Function

Under the purview of the chief operating officer (COO) at UOB Asset Management, the DD unit serves as the innovation function in the T-shaped team setup. Its main responsibilities include the following:

1. Serve as a bridge between the Tech function and other business units (BUs), and ensure that the needs of the business are fulfilled.
2. Drive adoption of emerging technologies, such as AI/ML, across all BUs.
3. Ensure governance is in place and is adhering to policies on the usage of these technologies.

The DD unit, led by Chua EnHao, is the link that bridges the spheres of business and technology in an AI/ML project. The work of the DD unit begins by identifying challenges faced by other business units and assessing whether there is an opportunity for the challenge to be solved by the use of AI/ML. The DD team identifies challenges by sitting in meetings, through interdepartmental collaborations, and by other BUs approaching the DD team with their challenges.

The DD unit is also responsible for driving adoption of AI/ML at a project level (micro) and at the company/regional level (macro). This is done through changing the mindset and evangelizing and promoting the adoption of technology in the business units. The DD unit does this by conducting workshops, talks, and initiatives to increase awareness and by offering courses to up-skill the workforce, with the aim of driving technological adoption. More of this information is explained in the "Providing a Learning Environment in UOBAM" section of this case study.

The DD unit also plays the role of governance, where the unit ensures that the technology, the models created, and all data involved are used in an ethical manner via the data ethics validation procedure (DEVP). The DEVP sets out the processes and procedures to ensure that the development and use of artificial intelligence and data analytics (AIDA) technological solutions comply with the Fairness, Ethics, Accountability and Transparency (FEAT) principles set by the Monetary Authority of Singapore (MAS).

Members of the DD unit have knowledge in both areas of technology and finance and have become the channel that translates between hard code AI methodology within the technology domain and the business (i.e., UOBAM investment) domain.

For example, Ryan has extensive qualifications and experience. He is a CFA charterholder, has experience in finance as an equity and futures market maker, and holds a master's degree in information technology. This unique background provides him with an in-depth understanding and insight into the best possible solutions available for business problems in the financial realm. Another member is Kimberly Yeoh, who has a degree in economics and has prior working experience using AI in a technology company.

The DD unit's knowledge and experience assisted it in operationalizing business problems and matching those problems with the best available technological solutions. Apart from the business knowledge they bring to the project, the DD unit members also have networking, critical thinking, communication, and collaboration skills, among others. When assessing the right solution for the problems, the DD unit has to play the role of futurist in ensuring that the solutions proposed are forward looking and are future proof.

The DD unit's ability to be an effective bridge between the business and technological domain, be a driver of technological change, and be a governor of proper and ethical use of technology and data is what gives UOBAM a distinct competitive advantage.

The Technology Function

To accelerate adoption of emerging technologies, such as artificial intelligence and machine learning, UOBAM builds its capabilities on the following fronts:

1. Engaging fintech companies with proven solutions immediately catalyzed and transformed how UOBAM operates, creating better products and delighting its customers
2. Partnering closely with UOB Group Technology, UOBAM has been able to craft technology roadmaps, execute in an agile manner, and see results of quick wins and MVPs (minimum viable products).
3. Consulting services from the UOB Data Management Office speed up learning curves and help shape how UOBAM will need to establish its own capability.

Workflow in AI/ML Adoption and Implementation

UOBAM has put in place an AI/ML development life cycle, which defines the framework to develop AI/ML and advanced analytics solutions to enhance business. The four major phases of the life cycle, shown in **Figure 4**, describe the major activities and interactions between stakeholders (including business users) to develop practical AI/ML solutions and bring them to production.

Phase 1: Ideation

At the ideation phase, employees from business units identify processes within the business that can potentially be enhanced through the adoption of AI/ML solutions. Once these challenges are crystallized into problem statements, these are brought forward to an innovation working group, comprising DD staff and business representatives who have an in-depth understanding of both the business and the applications of technology. The group evaluates and prioritizes various problem statements based on the impact to the business and the feasibility of possible solutions. The group also serves to maximize intra-project collaboration and minimize duplication as various business units may submit overlapping problem statements.

Subsequently, when the project receives approval from the working group, the DD unit launches the project by conducting meetings with the relevant stakeholders to capture detailed business objectives and requirements.

To encourage and elicit ideas to use AI/ML solutions from staff, UOBAM's DD unit also conducts regular workshops that involve the heads and staff of various business units. These workshops serve as a platform for employees to share the challenges faced by their business units and to brainstorm possible solutions. Different business units often discover that they face similar challenges, which can then be fine-tuned and consolidated to find one comprehensive solution.

Phase 2: Model Development and Testing

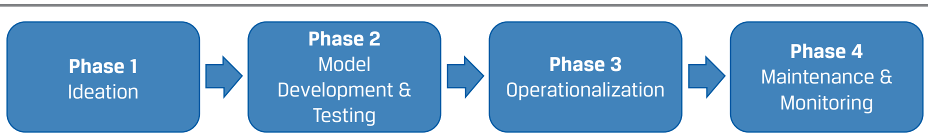
The approved projects then progress to Phase 2 for model development and testing. The first step is to ensure all requirements—including business objectives and functional and nonfunctional requirements—are properly captured. Resources, such as required data features, are also identified by the stakeholders and data scientists.

Subsequently, the data scientists begin the development of the AI/ML solution in an agile manner, delivering incremental features of the solution to the stakeholders for evaluation at the end of each sprint.

After the prototype solution is completed, the stakeholders of the project come together to determine whether the prototype solution can be piloted for wider testing. The pilot testing will enable stakeholders to validate whether the completed solution can meet the business needs or if it requires additional development.

Finally, when the proposed solution has been sufficiently tested and is able to meet all the business needs, the stakeholders can elect to move the solution to Phase 3 to operationalize it.

FIGURE 4. FOUR MAJOR PHASES OF AI/ML LIFE CYCLE



Phase 3: Operationalization

Before the solution is operationalized or deployed in a production environment, it has to be checked and validated by an independent internal team. Also, the model must adhere to the MAS FEAT principles. For example, the individuals or groups of individuals should not be systematically disadvantaged by the solution decisions unless the decisions can be justified.

In the last step before operationalization, stakeholders must present the solution before a management-led technology committee for approval. This ensures that the solution is aligned with the goals and philosophy of the business.

After final approval is obtained from the management-led technology committee, the Tech function will proceed to operationalize the solution and deploy it into the production environment for the business.

Phase 4: Maintenance and Monitoring

After the project is operationalized, the solution enters a maintenance and monitoring phase. The solution will be reviewed periodically by its users and stakeholders to ensure it remains relevant to the business.

The model also undergoes regular testing to ensure it is reliable. For example, if the solution includes a forecasting model, the model drift (the difference between the model forecast and the actual data) will be measured and reported.

In addition to tracking the solution performance, business users will also be required to incorporate such metrics as the cost-to-benefit ratio, productivity, and return on investment of the solution, where applicable. Solutions that do not meet business needs are either decommissioned or improved through a new AI/ML life cycle.

A Case within the Case: The Multi-Signal Predictive Analytics Project

In order to better understand how the T-shaped team has benefitted UOBAM, a case study of the T-shaped team at work is provided next.

Project Background

In 2019, the equities team, consisting of several portfolio managers and analysts, managed over 120 funds, which required analysts to cover over 3,500 equities within the Asia-Pacific (APAC) region. As UOBAM continued to expand its regional footprint within the ASEAN region, the portfolio of the team expanded faster than the size of the team. Analysts were also required to evaluate a large number of factors, and the team would have to rely on the experience and expertise of its portfolio managers. In order for UOBAM to maintain its standing as a regional asset manager with top-class performance, it would need to ensure that its investment team worked effectively to cover a larger portfolio and make more data-driven investment decisions.

With the advancement of AI/ML, the investment team decided to collaborate with the DD unit to harness the power of AI/ML to cover approximately 120 factors and a larger portfolio of equities. After incorporating UOBAM's investment philosophy, the project team developed a model that aimed to predict equity performance and portfolio allocation.

The Process

The project followed UOBAM's best practice model, the AI/ML life cycle shown in Figure 4, which begins with ideation (Phase 1) by the PM team through the digital pipeline. The PM team was searching for a more efficient way of analyzing the vast amount of equity stocks in the APAC region (as mentioned in the "Project Background" section of this case study). The PM team consulted with the DD unit to find the best technological solution that could assist the PM team in its business problem, and both teams concluded that applying an AI/ML solution would be the most effective approach.

The DD unit then assessed the viability of using AI/ML to solve the PM team's problem (Phase 2). After the teams assessed that there was a high probability of success in applying AI/ML to the problem, the functions conducted a more formal discussion to fine-tune the scope of the project. Subsequently, it was determined that the goal of this AI/ML project would be to harness the capabilities of AI/ML to create a portfolio of Asian (ex Japan, ex China) stocks that would be able to exceed the benchmark.

The PM unit set the business objective, while the DD team translated the objective into an actionable development workflow for the Tech team to work on. The project was presented to the technology committee, and the green light was given for development of a pilot. During the model development stage (Phase 2), the team faced several challenges (e.g., the model generated portfolios that exhibited high turnover rates, which would not be practicable for the business). This was where the DD unit was able to step in to advise the Tech team on the tweaks that should be made to ensure the model was aligned with UOBAM's business goals and investment philosophy. The pilot went through several iterations before it could go into production to be operationalized (Phase 3) in the business.

This project served as an eye opener for the PM team as the model was able to uncover hidden gems that would usually fly under the radar. Subsequently, the PM team understood the added value of introducing AI/ML into its business model and took the initiative to up-skill in said areas. Quantitative success measures include increasing alpha and efficiency of the analysts working on the resultant portfolio. The knowledge and insights the PM team gained allowed it to better assess the merits of technology partners that UOBAM may engage.

At present, a majority of the investment team have taken courses on artificial intelligence for investment professionals and have learned Python through DataCamp. Some have also gone on to attain professional qualifications (e.g., a professional certificate in Python programming and machine learning from SMU Academy).

Engagement of Fintech Companies

The asset management industry in APAC will continue to grow rapidly and will provide asset managers with vast opportunities. To maximize these opportunities, asset managers will have to leverage technology, at speed and scale, to give themselves a competitive advantage.

UOBAM has recently partnered with Value3 Advisory, a fintech company that offers a capital market AI platform for independent, predictive, and automated credit ratings, research, and analytics (UOBAM 2019). Value3's platform, which uses a combination of AI, ML, and NLP (natural language processing), empowers investment and risk managers in financial institutions to make better decisions in portfolio selection, risk monitoring, benchmarking, and early warning indicators. The platform combines financial data with unstructured online digital footprints, news, events, trends, and patterns of the companies from diverse sources to transform data overload into actionable insights.

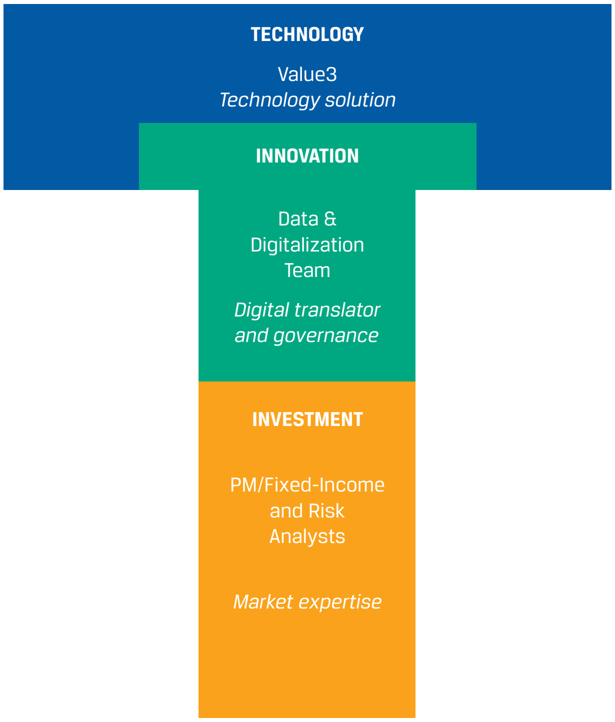
This strategic partnership serves as a win–win for both parties. In the development of the model, Value3 creates the prototype with its technological expertise and UOBAM refines the model with market intelligence gathered from its years of experience in asset management and bond valuation in the ASEAN region.

The UOBAM DD unit (i.e., innovation function) serves as the bridge between the domains of technology (Tech team) and investment (PM team), playing the role of digital translator to ensure that business needs are met in the model development. From a governance perspective, the DD team will ensure that the data are used responsibly and will work with Value3 to embed ESG considerations on the platform to facilitate responsible investing efforts. **Figure 5** depicts this model for a fixed-income ratings project with Value3 and UOBAM.

In "AI Pioneers in Investment Management" (CFA Institute 2019a), Larry Cao identified five major hurdles investment firms face in applying AI/ML and big data solutions: cost, talent, technology, vision, and time. UOBAM's collaboration with Value3 helps counter these challenges.

The cost of developing an integrated system—such as the one Value3 has—is generally regarded as a big-ticket item. UOBAM was fortunate to be able to tap a government grant provided by MAS in the adoption of the system. Talent is spread across the T-shaped team, with each domain providing input in its area of expertise. Technology is ever evolving, with new players entering the market providing niche solutions, and it is UOBAM's prerogative to be aware of these

FIGURE 5. T-SHAPED TEAM FOR THE FIXED-INCOME RATINGS PROJECT



niche solutions and evaluate whether they could provide value to the operationalization of the firm. UOBAM's evaluation requires forward-thinking vision to ensure that these niche solutions, if adopted, are viable to the firm's business needs, adaptable to future advances in technology, and, more important, in line with the mission, goals, and values of the firm. In this project, UOBAM has found that its time is predominantly spent on the refining of the model to suit business needs rather than in the development phase, which can be time consuming.

From a technological perspective, in UOBAM there has been a gradual shift from doing everything in-house to working with partners that are able to enhance and complement UOBAM's core business, which will provide the firm with a competitive edge in the future.

Providing a Learning Environment in UOBAM

UOBAM places a strong emphasis on employee learning and up-skilling of staff so that it can better meet the rigours and demands of an ever-evolving technological work landscape. UOBAM's digital strategy is based on the two pillars of people and technology. These two pillars form a symbiotic relationship in the firm's quest to be a digital-first enterprise.

This relationship is further illustrated in the four elements of digital transformation UOBAM has in place: solidify dataset, sharpen tool set, strengthen skill set, and shift mindset.

Solidify Dataset

Data are the fuel that provides a desired result. The quality and reliability of data will determine the accuracy of results in any model. Solidifying the dataset will include areas of data governance, strategy alignment, and data privacy and security.

Sharpen Tool Set

Technology tools greatly assist any AI/ML project, and the better the tool, the better the results. UOBAM has made improvements to its enterprise data architecture and governance (EDAG), which include a data lake and enterprise data warehouse (DLEDW) and a data discovery platform (DDT). The DDT was developed as a "sandbox" that allows businesses to perform data analysis and develop analytical prototypes. These are cyber-secured environments that enable pre-endorsed users (power users) to leverage on data from the data lake for analysis and generating insights.

Strengthen Skill Set

UOBAM realizes that to have a data-driven culture, employees will need data-related skills and knowledge. UOBAM has several training initiatives to ensure its employees have avenues to gain knowledge, which are illustrated next, in the fourth element of digital transformation.

Shift Mindset

The shifting of UOBAM's employees' mindsets is a critical component in the drive to be a digital-first company. The firm has initiated several programs to help its employees make that transition, including a series of training initiatives and resources for employees to tap into.

Training for the acquisition of various data-related skills can be found in UOBAM's in-house learning portal, iAMdigital. The portal has various classes on programming languages, such as R, Python, and SQL, as well as tutorials for AI and ML. Employees also are equipped with access to a DataCamp and LinkedIn Learning account, which offer courses at various proficiency levels so employees can improve their data and digital skills.

These training programs not only have facilitated the strengthening of UOBAM employees' skill sets but also more importantly have shifted the mindset of its staff in confidently adopting technology in their daily working lives.

Key Takeaways

Initiating change is never an easy process, and that process is exponentially harder with a large organization.

Leadership style within UOBAM has also evolved into a transformational style of leadership. There is a strong mandate from upper management to integrate technology in the work processes.

Management has also realized that while work processes can be automated, human intelligence is still needed to ask questions, identify problems, think of possible answers, and create solutions. Training is constantly being developed to ensure that staff are up to date with technological knowledge. UOBAM's

CEO, Thio Boon Kiat, has been a champion of the organization adopting and utilizing technology to bring better value to customers.

Technology is becoming more ubiquitous and will permeate almost every industry in the near future. This coming decade will see AI and ML play a significant and fundamental role in finance, particularly in areas of asset allocation, risk management, fraud prevention, and process automation, among others.

The COVID-19 pandemic has illustrated that no industry is safe from uncertainty. The pandemic saw multitudes of job losses, companies winding down, and many more facing financial crises. The normal we once knew was obliterated in a short period of time.

UOBAM recognizes the need to embrace technology and use it to assist employees in being more efficient in their job scope and better decision makers. The recent successes of the projects involving AI and ML serve as a testament to this notion. Being a company that is entrenched in technology will allow UOBAM to be agile and act swiftly to counter uncertainty in whatever form it may come.

CHAPTER 3. THE INTERMEDIATE STAGE ON THE AI AND BIG DATA ADOPTION JOURNEY

There are clear distinctions between firms in the early and intermediate stages on the AI and big data adoption journey.

WHAT DEFINES INTERMEDIATE-STAGE FINANCIAL INSTITUTIONS ON THEIR AI AND BIG DATA JOURNEY?

If senior management plays the most important part in propelling a firm into the early stage, then both senior management and the innovation function leader are important for the successful transition to the intermediate stage.

For a firm entering the intermediate stage, the innovation function head, with the support of senior management, has usually assembled a group of capable team members, developed some processes that formalize the selection of projects with input from both investment and technology functions and, most importantly, delivered a number of successful projects that have improved some of the firm's investment and/or business processes.

Both senior management and the innovation function leader are important for the successful transition to the intermediate stage.

In the intermediate stage, firms will continue to build on their organization structure and processes so that they can continue to drive AI and big data adoption across their organizations.

WHAT SHOULD INTERMEDIATE-STAGE FIRMS FOCUS ON?

We do not get asked this question a lot, because the majority of firms in the industry have not gotten to this stage yet. Still, we feel it is important to describe what the future (i.e., intermediate stage and beyond) may look like so firms can develop their own strategy accordingly.

Most firms will spend an extended period in the intermediate stage (and for many of them, this could be the highest level they reach—more on that in the next chapter). It is in this period that the T-shaped teams truly shine. They grow together with the organization's efforts and, if they are successful, the organization's performance.

We find that successful intermediate-stage firms tend to focus on the following three aspects.

Building Out the Team

Intermediate-stage firms tend to have a more elaborate T-shaped team structure compared with early-stage firms. As the number of projects and areas that adopt AI and big data increases, the demands on the T-shaped team increase as well.

The more elaborate team is usually reflected in two aspects: roles and caliber of staff. More people will join the team, and with increasing scale, team members will play a more defined role. This growth process is very similar to what start-ups go through following the successful launch of their products.

Honing the Process

Teams at intermediate-stage firms generally have developed more elaborate and better-defined processes in selecting projects. There is far greater demand on the efficacy and efficiency of processes at this stage, as AI and big data applications will start to expand to more parts of the investment process and more teams across the organization. They will also start to expand into the middle-office and back-office operations. Hence, the demand on the process also multiplies.

Juggling Multiple Projects

The most obvious sign that a firm is in its intermediate stage of AI and big data adoption is that it has multiple projects across the organization. In this stage, there is increased organizational buy-in for AI and big data technologies. More departments will open themselves up and welcome the opportunity to collaborate with the new talents from the innovation and technology functions. There will also be more leeway to take on higher-impact but also higher-commitment projects.

TO CENTRALIZE OR NOT TO CENTRALIZE?

Should data scientists be centralized or join individual portfolio management teams? This question similarly applies to the innovation function. So, should financial institutions build one T-shaped team at the firm level, or should they build multiple T-shaped teams, each at the level of the smallest investment unit? A related question is whether financial institutions should build one T-shaped team at the headquarter level or at each division/regional subsidiary.

There are two ways to look at this question of centralization. The simple way is to look at the number of projects the firm is taking on at any one time. In the early stages, when the number is low, it is difficult to justify having a T-shaped team for every investment unit. It is also important to centralize the knowledge building at that point.

As the operation matures and the number of projects increases, it will start to make sense to add a limited number of individual technologists in investment units, as needed. This will most likely take place in the intermediate stage. The decision rule that we recommend using is to see whether the individual or the function in question has more interactions with others in the central team on a daily basis or with the individual team.

The situation may change from time to time, and the staffing arrangement can change, too. In general, as operations continue to mature, we do expect to see multiple T-shaped teams operating at different divisions/subsidiaries/regions of a large financial institution, particularly in the advanced stage.

In addition to the T-shaped teams in different subsidiaries/departments that operate in parallel, a more complicated structure is multiple T-shaped teams at different levels of the corporate structure with their own hierarchical relationships.[21] There is a central team at the corporate level that supports the main business lines with a core technology function and innovation function. And the "mothership" also arranges satellite teams to support some of the business units, as needed.

CASE STUDY: NN INVESTMENT PARTNERS AND THE T-SHAPED TEAM AT WORK

The case was prepared by X. (Tracy) Zhang and P. (Prasenjeet) Bhattacharya of NN Investment Partners and edited by Larry Cao, CFA.

Company Background

NN Investment Partners (also known as NN IP) is a Netherlands-based asset manager operating in 15 countries in Europe, Asia, and the Americas. A global active asset manager for institutional and wholesale investors, it manages €300 billion in assets for pension funds, insurers, family offices, independent financial advisers, banks, and private individuals.

NN IP offers a diverse range of funds within fixed-income, equity, multi-asset, and alternative investment strategies. Fixed-income strategies account for almost two-thirds of the firm's assets under management.

Investment Philosophy

NN IP believes that markets are complex and not fully rational. The market ecology has shown to be more complex in nature, and while the efficient market hypothesis (EMH) remains vital, there are pockets of opportunities for active asset managers to exploit inefficiencies driven by the complex and evolving environment. NN IP has adopted tenets of the adaptive market hypothesis (AMH) as a foundation of its investment philosophy. The AMH not only offers an extension of the EMH that integrates the benefits and tools of modern finance theory, but it also adds insights that allow one to look at the market as an evolving entity within a complex and adaptive system. NN IP complements and enriches its investment philosophy with the application of artificial intelligence, such as machine learning and NLP, as well as traditional and alternative structured and unstructured datasets. This helps the firm capture the fast and slow regime shifts, new drivers of factor premiums, and timely insights on economic activities and nonfinancial factors, such as ESG factors.

The Organizing Framework

The information and technological age has begun to dominate parts of NN IP's communication. This age, along with improved data storage, computing power,

[21]One of our contributors referred to this as the Russian doll of T-shaped teams.

and the rise of open-source licensing, is causing exponential advancement in the area of big data and AI technologies.

Using data in new ways is essentially about augmenting the firm's experience with data. It is achieved by using advanced algorithms to unearth new patterns and nonlinearities and by implementing behavioral insights when working with information. In order to identify and democratize access to the sources of alpha derived from ESG factors, big data, AI, and behavioral science, NN IP brings people with domain knowledge and technical expertise together to work around three core objectives.

The first core objective is related to data. Getting access to datasets, including new and alternative data sources that have potential to bring fresh insights to the investment function, is the crucial first step. This also means making sure that internally generated data are more readily available and are in an accessible format. Accessibility and usability of data allow for faster cross-fertilization of ideas and insights.

The second objective relates to the technological environment. Advancing technologies, such as AI, will be disruptive to the asset management industry. To that end, the innovation platform and investment team work together to build new data engineering and computing capabilities and new analytical competencies. A scalable tech environment that can handle structured and unstructured data is very important for AI/big data–related work.

The third objective is related to research and experimentation. To make sure NN IP is continuously learning and challenging existing processes, models, and techniques, it has taken a more strategic perspective on all the research efforts within the company. This allows the firm to focus and unlock knowledge in the areas of data, technology, and behavioral science. Moreover, experimenting with applications of emerging technology and working with new behavioral science hypotheses within investing are also crucial aspects to build organizational knowledge.

To keep up with the pace of advancement and leverage upon it, an effective change management process is also crucial for organizations to experiment with and adopt AI and big data in their investment decision-making processes.

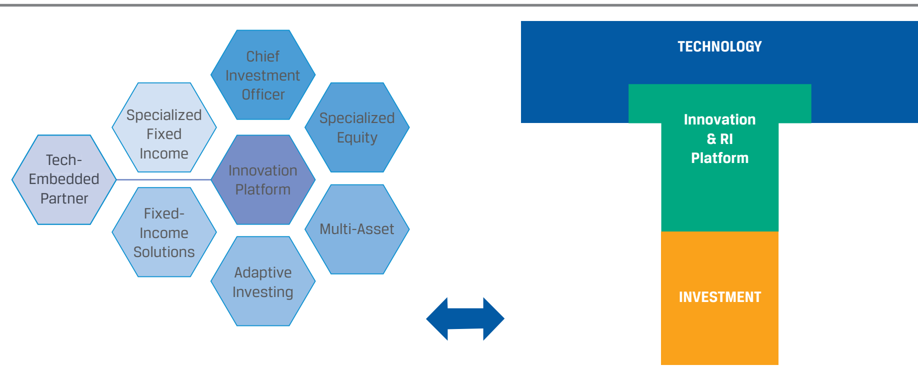
NN IP describes its way of working as inspired by the idea of working on the edge of chaos. That is, by combining the right level of chaos with structured checkpoints and methods, NN IP aims to control its innovation projects in the most efficient manner.

As part of NN IP's strategic direction, it reoriented the structure of its investment organization by placing ESG specialists and technologists (data scientists and engineers) in each investment team, as opposed to an earlier structure of a centralized team. This decentralization helped create both technological focus and ESG expertise within each investment team. It also accelerated the application of new data, technology, and research in investment processes. Another strategic step was to establish a centralized innovation and responsible investing (RI) platform. This way of structuring helped the firm build a T-shaped organization in its true sense. At the organization level, the innovation and RI platform is the linking pin between the technology and operations (Tech & Ops) department and the investment department (see **Figure 6**).

The Innovation Team

NN IP's innovation and RI platform sits in the middle of a beehive structure, which enables the investment teams to embrace responsible investing and new and

FIGURE 6. NN IP INVESTMENT TEAM STRUCTURE AND EMBODIMENT OF THE T-SHAPED STRUCTURE



emerging technology, understand the latest big data and alternative data trends, and think critically about their own investment decisions. The innovation team was created to bring people and technology together by inspiring, facilitating, and creating smart investment solutions for its clients and colleagues.

To provide and maintain an appropriate level of support across all investment functional areas, the innovation function is divided in two layers—the management team and the solution team—as shown in **Figure 7**.

The management team consists of senior managers from both the investment department and the Tech & Ops department, program managers, and subject matter experts of various investment strategies. This group of people operates across the functional area within the organization and serves as a center of excellence with a focus on the following:

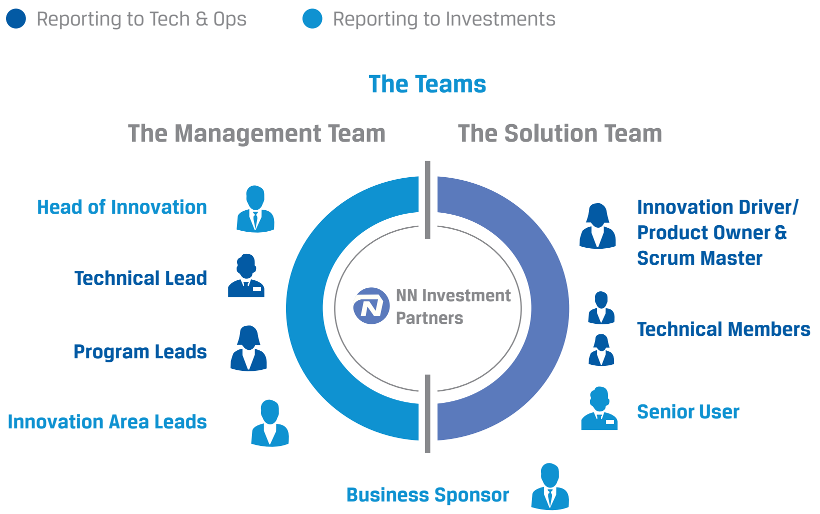
1. Providing thought leadership, vision, and direction
2. Establishing and maintaining the NN IP innovation ecosystem
3. Establishing best practices to adopt AI and big data
4. Overseeing all innovation programs/projects executed and assisted by the innovation platform
5. Supporting colleagues to gain either technical skills or investment skills through education and training

The solution team consists of innovation drivers and subject matter experts from both technology (e.g., data engineers, data scientists, software engineers) and investments (e.g., portfolio managers, analysts). The solution team works on various data, data science, and tooling-related projects.

Upon setting up the innovation team, it has been agreed with the CIO and the COO (chief operations officer) that the innovation team should consist of colleagues from both technology and operations, as well as investments, to bring combined domain knowledge to the table to develop the best solutions. In the management team, the head of innovation and innovation area leads come from the investment department, while the tech lead and program leads come from the Tech & Ops department. Similarly, in the solution team, innovation drivers and tech members come from Tech & Ops, while senior users are portfolio managers and analysts of different investment teams, who are responsible for bringing the business perspective to the projects.

The innovation team in itself is a T-shaped team that combines different skills, including domain, innovation, and technology expertise. **Table 2** highlights how the team members of the innovation and RI platform represent the skills in accordance with the T-shaped skills spectrum. The innovation team brings in deep knowledge about the investment domain, data science, and technology infrastructure to build scalable solutions. Combined with NN IP's way of working based on design thinking, lean start-up, and agile methods, this provides just enough structure to be focused on business value while allowing for creativity and adaptiveness. This combination of

FIGURE 7. INNOVATION FUNCTION



Source: NN Investment Partners.

TABLE 2. THE T-SHAPED INNOVATION AND RI PLATFORM

	Technical Skills	Innovation Skills	Investment Skills
Tech & Ops Department	• Software Engineers • Data Engineers & Scientists • Scrum Masters		
Innovation Platform	• Technical Lead • Technical Members	• Program Leads • Innovation Drivers	• Head of Innovation • Innovation Area Leads
Investment Team	• Quantitative Researchers		• Head of Investment Team • Portfolio Managers • Analysts & Strategists • Economists

skills helps connect the investment and technology functions of the company efficiently. The T-shaped innovation and RI platform focuses on inspiring new ideas, facilitating cross-team projects, and creating innovative solutions to enable NN IP to adopt AI and big data in its investment processes at scale.

Roles and Responsibilities

The head of innovation and RI is part of the investment management team and is responsible for the overall innovation portfolio and responsible investing. The technical lead brings a wealth of technical knowledge and expertise in managing the technical team. The technical lead has the technical knowledge of the solution and is able to identify potential technological gaps and risks in the solution. Along with the innovation area leads, the technical lead guides the product backlog prioritization and actively participates in the definition of the new innovation product strategy with the product owner.

In order to enable efficient collaboration and creation of practical yet innovative solutions, the innovation team works closely with an internal business sponsor. The business sponsor reports to the CIO and is a senior investment professional and head of an investment team. The business sponsor brings additional thought leadership and business perspective to the innovation function by covering the innovation project cost, bringing in insight specific to the investment process, and often providing resources from his or her team to jointly work on the project. Priorities within the innovation project are set by the executive sponsor.

To bring process innovation and practice leadership to the investment processes, the innovation area leads, program leads, and innovation drivers play a key role. An investment process has many components that are needed for an investment strategy to be successful. However, if one looks at a meta level, it takes only two inputs: information and experience with the information. The information could be about traditional indicators and financial factors or even big data factors. Experience refers to the understanding of the information and its application in making informed decisions. Here, AI and advanced analytics can help in augmenting human experience when engaging with traditional or new datasets. AI and machine learning techniques can identify the nonlinear relationships between the datasets and provide additional insights on the characteristics of the datasets. In order to integrate big data and advanced technology in investment processes, program leads and innovation area leads, such as the strategic R&D (research and development) lead and the investment science lead, bring their cross-functional skill in investment, technology, and innovation methods to identify the right approach to achieve investment process innovation with AI and big data.

The strategic R&D lead owns the research agenda of the investment engine, thereby having a complete overview of all the research activities. This helps in identifying areas of synergy within all the hives where big data and AI are being investigated. Since the collaboration between investment and data science functions is challenging, the R&D lead also leads the community of data scientists embedded in the hives to facilitate knowledge exchange in the areas of AI, machine learning, and big data and their applications in investing. The R&D lead's responsibility is not only coordinating the research agenda but also communicating the progress back to the C-suite and the management team of the investment function. More importantly, he or she leads the discussion around which competencies within AI adoption the company should focus on and prioritize. He or she is also responsible for getting the management team, data scientists, and data engineers to contribute to the discussion in a productive way. Thereafter, the R&D lead incorporates a cross-functional AI competency and is responsible for its overall success. In short, the R&D lead sets the strategic direction of the research activities around AI, machine learning, and big data adoption in investment processes, acts as a translator, and leads new AI competency development within the company.

The investment science lead manages the technical members, such as the data scientists and data engineers, of the innovation team. Jointly they focus on using AI, machine learning, and big data to develop novel investment solutions that investment professionals in the rest of the organization can use to improve their investment processes. These improvements typically come in the form of efficiency gains or enhanced alpha potential. Being part of the innovation and RI platform, special attention is given to responsible investing-related opportunities, which account for more than half of the investment science portfolio of innovation initiatives. Furthermore, he or she plays a crucial role in further scaling up the AI competencies prioritized as the strategic direction. He or she is also responsible for actively gathering insights from internal experiments and sharing these broadly with investment professionals, thereby inspiring them to adopt emerging technologies in their investment processes. More importantly, he or she also plays an important role as innovation ambassador, working together with other senior investment professionals in the sourcing of new ideas and distribution of the insights. The actionable and innovative solutions developed by the technical members of the team under the direction of the investment science lead enhance the investment processes of the teams by providing fresh insights on efficiency gains and alpha opportunities.

Both the innovation area leads are subject matter experts and thus function as knowledge engineers who bring in their investment expertise and insights on the emerging industry trends and translate these into action points that enable adoption of AI, machine learning, and big data in the investment processes.

Program leads are T-shaped professionals who have sufficient knowledge and understanding of both technology and investment. They are also experts in innovation methods and project management and work closely with the innovation area leads to ensure the function operates in an efficient and structured manner. They are responsible for managing and executing the specific elements within the innovation process. The program leads and the innovation area leads also actively engage in stakeholder management.

The Innovation Process

All big data and AI projects at NN IP follow the innovation process, which typically includes the following steps:

- Ideate
- Explore
- Experiment
- Execute
- Business-as-usual (BAU)

Figure 8 depicts this process.

Ideate

The amount of data and tooling in the industry is huge, growing, and mostly too immature to directly embed in investment processes. At the same time, many internal ideas and initiatives are somewhat fragmented and not yet aligned with the strategy. Ideation happens mostly within the investment hives themselves, where portfolio managers and analysts, together with technologists in the teams, sketch an investment idea or define an investment challenge. Such an idea or challenge will be brought to and centralized with the program leads of the innovation platform.

Explore

The idea/challenge will be explored, a team formed, the vision and mission of the team defined, and the scope

FIGURE 8. THE NN IP INNOVATION PROCESS

set. These decisions are made within the management team of the innovation platform. Further, this phase will result in a set of assumptions about the investment idea/challenge faced by investment professionals and the opportunities for the innovation platform to address this challenge. It is then determined whether resources and expertise can be allocated to experiment with the idea.

Experiment

The goal is to find a solution that fits the problem. When developing new ideas, the solution team tries to find, via experiments, whether the solutions are feasible, desirable, and viable. Continuously checking with senior users whether the solution can actually solve their problem is key. Using the build–measure–learn approach and allowing to tweak, pivot, and kill solutions, the team can easily adapt the solution as necessary.

In this phase, the solution team starts with a proposition in the form of a prototype and will seek to further develop it into an MVP (minimum viable product).

Execute (Pilot, Implementation)

The pilot phase is a test phase and delivers a lot of lessons that are essential to implement innovation in practice. The solution team is running the MVP in a pilot environment to collect feedback from the investment professionals. Before starting the pilot, the team creates success criteria, which need to be met in order to develop the product/algorithm further after the pilot. After the pilot, the team can further develop the project based on the feedback of the users. During the implementation phase, the product/algorithm is integrated into the business operations of NN IP. By making products fit the requirements of the ongoing business, the implementation is streamlined. During this phase, the innovation platform is still in the lead of the project.

Business-as-Usual

After the solution has been implemented, the project can no longer be seen as an innovation platform project. Depending on the nature of the project, it is handed over to either the investment or technology function.

The Stage-Gate Process

To keep a fast pace and a short time to market, NN IP works with a stage-gate process. A stage-gate is a meeting with the team and decision makers and is used to "unlock" the gate to the next stage. The stage-gate is used for three purposes:

1. Fail fast, following the agile innovation approach. This way, the team keeps up its fast pace.
2. Create transparent decision making by clear agreement of "definition of done" with the innovation platform and users.
3. Prioritize through scarcity; this will breed creativity and better results. This means that along the way, the firm explores/experiments with many ideas while only the strongest will follow through to the phase in/out stages.

During a stage-gate, an innovation team presents its innovative project to the leadership team and the business sponsor. After the presentation, the panel is able to ask questions about the project and decide whether the project receives a "go" to the next stage or a "no go." Stage-gates are organized with a certain frequency.

Impact of Innovation Process: Enhancing Existing Processes

The team has identified opportunities across the organization where AI and big data technologies can be used to improve current investment processes or develop new methods. Below are a couple of examples where the objective was primarily to enhance existing processes.

Scout

The idea originated out of a separate study of anomalies. Whenever an algorithm points to anomalies, it is not clear what exactly the firm is dealing with. It can be a data problem, something naturally fat-tailed, or it can be an interesting investment case. To figure this out, the firm needs input from an expert. On top of the algorithm on anomaly detection, the innovation platform developed a front-end process that enables analysts to inspect the latest batch of (securities) candidates and supply their opinion. To decrease overload, security characteristics that may be driving the candidacy are highlighted. In addition, analysts do not need to go through thousands of securities. Selection logic by the analysts is then imprinted in the model to improve the candidate generation process.

ImpuNet

In the world of financial data science, a good data source without missing values is an exception rather than a rule. This is especially the case within alternative data and unstructured data. The NN IP team proposed a new algorithm for estimating missing values, which is based on the idea of denoising autoencoders. Autoencoders are a family of unsupervised techniques in machine learning based on neural networks. In general, an autoencoder aims to learn the underlying structure of the dataset (e.g., relationship between features) without assuming simple linearity. Depending on the exact architecture, an autoencoder can, for instance, convert a big set of (potentially correlated) characteristics into a smaller representation that still retains the bulk of information about the observation (think, for instance, of a data compression task). Another popular flavor of autoencoder, called a denoising autoencoder, can reconstruct the missing data with imputed values. The approach can benefit from accelerated computing and therefore scale better to large datasets with a lot of samples and/or features. Second, by applying a generative model to produce realistic missing value patterns during training, we can relax the assumption of randomness in data gaps and increase out-of-sample accuracy.

Impact of Innovation Process: Exploring Emerging Technology and Experimenting

Below are a couple of examples where the objective was primarily to develop capabilities that previously did not exist at NN IP.

Building NLP Competency to Unlock Value from Unstructured Text

Until recently, most decision makers primarily relied on structured and organized datasets to reach their decisions. This was mainly due to the difficulty in processing unstructured data to derive meaningful insights. With the recent acceleration in new technology and processing capacity, most organizations are embracing advanced technologies to engage with 80% of this bulk. And those who fail to invest in such tools and technologies will face the 80% blind spot while making crucial decisions.

NN IP is building its competency in NLP technology to manage and analyze such datasets in efficient and scalable ways. Such competency will transform NN IP's capabilities to translate the 80% blind spot to 80% fresh insight. The NLP competency is being executed by a cross-functional team involving technologists, subject matter experts, and five different investment teams.

Super Forecaster App

Human predictions are inherently noisy.[22] Some people overestimate while others underestimate the probability that some future event will happen. When aggregating a sufficiently large number of individual forecasts, these errors tend to cancel out. This phenomenon is called "the wisdom of the crowd."

By tracking individual forecasts, it is possible to identify the "superforecasters" in the group. By giving a greater weight to their forecasts, collective forecasts can be made even more accurate. Moreover, through training and feedback, individuals can improve their forecasting skills over time.

Applying these insights, NN IP has developed a novel "Super Forecasting" app. Using this app, the investment professionals at NN IP will be making regular forecasts about various market-relevant topics. Furthermore, users will receive feedback about their performance and learn how to become better forecasters over time. The forecasts that are harvested with this app will be used as inputs in the investment process of various NN IP teams.

[22]See, for example, Mellers, Stone, Murray, Minster, Rohrbaugh, Bishop, Chen, Baker, Hou, Horowitz, Ungar, and Tetlock (2015).

CHAPTER 4. THE ADVANCED STAGE ON THE AI AND BIG DATA ADOPTION JOURNEY

Understandably, the advanced stage of the journey is where we know the least, so we will be brief. Readers can probably find answers to their questions in the accompanying Man Group case.

WHAT DEFINES ADVANCED-STAGE FINANCIAL INSTITUTIONS ON THEIR AI AND BIG DATA JOURNEY?

The natural evolution from the intermediate stage to the advanced stage is that AI and big data technologies are truly integrated into the business processes throughout the organization, from front to middle to back office and from global headquarters to remote outposts in emerging markets. Strictly speaking, hardly any firm is in that "final" stage today and may not be any time soon. Still, some firms are closer to that stage than others.

Another characteristic that defines advanced-stage firms is advanced technology. We suspect only the winners of the industry can "advance" to this stage, which requires that they use technology that is superior to that of their peers.

WHAT SHOULD ADVANCED-STAGE FIRMS FOCUS ON?

In the advanced stage, the T-shaped team structure and processes will become business-as-usual.

The evolution of a T-shaped team over its life cycle is interesting. It was designed to tackle a particular and critical problem. In the early stage, the structure and process remain simple as the team tries to get the hang of it. The focus is on getting a small number of quick wins, where luck could be as important as the process. Both the structure and process play an important role in the intermediate stage as getting a significant number of projects right demands a level of sophistication far beyond serendipity. It is thus interesting that in this "final" stage, structure and process are no longer the focus.

There are two reasons for this change. One is that the structure and process by now are ingrained in everyone at the organization. The project teams have become the organization because this is how they operate. The other reason is that in this stage, talent has finally become more critical than the structure and process. This is competition at the highest level. A team cannot expect to win in the industry simply because it has set up the right T-shaped team and processes. All members of the team need to be the best at what they do and deliver solid results. It may feel like you have gone full circle and have ended up exactly where you started. But if you look under the hood, all the machinery is now new and ready to move forward at a much faster pace and in a more steady fashion. It's a brand new world.

It may feel like you have gone full circle and have ended up exactly where you started. But if you look under the hood, all the machinery is now new and ready to move forward at a much faster pace and in a more steady fashion. It's a brand new world.

CASE STUDY: T-SHAPED TEAMS AT MAN GROUP

Larry Cao, CFA, prepared this case. It was reviewed and approved by Man Group.

In Spring 2009, Anthony Ledford, then head of research at Man AHL, hired a person with a PhD in machine learning to join the team.

Hiring another person with a PhD was not unusual. Many employees in the firm's core investment, research, and technology functions had received PhDs in STEM (science, technology, engineering, and mathematics) disciplines. A few others had backgrounds in economics or finance. But none of them, at that time, came from ML.

The ML specialist hire was a significant event in hindsight: 2009 was several years before the branch of ML called "deep learning" revolutionized scientific applications (and the game of Go),[23] having been shunned by most ML researchers for at least a decade. Once that had happened, tech giants, such as Google, Facebook, and Microsoft, were all over deep learning and pretty much hired every ML specialist they could find. Still, the investment profession had yet to show any real interest in the subject at the time.

A mathematician by training who previously worked as an academic statistician, Ledford was intrigued by machine learning. He wanted to see whether these new techniques could be applied to financial data to enhance Man AHL's systematic investment programs. What he and his team found out remains relevant for professionals today looking to apply AI and big data in their respective investment processes.

One of the first ML projects Ledford's team worked on, in part to gain experience in applying ML to financial data, was building a prototype long/short trading signal using an established machine learning tool called a support vector machine (SVM). Although the team knew this problem domain well, they tasked the SVM with discovering the relationship between a set of data inputs (or *features*, in ML parlance) and a set of look-ahead price changes (the *targets*). Other choices of ML tool were possible, of course, but they had to start somewhere.

The result? The SVM "discovered" predictive relationships correlated with ones the Man AHL team already knew!

With the benefit of hindsight, this is not surprising. The SVM was simply capturing the relatively strong data patterns their non-ML models already exploited. The lesson learned: If you want to discover *new* relationships with ML, then you need to be able to either "steer" the search away from relationships you already know about or focus on different data.

Undeterred but with this acquired knowledge now part of the mix, the team later applied a different suite of ML tools to develop new long/short trading signals. This time, the results looked different from the signals Man AHL already traded, potentially providing useful diversification.

Looking back at that experience today, Ledford thought the team learned a lot from the process, developing a comfort with ML models and invaluable know-how about applying them. These were just the first pieces of the puzzle, with vastly more research and experimentation undertaken in the ensuing years as the team expanded. Man AHL's first ML models went live with client assets in 2014. Over time, its ML team has expanded, and a platform has been built that today not only supports Man AHL but also extends across the entire Man Group. Here is their story.

Introduction

Man Group is a global investment management firm headquartered in London with more than US$135 billion in assets under management as of 30 June 2021. Its various investment subsidiaries, including Man AHL and Man GLG, manage investments separately but share centralized infrastructure, including a common technology platform.

In this case, we examine the T-shaped teams at Man AHL, a systematic investment manager, and Man GLG, a discretionary investment manager. We include how they collaborate across functions to apply various AI and big data techniques in their respective investment processes and how the centralized Man data science team supports both operations.

Man AHL

As noted above, Man AHL has been experimenting with AI/ML techniques since as early as 2009. It currently applies AI/ML and big data techniques—including deep learning, Bayesian machine learning, pattern matching, reinforcement learning, and natural language processing (NLP)—in its client investment programs. It exploits a wide range of data sources and data types as inputs to these investment models, everything from traditional market-originating price and volume data to mall traffic, the latest consumer spending and web traffic trends, weather forecasts, and text-based articles, including company filings/announcements, commodity reports, and transcripts of interviews.

Man AHL's initial foray into ML applications provided an extremely important lesson: The tools themselves were rather powerful, but careful deployment was required if new effects were to be captured. While rediscovering what you already know provides reassurance, it does not provide diversification—the prize all quantitative (quant) trading researchers seek. Armed with that understanding, when Ledford and the team decided to give ML models another shot, they knew they had to find something genuinely diversifying. Either you tune the ML tools to avoid things you already know (e.g., by penalizing similarity to existing signals or neutralizing these in the underlying data) or you extend the range of features and targets that are searched over.

[23]See https://deepmind.com/research/case-studies/alphago-the-story-so-far#what_is_go_.

The ML model that later entered the client investment program went through the same rigorous testing process that all of Man AHL's prototype models pass through on their way to client investment, from internal peer review to test trading with the firm's own capital. The only difference was the number of checks. The ML model and the signals were significantly different from those Man AHL already had, so more checks were required. The model performed similarly in live trading as it did in paper trading, confirming the accuracy of the backtest assumptions, and it was eventually given the green light to enter client trading.

In retrospect, Ledford believed the original ML research modelling and the strong validation and test-trading process combined to produce a robust strategy. The firm was also well positioned when the ML model became eligible for the client portfolio in 2014, as Man AHL already had a client investment program with a mandate that sought diversifying strategies with low correlation with mainstream quant signals, which made it particularly suitable for ML strategies. The firm also had some good luck with timing, as the strategy generated positive returns soon after entering the client portfolio. Whatever the reason, the experience gave senior management the confidence to approve building out the ML team at Man AHL.

Building out the ML team started in earnest in 2015 and put Man AHL head to head with the tech giants in recruiting ML talent.

Team

Currently, the Man AHL core investment team is structured around three functions: research and investment, technology, and data implementation.

- Research and investment: responsible for investing and monitoring client portfolios as well as developing the models used in that process.

  This unit houses a number of separate groups alongside the ML team, including those focusing on volatility, credit, liquid strategies, macro, equities, and fast trading. It is very similar to what you see at a systematic investment operation. The "quants" (quantitative trading analysts) at Man AHL usually have advanced degrees or have conducted postdoctoral research in diverse areas, such as econometrics, mathematics, statistics, computer science/AI, or engineering.

  The vast majority of these team members came to Man AHL with practical experience in working with data. The skills are often acquired in the field, although outside of investments. Still, it usually takes a few years of on-the-job training at Man AHL before they become efficient in working with financial data. Ledford, now chief scientist at Man AHL, believes ML techniques are often misaligned with financial data due to such issues as low signal-to-noise ratios and the nonstationary relationships that are frequently found. To make ML work in investment typically requires much know-how and judgment that is not found in textbooks. This is consistent with what we discussed in the second hurdle of applying AI and big data in investments in "AI Pioneers in Investment Management" (CFA Institute 2019a, p. 14).

- Technology: responsible for maintaining the technology platform the team uses both to develop models and to manage investments.

  The technology function staff typically have advanced degrees in computer science, often from a research-leading university. Man AHL's technologists work closely with the research function to develop and maintain trading strategies in production, as well as the entire production estate, which allows efficient implementation and reliable execution of investment strategies. They also create research tools and frameworks to increase research velocity.

  Man AHL switched to using Python across the investment and technology functions in 2011, which significantly simplified the workflow across the firm. Prior to that, researchers used programming languages such as R and MATLAB while technologists implemented production systems in Java and C++. Ledford thought switching to Python was a fortunate choice, with benefits that were not anticipated or even on the radar back then. For example, the research and technology groups today work much more closely compared with the days of separate computing languages, and together they make up a more continuous research-to-technology spectrum than the distinct groups that existed before the move to Python.

- Data implementation: responsible for ensuring that the existing and new pipeline datasets needed are available and can be integrated into the platforms and workflows supporting the investment process.

  The function performs similar roles as the Man Group data science team, with a focus on ensuring compatibility with the Man AHL platform. For more detailed discussion on the specific roles and skills required for this function, please refer to the section titled "The Man Data Science Team and Other Centralized Resources."

From a standard T-shaped team perspective, the research and investment function just described matches closely with the standard investment function; the technology function and the data implementation function combined play the role of the standard technology function. It will become obvious from the research process discussion that follows how the role of the innovation function can be played by any team lead and researcher.

Ledford maintains that the distinction between the aforementioned functions is rather fluid at Man AHL and that all staff work closely, with some staff playing interchangeable roles across teams.

Research Process

> "We start with a large number of ideas, and we need to work out which of these has the potential to produce sustainable returns for our investors."
>
> —Man AHL

When it comes to investing, the devil is in the details. Successful investment teams largely follow the same principles—namely, a tested process for generating ideas and the ability to vet and prioritize them. In this section, we highlight how the research machinery at Man AHL operates.

Table 3 shows how the research process at Man AHL can be divided into four stages, with three milestones in between that separate them.

In Stage 1, researchers, including ML specialists, generate a myriad of ideas inspired by academic and industry research across different fields. The data science team will work with researchers in data acquisition where needs arise. Accurate and comprehensive data collection, usually performed automatically, is essential. The hypotheses are then put through paper trading/backtesting, a simulation process that helps reveal how each strategy would have performed through multiple market cycles.

To ensure that models are robust, researchers also perform sensitivity analysis and examine performance results in different historical environments. Milestone 1 reviewers help vet the strategy by looking through possible issues—for example, too much exposure to a region or industry or drawdowns or transaction costs that may be too high. If the risk-adjusted returns look promising (i.e., the signal is strong and consistent across in-sample and out-of-sample periods, risk

TABLE 3. THE RESEARCH PROCESS AT MAN AHL

Stage	Oversight
Stage 1: Idea generation and paper trading (backtesting)	
Milestone 1: Research Review	Two independent reviewers with appropriate expertise. Are research results strong enough to embark on production version?
Stage 2: Test trading—Implementation	
Milestone 2: Test-In Review	Same people from Research Review. Representatives from technology, risk, compliance, and trade execution. All checks to be passed before test trading starts.
Stage 3: Test trading—Conclusion	
Milestone 3: Test-Out Review	CIO, CRO/risk officer, CCO/compliance officer, technology, execution. Has the strategy performed as expected? Have all issues been resolved?
Stage 4: Client trading eligibility	Allocation of AUM within a suitable client program (typically relatively small proportion of risk budget initially).

maintains appropriate levels, and correlation with existing strategies suggests meaningful potential diversification), then a production version of the strategy is constructed and a review is organized to seek approval for test trading to begin.

Milestone 2, the test-in review, is an important milestone as it separates an investment strategy with production-standard implementation code from a research idea with backtest simulations. Because of its importance, this is where the entire multi-function team is set in motion. The strategy is reviewed from the validity of the hypothesis to the efficiency of its implementation. The technology team will review the code thoroughly to ensure it reflects what the researchers intended, is robustly implemented, and replicates the original research results. The chief risk officer (or risk team representative) will determine whether the strategy adheres to acceptable risk parameters. Compliance will make sure the strategy is consistent with all relevant rules. The execution team will offer its opinion on whether the strategy can potentially achieve results in live trading similar to those in paper trading. If the strategy receives everyone's endorsement, test trading can commence. At this stage, the firm's own funds are used (i.e., no client capital is placed at risk).

Once a suitable history of live trading experience has been built up, another review is called in order to establish whether the strategy can leave test trading (Milestone 3, the "test-out review") and should be made eligible for client investment. The duration of test trading is flexible; for example, if a strategy is notably different from existing strategies, then a longer period is merited, as was the case for the previously discussed ML strategy. Issues that arose during the test-trading period and how they were addressed are reviewed, and the realized profit and loss (P&L) is validated against the paper trading research P&L over the test-trading period.

Test-out review is the most important milestone in the chain because a strategy can benefit investors in Man AHL's programs only once it enters client trading. Participants for the test-out review are the same as those in the test-in review plus C-suite representatives. They need to be fully authorized to greenlight the strategy for client trading, a significant responsibility. The participants closely review the live trading results and make sure that they perform in line with those in paper trading. Inputs from the operation and execution teams are both essential. If all checks are met, a strategy will have finally reached the end zone, becoming eligible for client trading.

In Stage 4, portfolio managers and the CIO gradually allocate funds to the strategy while continuing to monitor its risk, return, and diversification performance. Responsibility for the ongoing monitoring of the strategy and its validation against paper trading is retained by the original research team, ensuring that the people who know the strategy the best keep their eyes on it. Periodic reviews of all strategies across the entire client trading portfolio are also undertaken.

That, in a nutshell, is the process of how an individual strategy goes from an idea to becoming part of the investment process. Although the CIO oversees the overall process supported by the investment, execution, risk, and compliance teams, there is a high degree of autonomy within the individual investment strategy R&D teams, each having its own specialist research and technology resources. And most initiatives remain "bottom-up" in their origin, with C-suites identifying longer-term opportunities and themes. Usually tens of strategies are being researched and tested at any point in time, and regular firm meetings are held in support of these processes. Project meetings, in contrast, take place frequently but only as needed; they do not follow a particular schedule. It usually takes several months for a strategy to migrate from initial research through test trading and into the client portfolio.

Ledford believes that a collaborative culture is also about carefully documenting research results, both those that work and those that do not, so that all teams can benefit from the research conducted previously and the lessons thereby learned.

Oxford-Man Institute of Quantitative Finance

> At the Oxford-Man Institute (OMI) we aim to do academically outstanding research that addresses the key problems facing the financial industry. We create new tools and methods that can give deeper insight into financial markets—how they behave, how they become stable or unstable and how to extract value from diverse data at scales beyond human [powers]. . . . We achieve this through a unique combination of academic innovation and external engagement.
>
> —Professor Stephen Roberts, OMI Director and Chair of Machine Learning, Department of Engineering Science, University of Oxford

In the spirit of collaborating with academia to generate interesting investment research ideas and techniques and to ensure a pipeline of suitably qualified PhD-level quantitative finance researchers for both the industry and academia, Man Group and the University of Oxford jointly founded the academically focused Oxford-Man Institute of Quantitative Finance in 2007. Since 2016, OMI's focus has been academic ML and data analytics research with applications to quantitative finance.

Academic research undertaken at OMI can include areas that at first may seem unrelated to investment—for example, techniques for supernova identification. However, even there Ledford and his team saw applications for stock picking.[24] The key, he said, is to identify problems of the same *shape*. The supernova application involved combining many conflicting views about whether an astronomical photograph showed a supernova or not, while the stock picking application involved combining many conflicting analyst recommendations about whether the price of a stock would go up or not. It is essentially the same ML problem but with different *features* and *targets*.

Indeed, understanding where and how ML has been successful in other application areas is something Ledford believes to be crucial for deploying ML in financial applications, as virtually no ML technique has its origins in finance. The other ingredients he noted that are needed for success are diversification within the areas of alpha drivers, modelling techniques, trading frequencies, and tradable instruments/markets.

Man GLG

Man GLG is the discretionary investment engine of Man Group. It has a long history of using AI and big data techniques in equity and credit strategies. The efforts became more deliberate after Paul Chambers, a nine-year veteran of the Man AHL equities team, was chosen to head the quant group at Man GLG in September 2019.

Team

The investment team at Man GLG is made up of (1) the discretionary portfolio managers (PMs) and their respective analyst team and (2) the quant team, which includes quant researchers and technologists. The quant team structure is similar to the Man AHL team described earlier. The discretionary PM teams each have a unique focus by region, industry, or style; each has its own dedicated analysts.

GLG was a discretionary firm set up in 1995 and acquired by Man Group in 2010. The discretionary team's composition and background have not changed very much. Roles are not much different from a typical discretionary investment manager: Analysts research companies, and portfolio managers make portfolio decisions.

The quant team's goal is to help discretionary managers make more money. In addition, quants trade some portfolios directly using their models.

In an interview with Chambers, he asserted that a ratio of 1:1 is an ideal mix of quant researchers and technologists, although, like Ledford, he maintained that the boundary between a quant researcher and a technologist is increasingly blurred. They share a similar interest in coding and generally come from a scientific field of investigation. Their industry backgrounds and experience levels may vary, from a freshly minted physics PhD to a veteran trader in exotic options, but by and large their purpose is to distil actionable insights from data.

Research Process

How do the two functions work together? There is no standard process for the teams to follow, but it generally takes place in one of two ways.

Portfolio managers often have specific hypotheses/intuitions that have not otherwise been scientifically researched. The quant team can potentially back up the theory, enhance it, or reject it—all with data. Portfolio managers at Man GLG now have access to a dashboard of insights as their theories get investigated so that they can put them into use.

Alternatively, quants regularly propose their own ideas to portfolio managers. The data they rely on can come from many sources, including external sources and internal data on the portfolio managers' behaviour.

Chambers put the mix of the these two approaches at about 50–50. He helps prioritize the quant projects, where necessary. Portfolio managers, in contrast, prioritize their own requests to the quants.

Both functions sit on the same floor; in fact, all staff on the Man AHL investment team sit on the same floor as well. Chambers stated that sharing research work and collaborating on research efforts across the engines are encouraged. The insights can usually be incorporated into the portfolios in different ways given

[24]See Bew, Harvey, Ledford, Radnor, and Sinclair (2019).

their different investment processes, but transparency of the research agenda helps everyone.

For example, a discretionary investor might use a signal based on real-time news to inform a decision on an individual stock. Conversely, a quant team might use the same data to trade all 3,000 stocks in an investment universe and profit from a very small expected payoff across many names.

The Man GLG team also works closely with the data science team. The Man GLG team may go to the data science team with a specific data source, where the latter will simply operate as a project manager working with all internal and external parties involved to acquire the data, bringing it in-house quickly. The Man GLG team may also request specific data that the data science team then needs to locate and vet the vendor. The most complicated request comes in the form of a question for which the data science team will need to research the issue involved and find the right data to explain it.

Chambers emphasized that how quickly an investment team can bring data on board matters in this day and age. Project turnaround time at Man GLG can now be as short as a matter of weeks rather than months. So, working closely with the data science team and collaborating with other investment engines all help in that regard.

When interviewed for this case, he commented,

> My view is that innovation—incorporating the latest data and analysis—is and always has been crucial to the success of any discretionary investment manager. That said, it requires a very significant investment and a particular set of expertise. The same can be said of systematic investors, who need to work harder and harder to maintain returns. We're fortunate that we have both disciplines under one roof at Man Group so we can leverage each other's skill sets. I don't believe incorporating the latest data techniques is optional; those firms that are not able to keep up are at risk of diminishing returns and eventual closure. I'd say that this view is fairly consistent across our teams and our clients.

The Man Data Science Team and Other Centralized Resources

As different investment engines within Man Group started increasing their exploration and application of big data in their respective investment processes, it became evident to Man Group's executive committee that a central function responsible for dealing with big data would be required—becoming a shared resource for the entire group. Theoretically, the signal generated with big data should be able to add value to investment processes at large, be it a systematic strategy or a discretionary strategy.

Team

The central function was created in early 2020, with a total of 8 staff members, and has now grown to an operation of 15 between Man Group's London and Boston offices. Its structure has now expanded to include the following four groups.

- Data sourcing and strategy

  Often called "data scouts," this sub-team manages the full data acquisition life cycle, which typically starts from a request by the investment managers to legal and compliance review. A typical day's schedule involves scouting for new data vendors, maintaining vendor relationships, and attending weekly and monthly meetings of the investment managers so as to understand their needs and help resolve data-related issues. This group is constantly plugged into the data community, bringing new and interesting datasets to the investment teams for evaluation.

  The background required varies, from business to technology and from finance to data science. The key is knowledge about the big data landscape, including data points and vendors out in the market, and an appreciation of how big data fits into the investment puzzle.

- Data scientist

  This is where the magic happens. The data scientists aim to turn raw, unstructured data into insights for investment teams. Big data is prone to having much noise and is challenging to handle. This sub-team's main challenge is to distil insights from the seemingly random piles of data that can be used by investment teams. The process is not much different from what the Man AHL researchers do, except the end result here is not to create a stock forecast or an investment decision but to communicate insights from the data that can be applicable for a quantitative researcher or portfolio manager. As such, the data scientists also need to work closely with the investment managers who are end users of their insights. In addition, the data scientists work with technology to introduce various analytical tools for the benefit of Man Group's investment teams.

Data scientists usually hold computer science PhDs or advanced degrees in similar subjects, such as statistics, science, or finance. Some are CFA charterholders. The key is their ability to program, preferably with Python, and the ability to work with "big data" (i.e., to be able to process unstructured and/or large volumes of data and be good "storytellers" of the data).

- Data science engineering

  These technologists are often trained in computer science, although a PhD is not always required. They are embedded within the Man data science function. They are responsible for supporting data scientists, and their main role is to build and maintain the data platform infrastructure so as to speed up the process of getting data to the investment managers.

  They are usually paired up with data scientists at a ratio of two data scientists to one data engineer. This is higher than otherwise seen in the industry because some of Man Group's data engineers work in the centralized group operations, which is outside of this team.

- Data management

  This sub-team is responsible for the production aspects of data that feed Man's investment models and portfolios. The team manages Man Group's central security master, responsible for data tagging and metadata, quality assurance, and data management tools. The background required for this group also varies; however, their ability to program, preferably with Python, is a key requirement.

Process

The data sourcing and strategy team meets monthly with all investment teams to review investment themes and related data requests. A governance committee manages the governance framework and ensures data compliance throughout the new data production pipeline.

The typical process begins with a proof of concept during which a trial agreement is generally required. During the trial phase, the data scientists work with the vendor to ingest, transform, curate, and visualize insights for the investment teams. Once proven, the team secures sign off from legal and compliance teams and signs commercial data license agreements with the vendor. Costs are shared among investment teams based on data usage.

Critical factors for the success of a central function are agility and visibility. Four cross-functional teams require constant communication. They engage daily in "cross-team standups," data discovery blogs, and monthly "data demos" to ensure transparency across the entire staff. Visibility is key to prioritization and agility. The central function continuously engages with investment teams to ensure they are aware of the successes and failures around the application of big data. In other words, "Everyone is in the know," as Hinesh Kalian, who leads the central Man data science team, explained in an interview.

Centralized Execution and Technology Functions

In addition to the data science team, Man Group also has centralized execution and technology functions. As is the usual practice in the investment industry, risk, compliance, legal, and other corporate functions are also centralized at Man Group. We provide here some important highlights of the centralized execution and technology functions.

In 2017, Man Group combined execution research, execution technology, and the trading teams from Man AHL, Man GLG, and Man Numeric. The combined team now serves the trade execution needs of all Man Group investment engines, encompassing its own research, technology, and trade execution functions. The execution researchers are similar to the quant researchers at Man AHL and Man GLG, but they also have an intimate knowledge of trading and exchanges. The majority of trading is fully automated today; however, the desk traders provide an indispensable role in cases where human skill still offers a material advantage (e.g., in markets with limited liquidity or where electronic execution is not available or well developed). The trading execution team ensures all trading is carried out efficiently and with adherence to best execution.

In addition to the technologists at each Man Group subsidiary and the data science team that manages the specific technology needs of the unit, a platform team focuses on the quant computing needs of the front office. Its remit covers the whole data engineering function and includes

- maintaining the databases and data platform tools used in research and trading;
- the computer infrastructure underpinning the trading systems;
- the high-performance computing clusters used for research and, in particular, a large Spark cluster used for data science and machine learning jobs; and

- the research and development tools used by quants and engineers across the Man Group business.

In addition, a centralized Man Group technology function houses teams that look after corporate IT needs. These needs include desktops; laptops; phones; all of the finance, project, and reporting tools; the order management and settlement systems; the investment book of record; databases; the data centres; and cloud-hosted services. An NLP platform was also made centrally available and is now managed by the Man Group technology team.

Key Takeaways

Design Your Own T-Shaped Team

The T-shaped team structure and process is a general model of organizational structure and process that emphasizes team objectives over function or individual objectives. To make it work in the most efficient manner, Man Group operates a somewhat different form from what is seen at a typical investment firm. It could do so for the following three reasons:

1. Historically, the Man AHL staff across the core investment, research, and technology functions have rather similar backgrounds, so the need for a rigorous T-shaped structure with distinct elements is not as strong when there is fluidity across functions with shared knowledge and skills.
2. The staff have become familiar with the research process, which has become more or less part of everyone's habit and flows very smoothly.
3. Most importantly, complementary to the first two reasons, Man Group has nurtured a culture of collaboration, transparency, and accountability that is ensured by the peer review process.

Break Down Silos

Silos can come in many shapes and forms, but they share one common unpleasant trait that does not help the team and, ultimately, the organization achieve their objectives. Different investment engines within the corporate structure or different functional departments within an investment engine can all easily become their own silos that put their own interests first.

Man Group has made a conscious effort to avoid the downside of silos by building teams. Putting professionals from multiple functions with distinct cultures and skill sets together in one team helps them collaborate more smoothly and effectively. The fluidity in the process helps enforce the team's interests and objectives.

Align Incentives

Teun Johnston, CEO of Man GLG, made a conscious decision to embed a quant team in the firm so that the incentives are aligned across the Man GLG team. Evaluation of both the discretionary portfolio managers and the quants is based more on the overall investment team performance and how each professional on the team aligns with the team objective.

It is not unusual for discretionary managers to have doubts about using AI and big data in their process, despite the fact that these techniques tend to add to their performance rather than detract from it (CFA Institute 2019b, p. 16). Overcoming these initial hurdles is obviously important. Shared goals and aligned incentives will go a long way in easing the portfolio managers' concerns.

Similarly, this speaks clearly to the notion that the quant team is part of the alpha generation process and an equal partner in this journey.

Hire ML Specialists

This is an important piece of the puzzle that may get overlooked. Many quants can do ML, but to operate at the highest level, the team still needs ML specialists.

ML has become such a distinct discipline that it is difficult for people without dedicated training and work experience to be able to deliver the best results. Despite the fluidity in its processes, Man Group placed high importance in the special skills that each professional brings to the team.

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